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Machine Learning for Critical Internet of Medical Things

Applications and Use Cases

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Preface

In Internet of Medical Things (IoMT), Internet of Things (IoT) is tightly integrated with medical devices, enabling comfort for patients, cost-effective medical support, strong and efficient treatment at medical centers, and better personalized care. The promise of IoT-based healthcare is explored further to theorize how IoT can increase access to preventative public health services and help us migrate from our existing secondary and tertiary healthcare systems to a more proactive, continuous, and integrated approach. The intersection of the Internet of Medical Things (IoMT) for patient monitoring and chronic care management and the use of artificial intelligence (AI) and machine learning are becoming more promising than ever as the adoption of telemedicine continues to grow dramatically. Connected devices generate huge volumes of data based on real-time measurements of patient vitals, which is delivered to cloud-based applications that are monitored by medical specialists in virtual contact centers. The policy is applied per patient, and healthcare providers receive warnings and messages when a patient's heart rate, oxygen level, glucose level, blood pressure, or other measurement reaches a set threshold. Depending on the sort of telemedicine and telehealth platforms in use, this data is tracked and acted upon by specialists who monitor many patients for many different practices, and in other circumstances, this data is sent directly to the provider. AI in healthcare, as well as other crucial technologies, is essential for resolving the issue and producing future prosperity.

The book discusses the applications, challenges, and future trends of machine learning in medical domain, including both basic and advanced topics. In addition, the book presents how machine learning is helpful in smooth conduction of administrative processes in hospitals, in treating infectious diseases, and in personalized medical treatments and shows how machine learning can also help make fast and more accurate disease diagnoses, easily identify patients, help in new types of therapies or treatments, model small-molecule drugs in pharmaceutical sector, and help with innovations via integrated technologies such as artificial intelligence as well as deep learning. This book illustrates advanced, innovative techniques, frameworks, concepts, and methodologies of machine learning that will enhance the efficiency and effectiveness of the healthcare system.

The primary objective of this book is to enlighten various machine learning / AI-based technologies in modern healthcare.

The book comprises 10 chapters diving deep into Internet of Medical Things in fusion with artificial intelligence. Chapter 1, titled "Applications of Cloud and IoT Technologies in Battling the COVID-19 Pandemic," discusses the applicability of cloud computing and IoT in battling COVID-19 and likewise presents cloud computing and IoT challenges and solutions in combating the pandemic. The chapter also proposes a framework of an intelligent cloud-IoT-based healthcare system for monitoring COVID-19 patients. And the proposed framework advises and alerts medical personnel in real time about the changing health condition of COVID-19 patients to suggest preventive measures in saving lives. Chapter 2, titled "Prediction and Forecasting of Coronaviruses Cases Using Artificial Intelligence Algorithm," proposes a framework for comprehensive investigation of COVID-19 medical dataset. Exploratory data analysis was done to visualize how this infectious disease affected most nations of the world. Facebook Prophet model was built for prediction of active, confirmed, dead, and recovered cases; the model performance was evaluated using R-Score, and the score showed active, confirmed, or dead; and recovered cases were 0.9999, 0.9999, 0.9999, and 0.9998, respectively. Chapter 3, titled "Classification of COVID-19 CT Scan Images Using Novel Tolerance Rough Set Approach," proposes a Novel Tolerance Rough Set Classification (NTRSC) approach to classify COVID and NON-COVID CT scan images. NTRSC approach uses similarity metrics to compute the similarity between feature values. Then, NTRSC is applied on the test images, which is compared with the lower approximation values. The proposed NTRSC approach is applied to predict the COVID and NON-COVID cases based on CT scan images. The outcome of the proposed algorithm produces a higher accuracy of 0.95%, 0.88%, 0.96%, and 0.93% for Gray-Level Co-occurrence Matrix (GLCM 0°, GLCM 45°, GLCM 90°, and GLCM 135°) features, respectively. The proposed classification approach experiment is compared to those of other methods, such as Decision Tree classifier, Random Forest Classifier, Naive Bayes Classifier, K-Nearest Neighbor, and Support Vector Machine, to infer that the proposed approach is a less expensive way to predict and make decisions about the disease. The results show that the strength of the proposed NTRSC approach outperforms the other approaches. Chapter 4, titled "Artificial Intelligence of Things for Early Detection of Cardiac Diseases," addresses the control of cardiovascular diseases with well-timed prognosis detection, remedy, and monitoring and proposes Artificial Intelligence of Things (AIoT) based framework for ECG and cardiac disorder recognition. Chapter 5, titled "AIIoT-Based Smart Framework for Screening Specific Learning Disabilities," proposes a novel framework to predict children with SLD. The proposed framework allows children with and without SLD to take a test like a quiz with schoolteachers' assistance. Chapter 6, titled "Novel Designs of Smart Healthcare Systems: Technologies, Architectures and Applications," discusses the latest technologies, architecture and applications, and novel design elements of smart healthcare systems in big data. Chapter 7, titled "Robotic Technology in the Development of Prosthesis," presents a brief analysis and study on how this robotic technology can bring development in the field of prosthesis design. The study also presents a traditional core component knee-ankle prosthesis (C3KAP), which meets the specifications of real safe ankle and knee but also provides considerably high torque and power output. Robotic knee prosthesis an implant cone, monitor the width of the limbs and the alignment between the ankle and the knee, has been further studied. Finally, the chapter analyzes how energy can be regenerated using a robotic prosthesis so that it could provide more output and work with longer with a battery alone. Chapter 8, titled “Let the Blind See: An AIIoT-Based Device for Real-Time Object Recognition with the Voice Conversion,” highlights an intelligent system that can give a blind person the ability to navigate in an unfamiliar environment, either internally or externally, by guiding them through sound. Chapter 9, titled “An Intelligent IoT Framework for Handling Multidimensional Data Generated by IoT Gadgets,” presents a smart IOT system to handle multidimensional data generated by IOT sensors. In addition, the model presented showed that the accuracy and speed of data handling are high when compared to traditional models as well as current models. Chapter 10, titled “AiIoMT: IoMT-Based System-Enabled Artificial Intelligence for Enhanced Smart Healthcare Systems,” proposes an AiIoMT-based framework for diagnosis and monitoring of patients in real time. The model was tested using cytology image dataset and evaluated based on accuracy, sensitivity, specificity, F-score, and precision. Results show a greater diagnosis accuracy of 99.5%, which proves that the AI model is a promising algorithm for the diagnosis of diseases in an IoMT-based system. The diagnosis, prediction, treatment, screening, and medication in the healthcare system have significantly improved with the continuing expansion in the methods, having seriously reduced human intervention in medical practice.

The book will be a strong reference for students, researchers, medical practitioners, healthcare professionals, and leading industrial units of IoT in healthcare to understand fundamental to advanced concepts of AI in healthcare, dive more into Internet of Medical Things, and foresee the futuristic technologies in Internet of Medical Things.

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Contents

Chapter 1
Application of Cloud and IoT Technologies in Battling the COVID-19 Pandemic

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1.1 Introduction

The fresh severe infectious coronavirus respiratory syndrome called (COVID-19) has caused the greatest global challenge in public health after the pandemic of the influenza outbreak of 1918. Coronavirus disease (COVID-19) transmission has prompted significant changes in the populations' behavior around the globe. The first case of the infection outbreak was discovered in Wuhan, China, in December 2019 and was triggered due to severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) virus [1–3]. As reported by the World Health Organization (WHO), there have been 30,949,804 confirmed cases and 959,116 deaths of COVID-19 globally, as of 4:30 pm CEST, 21 September 2020, affecting more than 180 countries, and because of the shocking rise of national spread, WHO proclaimed COVID-19 to be a pandemic. These made different countries' governments take immediate control actions since the nations' public healthcare sectors have been distressed. These include the heavily affected regions' segregation; the cross-border

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activity suspension among nations; the closure of colleges, offices, and public places; and the general population activities' restriction by advising them to remain at home full time. Social life and economics had been significantly affected due to these measures put in place.

The societies face different challenges from education, healthcare, production, supply management, travel, tourism, and service provision under existing circumstances and in the post-COVID-19 environment. By way of instance, the overpopulated number of hospitals and healthcare facilities due to the rapid rise in COVID-19 cases and the failure to provide emergency care to regular patients due to reduced mobility are significant obstacles to the battle of the COVID-19 pandemic in the healthcare industry. Likewise, disruptions and increased resource requirement for physical contact monitoring and limited availability of efficient and automatic contact tracking tools inhibit the spread control behavior [109]. Therefore, it is the multiple parties' responsibility to operate with their maximum ability to monitor the evolving COVID-19 condition, actors such as health employees, government officials, academics, engineers, technology operators, and the wider community. To defend and deal with the post-COVID-19 environment, digitalization and the implementation of telecommunications would be critical. Tools such as big data, 5G communication, Internet of Things (IoT), cloud infrastructure, artificial intelligence (AI), and blockchain play a crucial role in protecting and improving people and societies differently. Technologists and engineers would continue to face obstacles essential to incorporate and appreciate these optimized solutions. Their advantages carry out elaborate findings regarding risk management, resources, cost, scope, and quality.

In most cases, mobile device platforms rely on automated hospital control services that use automated technologies (e.g., ultrasound, MRI, endoscopes, electrocardiograms) and computerized patient information systems (e.g., Picture Archiving and Communication System (PACS), Organized System of Care (OSC), and Electronic Medical Record (EMR). Smart healthcare technology platforms have been created. As such, geographic borders have been overcome by the smart healthcare industry and transformed into digital hospitals aimed at all-inclusive patient care and the quality of high-level medical services. Different, Information and Communication Technology (ICT) medical, and big data innovations are developing various services in the smart healthcare field in conjunction with wearable medical device-based artificial intelligence technology. The paradigm of patient care is moving from hospital-based therapy to customer prevention. For instance, the quantified movements used to track and retain daily personal health information, including the volume of blood glucose, heart rate, electrocardiogram, and nutritional information collected by wearable sensor or healthcare apps, have been distributed. The smart healthcare industry is also widening its deployment to telemedicine, mobile wellness, Electronic Health Record (HER)/EMR/ Personal Health Record (PHR), cellular medical facilities, and targeted therapy through a mix of IoT technologies.

Globally, the coronavirus cases keep on increasing regardless of all measure practices to fight the outbreak. In recent times, IoT has gained a strong position in academia and business studies, particularly in healthcare. The IoT movement is reshaping contemporary healthcare environments by integrating technical, social, and economic viewpoints. It develops from traditional medical systems to more customized medical systems, where patients can be more seamlessly diagnosed, treated, and surveilled. With plentiful technology in fields such as healthcare, entertainment, transportation, retail, business, and emergency services control, wearable body sensor networks have transformed the power to modify our lifestyle. The combination of wireless sensors and sensor networks with simulation and intelligent systems research has resulted in the development of an interdisciplinary definition of ambient intelligence to address the challenges we encounter in our daily lives. Creating a reliable and efficient wearable system for monitoring throughout the COVID-19 outbreak is critical. In COVID-19 situation, an IoT-based cloud computing system can be employed to lower the possible spread of the pandemic using enabled/linked devices aimed at people for early diagnosis, monitoring during social distance, quarantine time, and after recovery.

The IoT healthcare system has become one of the most indispensable parts of human lives. This has dramatically increased the medical information system that brings about big data. Healthcare practitioners are already adopting wearable devices based on the IoT to streamline the diagnosis, monitoring, prediction, and treatment process. The healthcare system that depends on IoT assists individuals and aids their vital everyday life activities. The affordability and user-friendliness of the usage of IoT start revolutionizing healthcare services. In recent times, billions of sensors, devices, and vehicles have been connected through the Internet using IoT technologies. Remote patient monitoring is one such technology common for the diagnosis, treatment, and care of patients. For continuous health tracking, wireless sensor networks can be implemented to augment patients' well-being, make the healthcare system more effective, and respond quickly to emergencies.

In reality, more than a decade ago, the transformations given by the cloud computing paradigm created a rich situation for even deeper variations [4]. Data quickly became the most valuable commodity, with algorithms in AI and data science enabling new insights about practically everything. Also, the development of hardware has resulted in various autonomous and interconnected devices' growth [5, 6], giving birth to the age of the Internet of Things [7]. Ultimately, emerging technologies and paradigms support systematic and successful critical decision-making, impacting the industry, sports, research, and even how urban emergencies are identified. Increasing life expectancy levels have left many developing countries with an aging population in need of medical treatment at a period when personnel (healthcare staff, community care, and financial services) are being stretched to satisfy this rising need. This circumstance has driven many health providers to pursue more innovative and cost-effective solutions to address this increasing dilemma. Cloud infrastructure can create some of the technologies required to resolve these issues [8].

Hence, it is possible to take advantage of the latest technical arsenal to build a new wave of smart cities that would forecast epidemic occurrences more accurately, supporting their claim. It's not quick, and as cities become more and more integrated, many problems will still arise. However, the adverse effects of the COVID-19 illness can give this process the requisite improvement. The optimal identification of possible eruptions would take advantage of retrieved data from various sources. In reality, cities and their local and international supply chains, travel networks, airports, and communities, which may be causes of contagion, are constrained by this overall problem. In such situations, to provide comprehensive data, sensor locations, public agent networks, social media, and even individual devices should be incorporated [9]. Therefore, this paper discusses the applications, challenges, and solutions of cloud computing and IoT in battling the COVID-19 pandemic. The article also proposes a framework of an intelligent cloud-IoT-based healthcare system for monitoring COVID-19 patients.

The paper is structured as follows: Section 2 describes the applications of IoT to combat the COVID-19 outbreak. Section 3 addresses the significance of the cloud in fighting COVID-19. Section 4 describes the challenges of IoT-based and cloud computing technologies for fighting the COVID-19 outbreak. Section 5 presents the framework of an intelligent cloud-IoT-based monitoring system for combating the COVID-19 pandemic, while Sect. 6 discusses the practical applicability of the proposed framework. Finally, Section 7 concludes the paper and discusses future work.

1.2 Applications of Internet of Things in Battling the COVID-19 Pandemic

The healthcare system in developing nations is fast changing as life expectancy increased considerably throughout the 1990s [10]. Infectious illnesses are also placing increasing pressure on healthcare systems in these countries [11]. During the twentieth century, life expectancy in advanced countries increased by around 35%. As a result, the number of elderly people is fast increasing [10]. In addition, the spread of chronic diseases has put strain on healthcare systems in some nations due to a lack of financing [11]. As health systems deal with a wide range of symptoms and treatment options, rising infectious diseases and an aging population pose substantial obstacles. Despite the growing patient population, successful techniques have demonstrated in-house telemedicine services to avoid overburdening health infrastructure and lower healthcare expenses [12].

During the COVID-19 outbreak, digital telehealth plays a critical role. Patients communicate with doctors through a portal, and therapy is delivered remotely. The advantage of using a secure IoT system in COVID-19 is that the physicians do not examine the patients personally, preventing the virus from spreading [13]. In this moment of crisis, many countries have begun to use digital telemedicine. Patients receive IoT-based healthcare devices from HealthArc [14], and their data is regularly monitored by medical staff. The data is analyzed, and patients receive recommendations and medicines via their mobile phones or tablets. Among the main telehealth service providers are ContinuousCare [15] and Health net connect [16]. A person with COVID-19 symptoms can use a digital platform assessment tool, such as the “COVID-19 Gov PK” smartphone app [17], which is viewed remotely by physicians. Patients are guided in a timely manner, and this instrument has the potential to save many lives. It also minimizes the number of hospitalizations, readmissions, and the number of patients in hospitals, all of which assist COVID-19 patients to have a better quality of life and receive prompt treatment.

Ambulance medical personnel are frequently confronted with high-pressure, error-prone circumstances [18]. During the present COVID-19 epidemic, the situation for medical personnel dealing with COVID-19 patients has become even more tight and stressful. Remote medical specialists propose required steps to the medical team dealing with the patient in the ambulance using IoT-based ambulances, which is an effective option. As a result, the patient receives prompt attention and is effectively managed. The equipment that uses radio-frequency identification (RFID) is linked to a wireless local area network (WLAN). The relevant medical staff has remote access to the patient's information.

Telemedicine platforms are quite diverse, and most are built to address a single therapeutic goal, such as mobile heart monitoring and stroke rehabilitation [12]. This feature of telehealth systems makes them cost-effective and overburdens health institutions, but it also shows a weakness when patient numbers and disease types grow. The Internet of Things is capable of meeting the demand for more genericity and reliability. To be sure, the Internet of Things combines traditional medical equipment's efficiency and security with the traditional capacity for dynamics, genericity, and IoT scalability. It has the ability to solve the aging problem and terminal illnesses by handling millions of sensors and being broad enough to cope with multiple diseases that require exact diversified checking and action parameters.

The use of IoT in the field of transmissible disease epidemiology is still developing. Nonetheless, the pervasiveness of smart technology, as well as the increased dangers of transmittable disease brought about by global integration and global interconnectedness, necessitates its application in anticipating, preventing, and monitoring COVID-19 pandemics [19]. In several countries [19], web-based monitoring tools and disease intelligence tactics have lately appeared to promote risk management and early detection of epidemics. Despite this, there is a dearth of systematic application of accessible technology. Local health authorities would be able to increase efforts to diagnose, control, and avoid contagious diseases by using IoT-implemented medical care surveillance in a global healthcare system [20].

Using travel data, it may quickly diagnose infectious patients and correctly forecast the spread of an illness to other locations. Essentially, rather than locking down major cities, borders, and enterprises, an IoT-based observation network may aid in the rebuilding of an epidemic and the restoration of the source nation's economies. By including numerous facilities, apps, third-party APIs, and non-health-related mobile sensors, mobile connection in the context of mobile health (mhealth) will boost the efficiency of a medical care network [21]. Medical and security services observing operations, such as wearable IoT, provide for real-time safety monitoring and global health trends. Due to the near impossibility of tracking these enormous geographic regions or groups [22], such advances could close gaps in current monitoring methods. Such methods have been used in computer science and healthcare analysis, but they are relatively new in the epidemiology of transmittable diseases [23]. Despite the current global situation, smart sickness detection techniques based on the Internet of Things can considerably progress current pandemic response efforts.

IoT can minimize the spread of disease by simply gathering and reviewing previously collected data for a lot of the technology currently in place (i.e., Android phones, wearable devices, and Internet connectivity). The collective responsibility of IoT and connected emerging types of machinery could influence the first detection of outbursts and deter the circulation of COVID-19 if the data was enhanced and used. Smart IoT-based disease detection systems will include continuous communicating and recording, end-to-end networking and availability, data variety and review, tracing, and warnings, including choices for inaccessible healthcare support in China and other impacted countries to diagnose and control COVID-19 outbreaks. The heart of the IoT is an Internet-based network that grows and extends; the user side can be extended, thus enhancing the sharing of knowledge and contact between "people." IoT is the science of intelligent detection, location, tracking, and AI services for COVID-19 patients using RFID, Global Positioning Systems, various sensing instruments, information exchange, and community services. If we can go deeper into its work, it will undoubtedly yield unpredictable results.

RFID readers can be mounted on robots in the therapeutic work of stopping severe acute respiratory infections (SARIs), and UHF stickers can be read when a drug is inserted into the device to validate the delivery of drugs. This clinical program has gained valuable expertise. When a robot triggers its RFID reader, it can collect the necessary information and quantities of all the medications in a cabinet. A prescription can be delivered to the medical units correctly by precisely matching the drug information. In Danville, Pennsylvania, the United States, the Geisinger Medical Center has implemented integrated RFID robotics to guarantee that a drug is reliably administered to all operation units, with images sent immediately.

RFID technology can also be used to create a medical waste management network that can effectively control and track all COVID-19 medical waste processes, including generation, recycling, transportation, and treatment. Managing suspected patients is a complex problem. The explanation is that it is only possible to recognize those with fever or who've fallen sick. The other potential virus carriers aren't isolated and are the next wave of infection. Tell them to live in their own homes or to remain in the neighborhood to minimize personal transition. The recommendations suggest self-protection by ensuring good hand and mouth health, keeping healthy eating habits, and avoiding direct contact with those with respiratory illness symptoms (such as coughing and sneezing).

Nevertheless, this policy's impact is not understood, so there is little quality assurance. Therefore, there is an immediate need that IoT be implemented to handle this group of patients better. Compared to conventional medicine, IoT will track the suspicious patients' clinical and medical status during the process, illustrating the management benefits of offering customized treatment strategies for various individuals' classes. By utilizing wireless radar gadgets and modern IT, patients will benefit from medical services, thereby guaranteeing suspicious patients' health and preventing their relatives' infection. The expanded health-specific edition of the IoT [24] is applied to the present situation. It should build a digital forum to help people access sufficient treatment at home and establish a robust network for policy and community organizations.

Persons with minor symptoms may receive treatment and healthcare supplies (protective gloves, thermometers, drugs, POC COVID-19 supplies for treatment, and infection control). Inmates may upload their medical position to the IoT (medical cloud storing) portal online daily and pass their records to regional clinics, the

Centers for Disease Control and Prevention (CDC), and state and resident medical offices. Infirmaries might then suggest operational wellness sessions built on each patient's medical status. The régime (the CDC local and national medical offices) may distribute resources and establish isolation places (guesthouses or consolidated isolation amenities) appropriately. This will minimize national health expenses, alleviate the pressures of medical equipment shortages, and deliver a centralized framework that would tolerate the régime to track infection transmission effectively, administer materials efficiently, and enforce response strategies. Figure 1.1 displayed prospective applications of IoT to fight the COVID-19 pandemic.

Personal and clinical IoT-assisted equipment are divided into two categories [25]. These devices keep track of the user's heartbeat, exercise, sleep, nutrition, and weight. These are beneficial in the fight against COVID-19 because rest and sleep are important elements for patients with this condition. Sleeping well boosts the body's immune system's ability to combat the virus [26]. On the portals given by these gadget producers, the patient can view his reports and, if necessary, provide information to the relevant physicians. If particular algorithms are integrated into existing devices, IoT-based wearable gadgets can help to prevent the spread of coronavirus. Wearable gadgets send out real-time alerts if:

- The social distancing procedure has been broken.
- There is a COVID-19 patient in the neighborhood.
- The government has labeled the area a danger zone due to the coronavirus outbreak.

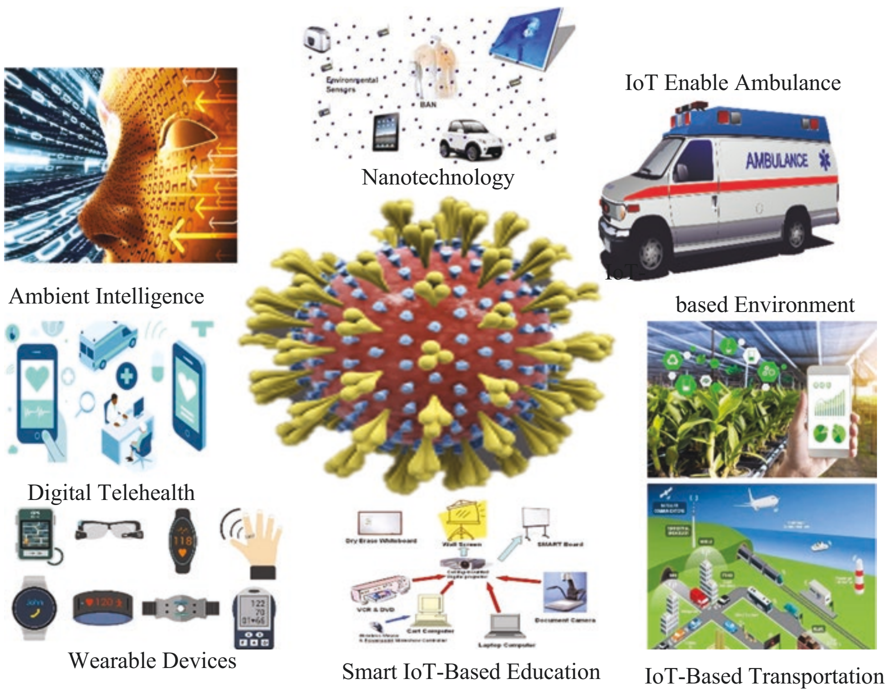

Fig. 1.1 Prospective applications of IoT to combat COVID-19

Many countries have installed autonomous human body temperature-sensing machines, which include a camera that is integrated with the sensor and delivers real-time data to a server. The system also uses artificial intelligence to recognize a face and compare it to a central database [27]. The usage of these gadgets aids in the tracking of COVID-19 patients. Enabling smart infrastructure that senses the environment and generates real-time reports for law enforcement agencies enforces social distancing [27]. Sensor data is continuously saved on an Internet database for continuous monitoring [28]. Hazardous gas or carbon content is reported to the environmental protection agency and updated on a server that may be accessed online [29]. Researchers are currently working on detecting the coronavirus, which can be used in the same way. Smart infrastructure solutions are provided by IBM, Microsoft, Huawei, and Cisco, among others [30].

Ideally, engineers and technicians would avoid warehouses, isolated locations, or busy places in travelling and visiting because they fear of being infected with the virus. Nevertheless, their physical appearance on site is needed because they can't get away with manually operating the equipment available. By using special sensors mounted in machinery and enhanced knowledge, real-world overlays, and remote expert feedback, IoT may help solve their repair problems and conduct machine operation remotely. AI may also anticipate when machines need repair (predictive maintenance) or when they might be faced with a challenge. In this way, physical visits will be significantly decreased, helping to safeguard workers' health and welfare, thus enhancing efficiencies at the facilities' level of service. When supermarkets continue imposing limits on sales of goods per customer, IoT and AI have also produced future alternatives. Smart shelves, smart fridges, video analytics, and an end-to-end integrated supply chain will help retailers deal with planning challenges and even reduce customers' extreme behavior due to hysteria.

A couple of years ago, a major US retail chain put IoT trackers in its trolleys to prevent daily theft. Perhaps it is time to start applying this to the store shelves of significant homes, sanitizers, and everything else that is already overselling in an attempt to control supplies and prevent hoarding behavior properly. Smartwatches and fitness trackers will be readily available in the not-too-distant future, and people with chronic conditions will be able to record temperature, asthma, and heartbeat without the use of intrusive instruments. For this fact, patients will be able to transmit real-time and past data to public or private hospitals anytime they feel unwell so that medical health IT departments will interact with patients' wearables and mobile devices. In this way, the treatment of coronavirus or other diseases may be prepared even more effectively and with minimal resources expended optimally. Smart connected medical devices, such as smart home ventilators, together with video and wearables, may support patients' monitoring at home, give updates to those in distress, or even alert when paramedics are required to come and move them to the hospital.

Ventilators are essential in treating people that have become contaminated. The health services have not been prepared to deal with this magnitude of a pandemic, and a resulting shortage is now widespread in only the most developed hospitals. An IoT 3D printing may be a lifesaver in the face of coronavirus-induced supply shortages, with an IoT 3D printer that offers critical medical equipment, for example, replacement valves. An Italian company called Isinnova does this, taking a 3D printer to a Milan hospital and manufacturing incomplete valves to be shipped to a hospital in Brescia, Northern Italy. Touch screens have been the chosen user interface (UI) until recently: tablets, computers, and even doors. Nonetheless, coronavirus being more quickly transmitted from a contaminated surface than by air has made direct contact sound risky. Many UIs that don't need any physical contact are also usable. Voice has already triumphed over tactile user interfaces, primarily through smart speakers and digital helpers. Despite people confining themselves inside the building, there will be increased interest in smart home apps and smart speakers' voice apps. Another functionality that gains ground in smartphones is beyond speech, biometrics, and their use for eye/face identification, such as facial picture identification to open phones or make payments. The most extensive penetration is in China, but the opportunity for the remaining part of the biosphere is enormous. Wearables, for instance, smart payment watches and other use cases (enabled by voice or close contact), can allow us to escape physical surface contact.

These technologies are now being implemented in major cities to reduce the pandemic. For example, for simultaneous tracking of COVID-19 inmates, the Shanghai Public Health Clinical Center utilizes physique fever monitors laterally utilizing facts transferred directly to the nurse post, thus minimizing possible sensitivity to healthcare workers [31]. Similarly, a device now used for medical interviews with sensors was installed in Boston to assess patients' breathing degree and physique fever. In Singapore, a contact-tracing mobile program utilizes Bluetooth wireless technologies to identify individuals similar to COVID-19 patients [32, 33]. Apple and Google are working on touch monitoring and detection software that will be made available to many countries worldwide that are intended to significantly step up the recognition that warns users who have been naively near to COVID-19 inmates. IoT won't solitarily combat the present pandemic but could also be used to deter potential outbreaks.

1.3 Applications of Cloud Computing in Fighting COVID-19 Pandemic

Cloud computing will play an essential part in absorbing healthcare transformation expenses, optimizing assets, and bringing the new age of technology to life. Emerging policies are targeted at obtaining data at any time and anywhere that can be achieved by transferring health data to the cloud. This contemporary distribution model will make healthcare more productive and operational and lower innovation expenditures [34]. Still, it also presents some obstacles due to issues regarding the security of sensitive health information and compliance with a specific criterion such as HIPAA. Healthcare providers, taking into account these security and privacy concerns, can unquestionably reap the benefits of cloud computing technologies and provide substantial benefits, such as expanding the eminence of service for patients and reducing healthcare spending [8].

Cloud computing's critical features are (1) self-service on demand, (2) wide grid access, (3) resource sharing with other occupants, (4) swift elasticity, and (5) calculated facilities. In complex resources, clouds offer benefits such as processing energy or storage abilities, universal access to resources from anywhere at any time, and high resource versatility and scalability. In several business fields, these advantages have been the purpose for the growing acceptance of cloud computing. This principle has also evidently been adopted in the area of healthcare in recent years. At least in the mainstream literature, it is provided by healthcare IT firms. Still, even in the systematic past, work done on cloud computing for healthcare applications is gaining interest; a continuously growing number of papers and books appear.

The capacity to share data between different systems would be one of the main advantages of cloud computing. This capacity is something that IT urgently needs for healthcare. For example, cloud computing can enable healthcare professionals to share data such as EHR, doctor's references, medications, insurance data, and research reports stored via various information systems. This is already happening in the radiological market. Many organizations have switched to the cloud to minimize their computing costs and promote the sharing of pictures [35]. Cloud computing has provided clinics, hospitals, insurance providers, pharmacies, and other healthcare companies the ability to agree to cooperate and exchange healthcare data to provide improved service quality and minimize costs. Looking at the industry developments, it seems that once all the obstacles it presents are resolved, cloud-based schemes will eventually turn out to be the standard in healthcare.

The healthcare system's ecosystem, which comprises health insurance providers, hospital and physician networks, laboratories, clinics, patients, and other institutions, is vast, diverse, and highly nuanced [36]. And all of these must operate under many government regulations [37]. Any sensitive details must be exchanged confidentially and safely between these agencies quickly and accurately to function efficiently and rapidly in this ecosystem. In the healthcare sector, protecting the patient's data is very sensitive to privacy issues. Possibly one of the reasons why the development of healthcare moving into the cloud has created negatively affected on medical privacy and security. Innovative technology and resources must be managed when it comes to cloud sharing. However, as they theoretically range between cities, states, and even nations, there are many other records, knowledge, and resources that can benefit from collaboration by cloud usage.

Private clouds tend to be deployed first because of security issues in the current scenario and then shift into public networks [36]. It may be a good idea to first set out the healthcare industry's top priorities and then analyze which cloud computing elements can be efficiently implemented to support them. The efficiency of services provided to patients and customers, privacy, data security and integrity, and catastrophe recovery seems to be at the forefront of today's rising global healthcare costs [37, 38]. Some of the inherent features can be leveraged to meet some of these objectives, such as flexible architecture, data centers for the provision of permanent data, protection models, and rapid access to information.

Cloud computing encourages IT facilities that are accessible from all locations and at all times [39]. It is a new mechanism, not a new technology, to deliver computing services [40]. Examples of nonmedical cloud services are Microsoft Office 365 and Google Docs, while examples of medical service apps are Microsoft HealthVault and Google Health platforms [41]. Compared to traditional computing, there are three significant enhancements provided by the cloud computing model: (1) computationally intensive solutions that are accessible on request, (2) service delivery without charge – customer upfront commitment requirements, and (3) flexibility for short-term use [42]. The cloud model has influenced many sectors, and it is estimated that approximately 80% of today's businesses will have embraced cloud computing by 2020 [35]. Companies that lack capital and infrastructure should also implement cloud computing to set up on-site applications [43]. Cloud computing, especially within the electronic health records (EHRs) field, transforms healthcare IT [44]. Cost minimization in IT investments will contribute to improved healthcare facilities [45–47]. It is estimated that drug costs can be decreased by 80%, and payment can be done within 2 hours for patients and insurance providers than up to 7 days with an implementation.

A cloud-based framework has been suggested to dynamically compute patient records with sensors attached to medical equipment to process data for collection, accessibility, and distribution. During the COVID-19 pandemic, this device can manually reduce typical errors or data collection errors manually [48, 49], not just simplifying the procedure but also increasing access to high-quality data [50]. By combining the ambulance services with patient records, the Greek National Health Service has built an emergency care program in the cloud, ensuring direct access for doctors while being willing to use all resources while maintaining low costs as much as possible [51].

In Australia, a partnership between Telstra and the Royal Australian College of General Practitioners (RACGP) suggested an e-health cloud [35]. This collaboration aims to develop diagnostic and response to medical software, medications, and training and referral facilities. Cloud processing technologies have provided successful support for bioinformatics research in the medical field [35, 52–55]. Although cloud computing has several value-added ideas driven by a novel paradigm of IT service distribution over the network, economic benefits appear to be the most significant factor in its popularity and widespread acceptance.

Lowering the cost of healthcare delivery is a significant catalyst for the implementation of cloud technology in healthcare. This expense has risen to such immense proportions that governments are facing severe problems with funding. The realization that patient care can be enhanced by technology while lowering costs has ensured that policymakers can drive the historically sluggish healthcare sector to a faster adoption rate. Big data development in healthcare is another significant factor [56, 57]. When the quantity of digital information grows, the capacity to manage this information is becoming an increasing challenge. This knowledge embraces the keys to future clinical developments but is also inaccessible to scientists. Cloud computing can be the supporting reason for large-scale knowledge exchange and convergence [58]. The paper [59] addresses high-performance computing (HPC) bioinformatics solutions, big data analysis paradigms for computational biology, and the challenges that are still accessible in the fields of healthcare.

In particular, the authors pointed out that, thanks to virtualization that prevents transferring too much big data, cloud computing solves big data management and analysis problems in many healthcare fields. Also, in the particular area of telemedicine, it is critical to have an infrastructure to support high-throughput, high-storage capacity and safe connectivity to allow effective management and automatic analysis of broader patient populations. Cloud computing can fulfil two criteria of horizontal scalability (i.e., the ability of a device to extend its resource pool for managing heavy loads efficiently) and spatial usability (i.e., capacity to retain performance, usefulness, or usefulness independent of local area concentration advancement to a more dispersed geographic pattern) [58]. In the medical imaging region, the amount of data can exceed petabytes thanks to high-resolution imaging instruments. It is also apparent that the cloud computing paradigm will render a significant benefit to addressing the computational needs relevant to medical image reconstruction and processing and facilitate the extensive exchange of digital images and also advanced control processing.

Cloud computing is a new and progressively evolving field of healthcare improvement. In combination with a pay-per-use model, universal, on-demand access to nearly limitless resources allows for new ways of creating, providing, and utilizing services. In an "omics setting," cloud computing is also used in genomics, proteomics, and molecular medicine computing. Medicine is a collaborative and highly data-intensive endeavor [60]. Advances in the omics fields produce large quantities of data to be processed and stored (genomics, proteomics, and the like).

The subordinate use of medical data with text or data mining techniques also implies an increasing request for complex, accessible services. These tools are also solitarily temporarily used so that stable infrastructure projects are challenging to justify and, alternatively, flexible on-demand services are pursued. Cloud computing seems to be a feasible alternative to meet these demands. Commercial providers such as Amazon and Microsoft pledge to make available hundreds of virtual machines at their fingertips, almost instantly, and only they're just wanted for the moment. The benefit of such deals is that they only have to be paid for the setup, scale, and period they are essentially used during these services.

Enormous medical costs and the maintenance of big data during the COVID-19 outbreak require technical advances so that at any time and everywhere, everybody has access to healthcare services. The development of technology has allowed telehealth to provide online healthcare facilities. For COVID-19 patients not permitted to travel, for villages in rural zones, and for individuals who do not have access to medical care, remote facilities help. Telemedicine uses include the transmission and storage of medical images, video conference patient counselling, continuing education, and facilities in the electronic healthcare field. Sadly, the use of telemedicine technology is hindered by technical and financial costs [61]. Studies have given cloud computing that offers, among other things, remote support capability; accessible, transparent resources; efficient, extensive Internet connectivity; scalable and resource pooling; robust medical data sharing and processing; and the sharing of big data patient records.

Many studies have found that inadequate patient information access explains most medical errors, especially during the COVID-19 pandemic [62]. The cloud-based medical system has been regarded as a possible system to increase openness and reduce the extent of medical errors during the COVID-19 period to correct health data [63, 64]. Many medical organizations have also chosen cloud storage to obtain and store comprehensive patient data and maintain their electronic health record systems. Electronic health records have evolved rapidly over the last decade, providing a gorgeous basis for data mining to recognize designs and styles in the big data industry in healthcare. Another common point for exchanging medical data is the interchange of electronic health records. By communicating a standard hub, these businesses facilitate healthcare sectors to transmit information rather than maintaining ties with many peer businesses [65].

Cloud computing also offers secure storage and sharing resources that can reduce local traffic to make organizations agile [66]. Lowering the cost needed for starting up automated medical records, which is lacking in many healthcare segment facilities, will improve the healthcare sector's efficiency [67]. During the COVID-19 pandemic, prescriptions and diagnoses, for instance, can be shared through the cloud over different systems. Therefore, for service enhancement and higher standards, hospitals and doctors exchange patient records. Electronic health record cloud storage's primary advantages are the capacity to exchange patient records with other specialists at home and overseas, the facility to pool data in one location, and the ability to access files anytime and anywhere. Electronic health record cloud computing enables patients to view, replicate, and transfer their secure health records [68]. Regardless of cloud computing influences to capture and store extensive health data, the prime problem is the failure of the network, protection, and privacy of patient information that users, hackers, malware, and so on are exploiting [69, 70].

Figure 1.2 displayed the applicability of cloud computing in fighting the COVID-19 pandemic. There is an increasing influx of people to urban areas today. Healthcare facilities are among the most critical characteristics that affect people arriving in city centers during the COVID-19 outbreak. Metropolises are therefore financing a digital transition to offer residents healthy environments [71]. On the other hand, because of its vast number, high speed, and remarkable variety, conventional models and methods for full conservational performance assessment are threatened by the advent of big data [72]. Also, because of their carbon emissions, traditional Information and Communication Technology (ICT) systems damage the atmosphere [73]. On the other hand, cloud services are a cost-effective medium for accommodating large-scale infrastructure systems that have gained considerable acceptance [31]. Therefore, the use of cloud computing is a significant phase in the green processing process that saves resources and protects the atmosphere. The use of sufficient equipment and cloud space saves the organization's resources and eliminates the costs of cooling systems, computers, and central servers. Nevertheless, cloud computing supports renewable computing with energy savings, rendering dangerous articles less harmful [74].

By using intelligent mobile computers, cloud computing has inspired healthcare specialists to observe patients' well-being at home remotely [75]. Also, IoT will build a network by leveraging integrated sensors to track the patient's real-time health status and control the treatment process. The IoT would also play an essential

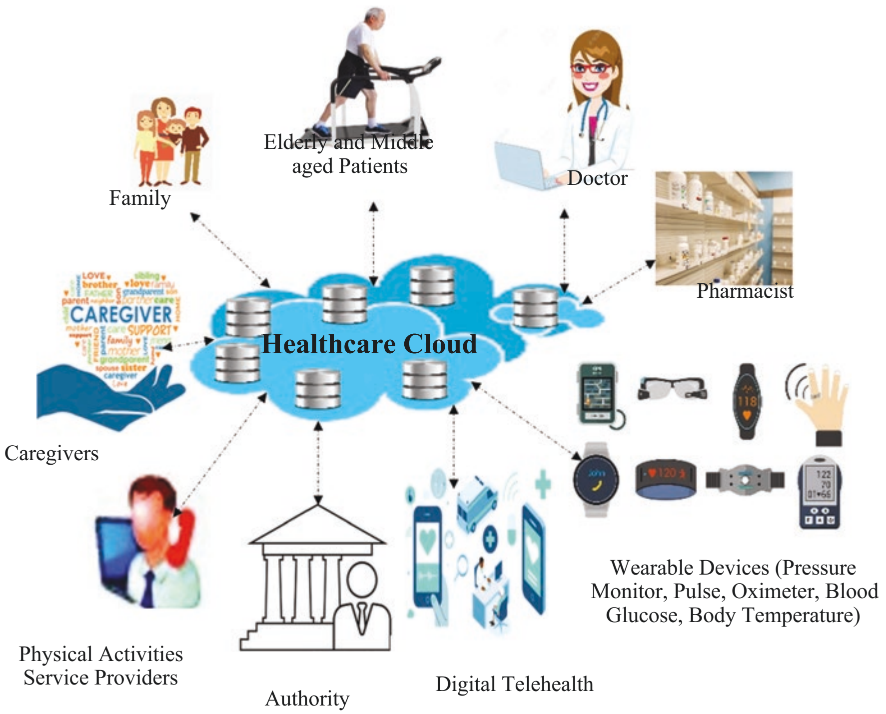

Fig. 1.2 Applications of cloud to battle the COVID-19 pandemic

role in the development of healthcare for the next generation. Although health monitoring systems for IoT-based patients are popular, observing them in outdoor hospital requirements increases the IoT's cloud computing capabilities for handling and storing health data [76].

1.4 Challenges of IoT-Based and Cloud Computing Technology in Fighting the COVID-19 Pandemic

The primary issue in using the Internet of Things in the current disease outbreak crisis of COVID-19 is the protection and safety of the data collected, special and crucial from the patient health perspective. The second problem involves taking precautions when implementing the data connection between the systems and protocols concerned. If the volume and variety of smart sensors that are integrated into IoT networks increase, the possible security hazard also increases. While IoT increases businesses' competitiveness and increases community life quality, IoT would also raise the potential attack surfaces for hacking and other cyber fraud. Hewlett Packard (2014) showed that 70% of the most widely deployed IoT systems contain significant defects. IoT systems have flaws caused by lack of transport encryption, unsafe network interfaces, computer security failure, and lack of authorization. On average, each computer contained 25 holes or the chance of breaching the network connection.

Usually, IoT computers aren't using data encryption methods. Any IoT technologies support critical utilities and strategic resources, like the smart grid and service security. Other IoT technologies will progressively produce large volumes of personal information on household, well-being, and financial situation that companies will exploit for their organizations. The failure of protection and privacy would build opposition to the IoT's acceptance by businesses and individuals. Security issues can be overcome by educating developers to integrate security technologies (e.g., intrusion detection mechanisms, firewalls) into applications and enabling consumers to use IoT security mechanisms installed into their smartphones.

IoT devices can offer a wide variety of IoT users' location and activity details, health status, and buying habits, which can give an upswing to main secrecy concerns as has been the practice for smart healthcare facilities and smart car rescue services. Protection of confidentiality is also counterproductive to facility providers in this case, as IoT-generated data is essential to enhancing people's health outcomes and reducing service providers' costs and improve efficiency processes. The IoT is necessary to promote people's standard of living. According to the 2014 TRUSTe Internet of Things Privacy Index, only 22% of cloud users believe that smart technology's advantages surpass any security issues [77, 78]. Although IoT began to build traction across smart home platforms and wearable devices, trust and adoption of IoT would rely on maintaining individuals' privacy.

IoT innovations (e.g., processors, sensors, cellular technologies) are emerging in an ultra-development period that is significantly longer than the traditional commercial product innovation process. There are already competing requirements, weak protection, privacy concerns, dynamic interactions, and an increasing range of poorly tested products. If not correctly built, multipurpose gadgets and interactive apps will turn our lives into confusion. In an unconnected universe, a minor mistake or failure may not pull down the system. Still, in a hyper-connected environment, a failure in one aspect of the system will cause disarray across the system. Smart home software and medical care and control module consist of integrated sensors, communication equipment, and regulators.

If the sensor of a medical surveillance and control device breaks down, the operator may obtain an erroneous response, which may turn lethal to the customer. It's not hard to picture smart home packages like thermostats and household power meters breaking down or malware attacking, causing unforeseen safety issues. Network connectivity can be overwhelmed with proliferating computer data traffic, causing system-wide latency issues. A single computer could have an irrelevant concern, but other linked devices' chain reactions may be catastrophic for the network as a whole. To avoid confusion in the hyper-connected IoT environment, companies need to make every attempt to reduce the sophistication of connected networks, increase the reliability and quality control of software, and ensure users' protection and privacy everywhere and anywhere on any platform.

The recent wave of digitizing patient records has contributed to a paradigm change in the healthcare sector. The sector is seeing a growth in the amount of data in terms of sophistication and heterogeneity. Big technology is emerging as a possible option with the potential to change the healthcare system. A paradigm change from reactive to positive healthcare will lead to a substantial reduction in medical expenses and potentially stimulate economic growth. As the health sector wields most big data, protection and privacy problems are becoming extremely valuable as new threats and vulnerabilities develop. Privacy and data protection should be thoroughly researched when dealing with health surveillance. Developers can help incorporate protection into computers, software, and programs [79]. As far as data exchange is concerned, designers should use a client-server model wherein the server transfers a certain sort of information with customers while holding other information covered by sufficient certificate [80].

With the emergence of these innovations, data protection has become a growing issue, primarily about the associated risks and misappropriation. A new field of information technology has arisen, called modern ethics [81]. This division of morals is the research of ethical issues related to data and knowledge, algorithms, and associated practices and infrastructures, defined in depth elsewhere [81]. Hospital and immigration must now be prepared to exchange vital statistics, such as data on a spike in the number of individuals with severe fever and individuals coming into or out of the country to the IoT system so that they can be tracked in real time. Also, all relevant systems, in particular edge servers and cloud networks with a 5G network, need to be deployed to ensure quick connection to all devices accessible by computer machines and the various layers of end users.

A more thorough analysis of the use of IoT in monitoring needs to be discussed and a more in-depth insight at the privacy issues that it poses. Event-based IoT detection gathers and transfers direct data from a wide variety of informal outlets (news stories, social media messages, Internet queries) to identify imminent outbreak incidents that propagate quicker than conventional, more restrictive approaches [82, 83]. This has contributed to advancements in infectious disease modelling and bacterium detection and diagnosis (immediate molecular recognition of microorganisms) [82, 83]. The deployment of robotics for this disease outbreak, racism, and secrecy is a crucial concern in using bots during the COVID-19 outbreak. The risk of making the wrong choice between clinicians and protecting the vast data gathered must be considered [84]. IoT is the innovation framework most probably to be used to handle the outbreak. Clinicians may use its facilities to detect their symptoms. It also tracks human health conditions. Most notably, it controls the diagnosis of cases by tracking the position of patients. Protection of collected data is the most critical problem with IoT deployment since data is distinct from one individual to another [85].

Getting a smart city can be immensely helpful in the battle against this disease outbreak by cooperation between healthcare facilities, communities, and various others [86]. The deployment of IoT-enabled smart city is among the most critical ways to react to the current epidemic. The IoT implementations mentioned above [87] highlight the significance of the smart city infrastructure idea as the globe is dealing with the COVID-19 outbreak. Data collection from smart sensors in IoT networks and the deployment of AI deployed at various locations (mostly airports and marketplaces) will help to tackle the present and future disease outbreak. Database distribution and method standardization will contribute to security and privacy concerns that need to be handled using acceptable protocols [88]. In short, the more smart city infrastructure interacts, the more easily the community can cope with such disease outbreaks [87]. Smart city technology will also help residents manage social distances by introducing transit system innovations, like crowd control, smart parking, and traffic redirecting [89].

Security issues, because the government has access to all the data needed to track the outbreak, is a key problem. In the long run, once the epidemic is over, what will be made with the data gathered from humans [90] must be decided. Since safety is the most significant thing for IoT devices to collect user data, considering paying officials may be essential for humans to enable the officials to control their details. Further studies on the use of IoT devices to provide reliable facts to avoid false news should be undertaken. They add to people's tension during an outbreak. Regarding the lockdown process, one of the biggest issues with self-quarantine is that the rate of respiration will deteriorate rapidly. Certain wearable systems introduced could be used for this function. For instance, chest braces with strain gauge sensors [31, 91], face masks with moisture sensors [92], and versatile patches with strain sensors [93] can be allocated for quarantine breathing surveillance. This innovation's reliability differs across smart devices, but it still has privacy concerns due to the unorganized collection of data from multiple devices. As a result of smart city, for example, handheld smart home applications will keep people from being contaminated throughout that outbreak. In general, the smart city idea may be a perfect weapon to battle COVID-19.

IoT sensors and systems produce large volumes of data that have to be analyzed and preserved. The data center's present design is not equipped to cope with the diverse existence and sheer amount of personal and business data [94]. Few organizations will spend enough on storage devices to store all the IoT data obtained from their platforms. Consequently, data for processes or replication would be prioritized based on needs and merit. Data centers would be more broadly spread to increase processing speed and responsiveness as IoT applications are becoming more broadly utilized and use more resources.

When more information is recorded for visualization and interpretation, the use of data mining techniques seems essential. Data consists of conventional discrete data and data streams generated from digital sensors in industrial machinery, vehicles, electrical meters, and crates. These data sets are about position, acceleration, sound, temperatures, moisture, and even chemical variations in the air. Data mining software may focus on corrective mechanisms to resolve urgent operating problems or notify management of results about competitive strategic steps and customer interest shifts that will affect their short-term and long-term market practices. Data needs to be tamed and interpreted using machine and computational methods. Conventional data mining methods are not explicitly relevant to unorganized multimedia content data. There is a lack of qualified data scientists in addition to the need for specialized data processing applications to extract streaming data from sensing devices and multimedia data. McKinsey Global Institute reports that the United States needs between 140,000 and 190,000 additional analytical expertise staff and 1.5 million analytical skills administrators and specialists to make strategic decisions focused on big data research [95].

The first concern is the security of data sent to the server. The HIPAA Protection Act, which provides a detailed list of security policies and guidelines and the applicable contractual requirements, must be enforced by the healthcare sector, including its network operators. Simultaneously, implementing the safety violation warning law for Health Information Technology for Economic and Clinical Health (HITECH) (together with associated enforcement and a significant number of safety violations affecting health data) has placed a heavy focus on maintaining the protection of medical information. One of the most critical and most tightly regulated health facilities' responsibilities is private patient data and medical information security.

Data protection is needed to secure data when it moves into or out of the server, making data obsolete if corrupted. It also requires reliable connectivity to interact, secure window access, and encoded data as it is transferred around the server and into the cloud. Conversely, the encryption process is very computed-intensive, relying on the advanced encryption protocol (AES) technique. This software-based cryptography method is centered on computed-intensive techniques that can influence the efficiency of the computer system, primarily when used ubiquitously to secure vast quantities of data that migrate to and from the server. Due to high-performance overheads, traditional encryption methods can create processing inefficiencies, rendering them less than optimal for securing cloud network capacity. Any application that utilizes OpenSSL will immediately enjoy the benefits of improvements on the Intel framework. Healthcare companies can efficiently use network infrastructure and provide widespread information security to and from the clouds without losing processing performance by accelerating encryption technology, secure session initiations, and bulk data transmission.

1.5 The Framework of an Intelligent Cloud-IoT-Based Monitoring System for Fighting COVID-19 Pandemic

The IoT-based healthcare system is the medical-care-precise variant of IoT that could be introduced to deliver remedy or cure to healthcare professionals and guarantee isolation compliance, which tracks disease sources [96]. With radars' assistance embedded in smart headsets, drones, robotics, and COVID-19, self-sampling experiments and data collection may be performed. The data obtained by these techniques would be forwarded for processing to a central cloud repository. The data created by such a system are provided to healthcare professionals, and government bodies are well prepared to respond to the COVID-19 tragedy. With these results, healthcare professionals will be able to offer more tailor-made electronic wellness appointments for patients. Such electronic facilities will also allow patients to seek more effective treatment while reducing their access and further spreading of the virus at the same time. Agency departments, together with resident public medical offices and the Centers for Disease Control and Prevention (CDC), will be well prepared to distribute resources, assess quarantine needs, track outbreaks, and use this information to enforce emergency plans [96].

The purpose of cloud-based healthcare systems has been sparked by the rising demand for remote patient management coupled with the cloud's storage capacity. Well-implemented surveillance systems have caused the incidence of COVID-19 cases to be minimized and minimize their side effects [97]. The patient and warden make advice about the vital indicators of their situation by multimedia due to patient monitoring's real-time function [98]. Versatile, actual, and hetero connectivity provides a platform for various innovations across the medical field to provide accessibility for participants [99]. This chapter proposes an intelligent cloud-IoT-based monitoring system for combating the COVID-19 outbreak globally. The proposed system allows the use of different wearable devices to monitor a person's health condition during the COVID-19 outbreak. The use of body temperature and pulse, for instance, helps to collect physiological signals. The sensor data collected from these wearable devices will be transferred directly to the cloud network to capture the data captured by these devices. Cloud technology was used due to the small computing power of the device node and storage and to avoid the use of a smart device as a processing device. The design process of the cloud-IoT-based monitoring system for COVID-19 is represented in Fig. 1.3.

The proposed architecture that can monitor people during the COVID-19 pandemic is based on the perceptions of cloud computing and IoT-based technology that accommodates several IoT devices, wearable body sensors or embedded WSNs, and artificial intelligence (AI). In the proposed model, IoT devices are used to collect and capture data and send them through their programmable devices, enabling them to examine the received data. Each device can be considered a diagnostic system due to its program using different machine learning techniques. The devices can be connected to the Internet through the IoT layer. The devices have no energy limitations compared with sensor networks. Hence, they are connected directly to the power. The AI methods become resourceful and paramount to achieve a suitable diagnosis system, and physicians monitor the systems. The systems can report any suspicious patient or person with COVID-19 symptoms to the related experts. As displayed in Fig. 1.3, the framework has three prominent layers.

The IoT-Based Wearable Devices

A wearable monitor and smartphone sensors are attached to the patient's body to gather clinical data. These sensors calculate vital signs, including inundation of blood oxygen, temperature, pulse rate, blood glucose, and SpO_2; a variety of healthcare sensors are available today [100, 101]. It is imperative to track these symptoms in the patient's body because any suspicious data may result in an infection [102]. For example, a decrease in the human body's oxygen level triggers sleep apnea, leading to death. Unusual blood pressure also causes kidney disease or diabetes; all

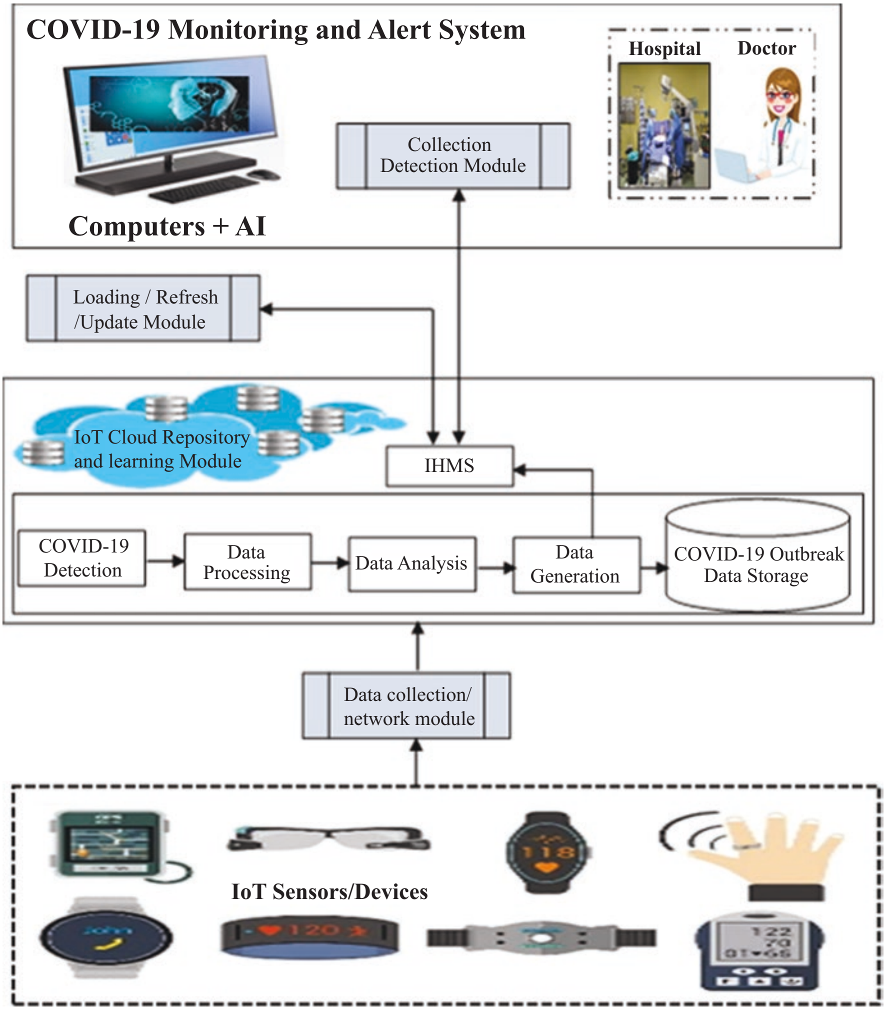

Fig. 1.3 The proposed cloud-IoT-based architecture for COVID-19 outbreak monitoring

these are symptoms of the COVID-19 outbreak, making them essential to monitor people during the COVID-19 outbreak. The sensitive data is transmitted through a Bluetooth connection to the person's mobile app and eventually to a database server. Also, devices can calculate and send data daily without patient intervention to automate it (IoT), thereby improving interface design efficiency and making it more convenient.

Cloud-IoT Based (Data Layer)

The cloud includes the location where information is deposited and processed on the network. Cloud allows patient data to be processed from their mobile over the network, and then, it is eligible for doctor assessments. Therefore, all document collection and handouts will be stored in the cloud for any condition identification in medical information. Thus, the irregular modifications in the patient data will be categorized dependent on patient condition and illness. All documents resulting will be either submitted to the patient and/or doctor's device or emergency room, or both will rely on the patient's condition. Therefore, the cloud-IoT-based monitoring system promotes cooperation and transmission of data through its platform that allows healthcare experts to store customer records, analysis, and diagnostics so that other specialists can automatically read the information around shared interests. It shows the patient records faster and real-time updates.

COVID-19 Outbreak Monitoring and Alert Platform (Hospital Layer)
This framework is the medium by which doctor and other experts track patients' information and sensory data. The physicians can review data from the cloud produced by the program, thereby taking immediate action. Information replication in this application in real time is done by deleting all information from the network server as soon as it arrives to ensure physicians are up to date with the patient's condition, and this helps paramedics take an immediate decision in the event of an emergency until the situation gets worse and avoid hospital admission. The other elements of a supported sensor network are mainly used to manage network pattern settings and connections between device stages and objects. Besides, domain-specific management inside the computer system is accessible in the software application to access and configure the device's similar activities, like active/inactive timestamps and sensing rate. Domain-specific management, therefore, works with both the public network to deploy sensor network configuration and new features and the part to inform/update network providers of the latest changes. Likewise, according to the services given, the data analysis aspect exists within the cloud server to handle data processing activities, such as statistical analysis.

Gateway
This component is responsible for communicating with IoT-based devices and patient devices to identify biological and physiological signs of a person and conduct primary data analysis. The result of this section is a description of the circumstances of patients sent to healthcare experts. Also, the framework can respond to signs of irregularity when it is identified, e.g., submitting a request for assistance (e.g., demand for an assistant care provider) or an urgent request (e.g., call for an ambulance) when an acute condition is detected.

1.6 Practical Case for Cloud-IoT-Based Monitoring System During the COVID-19 Pandemic

The primary essentials of this system's development and the proposed system's execution are discussed in this section, which aims to monitor vital signs for people at home and/or at work during the COVID-19 outbreak. Cloud-IoT-based monitoring system monitors patients' cognitive information like glucose, heart rate, temperature, and blood pressure chosen as these are some of the signs of COVID-19 patients. All information obtained will be transmitted from sensors to gateway and cloud-IoT server to scan for any anomaly or irregularity in the data recorded. Documents for the processing operation will be produced and submitted to the patient's physician and other bodies providing medical care (e.g., hospital) concerning data protection and confidentiality. The system's primary mission is to control physiological information gathered from the portable devices as per time and day, and signified data will be recorded and sent to be processed in the cloud server and ultimately accessed by official healthcare providers and physicians at any time through the dashboard of physicians.

When a link has been established on the cloud-IoT layer, a suitably equipped and validated IoT-based personalized healthcare model (IPHM) could be utilized to test, track, forecast, or evaluate any patient. This system also has an upgrade module that updates the local personalized healthcare model (LPHM) on the mobile phone automatically. In the event that the IPHM's Internet access is interrupted, the LPHM interface operates as the local intelligent device. To perform this switching, the system incorporates a link detection module that automatically detects whether the user's smartphone is connected to the network or not. This connection ensures a cloud-based architecture that is simple, reliable, and accurate for patient evaluation, tracking, forecasting, and treatment planning.

These devices have a remarkable impact on the prompt detection of the COVID-19 outbreak. For instance, IoT-wearable sensors can show any part of them that is not functioning well by capturing each patient's significant medical information. The results from these device users can notice any change in their health condition frequently and book an appointment with a physician before it is generated to actual disease or any symptoms appear [103]. It could be simpler to combat the COVID-19 outbreak by implementing IoT and smart wearables in the healthcare system. Also, remotely monitoring COVID-19 patients would be more convenient and reduce the number of patients admitted into hospital or isolation centers. The following are practical applications of the proposed framework.

For tracking purposes, the smartphone applications are empowered with IoT-based devices providing real-time information using Global Positioning System (GPS), geographic information system (GIS), etc. These have been extensively useful to intensify the chance of monitoring and detecting infected people [33, 104]. The implementation of smartphone applications with IoT-based platforms during the COVID-19 outbreak might benefit from getting a complete cloud service that can be tracked by health professionals and the government for the COVID-19 pandemic and allow the infected person to receive treatment from home. The online hospital and real-time health information can send their health-related records to the cloud using an IoT-based cloud database and receive guidance on fitness online from physicians physically present at the clinic. Treatment is being administered within this platform, and without expanding the contamination, the patient will be cured at home. The system is cost-effective when compared with physical appointments at hospitals and clinics. Reports obtained can be used by the government to make better decisions and action in future pandemics and will be able to manage the outbreak effectively [96].

A smart helmet with a thermal camera is an alternative suitable sensor when compared with the infrared thermometer gun due to its lower human interactions [105]. The image and location of the user's face are taken whenever an optical camera identifies the elevated temperature on a smart helmet and then sent to the assigned cloud-IoT database with an alarm. Then experts can differentiate the infected person and take necessary action immediately. The devices used allow physicians and other related officers to access facial recognition, temperature black spot viewing, and the user's knowledge in the crowds. The smart helmet has the storage capacity to keep all captured data within the helmet and thus serve as a backup for the cloud-IoT database [106]. Moreover, the smart helmet integrated Google Location, and its history can be used to identify the locations reached after discovering the infected human [107]. This wearable device has been used successfully in countries like Italy, the United Arab Emirates (UAE), and China to monitor crowds within two meters and has shown promising results [108]. For instance, a Chinese company produced a smart helmet called KC N901, which has a precision of 96% for elevated body temperature discovery and has been used by the countries mentioned above [109].

1.7 Conclusion and Future Directions

The global epidemic of COVID-19 has become the primary hub of scientific research. The new digital technologies will act as a perfect solution to this worldwide crisis. Cloud- and IoT-based monitoring systems can address detection, surveillance, mapping contacts, and controlling this viral infection. The introduction of cloud-IoT-based technologies to the present COVID-19 pandemic situation can build a social forum to help individuals access appropriate treatment at home and develop a robust repository on disease control for the government and healthcare organizations. The use of cloud-IoT-based healthcare devices can be used for diagnosis and obtaining data from a person with minor symptoms (preventive disguises, thermometers, medicines, personalized COVID-19 infection diagnosis, and control kits). Patients could submit their general well-being to the server clinical data storage online regularly and exchange their relevant data within hospitals, the Centers for Disease Control and Prevention (CDC), and national and local healthcare offices. Therefore, this chapter proposed an intelligent cloud-IoT-based monitoring system framework to fight the COVID-19 pandemic.

The chapter first presents the roles of IoT and cloud computing technologies in battling the COVID-19 outbreak. The framework can be used to obtain real-time data and information, which can be used by physicians and relevant experts in clinical sciences. The proposed framework is a platform that incorporates various IoT-based devices and includes generic on-board computational resources for detecting individual incidents, warnings, and interacting with numerous health information system providers. This is designed to provide enhanced supervision for patients during COVID-19, data collection in certain specific cases, and remote assessment for the patients. In the ongoing COVID-19 disease outbreak, IoT is offering so many innovative cloud-based facilities and infrastructure to more effectively support patients. During such a crucial period of lockout, the remote healthcare network has much sense. The system collects biomedical data from patients through smart technologies and transmits it to the cloud-IoT server to analyze and process the data. Thus, any identification of abnormality in patient information will be reported through the COVID-19 monitoring and alert platform to the patient's physicians. The cloud-IoT system has a treatable framework that can easily scale and extend, thus offering efficient, cost-effective applications for remote monitoring of the COVID-19 outbreak. Furthermore, the system's performance can make a positive contribution accurately to the improvement of medical care facilities using an impeccable device capable of tracking clinicians wirelessly and promptly. The system helps to control and manage people who are in remote areas for their medical needs. Future work will look into the security, privacy, confidentiality, and mobility control of the cloud-IoT-based system.

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Chapter 2
Prediction and Forecasting of Coronavirus Cases Using Artificial Intelligence Algorithm

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2.1 Introduction

The COVID-19 can spread complication before and after the onset, and it is extremely infectious. Monitoring and lockdown have to encompass anyone with symptoms and properly isolating persons who have been infected from those who are not, to allow good containment. Patients carrying the virus could either be minor symptomless (like fever, sore throat, and sneezing) or have serious clinical signs (such as respiratory failure, pneumonia, and eventually death) [1]. Transmittable SARS-CoV-2 condition is called "coronavirus disease" (COVID-19) [2]. Gratitude to the recent developments in analytical techniques of artificial intelligence (AI), information and communication technologies (ICTs), and big data will aid to manage the immense, unparalleled volume of data generated from patient monitoring, real-time tracking of disease outbreaks, now-casting/predicting patterns, daily briefings, and public updates [3]. According to the recent report, ages between 30 and

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79 years, approximately 86.60%, are susceptible to the COVID-19 pandemic of all patients infected so far and thus have a median age of 47 years [4].

The use of broad variety of advanced technology brought about the Internet of Things (IoT) that transform conventional objects into intelligent objects, from implanted devices and networking technologies to Internet protocols. In Gul et al. [52], the potential impact of IoT in driving the economic development of IoT-based services is expected to offer many business opportunities. Furthermore, industries like transport, agriculture, urban infrastructure, defense, and retail have an IoT market of approximately 15% overall. These estimates show the enormous and sharp progress of IoT products and produced data within a short period. In the years ahead, the estimated market share is expected to improve drastically. Kevin Ashton proposes the IoT for the first time in 1999, and many IoT methods have been created by various researchers, such as the Internet of Medical Things (IoMT), the Internet of People, the Internet of All, the Internet of Marks, the Internet of Info, and the Internet of Services [5, 6]. Therefore, the empirical investigation was done using artificial intelligence/machine learning (AI/ML) algorithm with the implementation of Plotly and Matplotlib visualization tool that may be used with Internet of Things (IoT) to support contact tracing that will be initiated in the future, and results showed the locations that are affected. This data-driven innovation can assist engineers, scientists, clinicians and healthcare experts around the world for deployment of vaccine, contact tracing, and curbing the spread of the coronavirus that is ravaging the whole world.

Artificial intelligence (AI) will create smart framework to automatically track and forecast the spreading of this outbreak [7–9]. A genetic algorithm may also be built to remove the visual characteristics of this infection. It has the potential to provide patients with daily alerts and also to offer better options for COVID-19 epidemic follow-up. AI can easily determine this virus' level of transmission by recognizing the fragments and "hot spots" and can effectively track the individuals' contacts and even monitor them. It can foresee the spread of the disease, its future path, and possibly its reoccurrence. These technologies can also monitor and predict the existence of the epidemic from the data, social media, and broadcasting channels present and the threats of the outbreak and its probable spreading. It can also forecast the number of useful cases and deaths in any area. AI will help recognize the areas, citizens, and communities most affected and take effective measures [10, 11].

Advent of coronavirus generated large amount of medical dataset that call for the adoption of machine learning (ML) techniques and applications as it enables computers to imitate and adapt humanlike behavior. ML techniques can interact with different applications to perform actions and produce something the system can learn and use as experience for the next action(s). The overview of analytics data method which enables computers to learn and do what comes naturally to human's mind was carried out. It includes machine learning's nomenclature and applications describing what, how, and why. The technology roadmap of machine learning was discussed to be understood and verified. The primary objective of the study was to give insight into why machine learning is the future [12, 13].

An empirical investigation was done using artificial intelligence/machine learning (AI/ML) with the implementation of Plotly and Matplotlib visualization tool that may be used with Internet of Things (IoT) to support contact tracing that will be initiated in the future, and results showed the locations that are affected. This data-driven innovation can assist engineers, scientists, clinicians, and healthcare experts around the world for deployment of vaccine, contact tracing, and curbing the spread of the coronavirus that is ravaging the whole world. The degrees of COVID-19 active cases vary in various countries of the world; Canada, Russia, the United States, and Brazil were among the countries of the world that have higher number of COVID-19 active cases, while Madagascar, Angola, and most of the African countries have low active cases. The extent of COVID-19 confirmed cases also varies in various countries of the world; Brazil, Canada, China, Russia, and the United States were among the countries with higher number of confirmed cases, while Angola, Libya, Madagascar, Zambia, and most of the African countries have low confirmed cases. The extent of COVID-19 death cases also varies in various countries of the world; like in other cases, Brazil, Canada, China, Russia, and the United States were among the countries of the world that have higher death cases. Many African countries on the other hand have very low death cases.

This may be due to the climatic and other environmental conditions in African. The extent of COVID-19 recovered cases also varies in various countries of the world as usual. Bolivia and Canada were among the countries with high recovery cases and very low recovery cases of COVID-19 in Algeria, Australia, Brazil, Kazakhstan, and Russia. The higher level of recovery cases in Bolivia, Canada, and few other countries may not be unconnected with the used and implemented contact tracing that might have reduced the spread. Most European countries implemented this at the early stage of the pandemic as a measure of curbing the spread. The forecasting results of active, confirmed, death, and recovered cases for the next 7 days were done using artificial intelligence/machine learning model built with Facebook Prophet. The evaluation of the model built for prediction and forecasting shows high degree of accuracy, having used three evaluation metrics to measure its performance. The model performance for forecasting model was evaluated using three performance metrics, the R-Score, mean square error, and absolute mean error. These evaluation metrics help to measure performance of univariance time series forecasting models in this AI/ML medical dataset study. The active, death, confirmed, and recovered cases forecasting models were evaluated. The evaluation results of the forecasting model showed R-Score of 0.9999, 0.9999, 0.9999, and 0.9998 and mean square error of 32950433.47, 43988753.26, 724820.40, and 43611232.23 for active, death, confirmed, and recovered cases, respectively, and, also, absolute mean error of 4229.98, 4776.94, 603.04, and 3814.23.

2.1.1 Organization of the Chapter

The organization of this chapter is as follows: Section 2.2 gives the detailed literature review of contract tracing during COVID-19; the dataset created during this pandemic was also reviewed. The AI and ML used during the COVID-19 pandemic were also reviewed. Section 2.3 discusses the methodology used in this chapter, the data collection, data preprocessing, explanatory data analysis, model building, prediction and forecasting of the dataset, and the performance evaluation. Section 2.4 contains the results and discussion. Section 2.5 is the conclusion of this the chapter.

2.1.2 Concept of Artificial Intelligence

Artificial intelligence (AI) is referred to the process of human intelligence simulation in machines that makes machine think, mimic human actions, and execute simple and complex tasks [14]. However, applications of AI are endless but are specifically more applicable to any machine that has traits associated with human being, such as problem-solving, reasoning, learning, and robotics. AI is evolving and beneficial to different industries, and its operations are guided by multidisciplinary approach like computer science, linguistics, mathematics, and psychology [15]. AI is an advancement of deep learning (DL) and machine learning (ML) and is creating a paradigm shift in virtually every sector of the technological industry today [14, 16].

The branch of AI that has a versatile and central role to play in the investigation of a global pandemic like COVID-19 and medical challenges generally is machine learning [17]. Data-driven innovation during pre-pandemic, pandemic, and post-pandemic period may be used by medical technologies and scientists to control the pandemic or cripple its spread. The far-reaching scientific discoveries and innovations in data science and AI/ML have the capacity to investigate the COVID-19 pandemic, put an end to its spread, and predict or forecast likely new cases or any related outbreak using the available medical data [18].

2.2 Literature Review

In December 2019, a series of atypical pneumonia cases occurred at Wuhan, Hubei, China, that were identified as coronavirus disease 2019 (COVID-19). It was first identified as a cluster of unknown patients with beta coronavirus pneumonia linked to the seafood wholesale market. It is a contagious respiratory and vascular disease and very infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) [19–21]. All evidence suggests that the coronavirus has already been actively disseminating some months earlier in Italy before it became a global problem [22]. On fifth March 2020, in China, about 80,000 people have been infected; this includes about 60,000 cases at Hubei province. After several confirmations of many cases from different countries, the World Health Organization (WHO) declared this epidemic to be a Public Health Emergency of International Concern on 31st January, 2002 [23].

The new disease was not comprehended well for a while. Although the previous studies have shown that the main symptoms are chest tightness, cough, diarrhea, difficulties in breathing, fever, and fatigue, the whole upper respiratory track symptoms are obstruction of the nasal passage, loss of taste and smell, sore throat, and running nose; for treatment and diagnosis of COVID-19, the symptom being some for the first 14 days of exposure to COVID-19, polymerase chain reaction (PCR) can be used to diagnose infectious person, the test identified by the genetic fingerprint [24–27]. There are numbers of ways by which COVID-19 spread, which primarily includes saliva, droplets of body fluid, and excretions that can make up small aerosols and droplets, which can also disperse through breathing, coughing, singing, speaking, or sneezing of an infected person(s). Coronavirus disease originated from bats, and it caused acute diarrhea syndrome in pigs in 2018, and it was learnt to have transmitted to bats, birds, camels, cats, humans, pigs, and rats [28, 29].

The suspected mode of transmissions of the virus is through direct physical contact with an infected person or contaminated surface [22]. Infection happens mainly when people are close to each other; it can spread within 2 days before infected persons can show symptoms and from asymptomatic individuals. Preventive measures cover sneezes and coughs, washing of hands, social distancing, quarantining, ventilation of indoor spaces, and sanitizing (alcoholic-based). Face shield used, face masks, or coverings have been recommended and established in public places like never before to minimize transmission risks. Three vaccines for the treatments of COVID-19 have just been found in a very limited quantity; they are Pfizer, Moderna, and AstraZeneca. These vaccines have national regulatory authorities but are yet to receive WHO approval, and there are plans to supply them to various countries of the world [30, 31], though there are other managements for the symptoms (experimental measures, isolation, and supportive care before and now) and control of the spread (contact tracing) that have been used before and now.

Some available contact tracing applications use the Internet of Things (IoT) which has greater capacity to monitor infectious pandemic, and it is a beneficial supplement to traditional surveillance system in data acquisition [32]. Coronavirus has become a pandemic, spreading all over the world. Engineers, scientists, and medical experts are working round the clock to develop the vaccine and kits for testing, enhance monitoring, and prevent the spread. Internet-based applications such as CoronaApp, StopCovid, and CovTracer have also been developed to monitor the coronavirus status of individuals with very little or no attention to possibilities of using IoT as many countries are yet to put in place IoT-enabled devices to operate that can be used to monitor and later curb the spreading of COVID-19. Some of these devices are designed either to sense and record and monitor and respond. The review of COVID-19 and IoT-related studies done in the research shows that much needs to be done to provide IoT-based architecture and monitoring techniques to curtail the disperse of coronavirus. The use of mobile phone and smart devices for healthcare delivery that have been impactful significantly to the world has potential technologies to deliver in this regard too; thus, the spread of COVID-19 can be curbed significantly and substantially to improve the healthcare sector through data-driven research that can be supported by IoT [28, 33].

There is a need to properly investigate any diagnosed and confirmed cases of coronavirus and all the previous contact traced so as to control the spread of the disease. According to the World Health Organization, the virus spread from infected persons to another primarily through droplet, discharge from the nose through contact transmission, or saliva [34]. To this end, contact tracing is an essential tool for the healthcare sector to control the COVID-19 transmission [35]. The contact tracing process which is to identify and yield people that are recently exposed to the infected coronavirus patient to limit further spread is done mostly through physical tracing and 14-day follow-up since the day of exposure to the infected person. If thoroughly employed, it can break the outsending chain of the current novel coronavirus and suppress the outbreak by giving a higher chance of adequate control and helping to reduce the pandemic magnitude, but the efficiency of the physical tracing and the stress involved is of high magnitude [18]. Most of the developed and developing countries of the world started employing digital applications for contact tracing and detection of coronavirus, most of which are digital applications and IoT-based. These applications include but not restricted to the Internet-based application, utilizing different technologies like Global Positioning System (GPS), Bluetooth, contact details, social graph, mobile tracking data, network-based API, system physical address, and card transaction data [18, 28].

The real-time digital contact tracing with the support of Internet of Things achieves better performance and more accuracy than non-digital process. All these digital apps are developed to collect individual personal data, which can be analyzed by AI and ML tools to trace a person who is vulnerable to the COVID-19 due to their recent contact. Access to these personal data can be achieved with the use of IoT, just as businesses around the world are adopting IoT as a means of enhancing business activities and provide security by extension. Medical field and health institutions have been adopting IoT technology for healthcare delivery; a relevant example is the use of IoT for contact tracing; about 36 countries of the world launched contact tracing application for COVID-19 in five continents. Details are presented in Table 2.1 [14]. Lalmuanawma et al. [18] presented 36 countries of the world who had successfully employed digital contact tracing techniques to manage the disperse of coronavirus by using decentralized or centralized techniques or hybrid of both techniques to lessen the effort and augment the effectiveness of both the orthodox and traditional healthcare diagnosis procedures. Table 2.1 shows the details of the continents, countries, contact tracing apps, and the dates that the applications were launched for the control of the spread of COVID-19.

2.2.1 Artificial Intelligence/Machine Learning and Coronavirus Pandemic

Artificial intelligence (AI) empowered machine learning (ML) to make clever machines that imitate brilliant conduct and support in dynamic with almost no human impedance. AI and machine learning are both extraordinary advanced tools

Table 2.1 Countries with COVID-19 contact tracing application

S/N	Continents	Country	Contact tracing app	Launch
1	Africa	Ghana	GH Covid-19 Tracker App	12th April 2020
2	Asia	Bahrain	BeAware Bahrain	31st March, 2020
3		India	Aarogya Setu	2nd April 2020
4		China	Conjunction with Alipay	Little information available
5		Cyprus	CovTracer	May 2020
6		Iran	Mask.ir	May 2020
7		Israel	HA Magen	March 2020
8		Jordan	AMAN App – Jordan	May 2020
9		Malaysia	MyTrace	3rd May 2020
10		Qatar	Ehteraz	May 2020
11		Singapore	TraceTogether	20th March 2020
12		Saudi Arabia	Corona Map	3rd April 2020
13		South Korea	Non-app-based	May 2020
14		United Arab Emirates	TraceCovid	May 2020
15	Australia/ Oceania	Australia	COVIDSafe	14th April 2020
16		New Zealand	NZ Covid Tracer	20th May 2020
17	Europe	Austria	Stopp Corona	March 2020
18		Bulgaria	ViruSafe	May 2020
19		Czech Republic	eRouska(sFacemask)	15th April 2020
20		Estonia	Estinia's App	April 2020
21		Finland	Ketju	May 2020
22		France	StopCovid	May 2020
23		Germany	CoronaApp	May 2020
24		Hungary	StopCovid	13th April 2020
25		Iceland	CoronaApp	April 2020
26		Ireland	HSE Covid-19 App	May 2020
27		Italy	Immuni	May 2020
28		Latvia	Apturi Covid	29th May 2020
29		North Macedonia	StopKorona	13th April 2020
30		Norway	Smittestopp	16th April 2020
31		Poland	ProteGO	May 2020
32		Switzerland	SwissCovid	20th May 2020
33		Turkey	Hayat Eve Sigar	April 2020
34		United Kingdom	NHS COVID-19 app	May 2020
35	South America	Colombia	CoronaApp	12th April 2020
36		Mexico	COVIDTracer	May 2020

that make significant additional intriguing use of suitable dataset and data science field in particular [16, 36]. Beyond COVID-19, AI/ML could be of help in predicting future pandemics, by the use of statistical-based means and converging with artificial intelligence and available data. This could position AI as a key enabler of medical transformation, from a reactive to a proactive system in the nearest future [37, 38]. This current global pandemic (COVID-19) makes the clinicians, healthcare, scientists, and other medical experts around the world keep on searching for a new technology to support in tackling the COVID-19 medical pandemic. The evidence of artificial intelligence (AI) and machine learning (ML) tools and the previous diseases encourage researchers around the world to investigate and develop application to the novel COVID-19 outbreak [18]. Table 2.2 summarizes some of AI/ML prediction studies available.

Table 2.2 AI/ML technology for prediction and forecasting of COVID-19

Author, year	AI/ML model	Data types	Predicted cases	Evaluation metrics	Results
Ribeiro et al. (2020) [42]	SVR and stacking-ensemble	Clinical data	Cumulative confirmed cases	The improvement index, symmetric mean absolute percentage error criteria, and absolute mean error	0.87%–3.51%
Gupta et al. (2020) [43]	SEIR model and regression model	Clinical data	Confirmed	Root mean squared log error	1.52 and 1.75
Khakharia et al. (2020) [44]	Autoregressive moving average (ARMA), XGBoost regressor (XGB)	Clinical data	Confirmed	Not stated	99.93%
Abdulmajeed et al. (2020) [45]	Combines an autoregressive integrated moving average model (ARIMA), a Holt-winters exponential smoothing model, and prophet – an additive regression model developed by Facebook	Clinical data		Not stated	Not stated

(continued)

Table 2.2 (continued)

Author, year	AI/ML model	Data types	Predicted cases	Evaluation metrics	Results
Santos (2020) [46]	Exponential smoothing model with multiplicative error and multiplicative trend components	Demographic and clinical data	Death	Not stated	Above 80% for the 10-day prediction
Yan et al. (2020) [47]	XGBoost classifier	Clinical and demographic data	Demographic, epidemiological, clinical, laboratory, and mortality outcome information	The mortality of individual patients	Accuracy was 90%
Siess (2020) [48]	SIR model	Medical data	Mortality	Not stated	75%
Ardabili et al. (2020) [49]	SIR and SEIR models	Medical data	Infection	Not stated	SEIR model
Chimmula and Zhang (2020) [50]	Deep learning network	Demographic and clinical data	The trends and possible stopping time of the current COVID-19 outbreak in Canada and around the world	Not stated	Not stated
Chakraborty and Ghosh (2020) [51]	Regression tree model and hybrid wavelet-autoregressive Integrated moving average model	Demographic and clinical data	New COVID-19 cases	Not stated	Not stated
Petropoulos and Makridakis (2020) [52]	Exponential smoothing model with multiplicative error and multiplicative trend components	Demographic and clinical data	Confirmed case	Information Criteria that measure the maximum likelihood of a model while penalizing for its complexity	Above 80% for the 10-day prediction
Anastassopoulou et al. (2020) [53]	Calibrating the parameters of the SIRD model	Clinical data	Forecast the evolution of the outbreak	Not stated	Not stated

So far, researchers use machine learning models to predict and forecast deaths and confirm survival/recovered cases of COVID-19 especially in a separate studies; there is no critical investigation of COVID-19 medical dataset across various countries of the world that has forecasted four different cases (active, confirmed, death, and recovered cases) of coronavirus at the same time with the same dataset using state-of-the-art techniques lying in AI/ML tools and visualizing the degrees of infection of the pandemic across various countries of the world. To address the concerns raised by the spread of COVID-19, this chapter proposed a comprehensive research framework responsible for the investigation of COVID-19 medical data across various countries of the world. The spread of coronavirus can be curtailed through a data-driven approach, but its contributions have not been impactful due to the lack of robust COVID-19 medical data which is also hindered by the requirement of data privacy, healthcare sector, and human-AI interaction. Massive diagnostic data gathering of infectious people and their contacts will be and essential AI-based solution to curtail economic loss and save lives. The proliferations of data on COVID-19 have cost the World Health Organization (WHO) a huge investment to collect data for predicting, forecasting, and monitoring of the coronavirus disease in order to ensure the curtailment of the disease [39, 40].

2.3 Methodology

This section provides method employed for the comprehensive investigation of the world COVID-19 medical data vis-à-vis artificial intelligence/machine learning (AI/ML) application in this chapter. The world COVID-19 investigation carried out in this chapter was an empirical investigation and experimental based. The outline of the methodology includes the experimental environment, data collection, data preprocessing, exploratory data analysis (EDA), building of model, prediction and forecasting, and evaluation of model.

2.3.1 Execution Environment

The execution environment was an HP Envy machine with 16 gb ram, 1 terabyte SSD 8th gen. The machine also has Python 3.8 installed; eight important Python libraries were imported for the experimentation. Matplotlib which is an Eastern Cooperative Oncology Group (ECOG) visualization tool that was designed by John Hunter to overcome the problem of single license of preoperatory software and can be used by multiple investigators was imported, as an important library for visualization. Pandas, Seaborn, Plotly, and other important libraries were also imported for model building, plotting of the graphs, performance evaluation of the model, and other experimentation purposes. Figure 2.1 reveals the details of the libraries imported for the prediction. This chapter also proposed framework for the prediction and forecasting investigation of COVID-19 that may be used for similar

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly
import plotly.express as px
import plotly.graph_objects as go
from fbprophet import Prophet
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
```

Fig. 2.1 Important libraries for the study. (Source: Authors)

infectious diseases; the proposed framework is shown in Fig. 2.2. The prediction and forecasting of infection across various countries of the world that were done through an empirical means in this chapter using suitable COVID-19 medical dataset which was sourced online and data wrangling which comprises of data preprocessing and cleaning were carried out. Prediction and forecasting as well as the visualization of the infectious area were anchored on the proposed framework depicted in Fig. 2.1. The model performance for prediction was evaluated using the R-Score, mean absolute error, and mean square error as the evaluation metrics. Four different cases were evaluated (active, death, confirmed, and recovered cases).

2.3.2 Data Collection

COVID-19 world medical dataset from reliable source was retrieved from [41]; the university has been providing quality data and other world-class educational resources for research around the world; the data was collected between January and May 2020, through the website of the National Centre for Disease Control of various countries. The dataset comprises the following features: province/states; country/region; lat; long; date; and confirmed, death, and recovered cases; this made it suitable for the studies compared to other available datasets. The population of the dataset stands at 172,481 people across various countries of the world within the period under review.

2.3.3 Data Preprocessing

The data preprocessing and data wrangling of the COVID-19 medical data retrieved have some features like date, which was converted from object format to date-time format to make the code and to recognize it as date feature. This is necessary in the forecasting and exploratory data analysis during the investigation. The dataset was sorted to make the latest cases appeared first and later grouped by countries in

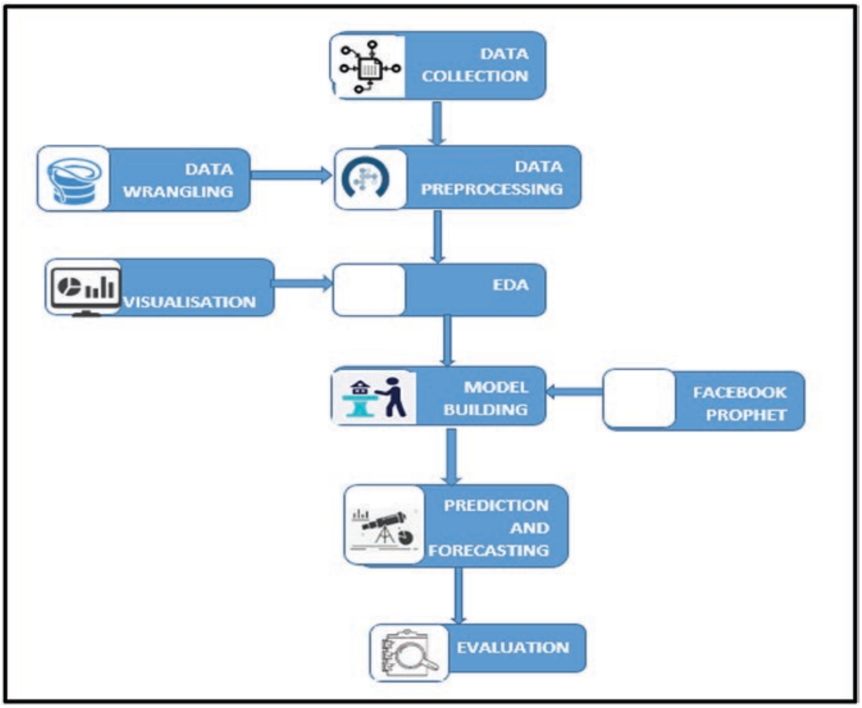

Fig. 2.2 Framework of the world COVID-19 AI-based investigation. (Source: Authors)

preparing the dataset for data visualization. Some features were renamed to make them readable to the code, and to remove ambiguities, features like province/state was renamed to state, country/region was changed to country, and "active" was created as a new feature. Active case was created by removing recovered and death from the confirmed cases to get the number of active COVID-19 patient in each case.

2.3.4 Exploratory Data Analysis

The exploratory data analysis (EDA) was done to get more insight to the COVID-19 medical data investigation. The EDA of world COVID-19 medical data in this chapter was carried out on choropleth map, which is one of the AI data visualization tools employed for the investigation. The tool was used to visualize four types of COVID-19 cases that were investigated in over 200 countries of the world. Plotly visualization library of Python was used as visualization tool for the geographical visualization on the choropleth maps that was made possible because the COVID-19 dataset used in this research contains longitude (long) and latitude (lat). Matplotlib is for chart labelling and Seaborn for chart plotting (line chart and bar chart) and easy interpretation (point plots).

2.3.5 Model Building

A frontline prediction and forecasting algorithm, Facebook Prophet was used to build models in this experiment; because of its univariate time series nature of the algorithm, this made it considerably more suitable to be used for this study; it also has better accuracy and is easy to build than most of the prediction and forecasting algorithm used in building machine learning model. Four distinct models were built; they are model to predict and forecast active, confirmed, death, and recovered cases using Facebook Prophet. The model scaling was done, and the dataset was split into test set and training set; the test set was 20%, while the training set was 80% so as to avoid overfitting and underfitting of the model.

2.3.6 Prediction and Forecasting

The prediction and forecasting of COVID-19 medical data in this investigation were to predict each case for 7 days, i.e., active, death, confirmed, and recovered cases. After the model had been built, the prediction was done, and the forecasting was done using point plotting and bar plotting.

2.4 Results and Discussion

The results of investigation of COVID-19 medical data across various countries of the world using AI/ML applications toward augmenting the investigation from multiple angles were presented. It also provides an enhanced COVID-19 medical dataset that can be relied on for a real-time COVID-19 treatment around the world. The results of the experiment showed the prevalence of the pandemic at the United States (North America) in the month of April; this could help in the understanding of the disease and consequently in curbing the menaces.

2.4.1 Results of Exploratory Data Analysis (EDA)

The investigation results of exploratory data analysis of COVID-19 data in various countries of the world are shown on the choropleth maps in Figs. 2.4, 2.5, 2.6 and 2.7 for the four cases: active, confirmed, death, and recovered cases. In Figs. 2.4, 2.5, 2.6 and 2.7, the higher the intensity of the color on the map, the higher the number of active, death, confirmed, and recovered cases and vice versa, and to know the number of confirmed cases in a country, the pointer/mouse can be used to point to that country, and that will be provided as shown in Fig. 2.3. The implementation was done using Plotly for map visualization, Matplotlib for chart labelling, and Seaborn for chart plotting (line chart and bar chart) and easy interpretation (point plots).

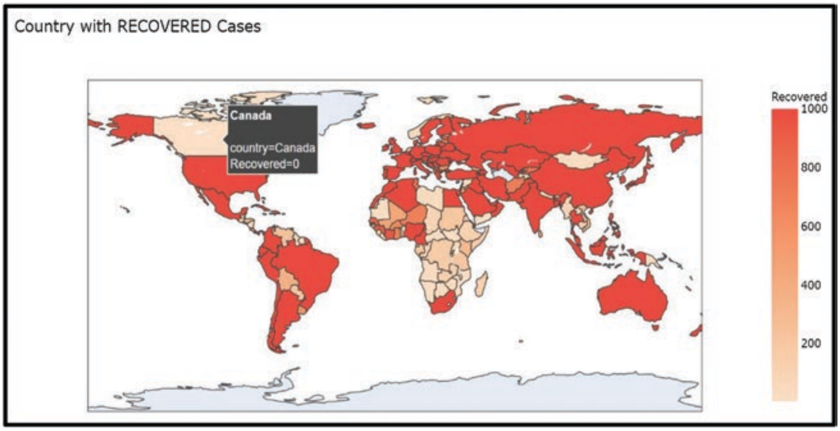

Fig. 2.3 World choropleth map showing Canada and the number of the recovered cases per 12,481 and 37,742,154 inhabitants in a particular week. (Source: Authors)

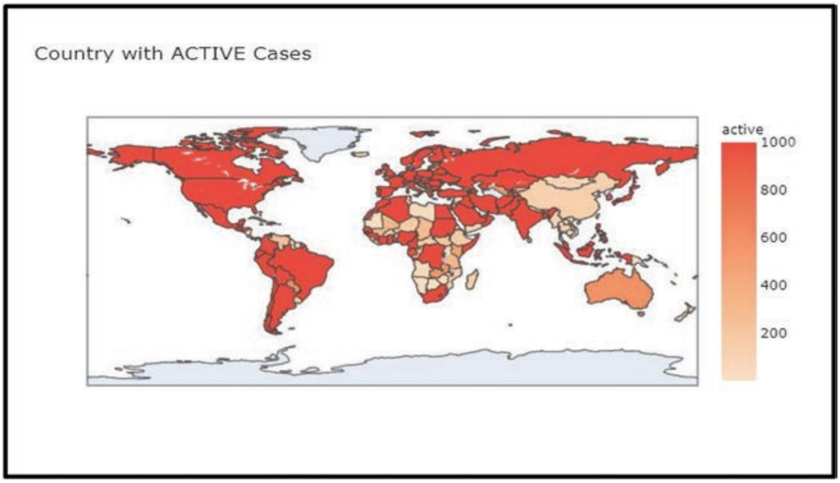

Fig. 2.4 World choropleth map showing the degree of the active cases around the world. (Source: Authors)

The degrees of COVID-19 active cases vary in various countries of the world as shown in Fig. 2.4. There is high level of active COVID-19 cases in Canada, Russia, the United States, Brazil, and so on. But Angola, Madagascar, and most of the African countries have low active cases of COVID-19.

The degrees of COVID-19 confirmed cases vary in various countries of the world as shown in Fig. 2.5. There is high level of confirmed COVID-19 cases in Brazil, Canada, China, Russia, the United States, and so on. But Angola, Libya, Madagascar, Zambia, and most of the African countries has low confirmed cases of COVID-19.

The degrees of COVID-19 death cases vary in various countries of the world as shown in Fig. 2.6. There is high level of COVID-19 death cases in Brazil, Canada,

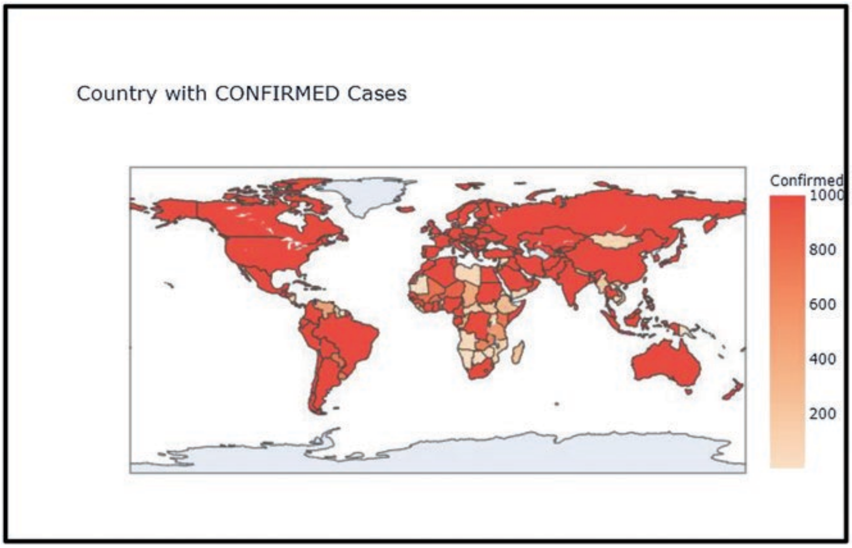

Fig. 2.5 World choropleth map showing the degree of the confirmed cases around the world. (Source: Authors)

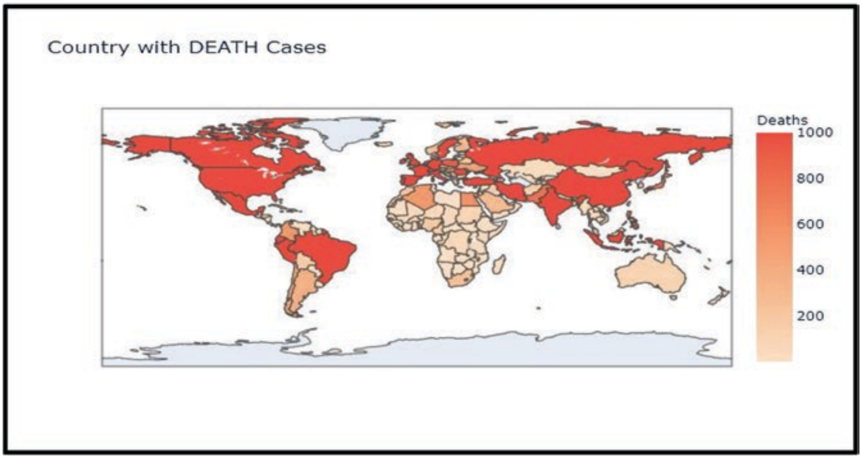

Fig. 2.6 World choropleth map showing the degree of the death cases around the world. (Source: Authors)

China, Russia, the United States, and so on. But African countries have very low death cases of COVID-19. This may due to the climatic and other environmental conditions in African.

The degrees of COVID-19 recovered cases vary in various counties of the world as shown in Fig. 2.7. There is high level of recovered COVID-19 cases in Bolivia and Canada; this may be due to the level of the preparedness in these countries as these countries implemented contact tracing and other measures for the timely curtailment of COVID-19. But there are very low recovery cases of coronavirus in Algeria, Australia, Brazil, Kazakhstan, and Russia.

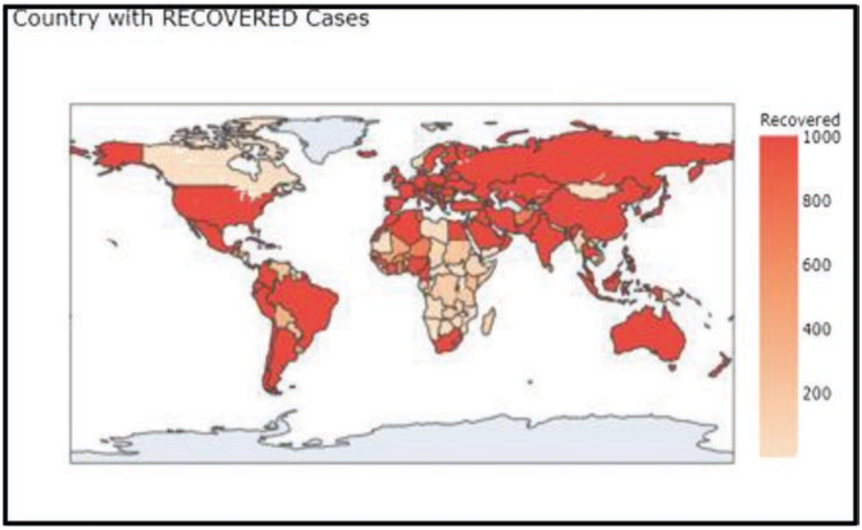

Fig. 2.7 World choropleth map showing the degree of the recovered cases around the world. (Source: Authors)

2.4.2 Exploratory Data Analysis of World COVID-19 Results

The results of top 20 countries of the world that have highest number of COVID-19 for the four identified cases were revealed in the investigation of COVID-19 pandemic across the world with AI/ML tools. These were represented with bar charts in Figs. 2.8, 2.9, 2.10 and 2.11.

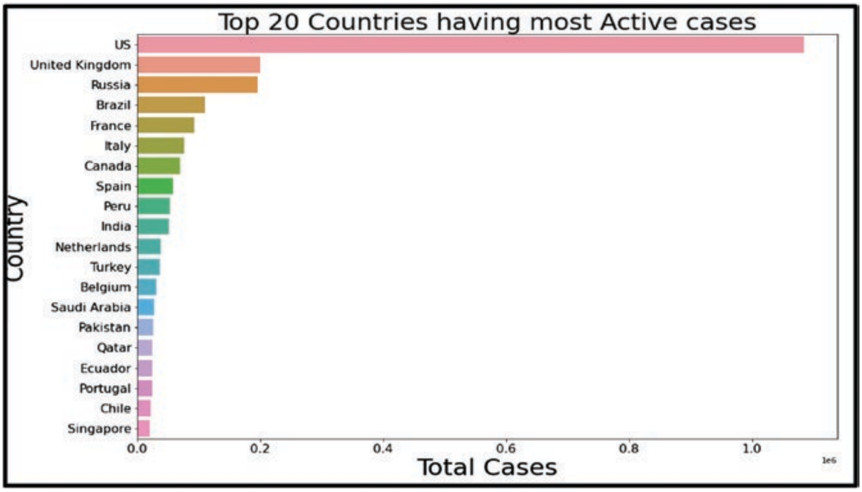

Fig. 2.8 Top 20 countries of the world with active COVID-19 cases. (Source: Authors)

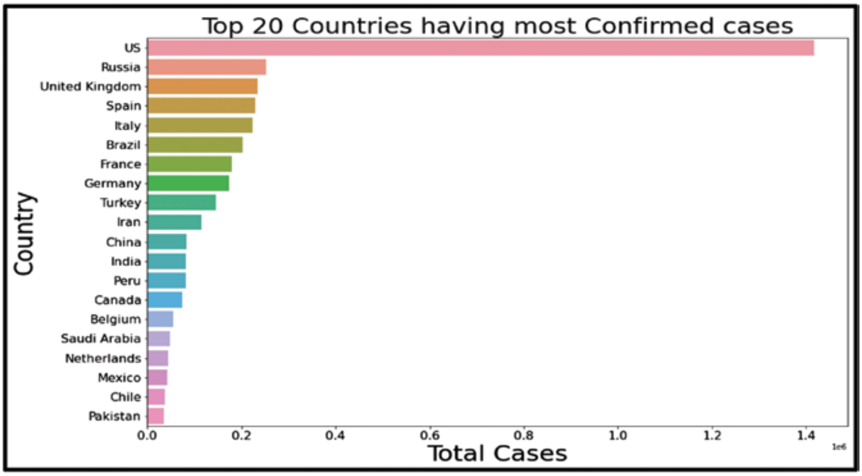

Fig. 2.9 Top 20 countries of the world with confirmed COVID-19 cases

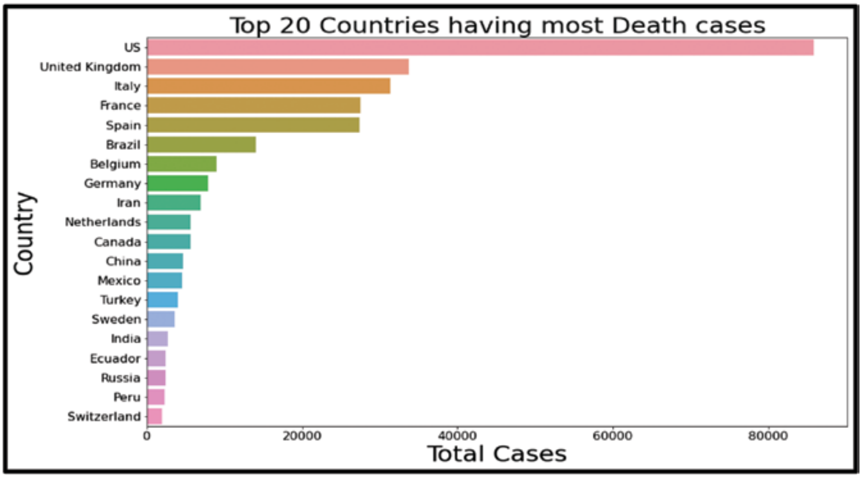

Fig. 2.10 Top 20 countries of the world with COVID-19 death cases

The investigation results in Fig. 2.8 bar chart reveal that the United States has the highest number of coronavirus active cases and Singapore was having the lowest number of active cases.

The investigation results in Fig. 2.9 bar chart reveal that the United States has the highest number of coronavirus confirmed cases and Pakistan was having the lowest number of active cases.

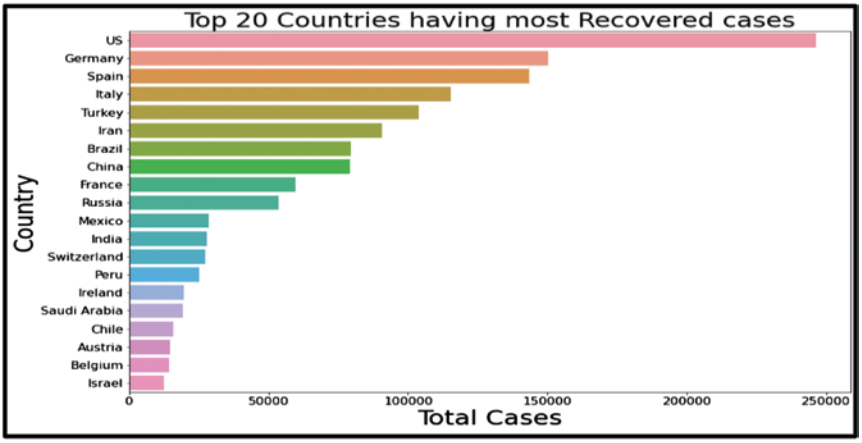

Fig. 2.11 Top 20 countries of the world with recovered COVID-19 cases

The investigation results in Fig. 2.10 bar chart reveal that the United States has the highest number of coronavirus confirmed cases and Switzerland was having the lowest number of active cases.

The investigation results in Fig. 2.11 bar chart reveal that the United States has the highest number of coronavirus recovery cases and Israel was having the lowest number of active cases.

2.4.3 Forecasting Investigation Results

The forecasting results of the four identified cases using AI/ML tools were shown in Figs. 2.12, 2.13, 2.14 and 2.15, respectively. The points on the figure shows the trend of the forecast for the whole world. Point plotting and bar plotting were used to represent the 7-day forecast. The total case of 100,000 were plotted against dates of each cases.

The active cases forecast for the next 7 days was on the increase as shown in Fig. 2.12; the areas with point plotting did not appear toward the tail end of the plot. The total cases in million were plotted against the dates (which was on interval of 15 days).

The confirmed cases forecast for the next 7 days was on the increase as shown in Fig. 2.13; the areas with point plotting did not appear toward the tail end of the plot. The total cases in million were plotted against the dates (which was on interval of 15 days).

The death cases forecast for the next 7 days was on the increase as shown in Fig. 2.14; the areas with point plotting did not appear toward the tail end of the plot. The total cases in million were plotted against the dates (which was on interval of 15 days).

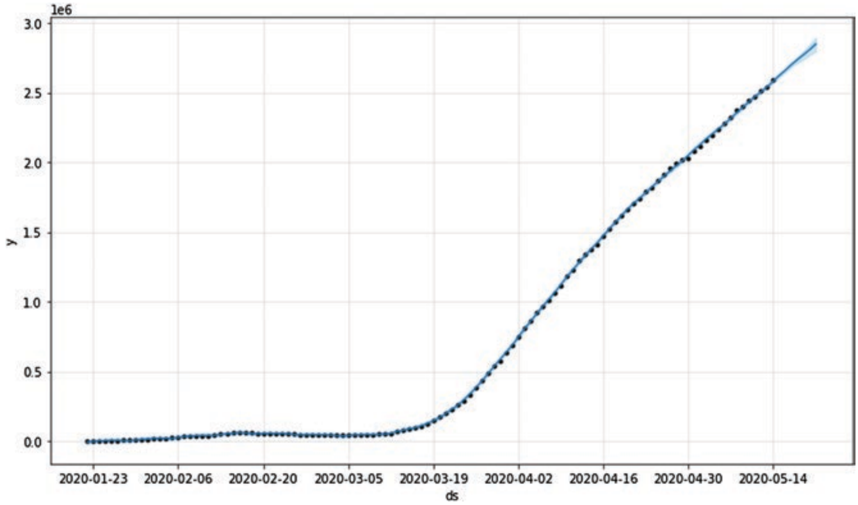

Fig. 2.12 World COVID-19 active cases forecast. (Source: Authors)

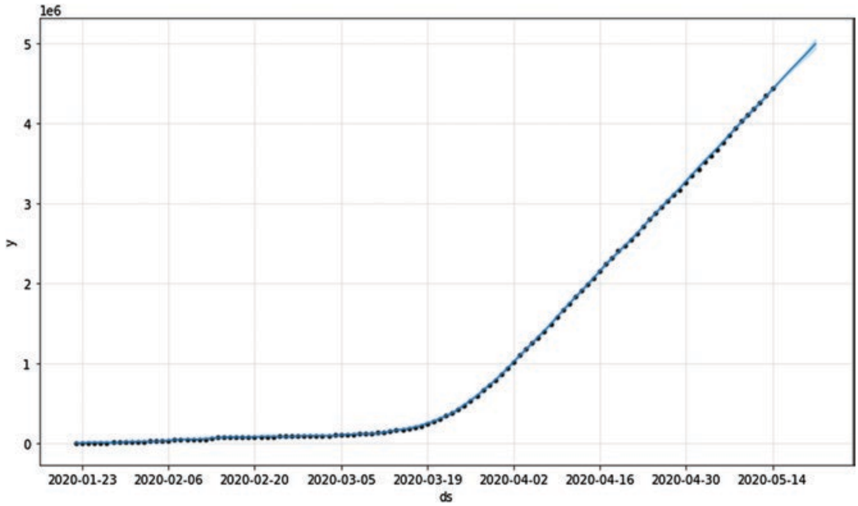

Fig. 2.13 World COVID-19 confirmed cases forecast. (Source: Authors)

The recovery cases forecast for the next 7 days was on the increase as shown in Fig. 2.15; the areas with point plotting did not appear toward the tail end of the plot. The total cases in million were plotted against the dates (which was on interval of 15 days).

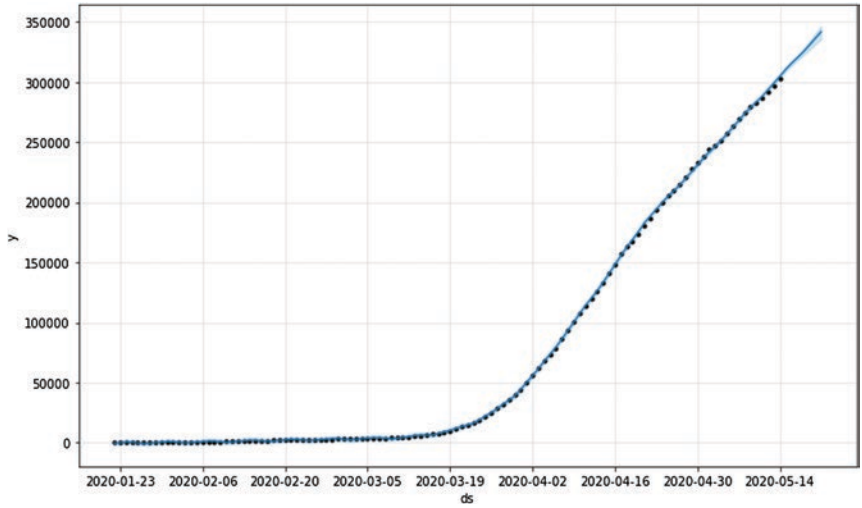

Fig. 2.14 World COVID-19 death cases forecast. (Source: Authors)

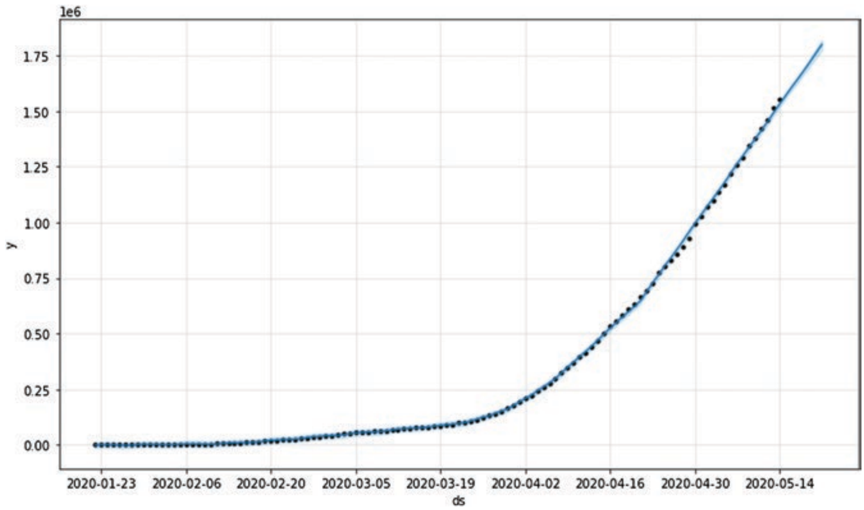

Fig. 2.15 World COVID-19 recovered cases forecast. (Source: Authors)

2.4.4 Performance Evaluations

The model performance for prediction was evaluated using the R-Score, mean square error, and absolute mean error as the metrics. These evaluation metrics help to measure performance of univariance time series forecasting models, and they were used in this investigation on the dataset. Four different cases forecasted were evaluated (active, death, confirmed, and recovered cases). The evaluation results of forecasting model showed R-Score of 0.9999, 0.9999, 0.9999, and 0.9998 for active, death,

Table 2.3 Performance of prediction model

Metrics cases	R-Score	Mean square error	Absolute mean error
Active	0.9999	32,950,433.47	4229.98
Confirmed	0.9999	43,988,753.26	4776.94
Death	0.9999	724,820.40	603.04
Recovered	0.9998	43,611,232.23	3814.23

confirmed, and recovered cases, respectively. Mean square error was 32950433.47, 43988753.26, 724820.40, and 43611232.23 for active, death, confirmed, and recovered cases, respectively and, also, absolute mean error of 4229.98, 4776.94, 603.04, and 3814.23. The summary of the evaluation result is presented in Table 2.3.

2.5 Conclusion

This chapter has provided a comprehensive investigation of COVID-19 dataset, using AI/ML experimental-based method through visualization and AI/ML also for many algorithms for prediction and forecasting. These algorithms are used for building different machine learning models used in prediction and forecasting; some of these algorithms has been used for prediction of coronavirus cases in a clinical or medical dataset, with the aims of analyzing the dataset for planning and controlling the spread of the pandemic. Coronavirus disease that is ravaging the whole world was studied with a view of predicting and forecasting four possible cases of coronavirus, the active, death, confirmed, and recovered cases using AI/ML tools, and visualizing the extent of active, death, confirmed, and recovered cases of the infection in various countries of the world. Matplotlib, Pandas, Seaborn, Plotly, and other important Python libraries were used for model building, plotting of the graphs, performance evaluation of the model and other experimentation purposes in the prediction, and forecasting and visualization of the world coronavirus medical dataset. A study framework was proposed and used in this chapter. The active cases, confirmed cases, and recovered cases of the world COVID-19 medical dataset were visualized using choropleth map and showing the extent of each of these cases on the world map. This chapter has used Facebook Prophet algorithm to build a machine learning algorithm for prediction and forecasting of active, death, confirmed, and recovered/survival cases of COVID-19. This study provides a strong insight into COVID-19 medical data making adequate plans toward combatting the pandemic. This study also reveals that contact tracing can be aided with IoT for controlling the spread and data access or data capturing of COVID-19 or another related pandemic. The possibility of predicting four different cases of COVID-19 was revealed. The point plotting and par plotting were used to represent the 7-day forecast on the chart. In the prediction of active cases for top 20 countries of the world, the prediction investigation results reveal that the United States has the highest numbers of coronavirus active cases and Singapore was predicted to have the lowest number of active cases in seven predictions. In the prediction of confirmed cases for top 20 countries of the world, the prediction investigation results reveal that the United States has the highest numbers of coronavirus confirmed cases and Pakistan was predicted to have the lowest number of confirmed cases in seven predictions. In the prediction of death cases for top 20 countries of the world, the prediction investigation results reveal that the United States has the highest numbers of COVID-19 death cases and Switzerland was predicted to have the lowest number of death cases in seven predictions. In the prediction of recovered cases for top 20 countries of the world, the prediction investigation results reveal that the United States has the highest numbers of COVID-19 recovered cases and Israel was predicted to have the lowest number of recovered cases in seven predictions. There is still room for deployment of real-time prediction and forecasting solutions to assist the medical personnel in the discharge of their duties; this is hoped to be achieved through integration of IoT to machine learning for contact tracing and other data science techniques that may lead to variation in the active, confirmed, death, and recovered cases which can help healthcare personnel in their plan toward the control of the pandemic.

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Chapter 3
Classification of COVID-19 CT Scan Images Using Novel Tolerance Rough Set Approach

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3.1 Introduction

As of date, Corona Virus Disease-19 (COVID-19) confirmed cases are 180,372,985 all over the world, with a mortality rate of 3,907,656 and a recovered rate of 165,098,641. The pandemic of 2019–2020 is a global public health emergency. The coronavirus affects not only the respiratory system but also other vital organs including the kidneys and liver [1]. Severe Acute Respiratory Syndrome Corona Virus 2 (SARS-CoV2) causes COVID-19, a coronavirus disease [2]. The Corona Virus Disease 2019 (COVID-19) is extremely infectious and can cause serious respiratory distress, pneumonia, multiple organ failure, and death. Symptoms can range from a common cold to fever, cough, shortness of breath, and acute respiratory problems, depending on the type of coronavirus. Handwashing periodically, wearing a mask, social distancing, and avoiding close contact with infected people are all general guidelines for preventing the spread of this coronavirus [3]. The COVID-19 virus has a 1-week incubation cycle, according to experts [4]. This is important because the infected patient serves as a virus carrier and unwittingly transmits the virus during this time. COVID-19 can be diagnosed using three different methods: blood tests, X-rays, and Computed Tomography (CT) scans [5, 6]. The use of CT scans and X-ray images of the chest has a very strong ability to diagnose the disease in the absence of common symptoms such as fever [7]. The first step is to identify the disease's symptoms and use distinct signs to correctly diagnose the coronavirus. To diagnose COVID-19, a medical professional will ask whether the patient has been

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in touch if he/she wears the mask and whether he/she follows the distance and hygiene laws. The second step is to examine the symptoms of the patient. In the third step, the Reverse Transcription Polymerase Chain Reaction (RT-PCR) test is used. The fourth step is to use the radiological imaging method. The Nasopharyngeal Swab, which includes exposing a swab to paper strips that causes negative antibodies intended to bind to coronavirus antigens, is the most popular diagnostic method. Antigens bind to the strips, resulting in a visible result. The procedure is quite quick and is used at the point of care. The sensitivity of the nucleic acid test is modest, ranging from 60 to 71%. Laboratory tests use samples from the nasopharyngeal swab, throat swabs, sputum, and deep airway material. However, radiological procedures may have a higher sensitivity than lab tests. Chest Radiography (Chest X-Ray) is used in the early stages. CT and ultrasonography are used when chest radiography is inadequate. Finally, the results of the blood analysis are investigated. From these results, the medical professional determines if the patient is affected by COVID-19 or not. CT imaging is currently clinically adopted as the major approach to confirm positive and suspected positive cases of COVID-19. When the patients were admitted to the hospital, 86.2% of the CT scans revealed abnormal symptoms. Ground-Glass Opacity (56.4%) and bilateral patchy shadows are the most common symptoms of COVID-19 patients as seen on CT images (51.8%).

CT images were found to have a wide range of COVID-specific lung infection patterns, including the presence of ground-glass opacities, mixed ground-glass opacities, or consolidation; the presence of an air bronchogram, interlobular septal thickening, or cavitation; the presence of a different number of lobes afflicted by ground-glass or consolidative opacities; and the presence of pleural effusion; thoracic lymphadenopathy; underlying lung illness, such as tuberculosis, emphysema, or interstitial lung disease; and various opacity distribution patterns, such as peripheral, central, bilateral, focal, multi-lobar, and diffuse. CT is a more accurate imaging method for the chest, with greater sensitivity and reliability than Chest X-Rays (CXR) [8]. According to the National Health Commission of China, chest CT may be used to detect nCoV infection. CT is a non-invasive medical imaging technology that was preferred because it is recognized as a powerful method for advanced internal porosity detection and characterization [9]. A chest CT scan may provide an abundance of pathological facts. As a result of its high sensitivity, chest CT has been used as an alternative method to detect nCoV infection [10]. When compared to first RT-PCR from pharyngeal swab samples, chest CT has a better sensitivity for COVID-19 diagnosis.

The main goal of this study is to use CT scan images to identify COVID-19-infected patient. For data reduction based on attribute dependence, a rough set is a suitable strategy. Rough Set Theory has proven to be a useful method for solving a variety of problems, including representing unknown or imprecise knowledge, knowledge analysis, evaluating the quality and availability of information in terms of accuracy, identifying and evaluating data dependence, and reasoning based on uncertainty. The inability of Rough Set Theory (RST) to deal with real-valued data is its major flaw. The number of rough set applications used today is much broader than in the past, with applications mostly in medicine, database attribute analysis, and process control. The tolerance rough set model can work effectively with real-valued (and crisp) data, resulting in minimal information loss [11]. The Novel Tolerance Rough Set Classification approach is used to incorporate a measure of feature value similarity and determine lower and upper approximations based on these measures of similarity. Tolerance rough sets are described by certain lower and upper approximations [12]. The efficacy of the proposed approach is compared with Decision Tree Classifier (DTC), Random Forest Classifier (RFC), Naive Bayes Classifier (NBC), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM). In this paper, we present a Novel Tolerance Rough Set Classification (NTRSC) approach for handling COVID-19 medical diagnosis system.

3.1.1 Research Objectives and Contributions

Several papers are presented, with an emphasis on coronavirus detection using machine learning and deep learning techniques. The applications such as medical imaging diagnosis, disease tracking, protein structure prediction, drug discovery, and virus infectivity use machine learning algorithms and deep learning architectures. The main objective of this work is to classify COVID and NON-COVID images using Novel Tolerance Rough Set Classification approach. It includes four main tasks such as preprocessing, feature extraction, segmentation, and classification. Initially, the COVID images are denoised using median filter. Then, Gray-Level Co-occurrence Matrix (GLCM) features are generated for the dimensions 0°, 45°, 90°, and 135°. Segmentation of the COVID images is done by using Otsu thresholding. For COVID-19 and NON-COVID images, segmented feature values are extracted from the datasets which are continuous values. To use rough sets, a discretization step must be performed first, which sometimes results in data loss. Therefore, Novel Tolerance Rough Set Classification is implemented for COVID and NON-COVID CT scan image identification to overcome this disadvantage, which improves the diagnosis system's performance. The tolerance similarity measure is used to find lower and upper approximation-based similarity values. The proposed approach is evaluated by comparing it to existing algorithms such as Decision Tree Classifier, Random Forest Classifier, Naive Bayes Classifier, K-Nearest Neighbor, and Support Vector Machine. The overall classification accuracy of the proposed NTRSC approach is 95%, 88%, 96%, and 93% for the GLCM 0°, GLCM 45°, GLCM 90°, and GLCM 135° datasets, respectively, based on the experimental results.

3.1.2 Research Motivation

Nowadays, many kinds of research were done for the pandemic of the new coronavirus (COVID-19), which is dangerous and threatening to people's lives. This paper contributed a Novel Tolerance Rough Set Classification (NTRSC) approach for the classification of COVID-19 CT scan images. There are four phases to the process

1. In the first phase, a denoising operation is performed to remove artifacts in the images.
2. In the second phase, Otsu thresholding-based segmentation is applied to the images.
3. In the third phase, Gray-Level Co-occurrence Matrix (GLCM) is used to extract relevant features from the COVID-19 CT scan dataset.
4. In the fourth phase, Novel Tolerance Rough Set Classification is applied.

Then, the effectiveness of various classification algorithms is assessed using appropriate classification scales.

3.2 Related Work

G.D. Rubin et al. [13] discussed 14 main questions based on the expected value of the information that thoracic imaging will be expected to provide, which corresponded to 11 decision points within the three scenarios and three additional clinical situations. The findings were compiled into five major and three supplementary guidelines to assist medical professionals in the use of chest radiography and CT in the treatment of COVID-19. Zhao et al. [14] proposed COVID-mechanistic COVID-19 diagnosis models using a CT dataset with 349 positive COVID-19 CT images from 216 patients. The authors tested the dataset's utility for developing COVID-19 diagnosis models in experimental studies. In this work, diagnosis methods are built based on multitask learning and self-supervised learning with an F1 of 0.90, an area under the Receiver Operating Characteristic (ROC) curve (AUC) of 0.98, and a precision of 0.89 using a CT dataset. Shan et al. [15] proposed that VB.Net is a deep learning-based system that uses chest CT to automatically partition all lung and infection locations. CT. Zhao et al. [16] discussed the relationship between chest CT images and pneumonia. The results have shown that COVID-19 pneumonia patients have imaging features that can assist with the early detection of highly suspected cases as well as determining the seriousness and severity of the disease. Wang et al. [17] developed the algorithm called modified inception transfer learning model, which is followed by internal and external validation. The internal validation was 89.5% accurate overall, with a precision of 0.88 and a sensitivity of 0.87. The external research dataset revealed a total accuracy of 79.3%, with a precision of 0.83 and a sensitivity of 0.67. Gozes et al. [18] proposed and demonstrated that deep learning-based automated CT image analysis tools for COVID-19 identification, quantification, and monitoring can distinguish patients from healthy people. They achieved area under the ROC curve (AUC) was 0.996, the sensitivity was 98.2%, and the specificity was 92.2%. Hasan et al. [19] proposed a promising technique for using Convolutional Neural Network (CNN) to predict COVID-19 patients from a CT scan. The modified CNN architecture in the current state to detect COVID-19 is based on DenseNet. With a 95% recall rate, the findings outperformed 92% accuracy. To diagnose COVID-19 automatically, Maghdid et al. [20] used a deep learning approach and transfer learning strategies. The structure is a hybrid of CNN and an enhanced AlexNet structure. On the X-rays and CT slice datasets, enhanced architecture accuracy hits 94.10%. Pathak et al. [21] presented Deep Transfer Learning (DTL) which is utilized to train the COVID-19 classification model. To avoid overfitting, tenfold cross-validation was used. The dataset's training and research ratios were set to 60% and 40%, respectively. A total of 10% of the training data was used for validation purposes, out of a total of 60%. The presented method obtains 96.2264% and 93.018% training and testing accuracy, respectively. Shaban et al. [22] proposed Enhanced K-Nearest Nneighbor (EKNN) which avoids the trapping issue of conventional KNN by using solid heuristics to choose the tested item's neighbors. EKNN selects only the qualified neighbors for classification after calculating the degree of both closeness and intensity of each neighbor of the tested object. EKNN will reliably detect infected patients with the least amount of time penalty. Dilbag Singh et al. [23] studied the deep learning model for classification of CT images based on Multi-Objective Differential Evolution (MODE) CNN. The proposed model is compared to models such as CNN, Adaptive Network-Based Fuzzy Inference System (ANFIS), and Artificial Neural Network (ANN). The proposed model outperforms competitive models in terms of accuracy, F-measure, sensitivity, specificity, and kappa statistics by 1.978%, 2.0928%, 1.8262%, 1.6827%, and 1.9276% respectively, in terms of ANN, ANFIS, and CNN models. Eduardo et al. [24] discussed artificially intelligent techniques that can determine if a person is infected with Severe Acute Respiratory Syndrome CoronaVirus 2 (SARS-CoV-2) by analyzing CT scans. They proposed eXplainable Deep Learning (xDNN) is a non-iterative method that relies solely on recursive calculations and prototypes. As a result, it is incredibly computationally efficient. xDNN produces 97.38%, 9.16%, 95.53%, 97.13%, and 97.36% in terms of accuracy, precision, recall, F1-Score, and AUC, respectively. xDNN outperforms the other deep learning models such as Residual neural Network (ResNet), GoogLeNet, Visual Geometry Group-16 (VGG-16), AlexNet, decision tree, and Adaptive Boosting (AdaBoost). Shaoping Hu et al. [25] proposed the weakly supervised deep learning framework for fully automatic identification and classification. This framework can help determine the specific location of COVID-19-induced lesions or inflammations. They can learn to detect and localize tumors on COVID-19 and Community-Acquired Pneumonia (CAP) and Non-Pneumonia (NP) CT images based just on image-level labels. The suggested framework provides good accuracy, precision, and AUC for classification, as well as promising qualitative visualization for lesion detections, according to experimental findings. Aayush Jaiswal et al. [26] proposed DenseNet201 to categorize patients as COVID-infected or not. The proposed model extracts feature from the ImageNet dataset using its learned weights and CNN. When compared to certain well-known deep transfer learning models such as Inception-ResNetV2, VGG16, and ResNet152V2, the DenseNet201-based CNN performs much better. The proposed system diagnoses chest CT scans as having 99.82%, 96.25%, and 97.4% training, testing, and validation accuracy, respectively. Siqi Liu et al. [27] discussed that COVID-19-related tomographic patterns on chest CTs from negative cases were generated using a Generative Adversarial

Network (GAN) model. The 2D network's Dice Similarity Coefficient (DSC) was increased from 0.623 to 0.645, while the 3D network's DSC increased from 0.657 to 0.706, which is equivalent to the inter-user variability DSC (0.7132 ± 0.1831). For the 2D network, Pearson's Correlation Coefficient (PCC) was improved from 0.908 to 0.939, and for the 3D network, it improved from 0.933 to 0.961, which is comparable to the inter-user variability range PCC = 0.957. Similarly, for the 2D network, the PCC for Percentage of High Opacity (PHO) improved from 0.906 to 0.927, and for the 3D network, it improved from 0.9099 to 0.9387. In addition to the research mentioned above, the following studies are described in detail. Table 3.1 presents the data of additional studies. When the table is reviewed, the methodology utilized in the studies, as well as the size and type of datasets, is shown.

Table 3.1 Summary of related work

References	Dataset	Technique
G.D. Rubin et al. [13]	Risk factors such as community conditions and resource constraints are represented in three different scenarios	To provide guidelines to physicians on the use of thoracic imaging in a range of healthcare environments
Zhao et al. [14]	https://github.com/UCSD-AI4H/COVID-CT	For binary classification of COVID-19 or NON-COVID-19, the DenseNet169 model was utilized
Shan et al. [15]	For validation, 300 CT images from 300 COVID-19 patients (from Shanghai) were gathered. For training, 249 CT images of 249 COVID-19 patients were gathered from other centers (outside Shanghai)	DL-based segmentation network: VB.Net
Zhao et al. [16]	In Hunan, China, data on 101 cases of COVID-19 pneumonia were collected retrospectively from four institutions	Early screening and tracking the diseases
Wang et al. [17]	Collected CT images from 259 patients, with 180 cases of standard viral pneumonia and the remaining 79 cases from three hospitals with reported SARS-CoV-2 nucleic acid testing	A deep learning-based prediction model
Gozes O et al. [18]	6150 CT images of the lungs with anomalies and lung masks	Deep learning-based automated CT image analysis tool
Hasan et al. [19]	2482 CT images in total while 1252 CT images were COVID-19 positive, and 1230 CT images were from noninfected COVID-19 images but who have other pulmonary diseases	Deep learning architecture DenseNet121 for image classification
Maghdid et al. [20]	5 different sources to form a dataset of 170 X-ray images and 361 CT images of COVID-19	An effective CNN model together with testing pre-trained AlexNet for the detection of COVID-19 images

(continued)

Table 3.1 (continued)

References	Dataset	Technique
Pathak et al. [21]	413 COVID-19 images, 439 – Normal or pneumonia images	COVID-19-infected patients are classified using a deep transfer learning algorithm
Shaban et al. [22]	216 COVID-19 images and 133 NON-COVID images	Enhanced KNN classification technique
Dilbag Singh et al. [23]	From January 21 to February 3, 2020, 73 individuals with COVID-19 were proactively collected in six hospitals	Multi-objective differential evolution-based convolutional neural networks
Eduardo Soares et al. [24]	2482 CT scans, of which 1252 corresponds to 60 patients identified with SARS-CoV-2 and 1230 CT scans corresponds to 60 patients not identified with SARS-CoV-2. These data have been collected from different hospitals in Sao Paulo, Brazil	eXplainable deep learning (xDNN) approach
Shaoping Hu et al. [25]	150 3D volumetric chest CT exams of COVID-19, CAP, and NP patients, respectively. In total, 450 patient scans acquired from two participating hospitals between September 2016 and March 2020 were included for further analysis	Weakly supervised deep learning method
Aayush Jaiswal et al. [26]	Dataset collected from Kaggle website. The dataset consists of a total of 2492 CT scans out of which 1262 are positive for SARS-CoV-2 infection, i.e., COVID-19 (+), and the rest of 1230 are negative for SARS-CoV-2 infection, i.e., COVID-19 (−)	DenseNet201-based Ddeep Transfer Learning (DTL)
Siqi Liu et al. [27]	Collected 2143 chest CTs, containing 327 COVID-19 positive cases, acquired from 12 sites across seven countries	Generative Adversarial Network (GAN)

3.3 Methods and Materials

Dataset is used in this work is available at https://github.com/UCSD-AI4H/COVID-CT [42] from the github repository: in this repository, 349 positive COVID CT images and 397 NON-COVID. The images in this COVID-19 CT Scan dataset have varying sizes : 153,491,and 1853 are the minimum, average and greatest heights respectively. These images were taken from 216 different patient instances. medRxiv and bioRxiv have been used to collect the positive images. To maintain uniform properties in our final dataset for studies, all images were transformed to Portable Network Graphics (.png) format. Both positive and negative class photographs were also downsized to 256*256.

3.3.1 Preprocessing

Preprocessing is a vital step in the automated disease detection process. Before computational processing, images are usually preprocessed by eliminating low-frequency background noise, normalizing the intensity of individual particle images, and removing or enhancing data images. Preprocessing includes conversion, image resizing, noise removal, and quality enhancement. Filtering is a technique for improving an image in which filters are primarily used to remove either the image's high frequencies, i.e., smoothing the image, or the image's low frequencies, i.e., enhancing or detecting edges [28]. The median filter resides on a rectangular region. During the filtering process, it alters the size of images based on the conditions. The median value in the three-by-three neighborhood around the corresponding pixel in the input images is stored in each output pixel. The filter's output is a single value that replaces the current pixel, value at (x, y) the time when S is oriented. The applied preprocessing technique not only saves time and also compares with various filtering techniques to determine the best pixel result using the median filter. Figures 3.1 and 3.2 describe the original COVID and NON-COVID images and different filtering techniques images.

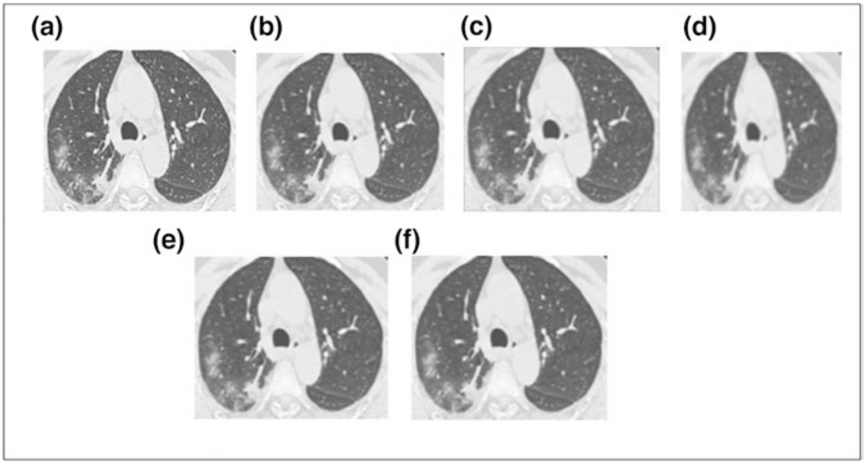

Fig. 3.1 Filtering using Different Techniques: (**a**) Input COVID Image, (**b**) Add Gaussian Noise to Image, (**c**) Gaussian Filter (**d**), Average Filter, (**e**) Median Filter, (**f**) Bilateral Filter

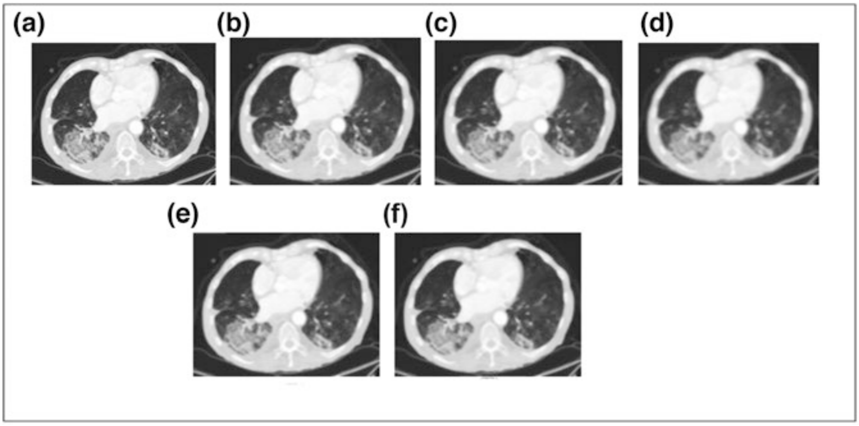

Fig. 3.2 Filtering using Different Techniques: (**a**) Input NON-COVID image, (**b**) Add Gaussian Noise to Image, (**c**) Gaussian Filter (**d**), Average Filter (**e**), Median Filter, (**f**) Bilateral Filter

3.3.2 Segmentation

The Otsu (Otsu) is a global adaptive binarization threshold image segmentation algorithm developed by Japanese researchers in 1979 [29]. As the threshold selection rule, this algorithm uses the maximum inter-class variance between the context and target image. The maximum between-class variance method is an alias of the Otsu method based on the same theory. According to the grayscale characteristics of the image, it divides it into foreground and background. The disparity between the two parts is the greatest when the better threshold is used. The maximum inter-class variance, which is a fairly common measure norm, is used by the Otsu algorithm. Otsu thresholding is used for the images in this study, and it is used to perform automatic thresholding in image processing. After segmenting the portion of an image, apply erosion operation to the images. The erosion process increases the number of pixels with a value of zero (background) while decreasing the number of pixels with a value of one (foreground). Figure 3.3 and Fig. 3.4 depict Otsu's thresholding-based segmentation applied on CT COVID and NON-COVID images.

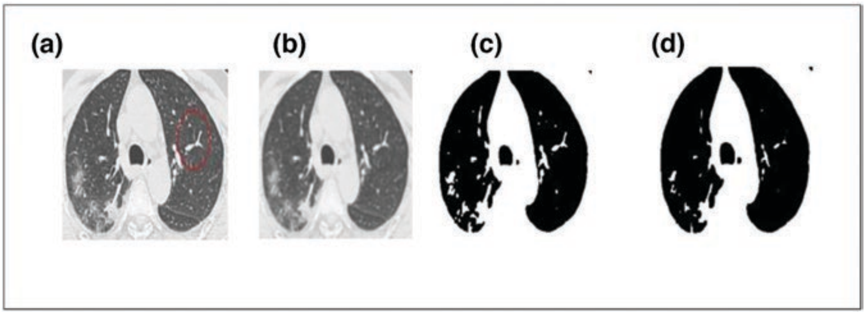

Fig. 3.3 Input and Output of CT COVID Images: (**a**) Original CT image of COVID Image, (**b**) Output of Median Filter for CT COVID image, (**c**) Apply Otsu's Thresholding for CT COVID Image, (**d**) The Output of Morphological Operation – Erosion of CT COVID

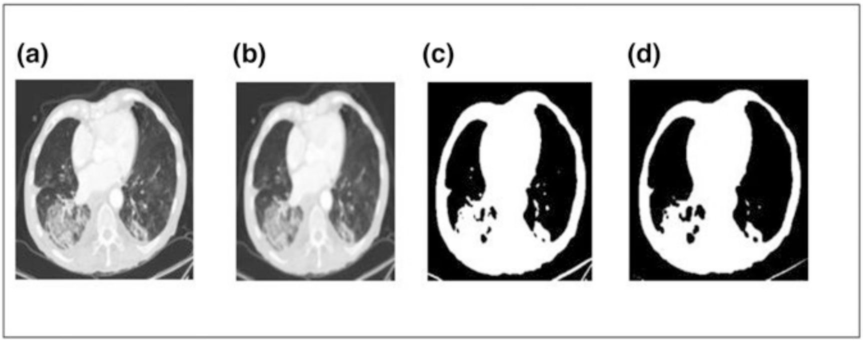

Fig. 3.4 Input and output of CT NON-COVID image: (**a**) original CT image of NON-COVID image, (**b**) output of median filter for CT NON-COVID image, (**c**) Otsu's thresholding applied to CT NON-COVID image, (**d**) output of morphological operation – erosion of CT NON-COVID image

3.3.3 Feature Extraction

A prominent texture-based feature extraction approach is the Gray-Level Co-occurrence Matrix (GLCM). The GLCM defines the textural relationship between pixels by executing an operation on the images second-order statistics. A matrix with the same number of rows and columns as the gray values is used to represent the GLCM properties of an image. For GLCM, two pixels are usually used [30]. The GLCM features used in this study are as follows: Contrast, Dissimilarity, Homogeneity, Energy, Correlation, and Angular Second Moment (ASM). GLCM is constructed in four spatial dimensions which are 0°, 45°, 90°, and 135°. For all segmented COVID and NON-COVID images, Gray-Level Co-occurrence Matrix is applied to extract the features in 0°, 45°, 90°, and 135° directions.

3.4 Background Study of Tolerance Rough Set

Pawlak introduced a new mathematical method called Rough Set Theory [31, 32] in the early 1980s to deal with vagueness and ambiguity in datasets. Many extensions of the rough set model have been suggested in terms of different criteria over the last 40 years, including the rough set model based on a soft rough set model, the rough soft set model, the fuzzy soft set model, tolerance relations, and rough fuzzy model [33]. The equivalence relation is used to identify Pawlak's rough set-based classification algorithms, which are only suitable for discrete datasets. If the attribute values of objects in typical rough sets are similar, they are grouped into equivalence groups. For continuous data, where values can only vary due to noise, this criterion may be too stringent. When using the Pawlak model to handle continuous data, the computation cost keeps increasing. Several extensions of rough set theory have been developed to replace analogous relations, dimensionality reduction, and classification systems, such as the fuzzy rough set model [34], probabilistic rough sets [35], similarity rough set [36], tolerance relation rough set [37], decision-making rough set [38], and covering rough set [12].

3.4.1 Tolerance Rough Set

Tolerance Rough Set (TRS) analyzes the indeterminate data found in the limit region of tolerance rough sets using comparability steps. This technique is used to present an estimate of highlight value comparability as well as define the lower and upper approximations using these similitude metrics. Tolerance rough sets are characterized by certain lower and upper approximations [39].

3.4.1.1 Tolerance Information Systems

If A = (U, A) is an information system and B $\subseteq$ A, then $INF(B) = \{Inf_B(x) : x \in U\}$ is the set of information vectors $Inf_B(x) = \{(a, a(x)) : a \in B\}$. If u ϵ INF(C) and B $\subseteq$ C $\subseteq$ A, then $u \mid B = \{(a, w) \in u : a \in B\}$. That is, $u \mid B$ is the restriction of u to B [12]. A tolerance information system is a pair (A, D) where

A = (U, A) is an information system,
D = $(D_B)_{B \subseteq A}$ and $D_B \subseteq$ INF(B) × INF(B) are a relation termed as the discernibility relation satisfying the conditions [12]:

(i) INF(B) × INF(B) − D_B is a tolerance (indiscernibility) relation.
(ii) $((u - v) \cup (v - u) \subseteq (u_0 - \upsilon_0) \cup (\upsilon_0 - u_0))$ & $uD_B\upsilon \to uD_B\upsilon_0$ for any u, v, u_0, υ_0 ϵ INF(B) that is D_B is monotonic with respect to discernibility property.
(iii) $non(uD_C\upsilon)$ implies $non(u| BD_B\upsilon|$ B) for any B $\subseteq$ C and u, v ϵ INF(C).

$A(B, D_B)$ tolerance function, $I[B, D_B]$: U → P(U) is defined by $y \in I[B, D_B](x)$ if $non(Inf_B(x)D_BInf_B(y))$ for any x, y ϵ U. The set $I[B, D_B](x)$ is called the tolerance set of x [12].

3.4.1.2 Definition 1: Tolerance Similarity Measures

Let $x_iT_ax_j$ epitomize the similarity between x_i and x_j in terms of the tolerance threshold attribute. x_i and x_j are identical in terms of attribute 'a,' where T_a denotes the tolerance similarity threshold relation for attribute 'a,' whose value falls within the T_a [0,1] range. As a result, we can apply the standard similarity measure $S_a(x_i, x_j)$ to the T_a that can be determined by a simple distance,

$$S_a\left(x_i,x_j\right)=1-\frac{\left|a\left(x_i\right)-a\left(x_j\right)\right|}{\max_a-\min_a} \tag{3.1}$$

where $a(x_i)$ and $a(x_j)$ are attribute values concerning x_i and x_j, respectively, and $\max_a$ and $\min_a$ are the maximum and minimum values of attribute 'a' [7]. T_a's and S_a's relationship is depicted below,

$$x_i T_a x_j \leftrightarrow S_a\left(x_i,x_j\right)\geq \tau \tag{3.2}$$

where t_a is the attribute a-based similarity threshold. The similarity measure in classification is based on the normalized distance function as follows:

$$S_a\left(x_i,x_j\right)=1-\frac{\left|d(a\left(x_i\right),a\left(x_j\right)\right|}{\left|d_{\max}\right|} \tag{3.3}$$

The maximum distance between two attribute values $a(x_i)$ and $a(x_j)$ is denoted by d_{max},

$$d\left(a\left(x_i\right),a\left(x_j\right)\right)=a\left(x_i\right)-a\left(x_j\right) \tag{3.4}$$

which is the distance function between two objects in terms of attribute values [40]. The similarity measure S_A (x_i, x_j) between two objects x_i and x_j is defined as an arithmetic average of similarity measures of all attributes between two objects x_i and x_j:

$$S_A\left(x_i,x_j\right)\frac{1}{|A|}\sum_{\forall a\epsilon A} s_a\left(x_i,x_j\right) \tag{3.5}$$

The number of attributes in A is represented by |A|. When all attributes 'A' is considered at the same time, we can apply the tolerance related to the similarity measure as follows,

$$x_i t_A x_j \leftrightarrow S_A\left(x_i,x_j\right)\geq t\left(A\right) \tag{3.6}$$

where t(A) [0,1] is an image classification similarity threshold dependent on all attributes A.

3.4.1.3 Definition 2: Tolerance Rough Set

The degree of similarity is calculated for each function in the tolerance rough set method as follows [41]:

$$SIM_a(x,y) = 1 - \frac{|a(x) - a(y)|}{a_{\max} - a_{\min}} \tag{3.7}$$

The feature or attribute is 'a,' and the maximum and minimum values for the features taken are amax and amin. Similarity can be achieved for a subset of features P as follows:

$$(x,y) \in SIM_{P,\tau} \text{ iff } \prod_{a\epsilon P} SIM_a(x,y) \geq \tau \tag{3.8}$$

$$(x,y) \in SIM_{P,\tau} \text{iff } \frac{\sum_{a\epsilon P} SIM_a(x,y)}{|P|} \geq \tau \tag{3.9}$$

Lower PτX and upper $\overline{P\tau X}$ approximations are demarcated as follows:

$$\underline{P_\tau X} = \{x \mid SIM_{P,\tau}\underline{(x)} \subseteq X\} \tag{3.10}$$

$$\overline{P_\tau X} = \{x \mid SIM_{P,\tau}(x) \cap X \neq \emptyset\} \tag{3.11}$$

Positive region and negative region are as follows:

$$POS_{P,\tau}(y) = \bigcup_{(X\varepsilon U|y\varepsilon U)} \underline{P_\tau X} \tag{3.12}$$

$$NEG_{P,\tau}(y) = \bigcup_{(X\varepsilon U|y\varepsilon U)} \overline{P_\tau X} \tag{3.13}$$

3.4.2 Proposed Approach: Novel Tolerance Rough Set Classification (NTRSC)

The proposed approach is shown in Fig. 3.5. This proposed NTRSC approach is used to provide a measure of feature value similarity and define lower approximations using the similarity measures. In the first phase, preprocessing and Otsu segmentation are applied to the COVID and NON-COVID images. In the second phase, GLCM features for four directions are extracted. In the third phase, the NTRSC approach was applied to the dataset. A classification dataset is separated into two parts: a training set and a testing set. The efficiency of a classifier is determined by presenting it with a testing set. In this NTRSC training approach, tolerance cosine similarity is constructed in step 1. In the second step, novel tolerance lower approximation of the dataset based on decision class C is constructed. With the help of tolerance approximation, we generate the rules which are certain rules. In the third

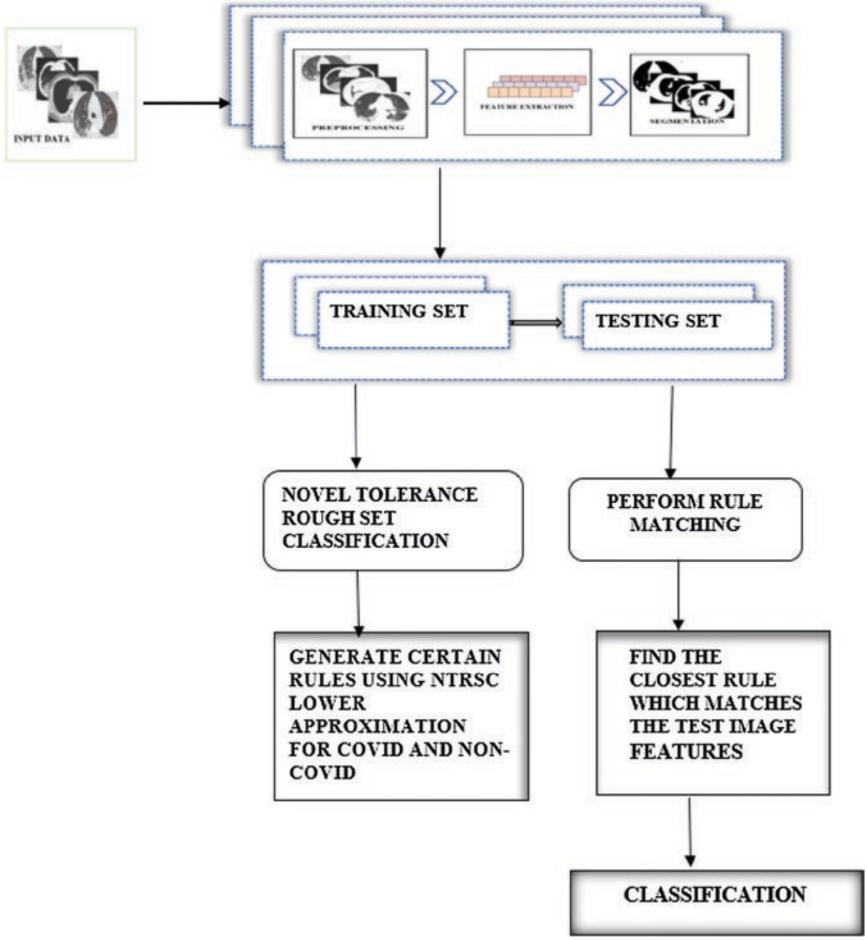

Fig. 3.5 The proposed NTRSC approach

step, certain rules are generated based on tolerance rough set lower approximation. In the testing algorithm matching, the closest decision rule is applied for the test data. Finally, classification measures are used to assess the effectiveness of different categorization procedures for COVID and NON-COVID diagnosis.

The experimental results for the proposed NTRSC and other benchmark algorithms are validated using classification validation accuracy measures. Table 3.2 shows the proposed Novel Tolerance Rough Set Classification (NTRSC) approach for the training dataset. Table 3.3 depicts the NTRSC testing algorithm. NTRSC algorithm is applied to generate certain rules for tolerance lower approximation space.

Algorithm 1: Proposed Approach – Novel Tolerance Rough Set Classification: Training Algorithm

Table 3.2 Proposed NTRSC approach for training dataset

Input: $<U, A \cup B>$,τ-threshold, U = {X_1, X_2, …, X_n}, A = {a_1, a_2, …, a_n} is the set of conditional attributes; D = {d_1, d_2, …, d_n} is the decision attribute.
Output: Set of rules for each class.
Step 1: Extract the features from COVID and NON-COVID images using GLCM
Step 2: Define the tolerance relation for the conditional attributes using
$[\mathbf{x}]_C \leftarrow \mathbf{C}$
Step 3: Construct the equivalence relation for the decision attribute:
$[\mathbf{x}]_D \leftarrow \mathbf{C}$
Step 4: Compute tolerance cosine similarity for the tolerance relation:
$\mathbf{SIM_a(x,y) = 1 - \frac{\lvert a(x) - a(y) \rvert}{a_{max} - a_{min}}}$
Step 5: Construct the tolerance rough set lower approximation space for each class:
$\underline{P_\tau X} = \{x \mid SIM_{P,\tau}(x) \subseteq X\}$
Step 6: Generate certain rules for each class separately using a tolerance rough set based on lower approximation

Algorithm 2: Proposed Approach – Novel Tolerance Rough Set Classification: Testing Algorithm

Table 3.3 Proposed NTRSC approach for testing dataset

Input: Set of decision rules
Output: Decision values
Step 1: Extract the features for each image in the test set
Step 2: For each class, perform feature matching with decision rules
Step 3: Use the closest decision rule to classify the image
Step 4: Output decision

3.5 Experimental Results and Discussion

An experimental evaluation of the proposed Novel Tolerance Rough Set Classification for COVID and NON-COVID images is presented in this section. All the experiments were run on an Intel® Core™ i5-10210U CPU at 1.60–2.11 GHz machine with 8 GB RAM. The NTRSC approach was implemented in Python using Anaconda. Experiments are carried out using a CT scan dataset. The COVID-19 CT dataset used in this study is open to the public (https://github.com/UCSD-AI4H/COVID-CT) [42]. 349 CT images from COVID patients and 397 CT images from

Table 3.4 PSNR and SSIM values for various filters

Image	Metrics	Noisy image	Gaussian filter	Average filter	Median filter	Bilateral filter
CO	**PSNR**	31.9639	38.9170	33.1507	41.2520	39.41192
	SSIM	0.85376	0.9770	0.88605	0.98514	0.974788
N-CO	**PSNR**	34.0622	40.538	34.1514	45.7168	41.89566
	SSIM	0.93808	0.9919	0.94818	0.99558	0.988984

NON-COVID-19 patients are included in the dataset. The experiments are carried out in the following ways: GLCM is used to extract the features of the COVID and NON-COVID images. Features were extracted from both training and testing images. Then, using NTRSC, each test image is matched with a lower approximation generated rule and matches the closest decision rule for classifying the image. In comparison to other filtering methods, the median filter yields strong Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) values. The PSNR and SSIM values of COVID and NON-COVID images after noise removal using different filters are shown in Table 3.4.

A confusion matrix is a method of summarizing a classification algorithm's results. A confusion matrix helps to get the summary of prediction results on a classification problem. Count values are used to sum and break down the number of correct and wrong predictions by class. True positive refers to correctly predicted NON-COVID images that are classified correctly. True negative refers to correctly predicted COVID images that are labeled as COVID images. False positive refers to the incorrectly predicted COVID images, and false negative refers to incorrectly predicted NON-COVID images. Precision, recall, specificity, F-measure, and G-Mean are among the useful performance indicators computed in medical applications. The findings are reviewed and compared to those of other decision-making classifiers. Precision is the prediction of a positive observation, accuracy is the accurate prediction observation to the total observations, and F1-Score is the calculation of the weighted average of precision and sensitivity. G-Mean is the product of the prediction accuracies for both classes. In this paper, we show the performance of a classification algorithm using well-known metrics including Accuracy, Sensitivity, Specificity, Error Rate, Matthews Correlation Coefficient, Lift, Youden's Index, Balanced Classification Rate, and Balanced Error Rate. The complete interpretation for each metric is depicted in Table 3.5 [43–51].

Several machine learning algorithms such as Decision Tree Classifier, Random Forest Classifier, Naive Bayes Classifier, K-Nearest Neighbor, and Support Vector Machine were implemented for the classification of COVID and NON-COVID images. Performance values were evaluated via confusion matrix as shown in Table 3.6 for GLCM 0°, GLCM 45°, GLCM 90°, and GLCM 135°. According to the empirical results, the proposed NTRSC approach accurately classifies COVID and NON-COVID images. The proposed NTRSC approach produces the correct predictions as the same output results which prove that NTRSC provides the best result than other classifiers. From all the classifiers examined, GLCM 0° NTRSC has 0.95% accuracy. The proposed NTRSC achieved better classification accuracy

Table 3.5 Various evaluation metrics

Metrics	Formula
Precision	$\frac{TP}{TP+FP}$
Recall (sensitivity)	$\frac{TP}{TP+FP}$
Specificity	$\frac{TN}{TN+FP}$
Negative Predictive Value	$\frac{TN}{TN+FN}$
False Predictive Value	$\frac{FP}{FP+TN}$
False-Negative Value	$\frac{FP}{TP+FP}$
F1-score	$2.\frac{PRECISION*RECALL}{PRECISION+RECALL}$
G-Mean	$\sqrt{PRECISION*RECALL}$
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Error Rate	$\frac{FP+FN}{TP+TN+FP+FN}$
Matthews Correlation Coefficient	$(TP*TN)-(FP*FN)/SQRT((TP+FP*(TP+FN)*(TN+FP)*(TN+FN))$
Lift	$\frac{(TP/(TP+FP))}{((TP+FN)/(TP+TN+FP+FN)}$
Youden's Index	$SENSITIVITY+SPECIFICITY-1$
Balanced Classification Rate	$\frac{1}{2}(SENSITIVITY+SPECIFICITY)$
Balanced Error Rate	$1-BCR$

[a] *TN* True Positive, *TP* True Negative, *FP* False Positive, *FN* False Negative

than other methods, and the minimum error rate of 0.04 is represented in Table 3.7. It also proves the efficiency of the proposed NTRSC approach. The output of the decision-making algorithms for the GLCM 45° dataset in the proposed NTRSC algorithm has an 88% overall accuracy and a 0.12% error rate. The proposed decision-making algorithm earns the highest score on Youden index, i.e., 2.83. For GLCM 90° in the COVID dataset, the classification accuracy of the NTRSC is higher than that of Decision Tree, Random Forest Classifier, Naive Bayes Classifier, K-Nearest Neighbor, and Support Vector Machine. It also demonstrates that the

Table 3.6 Confusion matrix, precision, recall, F1-Score, support, and G-Mean for various classifiers

GLCM features	Classification algorithm	Desired output	Output result for confusion matrix CO N-CO		Precision	Recall	F1-Score	Support	G-Mean
GLCM 0°	NTRSC	CO	97	7	0.96	0.93	0.95	104	0.94
		N-CO	4	116	0.94	0.97	0.95	120	0.95
	Decision Tree	CO	87	13	0.87	0.87	0.90	124	0.87
		N-CO	13	111	0.90	0.90	0.90	121	0.90
	Random Forest	CO	97	9	0.92	0.92	0.92	106	0.92
		N-CO	9	109	0.92	0.92	0.92	118	0.92
	Naive Bayes	CO	67	39	0.85	0.63	0.72	106	0.73
		N-CO	12	106	0.73	0.90	0.81	118	0.81
	KNN	CO	94	10	0.96	0.90	0.93	104	0.92
		N-CO	4	116	0.92	0.97	0.94	120	0.94
	SVM	CO	79	19	0.86	0.81	0.84	97	0.83
		N-CO	13	114	0.86	0.90	0.88	127	0.87
GLCM 45°	NTRSC	CO	98	8	0.97	0.70	0.81	97	0.82
		N-CO	10	108	0.81	0.98	0.89	127	0.89
	Decision Tree	CO	85	24	0.80	0.78	0.79	109	0.78
		N-CO	21	94	0.80	0.82	0.81	115	0.80
	Random Forest	CO	91	9	0.70	0.78	0.74	95	0.73
		N-CO	18	106	0.82	0.76	0.79	129	0.78
	Naive Bayes	CO	65	39	0.78	0.62	0.70	104	0.69
		N-CO	18	102	0.72	0.85	0.78	120	0.80
	KNN	CO	95	11	0.80	0.90	0.84	106	0.84
		N-CO	24	94	0.90	0.80	0.84	118	0.84
	SVM	CO	62	35	0.70	0.64	0.67	97	0.66
		N-CO	27	100	0.74	0.79	0.76	127	0.76
GLCM 90°	NTRSC	CO	110	9	0.99	0.94	0.96	119	0.96
		N-CO	2	103	0.94	0.99	0.96	105	0.96
	Decision Tree	CO	80	26	0.84	0.75	0.80	106	0.79
		N-CO	15	103	0.80	0.87	0.83	118	0.87
	Random Forest	CO	86	20	0.88	0.81	0.84	106	0.84
		N-CO	12	106	0.84	0.90	0.87	118	0.86
	Naive Bayes	CO	50	49	0.66	0.51	0.57	99	0.58
		N-CO	26	99	0.67	0.79	0.73	125	0.72
	KNN	CO	100	8	0.89	0.93	0.91	108	0.90
		N-CO	12	104	0.93	0.90	0.91	116	0.91
	SVM	CO	52	45	0.74	0.54	0.62	97	0.63
		N-CO	18	109	0.71	0.86	0.78	127	0.78

(continued)

Table 3.6 (continued)

GLCM features	Classification algorithm	Desired output	Output result for confusion matrix CO N-CO		Precision	Recall	F1-Score	Support	G-Mean
GLCM 135°	NTRSC	CO	110	9	0.97	0.90	0.93	119	0.93
		N-CO	2	103	0.89	0.97	0.93	105	0.92
	Decision Tree	CO	90	14	0.82	0.87	0.84	104	0.84
		N-CO	20	100	0.88	0.83	0.85	120	0.84
	Random Forest	CO	98	8	0.89	0.92	0.91	106	0.90
		N-CO	12	106	0.93	0.90	0.91	118	0.91
	Naive Bayes	CO	72	38	0.82	0.65	0.73	110	0.73
		N-CO	16	98	0.72	0.86	0.78	114	0.78
	KNN	CO	97	4	0.88	0.96	0.92	101	0.91
		N-CO	13	110	0.96	0.89	0.93	123	0.92
	SVM	CO	68	29	0.77	0.70	0.74	97	0.73
		N-CO	20	107	0.79	0.84	0.81	127	0.81

Table 3.7 Performance metrics for various classifiers

GLCM features	Performance measures	NTRSC	DTC	RFC	NBC	KNN	SVM
GLCM 0°	Accuracy	0.95	0.88	0.92	0.77	0.94	0.86
	Sensitivity	0.95	0.87	0.91	0.84	0.95	0.85
	Specificity	0.94	0.89	0.92	0.73	0.92	0.86
	Error rate	0.04	0.11	0.08	0.22	0.06	0.13
	MCC	0.89	0.76	0.84	0.55	0.87	0.71
	NPV	0.96	0.91	0.92	0.88	0.91	0.89
	FPV	0.05	0.11	0.06	0.28	0.06	0.13
	FNV	0.04	0.09	0.08	0.13	0.09	0.14
	Lift	2.07	1.94	1.93	1.79	2.06	1.98
	Youden's index	2.90	2.76	2.83	2.57	2.87	2.72
	BCR	0.95	0.88	0.91	0.78	0.93	0.86
	BER	0.04	0.11	0.08	0.21	0.06	0.13
GLCM 45°	Accuracy	0.88	0.80	0.86	0.75	0.84	0.72
	Sensitivity	0.90	0.80	0.83	0.78	0.79	0.69
	Specificity	0.89	0.79	0.79	0.72	0.81	0.74
	Error rate	0.12	0.20	0.13	0.28	0.15	0.27
	MCC	0.73	0.62	0.70	0.44	0.69	0.43
	NPV	0.75	0.78	0.92	0.83	0.84	0.78
	FPV	0.17	0.19	0.06	0.29	0.21	0.25
	FNV	0.29	0.25	0.08	0.22	0.17	0.30
	Lift	1.91	1.64	1.87	1.64	1.68	1.60
	Youden's index	2.83	2.59	2.75	2.72	2.43	2.43
	BCR	0.91	0.79	0.87	0.86	0.71	0.71
	BER	0.08	0.20	0.12	0.13	0.15	0.28

(continued)

Table 3.7 (continued)

GLCM features	Performance measures	NTRSC	DTC	RFC	NBC	KNN	SVM
GLCM 90°	Accuracy	0.96	0.82	0.86	0.67	0.91	0.72
	Sensitivity	0.99	0.84	0.87	0.65	0.89	0.74
	Specificity	0.93	0.79	0.84	0.66	0.92	0.70
	Error rate	0.03	0.18	0.14	0.33	0.08	0.28
	MCC	0.92	0.74	0.73	0.73	0.85	0.42
	NPV	0.99	0.92	0.88	0.79	0.90	0.85
	FPV	0.06	0.20	0.13	0.30	0.05	0.29
	FNR	0.00	0.09	0.13	0.36	0.10	0.25
	Lift	1.87	1.77	1.85	1.48	1.85	1.71
	Youden's index	2.92	2.64	2.71	2.32	2.82	2.45
	BCR	0.96	0.82	0.85	0.66	0.91	0.72
	BER	0.03	0.17	0.14	0.33	0.08	0.27
GLCM 135°	Accuracy	0.93	0.88	0.91	0.76	0.92	0.78
	Sensitivity	0.97	0.81	0.89	0.81	0.88	0.77
	Specificity	0.89	0.87	0.92	0.72	0.96	0.78
	Error rate	0.06	0.15	0.08	0.24	0.07	0.21
	MCC	0.86	0.72	0.81	0.40	0.80	0.55
	NPV	0.97	0.84	0.96	0.79	0.89	0.84
	FPV	0.10	0.15	0.06	0.27	0.08	0.21
	FNR	0.02	0.18	0.10	0.25	0.11	0.22
	Lift	1.84	1.76	1.88	1.66	1.95	1.78
	Youden's index	2.86	2.69	2.82	2.53	2.84	2.55
	BCR	0.93	0.84	0.91	0.76	0.92	0.77
	BER	0.06	0.15	0.08	0.23	0.07	0.22

proposed NRSC approach is more efficient than the KNN classification algorithm. For GLCM 135°, the proposed NTRSC outperforms all the algorithms, and NTRSC produces the 0.93% accuracy with a 0.06 error rate.

The effectiveness of algorithms is computed using various validation measures. Figures 3.6 and 3.7 present the performance of various classifiers: GLCM 0°, GLCM 45°, GLCM 90°, and GLCM 135° datasets. From this figure, the proposed NTRSC approach produces the best accuracy for all datasets and minimum error rate, i.e., it outperforms the other algorithms.

A Receiver Operating Characteristic (ROC) curve is a graph that shows how well a classification model performs overall classification thresholds. Two parameters plotted on this curve are true-positive and false-positive rate. The proposed NTRSC approach outperformed the other current classification algorithms on all datasets, including GLCM 0°, GLCM 45°, GLCM 90°, and GLCM 135°. The NTRSC algorithm's curve appears in the ROC graph's top left border. This indicates that the

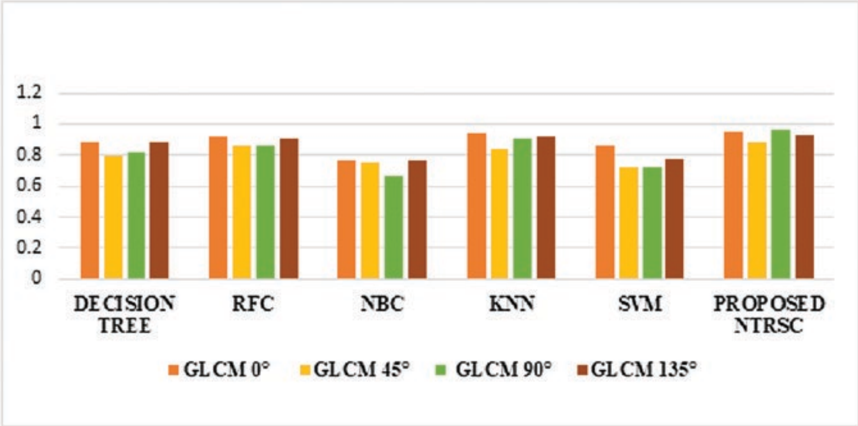

Fig. 3.6 Accuracy comparison for various classifiers

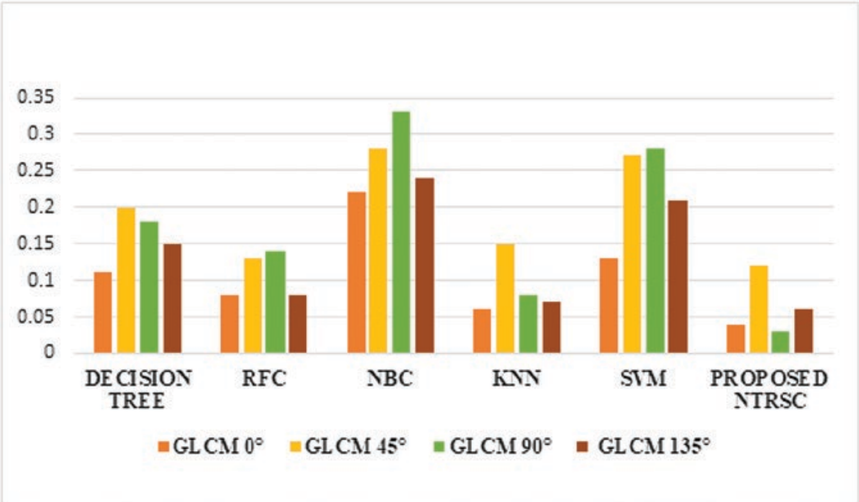

Fig. 3.7 Error rate comparison for various classifiers

proposed approach correctly differentiates between COVID and NON-COVID. The ROC curve comparison of the proposed NTRSC approach and current decision-making algorithms is shown in Figs. 3.8, 3.9, 3.10, and 3.11 for GLCM 0°, GLCM 45°, GLCM 90°, and GLCM 135° datasets.

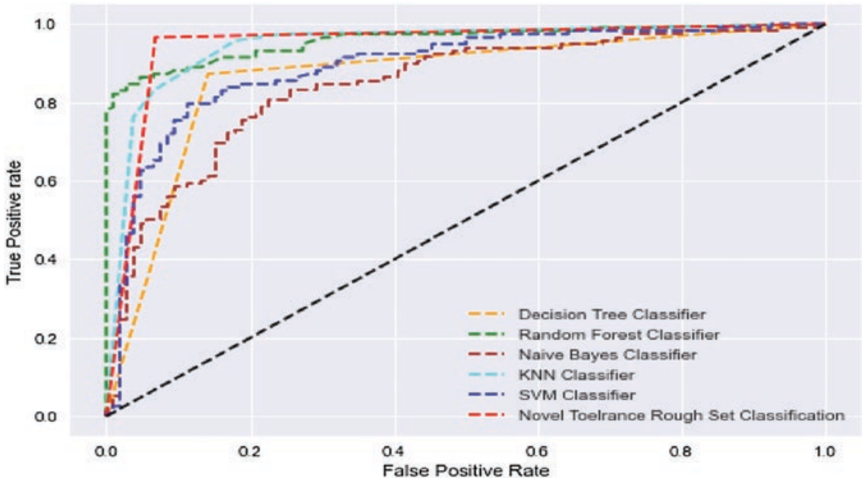

Fig. 3.8 ROC curve analysis NTRSC approach – GLCM 0°

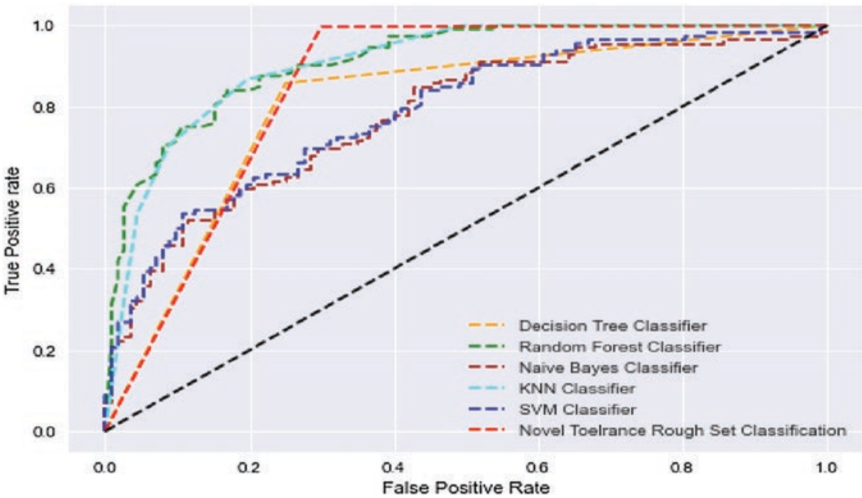

Fig. 3.9 ROC curve analysis NTRSC approach – GLCM 45°

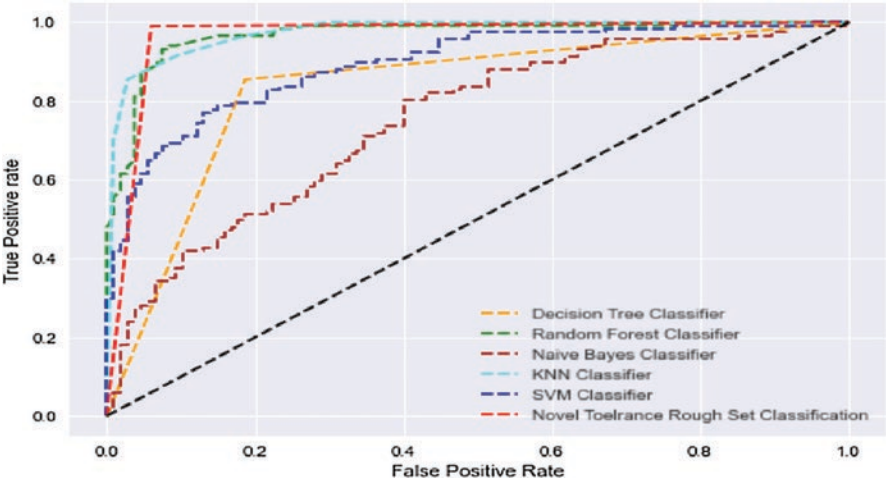

Fig. 3.10 ROC curve analysis NTRSC approach – GLCM 90°

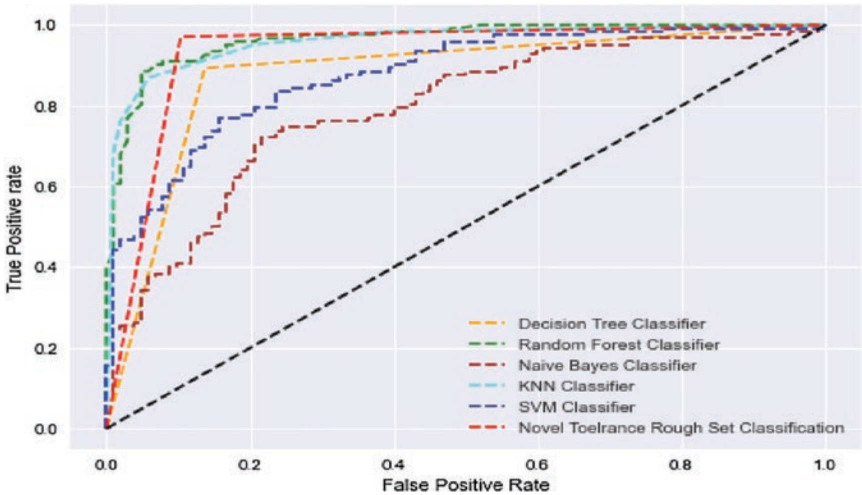

Fig. 3.11 ROC curve analysis NTRSC approach – GLCM 135°

3.6 Conclusion

Finally, in the current situation, where COVID-19 is still spreading, rapid and accurate diagnosis and disease progression analysis are critical. COVID-19 must be diagnosed early to treat and isolate individuals and prevent the virus from spreading. COVID-19 CT scan images for the GLCM 0°, GLCM 45°, GLCM 90°, and

GLCM 135° datasets were retrieved from the GitHub source, with accuracy values of 95%, 88%, 96%, and 93%, respectively. The chest CT dataset of COVID-19-infected patients and NON-COVID-19-infected patients is first decomposed into two sets: training and testing. Novel Tolerance Rough Set Classification (NTRSC) approach is applied in the training process, deciding on a collection of new information based on data acquired by lower rules and identifying the closest matches with the testing dataset. The experimental results were found to be highly compelling, and the approach was shown to be a helpful tool for COVID-19 screening on CT scan images of corona suspects. The presented approach is combined with current benchmark algorithms, and several classification measures are assessed. The obtained findings suggest that the proposed NTRSC approach has greater output accuracy with a low error rate than other algorithms. The obtained result demonstrates that the presented approach outperforms other comparative classification algorithms in terms of accuracy. Furthermore, the proposed algorithm achieves the greatest ROC. Finally, proposed Novel Tolerance Rough Set Classification approach for distinguishing COVID-19 and NON-COVID-19 images are classified accurately and helpful for diagnosis. Multiple illnesses such as pneumonia, bronchitis, and tuberculosis (TB), as well as COVID-19 of suspected persons with respiratory illness, can be detected in the future. As future work, the proposed approach might be extended to classify more lung illnesses. This can be accomplished by using multi-class classifier. For further studies, a larger dataset COVID-19 data will be collected, and deep learning architectures on the datasets will be tested.

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Chapter 4
Artificial Intelligence of Things for Early Detection of Cardiac Diseases

Tomina Thomas and Anna N. Kurian

4.1 Introduction

Much of the fatal illnesses are cardiovascular diseases (CVD) that might be coronary heart diseases. According to the World Health Organization (WHO) report, 17.9 million deaths related to CVDs were found in 2016, comprising 31% of all worldwide deaths. Medical scientific know-how is causing rapid strides in solving these problems and advances to solve those issues.

The past three decades have been characterized by an exponential growth in knowledge and advances in the clinical treatment of atrial fibrillation (AF). It is now known that AF genesis requires a vulnerable atrial substrate and that the formation and composition of this substrate may vary depending on comorbid conditions, genetics, sex, and other factors. Population-based studies have identified numerous factors that modify the atrial substrate and increase AF susceptibility. To date, genetic studies have reported 17 independent signals for AF at 14 genomic regions. Studies have established that advanced age, male sex, and European ancestry are prominent AF risk factors.

Other modifiable risk factors include sedentary lifestyle, smoking, obesity, diabetes mellitus, obstructive sleep apnea, and elevated blood pressure predispose to AF, and each factor has been shown to induce structural and electric remodeling of the atria. Both heart failure (HF) and myocardial infarction increase risk of AF and vice versa creating a feed-forward loop that increases mortality. Other cardiovascular outcomes attributed to AF, including stroke and thromboembolism, are well

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established, and epidemiology studies have championed therapeutics that mitigate these adverse outcomes. However, the role of anticoagulation for preventing dementia attributed to AF is less established

In the current clinical practice, the heart specialist adopts the ECG sign recordings and patient's questionnaire for the preliminary assessment of the patient's condition. However, this approach might also additionally fail to capture the severity of the ailment because of the restricted period of ECG recordings and the intermittent nature of cardiac arrest. Presently, artificial intelligence (AI) may also be able to solve this issue. There are many researches done in AI till date being used nowadays.

Natural intelligence shown or expressed by human beings and animals involves the consciousness and emotions. Artificial intelligence (AI) refers to the simulation of human intelligence in the machines which can be programmed to think like humans and mimic their actions. The term may also be called to any machine that exhibits the traits associated with a human mind such as learning, problem-solving, and speech recognition. The term artificial intelligence is linked with path of our everyday life.

Artificial intelligence (AI) and wearable technologies have been found to be big developments in the area of disease remediation. For the sake of everyday fitness treatment in an elderly population, if consumers can link a wearable monitoring app that can find suspicious electrocardiogram (ECG) signs and give a warning message to the hospital immediately, this tool can save you from several tragedies.

4.1.1 Objectives

The objectives of the chapter are as follows:

- Discussion on atrial fibrillation (AF).
- Study on various monitoring devices and applications.
- Cloud-based AI and database framework.
- Discussion on accuracy and efficiency of the framework.

4.1.2 Organization of Chapter

The remaining of the chapter is organized as follows: Section 4.2 includes related terminologies of reference articles referred to the study of our topic. Section 4.3 deals with the cloud-based AI and databases. Section 4.4 deals with cloud-based AI system. Section 4.5 deals with the experimental study and result comparisons. Section 4.6 concludes the application of novel artificial intelligence in the field of personalized care.

4.2 Related Terminologies

4.2.1 Wearable Heart Condition Monitoring Device for Artificial Intelligence of Things

The whole research establishes an artificial intelligence device for electrocardiogram (ECG) evaluation and detection of cardiac disorders [1]. The device consists of IoT-based front-end hardware, a smart device Application Personal Interface, a cloud database, and a cardiac disorder identification AI platform. This involves front end with IoT-based hardware, which detects portable ECG device consisting of an analogue front-end circuit and a Bluetooth module. The software on smart phones was unable to view users' actual ECG data more accurately, but it can automatically mark irregular notifications and early detection in real time. The cloud database server is used in order to store the ECG signal. It creates a big data archive for the AI algorithm to capture heart beat anomalies. The study's suggested algorithm depends on the convolutional neural network, and 94.96% is the familiar accuracy.

This research suggests a whole ecosystem of AIoT systems that is an interactive health care system that contains a database of hardware, apps, and cloud, which is intended to increase health. Compared to different algorithms, the AI-based cardiac disease classification model, which uses the advice of an expert cardiologist as a guide, has a simpler record of preprocessing success and an acceptable recognition sequence. Conversely, in order to resolve the problems of human variations and increase the responsiveness of the model, additional input from multiple therapeutic persons is required, which could be used to test the network and help control the role of preprocessing. Furthermore, this study takes a single lead ECG as the measure, so it cannot investigate a few forms of cardiac disease.

4.2.2 Large-Scale Arrhythmia Screening Artificial Intelligence System Focused on the Cloud

The significant source of arrhythmia is atrial fibrillation (AFib), and AFib patients have an increased risk of stroke [2]. These might result in sudden cardiac arrest. For screening arrhythmia, an artificial intelligence device, a cloud-based one specifically for AFib, is used to establish an efficient and sustainable technique for the detection of undiagnosed AFib. A cloud-based device for artificial intelligence (AI) which could exhibit arrhythmia screens in various outcomes. For a health checkup, a specialist combines the armband with the smart screen to display a vast number of participants within a small time period to receive news reports instantly. Hospital patients can take the bracelet home for a period of 7–14 days, screened with a smart phone app for tracking and getting the notifications. Both data from the systems may also be managed by an automated processing algorithm that removes unnecessary data and exports feedback for doctors to make final assessments.

4.2.3 Mobile Heart Attack Early Warning Approach Using Artificial Digital Stethoscope Intelligence Novel

The chapter reports the design of a mobile, low-cost device for early cardiac abnormality detection [3]. For monitoring coronary cardiac signals in actual and transferring it to our smartphone application for simultaneous cloud assessment, a special wireless stethoscope has been created here. Coronary heart sounds are preprocessed to detect improvements by algorithms such as audio slicing and segmentation and then transformed into top-notch spectrograms classified by our pre-trained cloud-based convolutional neural network (CNN).

4.2.4 Artificial Intelligence Management Allowed Smart Wearable Devices for CVD Early Diagnosis and Continuous Monitoring

Many researches addresses the therapy to regulate CVDs which are capable to timely monitor the patients [4]. Wearable devices are found to be an efficient way of overcoming the requirements of CVDs. In reality, even so, it is a basic pickup innovation that typically needs to be understood and cost-effective for which unique hints are determined to allow their still fully functional skills, such as solar-powered batteries in the unit. This will be used to evaluate the outcomes of implementing the era of wearable devices in the wellness of the patient with coronary heart diseases and their effects on the patients' lifestyle, as well as to aid for an assessment of the mechanism of the era of wearable devices on patients with cardiovascular diseases, to examine the effect of sophisticated artificial intelligence approaches on improving the speed and precision of wearable devices, and to discuss the potential problems of smart wearable devices that want to be solved.

4.2.5 Heart Disease Prediction Using Artificial Intelligence

Machine learning (ML) artificial intelligence is already found to be powerful in promoting the decision-making and forecasting of the vast volume of knowledge provided by means of the healthcare industry [5]. We have seen ML methods being used in new technologies in various Internet of Things (IoT) areas. Various studies give an insight into the prediction of coronary heart disease with ML techniques.

In this, a novel method aims at identifying main characteristics by ways of using system study technology to achieve the precision of disorder forecasting. With special configurations of abilities and many recognized classification methods, the prediction model is applied. Recognizing the production of raw patient information from coronary heart records will help save human lives and diagnose abnormalities in coronary heart problems early in the future. Computer study algorithms have been implemented to system data on this work and include a substitution and novel discernment of heart disease. In the clinical area, coronary heart disease estimation is challenging and potentially important. Even so, once the disease is diagnosed at the initial stage, the loss of life rate is routinely dramatically controlled, and prevention steps are followed as quickly as possible. Instead of only theoretical methods and models, further expansion of this analysis may be more useful to guide the studies to real-world datasets.

4.3 Cloud-Based AI and Database

A cloud-based artificial intelligence (AI) framework that can view heart condition displays screens in multiple scenarios. The cloud database server is used to capture the ECG signals of each individual, which forms a large-data AI algorithm database for cardiovascular disease detection. By means of an automated processing algorithm that eliminates redundant documents and export reports, all machine data can be processed for doctors to make final evaluations. More details are mentioned in Sect. 3.3.

4.3.1 Artificial Intelligence

Artificial intelligence (AI) [3] is a computational machine that is capable of conducting activities that typically involve human intelligence, like receiving environmental impressions and accomplishing goals using algorithms, pattern matching, heuristics, rules, cognitive computing, and deep learning (DL).

The continuing advancement of AI approaches, especially in the ML and DL subdomains, has increasingly drawn clinicians' attention to improving novel integrated, effective, and competitive strategies for delivering quality healthcare.

In cardiovascular medicine, imaging is the subject of concern and analysis in AI. In echocardiography, the benefits of using machine learning models lie in the elimination of inter- and intra-operator variability. It provides additional statistical information that could be too subtle for the human eyes to identify.

The relationship among cardiac CT and ML algorithms in people having these disorders has demonstrated the ability in clinical practice to take noninvasive methods and to identify functional knowledge beyond the characterization of atherosclerotic plaque. In addition to diagnostic imaging, automated identification of anomalies in electrocardiograms may be another interesting use of ML in cardiology.

4.3.2 Machine Learning

Machine learning (ML) [6] is a subset of AI that seeks to "teach" computers with the use of complicated computation and statistical algorithms to analyze vast datasets in a fast, accurate, and effective manner. Such models may recognize trends on new data that fit and render predictions based on current data they have already "learned from." It can be classified into three groups based on the way in which the predictive model learns and accumulates the data:

1. Supervised learning (e.g., logistic regression, Support Vector Machine, and neural networks): utilizes human-labeled databases that are typically often used build models that anticipate or describe potential events or know the most significant outcome variables. Figure 4.1 shows the block diagram of supervised learning.
2. Unsupervised learning (e.g., cluster analysis): in datasets through prior categorization of the training collection, the algorithm may recognize hidden framework (only when x is known). It identifies novel relationships within the results. Figure 4.2 shows the block diagram of unsupervised learning.
3. Reinforcement learning/semi-supervised learning: reward-driven learning (usually deployed in games and robotic apps), focused on atmospheric interactions where positive and negative reinforcements contribute toward the development of the predictive model. The computer must be designed with devices and facilities that not only promote learning but also take into account environmental features, such as sensors and cameras. Figure 4.3 shows the block diagram of reinforcement learning/semi-supervised learning.

Fig. 4.1 Supervised learning

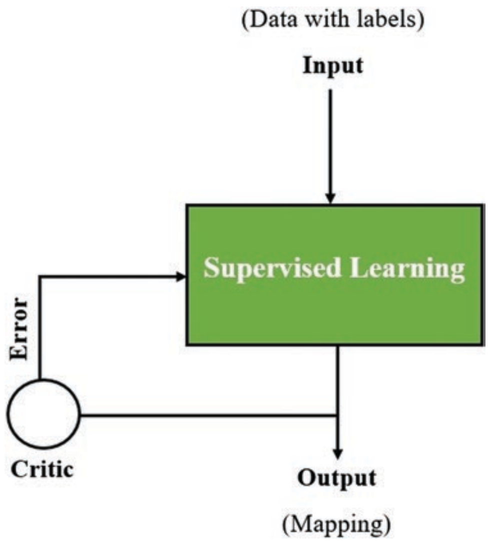


Fig. 4.2 Unsupervised learning

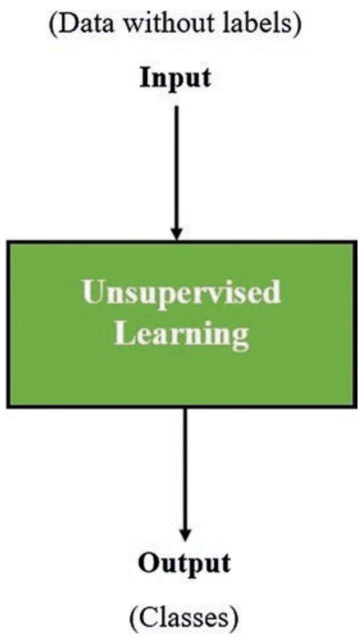
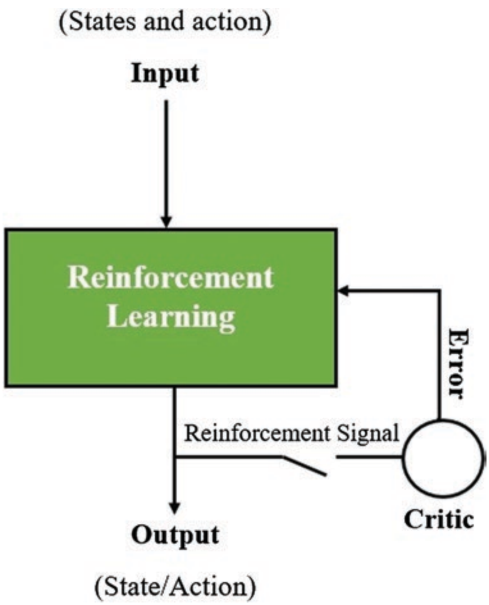


Fig. 4.3 Reinforcement learning/semi-supervised learning



4.3.3 Deep Learning

Deep learning (DL) [6] is a supervised approach to ML that utilizes neural networks which is defined by artificial algorithm process of capturing meaningful patterns of data collection. It imitates the complex human brain, being capable of learning from information with complex hierarchical representations that have multiple abstraction layers. The programmer incorporates known data into the machine which is designed to facilitate algorithms to effectively respond, even when exposed to completely new information. Via experience, the neural network knows and learns data, creates hierarchical structures, and offers advanced stages of input-output. This could catch dynamic nonlinear interactions among outcome variables of input-output. By calculating the weights toward the input and outcome data, the average error of results and their estimates can be minimized.

Based on their expertise, training, and cultural history, doctors diagnose them. At this stage, deep learning may be very effective and broadens and improves medical knowledge, particularly for nonexpert doctors.

Through utilizing more hidden layers, DL can investigate more complicated nonlinear patterns in the data than a classic neural network. For such a purpose, attributed to the rise in the volume and sophistication of data, especially in the field of imaging analysis, the applications of DL in the field of medical research have recently become popular.

In Facebook's image recognition software, DL also plays a leading role in speech recognition in Apple's Siri and Amazon's Alexa, Google brain and robots, etc.

Convolutional neural networks (CNN), recurrent neural networks, deep belief networks, and deep neural networks seem to be the most popular deep learning algorithms in the medical setting.

4.3.4 Value of Medical AI

In particular, laws and legislation have been established and enforced by governments and agencies around the world to create a safer medical climate for patients [3]. There are also many flaws in the modern medical system, including an unequal allocation of senior physicians, a high incidence of primary clinician misdiagnosis, lengthy preparation times for clinicians, scarcity of clinicians in undeveloped areas, and high medical costs for patients.

Even so, in recent times, with the growth and success of machine learning technologies, AI has steadily changed from concept to practicality. The numerous uses of AI in medicine are being illustrated. In turn, AI technology has been an influential factor that can impact the growth of the medical sector and increase the quality of medical services.

AI has numerous uses in the medical field [7, 8]. After that, AI will help doctors detect ailments and develop protocols for healing. Since being applied to traditional medical practices, AI can reduce the quantity of wrong diagnosis and improve diagnostic efficiency. Currently, with the advent of deep learning, AI has the ability to classify patient images and provide clinicians with more detailed diagnostic imaging information. Also, with the use of big data processing, AI systems can however generate very reliable results for patient forecasting (AI can analyze very large amounts of data which are impossible to analyze using standard data processing methods). AI would also help to encourage the development of drugs and improve the viability of new drugs being developed. Ultimately, the combination of AI and surgical robots will improve the accuracy of many complex and challenging operations. With the growth of AI, big data analytics, and cloud computing technologies, AI will deliver high-quality medical services to patients. In addition, the production of smart medicine and precision medicine will be strengthened by AI, shortening the time and cost of waiting for clients and receiving safe, affordable, and high-quality medical services. The implementation of AI deep learning in cardiovascular medicine will also benefit from the application of AI deep learning.

4.4 Cloud-Based AI System

The cloud infrastructure is intended to be able to provide a fast and efficient way to store the ECG data collected from wristband to a database [2]. Consequently, the system must also have functionality such as management, reporting, and editing as needed. To satisfy different screening requirements, the cell and web system architecture must be flexible to accommodate each one [9]. The United States licensed a wearable GUI. The Food and Drug Administration (FDA) was selected to record the 30 s ECG signals. Stored data can be transferred via Bluetooth Low Energy (BLE) to a mobile app within a few seconds. After the mobile app gets the collected info, the user can add his or her ID, date of birth, or several documents to produce a report. On the server side, after the file is obtained and imported into the algorithm, the ECG signal can be preprocessed with coding and filtering. Figure 4.4 shows the cloud-based AI system architecture [2].

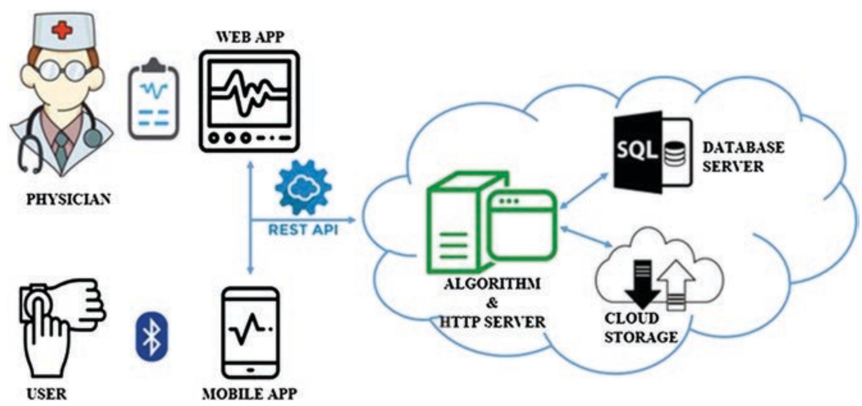


Fig. 4.4 The cloud-based AI system architecture

A technician or doctor on the website will review the final result. The wristband and smartphone app are connected by BLE opposed to a Bluetooth, which provides a simple connection and switch format with reduced power consumption. Following the data transferred toward the mobile app, the data can be sent to the server via HTTPS (Hypertext Transfer Protocol Secure) with additional documentation for further analysis.

4.4.1 Cloud Platform

In terms of cyber protection, Google Cloud Platform providers come under the framework of ISO 27001, 27,017, and 27,018 and help comply with the portability and transparency of Health Insurance Act [2]. The GCP compute engine service provides the size, efficiency, and cost to enable customers to build and operate virtual machines on Google infrastructure without problems. A consumer-friendly graphical user interface provides a highly flexible and efficient, quick, and completely controlled interface. To secure records, the database is designed to be automatically returned every day. To minimize the input-output burden of the database, the actual document transmitted by the mobile app should be stored in the Google Cloud Storage [10, 11]. Through this multiregional storage, the latency of the end users is being greatly reduced, and the service may be used to move data to cloud storage to reduce costs. With the server, database, and storage which are independently built over the GCP infrastructure, the cloud system could be replicated and transferred according to this model in a similar fashion, meaning that identical units could be customized for different purposes, such as medical facilities or public health centers.

4.4.2 Cardiac Disease Detection Algorithm

To reduce noise, the raw ECG data was filtered by band transfer, and the QRS peaks were identified using an adaptive threshold system [2]. A cardiac disease detector with a threshold of 0.725 can process the RR interval from the peaks to establish the segmentation of cardiac disease [2].

4.4.3 Screening Method

The screening system may be classified into two classifications: one to test and generate results upon instantaneous data transfer and the other to be used at home [2]. The calculation process was demonstrated to the respondents orally, and informed written consent was obtained. Once uploaded to the municipal health data registry, personal identity-related information would be secure. In order to analyze information from the wristband and connect it to the server, the immediate home measuring tool should be included for the smartphone. On-site screening is carried out by licensed technicians. In rapid estimation, they assist the condition and link the details of the topic to the measurement record [12]. The web app helps technicians, as per the specifications, to search data or change information on it. The document can be created to be used as a basis for final diagnosis by the doctor.

4.4.4 Application of AI in CVD

In cardiovascular medicine [3], AI technologies were used, such as precision medicine, clinical prediction, cardiac imaging research, and intelligent robotics. The application of AI in cardiovascular medicine has exciting outcomes.

4.4.4.1 Precision Medicine

For remote follow-ups, drug alerts, real-time condition therapy, and earlier indication warnings [6], AI would be implemented mainly on the focus from the patient's viewpoint. At the very same time, it helps to capture voice information (such as patient history), connect clinicians' electronic medical record systems, and reduce clinicians' workload. Cognitive systems (machine learning devices or deep learning algorithms that can solve challenges without any human assistance) help doctors make accurate decisions and also predict health future performance [13, 14]. A detailed treatment strategy that customizes healthcare for each patient is more likely to be introduced with the aid of AI. People agree that doctors would not be replaced by AI. Clinicians, on the other hand, must learn about using AI technologies and obtain expertise in the clinical practice of implementing AI to enhance the evaluation and management of cardiovascular diseases by big data processing, helping to enter the age of precision medicine. Precision medicine, which is more necessary to be completed with the aid of AI, can tailor healthcare for each particular patient. It is believed that AI is not going to substitute clinicians.

4.4.4.2 Clinical Predictions

AI can help doctors make very reliable patient forecasts via machine learning and big data analytics [5]. Data from Dawes TJW indicates that for patients with heart disease, AI may estimate future periods of death. In their research, AI program reported the findings of cardiac magnetic resonance imaging (MRI) tests and blood tests of 256 patients with heart disease. The program calculated the motion of 30,000 points in each heartbeat, which are marked on the heart structures. AI might anticipate the abnormal symptoms that lead to patient mortality by comparing this information with the 8-year clinical history of the patients [15, 16]. In comparison, their program was capable of predicting patients' survival rates for the next 5 years, and the estimation accuracy of patients' survival for the next year could comfortably exceed 80%. The estimation accuracy of the doctors, nevertheless, was just 60%. In addition, it established a predictive model for 10,030 suspected coronary heart disease (CHD) patients with the use of deep learning to determine the probability of death for the next 5 years. Their findings found that the AI-based risk assessment is superior to standard clinical decision and coronary computed tomographic angiography.

4.4.4.3 Cardiac Imaging Analysis

Cardiac imaging analysis [6] has demonstrated great growth opportunities in recent years, with the emergence of deep learning. Deep learning will discuss coronary angiography, echocardiography, and electrocardiography (ECG). The main treatment for cardiovascular disease in recent times has been heart surgery, especially CHD and acute coronary syndrome (ACS). While using deep learning, AI will be able to identify coronary atherosclerotic plaques more accurately than clinicians in the near future [17]. In comparison, for echocardiographic image analysis, AI will also be used, requiring automatic scale estimation inside each chamber and left ventricular (LV) function inspection. Moreover, systemic disorders, like valvular disease, may be measured to better identify the type and staging of diseases.

4.4.4.4 Intelligent Robots

With the advent of surgical robotics [6], the computer was ready to assist doctors conduct bladder graft surgery and hysteromyoma resection. In the future, the incorporation of AI and minimally invasive surgical systems, along with the da Vinci surgical robot, would make robotic surgery more realistic, minimize patient trauma, improve surgical protection, and shorten hospital stays. In contrast, AI could perform cardiac interventional procedures on patients rather than physicians with this kind of combination, like percutaneous coronary intervention (PCI) procedures and atrial fibrillation catheter ablation, which can use automatic subtraction angiography to reduce the radiation exposure of clinicians [18, 19]. By using reinforcement learning, particularly for use in repetition exercises, the knowledge of AI will be much superior to that of a human being. The AI can also practice more easily than human doctors how to perform procedures. In brief, the use of AI and surgical robotics at the same time will make the traditional medicine revolution simpler.

AI techniques such as machine learning, deep learning, and cognitive computing, especially in cardiovascular imaging, will change the practice of cardiology and cardiovascular medicine (e.g., how we produce information, analyze data, and make decisions).

4.4.4.5 Echocardiography

Throughout the diagnosis and treatment of cardiovascular disorders, but in the effective research method of cardiac development and function, the task of echocardiography is critical [6]. Even so, this also relies mostly on operator and knowledge with inter-variability. Throughout the study of medical echocardiography, AI technology, specifically machine learning, offers new ways to expand the accuracy of image analysis, particularly between nonexpert clinicians. A broad variety of complex disease dynamics can be defined by ML models that learned to learn unique attributes in an image, taking into account each pixel and their experiences.

ML models can automatically reflect unused data obtained by the advent of multidimensional imaging modalities (such as 3D echocardiography and speckle tracking) [20]. This leads to the advantages of decreasing analytical time and increasing reproducibility.

3D echocardiographic automatic evaluation can indeed be performed out by Heart Model, a software program that implements a model-based algorithm. In a few seconds, the software-integrated algorithm can quickly allocate the accompanying (i) volumes of the left chamber (atrium and ventricle), (ii) systolic flow, and (iii) LV ejection fraction from the 3D echocardiographic information obtained. In addition, from a certain eco-3D dataset, the app often attains the atrium volume simultaneously, providing a fuller estimation of the atrium function relative to traditional measurement methods. Another notable component to the analysis is that it was designed to examine eco-3D datasets acquired in single-beat mode. This may be particularly efficient in patients where 3D interpretation is difficult, such as those with repeated arrhythmias or those with respiratory problems.

ML models of clinical echocardiography practice may benefit from a broad range of cardiovascular diseases. Also, it demonstrates that supervised learning algorithms might more appropriately distinguish athlete's heart and hypertrophic cardiomyopathy from traditional measurement systems using STE (Secure Terminal Equipment) data. Some other possible area of use for ML models of echocardiography is heart valve disease (HVD). HVD is an extremely frequent disease that may benefit from ML cardiac imaging incorporation via early detection, treatment, or surgical preparation. It assessed that without the need to measure the left ventricular outflow tract (LVOT), AI will allocate the aortic valve area (AVA) to aortic valve stenosis from other echocardiographic information; a high accuracy (0.95) was acquired.

Recent research has also shown that AI tools can be used to improve HF diagnosis, identification, intensity estimate, and estimation through echocardiographic data and clinical factors of side effects, especially in patients with retained ejection fraction.

4.4.4.6 Magnetic Resonance Imaging

One of the fields of cardiac MRI [6] which has more potential for the implementation of ML models is ventricular segmentation. It enables volumetry to be quantified and diagnostic monitoring accuracy and reproducibility to be increased. For the automated classification and extraction of the right ventricular (RV) chamber, deep learning algorithms (i.e., convolutional neural networks and stacked autoencoders) trained by cardiac MRI datasets were used to predict the performance of such algorithms [21]. Likewise, for left ventricular segmentation, especially for cardiac cine MRIs, multiple artificial neural networks were successfully introduced. Subacute or chronic myocardial scar recognition is another use of ML in cardiac MRI.

4.4.4.7 Cardiac Computed Tomography

In the treatment and risk assessment of coronary artery disease (CAD) [6] and atherosclerosis, methodologies for ML image processing in cardiac CT are progressively utilized (e.g., coronary artery calcium scoring and fractional flow estimation). A noninvasive way of diagnosing coronary heart disease is coronary computed tomographic angiography (CCTA). It usually exaggerates the severity of stenosis compared with intrusive angiography, and where fractional flow reserve (FFR) is used as a guideline, angiographic stenosis does not really immediately indicate hemodynamic importance [22]. So many ML models have therefore been found to evaluate noninvasive FFR and enhance CCTA efficiency by correctly reclassifying hemodynamically nonsignificant stenosis.

Automatic coronary artery calcium scoring in CCTA using ML models provides additional therapeutic benefit by reducing false positive and inter-observer uncertainty in order to characterize coronary plaque. Some other use of ML to cardiac CT in the prognosis and management of myocardial infarction is the use of texture analysis techniques.

The early findings of the SMARTool project have implemented a new approach focused on ML treatment outcomes and quantitative biomechanics for CAD patient care (diagnosis, prognosis, and treatment) [23]. A retrospective and prospective ML study (clinical, biohumoral, CCTA imaging, lipidomics, etc.) was conducted to differentiate patients from those at low to moderate to high risk. The CAD diagnostic module is focused on 3D coronary artery reconstruction and noninvasive smart FFR estimation, while CAD projections are focused on complicated numerical models of plaque formation.

4.4.4.8 Applications in Electrocardiography

In addition to diagnostic imaging, electrocardiography [6] is other area which may also benefit again from incorporation of ML to its practices. The most commonly used method to detect abnormalities of electric cardiac function is the electrocardiogram (ECG). ML models, in particular the DL subfield, have made it possible to detect irregularities automatically in electrocardiograms, reducing interpretation time and reliance on human heterogeneity [24]. In order to help classify the heart rhythm, supervised learning algorithms were largely designed. Essential features like PhysioNet Project's MIT-BIH Arrhythmia allow the ability to both exercise and test the various algorithms. In addition, in the unsupervised learning analysis, the learning can take place in queries that do not have a default classification [25]. Data not historically named is viewed with this methodology and subsequently divided into subgroups of ECG phenotypes with various approaches. Specifically, by compiling data with identical architectures, ECG phenotypes correlated with arrhythmic risk markers for hypertrophic cardiomyopathy have been established and categorized.

4.5 Experimental Study

For medical trials that can be performed by patients at Tainan Hospital, Ministry of Health and Welfare, the assessment of this AIoT method is sent to the Ministry of Health and Welfare. Each section can be tested in these tests, including the wearable ECG-sensing method, application user interface, cloud service, and AI-based method.

4.5.1 System Design

In order to minimize the risk of major heart attacks, the Artificial Intelligence of Things (AIoT) system aims to test actual ECG signals throughout this review. A smart machine user interface, a cloud database, and an AI-based cardiac disease monitoring algorithm for real-time identification, low power consumption, and long-term use, as well as a compact front-end ECG-sensing platform form the complete device design. Figure 4.5 shows the device block of the acquisition and implementation of ECG signals [1].

4.5.2 Wearable ECG Monitoring Device

This study proposes a monitoring hardware structure that involves a low-energy analogue front-end circuit, an integrated commercial energy management (IC) circuit, and a commercial Bluetooth module [1]. A self-designed chip system (SOC),

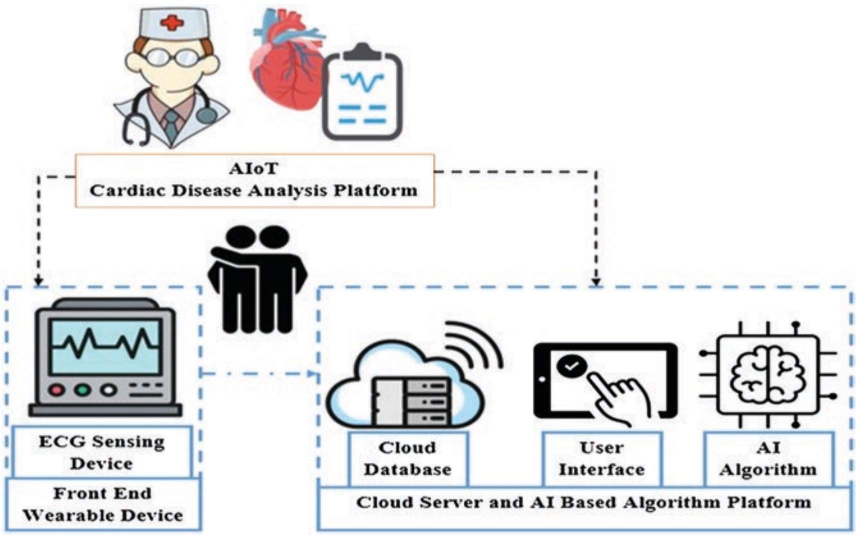


Fig. 4.5 Device block of the acquisition and implementation of ECG signals

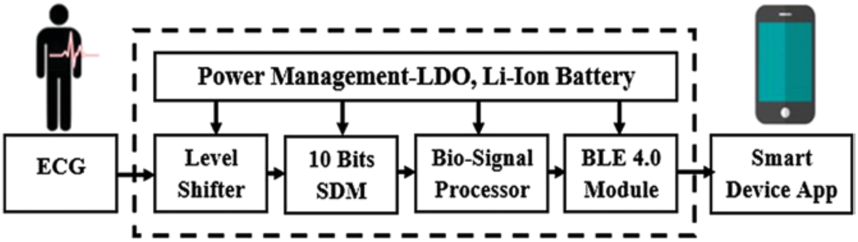


Fig. 4.6 Block diagram of the front-end system of the deployed ECG acquisition

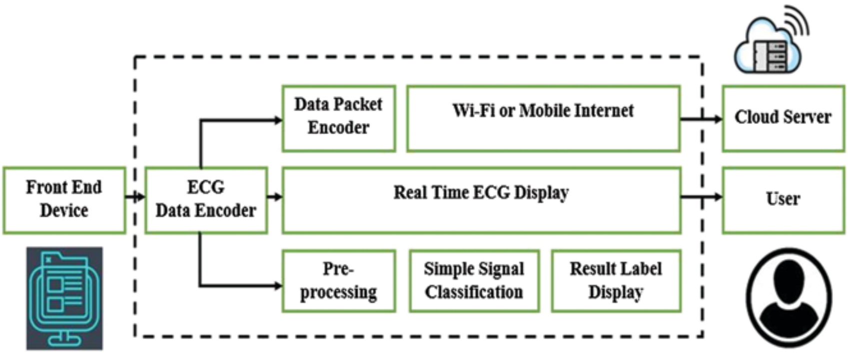


Fig. 4.7 The smart device APP structure

with a 10-bit sigma-delta analogue to digital converter, a degree shifter, and digital signal processing units, is the analogue front-end circuit [26]. The commercial Bluetooth module incorporates Bluetooth Low Energy 4.0 to transmit the ECG signal obtained from the front-end SOC automatically to the APP. The compact single-lead ECG tracking unit is connected to the chest with wet silver chloride electrodes and can be used for up to 24 h of daily use. Figure 4.6 shows the block diagram of the front-end system of the deployed ECG acquisition [1].

4.5.3 User Interface on Smart Device APP

A device interface also includes three key elements: an ECG display feature, an AI-based function, and a function for receiving and transmitting data [1]. The real-time ECG signal can be represented on the computer, and the AI method has been utilized to distinguish the user's ECG signal with different heart problems in a similar way. By taking into account the processing capacity of current electronic devices, the smart device classification defines the two effective classifications: usual and abnormal. Figure 4.7 shows the smart device APP structure [1].

For the extra category, to receive an additional specific arrhythmia form from the user's ECG signal, the category may be filled out over the cloud server. Not only will the collected ECG data be processed on local mobile devices and transmitted to the cloud servers. All data can be encrypted and produced with time stamps in the sake of data confidentiality and rightness.

4.5.4 Cloud Server and Database

The server [1] contains a large-data database that also comprises three sections: AI-based algorithm of data retrieval, online user interface, and cardiac condition analysis. Initially, data storage is responsible for handling data plans from intelligent front-end systems, and the data packages are decrypted as ECG indicators [27]. Moreover, as per the quantified artifacts and the time stamps, the ECG signals could be saved one at a time. Next, the web user interface shows a systematic data platform for doctors, patients, and patients' families. Physicians can determine the state of patients more clearly through the retained ECG records, and family members can understand something about their everyday ECG signs. Finally, for many minutes, the AI-based algorithm can identify uncommon signals from a lot of information. In general, around 100 thousand pulses a day are generated by a person, and many of them are ordinary ECG signals; only some are erratic [31, 32]. Despite this cause, physicians face a major challenge in identifying long-term ECG data successfully. The AI-based method can easily identify irregular signals displayed on the web user interface via this cloud platform. Figure 4.8 shows the cloud sever and database structure [1].

There are two elements within the structure of this method: data preprocessing and the CNN model. Standard ECG signal processing, such as time frequency analysis, feature extraction, and R-peak and QRS complex detection, is not really performed in addition to making the CNN model provide improved feature learning. Three steps are used in the preprocessing method suggested in this analysis: noise reduction, baseline removal, and image creation, as seen in Fig. 4.9 [1].

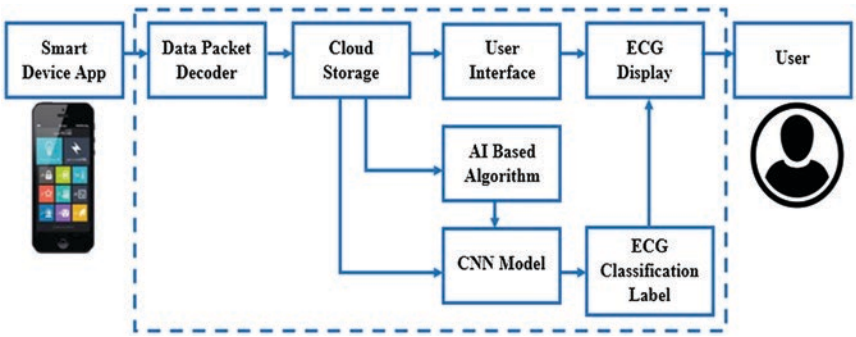


Fig. 4.8 The cloud sever and database structure

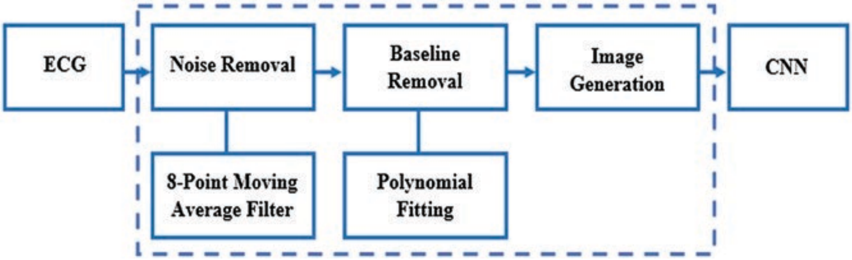


Fig. 4.9 The preprocessing structure

4.5.5 *Comparative Study*

It is also generally used by the Ministry of Health and Welfare for medical studies to validate the procedure that the Ministry of Health and Welfare can perform for patients at Tainan Hospital. Each portion could be evaluated in such trials, along with the wearable ECG-sensing device, software user interface, cloud server, and AI-based arrhythmia classification method.

4.5.5.1 Wearable Device

It is an ECG sensor system with an ECG-sensing-enabled front-end device that measures 84.55 mm × 39.38 mm × 18.31 mm [1]. The calculation of the ECG is single lead with a length of 24 h. It is connected to the patient's chest portion that also involves a low energy consumption analogue front-end circuit, with an integrated commercial energy management (IC) circuit and a commercial Bluetooth module. The single-lead wearable ECG tracking device is connected to silver chloride moist electrodes on the chest which could use up to 24 h of daily use.

4.5.5.2 User Interference APP

In the personal interference APP [1], the upper section shows the original information from the individual's ECG signal, whereas the bottom portion shows the performance results of the algorithm for arrhythmia classification. Each ECG signal can be identified as an irregular or frequent ECG signal. The actual ECG signal can be viewed on the computer, and the AI algorithm is often utilized to identify the consumer's ECG signal into particular heart conditions in the same way. The smart device section explains the most effective classifications by taking modern mobile devices' processing capacity into account: usual and abnormal.

4.5.5.3 Cloud Server and Database

The online user interface could extract the consumer's historic ECG data and go through more consultations with physicians [1]. The online user interface is somewhat identical to the UI of the smartphone. The top and bottom sections then represent the ECG original information and, accordingly, derive values from the arrhythmia group method. Each ECG data could've been categorized as several ECG forms, comprising of numerous types of irregular heartbeats that vary substantially from the APP user experience.

4.5.5.4 AI-Based Algorithm

Various data preprocessing operations are required in order to provide a sufficient input dataset [1]. First, with and without noise removal, is the variance between the data. It is discovered by using a common filter for eight-point shifting. Second, by polynomial fitting, baseline removal is completed [33]. This research establishes a single-dimensional CNN. With four convolution layers and three completely connected layers, the CNN edition is undoubtedly intended, taking into account the probabilities of recognizing this variant by digital IC layout and the effect after many tests. The load decay, learning rate, and learning rate decay parameters are determined as 0.0001, 0.1, and 0.9 after each epoch, depending on multiple test results.

Not only the information from medical studies, as well as the dataset, is processed by the CNN-based version. Outcomes are illustrated in Tables 4.1 and 4.2 [1]. The typical reliability of the data and the findings from clinical trials was 95.73% and 94.96%. In Table 4.3, associations between this discovery and past research are seen [1].

Table 4.1 Open-source database testing result

	NSR	AFib	AFL	FA	Accuracy
NSR	272	9	0	0	96.69%
AFib	15	371	3	0	95.37%
AFL	9	1	69	1	93.24%
FA	0	0	0	7	100%

Table 4.2 Clinical trial database testing result

	NSR	AFib	AFL	FA	Accuracy
NSR	9531	130	15	17	98.35%
AFib	16	249	9	5	89.24%
AFL	0	0	0	0	–
FA	0	0	0	0	–

Table 4.3 Performance comparison

	2019	2017	2016	2015
Classification target	NSR, AFib, AFL, FA	NSR, AFib, AFL, VFib	NSR, AFib, AFL, VFib	AFib, AFL, VFib
Model	CNN	CNN	Rotation forest	Decision tree
Accuracy	Clinical trial testing is 94.96% MIT-BIH testing is 95.35%	94.9%	98.37%	96.3%
Testing database	Clinical trails	Open source	Open source	Open source

4.6 Conclusion and Future Scope

Today, cardiovascular diseases are the most important challenges of healthcare worldwide. The early detection of cardiovascular disease, which will help to an extent, reduced the occurrence of sudden cardiac arrest. Prevention and control of cardiovascular diseases require a pervasive and complete device for recording data. Information of patient's records is one of the most important data, which must be classified for easy and fast remedy process. From this study, it is observed that the usage of artificial intelligence for early detection of cardiac disease detection is more effective to reduce sudden death. Through the use of AI application, abnormal heart rate can be detected. In addition to predicting prognosis, some studies have shown the incredible ability of AI in the analysis of coronary artery disease and cardiomyopathy and in the assessment of cardiac function over the past few years. In multiple unique cardiac areas, cardiac AI has recently shown its potential to outperform human vision. These trends in cardiac imaging advanced the day-by-day exercise of cardiac imaging and could significantly display its effect in the near future. The challenging problem with the devices is general acceptance, privacy problems, effective management, etc. To clarify the AI-based optimizations on the device, this analysis aims to verify the results as soon as possible in the future. As the technology would develop exponentially, it will be an enormous aid in building high-quality and readily available healthcare. The artificial intelligence in the field of cardiology brings a wide possibility also to provide new personalized care.

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Chapter 5
AIIoT-Based Smart Framework for Screening Specific Learning Disabilities

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5.1 Introduction to Specific Learning Disabilities

5.1.1 Overview

In the year 2018–2019, a higher number of children aged from 3 to 21 undergone special education care for particular developmental difficulties than for any other form of disability [1]. According to National Center for Learning Disabilities, learning disorder affects the brain's reading, processing, storing, and responding capacity of the children [2]. In simple terms, learning disability is a learning disorder where their brains are wired differently; i.e., information receiving and processing can make the children differ from others. Basically, the children and adults who suffer from learning disabilities can see, hear, and understand new things differently and struggle to learn and use new skill sets.

5.1.2 Types of Learning Disabilities

Generally, learning disabilities can be categorized [3] under the following:

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- Spoken
- Written
- Arithmetic
- Reasoning

Based on these categories, some specific difficulties are present in the processing of information. The most common types of specific learning disabilities [4] (SLD) are the following:

- Dyslexia – Difficulty in reading and understanding of words. Otherwise called as reading disability
- Dyscalculia – Difficulty in memorizing mathematical concepts and taking much time to solve arithmetic problems. Otherwise called as mathematical disability
- Dysgraphia – Difficulty in wring and drawing things within a limited space. Otherwise called as drawing or writing disability

These learning disabilities vary from one child to another child. For example, one child may struggle with reading or spelling; another child may have a problem understanding math. Moreover, some of the children have the problem of understanding communication. A combination of those problems may also occur in children. It is important to note that many famous and successful people had a learning disability.

Example:

- Dyslexia [5] – Albert Einstein, Leonardo da Vinci, Walt Disney, Alexander Graham Bell, Winston Churchill, etc.
- Dysgraphia [6] – Thomas Edison and Agatha Christie
- Dyscalculia [7] – Benjamin Franklin, Bill Gates, Mary Tyler Moore, Henry Winkler (both dyslexia and dyscalculia)

5.1.3 Causes for SLD

The causes of learning disabilities are not fully known, and there is often no clear reason. However, some of the causes of neurological conditions include the following:

- **Heredity and genetics**
  Disabilities in learning are related to the family by genetics. Children with intellectual disabilities are still the same parents in combat. Children of parents under the age of 12 are more likely to be unable to read. These children undergo a sponsor mutation with the potential to produce developmental defects and intellectual disabilities (that is not present in either parent) [8]. A study [9] showed that about one out of every 300 kids had such random mutations.
- **Problems during pregnancy and birth**
  A learning disorder may arise from defects in the brain, condition, or damage that occurs. Fetal exposure to alcohol or narcotics and low birth weight are risk factors (3 pounds or less). In math or reading, these children are more likely to

develop an impairment. A learning disorder is most common for children born early or late, having a more extended workload than expected, or having difficulty receiving oxygen [8].

- **Accidents after birth**
  Head trauma, malnutrition, or chemical contamination can also affect learning difficulties (such as heavy metals or pesticides).

5.1.4 Symptoms and Sign of SLD

Some of the major symptoms and signs of children with SLD are listed below based on the school level. Some of the common characteristics of learning disabilities described by the Learning Disabilities Association of America [10] are as follows:

- Writing speed is slow.
- Writing process is challenging and tiring.
- Poor handwriting.
- Difficulty in choosing correct spelling.
- Poor in sentences and paragraph formations.
- Difficulty in oral rhyming, mixing, and separating words in words.
- Speed and language development is slow.
- Slow in reading vocabulary.

These characteristics are present in all persons at any point in their development, irrespective of impairment. However, an individual with a learning disorder can have more than one of these characteristics. Depending on the age and maturity of a student, a learning disorder's features can also change.

The main aim of the proposed research work is to design framework for predicting the children with SLD at the earlier stage, making the schoolteachers and parents to get to know about their children's problem and practicing them according to their difficulty level. The proposed chapter is organized as follows: Section 5.2 describes issues and challenges faced by the children with SLD. The studies conducted and tool proposed for screening SLD are explained in Sect. 5.3. The role of AI and IoT in special education is explained in Sect. 5.4. The design of proposed framework and methodologies adopted for screening SLD is explained in Sect. 5.5. The result findings and analysis are explained in Sect. 5.6. Finally, Sect. 5.7 deals with conclusion and future research works.

5.2 Issues and Challenges Faced by Children with SLD

Children suspected of learning disability have reduced psychosocial and development growth, thus causing frustration to the child and their parents and teachers. The learning disability includes a problem with cognitive and mental skills and attitudes, as well as academic difficulties, and some children with learning disorders are struggling to maintain relationships with other and social interactions. Many problems are unnoticed. The severity of these problems is further increased by the low economic, cultural, and worst environment [11]. Some of the issues faced by them are as follows:

- Poor academic achievements – Leads to discontinuity in education
- Healthcare problem – Psychological stress leads to health issues.
- Social isolation – Major problem for many children with learning disability. Only few children may not come under this.
- Employment – One of the most important issues of people who have a learning disorder.

It is challenging to identify the children suspected to have a learning disability. Children with a learning disability never know why they have these sorts of academic and employment issues or are involved with family and companions. So, regular supervision of children's educational status with a learning disability needs to be monitored, which is the most critical health supervision factor. The educational status has significant effects on long-term health. The factors associated with positive health outcomes include attending a high-quality preschool, social-emotional status in elementary school, and completion of high school.

5.2.1 Health Issues of Children with SLD

Many children with SLD need healthcare attention than children without SLD. Learning disorder is not the same as a mental health problem, but those two can be closely linked together. For both children and adults, delay in recognizing learning disabilities can increase the risk of anxiety and depression. SLD can cause a feeling of inadequacy when all their academic achievements do not yield any success.

In some of the cases, the child can accept that sense of despair leading to depression. By giving proper attention to the children with SLD, all of these minor cases of depression would be apparent in resolving the underlying learning disabilities.

A child can outdo the sense of failure by class interruption, skipping school, or alcohol or prescription consumption in other situations. Of course, these negative habits will make learning much more difficult. Nowadays, an increasing number of children with SLD have essential health needs. So, those children have increased life expectancy, thus reducing the possibility of age-related diseases; e.g., heart-related disease, stroke, chronic respiratory disease, and cancer are likely to be of particular concern. They mostly have mental illness and suffer from long-term health problems, a neurological disorder (epilepsy), and physical impairment and sensory disabilities.

5.2.1.1 Health Issues of Adult People with Learning Disabilities

A study showed that people with learning disabilities were much more likely to experience mental disorders than the general population. A study done in England shows [12] that people with learning disabilities have a 60% greater rate of mental health issues. There may be variations on how accurate the correct requirements should be to assess the prevalence of specific mental health disorders properly. For example, specific criteria include comparing the rates between males and females, while other criteria do not.

People with learning disability have an estimated life expectancy of 18 years, which is lower than the average life expectancy of someone without learning disabilities. Significant research has found that men with learning disabilities have a lower life expectancy than those who do not have learning disabilities [13]. According to the Learning Disability Mortality Report, the median age at death is sixty for males and fifty-nine for females (or above) who died within the period of April 2017 and December 2018. A survey [14] stated that men live to an average of 83 years of age and women to 86 years of age in the general population. The life expectancy of people with learning disabilities is lower than the average life expectancy. For men, the median mortality age is 23 years. For women, the median mortality age is 27 years.

Another research [15] showed that 52.5% of people with a learning disability received breast cancer screening in the year 2017–2018, compared to 68% of women deprived of a learning disability. Another 31.2% of females with a learning disorder are accused of having cervical screening as compared to 83.7% of people without; 77.8% of individuals with an intellectual disability were screened for colorectal cancer screening. This survey also highlights how many health challenges people with learning disabilities face and how low-quality health services can cause preventable deaths [16].

The latest evidence suggested that people with a learning disorder are more likely to develop seizures compared to those without a learning disability. Estimates differ, but in a study of 38 research, the pooled level of epilepsy incidence of individuals with cognitive impairment was 22% [17].

5.2.2 Barriers for Getting Good Healthcare Service

Some different methods and strategies are being used by professionals [18] in order to help people with learning disabilities. They are the following:

- The lack of adequate reforms could impede access to healthcare.
- Persons that are not recognized as having a learning disorder.
- People are not aware about and do not understand learning disability.
- The health issues of children with learning disabilities need not be known and recognized.
- No adequate diagnosis is made.
- Lack of collaborative work from various care providers.
- Altogether inadequate aftercare or follow-up care.

It is mandatory that good and quality multidisciplinary specialist services needed to be available to attain the needs of children with learning disabilities. Children and adults with intellectual incapacities will learn and thrive with special attention, support, and a lot of effort [19]. Children suspected of learning disability should be diagnosed, evaluated, and identified at their earlier stage. For finding these, deep learning approaches are used in real time.

5.3 Studies Conducted and Tools Proposed for Screening SLD

In the early years, the basis of education is formed by the development of intellect, personality, and social behavior. Learning takes place quicker than at any other time, and trends with far-reaching effects are decided [19]. In order to provide proper attention and protection to the brain of children from early childhood up to high school based on education based on children, parents, and teachers, it is critical to have good-quality measures in elementary schools with many prospects (educational indicators) created and supported in all of the four regions of the country. In several reports, the importance of investments in the early years was recognized. In terms of schooling, health, and economic productivity, high returns were recorded. Screening corresponds to the specific detection by scans, tests, or other procedures of an unrecognized or undetected defect disorder, indicating the possibility or identification of the disorder. Many selection assessments, from auto-administered written tests to teacher rating resources, are available. While globally validated tools are readily available, most studies use locally designed tools. Children who perform the actions described and found by the screenings must all be referred to clinicians for diagnosis and assessment and follow-up care compared to recognizing and handling the particular capabilities of the brains of children [42].

It is hard to identify and classify different disabilities, such as attention-deficit hyperactivity disorder and autism spectrum disorders, when they are young because they usually appear when a student can generally communicate while writing, spelling, and reading. This section lets us discuss some of the studies conducted and tools available to identify and intervene in SLD.

5.3.1 Studies Conducted for Intervening SLD Around the World

The Child and Adolescent Mental Health Unit of the National Institute of Mental Health and Neuro-Sciences has developed a successful test to classify learning disabilities in primary school children. The different types of tests for intervening SLD problem are attention, vocabulary, reading, listening, spelling, writing, dictation, sensory integration, sensory perception, verbal processing, and mathematical ability.

A preferred screening method for SLDs is curricula basic evaluations [20]. E.g., to detect SLD in schools across Maharashtra, locally established criteria referred to test based on the curriculum of the Maharashtra Education Board are used. This requires examining particular aspects of literacy, such as fundamental learning abilities and awareness of reading.

Over the years, the prevalence of SLD has increased, which may be due to the availability of different test methods and children's facilities. The DSM-IV (2000) [21] for multiple mental health-associated conditions and ICD-10 [19] were released after the diagnosis and diagnostic guidelines given by several studies. The prevalence of SLD study was studied in the Ogliastra gene pool on the island of Sardinia, Italy. For thousands of students in America's high schools, the pollers will be asking the question for the 49th consecutive year of their midterms (24 students in first year and 25 students in second year). In the neuropsychological study, 720 students entering the first grade (293 women and 317 men) were participated. The cutoff score varied up to 3% (KG1 to KG6).

Among the eighty-three subjects at risk, with 6-month training program, it was concluded that instruction was beneficial. During a group reassessment, the SLD rate was 6.06%, and the dyslexia rate was 4.75%. In this study, the condition was expressed either themselves or in comorbidities, such as absence or presence based on the first countrywide epidemiological investigation, which was performed in Italy. The incidence of dyslexia is between 3% and 3.2%, which is comparable to the cases found in the way of dyslexia. It's found that there are both males and females within this learning disability category and that there are ratios that affect the number of males versus females [22].

An analysis by Fortes [23] et al. of 1,618 second- to sixth-grade school children and teenagers living in four different cities in Brazil, the prevalence rates for SLDs were compared, and their comorbidities were also compared in patients with healthy people. At fifteen years old, the children were administered a national academic test consisting of reading, writing, and mathematics capabilities. Kiddie-Sads-Present and Lifetime Version K-SADS-PL was added with the questionnaire, screening, and diagnostic sets. The globally perceived weakness rate of 7.6% for an individual is written ability, 6% for math, 7.5% for reading, 6.0% for problem-solving, and 17.5% for spelling. As far as the comorbid conditions of learning disabilities and arithmetic disabilities, only a statistically significant relationship was found ($p = 0.031$). However, the relationship was most vital in people with arithmetic disabilities. The estimated prevalence rates were significantly different between the global disability sample and several socioeconomic correlates: age, gender, IQ, and socioeconomic status among cities. The presence of psychiatric comorbidities significantly affects the left-sided language impairment rates and the geometric disability cases.

Altarac and Saroha [24] investigated how many learning disorders were present among US children over time by considering the sociodemographic and family functional features (particularly, attention paid to the children with special healthcare needs). Some of the kids were randomly sampled using polling method by National Children's Health Survey. The survey estimated the time duration of lifetime learning disorder. In order to address specific concerns within the implementation of lagging, a wide range of sociodemographic and familial factors was analyzed along with learning disorder measurement. For US children, the lifetime prevalence of learning disorders was over 9.7%. While the number of children who are now literate is 2.4 million (6%) fewer than the number of children dealing with different special needs, plus 2 million (9%) people with special care needs and 5.4 million (34%) people with special problems in British tablets, the overall number of children with health problems is growing. In the mediating effect analysis of self-concept deficits among children with learning disorders, it was concluded that learning disorder was more prevalent in children who also had self-concept deficits.

Using a large sample (34 schools in Southern Ontario's southwest region), Archibald [25] found that in 2013, there were many more male children than females (including five rural schools). The study was conducted for kids aged from 4 years, 10 years, and in the 4th grade, respectively. In around 5,967 authorization forms, 1605 have returned the document, and only 1387 have participated in the analysis. A set of uniform vocabulary, reading, math, intellect, and working memory problems were carried out. Both general teaching profiles indicated substantial or insufficient success through metrics and particular learning profiles that included weakness, faint reads, weak mathematics, and reading. Seventy percent of children with evidence of intellectual difficulties were characterized by the four profiles mentioned above. The common findings were found for predicting linguistic deficiency by short-term phonological memory and low or variable phonological perception of the weakness. These phonological defects were not shown by the low mathematics. The findings indicate various etiologies for text-based language disorders, literacy, math difficulties, reading and mathematics impairments, and isolated mathematical disabilities.

Yao and Wu's research findings suggest that the LD prevalence rate is significantly higher in Chinese children who are struggling to learn compared to those who are performing at a more or equal level. As per the data from the Centers for Disease Control (CDC), the LD problem is a significant public health problem in China. To provide better work and living environments, proper legislation needs to be passed [26]. The studies mentioned above suggest that, despite research performed in several countries, the prevalence rate varies between countries and states.

The discussed studies give importance of screening tools for learning disabilities so as to predict the SLD problem in an effective manner. These types of paper-based screening methods and studies consume time and sometimes produce less precise results.

5.3.2 Tools for Proposed Screening SLD

Many technological-based and automated screening tools are proposed instead of paper-based prediction for children with SLD. These automated and technological-based tools produce more precise results and reduce the time needed for screening the children with SLD problems. The technological-based approaches are an alternative method of special learning methods. These methods recommend a personalized learning method and intervention to prevent developmental and socio-emotional difficulties suspected to occur in the future [27]. The outcomes of those methods enhance the overall improvement in their language and math ability, increasing inspiration, giving new hope, and opening up a whole new world for the children with SLD problems. Let us discuss some of the proposed tools in this section.

5.3.2.1 Soft Computing-Based Screening Methods

A. **Fuzzy Expert System**

The proposed system [28] classifies the type of learning disabilities such as dyslexia, dysgraphia, and dyscalculia. The proposed system achieves accurate results and performs mass screening of children with learning disabilities. The proposed reasoning logic of the system matches with the human reasoning. Instead of focusing on crisp data, the proposed system allows for estimated values and inferences and incomplete and unclear data. In the proposed system, the crisp data is collected and converted into fuzzy set. Based on the set of rules, some inferences are made. Finally, the output result is mapped into crisp output. The proposed system is simple and easy for mass screening and provides robust performance based on agreed benchmarks.

B. **Artificial Neural Network and Adaptive Neuro-fuzzy Inference System-Based Prediction Tool**

The proposed tool is used to measure percentage of learning disabilities [29] in school-going children and determine the major function of the preprocessing in the classification. The proposed design is integrated using artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS). On the collected dataset, the data preprocessing is applied using closest fit algorithm and principal component analysis (PCA). After this, ANN and ANFIS are applied. The GUI application is designed with different text buttons for performing the operations. The obtained knowledge-based information is used to identify the new data that contained possibility of LD and its percentage. The repeated data and unwanted attributes are discarded, and missing values are identified. In the proposed methodologies, the closest fit algorithm is utilized to impute the missing values and the PCA for attribute reduction. The proposed methodology was carried out for 1020 real-time datasets. The final obtained results were compared with others in order to show how better technologies are adopted for classification and accuracy terms. The proposed tool provides an area for collecting student's information in order to save the children's details in the student database.

C. **DysDcomputational Tool**

The proposed tool [30] designed as layers of solutions contains several modules. The data is received in the web layer via a collect module and can be stored in the database module. The received data is normalized, and statistical analysis is performed on it in the data processing layer. This operation is taken before the use of an intelligent layer. A neural network layer processes the data which needed to be stored. The processed information can be sent to the screening module and a logic module. The logic module processes the sent data and chooses the computerized protocols provided by authority and then transfers it to the screening module. The processed data was stored on the database sheet. The maximum classification accuracy is obtained. The collected data to be transformed in graphics is sent to the specialist via data processing module. The chosen techniques are converted into graphics by the data processing layer. It may be used in various phases and levels of difficulty, e.g., letters, numbers, sequels, colors, geometric objects, and games. At last, the results were passed to an intervention module and stored in database layer. By doing so, the people with dyslexia at risk can be identified.

5.3.2.2 Computerized and Multimedia-Based Methods

A. **i-Dyslex Tool**

This tool [31] was specifically developed to screen school-going children with dyslexia problems in Malaysia. The tool was developed as a computerized tool and consists of five modules such as “Mendengar,” “Membaca,” “Berfikir,” “Mengeja” and “Menyusun.” The primary language used is Malay so that the children can be able to understand the problem clearly. This analysis was carried through a heuristic assessment to determine its functionality. The final results shown that the assessor graded most of the test domain questionnaire scores as average and above average. Besides, positive comments and feedback were also given by the assessors. Such assessment and professional reviews are essential for further enhancement of the application to satisfy the customer’s specifications and preferences.

B. **MathLexic**

This proposed multimedia-based application is used to identify people with dyslexia in order to improve their mathematical abilities [32]. The proposed application included activities and tutorials, where the tutorials consist of recognition and sequence of numbers, math operations, and math symbols. The activities include all these tutorials and enhance understanding capability of children with dyslexia. In the proposed application, the children with dyslexia are assisted by text and voice. The proposed application is easy to use and enhances the learning process. In order to evaluate the application, the user acceptance training is performed with dyslexic children and special education instructors. Most teachers agreed that the proposed application is beneficial and useful for dyslexia and appealing, user-friendly, and a fascinating teaching aid. The multimedia elements and its principles’ integrated application can motivate children with dyslexia to learn math and enhance their skills.

C. **Smart Lexic Application**

This application [33] is specifically developed for children in the age group of seven to nine at primary school in Malaysia. The application used Bahasa Malaysia as a primary language for better understanding of the information by the children. The proposed application consists of three modules such as identifying numbers (Kenalpasti Nombor), identifying letters (Kenalpasti Huruf), and identifying direction (Kenalpasti Arah). Each module includes many test questions for different kinds of evaluations. Based on their teachers' observations, the application is tested for students who are suspected to be dyslexic. By using paper-based and multimedia screening tools, the students carried out the test. The psychological study findings indicate that visual acuity reinforces the performance of students who have dyslexia because the target readings achieved by those students are higher than the results obtained in manual screening test processes.

5.3.2.3 Based on Machine Learning Technologies

A. **DysLexML**

The proposed tool [34] is used for screening cognitive developmental dyslexia. With the help of the proposed eye-tracking technique, the eye movement when the children read the words was measured. The different machine learning (ML) algorithms are used to evaluate eye movement points collected when children silently read the words. The proposed tool evaluates the performance by conducting systemic field study in order to detect learning and reading problems with them. In this study, 69 native Greek speakers, including girls, participated. Out of it, 32 children were already diagnosed to be dyslexic by the government's official agency. The wide variety of characteristics were identified based on statistical properties of obsessions and stereovision motions. These characteristics were classified with the substantial predictive ability so as to minimize dimensionality. The noise effect on the fixing positions was analyzed. With the linear support vector machine (SVM), the proposed tool achieves high accuracy and performance.

B. **EEG Local Network Features**

The main goal of the proposed framework [35] is to create a neurological classifier to make a distinction between the group of children (one group with dyslexia and the other group without dyslexia) based on a machine learning classifier fed by local characteristics from electroencephalographic (EEG) data. The EEG resting-state data of twenty-nine dyslexics and fifteen readers from grade 3 were used. The graded matrices for multiple frequency bands were calculated using phase lag index (PLI). From the graded matrices, the graded matrices graph was derived. Many local network measurements were determined, and the false discovery rate (FDR) corrected features were chosen as the input to SVM and K-nearest neighbors (KNN) classifier. The cross-validation operation was performed to test the efficiency of machine learning and randomized shuffling so as to ensure the appropriate classifier performance and avoid overfitting features. Based on local network features from multiple frequency ranges, the children were categorized with 95% precision. The proposed automated classification method applied to EEG graph showed that it is robust and reliable for differentiating normal and dyslexic people.

C. **EEG Signal Analysis**

EEG signal plays most important role to predict the neural behavior and aims to gain valuable information by monitoring electric activity in the brain. Therefore, neurological disorders are crucially detected. The particular specific EEG dyslexia patterns are recognized, which are neurologically related intellectual disorders [36]. Although EEG signals provide valuable insights into brain behavior, they are not necessarily straightforward because of their complexity. So, this problem can be avoided by using machine learning technique, which discovers unique EEG signals generated during writing and typing in adults with dyslexia as well as best EEG electrodes and brain regions for classification. This analysis found that the higher degree of problems observed in people with dyslexia while writing and typing is reflected in the brainwave signal patterns relative to normal controls.

D. **Diagnostic and Classification System**

The system [37] is trained by professional analysts who graded results from 857 school children in different assessments. By performing another fundamental test analysis for people with dyslexia, the data are gathered. Twenty-five percent is considered as the threshold. If the test scores equal to the threshold, then the children are suspected to be dyslexic. The proposed system consists of a diagnostic module used for diagnosing the effects of dyslexia by professionals, skilled users, and parents; a classification module used for classifying children into two classes, non-dyslexics and dyslexia-suspicious; and an analytical module for researchers. The findings revealed that 20.7% of students were suspected to be dyslexic out of 257 in the data collection confirmed by human researchers. From all the stated studies and proposed technical-based tools, some changes can still be made to predict children with SLD problems effectively.

All the studies conducted and tools' proposed methods can be developed and proposed to reduce either dyslexia, dyscalculia, or dysgraphia. The recent technologies cannot be incorporated to predict all the SLD problem in children effectively.

5.4 Role of AI and IoT in Special Education

Fundamental education is the right of all the people; no one should be refused a right to education regardless of their skill or inability. A fundamental change in the education system is needed so that schooling is equal for all. Suppose the children with learning disabilities are named or called learning impaired children or special children, which distinguishes the children from the other children and keeps them from other essential social growth stages. The amount of education offered worldwide increases opportunities for people to come up with more ideas that will change the world.

Although AI and IoT have many uses for the business world, there are also many educational prospects, especially for people with disabilities. Since more individuals globally today have greater access to the Internet, it provides the potential for a vast universe of opportunities. The development of hybrid and digital programs in the educational environment is expected. This type of technology will also continue to be used by many schools as a platform for educating students in the near future. It is important to recognize the role that IoT and AI have to play in advancing education for both of these prospects [38].

The recent Microsoft's Shareholders Report [39] highlighted the impact of technology on all facets of life, employment, and culture as a whole. It has proven that a secure technology that can help people and society is important for the future. Digital technologies and tools can allow individuals with and without disabilities to be innovative [40]. The technological advances have allowed Microsoft to empower people with disabilities, such as providing learning tools that have helped children with dyslexia learn more. This has extended the scope of AI. In order to perform high-level computer tasks, AI and IoT technologies were developed using computer tools to make it easier for people to use. Although machines can never replace people, they can help them for better job arrangement. Recent developments in AI and IoT can develop the education and learning sector to empower people with special needs in education.

Even though IoT is a new technology connecting millions of intelligent devices [41], it has flaws. For example, criteria such as precision and speed of IoT data transmission have still to be increased. Besides, an artificial intelligence system resembles how people work to complete the tasks and learn from what it designs.

From the above-stated AI and IoT advantages in special education, the proposed research focuses on integrating these two technologies and proposes an innovative solution to children with special needs.

5.5 Proposed Smart Screening Framework

The main objectives of the proposed screening framework are to

- Identify the children with SLD at their earlier stage itself effectively
- Inform their parents and teachers to practice them according to their difficulty levels

5.5.1 Proposed Screening framework

The proposed framework is an interactive multimedia-based interactive computerized application. This application allows the schoolteacher to perform one-time registration of the children with their details. The question is framed and loaded into the application as per the guidelines of the Wechsler Intelligence Scale for Children (WISC) – Fourth Edition (Indian Adaptation) and Woodcock-Johnson Tests (WJ

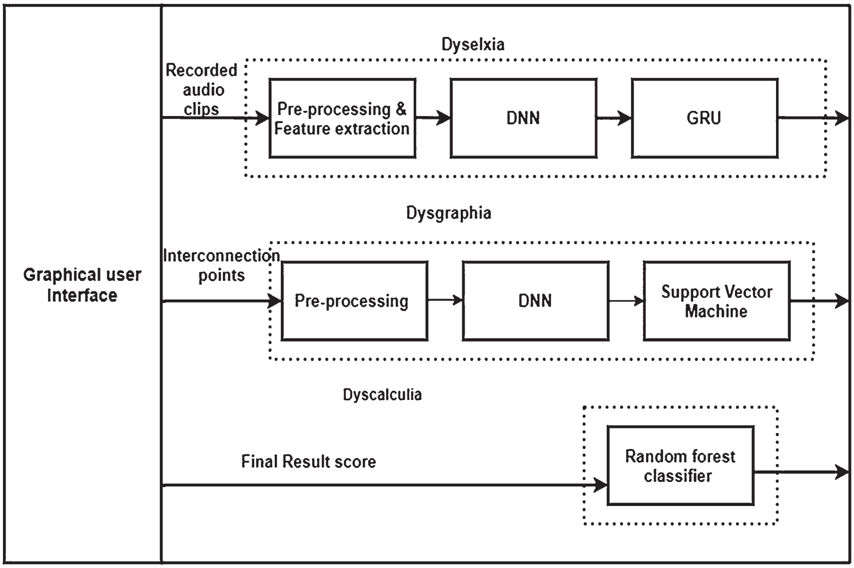

Fig. 5.1 Proposed screening framework

Fig. 5.2 (**a**) Single letter (**b**) Two letters (**c**) Three letters

III). Sixty children at the age of 8–10 are selected for taking the quiz test. Schoolteachers assist the children with and without SLD to take the quiz. The block diagram of the proposed framework is given in Fig. 5.1.

5.5.2 *Methodology for Screening Dyslexia*

In this screening method, pronunciation-based tests are performed in order to identify the children with SLD and children without SLD. The single letter to be pronounced by the children is displayed in Fig. 5.2a on the screen. The difficulty level is progressively increased up to three-letter words as in Fig. 5.2b, c.

The pronounced words are recorded. Deep Neural network (DNN) is trained based on data collected from 100 children without SLD schools within the age range in a school to achieve reliable performance. Since the audio-recorded samples are captured in real time, noise reduction is needed to be performed; i.e., preprocessing is needed to be done. An array of audio clip vector with the fixed size is prepared and provided to DNN. The feature extraction is done by using mel-frequency cepstral coefficient (MFCC).

To reach a high degree of precision, the number of periods is raised to 170. A root mean square propagation (RMSProp) is used as the optimizer function. The real-time data is collected from both children with dyslexia and children without dyslexia. This data is fed into the GRU. Parameters of GRU are as follows:

- Probability of pronounced letters
- Total number of correctly pronounced letters
- Total number of incorrectly pronounced letters
- Total time is taken to complete the task

Based on these parameters, it will predict whether the children are suspected of having dyslexia or not. Assuming that the children are predicted to be dyslexic, it automatically recommends procedures. For greater precision, the findings are fed back to the model. The children attend a rehabilitation curriculum in dyslexia focused on the use of vocabulary in images. They are then tested in two steps, where in the first step the children can choose the corresponding letter and then pronounce the word.

The level of competence is measured by the total time taken and the total amount of procedures attempted. If intervention processes are sufficient, then the users would be redirected back to the screening processes. Otherwise, the users are continued for further practice in the intervention stage.

5.5.3 *Methodology for Screening Dysgraphia*

In this dysgraphia screening method, the children are instructed to write a single dotted alphabetic letter with three attempts, as shown in the Fig. 5.3a. Two dotted alphabetical letters with an equal number of attempts are simultaneously written by the children, as shown in Fig. 5.3b.

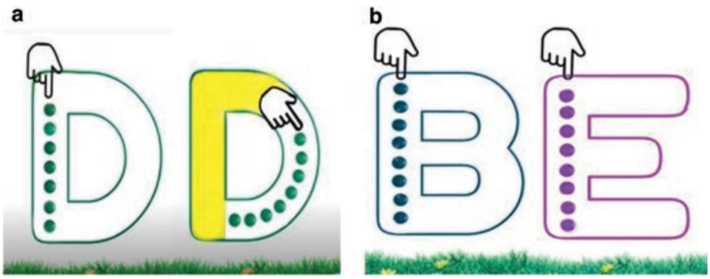

Fig. 5.3 (**a**) Single dotted alphabetic letter (**b**) Two dotted alphabetic letters

For creating the model, 200 images obtained from the non-dysgraphia children between similar age groups are used. The DNN model is used for handwriting recognition. Binary images were transformed and preprocessed in order to remove noise via the binarization process. The preprocessed and standardized images are divided by segmentation into individual letters. Ten inputs are given to SVM, namely, the probability of success for written letters; complete, correct count of written letters; total incorrect letters count; and total time taken for completing the tasks from both children with dysgraphia and without dysgraphia problems. Using an SVM classifier, it predicts whether the children have dysgraphia or not based on the parameters.

If the children are predicted to be dysgraphia, they are managed to navigate for intervention. They have been taught to write letters with precise beginning and endpoints in a given range with animation. The children can write letters independently in these latter phases within the given framework. The level of expertise is determined. The children should write two letters within reach and note the total number of protected nodes and the letters' development direction. The final report of the screening is shown to the schoolteachers. If the intervention is provided incorrect results, then children will be rescreened.

5.5.4 Methodology for Screening Dyscalculia

In this dyscalculia screening method, sequences of necessary mathematical tests are carried out to check mathematical ability. Some of the necessary skill tests used to predict the children with dyscalculia are given in Fig. 5.4a–d.

- Basic addition and subtraction: This test is used to measure numerical remembrance capacity of the children:
  For example: 1+1=2
- Missing numbers: This test is used to measure the numerical ability to check missing numbers in the shown series:
  For example: 1,3,…, 9
- Number comparison: This test is used to check the capabilities of the child to count the numbers and compare:
  For example: 2 > 3

The dyscalculia screening test is classified into the three levels above. The first phase tests the counting capacity, and the second phase checks the number capacity. The final phase is to perform a simple arithmetic supplement. The average time is taken, and each step's cumulative value are the parameters considered in dyscalculia screening, and the model is developed using the random forest algorithm. The children will be tested by three stages, containing ten mathematical questions, until the screening process is underway. The questions are drawn from the bank of the quiz.

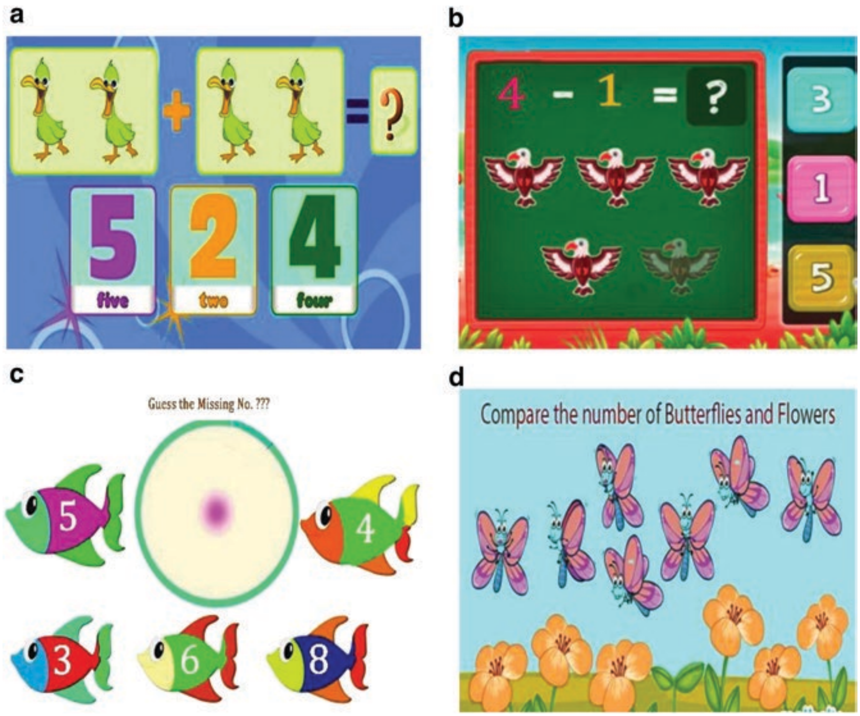

Fig. 5.4 (**a**) Addition (**b**) Subtraction (**c**) Missing number (**d**) Number comparison

If the children are predicted to have dyscalculia, they will concentrate on the interventions that display mathematical problems graphically. An initiative includes measuring instruction, counting training, and arithmetic addition training.

5.6 Results Discussion

The proposed screening framework is tested by using sixty children in schools. The findings are most precise when the children are tested by using the proposed screening framework to predict dyslexia, dysgraphia, and dyscalculia. The screening of SLD is analyzed using ROC curve. The graphical ROC curve illustrates the diagnostic ability of the classifier system. The diagnostic precision of the ROC is not influenced by the prediction criteria, and it is independent of disease prevalence because of its sensitivity and specificity. By using ROC, various diagnostic processes can be compared at the same time. So, the ROC analysis method is adopted in the proposed framework.

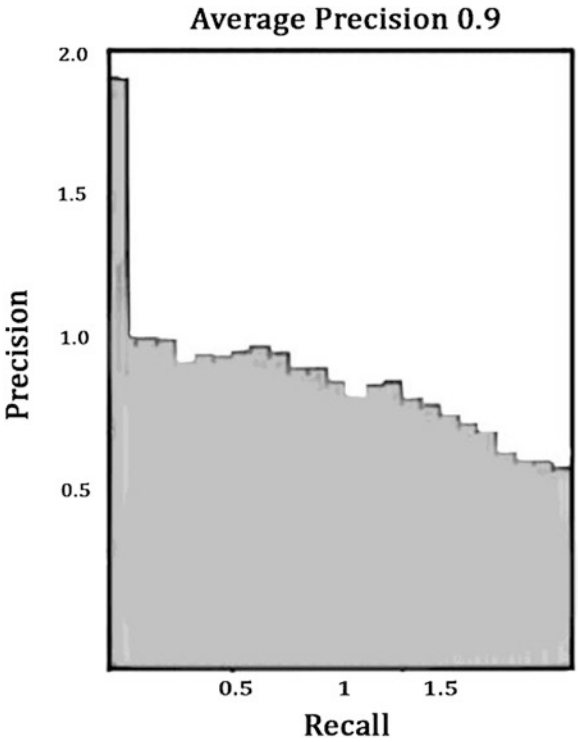

Fig. 5.5 Dyslexia screening using ROC curve

A. **Proposed Dyslexia Screening**

Five hundred audio clips for each letter with 1-second duration are fed to the DNN model as training data for each letter for 1 second, obtained from children from non-dyslexic schools. The DNN understands whether the children pronounced letters correctly or not. The DNN will predict whether the children have dyslexia or not with the five parameters mentioned above collected from both dyslexic and non-dyslexic children in schools.

With the help of DNN, 88% of training precision and 70% testing accuracy are achieved during dyslexia screening. The dyslexia screening is conducted for 60 children, where 30 children are pre-diagnosed with dyslexia. Once screened through framework, 27 are correctly identified with dyslexia with an accuracy of 90%, as shown in Fig. 5.5.

B. **Proposed Dysgraphia Screening**

In the dysgraphia screening, 600 images from non-dysgraphia school children are obtained and normalized. To identify whether the children are suspected of having dysgraphia or not, the preprocessed and normalized images have been provided into DNN models as training results. The neural network achieves 96% training precision and 88% evaluation precision. The SVM will predict whether the children are suspected of having dysgraphia or not based on the above-said parameters.

Fig. 5.6 Dysgraphia screening using ROC curve

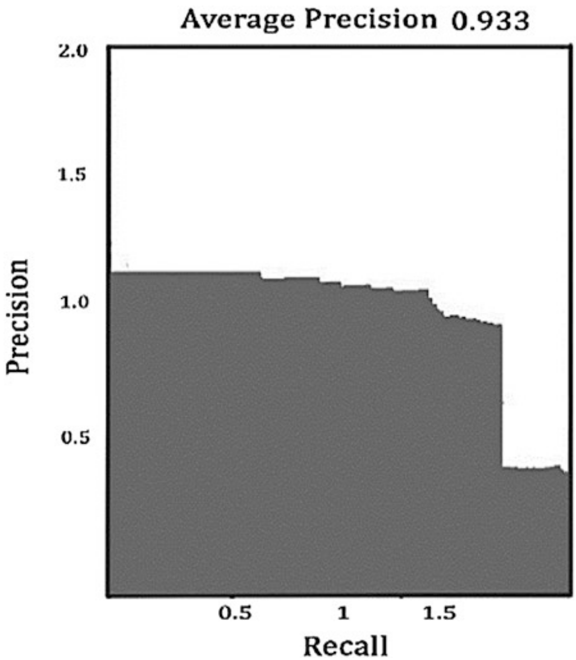

Table 5.1 Dyscalculia screening criteria

		Screening Prediction		
		Positive	Negative	Total
Test	Positive	True positives	False positives	Total number of positive
	Negative	False negatives	True negatives	Total number of negative
		Number of children with dyscalculia	Number of children without dyscalculia	Number of children screened

For dysgraphia screening, out of 60 screening subjects, 30 are pre-diagnosed with dysgraphia. Through the screening process, 28 subjects are correctly predicted with an accuracy of 93.3%, as shown in Fig. 5.6.

C. **Proposed Dyscalculia Screening**

For the SVM classifier, the diagnostic dyscalculia screening criteria is given in Table 5.1.

For dyscalculia screening, out of 60 screening subjects, 30 are pre-diagnosed with dyscalculia. Through the screening process, 27 subjects are correctly predicted with an accuracy of 90%, as shown in Fig. 5.7.

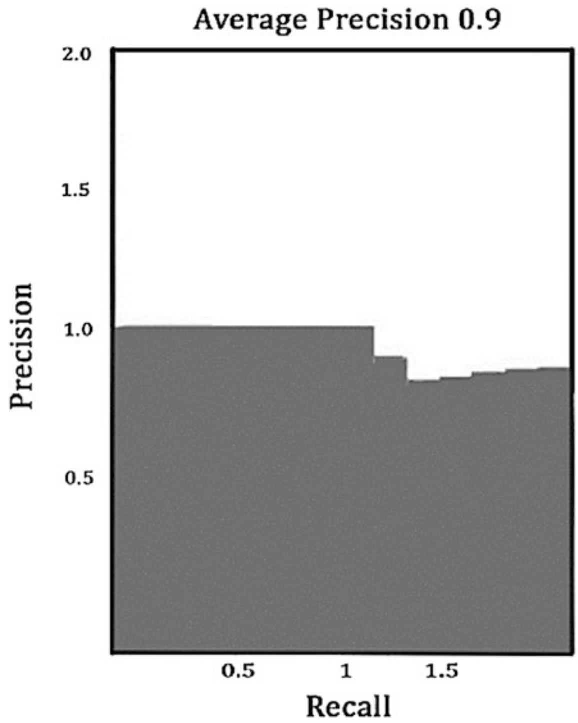

Fig. 5.7 Dyscalculia screening using ROC curve

5.7 Conclusion and Future Scope

The single screening framework is capable of predicting learning disabilities such as dyslexia, dyscalculia, and dysgraphia. The proposed method is simple to grasp and enforce, and it predictions the children with SLD problem in an earlier stage itself. The prediction results obtained for dyslexia is about 90%, dyscalculia is about 93.3%, and dysgraphia is about 90%. The above prediction results for dyslexia, dysgraphia, and dyscalculia represent the proposed screening system's efficacy because of the highly precise screening methods. The proposed framework plays a vital role for identifying and intervening children with SLD problem in necessary learning skills. So, the children's progress in academics and career can be improved. The proposed screening work can be framed based on universal language, i.e., English. For future scope, the proposed framework can be developed as a prototype, expanded to support other local spoken languages and incorporate future enhanced algorithms.

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Chapter 6
Novel Designs of Smart Healthcare Systems: Technologies, Architecture, and Applications

Aboobucker Ilmudeen and Anand Nayyar

6.1 Introduction

Today, the field of big data has promptly grown up in which a considerable volume of data is produced from numerous heterogeneous sources. Big data is receiving ever more acceptance by the industries for various form of applications; for instance, eHealth, mHealth, and the Internet of Medical Things [1]. More recently, the field of big data and healthcare has been strongly interconnected which is enabled by state-of-the-art modern technologies. Hence, the advances in healthcare services, for example, patient's electronic health records and amalgamation of eHealth, mHealth, smart health, and telehealth smart devices, have created ultramodern healthcare systems that facilitate the accuracy of medical treatment and tailored healthcare solutions.

The Internet of Things (IoT) is a set of devices, sensors, actuators, and moving objects that are networked and fixed with software, applications, and networks to gather data for real-time exchange among them [2]. The healthcare and IoT are widely studied as it has many values for human life that deal with the healthcare regulations [3]. The advancements in modern technologies in fog computing, edge

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computing, IoT, cloud computing, and big data have extended the prominence as a result of their strength and capability to offer various functionalities for healthcare systems [4, 5]. Big data has the capability of analytical power that deals with the huge dataset to mine unseen correlations, hidden links, insights, visuals, and various trends from healthcare data.

In general, healthcare data is complex in nature and is strongly intertwined. Hence, the necessity for an effective big data-based healthcare system is required to monitor and detect patient's disease symptoms and take clinical decisions by the healthcare officers on time. The increasing necessity of healthcare usage and the advancement in big data analytics entail the advanced tools that solve the challenges encountered by big data volume, variety, and velocity [3]. Big data analytics is well renowned for its unique capabilities as it has analytical power, design elements, superior methodological approach and viable solution, and flexibility [6]. Further, simplifying the complexity in data, exploring the interlinks among healthcare factors, and the selection of targeted features for healthcare analytics need to be considered for healthcare system development [7].

In the face of rising healthcare demand, conventional healthcare systems are rapidly becoming inadequate [8]. Big data in healthcare contains a variety of structured, semi-structured, and unstructured data that are produced from different bases that cannot be effectively processed by the traditional algorithms, frameworks, tools, and techniques [9]. Most of the present big data tools and techniques for storing, processing, extracting, and analyzing the heterogeneous large volume of big data are insufficient [10]. The traditional data processing tools, techniques, and frameworks were less capable of handling huge amount of big data [9]. Similarly, the IoT effect is yet in its early growth stage in the healthcare domain [11]. Hence, it required a big data-based framework that eases the process of gathering, storing, mining, sorting, modelling, and processing of huge heterogeneous data [9].

This chapter discusses the detailed outline of most general techniques, architectures, and models in big data analytics. Accordingly, Section 6.2 highlights the role of big data in healthcare, Section 6.3 discusses big data analytics tools and techniques, and the next section proceeds with novel design elements in smart healthcare using IoT. Section 6.5 elaborates on the big data techniques, tools, and frameworks. Section 6.6 discusses the challenges and future directions of healthcare systems. Section 6.7 discusses in detail the latest techniques and technologies that support healthcare 4.0. The next section proposes the conceptually designed healthcare systems using big data analytics. Finally, this chapter concludes with smart healthcare applications using real cases.

6.2 Role of Big Data in Smart Healthcare Systems

With the recent advancement and modern technologies in big data analytics, its effect in healthcare has made to detect several data sources, for instance, telematics, sensor and wearable devices, and social media platforms [7]. By integrating the IoT devices and big data, it creates a unique avenue for offering healthcare services to users by using machine learning, cloud computing, and data mining techniques [12]. When we take the healthcare industry, a huge amount of data is being kept by drug and pharmaceutical manufacturing companies. These data are extremely complex in nature, and sometimes, these cannot be connected with other information by the practitioners, but it has some potential insights for better decision-making. As a result, the latest state-of-the-art technologies can extract the unseen correlation, links, and pattern of the diseases from these complex healthcare datasets.

Nowadays, the big data analytics in the healthcare domain has received much attention. In this line of thinking, the issues such as security, privacy, legal procedures, and establishing standards to improve big data technologies will draw much more attention of the healthcare developers and users. Hence, the preparations such as more operational platforms for data processing, smarter technologies for collecting data, intelligent and accurate computational analysis, visualization, and storage techniques need to be established to extract the value from the data. The applications of big data in healthcare can offer noteworthy advantages, for instance, identifying diseases at an early stage that can be detected more quickly and efficiently. Pramanik [13] denote that big data analytics is the advanced *healthcare informatics and analytics* technologies that are employed in evaluating the large volume of heterogeneous datasets, mining the big data, and statistical analysis.

In healthcare, the data sources can be generally categorized into the followings. First, *structured data* refers to the data that follows well-defined data type, structure, and format, for instance, the classified terminologies of different diseases, information about disease symptoms and diagnosis, laboratory results, electronic health records, information about the patient like admission histories, and clinical and drug details. Second, *semi-structured data* refers to data having self-describing nature along with being organized in a minimal structure, for example, the IoT and sensor device-generated data for patient's health conditions, doctor-to-patient email, social media, and web. Third, unstructured data describes no natural structure such as medical prescriptions written by physicians/doctors using human languages, clinical records, biomedical description, discharge records, claims, and informal texts [14]. explored from popular databases and systematically reviewed the supporting technologies for fog computing in the context of healthcare IoT systems.

Scholars claimed that there is a massive volume of healthcare big data produced from smart IoT; hence, it would be a great fortune to explore many hidden insights [15]. The data that are stored in the cloud or healthcare repositories can be processed using big data analytics techniques; hence, the superior decision can be taken for diagnosis and medical treatment [16]. In the aspect of security, the blockchain permits data sharing while confirming the data origin, inspection, and governance for the stored and shared healthcare big data among the participating entities [17, 18].

Evolving advancements such as big data, IoT, and AI have sparked healthcare innovation all over the world. The purpose of healthcare innovation is to create smart healthcare systems and provide better healthcare services. Today, the patient's electronic health records are integrated with IT applications such as the Internet of Things, big data, cloud computing, sensor technologies, mobile applications, and artificial intelligence to create a range of innovative healthcare systems. Machine learning and blockchain technologies are currently being heavily considered for a variety of industrial applications. It has been found that healthcare systems and intelligent technology, as well as their amalgamation with blockchain, have a closer relationship. As a result, machine learning and blockchain technology's traceability, accountability, protection, and decentralization will allow the healthcare industry to enhance and uplift several areas, including patient healthcare management, medical insurance management, and patient record and file management, as well as increasing the effectiveness of various connected applications and systems.

6.3 Big Data Analytics Tools and Techniques

Big data analytics is defined as the approach of handling and exploring unseen patterns, unknown associations, and other valuable insights from a large amount of datasets containing various data types, generated from numerous sources [6]. The developments in the sphere of big data analytics are one of the greatest important factors to investigate big healthcare data. The software vendors across the globe have moved the traditional software development approach to new forms such as data analytics, data mining, big data, data visualization, and statistical modelling [19]. In recent years, big data analytics and healthcare systems are getting much more attention and more popular among both practitioners and researchers [13]. Especially, the data analytics software developers build and tailor healthcare tools that are linked to heterogeneous data sources to collect electronic health records (EHRs).

With the increased demand for healthcare-based analytical tools, several software developers are shifting their design, development, and manufacturing of the healthcare tools in the healthcare domain [19]. To extract insights and knowledge from big data, the healthcare system necessitates state-of-the-art and modern data storage capabilities, management, analytics, and visualization tools and techniques [13]. Hence, machine learning includes various types of techniques, tools, and frameworks which can be used to handle the difficulties created by complex data [20]. The big data analytical platforms are generally open source; for instance, Hadoop was originally established by Apache. Hadoop allows for handling a large volume of heterogeneous data in which the data is requested into diverse sub-unit and then scattered to diverse servers to calculate various units of a complex problem [13]. There are methods such as statistical modelling, text mining, data mining, machine learning, data visualization, web mining, simulation, optimization, forecasting, and social network analysis used to handle big data [20]. Figure 6.1 depicts about cloud computing-based healthcare platform that integrates different healthcare system components.

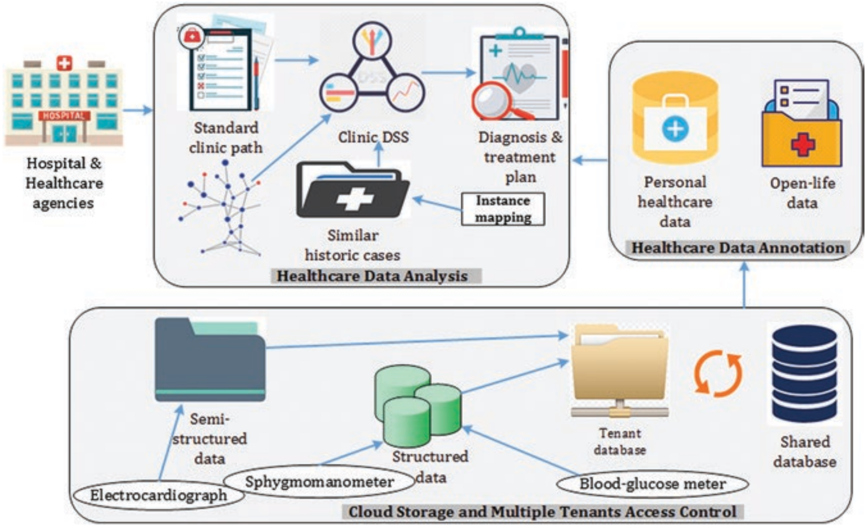

Fig. 6.1 Cloud computing-based healthcare platform

6.4 Novel Design and Smart Healthcare Using IoT

Scholars claimed that IoT is a novel Internet advent, in which the devices are systematized to create intelligent healthcare systems [11]. Today, the advancements in recent technologies and their integration are making the healthcare industry more modernized with the inclusion of smart healthcare services. The modern developments and advancements in the sphere of IoT create a distinctive method of using the healthcare systems [3]. The integration of IT and medicine renovate the healthcare sector to be more innovative such as precise and effective health services, IoT-enabled clinical services, and healthcare applications. The primary IoT-based healthcare system must provide efficient, easy-to-use application access to IoT data and devices that aid designers in creating visualization dashboards, analytics application, and healthcare-IoT application [11].

The IoT makes an atmosphere for smart house, smart healthcare, and smart business operation by transferring data through the Internet, whereas cloud computing instead powers the ability of IoT by offering computation power and storage capability to each smart artifact [21]. The healthcare solutions enabled by IoT linked devices anywhere, anytime, and with anybody seamlessly connected with any network and any applications, which brings to smart healthcare [11]. Researchers studied the medical applicability of nanotechnology, Internet of Nano Things, and nanobiosensors [22]. Similarly, [4] proposed a novel fog-based smart healthcare system called HealthFog to diagnosis heart diseases by using deep learning and IoT. This offers greater healthcare services and powerfully handing heart patient's data that is generated by various IoT devices. In the prior study, scholars have stated three paradigm shift trends in smart health and smart city study. Accordingly, (1) in healthcare, the traditional health to ubiquitous health, and smart health (2) in the city, the traditional city to digital city, and then to smart city (3) in data, database has shifted to data mining that is enabling big data [23].

Today, remote healthcare is becoming popular as it uses technology such as biosensors, efficient health records management, and computerized healthcare equipment to track a patient's health from a distance [24]. The rapid advancement in IoT, cloud computing, and a growing number of IoT and cloud computing-related applications in healthcare has received much more interest among researchers and healthcare stakeholders. As a result, the modern advances in nanotechnology drive the IoT toward it. The applications of nanotechnology in healthcare are, for instance, smart drug management, nanoscale surgeries, and epidemic spread detection and control. Nanomechanics can execute various functions inside the patient's body. Accordingly, it can build a nanonetwork inside the body and directly connect to the outside smart devices such as smart gadgets, smartphone, or access point [25].

6.5 Big Data Techniques, Tools, and Frameworks for Healthcare Systems

The ultimate success of the healthcare system merely rests on the primary architecture and the deployment of suitable techniques, tools, and frameworks that have been recognized as novel research areas in the big data domain [7]. There is literature evidence for many healthcare-supported big data frameworks to process a huge amount of heterogeneous data from different data sources to generate insightful patterns and trends that have been identified in recent times. The big data-related tools, techniques, and frameworks are classified based on the following aspects, for instance, (1) the programming model, (2) the programming languages that are supported, (3) type of available data sources, (4) the capability to allow for iterative data processing, (5) platform compatibility with existing master-learning libraries, and (6) the defect tolerance strategy [10]. In literature, there are prior studies that have tried to assess the big data tools, techniques, and frameworks [e.g., 7, 10, 12, 29]. The below division discusses novel design aspects from scholars around the world and their views for healthcare systems that have incorporated big data tools, techniques, and frameworks (see more in Table 6.1).

Accordingly, Rahman and Bhuiyan [30] suggested an RFID framework resolves two privacy issues in RFID-centered healthcare system, namely, (1) authentication protocol for identification and monitoring purposes and (2) access control to control illegal access of protected data. Their research work exposes the security and privacy aspects in the technical design of RFID systems in this healthcare field. The privacy and sensitivity of healthcare data must be restricted with security measures and data quality requirements. Pramanik and Lau [23] proposed a big data-based smart healthcare framework with a three-dimensional structure of a paradigm shift

Table 6.1 Novel designs of IoT in smart healthcare systems in recent studies

Studies	Novel designs/ features	Key characteristics	Data sources	Big data tools/ systems	Analytical capability/ performance	Key highlights
Pramanik and Lau [13]	Proposed healthcare informatics and analytics (HCI&A) framework	Covers underlying technologies, system applications, system evaluations, and emerging research areas	–	HCI&A framework under the context of big data	HCI&A is conceptualized in three stages, such as HCI&A 1.0, HCI&A 2.0, and HCI&A 3.0	Bibliographic study is conducted on HCI and HC information systems
Tuli and Basumatary [4]	Proposed a framework by adding deep learning in edge computing devices for heart disease analysis	Framework offers healthcare as a fog service by IoT tools and powerfully handles the data of heart patient's requests	Heart patient's data from IoT devices (blood oxygen, heart rate, respiration rate, EEG, ECG, EMG, blood pressure, glucose level)	Fog-enabled cloud, FogBus framework	Deployed and test the performance considering power utilization, jitter, delay, bandwidth, correctness, and execution time	It offers greatest quality of prediction accuracy, in various fog computation states and for different user requests
Fang and Pouyanfar [26]	Health informatics processing pipeline	Machine learning techniques and algorithms compared	Electronic health records, public health, genomic, behavioral data	Feature selection machine learning (classification, regression clustering)	Decision support system via computational health informatics for practitioners	Data capturing, storing, sharing, analyzing, searching, and decision support through computational health informatics
Lin and Dou [27]	Cloud-based framework for self-caring service	Lucene-based distributed search cluster and Hadoop cluster are used	Patient profile, data, and clinical data	Hadoop cluster is used for highly concurrent and scalable medical record retrieval, data analysis, and privacy protection	Home diagnosis – Self-caring service	Home self-caring based on historical medical records and disease symptom

(continued)

Table 6.1 (continued)

Studies	Novel designs/ features	Key characteristics	Data sources	Big data tools/ systems	Analytical capability/ performance	Key highlights
del Carmen Legaz-García and Martínez-Costa [28]	Semantic web-based framework for interoperability and exploitation of clinical archetypes	Semantic web technologies for interoperability and exploitation of archetypes, EHR data, and ontologies	Electronic health records (EHR), ontologies	OWL-based ontology	Classification based on clinical criteria	Integration of semantic web resources with EHR
Mahmud and Iqbal [12]	Cloud-based data analytics and visualization framework – Health-shocks prediction	Amazon web services linked with geographical information systems and fuzzy rule summarization technique	Healthcare data focused on social, economic, cultural, and geographical conditions	Generated predictive model using fuzzy rule summarization	Public households to increase healthcare facilities	Cloud-enabled geographical information system
Sicari and Rizzardi [29]	Policy enforcement framework IoT-based smart health	Security and quality threats in dynamic large-scale smart hearth environments. Cross-domain policies have been defined using XML	RFID and instrument-generated data, patient and environmental data	Policy-based access control mechanism for availing healthcare resources	Smart health applications to prevent security threats in large-scale heterogeneous health environment	Implementing policy framework for smart healthcare
Rahman and Bhuiyan [30]	RFID-based framework to preserve two privacy issues in healthcare system	Authentication and access control are ensured for RFID tag application in healthcare domain	RFID tags	Techniques to preserve privacy in RFID	Protecting healthcare domain services	Better privacy mechanism to protect RFID applications in healthcare domain

Pramanik and Lau [23]	Big data-aided framework for smart healthcare system	State-of-the-art design and architecture of smart healthcare services	Electronic health record, patient diagnosis and biometric data, social media and surveillance data	Smart healthcare services at smart cities via advanced healthcare systems	Smart integration and technologies to provide state-of-the-art healthcare services	Combining big data and healthcare-designed smart services for the smart city
Forkan and Khalil [31]	Cloud-centric big data framework for personalized patient care through context-aware computing system	Knowledge discovery-based context-aware framework	Profile data, patient medical records, activity logs, vital signs and context cum environmental sensor data	Mine trends and patterns with associated probabilities that used to learn proper abnormal conditions	Classification to identify real abnormal conditions of patients having variations in blood pressure	Personalized healthcare services through context-aware decision-making approach
Hossain and Muhammad [9]	Voice pathology assessment big data framework	Machine learning algorithms	Speech signals	Classifiers such as support vector machine, an extreme learning machine, and a Gaussian mixture model	The audio features classified as normal or pathological	A framework to handle healthcare big data
Syed and Jabeen [32]	Smart healthcare framework using internet of medical things and big data analytics	Parallel process in Hadoop MapReduce used	Multiple wearable sensors	Multinomial naïve Bayes classifier that match with the MapReduce	Smart healthcare for ambient assisted living	Smart healthcare facilitates to remotely observe health status of elderly people
Raghupathi and Raghupathi [33]	Conceptual and architectural big data framework	Outlines methodological and architectural design of big data	Multiple location's physically dissimilar data sources in many formats	Analytical queries and generating reports	Healthcare design domain	Proposes a state-of-the-art model for designing healthcare big data framework

and three technical branches of big data healthcare systems that address the potential challenges and opportunities in executing this system to the healthcare business context. Likewise, Raghupathi and Raghupathi [33] suggested a big data framework that takes into account the theoretical and methodological facets in which the proposed conceptual architecture of big data analytics contains big data sources, the transformation of big data, existing platforms and tools, and the applications of big data analytics.

Furthermore, [29] have proposed a policy enforcement framework to address security threats that are expected during the development of IoT-based applications for smart health. Their modelling is suitable for heterogeneous IoT-based applications and their architecture in this smart healthcare context [32]. developed a smart healthcare framework that can monitor the physical health condition of aged people by using the Internet of Medical Things and analyzed by machine learning algorithms. Their proposed system applied the multinomial naïve Bayes classifier that supports the MapReduce paradigm, and the system consists of a faster analysis of data and better disease decision-making with better treatment recommendations in which the elderly people's health conditions could be remotely monitored. Similarly, Youssef [34] introduced big data analytics-based healthcare information systems framework in mobile cloud computing environments. Their proposed framework offers features such as interoperability, high integration level, and accessibility and data sharing among health workers, patients, and practitioners and enables them to find valuable insights for practitioners' effective decision-making at the right time.

6.6 Challenges and Future Directions of Healthcare Systems

There are various challenges in the aspects of design, development, implementation, and maintenance of IoT-based healthcare systems. For instance, the varied use of various IoT devices has challenges such as authorizing the IoT smart devices for the healthcare system, accumulation, and handling of real-time data [3]. Mutlag and Ghani [14] claimed that there are challenges for healthcare applications particularly in resource management and different requirement challenges such as adaptability, flexibility, consistency, privacy and security, low latency, and energy efficiency for intelligent global healthcare systems.

Though fog computing has various benefits in healthcare IoT systems, it is obvious that it also has some restrictions and challenges in resource management [14]. The fog computing latency and response time are identified as the key factors that make improving the quality of service in real-time healthcare applications difficult [14]. Similarly, IoT smart devices in healthcare system generate a large volume of big data that has challenges like processing and storage [21, 35]. The attack of patient privacy is identified as a serious concern using the healthcare big data analytics; moreover, big data security and privacy challenges, technical challenges, and skilled talents are also identified as challenges [36]. Similarly, the IOT's most puzzling problems include setting up system capabilities, safety, and reducing differences between individuals and sensors [11]. Din and Paul [3] identified several challenges for healthcare in big data in literature such as data aggregation, data format, incompleteness, timeliness, scaling, normalization, noise removal, and queuing.

For the future direction of healthcare systems, there are specific techniques needed in communication and IoT mobile applications to aggregate, store, and handle big data [3]. In the near future, the advanced technologies and standards will be addressing the privacy and security aspects of users, data, applications, and network [11].

6.7 Overview of Latest Technologies and Methods Supporting for Healthcare 4.0

In recent times, industry 4.0 has enabled healthcare 4.0 that includes IoT, industrial IoT, AI, cognitive computing, edge computing, and cloud and fog computing in the healthcare domain [5, 37]. Healthcare 4.0 integrates smart devices and advanced technologies in the healthcare sector. Hence, healthcare 4.0 aims to integrate with big data, AI, blockchain, cloud computing, IoT, and fog and edge computing analytics to offer better healthcare support [38]. Big data analytics, cloud computing, IoT, and blockchain technologies have involved healthcare 4.0 to process, store, analyze, and respond to medical records [39]. Moreover, in recent time, the remote healthcare services in which the patients are not moving for the medical treatment or clinics have become a new trend in smart healthcare [40]. The below section discusses in detail various techniques in healthcare.

6.7.1 Cloud Computing and Architecture

Cloud computing is a computing architecture in which all computing resources including storage capacity, memory allocation, and computing power are used collectively in the cloud-based environment on the Internet. With the arrival of modern technologies, the world is encircled by numerous intelligent mobile smart devices that are used to connect the world in which the data is stored and retrieved from the cloud. The features in cloud computing such as storing capacity, managing server, benefits in bandwidth, and network efficiencies that enable to coordinate with connected devices have made cloud computing as one of the foremost reasons big data becomes so popular [26]. Mainly, the web applications are used in the cloud computing platform to access the resources, and it can be flexible in a way that scales up and scales down the resources based on the computing requirement [21]. The figure shows the architecture of IoT-based cloud computing in healthcare in which the connected devices are interacting to share data and information (Fig. 6.2).

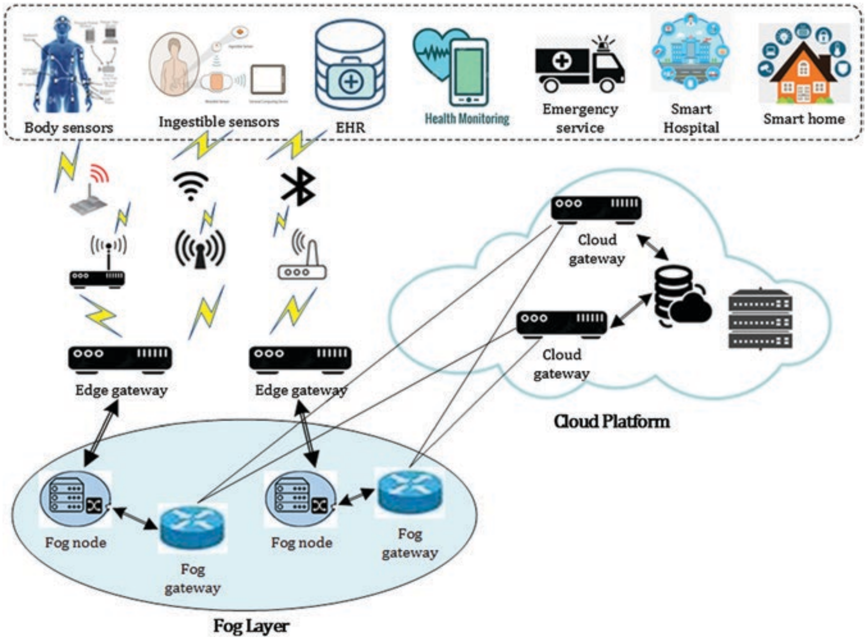

Fig. 6.2 IoT and cloud computing in healthcare architecture

Cloud computing has been identified as the most widely adopted architecture by healthcare application developers being a key big data client for deploying the application on the cloud environment [12]. The IoT-supported cloud computing can be adaptable to extend the development of innovative applications services in the healthcare sector over the smart platform [41]. Cloud computing offers data analytics, exploring new insights, and mining critical results; thus, it can speed up many analytical decision in healthcare systems [12]. As a result, healthcare systems commonly use cloud storage platforms to save information between the data originator layer/sensor device and the data analyzer layer/end-user applications for real-time disease analysis [42].

6.7.2 Fog Computing and Architecture

In recent years, the paradigm shift is from cloud computing to fog computing in healthcare [43]; that reduces many drawbacks in cloud computing such as storage shortage, computing power, and network delays [44]. Fog computing is defined as the physically isolated heterogeneous devices that are connected with the network to share computing resources and to offer storing capability, flexible connection, and calculating power [14]. Fog computing employs nodes, gateways, and routers to deliver services with the lowest network latency, response time, and energy utilization [14]. For healthcare system development, the fog computing has been identified as appropriate as it has the abilities that the application needs for greater availability, superior response, minimum latency, and real-time availability [14]. Fog computing is an improved layer in addition to cloud computing that has developed as an emerging paradigm with shorter delay and improved network efficiency for healthcare systems [45]. The significant benefits of fog computing are to increase the scalability and storage capacity and improve efficiency for collecting data, storing, processing, and analyzing [45]. In fog computing, the well-networked device, capacity to store, computing power, and geographically distributed nodes are facilitating the real-time, low-latency, and increased responses for healthcare systems [39]. On other hand, fog computing supports surmounting drawbacks in big data processing [44].

Figure 6.3 illustrates the design-layered architecture of fog computing for a healthcare network. It contains three layers such as the smart terminal layer, the fog computing layer, and the cloud computing layer. The smart terminal layer contains various

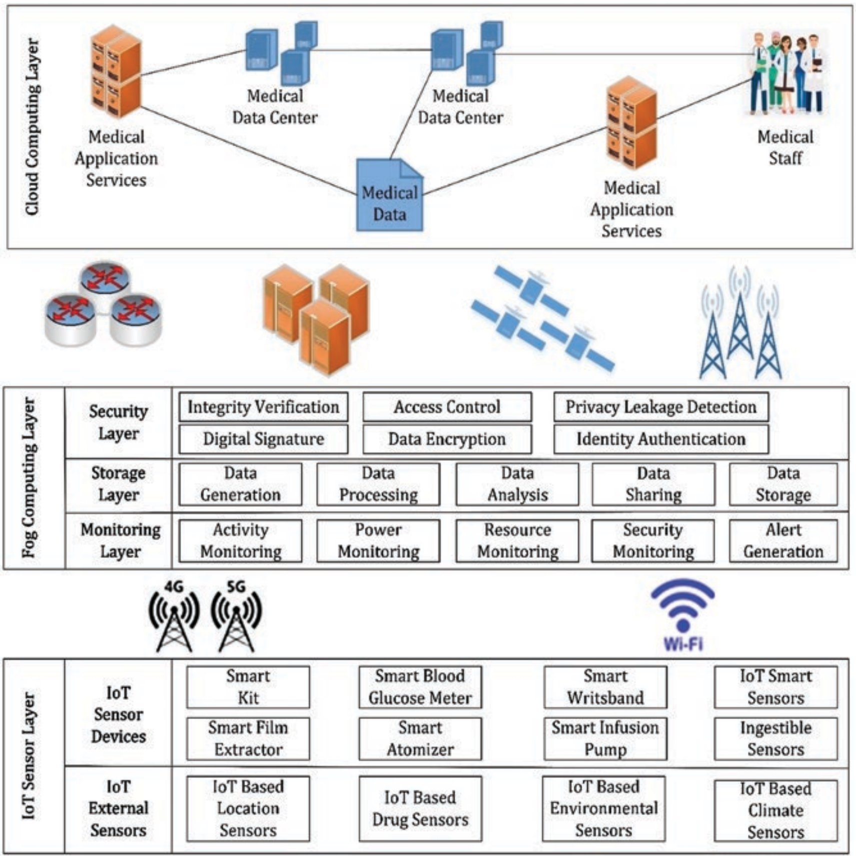

Fig. 6.3 Fog computing architecture for healthcare network

smart intelligent devices and tools that are used to gather healthcare data from the patient. Then, the gathered data are transmitted to the fog computing layer for additional data processing. This fog computing layer functions as a middle layer between the smart terminal and cloud computing layer. This layer contains actions to preprocess, handle, analyze, distribute, store, control, encrypt, and distribute the data. Finally, the cloud computing layer is responsible for the data processing and transmission and supplying the healthcare data to relevant entities and healthcare users. Accordingly, fog computing offers computation, networking, storage, and management services among the end-user applications or edges and the cloud data centers [44].

Due to the bottlenecks such as latency and inadequate scalability in cloud computing, modern healthcare and surveillance systems necessitate greater computing power to handle huge amounts of big data that are transmitted between centralized database to cloud data centers. Hence, the new models of fog and edge computing offer state-of-the-art solutions by providing low-latency and energy-efficient solutions for data handling than cloud domains [4]. Fog computing has several benefits, for instance, reduced latency, improved bandwidth, reliability, energy-efficient operation, safety, and flexibility [46]. It can offer instant outcomes and offer sophisticated healthcare, well-improved diagnostics, and treatments [42]. The foremost notion of fog computing is to improve the effectiveness and flexibility and reduce the volume of the data that can be transferred to the cloud-based components for analyzing, managing, and processing big data.

6.7.3 Internet of Things (IoT) and Its Architecture

The future will be the era that connects the physical things with the Internet in which the things include sensors, machine, and appliances; even the humans also become the part and partial of it. The IoT is the future technology to renovate an artifact into smart things by linking them to the Internet. IoT plays a noteworthy function in smart healthcare system development. The IoT contains various tools and technologies such as sensors, controllers, and wired and wireless connectivity services that allow links among physical things and virtual connections [47]. The reason for joining healthcare with IoT into smart medical devices advances the quality and efficiency of healthcare service, offering high value for elderly patients with chronic conditions and need for regular observation [25]. The IoT architecture involves various tools that enable the IoT to incorporate technologies to make the IoT system for modularity and extensibility for diverse situations [11].

The IoT system architecture consists of layers for various functionalities such as sensor, gateways and networks, management service, and application layer [11]. The IoT and cloud computing have emerged as a combined platform that offers a vital role in healthcare services to the connected users by minimizing the cost and time related to the data collection. In the context of healthcare, IoT-based applications can be applied to monitor patient health conditions, ubiquitous healthcare management, and telemedicine and identify clinical issues and diseases, maintenance, and logistics arrangement in the healthcare systems [29]. Scholars suggest that for the smart healthcare system development, experts from information and communication technology, electronics, and healthcare professionals must work seriously [48]. The efficient implementation of IoT for gathering, processing, and supplying data produced by medical devices, sensors, wearables, and humans is important for modern healthcare systems.

6.7.4 Internet of Medical Things (IoMT)

It's a radical shift for the healthcare industry with the Internet of Things. The growing applications of IoT and the Internet of Medical Things electronic devices have made medical treatment more systematic, and the healthcare records can be handled and well organized [49]. The recent emerging advancements in healthcare equipment, usage of IoT devices, and state-of-the-art wireless and computing power have enabled the extensive applications of the Internet of Medical Things [50]. Therefore, the practice of data handling in healthcare is improved particularly by employing techniques like machine and deep learning, data mining, artificial intelligence, and algorithmic modelling. The Internet of Medical Things connects with diverse objects such as end users, sensor devices, and network nodes that operate on a simultaneous basis for supreme disease analysis and diagnosis; as a result, it increases to have reduced cost, finest analysis, superior supervision of clinical procedures, and more precise cures [51]. Equally, the Internet of Medical Things devices have been extensively employed for detecting symptoms, predicting weather and the climate, virtual observation, and superior connection of healthcare devices.

6.7.5 Wireless Body Sensor Network

The wireless body sensor network is an emerging healthcare technology that requires modern micropower bases with great energy density, extensive lifetime, and worthy biocompatibility [52]. It assimilates the technology of detecting nodes, smart data handling, computing power, and communication [53]. The wireless body area network is a system of interconnected sensor devices, digital objects, and people that are offered distinctive identifiers and the capacity to transmit data over a network [54]. The wireless body sensor network is a set of smart and intelligent medical sensor devices implanted or on the surface of patients' body, which is employed to constantly monitor sign, symptoms, and patient's condition and for remote health tracking on a real-time basis to share them with a doctor or patient [e.g., 55–58]. Its healthcare monitoring includes blood pressure, pulse rate, heartbeat rate, pressure, oxygen level, temperature, and respiration rate [59, 60].

The applications of wearable IoT healthcare devices especially for patient's remote monitoring and the design of wireless body area network have facilitated the modern healthcare system. The wireless body sensor network is important and vital for elders who require continuous monitoring without others' support or being hospitalized. Further, as the aged people require more medical services health monitoring, the wireless body area network supports to remotely control and monitor various diseases [61]. The body sensor network contains similar and/or various detecting nodes including wearable and biocompatible sensors [53]. The wireless body area network has made continuous health monitoring possible; thus, the users can get unlimited medical services on space and time [62]. The wireless body area network has been not only used to prevent and cure different diseases but also employed in elders and disabled people's healthcare [62]. Similarly, it has various advantages such as reducing medical cost and human mistakes, increasing the patient's comfort, and no longer need to wake for physical checkup [60].

The intelligent biosensor-enabled body sensor network facilitates for healthcare monitoring, remote health tracing, and even offering alerts to physician or doctor through the Internet and mobile devices that are beneficial in terms of accuracy, cost, and reply time [58]. Based on the patient's symptoms, continuous treatments for emergency conditions are done with the help of body sensor devices. Body sensors are widely used for diagnosis and continuous monitoring of patients undergoing emergency care [63].

6.7.6 Blockchain in Healthcare

Today, the modern technologies, innovative applications, privacy, and security of healthcare data have become the utmost importance. The applications of blockchain technology are in many sectors, for instance, finance, healthcare, big data, cybersecurity, supply chain management, and law [64]. The blockchain, initially introduced from bitcoin, that has modernized and was applied in various industries in the past now has become one of the state-of-the-art technology in today's world [65]. The blockchain-centered architecture provides a new model focusing the data in the aspect of safety, integrity, standardization, and compatibility for accessing and sharing data [15, 37]. Healthcare records, laboratory tests, physician prescription, and exact healthcare details can all be decentralized using blocks and transactions in healthcare [66]. The big data in healthcare can optimize the blockchain by exploiting big data-driven business intelligence for various supportive services like insurance policy [15]. Currently, the blockchain has developed as an appropriate way to advance the privacy and security of healthcare data and its participating entities [16]. Further, the blockchain has been identified as a means to elucidate challenges encountered by healthcare, such as the secure transmission of healthcare records and data privacy compliances [67].

The blockchain with other state-of-the-art recent technologies has the ability to renovate the present intelligent healthcare systems from an integrated and susceptible system to a distributed, decentralized, and highly safe system for enlightening the quality of healthcare services [16]. Similarly, researchers highlighted that the blockchain enables decentralization as it has distributed ledger technology, improved safety, authentication, stability, computing infrastructure, and compatibility [e.g., 17, 67–69]. In healthcare, the foremost characteristics of blockchain are interoperability with data sharing, various systems, and participating entities. The blockchain has various benefits in healthcare such as clear data for all participating entities while keeping the privacy and preventing malicious attacks and data thefts and offers cheap and secure healthcare and supportive services for related entities (e.g., suppliers, insurance, healthcare researchers, pharmaceutical and drug companies) [16]. Though the blockchain has several benefits, still, there are concerns and vulnerabilities such as data mining attacks and mining incentives, anonymity, data privacy, and authentication issues [17].

6.7.7 Machine Learning

There are well-known healthcare analytical techniques to be applied for healthcare data such as machine learning, modelling, visualization, statistical analysis, and data mining. Above all, machine learning is the highly used technique that gives massive potential in the domain of healthcare predictive analytics to advance the results [20]. The Internet of Medical Things and cloud server frequently gather and share data that can be handled and analyzed by using the machine learning and big data analytics techniques [32]. Scholars claimed that further development should be taken on the machine learning decision support systems that will offer clarifications and healthcare officers' interactive visualization tools to study the consequences of potential effects [20]. Supervised, semi-supervised, and unsupervised classifications are the major types of machine learning algorithms [70].

Machine learning is the perfect method to exploit the unseen insights and pattern from the large volume of the dataset with the least support from the human direction [6]. Machine learning contains a range of techniques such as predictive analytics, data mining, pattern recognition, and various modelling. The healthcare industry is powerful in utilizing the applications of machine learning techniques into actionable knowledge bases by executing predictive and prescriptive analytics to support intelligent clinical services. Scholars define machine learning as a kind of artificial intelligence that enables the machine to learn without being programmed and is used to increase future outcome based on past results [47]. In healthcare, machine learning techniques are being used for predicting disease severity and reasoning, decision support for medical surgery or therapy, extracting healthcare knowledge, analyzing various health data, and drug discovery [23]. Different machine learning techniques are executed for mining from large-volume datasets, for instance, decision trees, support vector machines, neural networks, and dimensionality reduction [6].

6.7.8 Deep Learning

Deep learning is a subset of machine learning that involves extracting high-level, complex abstractions as data representations with the support of a hierarchical learning process [6]. Deep learning aims to predict and classify extremely high accuracy of healthcare data. Deep learning's main feature is its ability to analyze a huge volume of unsupervised data, which is critical in big data analytics because the data is unlabeled and unclassified [6].

6.7.9 Intelligent Computational Techniques and Data Mining

The traditional methods for handling health data have reached limited success because they are incapable of treating a large volume of complex data [26]. Big data is used for the sole reason of analytics in which knowledge and significant insights are mined from big data. There are various data sources such as media, cloud, web, IoT sensors, and database which can be used to collect a large volume of big data [71].

Pramanik and Lau [23] identified three comprehensive technical branches such as intelligent agents, text mining, and machine learning as the modern healthcare technologies in their smart health in smart city study. Intelligent agents in healthcare are defined as the entities that gather instructions and interrelate with environments in which they recognize the physical and virtual settings by using various sensing devices to perform the given tasks [23]. The application of intelligent agent in the healthcare domain is retrieving health information from big data; disease diagnostic decision support systems; planning and scheduling task for doctors, nurses, and patient; medical information sharing; medical image processing; automation; simulations; bioinformatics; medical data management; and health decision support systems [23].

In healthcare, text mining enables to mine important knowledge insights from textual data in which some analytical models can spontaneously code unstructured information with text mining grouping, research activities on the biomedical field, and knowledge management and discovery [23]. In healthcare, various data mining procedures can be used such classification, association rule mining, regression, clustering, detection, analysis, decision trees, and visualization to extract effective details [12, 71]. Data mining is the technique that extracts patterns and connection that can generate knowledge or insights from databases or large datasets [71]. The powerful amalgamation of healthcare informatics and data mining by employing big data analytics techniques will increase the quality of healthcare services with effective decision-making [72].

The machine learning technique is applied to extract pattern and model, whereas data mining is a mixture of statistics and machine learning that are mostly involved with large datasets and analyze huge, complex, and unstructured/structured data [26]. Researchers have identified the fuzzy logic systems as a perfect option to design healthcare systems as they can handle uncertainties, inaccuracies, complications, and comprehensiveness of the data. Further, fuzzy systems offer apparent and convenient rule-oriented models that can be a methodology for designing predictive models and cataloguing by employing imprecise cognitive of uncertain data and information [12].

6.7.10 Hadoop Architecture

In healthcare, several techniques, tools, and frameworks have been established to process the big data in which Hadoop is the distributed data processing framework that is used to store and process a large set of data by employing the MapReduce programming paradigm. Hadoop is the famous open-source distributed processing platform for big data analytics that can function as the data analytics and data organizer in the Apache environment [23]. Hadoop and MapReduce have the ability such as flexible and computational powerful cloud computing environment to execute healthcare ontology quality assurance [20]. Apache Hadoop is the most frequently used computing platform for big data analytics tools in healthcare.

The Hadoop contains two key components, namely, *Hadoop Distributed File System* (HDFS) for data storage and *Hadoop MapReduce*, aimed to deal with parallel processing of huge datasets. The application depends on Hadoop for processing big data issues, and the users can request only smaller amounts of data to the statistical software [20]. To solve the key drawbacks in Hadoop, a new architecture was established, namely, YARN, which has the resource management infrastructure and gives many scheduling functions [20].

6.8 Proposed Novel Conceptual Design of Healthcare Systems Using Big Data Analytics

Sensor and wearable devices are regularly generating a large volume of data that contains structured and unstructured data. Table 6.1 lists a comparison of big data-related healthcare system features in prior and present studies. Following a comprehensive review, a big data-based conceptual framework is proposed in healthcare systems that contain IoT sensors, data sources, big data types, big data analytical platform and tools, analytics data output, patient health monitoring, and recommender system, which are presented in Fig. 6.4.

6.8.1 Proposed System Functionalities

6.8.1.1 Data Sources

This section describes the functionalities of the proposed system. The healthcare-related data will be collected from embedded sensor devices that are placed on the patient's body. The heterogeneous data resources in healthcare, namely, clinical, patient, pharmacological, and drug-related data, must be correctly handled and examined to develop the latest healthcare systems. Similarly, there are a variety of healthcare data available on social media and websites that can also be collected for this healthcare system. The generated data will be transferred to the cloud data storage server. In the meantime, the data-handling portion will migrate the patient's symptoms and body condition-related data to the fog computing environment. Once the transferred data has been compared with the existing data in the database, a report describing the current state of the patient's health will be produced, along with the necessary tentative care/medical therapy to be taken. The healthcare data

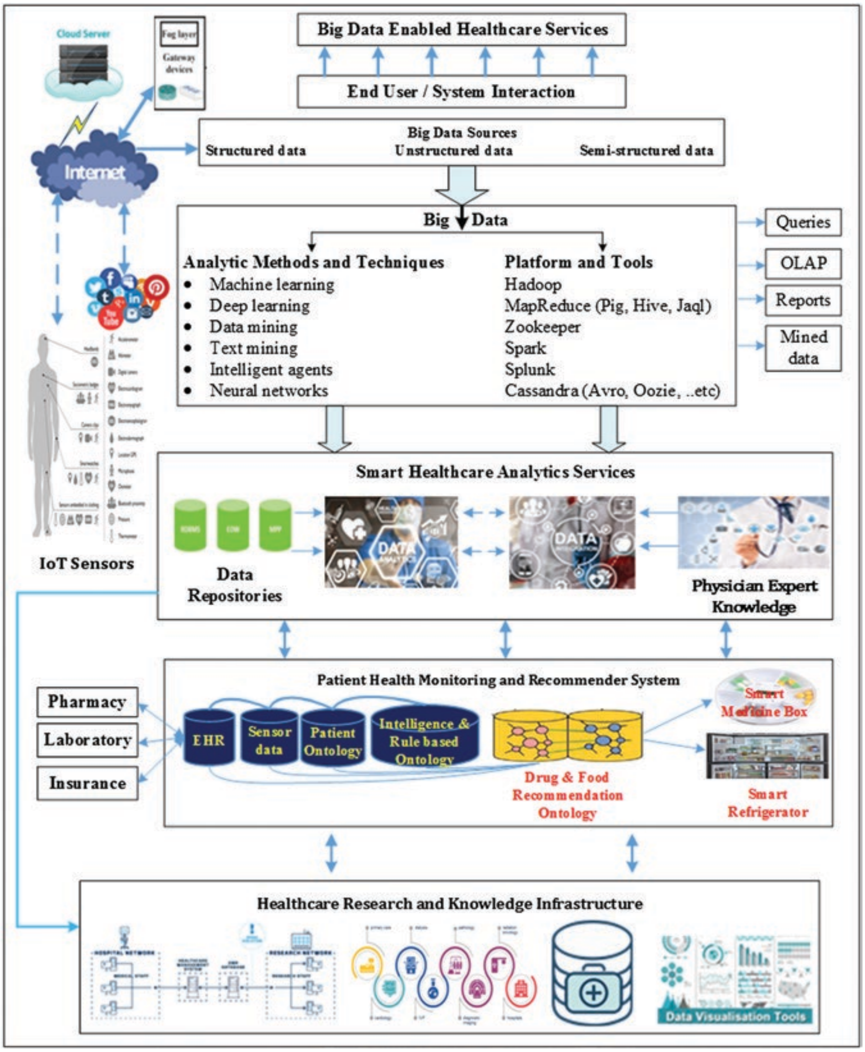

Fig. 6.4 Proposed big data-based conceptual framework in the healthcare system

collected from the patient's body/social media can be in any format, including structured, unstructured, and semi-structured data. To handle these kinds of data, there are several big data analytics methods, techniques, and platform tools that exist. These techniques and tools will be used for analyzation based on the data types. The output of these analyses will be in any form such as queries, reports, Online Analytical Processing (OLAP), and extracted data mining.

6.8.1.2 Patient Healthcare-Related Data

The modern developments especially in IoT and sensor devices have made patient's monitoring more advanced, and that aims to offer superior healthcare service delivery to sick persons. Healthcare records may include a variety of symptoms and patient health issue data. For instance, it may include body symptoms such as fever, headache, pain in the bones and joints, skin eruption, body pain, red eyes, nausea, vomiting, and myalgia. To collect these symptoms, IoT sensor devices or physical test will be used. If it is an IoT device, it will be embedded in the victim's body to identify or detect the conditions. The symptoms detected by the IoT sensors will be transmitted to the fog computing environment which is linked through cloud computing to store in single or multiple data storage components.

6.8.1.3 Cloud and Fog Computing Components

In this proposed system, cloud and fog computing environments have been employed. As the healthcare data seems to be highly sensitive and private, there is a need for the protected transfer of these medical records, hence, to make sure the data security of the data encryption mechanism will be employed. The cloud layer saves data from the Internet for the concurrent retrieval of data by the devices linked with this ecosystem. The data which require further sorting or handling will be transmitted to the cloud layer. The cloud layer is responsible for storing, managing, and processing records as the fog computing layer cannot manage. The fog computing component gathers data from the Internet for further analysis. This fog computing component is responsible for data storage, data processing, data transmission, and communication-related activities. Therefore, the patient's health condition associated with symptoms and sign will be collected, transferred, handled, and analyzed at this fog component. Further, this fog computing component is used for the real-time data handling and processing of data from the IoT devices. The sophisticated cloud and fog computing applications have received greater attention in the recent healthcare system development.

6.8.1.4 Big Data Analytics Methods, Techniques, and Platform Tools

The output from the big data analytics techniques and platform will be transferred to smart healthcare analytics services that include data repositories, data analytics, data integration, and physician expert knowledge. The healthcare-related big data will be systematically analyzed with modern state-of-the-art techniques, and each component in this category will collaborate effectively. The component will offer updated valuable insights, disease analysis, medical therapies, drug suggestion, healthcare clinical management, healthcare scheduling, and many other services. Applying the machine learning techniques and inference algorithms in IoT-based healthcare system can properly learn from sensor devices and patient medical history to alert the status of the present and future health status of the patient and even

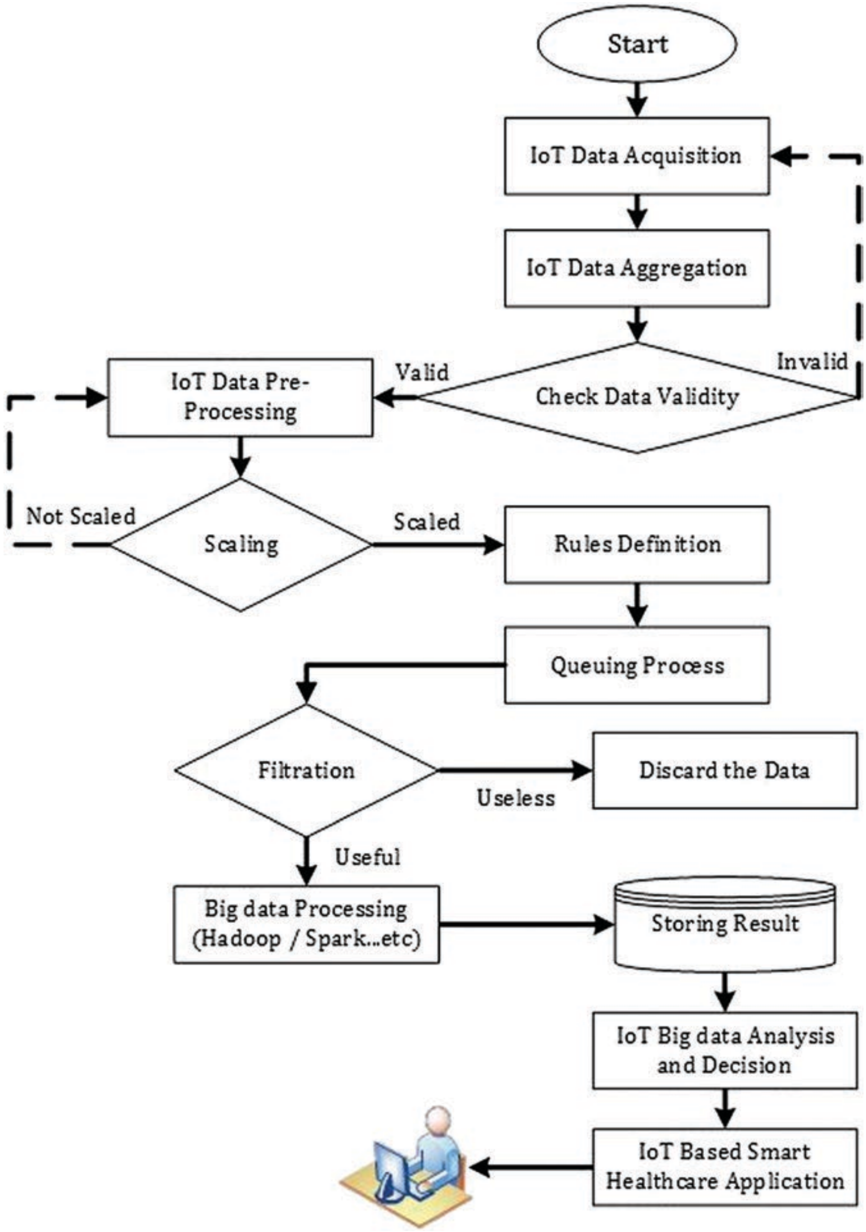

Fig. 6.5 IoT data acquisition and data processing flow chart

make alarms to the healthcare officers and to the patient if needed [1]. Accordingly, the data collected by the IoT devices can be processed and analyzed via the MapReduce platform that can handle the large volume of data by employing machine learning techniques to decide subjects' actions over time. Figure 6.5 demonstrates the process of IoT data acquisition and processing flow chart.

6.8.1.5 Patient Healthcare Monitoring and Recommender System

This component database includes electronic health record (EHR), sensor data, patient ontology, and intelligence rule-based ontology. The data will be gathered for these databases from various healthcare units/departments that are located across the country, for instance, clinical and administrative departments such as pharmacy, radiology, medical laboratory, billing, and insurance. The above departments are linked via the EHR unit in the cloud that allows data sharing and interoperability. Further, the EHR consists of patient records that are linked from different units (pharmacy, lab, insurance, etc.) such as city, state, or region and stored in the cloud.

The second component is the food and drug recommendation ontology. The recent developments in Internet-based technologies have made greater alternatives for a recommender system to support patients for their routine lifestyle [73]. There are a sophisticated collection of smart devices, agents, techniques, and linking components that are supporting to make this recommender system. Further, the needed data for patient drug and food will be gathered and preprocessed to recommend by looking at the patient status. This contains a collection of data for drugs, for instance, its dose, chemical structure, and properties. With regard to meals, the data, for example, its nutrition values and ingredients, will be considered for the recommendation. Furthermore, this recommender system is paired with specifics such as the spice level and choices such as vegetarian or nonvegetarian for the patient's diet favorites.

6.8.1.6 Healthcare Research and Knowledge Infrastructure

This layer includes healthcare-related various research, innovation, and knowledge infrastructure components. The purpose of these components is to build a system that offers state-of-the-art healthcare services and support for patients, researchers, hospital management, medical professionals, healthcare agencies, government organizations, and policymakers. The databases and knowledge repositories in this layer keep the symptoms, diseases, drugs, drug composition and dose level, clinical records, clinical procedures, disease prediction, prevention mechanisms, medical practices, etc. to explore new insights and trend for future usage and knowledge discoveries. Researchers and data scientist will use advanced simulations, data visualization, data mining, classification, and modelling to support the knowledge demand of medical professionals and policymakers.

6.9 Smart Healthcare Applications Using Big Data: Real Cases

The need for smart healthcare systems is necessitated for the patient's accurate health monitoring in various circumstances. Accordingly, there are several practical applications or development of smart healthcare system in the practice. This section describes such real practices or system development in detail. Nayyar and Puri [58] proposed an Internet of Medical Things-based monitoring system to measure patient heartbeat, temperature, and oxygen level and to notify these details to the doctors. This system was tested with more than 50 patients, and the results proved 90% accuracy compared to the available health monitoring system. Mahapatra and Krishnamurthi [74] discussed different models and algorithms for the security and privacy of healthcare records. Their focus is on the recent development of various security and privacy aspects in developing healthcare applications. Similarly, Kumar and Krishnamurthi [37] worked on the novel designing, modelling, and implementation of healthcare systems in the aspects of integration and compatible blockchain 3.0 and healthcare 4.0. The simulation and test of the system showed good performance overall [63]. proposed a cloud-based healthcare test case selection and prioritizing framework to identify the fault recognition rate, in which their experimental results of this framework reveal a better fault detection rate compared to earlier fault detection methods.

6.10 Conclusion

The role of big data analytics in the healthcare domain contains the approaches of evaluating the large volume of healthcare records associated with patient healthcare and symptoms. The IoT will be the future revolution that will be heavily integrated with big data in the healthcare domain. The size of big data has increased exponential, and the process involved to gather, store, extract, analyze, and optimize these data that also become very much important in healthcare systems. Hence, the mixture of big data and healthcare systems can accelerate the potentials benefits in the healthcare sector. This chapter discusses various big data-related techniques, platforms, architectures, and challenges in the field of big data analytics in healthcare systems. In addition, this chapter proposed a conceptually developed big data analytics that illustrate various aspects of big data for a healthcare system. The key contributions of this chapter include a systematic review of big data analytics in the healthcare system context and various big data- and analytics-based methods, techniques, and platforms and proposed a modern conceptually designed healthcare system framework.

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Chapter 7
Robotic Technology in the Development of Prosthesis

Tomina Thomas and Anna N. Kurian

7.1 Introduction

Walking is one of the easiest ways to exercise which helps us to stay healthy. Over generations, humans walk about 10,000 steps per day and become skilled walkers. Experts recommend at least 2.5 h of moderate activity (walking, cycling) a week. However, walking can be difficult for amputee patients apart from a healthy one. Amputation is the removal of limb by any diseases, accidents, or surgery. A person who is suffering from the difficulty of amputation is called an amputee. Amputees normally find the difficulty of sitting, balancing, and support and weight distribution. They often face instability if not provided with proper balancing measures. In total, an amputee would use around 80% more strength to steer than a human with two legs. For stable people, walking on flat land takes less energy, whereas prosthetic amputation absorbs considerably more power at all walking rates than non-amputees. As a consequence, the amount of energy consumption needed to conduct normal activities can restrict the activity level of the amputee and thus the types of tasks that they can engage in.

A prosthetic limb is a man-made organ that covers a defective component that may be removed due to injury, trauma, or condition at birth. Prosthesis is specifically meant to restore the things that a stable person would perform and to enhance someone else's quality of life. The prosthesis of an individual should be built and

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constructed based on the appearance and practical requirements of the person. The sort of prosthetic limb is determined by the degree of the amputation. The prosthesis is classified primarily as upper limb prosthesis and lower limb prosthesis. Upper limb prothesis is used at different levels of amputation, such as forequarters, disarticulation of the shoulders, prothesis of excessive extent, shoulder pain of the elbow, transfemoral prosthesis, disarticulation of the wrists, entire arm, partial arm, finger, and partial fingers. The prothesis of the lower limb is already in great demand and is reachable for multiple functions. The prosthesis of the lower limb is unnaturally covered by limbs at the hip or lower level. Transtibial and transfemoral are the two significant subdivisions of implantable products of the lower limb.

During the past years, wood and metal prostheses were used which were later replaced by developing technologies and human intelligence. More lately, robotic engineering has discovered the best and most efficient way to replace the present drawbacks of prosthesis, a development that combines science, engineering, and innovation that creates devices that mimic human behavior, called robotics. A robotic prosthetic's primary function is to provide constructive activation when walking in order to boost the biomechanics of motion, including amputees' mobility, symmetry, or energy expenditure. There are so many commonly produced powered prosthetic legs, including fully controlled legs within which sensors consciously operate the joint and semi-active legs that use limited amounts of energy and a tiny actuator to change the mechanical properties of the leg which do not pump net positive energy to the posture. During the past several decades, various analytical groups have also been playing with robotic feet. The major problems addressed include the calibration of the system's behavior during the stages and swing cycles, knowledge of the current postural control mission, and numerous mechanical design issues such as reliability, mass, battery life/efficiency, and noise quantity. The bulk of prosthetics can be nonpermanently fixed to the exterior of the body. A few of others could, though, be connected indefinitely. In addition to the usual artificial limbs for daily use, most amputees or congenital persons have limbs and special equipment that encourages interest in athletics and sports activities.

7.1.1 Objective

The complications associated with new prosthetic system restrict the standard of living of amputees. Such prostheses cause amputees to walk very slowly, expend more power, and collapse more often.

The overall objective of this chapter is as follows:

- To identify the defects behind the existing prostheses.
- To modify them to obtain a well-defined robotic prosthesis that improves walking performance, posture control, and so on.
- The newly developing prosthesis using robotic technology is simple, portable, economical, and scalable.

7.1.2 Motivation and Organization of Chapter

A highly efficient and well-defined prosthesis is important for bringing an amputee to lead his life like a normal one. Problems that arise from amputation and from replacement of a missing part by a normal prosthetic device may be complex. Thus, in order to improve the efficiency of performance, a properly designed robotic prosthesis is chosen.

The remaining of the chapter is organized as follows: Section 7.2 includes related terminologies. Section 7.3 deals with the design methodology and control strategy of various robotic prosthesis. Section 7.4 deals with the experiments done for some of the designed prosthesis. Section 7.5 concludes the emerging and newly developed robotic technology in the field of prosthesis design.

7.2 Related Terminologies

The relevant to the area of topic are summarized from the following sources of documentation: (1) An Open-Source Robotic Leg Prosthesis architecture and characterization, (2) robotic prosthesis that maintains flexion posture, (3) common core component knee-ankle prostheses (C3KAP), (4) a novel robotic knee-ankle prosthesis device structure and control, (5) regeneration of energy from human electromagnetic induction dynamics for robotic prostheses of lower extremity, and (6) artificial gastrocnemius quasi-passive on transtibial amputee gait.

The aim is to identify the right innovations for amputees to regain their lives as usual and allow them to conduct everyday locomotive tasks that are varied and energetically demanding, far beyond capabilities of the passive prothesis. This chapter gives a brief idea about different types of robotic technologies that can be implemented to develop an advanced prosthesis and improve the efficiency of currently existing ones.

7.2.1 Open-Source Robotic Leg Prosthesis

An Open-Source Leg (OSL) [1] is a robotic prosthetic limb that enables creation and comparison of the control mechanism. In the time-frequency limits, we address the overall design priorities, transport choice, working principle, and specification. The purpose of the OSL is to provide a shared hardware forum to compare control techniques, reduce the prosthetic study entry barriers, and enable experimentation within the laboratory, society, and at home. In order to connect with highest process control chosen by scientists, the OSL contains the prosthetic limb hardware, sensors, reduced control applications, and an application peripheral interface (API). This is a plain, scalable, compact, adjustable, and inexpensive prosthesis.

In this framework, both the knee and the ankle pursue a same construction technique. In order to boost the torque at the output, both have been used an electrical motor connected to a multistage belt transmission drive. Belt drive transmitting configurations are achieved by taking into account the average amount of transfer, the numbers of belt stage, the pitch within each stage of a belt, the width within these each stages, the number of active teeth, the simplicity in the assembly, and the length and width accessibility of a belt. For their flexibility, lower weight, low price, and silent operation, timing belt drives were being used. Newly designed PowerGrip GT3 belts have been selected because, compared to other belts, they have longer belt drive life span, improved load-carrying capability, and quieter operation. For both the time domain and frequency domain, the electromechanical efficiency of the OSL was defined. For both location and current control systems, the time domain and frequency domain experiments were carried out. The actuator was secured inside a testing ground (supplying a response torque); throughout testing of the control current system, each joint was rotatable during testing of position control. The ankle and knee were analyzed individually, and these preliminary tests did not provide sequential elasticity. The higher-tier control system, at ~750 Hz, recorded all the information.

The OSL is developed to conform with the kinematics or kinetics of capable locomotion through a number of types of ambulation, particularly level-ground movement and ascent/descent of stairs. The knee can. be designed as a series elastic actuator (SEA) with custom twisting springs using customizable normal elastic properties, or as a non-SEA. Eventually, structural reinforcement, stability, and belt tension capacities are offered by clamshell-type enclosures. Figure 7.1 shows the major components of the OSL, highlighting the transmission, electronics, and load cell [1].

7.2.2 *Robotic Prosthesis that Maintains Flexion Posture*

In this, the architecture and features of a robotic prosthesis capable of retaining the state of flexion was studied [2]. As a result of this study, we have generated a robotic prosthetic limb to ensure order both while walking and during fast running. A ratchet device has been applied to the knee joint, and the bending and expanding function of the knee has been replenished. A ratchet mechanism causes continuous linear or rotational movement in one direction while limiting movement in the other direction. A spool is also attached to the ratchet mechanism which is a device on which tape and other materials can be wound. A belt is wound on the spool. The flexion and contraction of the knee joint are caused by the wrapping and unwinding of the belt. We have attempted to track the movement of the claws of the ratchet system electronically for this model, based on the finite-state machine (FSM) state transfer mode. The claw is pushed by a drive solenoid till it joins with gear and therefore forms the latching mechanism. It is necessary to provide no resistance in the direction of expansion and a lock on the direction of flexion by using this method. An encoder is also used in this model to measure the angle of knee joint based on modeling of (finite-state machine (FSM).

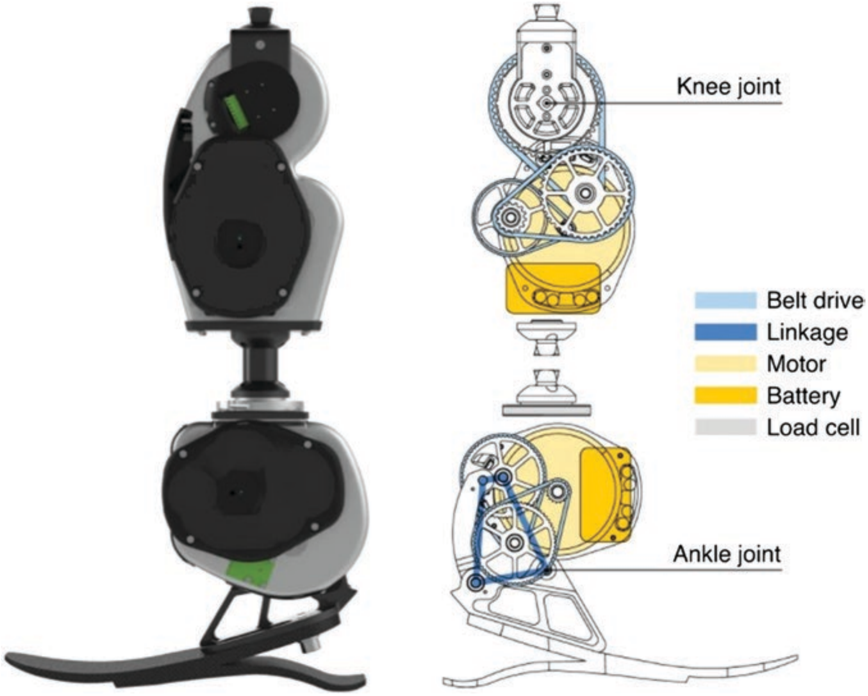

Fig. 7.1 Major components of the OSL, highlighting the transmission, electronics, and load cell

Model the standing and walking pose in FSM simulation in order to assess the push solenoid pacing. A control mechanism is built here that stimulates the solenoid to lock the joint flexion at an acceptable moment. The walking condition is detected using sensors. The finite-state machine (FSM) designs the walking and standing model, this will be a model of behavior composed of a countable number of states and shifts. We used change as a transfer condition in the knee angle and modelled the role of walking and standing. An FSM is characterized by four acts such as regular walking intermittent movement with constant maximal knee flexion angle, irregular walking particular to the highest user-specific knee flexion angle, standing overall knee joint expansion, and flexion posture maintaining the knee bends, but the angular velocity is zero (deg/s).

7.2.3 Common Core Component Knee-Ankle Prostheses (C3KAP)

Specifically [4], the analysis in this chapter aims to unify joint architecture as a main objective and explores the dual details that decide the knee/ankle robotic models: (1) biomechanical characteristics, especially torque, speed, and range of motion, and (2) shape factor specifications associated with the knee/ankle joints. In compliance with these requirements, a unified knee/ankle specificity has been developed and features a single transmission process and unit configuration while still retaining the required degree of flexibility by switchable timing belt rollers. The biomechanical aspects of the knee and ankle while walking are studied in the following segment, and the findings are the basis of the following driven joint design.

The bio-micro mechanics of normal walking are very significant, providing the foundation for the design of the automated ankle and knee prothesis. The individual level-ground walking gait loop starts when the heel touches the ground with 1 ft and ends with the matching heel brush with the same foot. The entire gait cycle is divided into two phases: the stance phase as well as the swing phase. The initiation process accounts for approximately 60% of the swing phase, and the swing phase accounts for the remaining 40% of the gait cycle. The study of walking kinematics and kinetics was used as an effective tool for calculating the movements and stresses of the lower limb joints in this segment.

Ideally, the form and design of the robotic prosthetic limb should be equivalent to the size and shape of the lost limb and, most notably, to the ease of everyday use for aesthetic appeal. Size and shape are both very critical aspects of the design of the prosthetic leg, which are largely determined on the basis of human biology principles. Only tall prosthetics or amputations with short remaining limbs should be used where the length of the prosthetic leg is too long. Besides, the diameter of the prosthetic limb must be compact to stay within the normal anatomical envelope. And the volumetric profile of the limb differs greatly depending on race, age, and racial differences. Because bulky prostheses require extra caloric energy intake for locomotion, the weight of the prosthetic limb must be within the weight of the respective limb parts.

The purpose of this chapter is to render common core components of a knee and ankle prosthesis (C3KAP). The design of such a prosthesis is determined by a need for a compact device that satisfies the criteria of a true healthy knee and ankle but still has a substantial high torque and strength performance. For our application, the two parallel systems were chosen. A transport mechanism for the timing belt drive was the very first stage, and a framework for harmonic drive transmitting was the second phase. The thorough architecture and features have been studied in the following paragraphs.

7.2.4 A Novel Robotic Knee-Ankle Prosthesis Device Structure and Control

The concept and management of a modern robotic knee and ankle prosthetic device are discussed here [3]. The robotic prosthesis device for the knee and ankle includes a robotic deformity for the knee and a robotic implant for the ankle, bound by a prosthetic cone, which controls the length of the stem and the balance between the knee and the ankle. In order to convert the straightforward motion of the continuous elastic actuator to the revolving motion of the knee and ankle joint, we propose a new mechanism combining a series elastic actuator and crank mechanism. The mechanism of the crank gives each joint a variable transmission ratio. The knee should be given this unusual attribute at once: the torque needed to help get out of a chair and also the momentum obligatory to waver the leg straightaway when walking.

The ankle joint torque increases slightly to the variable transmitting ratio as the angle of the ankle is bended through plantar flexion to dorsal flexion, and this characteristic has a comparable tendency to the relationship of the human ankle joint torque angle. Robotic ankle protheses are an engineered physically separable device composed of actuation, circuitry, and power and can be operated separately. The knee is served as a maestro, and the ankle seems to be a slave, and as one unit in this article, they are interconnected by electrical wire to relay control signal from maestro to slave in coordinating knee and ankle motion. A template was developed, and a transfemoral amputation was performed as a preliminary study.

Two 200 W brushless DC (BLDC) motors are used to operate knee and ankle joint correspondingly. The portable motor drive and control system was used in the model and route-tracing process based on human pace details to trace the knee and ankle joints on level-surface walking. The mechanical architecture is not only important for the construction of the compact and lightweight prosthesis; the electronics also contribute to the mass and scale of the robotic implants.

7.2.5 Energy Regeneration from Lower Extremity Robotic Prostheses

This deals with the design and characteristics of an energy regeneration system using a robotic prosthesis [5]. The basic concept is that the mechanical energy used for human dynamics (walking, running, etc.) is converted into electrical energy using the principle of electromagnetic induction and stored. Here, we can understand how human dynamics can be efficiently utilized to explore the variation of energy. Mechanical energy is converted into electrical energy during early stance phase due to ankle joint movement, and this electrical energy can be regenerated to certain form that can be regulated freely. Energy regeneration from human dynamics using a robotic prosthesis is more efficient than normally used piezoelectric effect. No other mechanical structures are used in this system, which makes it lighter and can enhance the amputee's walking ability.

This concept uses six MOSFETs, an ultra-capacitor, and two DC-DC boost converters. An EMF can be generated in the motor due to electromagnetic induction and hence acts as a generator. Six MOSFETs, which were powered on/off, acted as an EMF inverter according to a predetermined service cycle. An ultra-capacitor thus flows into the inverted current. Two hierarchical methods of restoration have been used in order to improve energy efficiency. In order to prevent losing electricity in the buck circuit propagation, the low-side voltage regeneration was to be set up. The regeneration of the high-voltage side was set up to ensure protection if the ultra-capacitor voltage exceeded the rated voltage. The cumulative strength is the sum of batter power, constant low-side regeneration power, and a separate high-side regeneration power for a robotic prosthesis. In addition, the built robotic prosthesis is capable of self-charging, which improves the efficacy of walking. Figure 7.2 shows the installed electricity harvested on an orthopedic knee brace [5].

Researchers have found that the lower limb generates a lot of kinetic energy by swinging motion walking for humans. A generator may also be placed on the knee brace, as seen in the Fig. 7.2. The operating theory is the same as that of the electrical hybrid car's energy storage braking. Not only is it able to generate more electricity than the insole generator, but it is smaller than the insole generator, generator for backpacks. Travelers or military may use it to get through a disaster under which control procurement is temporarily inaccessible. In comparison, in a portable knee joint plucked energy magnetic fields, research teams engineered the harvester to scrounge energy from knee joint motions during human movements, walking and powering a wireless energy-aware network device for data sensing. Something that is important for research leading to the harvesting of inertial energies is introduced, which is a free rotation. A block of inertia and a constant coil are used to build a system for energy production to catch the kinetic energy, the energy of moving humans. This method is more satisfying than the self-winding watch that uses the acceleration of the user's arm in order to speed up a tiny inner volume.

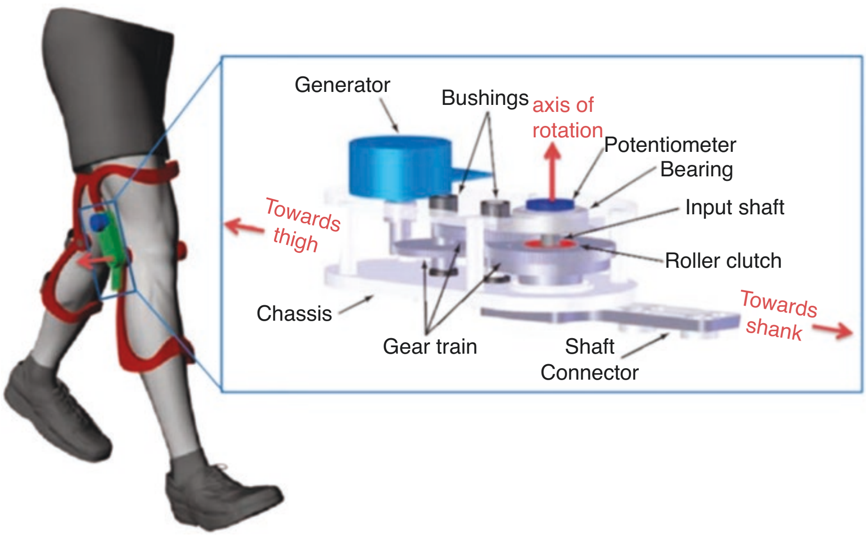

Fig. 7.2 Installed electricity harvested on an orthopedic knee brace

7.2.6 *Artificial Gastrocnemius Quasi-Passive on Transtibial Amputee Gait*

The quasi-passive aspect of this novel artificial gastrocnemius means massive components such as massive battery or engines could be omitted from the architecture [6]. But also, to support people with transfemoral amputation, this system has the capacity to generate cellular levels of knee moments. The reduced power pull also tends to make this system realistic for everyday use, since over the span of a day battery performance will not possibly be an issue.

In recent years, the advent of controlled ankle-foot prostheses has led to robotic advancements in prosthetic technology that, unlike passive traditional systems, offer amounts of physical power similar to those done by the living being ankle-foot complexion. Many of the above gait afflictions have been significantly decreased as a result of this functional change. Amputees using powered prosthetic limbs have preferred walking rate, physiologic expenditure at a steady speed, and contralateral leg influences that are not significantly dissimilar from those of non-paraplegics. Such enhancements are assumed to derive from the percussive net physical work given to the holder by these instruments, since this propulsion tends to divert the mass center, thereby lowering crashes of the lateral cortex limb. That propulsion of the ankle will also support the impacted limb swing initiation. Figure 7.3 shows the quasi-passive artificial gastrocnemius [6].

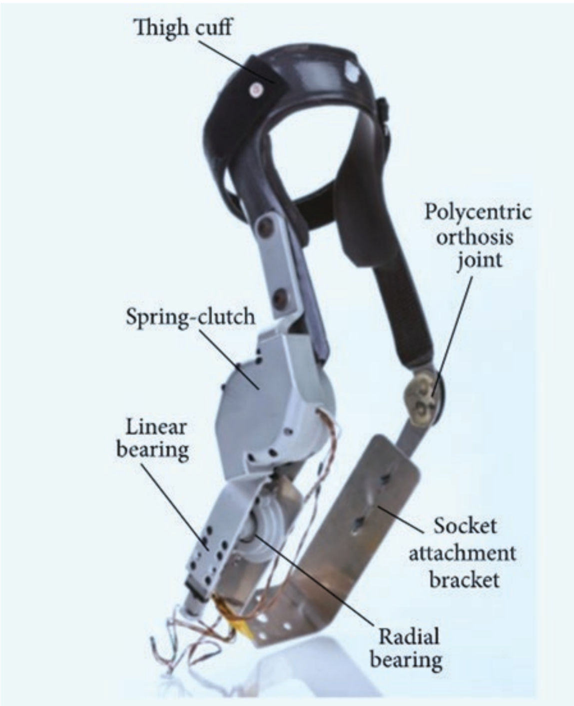

Fig. 7.3 Quasi-passive artificial gastrocnemius

The gastrocnemius [7, 8] offers not only a period of plantar flexion in the ankle but also a period of flexion in the leg. The gastrocnemius offers not just a period of plantar flexion in the ankle but also a period of flexion in the leg. Compensatory mechanisms are necessary without any of the knee-flexing feature. Indeed, throughout level-ground walk, transfemoral amputees show greater hamstring muscle involvement than nonamputees, likely in an effort to strengthen or stretch the knee rather than the nonfunctional gastrocnemius muscle. This greater muscle movement is still evident when people with disabilities walk with the driven leg prosthetics, suggesting that monoarticular action alone at the foot-ankle complexion will not be adequate to regain biological imperative. This abnormal muscle movement can have adverse effects on the gait of amputees. However, a few studies have been carried to build devices to restore this missing feature of gastrocnemius [9].

This section focuses with the efficient and improved architecture and characteristics of distinct robotic prosthesis. Many prostheses were developed to support the life of amputees, but a prosthesis that can enhance the life of an amputee like a normal human is very important. It is evident from the chapter that a robotic prosthesis succeeded in doing so. The succeeding the chapter helps to analyze more about the methodologies used, and certain experiments were also analyzed.

7.3 Methodology of Robotic Prosthesis

This chapter deals with the design and methodology of different robotic prosthesis. Electrical, electronic, and mechanical characteristics and design were analyzed in this section. The most efficient one can be finally obtained by analysis.

7.3.1 Design Methodology of Open-Source Robotic Leg

Open-Source Leg (OSL) [1] is a robotic knee/ankle deformity that is versatile and facilitates the study of control strategies. Without mechanical power off, some procedures, including stair and ramp ascent, are extremely challenging for people with amputations [10]. Prosthesis control systems must be capable of performing many functions, such as identifying the desired movements of the amputee (high-level control), applying an effective control rule based on the preference of the amputees (mid-level control), and using local feedback to control the prothesis actuation systems (low-level control).

Although recognizing both knee and ankle engineering [11, 12] and installation and control elements, both adopt the same construction procedures. In addition to data from ascending/descending stairs, the torque/velocity or current/voltage specifications collected from data from walking at unhurried, self-picked, and rapid speeds were used for the mechanical architecture.

A three-stage belt drive transmission is used in the knee architecture technique. Selectable series elasticity is the ability to set up series elastic actuators (SEA) where continuous flexibility is obtained using custom torsion spring discs. With an internal gear-shaped shaft, torsion spring discs are utilized. The shaft has tooth which assemblages with each cantilever's tip. Relative movement in between the inner gear and the spring disc allows the cantilevered beams to deflect mainly by rolling interaction, contributing to better storage of energy. In order to minimize the total size/height of the ankle prosthesis, the ankle configuration uses a two-stage timing belt drive transmission combined with a four-bar tie-in system. The motion of the tie-in is guided by the two-stage output pulley circulation which results in the ankle joint gyration. The inclination of the linkage rocker correlates to that of the joint of the foot [13]. The rocker pairs the transmission to a deformed foot; in addition to that, the ankle can be attached to a foot of carbon fiber, which, without the extra size and complexity, offers some of the advantages of succession elasticity.

7.3.1.1 Structural Support

Within clamshell-style shells, the transmissions of each deformity joint are fixed. The configuration of the clamshell style has two parts that are merged in conjunction to ease the assembling procedure and minimize pinch points which will result in injuries to the customer or researcher [14]. The housing locates the timing pulleys and provides the prosthesis with structural reinforcement. Inside the clamshell, a basic belt tensioning mechanism is often housed that makes smaller changes to the span between pulley shafts. Reasonable tensioning of the belt is needed to guarantee that the belt drive transmission has full torque power. The housing also uses mechanical hard stops to make sure that the OSL does not circulate to biomechanically hazardous states. At the end, there is also room for batteries and devices in the housing, thereby forming a self-contained, compact prosthesis [15].

7.3.1.2 Control Strategy

At each joint, the OSL uses a brushless electrical motor to provide the mechanical control. For the 21 pole pairs in the engines, Dephy actuation technology (built for portable robotic applications, the open-sourced brushless drive and motor controller) uses field-directed control commutation and is related on an embedded unhindered access platform. Often, feedback loops are used [16]. Onboard sensing involves motor spiraling and bus electrical states and also a nine-axis inert measurement unit, sensing of temperature, and a 14-bit absolute motor encoder. To acquire data from an integrated six-axis load sensor at 1 kHz, a custom, embedded six-channel amplifier and 16-bit ADC are also utilized. Commands for the monitoring system are distributed from a single-platform PC using a custom python-developed API. Two equivalent batteries provide electrical power; i.e., two different electrical power sources have been selected to avail the usage of both joint individually.

7.3.2 Design Methodology of Posture Controllable Robotic Prosthesis

The working of the model was based on a control system which activates the lock mechanism [2]. Here, we look forward to the walking and standing model, and finally, an integrated form is summed up.

7.3.2.1 Modeling of Walking

The walking period is essentially divided into stages of pose and swing. In this model, the FSM's transformation situation is dependent on the utmost angle of knee bending inclination θmax, and the state is navigated in consonance with the θmax ratio [17, 18]. The walking cycle's stance phase is divided into initial touch, loading reaction, mid-position, and terminal stance, and the pre-swing, initial swing, mid-swing, and terminal swing are divided into the swing phase. Using full knee flexion angle, these eight phases are modelled, θmax, and fully extended knee angle considering knee joint (=5 [deg]). The push solenoid gets triggered at the midway of swing to stop knee bend.

7.3.2.2 Modeling of Standing

Normally, standing pose is characterized by $\theta \leq$. After knee bending starts, if we use the lock system, it might be difficult to stop dropping when the knee flexes more than 50 times. Therefore, if the lock is utilized to avoid bending when the user holds a standing stance, there will be no chance of slipping and that will provide steadiness.

7.3.2.3 Walking Model by Finite-State Machine (FSM)

We include both the standing and the walking model in this, that is, a paradigm that goes from standing to walking. An irregular walking model is included in between standing and walking model. Our knee joint utilizes a knee joint micro desktop system that reads a monitoring device. As a consequence, when state numbers S2, I4, and N7 are observed in the midst of travel, the solenoid is triggered [20].

7.3.3 Design Methodology of a Novel Knee-Ankle Robotic Prosthesis

The prosthesis explained just above is used for providing stability during standing and walking. The inventions for more advantageous prosthesis were occurring rapidly. This prosthesis is an advanced type that introduces a robotic implanted leg composed of a robotic knee deformity and a robotic prothesis of the ankle, connected by a prosthetic pylon, changing the length of the shank and balance between the knee and the ankle [3]. Both the ankle and knee are interconnected structures that are physically separable. Both mechanical and electronic designs were included in this chapter.

7.3.3.1 Mechanical Design

The apparatus would adjust the effective joint arm to achieve the overall variable transmitting ratio. The side one of the screw balls is fixed on the static plate of the ball screw, and the other side is fixed on the support plate of the ball screw, and both are fixed on the frame. On the ball nut, two springs are mounted, and the one on the top is for dorsal flexion, and the one on the bottom is for plantar bending. Inside a cylinder are two coils, and they are coaxial with a ball screw. The cylinder is enclosed by a piston plate that is attached by a crank rod to the ankle joint. SEA consists of an engine, a pulley, a ball screw with a ball nut, two cylinder springs, and a piston. Motor induces SEA straightaway motion and transforms it by slider crank process to circular motion of the ankle joint. The sensor for force is attached to the setup, and the force plate is connected to a pyramid connector. The length of the leg could be adjusted by the pylon of the prosthesis.

7.3.3.2 Electronic Design

The motor drive and FPGA motor control board are very compact and lightweight. The drive panel and control panel of the motor are mounted one above the other. They are found in the knee joint in the anterior part. Between the pylon pyramidal connector and the main frame, a six-axis dynamometer is used to capture data on time and force in the gait. The A/D conversion board is used to transform the sensor's analogue data to digital control data. The absolute encoder (to read the position of the knee and ankle joint), the inertial moment unit, and the motor temperature sensor are attached to the sensor processing panel unit that is attached to the FPGA motor in turn. The 24 V LiPo battery supplies motor power of 24 V, FPGA motor control board power of 12 V, and A/D conversion panel power of 12 V [21, 22].

7.3.3.3 Control Strategy

A finite-state machine is used on level-ground walking to separate the gait interval into three stages of stand position, flexion of swing, and expansion of swing. If stumbling happens throughout swing expansion, power will be given to help directly extend the knee. And if knee buckling unexpectedly happens in the stance process, power will be given to regulate the buckling of the knee and dropping down. The swing trajectory is governed by the following equation:

$$\varphi\left(t\right) = b \cdot \theta\left(t\right) + \mathrm{c} \cdot \Theta \cdot \left(t\right) \tag{7.1}$$

where $\theta(t)$ matches the trajectory curve based on human knee joint data.

In the ankle joint, posture modulation is used, and the gait cycle is split into four sections: plantar flexion, dorsal flexion, step-off, and stage of swing. Each phase is controlled by using the corresponding phase springs which were powered by the motor. The motor control is based on the following equations:

$$\text{Plantar flexion}: \varphi\left(t\right) = \theta\text{equi}$$

$$\text{Dorsiflexion}: \varphi\left(t\right) = \theta\text{equi}$$

$$\text{Push off}: \varphi\left(t\right) = \theta\text{equWe} + b \bullet t$$

$$\text{Swing phase}: \varphi\left(t\right) = \theta\,\text{max} - \text{c} \bullet \text{t}$$

where, while the ankle joint angle is neutral and defined as 0°, θequWe is the motor angle. θmax means the angle of the motor when the angle of the ankle joint is at full plantar flexion. B and c are step-off and swing step hills, respectively.

7.3.4 Common Core Component Knee-Ankle Prosthesis (C3KAP)

This idea could bring more advancements in the previously explained robotic prosthesis models [4]. The basic objective is to satisfy the actual healthy knee and ankle's form, size, and weight requirement but also delivers sufficiently high torque and power output. There was a two-stage belt transmission system chosen in the design. A timing belt drive transmission system was the first phase, and a harmonic drive transmission system was the second level [23]. In the first stage, a 70 W permanent-magnet brushless motor was preferred to give a maximum torque of 0.20 Nm with a peak speed of 10,000 rpm. A lightweight, compact, and commercial harmonic drive gear set was selected in the second level. A cross roller bearing was chosen to support the loads and bendings. The motor was connected to the belt drive input pulley, and the pulley output was coupled to the harmonic drive input and supported by an intermediate shaft output pulley support. All transmission segments were fixed on a support plate, providing mounting space for the motor and input pulley assembly. An output adapter assembly is connected to the output pulley. Via cross roller bearings, one end of the adapter is connected to the flex spline, and the other end is attached to the output pulley [24]. In the C3KAP model, a special attribute was included, which is a unidirectional leaf spring that can produce additional ankle push-off torque when walking.

7.3.5 Energy Regeneration Using Robotic Prosthesis

In this model [5], the energy is generated during human dynamics to extract electrical energy and regenerate this to a form that can be regulated freely. In this, generating the electrical energy without using any mechanical structure makes it more advantageous. Using electrical energy regeneration, the robotic prosthesis will increase the length of its use, decrease weight, and increase the walking performance that can be positively embraced by amputees [25].

7.3.5.1 Design Methodology

We use six MOSFETs in this, an ultra-capacitor, and two conversion units of boost DC-DC. The circuit works the motor (50 W BLDC motor) in an operating mode during the swing phase, the motor spins, and an EMF will be caused by electromagnetic induction principle, and the motor acts as a generator. The working mode function is to allow the ankle junction to come back to its starting position and stop it from reaching the ground. During the stance process, via six MOSFET converters that act like an inverter, the ultra-capacitor harvests induced energy because of human dynamics. The inverted current is then given to an ultra-capacitor which was later transferred to the two hierarchical regeneration circuits. Depending upon the duty cycle of the inverter, the output power will be given to high (motor) and low power supply (control and sensor) [26, 27]. Two types of sensors were used, one sensory carbon footplate for detecting pace events and sensor with one angle (Angtron-RE-25) for measuring the inclination of the turning ankle. The motor is then driven for the movement of the prosthesis. The overall power would be equal to the battery power with an uninterrupted low-side regeneration power with a single high-side regeneration power for a robotic prosthesis.

7.3.5.2 Control Procedure

Two operating modes are employed in the prosthesis: active mode and regeneration mode. The robotic prosthesis supports the amputee's ankle joint in the active mode that occurs in the swing process to come back to the commencing position to avoid foot-dragging. The motor consumes electrical energy in this process and transforms it into mechanical energy. Thus, establish a PD position control strategy to achieve active control. The ultra-capacitor gathers electrical energy from electromagnetic induction through human dynamics in the regeneration mode that occurs in the stance stage. The robotic prosthesis is then supplied with the extracted electricity. A low-voltage power supply is required for both the control and the sensor module.

The design methodology of different robotic prostheses was analyzed in this chapter. The prostheses were arranged according to their performance, and we can summarize that the succeeding one is an advanced form of the preceding one. The finally analyzed prosthesis is the most advanced design which does not use any mechanical structure and thus improves the walking performance of the amputee [28].

7.4 Experimental Study on Robotic Prosthesis

7.4.1 Experiment on Robotic Knee-Ankle Prosthesis

A preliminary experiment on a transfemoral amputee has been performed [3]. The participant chosen for the experiment is as mentioned: 30 (age); male with a height and weight of 170 cm and 63 kg, respectively; and the state of disfigurement being residual unevenness of about 15 cm (right leg). B and c are set to be 400 and 0, respectively, for the experiment, where b is push off and c is swing step slopes, and b and c are optimized to be 350 and 75, respectively. The junction angle is determined by the exact encoder sensing device of each joint, and motor current is measured by the device as well. In one gait period, the knee angle and motor current in the knee junction is measured. During the stance process, we can observe that the knee angle seems to be zero as the knee joint is held upright by changing the implant's orientation to conserve energy. In effect, after late loading of the subject's weight, the knee joint may be hyperextended, and this hyperextension may be detected by the absolute encoder sensor. With the patella exact encoder sensor and sensor of force, the force sensor will identify if the toe is off the floor after a delayed position, so jumping from one position to another is observed. In the swing step after toe-off, in bending and stretching, it represents that the highest bending inclinations is around 60°. Knee is regulated to be in the position phase in a neutral position, the motor current is decreased in a narrow range, but it is hyperextended with the subject load. In particular, as the time of the subject load in the late position becomes great, the motor current is also greater. For bending, the knee is fed, and the motor's maximum current is around 3 A. Although the knee is extended in the late swing process, as a result of the terminal effect, there has been less motor current.

In one gait loop, the angle of the ankle and the motor current in the ankle joint measured. To maximize the contact area between the foot and the floor after the heel, the plantar ankle is folded approximately 7°. As the motor is operated to maintain the balanced stance, the inclination of the motor seems to be 0°, and the tightness of the dorsal flexion spring with the topic weight leads to 7° of plantar flexion, which may help withstand the shock when reaching the heel. And after the first plantar flexion, the spring is exposed to initiate dorsal flexion before the ankle junction becomes stable. The ankle is dorsifixed by pushing the plantar bending spring by the weight of the subject up to 12° full dorsiflexion. After full dorsiflexion, the plantar flex spring liberates energy to return to the neutral place. In this phase, the motor's angle is always about 0°. The motor is utilized to drive the ankle, and the inclination of the ankle junction goes to full plantar bending, and the angle of the motor also goes to maximum when the ankle is plantarflexed the second time before the neutral position. With a location review following full plantar bending, the angle of the ankle returns to neutral. During phases one and two, current of the motor is very low, and throughout phase three, there will be a maximum current at full plantar lateral bending. To help the subject take off and step forward with ease, the energy of the motor and the energy of the spring should provide energy [29].

7.4.2 Experiment on Robotic Prosthesis That Maintain Flexion Posture

An analysis was made to check the efficiency of the robotic implant in order to prove whether the designed robotic deformity could give firmness while on foot and walking. Two points were confirmed in the experiment [2]. The first was to find out if, without the risk of dropping, the topic could take a pen on the ground, which is a complicated maneuver for a traditional knee junction. The other was if the state of operation can be adequately identified by the control system and allow a state change. In the context, a 20-year-old man was the subject. He mimicked an amputee's march across the knee. He walked several cycles prior to the experiment and maintained a slight bending stance and calculated its own angle and constructed a corresponding pattern. It successfully took the pen by shifting his center of gravity ahead when putting his weight onto the deformity due to the lock that is able to sustain bending. After going through the irregular walking stage for the first time, the respondent moved normally for two walkable periods and reached the pen. Subsequently, since a slight bending pose of just under 30 (degrees) was retained, the control scheme considered it to be in the repairing mode of bending pose and enabled the pushing solenoid to strap the knee junction. Owing to the displacement of the center of gravity, the knee angle became constant until the knee bent in the knee joint play. By stopping the knee joint from bending more than playing, the topic was capable of safely retrieving the pen. These results indicated that the flexion movement of the knee joint can be locked at an acceptable time and the standing posture can be done in a controlled manner. Thus, this showed the efficacy of the robotic prosthesis that has been created.

7.4.3 Experimental Study for Energy Regeneration Using Robotic Prosthesis

Five unilateral amputations [3] are below the knee with traumatic amputation (*N* is 5; age of 39.8 ± 12.4 years; mass). Participants in this study were of about 69.6 ± 7.1 kg and height of 170.2 0.4 cm (postamputation 12.8 ± 3.9 years; mean ± SD). Each amputation in this experiment has to wear robotic prosthesis for at least 20 progressive hours. Two conditions must be experienced by each participant: (1) walking at four set speeds on a treadmill (0.7, 0.9, 1.1, and 1.3 m/s) and (2) 100 m outside moving at a self-picked velocity. The participant was expected to walk a minimum of 3 min for each treadmill walk. The 100 m outside walk was to check the efficiency of the robotic implants in daily life to restore electricity. Our studies deal with both fixed speed and free-speed. The equation for calculating the working hours of prosthesis is defined as follows:

$$TB = \mathrm{QCap} / \mathrm{PTotal}$$

$$TB\,\&\,\mathrm{R} = \mathrm{QCap} / \mathrm{PBattery}$$

$$\mathrm{QCap} = 2.6\,\mathrm{Ah} \times 3600\,\mathrm{s} \times 24\,\mathrm{V\,J}$$

in which QCap is the overall capability of battery. When the battery alone provides the control, TB is the prosthetic work period. In which the battery and the electrical regeneration unit give power to the robotic implants, TB&R is the working time of the prosthesis. When walking, PTotal is the power total required by a robotic deformity. When a regeneration unit gives energy, PBattery is the output power of the battery (PBattery is equal to the total power of PTotal minus the regeneration power of PReg). The number of walking steps is set to the following:

$$NB = \mathrm{QCap} / \mathrm{Total}$$

$$NB\,\&\,\mathrm{R} = \mathrm{QCap} / QB$$

where NB is the number of steps on foot when the energy is given by the battery alone. NB&R is the number of moving steps in which the energy is given by both the battery and the electrical regeneration unit. QTotal is the total energy consumed by a robotic prosthesis in one gait cycle while walking. QB is the battery output energy when the electrical generation unit is used throughout one gait cycle.

7.4.4 Experimental Result on Energy Regeneration Using Robotic Prosthesis

Regeneration power is the energy per unit time (W is the unit) and can be recycled and returned to the robotic implants, i.e., the supply of power and motor motion of the circuit [5]. The statistical significance indicates that the greatest regeneration power can be gained with the increase in the speed of the treadmill. More specifically, while the speeds of the treadmill ranged from 0.7, to 0.9, to 1.1, to 1.3 m/s, the power of regeneration enhanced to 0.89 ± 0.17, 1.08 ± 0.14, 1.24 ± 0.11, and 1.46 ± 0.23 W. In the meantime, the total power required increases as the speed is increased. However, more importantly, the proportion of regenerative energy to total energy needs rises by 27–35% as speed increases. Furthermore, we found that for a runway of 100 m at 1.1 ± 0.1 m/s, the regeneration power (1.69 W) is greater than the power (1.24 W) with the speed of 1.1 m/s. It should be stated, though, that the total power needed for the external stage of 1.1 m/s (4.18 W) is greater than for the 1.1 m/s inner treadmill (3.86 W). The mean electrical reproductive capacity (inward treadmill and outward track) is 1.27 ± 0.31 in total. The robot implant has an average power consumption of 3.85 ± 0.38 W. The proportion of regenerative energy to absolute energy available varied in the range 27 ± 5% to 40 ± 4%, with a mean of 33 ± 5%. (1/3rd) [31, 33].

The approximate work time is determined according to the battery capability (2.6 Ah, 24 V). If the energy is supplied by the lithium battery alone, the operating period is approximately 18.8, 17.3, 16.3, 14.9, and 15.1 h, respectively, at 0.7, 0.9, 1.1, and 1.3 m/s and the self-picked speed. If few energies from human textures are obtained relative to the energy from the battery alone, the timing of the prosthesis is improved by 37% (25.8 h), 44% (24.9 h), 49% (24.3 h), 56% (23.2 h), and 67% (25.2 h), respectively, with electrical recovery energy at 0.7, 0.9, 1.1, and 1.3 m/s and self-picked velocity. Generally, an additional walking period of 8.2 hours can be offered on average with electrical regeneration energy.

Compared to standing mode, because of the regrowing energy, the battery power needed at a self-selected walking pace has been lowered. The ultra-capacitor ensures adequate energy for the control and circuits for sensors via the DC-DC upgrade (referred to as low power supply). The toggle for the high-power source was switched ON when the ultra-capacitor voltage exceeded 3.5 V. Then, through use of a more efficient DC-DC converter, the ultra-capacitor starts to supply the robotic system with more power. On the other side, the key is disabled when the ultra-capacitor becomes less than 2.5 V. It was still off before the energy had been stored. This is called switching hysteresis. Each running cycle involves a tiny peak, suggesting that during the stationary period, mechanical energy can be stored as electricity. The energy of low-side regeneration of the robotic implants was balanced during the steady walking process (approximately 0.5 W). The energy of high-side regeneration was discrete and regulated by swapping to hysteresis. The regenerating power (low and elevated side) is 1.23 W in this illustration, and the power source is 2.13 W. The cumulative power equals the regenerating power plus the capacity of the battery (3.36 W). The regeneration energy proportion (1.23 W) to the overall energy demand (3.36 W) is around 36.7%. We may therefore infer that energy regeneration using a robotic implant from human dynamics is much more effective than that of piezoelectric effect and insoles for harvesting energy.

7.4.5 Experimental Study on Characterization of Robotic Leg Prosthesis Open Source

The electromechanical efficiency of the OSL has been best described within the time domain and frequency domain [1]. The time- and feature-based tests were concluded by both location and current control procedure. During an assessment of the existing. In a test system, the actuator was positioned, while the control of the position was being tested, and each joint was rotatable. The knee and the ankle were examined one at a time, and sequential buoyancy was not involved in these commencing studies. All the data was recorded by the better level control system, at ~750 Hz.

7.4.5.1 Step Response

The step response test is performed to measure the capacity of the OSL to monitor a reference update. In joint coordinates, motor enciphered phase responses were registered at 5°, 10°, and 15°. Move results from the halfway point of each set of motion of the joints were coordinated. Similarly, at 2 A, 4 A, and 6 A (phase-phase), isonomies to 1.2 A, 2.3 A, and 3.5 A, motor current stage responses were recorded with the common brushed DC electromechanical framework. Present responses were organized close by the end of each operation set of joints, when the junction was fixed mechanically. Based on the kinematic propagation ratio of the ankles, this existing guidance leads to round about 6 Nm, 12 Nm, and 18 Nm for the knee and 9 Nm, 18 Nm, and 27 Nm for the ankle.

7.4.5.2 Frequency Response

Frequency response trial has been carried to measure the set of frequencies at which the OSL can monitor a referred instruction. A Gaussian white noise signal, to approximate the frequency response, was the relative instruction. This pulse was sized to calculate the frequency response for the maximum junction spot at the amplitudes of 5°, 10°, and 15° and the peak current of motor at the positions of 1.2 A, 2.3 A, and 3.5 A, respectively, for the position and current controls. For the location and current tests, data for 15 and 60 s were obtained, respectively. To evaluate

Bode maps, where auto-spectrum and cross-spectrum are divided into frequency domes, Blackman-Tukey spectral analysis was used.

7.4.6 Experimental Result on Characterization of Robotic Leg Prosthesis Open Source

7.4.6.1 Step Response

Reliable, replicable phase results throughout a variety of stage sizes are shown in the time domain motor position and motor current characterization [1]. In comparison, joint location phase responses around the motion continuum of the knee and ankle are reliable.

7.4.6.2 Frequency Response

The frequency response Bode plots illustrate that the controller output varies according to the amplitude. In particular, the position of joint and bandwidth of motor current were 10–20 Hz and over 200 Hz, respectively; the OSL is thus willing, with high fidelity, to track instructed inclination and currents below these frequencies.

7.5 Conclusions

From the entire study, we understand that the robotic prosthesis control is a method of controlling prosthesis in such a manner that a person can restore his/her healthy life like a normal one by using a robotic prosthesis more efficiently than other currently existing prosthesis. In the whole seminar, we analyzed the different robotic technology for providing stability and improved performance for a prosthesis. We have also analyzed and studied prosthesis with and without using mechanical structures, electronic control methods, and so on.

An open-source robotic leg, a prosthesis capable of maintaining flexion and extension, a unified knee-ankle robotic prosthesis, a newly developed and advanced limb prosthesis, and finally a robotic prosthesis capable of energy regeneration were studied in this chapter. The main objective of robotic technology is to design and build smart machines that can guide and help human beings in their everyday activities. The accomplishments of computer engineering, mechanical engineering, electronic engineering, and others are focused on robotic technology. Robotic technology generates human robots that can mimic human behaviors such as walking, sitting, and speech.

A special unit of management that focuses on the interaction between robotics and humans is robotic prosthesis control. Many researches have been done in the field of robotic technology. At the end, we are capable of concluding that with the development of technology and human idea, robotics has become one of the most advanced and eminent technologies that can enhance many existing challenges we are facing now. And one of those examples have been analyzed here in this chapter.

As the technology is developing, new inventions have also been progressing. Robotics, being one of the rapidly emerging technology recently, can bring huge development in the field of prosthesis too. In our study, we have analyzed robotic technology for improving walking performance in different parameters. In future inventions, it would be better to bring up something which can integrate all such parameters and thus provide a better outcome than ever before.

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Chapter 8
Let the Blind See: An AIIoT-Based Device for Real-Time Object Recognition with the Voice Conversion

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8.1 Introduction

India is unfortunate to have the largest number of blind people in the world. Poverty is a disability that a person can overcome with proper training, guidance, and support. It is estimated that out of 285 million visually impaired people worldwide [1] 39 million are blind, and 246 million have poor blindness (moderate disability). Around 90% of the world's blind people live in growing countries (like India). Of the 39 million blind people worldwide, more than 15 million are Indians. Globally, faulty errors are a major cause of visual impairment. Most of the people in developing countries cannot afford expensive solutions. Sixty-five percent of the visually challenged and 81.9% of the blind are above 50, even though this age group is around 20% of the people worldwide.

8.1.1 Vision Impairment

Visual acuity (VA) usually refers to the sharp sight of vision. The strength of visual acuity depends on the physical and internal factors, namely, (i) the intensity of the retinal focus within the eye, (ii) the fitness and function of the retina, and (iii) the tact of the brain's interpretive intelligence. Visual impairment is divided into two groups, the distance and the closest to introducing visual impairment.

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Visual Impairment

- Mildness –introduces visual clarity poor than 6/12.
- Medium – introduces visual acuity poor than 6/18.
- Powerful – introduces visual clarity poor than 6/60.
- Blindness – introduces visual acuity poor than 3/60.

Nearby Sight
Presenting near-visible weight is much poorer than the N6 or N8 at 40 cm by the ongoing adjustment.

Blind people face many challenges in their daily lives, most important of them is identifying the surrounding objects in nature while moving. Majority of the time, they accept travel restrictions because often they get lost when they are moving alone. Visual impairment or snow blindness cannot be completely cured. But with the support of modern science, their suffering can be decreased.

Computer and IoT surveillance [15] technology, especially distinct artificial neural networks, have grown swiftly in recent years. It is promising to use cutting-edge computer viewing techniques to help people who have lost sight. In this study, we proposed a device that can see objects around us.

There are many tools available to use computer vision systems to help blind people. The proposed function includes a Pi camera connected to a Raspberry Pi device. Raspberry Pi device and sensor are then attached to a lightweight non-heavy rod that one can carry while walking. Ultrasonic sensors are used for pre-scanning. The area around the blind is determined by blind signals.

The camera takes pictures of the surroundings, and the object recognition algorithm detects nearby objects in the image, and the sensor works by calculating its distance to feel an object closer, and when certain risk objects move near the person, then the sensor gives the signal and through the audio jack gives audio/vocal information about the object to the person through which we can make them aware of that object. Audio guidance will help the person navigate alone with safety and avoid any obstacle encountered, whether fixed or mobile obstruction. This sensor-based obstacle detection device will improve the mobility of both blind and blind people in a specific area by detecting obstacles, and it even recognizes pits and manholes on the ground to make them free to walk. We are detecting objects using this entire setup and giving voice instructions about those objects. It tells people about obstacles and also provides information about the appropriate barrier-free route.

8.2 Related Works

The literature survey will critique the discovery of object detection in many prospects, which includes historical instruments. The discovery has gone through two historical periods: “traditional discovery time” and “discovery time based on in-depth learning in the deep learning period.”

The history of real-time detection of anthropomorphic faces without obstacles (e.g., skin color separation) originates from P. Viola and Mr. Jones who followed a more forward-looking approach, i.e., moving windows: bypassing all the areas and criterion available in the picture to realize if there is a window containing a human face.

N. Dalal et al. [3] stated HOG (Histogram of Oriented Gradients) algorithm [2] can be regarded as an essential developmental variable factor and the standing conditions of its duration, evaluating the variability of a feature (including translation, scale, brightness) and nonlinearity (in classifying various categories of objects).

D. T. Nguyen et al. [4] analyze the parameters used in the SSD detection and state that there is a need for adjustment to that. Introducing the fusion SSD model for the limited-access factor, this algorithm improved the acquisition of small objects in a traditional SSD.

Love Lin et al. [5] found the reasons behind it and proposed RetinaNet in 2017. They said the excessive inequality of the front-back section experienced during the preparation of thick locators is a significant reason. Until this point in time, another deficit work called "fixed shortfall" has been presented on RetinaNet by adjusting the ordinary cross-entropy deficit with the goal that the identifier can zero in additional on erroneous models during training.

R. Girshick [6] introduced the Fast RCNN detector, an approach based on the continuous development of RCNN and SPPNet [16, 17]. The fast RCNN empowers us to concurrently train the detector and the controller of the connecting box with similar network parameters applied to both. In the VOC 07 database, Fast RCNN improved the mAP (mean average precision) from 58.5% (RCNN) to 70.0% with 200 times recovery speed than that achieved through RCNN.

H. Zhao et al. [7] stated that face detection is a crucial task, and its proper detection is a must. The Fast RCNN algorithms work well as they use two stages of detection. The disadvantages of YOLO model were eliminated by the use of the provided technique, which is YOLOv3 face based on YOLO v3 model. The result was more accurate for face detection in the presented method.

W. Liu et al. [8] proposed SSD with the main contribution toward the proposition of the multi-reference and multi-goal identification methods which significantly improves the exactness of location of a uni-stage indicator, solely for some minor items.

Limit W. [9] has improved the acquisition of an object-oriented approach that combines visualization above and the separation of the image below and above. The two foremost steps in this process are the production of the hypothesis step and the verification step. If we talk of the top-down hypothesis generation step, it is designed with an advanced Shape Context feature, which shows robust behavior toward counter flexibility and contextual tension.

Redmon J. [10] introduced YOLO, a new acquisition method. Pre-discovery function restores classifiers to perform detection. Instead, the detection of an enclosed object is a big problem of retreating into geographically separated boxes and corresponding phase opportunities. One neural network predicts binding boxes and class opportunities unswervingly from full-scale images in a single test. As the entire acquisition pipe is a solitary network, it can be possibly configured to end after the acquisition operation.

Ren S. [11] introduced the region proposal network (RPN) which transfers complete picture signals to the acquisition network and consequently enables less expensive regional proposals. RPN is a complete network of solutions that concurrently predicts parameters of object and opposition total in each area. RPN is instructed endwise to produce excellent regional proposals, which Fast RCNN uses to find.

Srinivasan L. [12] proposed a hybrid system that uses the multilayer convolutional neural network (CNN) to produce graphical lexicons and long short-term memory (LSTM) to organize sound sentences using generated keywords. The convolutional neural network compares the image to a large database of training images and creates an accurate description using trained captions.

Mettah et al.'s [13] proposed model is the last to the end and uses both letter and voice presentations. Character presentations are read during model training through the convolutional neural network (CNN). For word-level representation, it includes several trained embeddings (Word2Vec, FastText, and GloVe). To address the issue of poor access to unspecified communication data, the transfer learning (TL) approach has been implemented.

Shahira et al. [14] developed a help program that detects a blockage, classifies it, and alerts the handler with a voice-over. Sensitivity and measurement of the barrier's distance from the surface using an ultrasonic sensor, were detected. Obstruction of the barrier was performed using the YOLOv2 algorithm in a picture obtained through a laptop webcam.

8.3 Proposed Model Component

Usually, a blind person uses a white cane to get a guide through difficult situations. Most of the surrounding area can be covered by this cane. But things far from reed are not easily accessible by the person. Proposed items provide information about user constraints as well as proper or constraint-free paths. This proposed system consists of hardware as well as software combination which can sense short as well as far distance and update person about it. The use of object detection techniques can open up new possibilities in assisting indoor navigation for blind and blind people.

8.3.1 Hardware Components

The system includes the following hardware components: Raspberry Pi Model 3B+, Pi camera, microSD card, sound sensor, and lightweight rod.

8.3.1.1 Raspberry Pi (Model 3B+)

Researchers used the Raspberry Pi as a small computer unit, which means that the microprocessor, memory, and input-output unit are all on one circuit board. Pi is a Linux computer, such that it can perform everything as a Linux computer can do like programs, libraries, and providers.

TensorFlow 1.4 officially supports Raspberry Pi when we are running Raspbian, since then we need to install Raspbian (Pi's OS). The quad-core Raspberry Pi Model 3B+ is both faster and more capable than its predecessor.

Its features are system on chip (SoC): Broadcom (BCM2837); CPU: quad-core ARM Cortex-A53, 1.2 GHz; GPU: Core IV Broadcom Video; RAM: 1 GB (frequency: 900 MHz); networking: 10/100 Ethernet, 2.4 GHz 802.11n wireless; Bluetooth: Bluetooth 4.1 Classic, Bluetooth Low Energy (BLE); storage: MicroSD card; GPIO: 40-pin header, populated; and port: HDMI, 3.5 mm analog audio-video jack, four USB 2.0, Ethernet, camera serial interface (CSI), and display serial interface (DSI).

Figure 8.1 shows the Raspberry Pi Model 3B+ used in the proposed system and its basic features and input-output unit supported by the development board.

8.3.1.2 Camera

We have used a 5 MP Raspberry Pi camera for capturing frames.

Figure 8.2 shows the Raspberry Pi camera used in the proposed system and its connection with the mainboard.

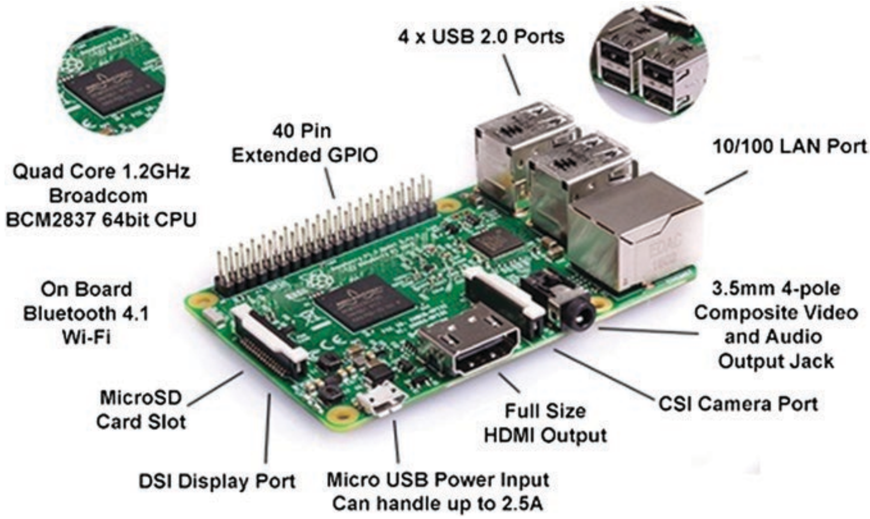

Fig. 8.1 Raspberry Pi Model 3B+ [17]

Fig. 8.2 Raspberry Pi with camera module [17]

Fig. 8.3 Ultrasonic range sensor (Hc-Sr04) [18]

8.3.1.3 MicroSD

We also need a microSD card, with 16 GB of storage memory which is required for building a workable OpenCV procedure. We have put all our required libraries, object recognition files, and other necessary dependencies since the board does not have any built-in storage.

8.3.1.4 Ultrasonic Range Sensor (HC-SR04)

Figure 8.3 shows the ultrasonic sensor model Hc-Sro4 used in the proposed system for detecting an object. This sensor can detect objects by emitting ultrasonic sound. The range up to which they can detect the object is 5–6 m. The ultrasonic sensor can be connected to Raspberry Pi with the help of the breadboard.

The sensor can detect distance with an object and send it to Raspberry Pi in the GPIO pin (5V).The ultrasonic sensor has four pins:

8.3.1.5 Ground Pin (GND – Pin 6)

- Echo pulse output pin (ECHO – Pin 23).
- Trigger pulse input pin (TRIG – Pin 12).
- 5 V supply pin (VCC – Pin 2).

The proposed system empowers the module utilizing VCC (5V) and granulates it utilizing GND and our Raspberry Pi that impart the info sign to TRIG, which makes the sensor communicate ultrasonic heartbeat/sound. Blowing waves detonate on any close item, and some are visible sensors. The sensor identifies these return waves and measures the time between the ammo and the recuperated beat, which at that point imparts a 5V sign to the ECHO pin.

The 5V output coming from the ECHO pin is then converted into a 3V signal using a voltage divider. Then, the 3V signal is then sent into the GPIO pin of Raspberry Pi.

8.3.1.6 Jumper Wires

Figure 8.4 shows the jumper wire used in the proposed system for connection between different components. Jumper strings are used on breadboards to "jump" from one connection to another. It has different connectors at each end. The end of "pin" will go into breadboard.

8.3.1.7 The Breadboard

Breadboard provides a way to connect the ultrasonic range sensor and Raspberry Pi without mixing them. Holes in the breadboard are connected by a pattern. The jump wires are connected to the breadboard.

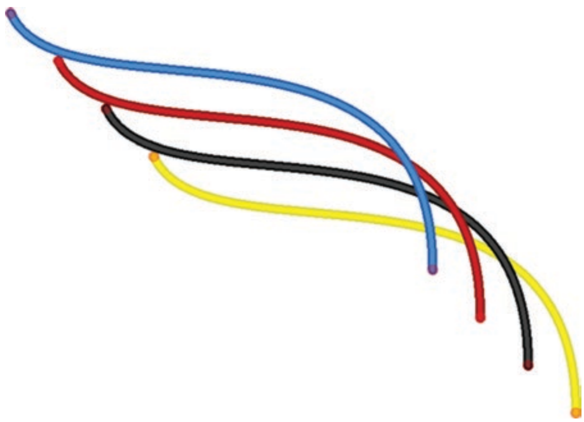

Fig. 8.4 Jumper wires for device connection

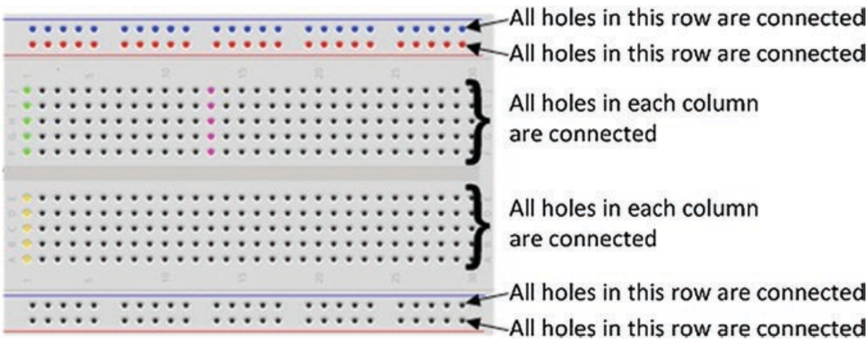

Fig. 8.5 Breadboard [19]

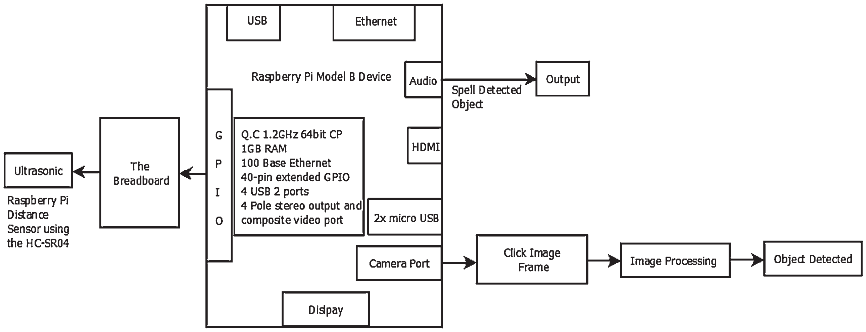

Fig. 8.6 Architectural of proposed real-time object detection

Figure 8.5 shows the breadboard used in the proposed system for adding different components required in the system.

8.4 Proposed System Architecture

The proposed system of this paper consists of a Raspberry Pi camera, a voice recognition device, an image processing unit, the Raspberry Pi Model 3B+, and an ultrasonic sensor.

The first proposed system detects the object as it comes in front of the system with the help of an ultrasonic sensor; after that, Raspberry Pi camera captures the image of the object and processes it using SSD technique to detect and recognize the object and after that convert its voice from the text.

Figure 8.6 shows the architectural design of the system and included different component and their connectivity to perform a dedicated operation.

8.5 Methodology

8.5.1 Object Detection Algorithm

Various algorithms are available such as RCNN, Fast RCNN, SSD, and YOLO, to observe objects from nearby. RCNN uses a field motion method to generate possible bounding boxes in an image. It applies different converts to classify each box and then output the result with a bounding box and label it with the classified object. But the RCNN model is difficult to train.

Fast RCNN uses maximum pooling to find regions and then combines the computation of ConvNet to locate features from each region and produces facilities from all regions at once.

Fast RCNN is based on RCNN with some improvements. After the last layer of the caster, RCNN includes a region-based network. Both RCNN and Fast RCNN methods increase computational time with precision. But pipelines of these methods are still relatively complex and difficult to adapt. All these methods were inappropriate for locating objects in real time.

Therefore, considering the need to find the real-time objective in our project, we use the SSD algorithm. SSDs can efficiently detect relatively good objectives with high speed.

SSD The SSD algorithm is designed for real-time object detection. SSD runs a convolutional neural network (CNN) image. CNN scans the image only once and calculates the related feature map. The 3×3-sized CNN kernel is working on the feature map to force bounding boxes and also calculate the possibility of a hierarchical object.

Figure 8.7 describes the architecture of SSD with different boundary box; these border boxes are hand-selected. SSD characterizes the scale as an incentive in each layer of the element map. Beginning in the left, Conv4_3 gets things with at least 0.2 (or 0.1 here and there) and afterward rises individually in the correct layer on a size of 0.9. Consolidating the size of the scale with the components of the objective components, we figure out the width and height of the default boxes. For layers that make six forecasts, the SSD begins with five objective sizes: 1, 2, 3, 1/2, and 1/3.

Figure 8.8 shows the architecture block of a convolutional neural network (CNN). The SSD takes a single shot at the image to detect multiple objects. In the case of high amplitude, the SSD faster works better than the RCNN. SSD has two components:

1. **Spinal model:** The backbone model is a pre-trained image classification network with a profound neural organization that can pull out from the picture. It does not usefully join layers. Two hundred fifty-six 7×7 feature maps have been created from the backbone model.

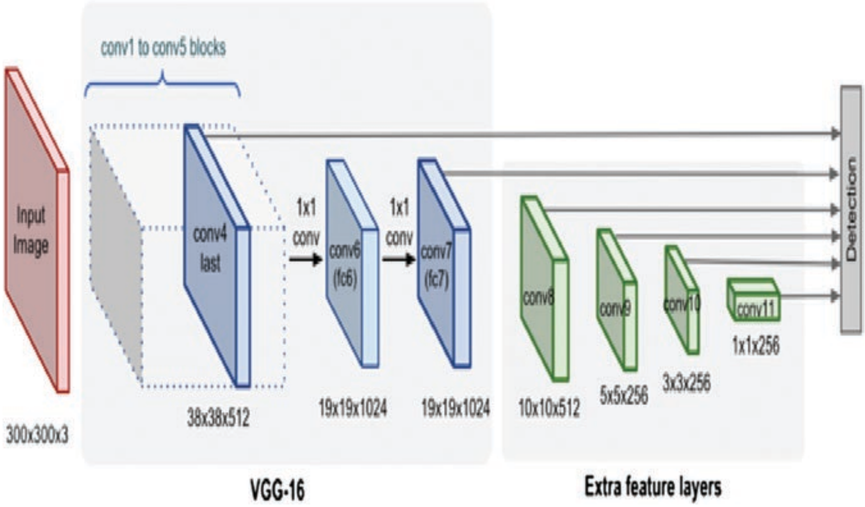

Fig. 8.7 Architecture of SSD [21]

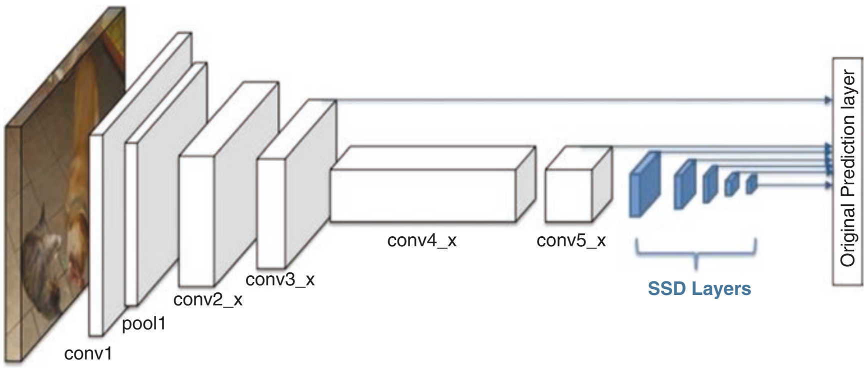

Fig. 8.8 Architecture of a convolutional neural network with an SSD detector [20]

2. **SSD head:** The head of an SSD is at least one concentric layer that is added to this spine. The head is responsible for the bounding of boxes at the spatial location of the object and identifies its orbit in the last layer activation.

Grid Cell

The location and size of that object are output in each network cell. Rather than utilizing a sliding window, the input picture (feature map) is divided into several grids, where the network cell is answerable for finding objects here of the cell picture.

This implies foreseeing the square and area of an article inside that territory. This is done in the major part of SSD. Ignore space if there is no object in the cell.

Figure 8.9 shows how an object can follow a grid cell. If a single grid cell contains multiple objects or contains various items for identifying numerous objects of various shapes, an anchor box and responsive field are used.

Anchor Box: Initially, every network cell is appointed with various covered anchor/earlier boxes/default boxes. Such anchor boxes are pre-characterized. SSD contains 8732 default boxes.Everyone is liable for the size and shape of a network cell. While training, SSD matches the fitting presenter box with the proper framing boundary boxes of each ground truth object inside a picture. The presenter box with the most extensive level of cover with an object is then anticipated with the item's class and position. This property is utilized for preparing the organization for foreseeing the distinguished objects and their areas.

Figure 8.10 shows two boxes that covered the object in horizontal and vertical length.

Aspect Ratio: All things are not square. Some are longer, and some are excessively broad. Aspect ratio parameter is used to demonstrate the assorted point of view extents of the presenter box accomplices with each grid cell at each zoom/scale level.

Figure 8.11 shows a bounding box that covered the complete bottle with proper object detection accuracy

Zoom Level The zoom boundary is utilized to indicate how much vertically up or down the anchor boxes should be about every grid cell.

Receptive Field This is the territory of the input space. Various layers of CNN have various sizes of shapes. As the CNN layers develop, the size is recognized by

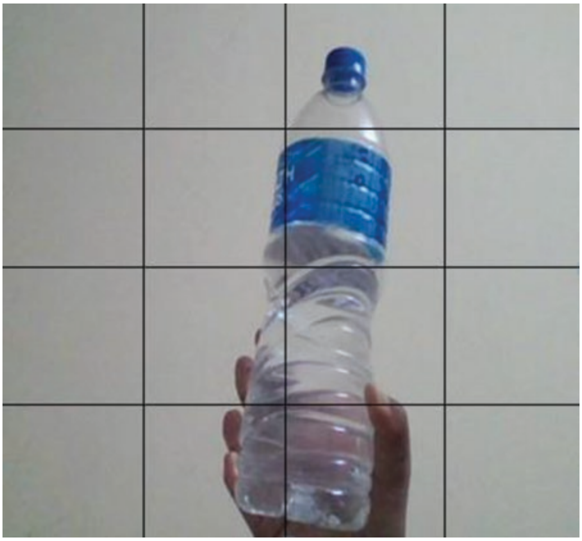

Fig. 8.9 Example of a 4×4 grid

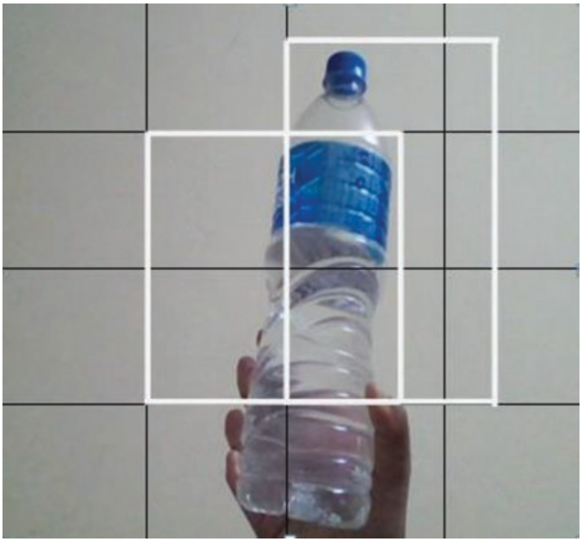

Fig. 8.10 Example of two anchor (presenter) boxes

Fig. 8.11 The bounding box of the bottle (category_44 is the alias of the bottle)

the expansion of the component. In the example underneath, the base layer is 5×5, and afterward, in the wake of applying a convolution, it changes into the center layer (3×3), where a feature (green pixel) can be recognized to the 3×3 region of the input layer (base layer). And afterward, again, applying the convolution to the center layer brings about the top layer (2×2), where each property relates to a 7×7 zone on the info picture. These feature maps (orange, green) apply a similar feature extractor to various areas of the information map in a sliding window way.

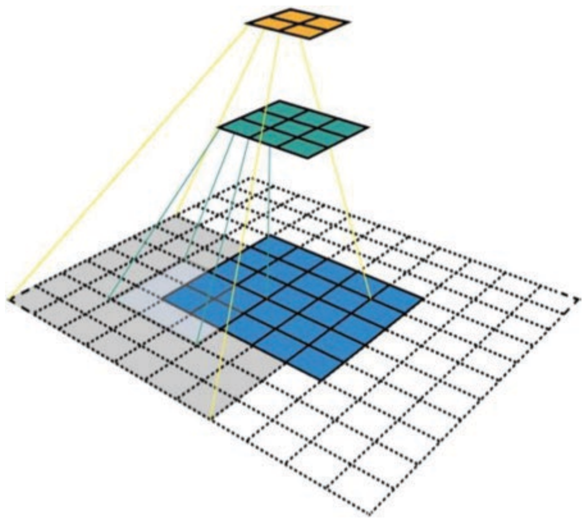

Fig. 8.12 Visualizing CNN feature maps and receptive field [21]

Figure 8.12 shows the complete visualization of the CNN feature map and receptive field with its different levels of layers from the top layer and a center layer.

8.5.2 Proposed System Flowchart

Figure 8.13 shows the proposed system flowchart for describing each step and its result for further processing.

The following steps explain the above-drawn flowchart:

1. The first ultrasonic sensor detects an object such that if it detects an object in a range less than 5 cm, then the vibration motor starts vibrating and the camera connected with the system gets enabled.
2. Now Pi camera captures the image and sends it to Raspberry Pi for recognition using the SSD algorithm.
3. After recognizing an object, its text value is passed to the text to speech module which converts it to voice for the speaker.
4. The user can get directions for a particular location by sending a voice signal to the mic attached with the device. Then, voice to text system converts it to text. Now, using the GPS location system, we get a minimum path, and the speaker gives step-by-step instruction for a particular location path.

Figure 8.14 shows the flowchart for single-shot multiple-object detection (SSD) for object detection from an image frame.

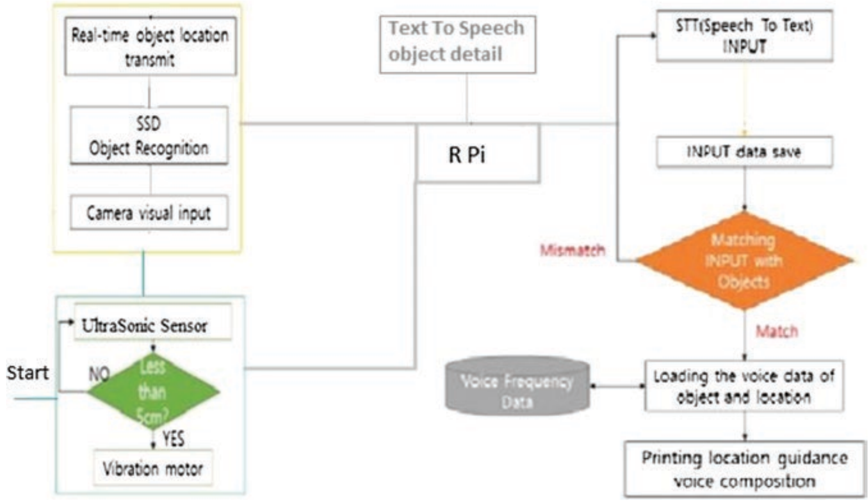

Fig. 8.13 Proposed system flowchart

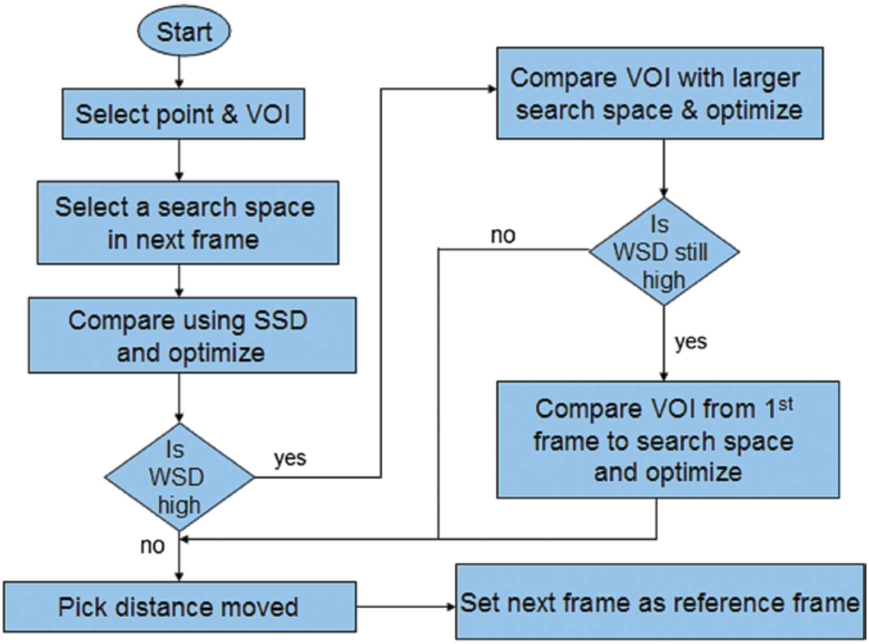

Fig. 8.14 Flowchart of SSD algorithm

8.5.3 *Pseudocode with Description*

8.5.3.1 SSD Algorithm Steps

Choose the height of the box b.

Input Data
P(x)←Input Picture
Col←Convolutional Layer
W(b)←Size of Box
M(f)←Feature Map
dim←dimension of boxes 4×4, 8×8, 16×16
P(i)←Change in Intensity of pixel

Output Data
B←2^{nd}no. of boxes in W(b)

Method

```
Introduce the size 1 till dim
  loop1 will be continued till W(b) recognize M(f)
  {
    a. M(f) ← { Min Col +Max P(i)}
  }
  loop2 continue till each P(i)
  {
    if P(i)==1
    {
    compute
    i. Breadth (b)= Col × P(i)
    ii. Peak  point (p)= Col ÷ P(i)
    }
    otherwise
    {
    alter the size of box with another conceivable measurement
    }
  }
```

8.5.3.2 Strategy in Recognizing Box Capacity

Calculation 2: Set of matchbox M(B).

Sources of Info
α←Boundary value
t←No. of actual box

b←Number of unused boxes
$B_\epsilon 2^b$←Set of boxes
$T_\epsilon 2^{t\times 4}$←actual boxes set
c[l]←Types of labels set
N←Total no. of types of labels set
O←Final item

Technique

```
   Introduce all items with default esteems loop1 continue till
each B[i]
    {
      loop2 continued till actual box having c[l]
      {
       Similar box (B[i],class[l])=1- M(f)←{ Min Col +Max P(i)} on
condition that(B[i],c[l])≥α
        {
       c[l]=1
          i. Recognize the item (O)
          ii. Label the item (c[l])
       }
       Otherwise
       {
        c[l]=0
        Continue to step no. 2 until the class label recognized
       }
      }
    }
```

Output
Q←Total no. of class labels
I(p)←Indexed positive boxes

8.6 Implementation

8.6.1 System Configuration

The accompanying setup is utilized for the usage of the calculations built-in: Python programming language, IP-based HD camera, 15.6 in HD contact screen (1366 × 768), Intel Core i7-1065G7 1.3 GHz up to 3.9 GHz, 8GB DDR4 SDRAM 2666 MHz, 512GB SSD, HD audio with sound system speakers, Realtek

RTL8821CE 802.11b/g/n/ac, Bluetooth 4.2, one HDMI 1.4, one USB 3.1, and two USB 3.1. Python programming was running on a Windows 10 OS.

8.6.2 Dataset Description

We have used the dataset from the IoT-based system, the image dataset, and the video dataset. Image dataset consists of around 2000 images which are used for object detection like humans and many other objects. Image datasets are collected from the SGSITS (Shri Govindram Seksaria Institute of Technology and Science) college event, some family events. In our experiment, we have used a training and testing ratio of 80:20%.

8.6.3 Performance Analysis

8.6.3.1 Real-Time Object Recognition

The performance of the proposed object recognition system based on SSD technology was configured to operate on the Raspbian OS with a Raspberry Pi microcontroller. However, the deep learning technology required a lot of computational processing, which proved too much for Raspberry Pi's processing power. While the SSD model organized the TensorFlow object detection API code in the Python development language, the SSD model consumed 18.106504 seconds. Also, when real-time object recognition was performed, the SSD model performed at 17 FPS.

The proposed object recognition system as shown in Figures 8.15, 8.16, 8.17, and 8.18 found the object and provided the location information invoice format.

Fig. 8.15 This shows object detections in a vehicle mobile environment

Fig. 8.16 This shows object detections in a vehicle and human mobile environment

Fig. 8.17 This shows object detections in a human mobile environment

After that, the test subject found objects with only voice-guided location information. The above experiment was conducted 50 times by changing the position of the object, and the test subject pinpointed objects 46 times. Thus, we pegged the accuracy of the proposed object recognition system at 94.16%.

Fig. 8.18 This shows object detection in a steady environment

Table 8.1 Results for hardware performance in our model

Evaluation list	Performance
Image analysis rate (on i7 CPU specs)	SSD: 18.106504 seconds
The real-time object recognition rate	17 frames per second
STT rate	2-second latency
Object detection system	The average accuracy of 94.16%

8.7 Result

The developed system has been using Raspberry Pi for detecting objects and GPS for particular location search. Object detection in the range of 5 cm is done by the ultrasonic sensor which causes us to distinguish the article close by, and it gives caution to alarm them about the nearing object. System performance is observed at the hardware level as well as a concerned individual algorithm level.

Table 8.1 gives the numerical values for hardware performance obtained for the image and video dataset that issued for the AIIoT-based real-time object detection.

8.7.1 Algorithm Performance

Develop system using single-shot multiple-object detection (SSD) for object detection and algorithm performance in terms of accuracy is 94.6% on 2000 images dataset. The algorithm is implemented on Raspberry Pi development. The following is the result of the algorithm for the training dataset.

Table 8.2 gives the numerical values obtained for the image and video datasets that are trained for the SSD model of the IoT-based system. The obtained values are satisfying. The results show that the model is well trained for any incoming inputs.

Table 8.2 Results for training dataset in SSD

Data	Precision	Recall	F1
Image 1	0.97	0.92	0.95
Image 2	0.98	0.90	0.94
Image 3	0.98	0.89	0.93
Image 4	0.97	0.88	0.92
Image 5	0.98	0.84	0.94
Image 6	0.99	0.89	0.96

Table 8.3 Results for testing dataset in SSD

Data	Precision	Recall	F1
Image 1	0.97	0.89	0.93
Image 2	0.99	0.90	0.95
Image 3	0.98	0.84	0.94

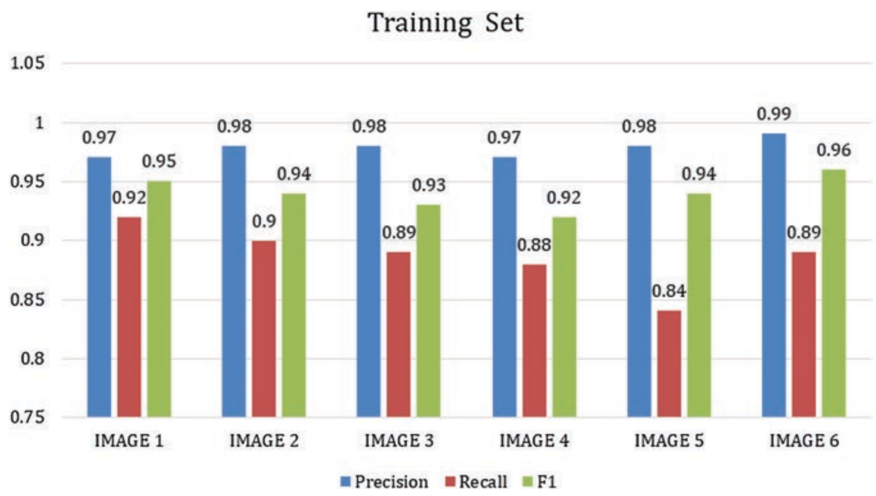

Fig. 8.19 The figure for training dataset in SSD

The training dataset observations in Figure 8.19 for the SSD model have been stated in the graph. The results obtained are more accurate. The average precision is 0.98, the average recall obtained is 0.87, and the average F1 measure is 0.94.

Table 8.3 shows results obtained for the testing dataset used for the SSD implementation from an IoT-based system have achieved greater heights. The image and the video datasets were used here for the evaluation. The average value obtained is 0.95, 0.84, and 0.90 for precision, recall, and F1 measures, respectively.

The graphical representation in Figure 8.20 shows the numerical values obtained for all three parameters, i.e., precision, recall, and F1 measure. The values obtained at an average is far better in SSD for the IoT-based system.

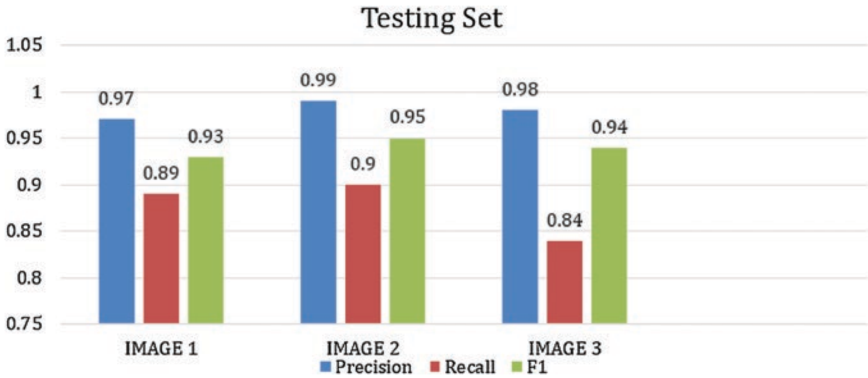

Fig. 8.20 The figure for testing set in SSD

8.8 Conclusion

In this paper, we develop an object observation system using a deep learning object recognition technique and voice recognition technology. This system's voice synthesis provides convenient features for the visually impaired. As one of the areas where deep learning technology can be applied, our study was conducted by focusing on how to effectively aid the blind. As a result, voice recognition and voice guidance technologies were added to the system, and its performance was tested. For security reasons, wired serial communications were used instead of a wireless server. If the information is linked to a server, it could be leaked onto the Internet. Since the information in question contains a lot of privacy- and camera-based observations, such leaks could create critical security issues for users. However, a wired connection can secure the information by keeping it offline. Continuous research is expected to solve server security problems, eliminate blind spots in observations by connecting the Internet of Things (IoT) cameras to a secure network, and increase precision in object recognition. This study can be used widely to provide the blind with privacy and convenience in everyday life. Also, it is expected to be applied to industrial areas where diminished visibility occurs, such as coal mines and sea beds, to greatly help production and industrial development in extreme environments.

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Chapter 9
An Intelligent IoT Framework for Handling Multidimensional Data Generated by IoT Gadgets

V. Lakshman Narayana, G. Srinivasa Rao, A. Peda Gopi, and R. S. M. Lakshmi Patibandla

9.1 Introduction

Emerging technologies and significant changes to Internet protocols and operating systems in recent years made it easier than ever to communicate between various devices. The predictions for connectivity to the Internet are estimated to cross between 25 and 50 billion devices by 2020, according to various forecasts. This led to the newly created Internet of Things (IoT) idea. IoT integrates embedded technology with wired and wireless communications, sensor and control units, and Internet-connected physical objects. One of the computation's long-standing goals is to streamline and enhance human behaviors as well as interactions (e.g., see "The *21st Century Computer* or *Computing for Human Experience*). To achieve this intelligently, data is required by IoT to provide either better user services or to improve the IoT system performance. Methods must thus be capable to access metadata as of various network resources and analyze these facts for knowledge extraction.

As IoT is among the leading causes of innovative information, data science would mark a major impact to intelligent IoT applications. Data science is a fusion of various scientific arenas that customize data mining to find models besides new ideas from data, machine learning, and other techniques. These methods include a wide variety of algorithms for various fields. The application of data analytical methods in specific areas includes identifying data types including length, diversity, and rapidity; data simulations such as neural networks, clustering, and

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classification; and application of competent processes that fit data characteristics. The ensuing is taken from our reviews: Firstly, it is essential to espouse or improve processes that can switch data features as data is produced from various sources with unique data types. Second, there is not without the problem of size and speed and the large number of resources that produce real-time data. Finally, one of the key concerns for pattern recognition and a restored exploration of IoT data is to find the finest data exemplary that matches the facts. These problems opened up a wide variety of opportunities to expand new technologies.

Internet of Things (IoT) aims to build a smarter world by saving time, energy, and resources and to simplify the way things live. Expenses in various industries can be minimized using this technology. IoT has become a rising trend in the last years thanks to huge investments and numerous studies on IoT. In order to maximize their output, IoT comprises a group of allied strategies which are able to permit data to each other, actions that take place automatically, without any human consciousness or feedback. IoT consists of four main components: (1) cameras and sensors, (2) networks processing, (3) data analyses, and (4) control of the system.

The new developments in IoT started with more frequent application of RFID tags, increased availability of lower-price captures, web technology built, and protocols for communication modified. The IoT is built into different technologies, and connectivity is an essential and adequate requirement to operate. Communication protocols therefore are components of this improving technology.

Communication protocols in IoT can be broken down into three main components:

1. Device to device (D2D): this allows contact between close by mobiles. This is the new wave of mobile systems.
2. Server system (D2S): all data is transmitted to servers that may be near or far-off devices in this form of communication device. The main purpose of this kind of contact is cloud computing.
3. Server-to-server (S2S): servers transfer data between them in this form of communication. Most cellular networks are used for this form of communication.

It is a vital task to process and prepare data for such communication. Different types of data processing, such as edge analysis, stream analytics, and database IoT analysis, are essential for responding to this challenge. The choice to use the least of the practices listed hinges on the specific use and its desires. Fog and cloud computing are two types of analysis that are used before data are transferred to others for processing and preparation. The entire IoT task is summed up as follows: initially, sensors and IoT devices gather environmental information. The following is the extraction of information from the metadata. Data are then all set to be transferred through the Internet to other things, computers, and servers.

9.1.1 System for Computing

The computational system for processing data, which is best known as fog and cloud computing, is another important part of IoT. Depending on the program and the process venue, IoT apps use both frameworks. Data should be processed after generation in more or less applications, although data need not be managed immediately in other applications. Fog computing is defined as the instant data processing and the network architecture it supports. These are collectively used in edge computing.

9.1.1.1 The Fog Model

The fog computing architecture is implemented here to transfer info from a data center task to the server edge. An edge server is the basis of this architecture. Fog offers restricted computation, storage, and network services, as well as logical intelligence and data screens used for data centers. This design is in an essential area, for instance, eHealth and military applications, and is being implemented.

9.1.1.2 Controlling Edge

The processing is carried out at an expanse from the center to the edge of the net in this architecture. This kind of handling allows the initial processing of data on edge computers. Devices on the border may not be continuously linked to the network, which means a replica of the master data/reference information is needed for offline handing out. Continuous devices have various characteristics: (1) security enhancement, (2) data filtering and cleaning, and (3) local data storage for local use.

9.1.1.3 Computing in the Cloud

Data is sent here to data centers for processing and accessible after analyzing and processing. This design consumes a huge latency and a huge load balance which shows that this design does not work at high speeds in order to process IoT data. The capacity of the data is huge, and large-scale data handling would raise cloud server CPU convention. Cloud computing is available in many ways:

1. Infrastructure as a Service (IaaS): where the organization buys all resources, such as computers, servers, and grids.
2. Platform as a Service (PaaS): all the above tools are employed for Internet rental.
3. Software as a Service (SaaS): where there is a distributed model of software. All practical software is hosted and open to users on the Internet by a service provider in this model.

4. Mobile backend as a service (MBaaS): also named as backend as a service, this offers a route to a web or a mobile app to link it to a backend cloud storage application. MBaaS offers user management features, push alerts, and social network services incorporation. Application programming interface (API) and software development kits (SDKs) are used for this cloud service.

9.1.1.4 Distributed Computing

This design is intended for huge data processing. Big data problems arise in IoT applications, as the sensors repetitively produce data. Distributed computing is intended to split data into packets to solve this situation and to delegate packets to various processing computers. This distributed machine has numerous frames such as Spark and Hadoop. The following phenomena arise while transferring from the cloud to the fog and in distributed computing: (1) reduced network charging, (2) higher data processing speed, (3) reduced CPU use, (4) lower energy use, and (5) increased capacity for data processing.

9.1.2 IoT Architecture

The span Internet of Things (IoT) raises to an assorted grid of physical and virtual substances integrated for every sensor, electronics, software, and connectivity which enhances the value and service of objects by interchanging information through the Internet with other linked objects. When IoT is considered, the machine learning process considers IP address and the data transfer is initiated. The integrated transport system, which could dynamically be routed and reorganized to meet changed traffic requirements and conditions, is an example of an IoT-enabled environment. In healthcare, IoT was used to track rehabilitation of patients and evaluate the use of IoT-enabled devices against a range of patient-unique parameters. The collected data can also be used to compare patient response to care at a global scale in various ambient contexts. The use of intelligent IoT strategies can also be utilized for energy monitoring and control. IoT may be used for production in the agricultural sector and food production to control and track the nutriment invention variables like endurance, political and monetary indicators, natural disasters, ingestion, and crop and intuitive syndromes. Helping people with physical disabilities, long-term conditions, social and aging problems can help address the need for independent living in an overall context.

The IoT device architecture is shown in Fig. 9.1. The physical sensing layer comprises built-in devices that collect data from the real-world using sensors.

The scale and heterogeneity of expected growth add to the current relation and integration problem extra complexity and urgency [1]. In addition, IoT systems are probably spread across various fields of application and geography, establishing

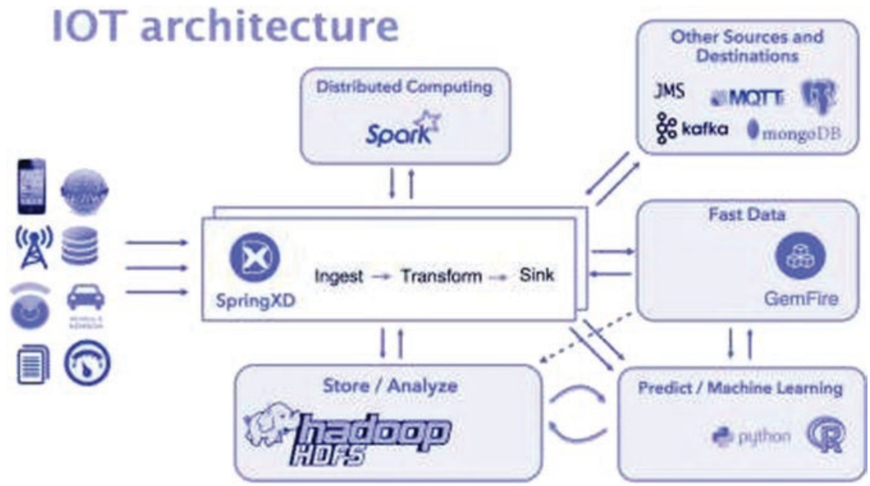


Fig. 9.1 IoT basic architecture

covert dependencies across domains, networks, and services. This has significant consequences for the development of IoT systems. Thus, it has become a must to provide an intelligent connection-conscious system. A strong mechanism to promote networking, interoperability, and convergence in IOT systems, the service-oriented architecture (SOA) is the cornerstone of the current IoT frameworks. Although SOA's purpose is to increase interoperability with the IoT application in particular, its enormous use in modern IoT framework assisting enhances the scalability issue, particularly with the huge number of forecast "stuff" In IoT structures; the SOA architecture becomes too immovable to accommodate the extensibility of device over time. In order to properly address system evolution and extensibility, microservice intends to fragment various IoT structures based on system archetype. This chapter analyses existing architecture for IoT integration and proposes a solution to weak integration of operation, scalability, extensibility, and fault toleration in IoT, which is partly explored and yet promising.

9.1.3 IoT Collected Data

The primary fusion of data consists of straight synthesis of sensor data as of sensor expedients. It includes a major extraction of functionality monitored by mixture of data. The improved scheme consists of abstraction of features and uniqueness and merging of data [2]. This approach permits a high degree of knowledge inferences and very precise decision-making. The use of new technology has revolutionized the expansion of IoT sensor data processing in the cloud, fog, and edge computing in recent years. These technologies enable the consumer to control complex and heterogeneous sensor data using a comprehensive, accurate, and convenient platform. The goal of the data analytics layer is therefore to create intelligent functions for a broad range of IoT-based applications. The aims of these systems are to moderate the costs of storage and measurement, expand the reliability of setup diffusion, reduce setup delays, enhance IoT network protection and privacy, ensure scalability, and allow IoT solutions without failure and risk.

9.1.4 IoT Sensor Data Features

In succession or with the trigger of an external event, the IoT sensors generate data. Another method is the collection, aggregation, analysis, and visualization of sensor node data to gain useful information [3]. The following is the process. These details are then interpreted to generate the representative shape, which can be delivered, and the external cause reaction. Other sources also have data streams in accumulation to the information provided by sensor networks. The data generated must be aggregated and processed unprecedentedly and streamed to remote situations for ancient data exploration at a particular network data rate. There are, however, some sensor data properties and related problems. The authors address the difficulty of information with sensor data based on factors such as the large volume, dynamic data, actual updates in real time, vital data aging, and interdependency concerning data sources. The sensors are usually inserted into the humanoid frame, artifacts or places. As such, the important features of IoT sensor facts are as follows:

Technical restrictions – Sensor scope limits computational power, battery power, network bandwidth, storage capacity and memory, and technical limitations. As such, these sensors are extremely vulnerable to malfunction, attacks, and a simple failure, which result in sensor data losses and inaccurate information.

Effective phase dispensation – The sensor setup would be able to perform more multifarious interacting responsibilities and turn crude sensor data in real time into more useful and comprehensive information.

Scalability – There are multiple sensors and actuators in the physical environment in the sensor network. Sensor setups are prerequisite to be accessible to put up sensors and actuators, exponential development, and data processing and meet different IoT-based application's objectives.

Data representation – The general sensor data format is a short, structured data tuple. The sensing values are Boolean, binary, featured values; continuous data; and numerical values in the various representations.

Heterogeneity – Data from the IoT sensor is heterogeneous. Different sources of data include rigidly organized information sets, real-life data generation grids, embedded sensor systems, social media streams, and other participatory sensor networks.

9.1.5 Processing IoT Sensor Data

Wireless communication protocols for the info sharing progression are commonly used in the IoT sensor networks. These communication protocols act as unlicensed frequency bands that make sensor deployments more flexible and scalable. However, uncontrollable interference is caused when Wireless Sensor Networks (WSN)'s communication protocols are used in unlicensed frequency bands. Interference can cause incorrect transmission of data and sensor data with noise, missing values, outlets, and redundancies [4]. The following section discusses the various data analyses carried out to manage IoT sensors such as denoising, missing imputation of data, identification of data outlines, and aggregation of data.

The capacious sensor data produced in the IoT network require data analysis, mainly in real life. The sensor data's features are complex with high speeds, large volumes, and vigorous standards and forms. Furthermore, the sensor facts infect by maintaining various impediments before the data analysis, and supervisory processes are necessary in real time [5]. Noise is a signal-uncorrelated component that changes the original vectors of the signal and modifies them unwantedly. The noise function results in the inefficient use of resources to handle the data which is not used. The transforming wavelet methods will effectively represent the signal and address the signal estimation problem. The transformation of the wavelet significantly maintains the imaginative signal coefficients by eliminating the noise inside the signal. The coefficient of noise signals is threshold, so the seamless threshold structure is vital. The wavelet transformation is a popular technique for analyzing and synthesizing signal dynamism in continuous times.

9.1.6 Missing Data Imputation

Imputation for the management of incomplete data is an imperative preprocessing job in data analysis. The Internet of Things is used as a main expertise that makes a lot of information in various areas and industries like towns, health, GPS, and smart transport. In general, the learning algorithms that analyze IoT data adopt that the facts are ample. Although mislaid data is usual in IoT, missing or incomplete data analysis may lead to improper or unreliable results. For IoT, it is therefore appropriate to estimate the missing value. To solve this dilemma, three key tasks need to be carried out. The first move is to determine why data are lacking. The incomplete results have been due to the numerous reasons of poor connection to the network, defective sensors, and environmental and synchronization problems. The mislaid data is shared into three types: random missing (MCAR), random missing (MAR), and randomly missing (NMAR). The next step is the study of missing data trends. The two tactics are single mislaid patterns and random mislaid patterns. The two approaches are Amplifier approach and signal approach. Finally, the IoT model is used to infer the value of the missing data by using a missing value imputer model.

Some of the missing algorithms for the imputation of values hold solitary processes, multivariate systems, etc. In the literature, the conventional process for imputation is not sufficient for IoT data. Some algorithms are primarily used to impute missing data, and they are provided in the following section.

The Gaussian mixture model (GMM) is a clustering algorithm. It is a model that customizes an easy clustering framework to allocate data points toward various clusters.

The following is represented by a Gaussian mixture: $G = \{GD_1, GD_2,\ldots,GD_k\}$; the number of the clusters is indicated by k. The GMM function f_k (GD_i) represents the probability density function of the kth component, given that a data set D is caused with k components. As indicated in Eq. (9.1), GD_i's probability, $P(GD_i)$ produced via GMM, is as follows:

$$P\left(GD_i\right)=\sum_{i=1}^{k}\pi_i\, f_i\left(GD_i|,\mu_i|,S_i\right) \tag{9.1}$$

To switch the mislaid data charging of the IoT sensor data using a GMM model, the development, clustering, classification, measurement, and filling of data are a five-step process. First of all, in the data set D, the instances are divided into D_1 and D_2. D_1 includes all cases shorn of mislaid standards, while D_2 includes all instances of the missing values in the data set. The second is for the clustering of the entire D_1 data set, the GMM model based on the EM algorithm. The cluster center is calculated for each cluster. Then, the cluster in D_1 will be calculated for each case. Third, the incomplete D_2 data set is considered a test set. In D_2, every instance is sorted by the clustering outcome.

9.1.7 Models for Data Processing

The Internet of Things (IoT) is an emergent subject of technological, societal, and monetary importance that stimulated the research of the IoT communication models in Santosh Kulkarni and Prof. Sanjeev Kulkarni.

The duo concluded that the idea of integrating machine, sensors, and networks for monitoring and controlling devices was around over decades, but a novel certainty for the Internet of Things emerged as the recent confluence of key technology and consumer developments. The IoT's main vision is to create an intelligent and innovative universe that is completely interconnected, with closer connections among objects and their environments and objects and individuals. However, when the system is more complex, this vision can be hindered by a number of probable contests – particularly in areas such as safety, secrecy, interoperability and criterions, legal, supervisory, and legal problems as well as the enclosure of emergent frugalities. The Internet of Matters obviously includes a diverse group of stakeholders with dynamic and changing technical, social, and policy considerations.

Although the end user benefits from effective communication models, efficient IoT communication models often foster technological creativity and open commercial growth opportunities. The use of IoT data sources, which have not been available previously, as a catalyst for more innovation can be planned for new products and services.

Indeed, IoT devices are found throughout the world and will empower environmental intellect in the prospect. The synopsis of the numerous replicas of communication in IOT, provided below, is therefore extremely valuable. The IoT allow you to link people and stuff with anything anywhere, ideally with any path/network and any service. It is worth considering how IoT devices are linked and communicated before deciding from an organizational perspective with respect to their models of technological communication:

- The communication model device to device consists of two or more devices connecting and communicating directly between each other, instead of using an application intermediary. These devices connect through several network types, such as Internet or IP networks. Often these devices, however, use protocols such as Bluetooth, Z-Wave, and ZigBee to communicate directly on a computer.
- The IoT interface links to an Industrial Control System (ICS) like the application service provider for data sharing, and messages switch directly in a device-to-cloud communication model. In order to link the computer and the IP network which eventually connect to the cloud service, the approach is also used using obtainable communication devices as conventional reinforced Ethernet or wireless Internet connectivity.
- The data-sharing back end is a communication architectural model that allows employers to transfer and analyze intelligent object data in conjunction with data from other sources from a cloud service provider. This design supports “the user’s wish to allow third parties access to the sensor data uploaded.” This approach extends the single communication model from mobile to cloud, allowing for data silos in which “IoT devices upload data to a single service provider.” The inclusive benefit of the system is obviously enlarged, but these interacted advantages are compensated for, by allowing the users to better access IoT and its data. The cost burden incurred for users to link to cloud services should be considered carefully when taking account of an infrastructure, expressly in provinces wherever user connectivity expenses are extraordinary.

9.1.8 Data Management Techniques

According to research conducted by Cisco Systems, the Internet of Things will be a \$19 trillion industry by 2020. Internet of Things (IoT) is a technology that puts together the world’s devices to form a single communication network. It can fuel growth and change tomorrow’s lifestyle greatly. Today, data travelling through the networks is rising every day. There are no comprehensive and varied volumes of knowledge. Furthermore, there's nothing but exponential development in these data structures. For many organizations, the great challenge faced by the big data is very difficult and troubling. In an International Data Corporation survey, just 1% of the world's data appears to be collected by data crunchers from companies. Big data, on the other hand, also offers companies several market advantages. This will provide market perspectives that are challenging or unobtainable otherwise. The advent of IoT would further increase the data produced worldwide. The largest number of respondents answered "information" in a survey, when asked about the main field which will make a difference in IoT solutions. It is the processing of the huge amount of data that most people see in relation, which can be quite a challenging first step of IoT (Fig. 9.2).

Device management Internet of Things (IoT) consents consumers to properly and safely track, control, and attain the devices after deployment. Billions of sensors communicate with and beyond individuals, households, towns, fields, offices, cars, clothing, and medical supplies. The Internet of Things (IoT) transforms our lives from home appliances to automobiles. Apps will now tell us what to do and where to go. In controlling processes and forecasting faults and catastrophes, we use IoT industrial applications. IoT platforms support parameters to enhance and store data accordingly and to manage them (Fig. 9.3).

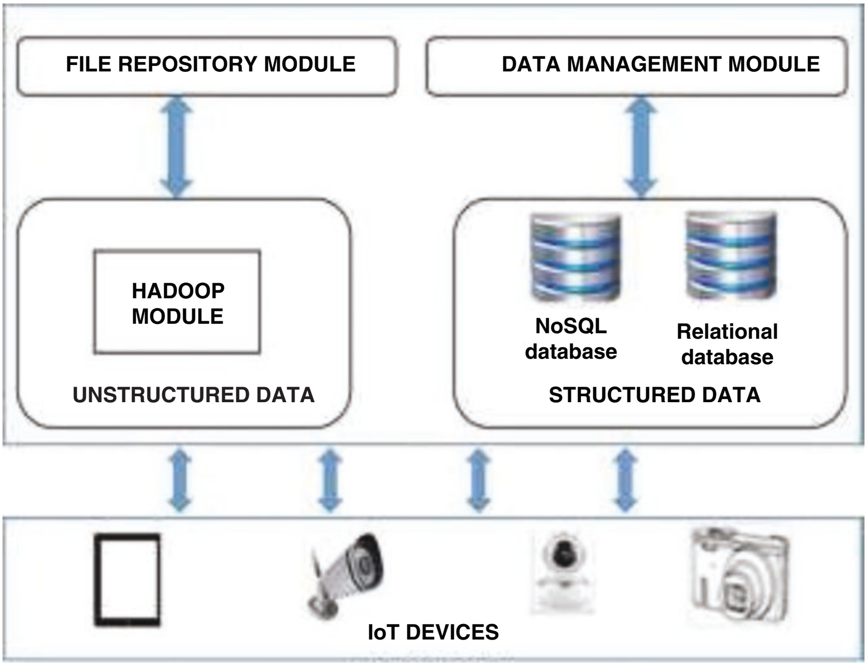


Fig. 9.2 IoT data management

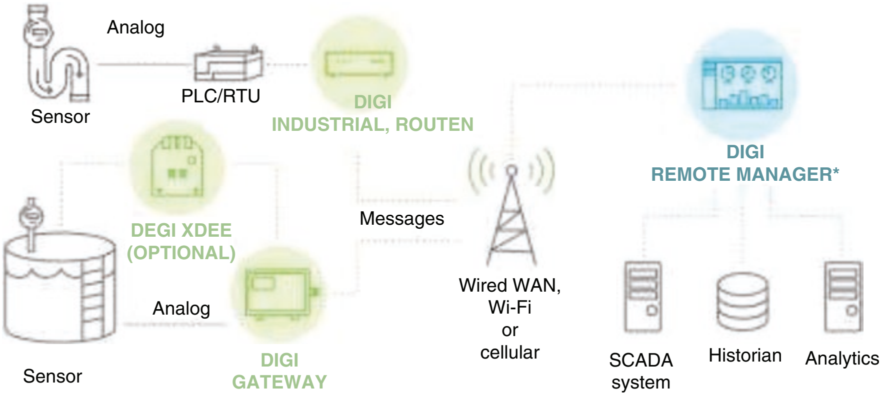


Fig. 9.3 Control of IoT data

9.1.9 *Control of IoT Data*

Data management is the method of collecting and refining the total data available. Various devices send vast numbers and varieties of information from various applications. All of this IoT knowledge is managed to build and enforce architectures, strategies, practices, and procedures that can fulfil all the needs of the data life cycle. Things are operated by intelligent machines so that we can save time. Smart things can capture, communicate, and understand information. However, a tool is necessary to add data and draw inferences, trends, and patterns.

Embedded systems and software developers and manufacturers need to design systems that respond to data management requirements. You must develop a structure for data management compatible with all the software and hardware that is involved in the assortment, administration, and distribution of data. The design must be productive to speed the final product into the market. For analytical purposes, IoT computer data is used. Data that organizations gather and store, but which remains largely static, is named shady data since it is not being recycled to analyses. It includes demographic data for customers, buying history and level of satisfaction, or overall product details. Shady data is important to companies in order to better understand consumers, as it enables them to more effectively discover new insights. IoT data administration involves field testing before a product is published. Arena test data contributes to the project of the product and to the creation of a better product. The collection of postlaunch field data helps to develop products continuously by updating software and detecting anomalies. This also offers valuable insights into the method of developing new goods.

This is important in manufacturing, commercial, and consumer applications such as a connected home and industrial applications. It enables customers to handle a wide range of equipment such as systems for operating technologies, cameras, computers, cars, and equipment (Fig. 9.4).

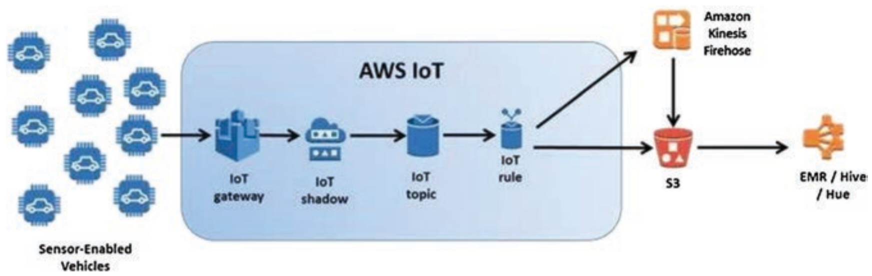


Fig. 9.4 Control of AWS IOT system

Device control work for AWS IoT enables the use and performance measurements to be tracked for equipment in industrial sectors such as construction, oil and gas, and mining. It allows metadata and policy changes to be monitored with service notifications to report any changes to the configuration of the devices. It also enables suspicious behavior on a system to be identified and mitigated. It provides safe onboard, coordinate, track, troubleshoot, and send firmware updates to the air Over The Air (OTA). It allows you to add device attributes including device name, type and year of production, certificates, and IoT registry access policies. It then assigns them to users and rapidly prepares linked devices for operation. This allows you to easily locate and scan every IoT device in almost real time across the entire device floor. Devices are easily found based on a mix of attributes such as device ID, status, and form so that in addition to troubleshooting, action can be taken. Remoteness can also be done for acts including reboots, factory reset, and security patches.

The main problems that industry experts have established include the following: In time, the number of IoT devices will rise, and the challenges for processing and analysis in real time will be increased to minimize storage time. In order to ensure adequate room for new knowledge, space must be configured for metadata including user IDs and passwords. Real-time data are used to support functions such as adaptive maintenance, predictive repair, protection, and process optimization. It is a challenge to choose the right tools because the integration of various sensors should be demonstrated and its compatibility verified. If there is no relation, devices do need insight, decision-making, and data delivery planning. Significant considerations are the interoperability, scalability, protection, and standards of software technology for building IoT's products behind the IoT device management framework. Protecting data against unlicensed access and tampering is essential. Organizations must comply with national data protection laws and regulations. Quality checks are also required for IoT device data. A large attack surface, which can be mitigated through the channeling of data through a protected gateway, is available for several different devices linked directly to the cloud.

1. Multisource Data Integration

A new user culture has been created by extensive use of intelligent devices and the simple and free access of the cloud. Users use web technologies, applications, and systems interconnected with the transition from computer to device without interruption. The huge data produced thus has brought organizations a unique challenge – the collection of data. Companies must take into account factors such as data handling, sources of data, installation of equipment for the collection of physical data, and best data collection methods. In addition to the processing of new data, preexisting data must also be upgraded to analyze inside the business. This shows how difficult it is to integrate data from various IoT sources – particularly when there are broad sources. Such data cannot be copied to any core node, so it cannot be physically or economically feasible, forcing companies to search for alternative means that collect and interpret big data as a single logical database instead of an unrelated mass of data. These tools are especially useful for IoT applications which rely on data from a wide range of distributed resources, including embedded sensors, video cameras, and third-party data sources. Multisource data integration is difficult. In addition to methods, the most precise outcomes are achieved by tremendous preparation and foreground thinking. However, time is worth investing on the outcome of a successful integration project. Projects for data integration will provide you with data that you must settle on, handled correctly.

2. Data Collection Process Automation

After IoT data is obtained and incorporated, companies have to allow the data at the precise time to be analyzed in the precise place. This involves evaluating the data so that it can be transferred or analyzed wherever it is at the end of the user (on the device) or wherever it is transmitted, for storage and processing off-site. In some circumstances, it is necessary to process the information at the user's end, while in other situations, the information is transferred in detail to the data center or cloud. Organizations must call and determine how data are to be analyzed. Before you automate IoT data, certain factors you need to consider: IoT application's performance criteria is a low-latency criteria that will affect the processing of the data. Certain cases of IoT use may be appropriate in low latency. Preprocessing data opportunities: In many situations, all data generated with an IoT solution should not be transferred to the cloud for processing, until transmitting IoT data to the cloud or transmitting select data can make sense. Highly distributed IoT applications: Some IoT applications require a high data distribution, which makes it essential to process data near the end of the user. In order to transfer, analyze, and then transfer the data, critical data generated in large quantities will need a very good database speed. Some domains that generate 1–2 TB of data per day will take longer than necessary to prevent the need for real-time analysis. This method is necessary. In such cases, IoT data should be analyzed in the nearest possible user end in order to prevent a difference in time. A survey shows that the majority of the data produced by their IoT systems is processed close to the point where it is generated – with intelligent devices and appliances – over the next 3 years.

3. Data Analyzed to Collect Insights That Can Be Used

In order to find actionable insights which can be used to improve user involvement, IoT data must be analyzed. Nobody will benefit from data that is not processed and refined. The lack of instruments and equipment dealing with increasing scale, speed, diversity, and dissemination of data also lacks analysis abilities for organizations. Sometimes, the solution needs the ability to access accurate details in real time.

Device Control Potential for IoT

The software IoT device management allow users to control, track, and manage physical IoT devices so that after deployment, they can function correctly and safely. These tools also allow you to update devices and fix problems on software and firmware remotely. They also have permissions and protection to ensure that every system is vulnerable. The IT managers use these solutions to monitor the performance, protection, and general status of each connected computer. These solutions exploring IoT information on the ground give a greater understanding of how the product works in the everyday life of the consumer. IoT data management allows the user to refine intelligent algorithms by viewing sensory data and time points when a user has changed. The customer will then update or retrain the product to provide the user with a better experience.

9.1.10 Procedures for Data Storage

Maximum precision with real-time data protection. This way all data generated by each IoT device can be accessed. But this typically means large quantities of data are obtained. It is challenging to set the appropriate time stamp to sort data from multiple IoT devices. Systems which can handle the speed and volume of the incoming IoT data should be considered. The choice of a straightforward justification in order to obtain and analyze all available IoT data in real time. The sheer volume of information may otherwise have an excessively large effect on the cloud systems, namely, the network resources and computer resources needed to sustain the inflow of IoT data.

Specific IoT applications should also be considered. The latency, energy use, and accuracy criteria are special. Delays can occur in some applications. Others are seen more as time critical and cannot be allowed to be overdue, such as security applications. In certain instances, high precision might not be necessary, and data can be sent in batches. You also get a record of all the information whether the information is submitted in battles or micro batches. This takes place only at pre-established intervals, not in real time. The selection of a specific case depends on the criteria. You need precise real-time information for your analysis in certain scenarios. Historical data will do the same in other cases.

If you are planning to analyze the incoming data, you need a forum for intake of data in real life from a wide range of IoT devices. A network like this must be able to adapt to temporary communication problems. A lost link, malfunction, or server failure may be included. The platform helps to eliminate data loss. Consequently, you risk not sacrificing the quality of the data to be produced. On the platform, data is processed for data modelling and analysis in a ready-made form.

The method chosen to collect and store IoT data in broad-based brushstrokes again strongly depends on the target needs of a particular case of usage. These comprise, but are not limited to, processes of collecting data centered on so many different requirements such as data quality, energy usage, response times, and protection of privacy. Data aggregation, filtering, interpretation, and compression at sensor or IoT edge level are established methods for reducing the volumes of IoT data collected as close as possible to the data source.

Organization of the Chapter

The rest of the chapter is organized as follows: Sect. 9.2 discusses briefly about the literature survey, Sect. 9.3 discusses about the sensor data processing and storing, Sect. 9.4 illustrates the results, and Sect. 9.5 concludes the chapter.

9.2 Literature Survey

Modern technologies such as IoT, sensors, big data, and machine learning can be used for tracking and can play a significant role in disease forecasting, production improvement, reduction of costs, early alert system provision, and better management decision-making. Several IoT-based monitoring systems experiments have been carried out, and there have been substantial benefits. The system was designed to control the humidity of citrus soil and its nutrients for the decision on fertilization and irrigation.

Current studies use IoT sensors to assess the conditions at a real facility so that sensor data can be viewed in real time. In several areas of study, including smart building and healthcare, IoT-based sensors provide an effective solution. Several researches on device performance improvement have been carried out, and important results have been shown for IoT sensors. The monitoring system for IoT-based sensors for intelligent buildings in a simulation environment and the proposed system was implemented. The results showed that the use of multiple IoT sensors would achieve a better monitoring system in a smart building. The proposed system would both enhance energy efficiency and promote green, intelligent buildings.

IoT is a challenge in the field of computer science because it is a modern concept for Internet and intelligent data. Someone proposed four data mining models for processing IoT data. The author recommended the use of four data mining models. The first model is a multilayer model, based on a layer of data collection, an event processer model, and a layer of data mining. The second model is a distributed data mining model for data storage at various locations. The third is a grid-based model of data mining in which the authors are working to incorporate high-power and heterogeneous applications. The final model is a multi-technology convergence data mining model, defining a corresponding architecture for the future Internet. In this research, they examined such data mining functions such as grouping, clustering, analyzing associations, analysis of time series, and identification of contours. Data from data mining applications, such as e-commerce, industry, healthcare, and municipal administration, have been shown to be close to IoT information. Based on their results, they assigned the application the most common data mining feature and decided which data mining feature was most suitable for the processing of data from each application.

Chatterjee et al. [6] conducted a survey on the development and processing of IoT data through data mining techniques, to respond to some of the challenges. The study was divided into three main areas. IoT, data, and challenges exist here, such as developing a model for mining and mining algorithms for IoT, and are explained in the first and second sectors. In the third part, the potential and openings in this area are discussed. The following is a description of three major issues in data mining on IoT data: Next, the processing of the data must demonstrate that the chosen issues are resolved. Next, the characteristics of the data generated must be extracted, and according to the algorithms and data characteristics, a suitable algorithm is selected [7].

Alfian et al. [8] tried to clarify IoT's smart city technology to promote value-added services for city administration and residents. The discussion took place on the advanced communications. Authors study the technologies, protocols, and architectures that are ideal for intelligent cities in detail.

Several studies in manufacturing have been performed and showed major benefits in terms of improved work environments from IoT-based sensors, preventing misconceptions, providing fault detection and output forecasts, and enabling managers to make better choices.

Hu et al. [9] have developed an IoT-based air quality sensor inside the plant. Data were collected and transmitted via wireless communication on temperature, moisture, CO2, dust, and odor sensors. The proposed system is robust enough, able to precisely quantify the environment in the factory in real time, based on experimental results, and is expected to support managers in maintaining the optimal working conditions for the fabric workers. In order to prevent errors during the design stage in additive production, an environmental monitoring device based in low-cost IoT sensors. Temperature and humidity data were collected from the sensors. The study showed that environmental awareness can help avoid mistakes during the design process in the manufacturing of additives. Chen et al. [10] used IoT sensors to collect data on mine hoist fault diagnostics. The study found that IoT sensors would contribute to the provision of complete diagnostic data and improve diagnostic performance. By using IoT and machinery training to forecast product quality and improve operational monitoring, Putri et al. [11] have proposed a framework. As a real-life implementation of the proposed scheme, metal casting has been used. The device proposed was able to predict the consistency of the metal casting and to improve operational control efficiently. Finally, for the fourth industrial revolution platform, the integrative sensors and Supervisory Control And Data Acquisition (SCADA) method are used. Experimental findings demonstrated the viability of the proposed system that will help managers migrate legacy systems to the platform Industry 4.0. There is a huge increase in the number of IoT sensors and related components. The adoption of IoT in production makes the transition from conventional to modern digital production. The potential for new technologies that can manage large quantities of sensor data using big data technology also increases as the number of devices that manufacture sensor data increases. In order to facilitate critical decision-making, Angrish et al. [12] built a conceptual structure by incorporating big data technology into IoT. Through using big data processing, it is possible to handle and effectively present the enormous amount of data generated by many heterogeneous tools (sensor devices) and to help managers make better choices.

9.2.1 Big Data Processing

Data produced by manufacturing systems is expected to increase exponentially, resulting in so-called large data, with the growing number of IoT and sensing devices. Big data in four Vs is often represented. The first V refers to the volume of the data, the second V to the various data types/formats, the third V to the speed of data generation, and the fourth V to the accuracy of the data reliability. The last V to the data is the velocity of data generation [13]. With various types and formats (i.e., process logs, incidents, images, and sensor data), the data produced during manufacturing is expanding every day and thus processing and storing of such data become an onerous issue to resolve. Big data analytics in the automotive sector has many uses. Zhang et al. [14] suggested an energy-intensive manufacturing industry large data system to reduce energy usage and emissions.

In order to explore the logistics of RFID-enabled mining expertise, Zhong et al. [15] suggested a big data system. The effectiveness of the proposed method was demonstrated by an experiment, and the findings showed that the information derived from large data could be used for production planning as well as logistic planning. In order to mitigate the social risk of the supply chain, examine the application of big data analysis. The application of big data analytics in the supply chain was established with a case study. Big data analytics have shown that management can help predict different social issues and mix up social risks. Lastly, Li et al. [16] proposed a dig data architecture in order to actively sensitize and manufacture complex events. A relationship model and unified XML-based production processes were built to successfully process complex event big data, in order to find a frequent pattern from the complex event data, the Apriori frequent item mining algorithms. With the implementation in a local chili sauce production business, feasibility and efficiency of the proposed system were confirmed. The proposed model should provide realistic guidelines for decision-making in management [17–21]. The signal to noise ratio (SNR) to the signal obtained from IoT sensor devices are calculated but cannot reach the required bit error rate (BER) for the signal. The only solution is to delete the lower wavelet coefficients in order to resolve certain problems. This removal increases the SNR on the basis of a certain threshold. The smaller coefficients appear to produce more noise than the desired signal data. This is possible. In addition, the energy signals are focused on a certain portion of the signal spectrum. This increases the SNR value if the certain portion of the signal spectrum is transformed with wavelet coefficients. Furthermore, the signal feature plays a key role in improving signal energy if it has wide areas of irregular noise and small smooth signal regions [22–26]. So, if some signal feature becomes polluted by greater noise, the coefficients of the wavelet are influenced by the minor part of the coefficient of the wavelet. The original signal is included within the small wavelet sections. The preservation of the correct threshold limit will then remove much of the noise signals and preserve the original signal coefficients. In this article, the authors discuss the streaming of sensor data and raw sensor signals to detect the features and the different noise issues associated with the sensor signals.

Repeatedly, data detects sensor nodes. Since sensor data are time-sensitive, other sensor data for analysis can be used to obtain different results. There is no identical relation between the sensor nodes at various times, so the correct analytical data needs to be selected. The data must be adequately sampled for reliable data analyses, according to the authors. In order to estimate the missing information, the authors suggest the time and spacious correlation algorithm (TSCA). First, it simultaneously saves all sensed data and selects the most important series as an analytical sample that greatly enhances the efficiency and accuracy of the algorithm [27–30]. Second, it calculates the time and space values that are lacking. The weight is attributed to these two dimensions. Third, there are two methods that improve the applicability of the algorithm to deal with extreme data loss.

A new approach for nearest neighbor imputation, based on spatial and temporal correlations of sensor nodes, is to calculate missing values. The k-d tree data structure was used to increase the search time. Due to the missing value, the k-d tree was produced by weighted variances and weighted Euclidean distances. The algorithm described in the model proposed follows the steps, as the lacking value threshold is first identified as T. The percent P is then determined for the missing values in the selected data collection. If P is within the threshold, then spatial correlation will find the sensors nearby n. Using the Pearson correlation coefficient, the correlation between sensors with the missing values and n close sensors is determined. The missing sensor data are then indicated by the time measurements of the closeness sensors. The data set is done. The result is then contrasted with the results of other imputations. The precision of the root mean square error (RMSE) is again assessed.

Protected Management Frames (PMF) is used in the algorithm to construct a single matrix in two matrices [31].

By factorization, dimensionality can be minimized. You can retrieve the missing values in the original matrix with the ability to obtain the original matrix from the product of two-factor matrices.

9.2.2 Data Outlier Detection

Sensor nodes are distributed and heterogeneous throughout the IoT sensor network. It should be noted that, because of many external factors, this configuration in a real physical environment causes massive failure and risk associated with sensor nodes. That leads to modifications and data outliers of the original data produced by the

IoT sensor network. Therefore, before data analyses and decisions are carried out, it is vital to recognize certain data outliers. In order to achieve this goal, spatial data outlines are detected by three common methods, namely, majority voting, categorization, and main component analysis. Mechanism for voting: This approach identifies a sensor node as abnormally functioning, when the reading differences with surrounding sensor nodes are detected. The Poisson distribution, according to Shahraki et al. [32], is the typical method of data generation in different IoT network sensor applications. The created data sets include short-term, non-periodical, and insignificant variations in data patterns in the IoT sensor network. In the Poisson distribution of the IoT sensor network data collection, standard deviation and boxplot are simple and effective statistical methods for outlining. The Euclidean distance between data produced by the defective sensor node and the data generated by its immediate vicinity nodes is also calculated in a distributed setting. If the estimated difference in data is greater than a particular threshold limit, the data produced by this node shall be described as an outlier. Although this technique is simple and less complex, it depends excessively on the neighboring sensor nodes. In addition, for the sparse network, the accuracy is poor. The classifiers are a two-step approach, with a standard machine learning model firstly training for the IoT sensor data. Second, the data are identified with either normal or anomalous classifying algorithms. The most popular classifying algorithms are the support vector machine (SVM). The normal data is created for half of the data search space. Subsequently, data is analyzed and categorized by SVM to detect standard or otherwise unnatural data from the qualified data. The classifier algorithm's demerits, however, include its high computational complexity. The main objective of PCA is to evaluate the residual value by extracting the main components of the given data set. The remaining estimated data values will be evaluated through detection mechanisms such as the T2 score and the Square (SQR) Single Pair Ethernet (SPE) to identify the data outliers [33–38].

The authors discussed outlier detection using the Tucker machine and genetic algorithm on the IoT sensor results. The IoT sensor network, which displays spatial attributes and sensor data, is involved in various sensor nodes. In addition, the produced sensor data is dynamic for the time being. The comprehensive sensor data generally contain mode failure abnormalities. Vector-based algorithms are the popular means of detecting outliers. Vector-based algorithm demerits interrupt the original sensor data structural details and have a side effect on dimensionality [39–45]. For outlier detection, a tensor-based approach uses Tucker factorization and genetic algorithms. Without disrupting the internal sensor data structure, the experimental results showed improvements in the efficiency and precision of outlier detection [46–51].

9.3 Proposed Model

Wireless protocols are commonly used for the sharing of information in IoT sensor networks. The protocols for communication act as licensed frequency bands that make sensor deployments more flexible and scalable. But uncontrollable interference is caused by the use of communication protocols for WSN with unlicensed frequency bands. Inaccurate data transmission and sensor data may result from interference signals with noise, missing values, outlets, and redundancy. This section addresses the different analyses of IoT sensor data such as denoising, missing data imputation, data identification, and data aggregation conducted.

Fusion of the sensor data as contexts needs to take their heterogeneous features and capabilities into account. Data from various sensors are highly complex (various models, large volumes, and connections between sources) as well as dynamism (actual update) and insecurity (precision and timeliness). Data from a variety of sensors are highly complex. The unwanted noise is created in wireless transmission of raw data through the sensors. This results in sensor data uncertainty problems that can be outdated, incomplete, inaccurate, and contradictory. Noisy sensor data can lead to a background misunderstanding, leading to improper application behavior. When sensor uncertainties exist, traditional background modelling, rationalization, and data mining models that operate well with comprehensive data cannot be used. Machine learning probabilistic methods enable several sensor-based context awareness techniques. For low-level contexts such as symbolic position or classification of hot/cold temperature, the simple threshold rules can be applied at sensor notches. Different methods in literature are probabilistic logic, furious logic, Bayesian networks, hidden Markov models, and Dempster-Shafer proof theory for dealing with source uncertainty. Theory of evidence unattended classification algorithms such as the Kohonen Self-Organizing Maps (KSOMs) were used for exploration of data processing of unknown unlabeled data. The sensor data gathered is arranged in a structured order using the following equation:

$$S(D) = \frac{DS(i) + nP't_{onP'}(D')}{\dfrac{1}{\mu\left(\dfrac{T}{P}\right)} - \dfrac{1}{\mu\left(\dfrac{T}{P'}\right)} + \dfrac{nPt_{onP}(tD)}{sD}} \tag{9.2}$$

The proposed work is divided into four steps, i.e., data set for input, data partitioning and parallel architecture and tree construction (Fig. 9.5).

In the scattering of data, there are different techniques of geospatial data partitioning. In order to process large volumes of geospatial data efficiently on many computers, this data set must be divided into small parts, with every single part processed on a different computer. Parallel computing performance is entirely dependent on partition consistency. There is a high need to incorporate a good partition strategy in order to achieve good load balancing. In theory, two major types of

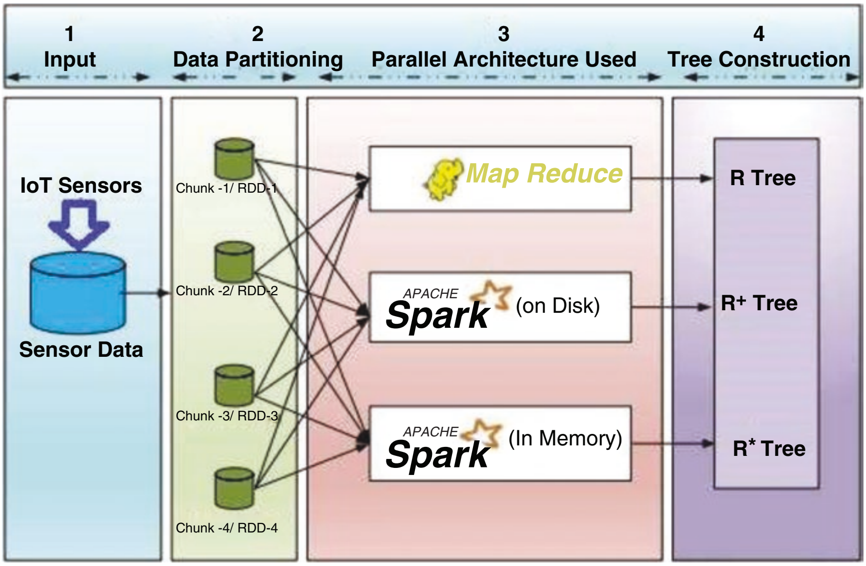


Fig. 9.5 IoT sensor data processing

spatial and data-oriented partitioning strategies exist. Space-oriented partitioning techniques spatially deconstruct the actual partition boundary into two equivalent subspaces, which create sub-partitions. Data is only dependent on the space in the decision to partition. Such partitioning is prone to data skews. The data-oriented partitioning technique produces a subsection when it finds a cut that contains about the same amount of data for each sub-partition. We used the second method in our case, i.e., a technique of data-driven partition. The duplicate data gathered by IoT devices is identified using the following equation:

$$\lambda\left(sp,tP'\right)=\frac{t_cP\left(Dn\right)}{t_oP'\left(nD'\right)}\left[1-\frac{\mu\left(\frac{sD}{P}\right)}{\mu\left(\frac{sD'}{P'}\right)}\right]+\theta \tag{9.3}$$

The sensor missing values are calculated as follows:

$$sW_\psi\left(\alpha,\beta\right)=\int_{-\infty}^{\infty}\frac{1}{\sqrt{\alpha}}\psi_0\left(\frac{\lambda-\beta}{\alpha}\right)+\lambda+T \tag{9.4}$$

$$I_{ij}=\begin{matrix}1, & \text{if } sP_{ij} \text{ is not missing}\\ 0, & \text{if } sP_{ij} \text{ is missing}\end{matrix} \tag{9.5}$$

Subsystem Sensor Data Storage

Sensor data generated is typically stored in some kind of data storage solution. But as the number of sensors and thus the volume of data increases, the ongoing storage is a nontrivial challenge. For only certain periods of time, conventional data storage sensor solutions advise data storage. The data obtained from the sensors are therefore of value, as they can contain secret reasons for defects or knowledge about diagnostics. Therefore, until evaluated, we have built up a scalable, distributed data storage subsystem to store sensor data.

Open-source NoSQL databases provide high-efficiency solutions for large volumes of data storage sensors. We used the famous NoSQL database, MongoDB, in this report. MongoDB is a document-focused database with JavaScript Object Notation (JSON) storage support. Their performance, high availability, and easy scalability are guaranteed. MongoDB documents can be mapped to language datatype programming. Supporting dynamic schema makes it simple to introduce polymorphism. With the automated failover master, MongoDB servers can be replicated. Automatic clustering distributes data collections across devices to scale databases.

Subsystem Sensor Data Analysis

The device has a very important function of storing sensor data indefinitely. Nevertheless, it is essential to analyze sensor data to find important information like alert messages and failure messages. It can be achieved with the simple application of statistical methods and with the addition of more advanced algorithms for data mining or machine learning. We developed a scalable, distributed data processing subsystem utilizing large data technologies in this research. Our goal is to run advanced sensor data machine learning algorithms to find useful information.

Big data processing typically includes processing power and storage support by clusters. Traditionally, clusters have been created on several servers, but virtualization helps us to optimize resource usage and lower the cost of building clusters. Virtualization allows us to run several operating systems on a single computer that can be used as cluster nodes in turn. On the other side, we use open-source cloud software called OpenStack to build Hadoop cluster computing nodes because many of the virtualization software require large licensing fees and a strong technical background (Fig. 9.6).

The data produced by the manufacturing industry (e.g., production line sensor data, environmental data) should be evaluated in order to support decision-making for managers. Applied in different fields such as failure detection, quality prediction, defect classification, and visual inspection, machine learning methods can be considered state-of-the-art technology with high data analysis potential. With fault forecasting, machine learning algorithms, like random forest, are highly successful in detecting irregular events in a network and can thus help to prevent loss of productivity. Machine learning algorithms are therefore confronted with external data problems that can minimize the accuracy of the model classification. For the identification and elimination of outliers, the external detection can be applied, thus enhancing classification model efficiency. Density-based spatial clustering of applications with noise (DBSCAN) is one of the techniques used for outlier detection.

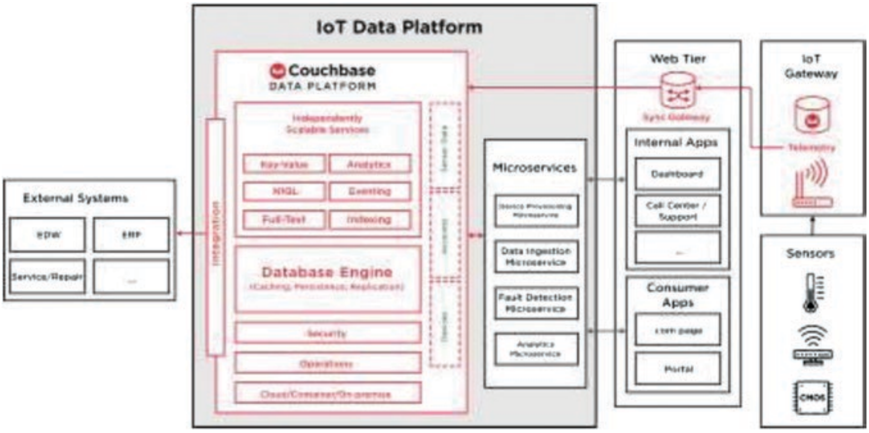


Fig. 9.6 Data handling mechanism

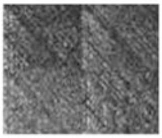
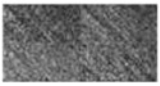
Input Image	Compression Ratio	Result of Compression and Encryption	Decrypted Image	PSNR (dB)
	4:3			34.19
	2:1			29.82
	4:1			25.93

Fig. 9.7 Work flow model

DBSCAN has been applied in numerous fields and has been shown to detect true outliers effectively. In order to detect abnormal events more accurately during manufacturing, DBSCAN-based outlying detection and random forest integration are required (Fig. 9.7).

The root mean square error of the proposed model is calculated as follows:

$$\text{RMSE} = \sum_{i=1}^{N}\sum_{j=1}^{M} I_{ij}\left(P_{ij} - U_i V_j^T\right)^2 \tag{9.6}$$

9.4 Results

We use distributed machine learning algorithms to analyze data on this architecture. An open-source distributed platform for big data analysis is Apache Mahout and MLlib by Apache Spark. We use both frameworks for implementing clustering analysis on the GPS sensor data. For road planning or to find most crowded places in towns or common destinations, density of transport in certain time periods, and so on, the cluster result can be used. We map data saved on cluster nodes in MongoDB to HDFS.

GPS sensors give us a number of important pieces of information, including latitude, longitude, object altitude, time, and soil velocity. These dimensions are suitable for different purposes. In this analysis, we have been using GPS sensor latitude and longitude data.

Machine learning and data mining algorithms on spatial data have been used in various studies. The data size is, however, a considerable limit to the execution of such algorithms since many algorithms are computer-complex and need many resources. Big data technology can be used for very large spatial information systems (Figs. 9.8, 9.9, 9.10, 9.11 and 9.12).

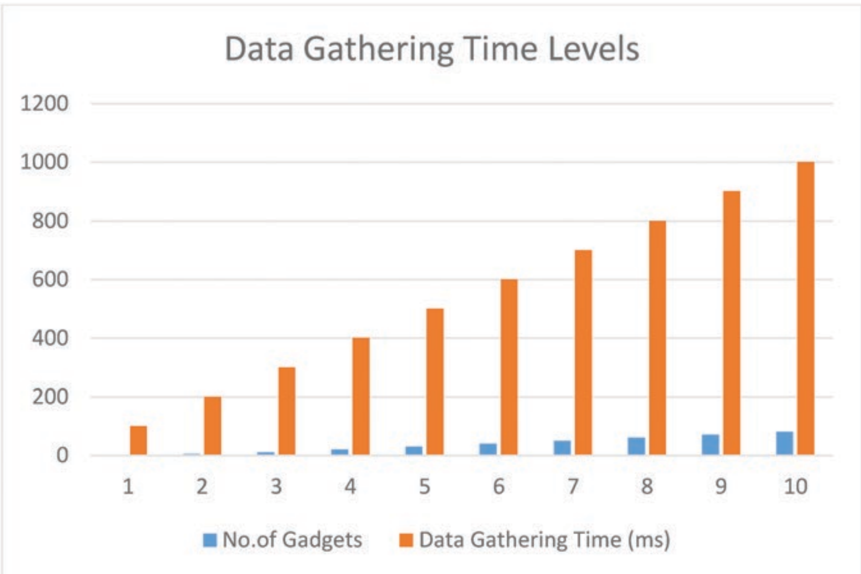


Fig. 9.8 Data gathering time levels

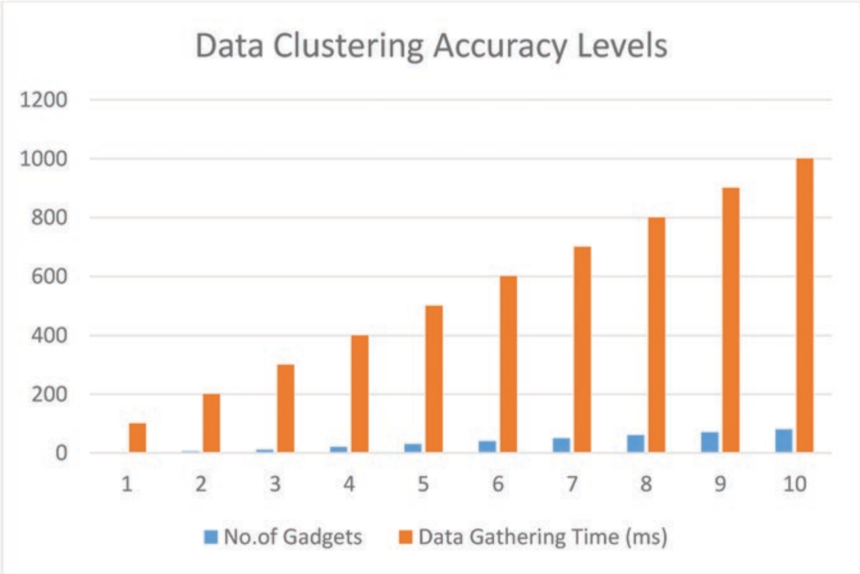


Fig. 9.9 Data clustering accuracy levels

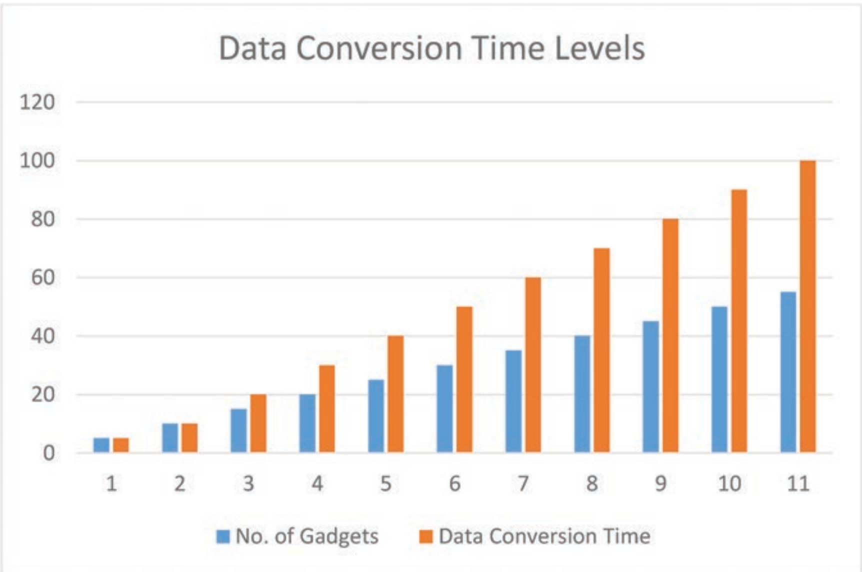


Fig. 9.10 Data conversion time levels

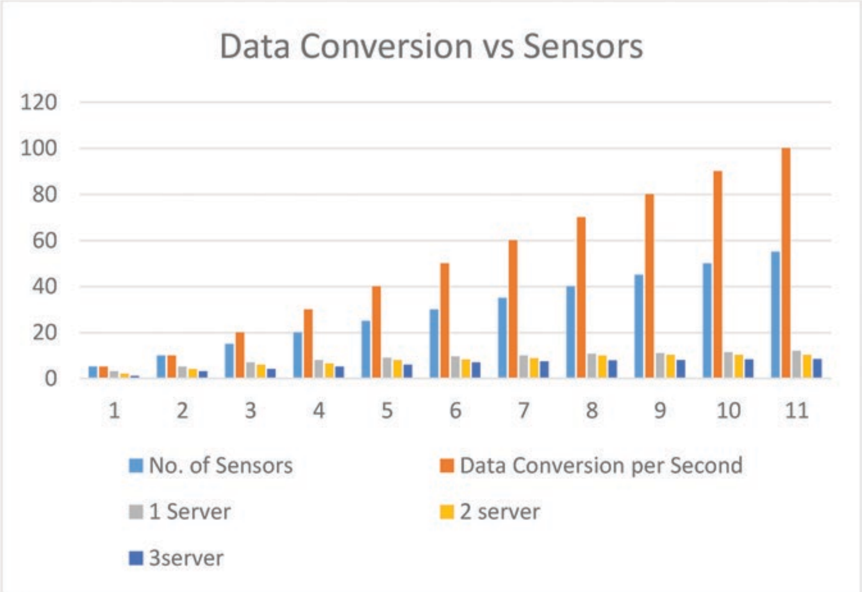


Fig. 9.11 Data gathered vs sensors

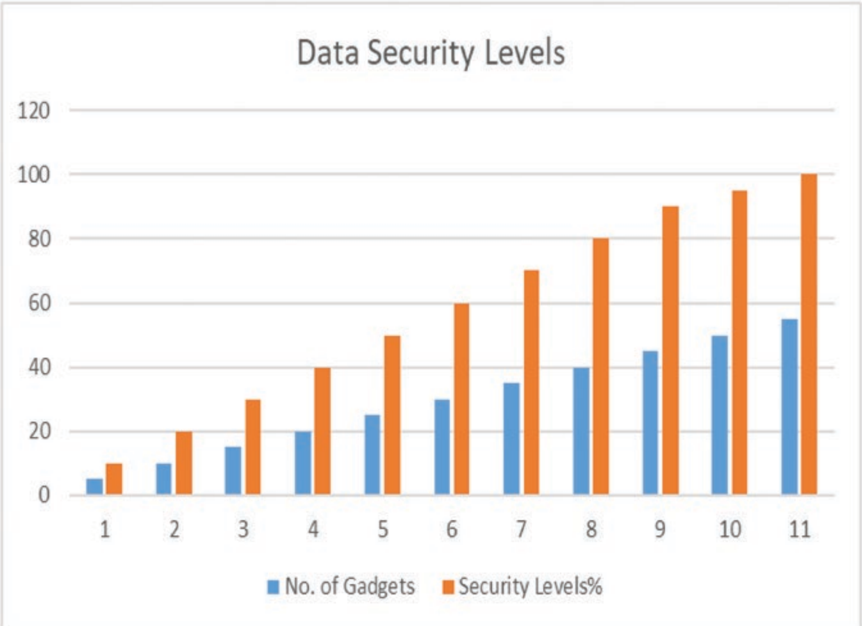


Fig. 9.12 Data security levels

9.5 Conclusion and Future Scope

We presented in this paper an architecture for scalability and delivery in real time for devices and data processing. In addition, a robotics application based on this platform was addressed. We also examined how the method can be measured with thematically oriented publishers and a distributed stream processing engine in the cloud. We evaluated the device performance and showed that low latencies can be achieved with moderate cloud hardware. It is possible to scale the architecture to accommodate multiple sensors and the huge data scale. It can be used to support distributed geographical sensors and to collect sensor data through a high-performance server. The test results demonstrate that the device can implement computer-complex data analytics and demonstrate high performance with large sensor data. We therefore demonstrate that modern cloud computing and big data applications can therefore be used with open-source technology for large-scale sensor data analysis needs. The findings also suggest that hundreds of connected devices can scale the architecture. The scalability of Kafka brokers will support applications with huge quantities of devices without strict latency requirements. The findings also show that it is possible to preserve reasonable uniform behavior, an important factor in modelling with the most difficulty, with message transmission latencies. We found that the latency of our applications is different. The processing latency with hard limits is essential in some applications. It is important to look at ways in which such assurances can be given for our applications. At the same time, we are working on our framework to develop new robotic applications. In the future, a central node authority needs to be considered for IoT data management and analyzing the data that improves the security levels.

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Chapter 10
AiIoMT: IoMT-Based System-Enabled Artificial Intelligence for Enhanced Smart Healthcare Systems

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10.1 Introduction

The emerging new trends in technologies contributed to the commencement of the Internet of Medical Things (IoMT) and are acquiring worldwide concentration as well as becoming obtainable for monitoring, diagnosing, forecasting, and preventing arising communicable ailments. The IoMT, artificial intelligence (AI), and big data are related areas in personalized healthcare that have a significant impact factor on the creation and design of a better system. The combination of AI and IoMT called AiIoMT in medical sectors is advantageous and enabled suitable controlling of diseases by using interrelated wearable sensors and networks. IoT is an evolving area of investigation within infectious disease epidemiology. However, the

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augmented dangers of communicable ailment transmitted over worldwide integration and the pervasive obtainability of smart types of machinery, including interrelatedness of the world, require its utilization for monitoring, averting, predicting, and managing transmittable viruses.

AiIoMT is an innovative way of combining healthcare gadgets and their applications to interact with the systems of human resources and data innovation. An inquiry is needed on the possible outcomes of defying progressive diseases by adopting the AiIoMT strategy when providing care to all groups of patients without any partiality in the poor and wealthy. The various cloud-based IoT administrations are the exchange of knowledge, report verification, investigation, patient monitoring, data social affair, cleanliness clinical consideration, and so on. It can change the working format of the medical services while rewarding the huge volume of patients with a prevailing degree of treatment and more fulfillment, especially during infectious disease diagnosis and monitoring. By functioning as an early warning system, IoT devices such as the geographic information system may be used as an important tool to curb the spread of these pandemics. Sensors like temperature and other signs might be used to detect people with any disease.

The IoT-based system creates a huge amount of data named big data and thereby influences the creation and growth of better-customized healthcare systems. Wearable medical devices can have active surveillance functionality that can gather a vast amount of medical data, resulting in big data, from which physicians can foresee the future condition of the patient [1]. This observational study and the extraction of information are a dynamic process that must ensure enhanced security methods [2]. The use of AI on generated big data from IoT-based system offers several opportunities for healthcare systems [3]. The application of AI in the process of generated big data can significantly improve global healthcare systems [4–6]. The IoT-based system has been used to reduce the global cost of infectious disease prevention. The IoT-based system can be used in real-time data capture to help patients during self-administration treatments. The integration of mobile apps is commons in IoMT-based sensor data capture for telemedicine and mHealth systems [7].

The data interpretation becomes easier with AI-based data analytics and decreases the time needed for data performance analysis [8]. Besides, a new system has been created, “Personalized Preventative Health Coaches.” It retains relationships and can be used to clarify and understand data on health and well-being [9]. For efficient health monitoring, the networked sensors enable people without direct access to medical facilities to be appropriately monitored [10]. The use of an AI-based system with wireless communication has helped physicians to make appropriate recommendations to patients. A thorough analysis of the IoMT framework in the medical areas has greatly helped in reducing the cost of diagnosing a patient in the healthcare system. Furthermore, the Internet of Medical Things helps in several healthcare systems like the generation of big data through the use of sensors and devices for vital physiological and biophysical parameters supervision, and big data analytics can be performing on them in other medical decision-making support methods.

The healthcare system in developing nations is fast changing as life expectancy increased considerably during the 1990s [10–13], and the infectious diseases are also having a detrimental effect on these countries' healthcare systems [14]. During the twentieth century, life expectancy has increased with almost 35%, and as a result, there is increase in the number of aged and senior citizens [11]. Also, due to lack of medical resources in developing countries, the spread of infectious diseases has created negative impact especially in the life of elderly citizens [14–16]. The healthcare has overburden due to the increase in the number of elderly patients and increase in the spread of infectious diseases in recent years; thus, this creates substantial obstacles to healthy living among the populaces. In-house telemedicine services have improved and prevented the overcrowding in hospital and reduce the capital investment from the part of the government of several nations [17].

Telemedicine platforms are quite diverse, and most are designed to address a single therapeutic goal, like in the case of mobile heart monitoring or heartbeat monitoring [18]. This has brought about cost-effectiveness in healthcare system and reduced the overburdening in our hospital in developed countries with great impact on the healthcare systems. But the systems still pose some challenges as a number of patients and infectious diseases are increasing. The IoT is capable of meeting the demand for more genericity and reliability. The IoT has improved the security and privacy of conventional medical equipment and brought about efficiency, flexible, and scalability into medical systems. The use of various sensors and devices in IoT-based systems has really help in solving the problems of overcrowding in hospital and reduced the effect of death as a result of terminal illness and infectious diseases. This also helps in the treatment and monitoring of aging population in real time and helps them avoid visiting hospital often. Hence, the combination of AI and IoT will greatly improve the healthcare system and significantly help in disease diagnosis, monitoring, predicting, and patient treatment.

10.1.1 Organization of the Chapter

Section 10.2 highlights the applications of AiIoMT in healthcare system under the following subheadings: disease diagnosis, prediction and forecasting methods, monitoring systems, and personalized treatments. Section 10.3 presents the challenges of AiIoMT based in healthcare sectors. Section 10.4 discusses the flowchart of the proposed system. Section 10.5 presents the results and discussion, and finally, Section 10.6 concluded the chapter with future work.

10.2 Applications of AiIoMT in Healthcare System

AiIoMT-based techniques are still a popular science and technology topic in space exploration, and they're spreading into other fields like industry, healthcare, and gaming. The smart healthcare system has really witness tremendous changes with the introduction of AiIoMT-based techniques in medical sectors and is very useful in dealing with real-time health monitoring, diagnosis, management of elderly patients, and classification of huge generated data. The use of AiIoMT models has increase the use of sensors and devices for detection, treatments, tracking, and the review of administrative process, thus improving clinical management of health-related issues. AiIoMT-based systems can model according to environmental conditions based on the consideration of complexities of health data and clinical procedures.

The application of AiIoMT has transformed the healthcare system. Health professionals are in desperate need of technology for decision-making to tackle the outbreak of infectious diseases and a system that allows them to get timely feedback in real time to prevent transmission of such diseases. AI works to simulate the human intellect competently, and suing the methods to enhanced IoT-based systems will be of great benefit. Also, AI with an IoT-based system plays a crucial role in interpreting and recommending the creation of a vaccine for any pandemic outbreak. This result-driven engineering is used to better scan, evaluate, forecast, and monitor current clinicians and patients expected to be future. The application of AiIoMT in any disease outbreak can expedite the diagnoses and monitoring of such illness and minimizes the burden of physicians during these processes. Therefore, this section discusses the areas of applicability of AiIoMT in enhanced smart healthcare systems.

The application of AiIoMT in the smart healthcare system has increased tremendously. This has been used to achieve a precise diagnosis accuracy and reduce the burden of healthcare experts. Also, the system reduces the time of evaluation and diagnosis associated with the conventional approach in the detection procedure. The AiIoMT techniques are seen as a major aspect in identifying the risk of infectious diseases in enhancing the forecasting and identification of potential world health threats. The continued expansion of AiIoMT for infectious disease has dramatically improved monitoring, diagnosis, analysis, forecasting, touch trailing, and medications/vaccine production process and minimized human involvement in nursing treatment.

The data science analysis using AI with IoT-based system is newly evolving, intending to empower healthcare systems to connect and harness information and convert it to usable knowledge and preferably personalized clinical decision-making. Utilizing AI, the implementation of IoT based in the field of infectious diseases has implemented a range of improvements in the modeling of knowledge generation. Big data can be interpreted, stored, and collected in healthcare through the constantly emerging field of AiIoMT models, thereby allowing the understanding, rationalization, and use of data for various reasons.

The extraction knowledge from healthcare data has been made easier with the use of human intelligence with mathematical models due to the amount of huge data generated from IoT and thanks to the AiIoMT integration. As a result, AI combined with IoT-based systems can be utilized to simulate infection occurrences at diverse scales [1]. In recent years, AiIoMT-based system has provided rapid adoption of cloud-based network hardware and software components to encourage the digitization of healthcare data for use in automated medical systems for a variety of applications. The healthcare sector is rapidly utilizing AiIoMT-based technology to improve healthcare delivery while lowering costs. The application of AI-based models has been well established in the areas of diagnosis, prediction, and monitoring, and AI combined with IoT-based systems is rapidly being utilized to influence healthcare management decisions. Figure 10.1 depicted an architecture for the AiIoMT-based system for disease diagnosis and monitoring of patients.

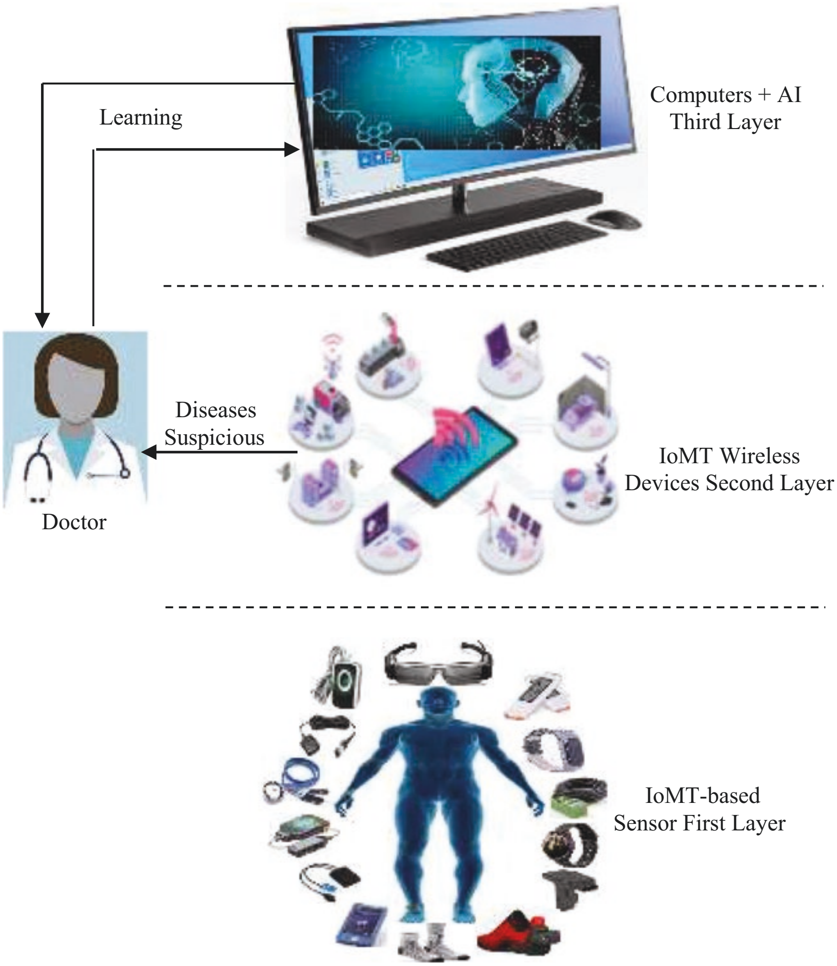


Fig. 10.1 The architecture of an AiIoMT for disease diagnosis and monitoring

The framework contains three major layers; the IoMT-based sensor layer was used to capture data and transfer the same through established channel called the gateway to the cloud database. The second layer serves as the gateway and the cloud database by collecting the capture data and storing the same on the database. The third layer is the AI and computer layer for the diagnosis and monitoring of patients. Each device can be considered to be a diagnostic system due to the way they are programmed using different machine learning techniques. The AI layer is very important and paramount to achieve a suitable diagnosis system, and physicians are to monitor the systems. The systems report any suspicious patient with disease symptoms to the related physicians' registry to use the system.

10.2.1 Disease Diagnosis

Accurate and quick diagnosis of any diseases can be useful using IoT-based devices in generating data to train AI models. The information is also imperative and important in limiting the spread of the disease and saving lives. AI may provide valuable input in making a diagnosis based on images of chest radiography. AI can be as accurate as human beings in the diagnosis of various diseases that are peculiar to a human being. It means that it can save the time that physicians deploy in the diagnosis of the disease. It also performs the diagnosis at a cheaper standard than a physician or radiologist, and it is quicker than a human. Technologies like CT and chest x-ray (CXR) can be coupled with AI to ensure the detection of the disease. Most disease test kits are very expensive and in short supply, but all hospitals have CXR machines [19]. The technology can be used in smartphones to scan CT images. Many initiatives have been deployed to help understand the conditions, such as the deep convolutional neural network (CNN) that uses CXR images to detect infectious diseases like the COVID-19 pandemic.

The main aim of IoT is to make the environment smarter by providing the requisite historical or real-world data and automatically applying AI to make smart decisions. Several forms of research have been documented in current contributions and are capable of enabling early detection and prognosis based on different techniques [20, 21]. AI typically consists of several methods, such as help vector machine, decision tree, and artificial neural network. The evaluation of the information is varied by each method [22, 23]. IoT devices use lung cancer knowledge to understand and control complex environments, facilitating great automation, greater performance and accuracy, wealth creation, productivity, and better decision-making [24]. The timely processing of huge quantities of data to produce highly steady and reliable analyses and recommendations so that IoT can fulfill its promise is a serious obstacle in these conditions.

Numerous illnesses, such as hypertension, glaucoma, and pulmonary disease, must be evaluated and monitored on a regular basis in the hospital. The conventional medical system demands patients to book an appointment with medical doctors for a medical evaluation. This creates problems for several patients due to the problems of going and coming back that characterized the traditional healthcare system of seeing a physician. IoT-based systems will remove the problems since patient did not need to see the physician physically before they are attended to. This will help in reducing the number of patients that visit the hospital for just seeing a physician. For instance, the problems of hypertension or elevated blood pressure can be managed in real time using IoT-based sensors and devices; with this, the patient can monitor their health conditions without going to hospital to see any physician. In many applications, IoT has increasingly begun to emerge and improve; nevertheless, IoT-based system is still restricted in several medical areas [25].

Patients benefit from emergency response, real-time ambulances, and vehicles provided by emergency services. They presented a system that uses sensors to detect and send distinct body health information in the event of a patient emergency. This information is only used for health surveillance and emergency response. Furthermore, no specific ailment is mentioned. Neyja et al. [26] proposed a cardiovascular disease surveillance approach. An ECG monitor is used to send heart rate data to the hospital. They proposed an algorithm that is only activated in the event of an abnormal situation, allowing medical personnel to respond quickly.

Gia et al. [27] suggested a glucose monitoring platform based on IoT technologies. A sensor interface, a gateway (smartphone), and a cloud back-end system make up their suggested system architecture. Doctors can track patients using an application or a web browser on this device at any time and from anywhere. At the gateway, notification systems are introduced to alert doctors and patients only in the event of an emergency. In addition, their proposed method limits its measurements to glucose monitoring only. Li et al. [28] suggested a tracking device for heart disease using IoT. The sensing layer, the transport layer, and the application layer make up the device's architecture. Sensors keep track of the patient's blood pressure, ECG, SpO_2, heart rate, pulse rate, blood sugar, blood glucose, and location. They divided the transmitting data procedure into two sub-processes, the first of which employed Bluetooth. The second method employs wired cellular and internet infrastructure, as well as four separate data transfer types, and also introduced a prototype.

Besides, for atrial fibrillation identification, mobile cardiac telemetry systems are important. For the prolonged duration of heart rhythm, these systems conduct real-time monitoring and lead to the detection of an arrhythmia. Also, medical wearables and AI can be used through remote patient monitoring to establish effective methods for diagnosing heart disease [29]. Symptoms of heart disease can be detected by a machine learning system (MLS) by reviewing scan data from recent patients and by analyzing previous data. Besides, MLS will estimate the probability of a potential occurrence of a heart attack. Researchers investigated the use of AI and ECG at the Mayo Clinic. MLS has been used to measure electrocardiography and classify pulmonary vascular immunocompromised dysfunction (PVID). A coevolutionary neural network was run by these researchers. The study shows that CNN uses ECG data to identify ejection fraction by 35% for ventricular dysfunction patients [30]. The findings demonstrate that AI-based model on ECG data is a low-cost method for detecting ALVD in asymptomatic people.

In the IoMT sense, AI framework is able to enhance sensor data for disease detection and medical research. The use of cluster analysis and differential private data clustering (EDPDCS) has been used to accomplished data classification based on MapReduce architecture [31], using k-means model to analyze the normalized intra-cluster variance (NICV). Even, with grasshopper optimization, there is an effective hybrid Neural Network (NN) method that has major influence on optimization problems, particularly for versatile and adaptive results for ML search mechanisms [31]. This method has been successful applied in the classification of Parkinson disease, heart-related disease, diabetes, and breast cancer.

Another initiative from March 2020 that uses an AI model to diagnose COVID-19 deploys CXR images and has been used in the past to diagnose pulmonary tuberculosis (TB). The potential has not yet been implemented in clinical practice settings, but several hospitals in China have used radiology technologies based on AI. Other radiologists have expressed concerns over the amount of data available to train AI models. Many hospitals in China are bound to suffer from selection bias because using CXR and CT scans can contaminate equipment and result in the increased spread of the disease [32]. The use of such scans in European hospitals was reduced significantly after the pandemic broke to reflect the concern. Once an individual has been diagnosed with the condition, the fear intensifies, and it may affect the patronage of the hospital. However, the point remains that ML algorithms can develop prognostic prediction models that predict mortality risks of infected individuals. They can provide more than 80% accuracy concerning an individual who has been infected and determine if he or she can develop acute respiratory distress syndrome.

10.2.2 Prediction and Forecasting Method

Prediction is a data exploration approach that uses an impenetrable simple mathematical data classification approach for a novel evaluation. To discover a statistical result, this word can also be used. The teaching dataset, analogous to classification, comprises the contributions as well as their corresponding statistical output values [37]. The replica or predictor is taken from the system, and the replica will discover an arithmetical result until new data is discovered, as stated in the planning dataset. Unlike categorization, this process does not have set features and predicts the outcomes of the systemic value of an unbroken value, and regression is always used for the prediction [36]. An example of a forecast is the house's value based on a few facts, such as the number of rooms and total area. Another instance is an organization that discovers the total currency spent by the customer during purchases [38].

Prediction is the method of learning about the future or uncertain occurrence from historical data to make predictions. In healthcare systems, the predictive analytics resulted to a reliable decision-making, enabling the result to be customized based on each patient peculiarity [37]. The medical scientist would assist in seeing an improvement in patient access, reduced costs, increased income, increased usage of assets, and also enhanced patient experience when the prediction is made correctly in healthcare. Predictive analytics, on a larger scale, aimed to combine what doctors had been doing with the ability to make sense of previously unknowable data. The methods were introduced to produce a better measurement with a quantitative and psychosocial data, and biometric data is with the most improvements introduced by predictive analytics, so the wheel is not reinvented [15, 39]. Individual treatment can be tailored to each person, allowing the finest healthcare decisions to be made. Predictive healthcare science's goal is to reliably forecast the unexpected data for a better result that caused good policymaking. The form of the question asked with a high certainty of reaction is influenced by confidence in predictions. A historical query such as "what did I eat today?" can, for example, be answered with a high degree of confidence.

The use of data analytics in medical sciences helps to improve organizational quality, planning, and execution of crucial healthcare delivery and also resource use, medical processes, personnel schedules, and patient intake and aftercare. These has resulted to better utilization of medical equipment and cost-effectiveness that result to a better patient experience. The model is a subset of simultaneous analytics that combines two or more types of AI approaches. The main goal of predictive model is to use a multivariate array of predictors to forecast events, repercussions, or occurrences [13, 16]. The models were also utilized in healthcare to examine patient lifestyles, characteristics, psychographic segmentation, and interests, which medical scientists may then use to develop conclusions that are beneficial to both patients and clinicians, and can be distributed through various channels.

AI can be used in managing any disease especially infectious diseases through the deployment of thermal imaging. The technology is useful in scanning public spaces for specific individuals who have the potential to be infected. It is then valuable to enforce lockdown and social distancing measures. Infrared cameras are used in train stations and airports across China to scan individuals for high temperatures. They were also deployed in facial recognition to pinpoint individuals with high temperatures. Baidu is one of the producers of infrared cameras that use computer vision in scanning different individuals in the crowds [40]. The camera can scan 200 individuals every minute and recognize body temperature that exceeds 370 °C. However, thermal imaging has been inadequate in identifying a fever in individuals wearing glasses because the most reliable indication was the deployment of scanning of the inner tear duct. It was also hard to determine if a person's temperature was increased due to any disease/outbreak or other sources.

As noted earlier, AI is useful in predicting and diagnosing diseases, but it is hampered due to the lack of historical data. However, robots and computer vision cannot be hindered by such limitations. This type of AI will be useful for social control. Related technologies like mobile phones with wearables and applications that have AI can help locate and control whole populations. In line with this, Barstugan et al. [41] did research to determine the effectiveness of social distancing in Europe which was conducted by the application of the AL concept to determine the impact of social distancing on the spread of COVID-19. The very first and basic action that was taken against the coronavirus was social distancing so that the virus may not spread more rapidly or maybe to control the virus. Although social distance measures may be awkward to normal social norms and some medic-patient interactions, it was still adopted because the condition is becoming a matter of life and death.

Apart from social control, AI can be useful for predicting and tracking individuals with infectious diseases. The development follows a previous pandemic called the 2015 Zika virus whereby AI helps in developing a dynamic neural network to understand the spread of the disease. Such models can be used with data from any pandemic, but they require retraining. The lack of unbiased and historical data to train AI models and the different characteristics of COVID-19 compared to previous epidemics and panic behavior on social media may result in the lack of a model to predict and track COVID-19 [41]. The continued spread of the infection has resulted in the subsequent increase of traffic on social media, making it hard to determine the prevalence of the disease. One of the best ways to deal with the algorithm dynamics and the avalanche of big data is the deployment of content moderation on social media platforms. Most of the current models are not yet reliable and accurate, which means that several models to track and forecast infectious diseases do not deploy AI models. Instead, the population uses susceptible infected and recovered models, such as an epidemic tracker, to predict the disease's spread. AI can be useful in reflecting success measures that can slow down or reduce the range of any pandemic. They can further evaluate how scientists and governments are flattening the epidemiological curve of infectious disease.

To regulate the dosage intakes by patients in monitoring disease progress, illnesses like diabetes, heart failure, hypertension, and blood pressure are monitored and controlled by IoMT-based system using wearable device setup for clinical monitoring. For all procedures, the physician serves as the central access. In order to determine the patient's health conditions, the network nodes are linked to the cloud database where records and future forecasts are accessed. This remote tracking helps reduce the cost of management of infrastructure, human resources, etc. The encryption methods are used to guarantee the security and privacy of the transfer and sensitive information stored on the cloud database.

IoMT-based systems are particularly useful, efficient, and precise in regulating the battery life cycle and energy of resource-constrained tiny wearable devices while monitoring diseases and fitness programs, and medical data has to be stored in the cloud for real-time analysis. K-means clustering under several privacy-related methodologies was suggested to confront the privacy budget and select the centroids for initialization. The number of iterations can be calculated using methods that denote fixed and unfixed iterations using an upgraded k-means algorithm. The mean square error between the noisy and true centroids is calculated during the selection phase to determine the budget allocation and iterations. Random collection and fair division of datasets are often done to compensate for the uncertainty in the production of the datasets instead of selecting a method for allocations. Okay techniques were developed to improve the initial centroid selection for the k-means algorithm by dividing each subgroup by the original dataset. The distributed architecture has been designed to lower the execution time of ensemble analytical convergence efficiency. MapReduce can be used to do distributed activities by growing the parallel k-means algorithm, which is more efficient than sequential programming and is based on periodic revision of nearest centroids.

A higher level of IoT-based system invention for disease prediction has been achieved through illness diagnosis and examination. The knowledge given by IoMT devices is rising in lockstep with the growth of the technologies in the research community; data analytics have to be used to analyze the datasets. Without any class label, clustering can be used to analyze huge data without loss of any paramount data in the process. There is a strong probability of leakage of the data, which includes privacy information, in case of problems. While there are some privacy-preserving strategies, there are still various loopholes to be plugged using algorithms for privacy protection, such as k-anonymity, diversity, and differential privacy. The trade-off between delivering good accuracy and preserving privacy must be digested to get the desired result [33–35].

There are major ongoing attempts to enhance human health programs, where IoT technologies have achieved considerable success as part of AI techniques. However, it is still important to further explore the awareness and application of these fundamental processes, the IoT application, concerning healthcare practices. The science of behavioral analysis aimed at avoiding health issues of people such as mild cognitive impairment (MCI) and frailty is an important endeavor attributed to the AI paradigm [12, 35]. The use of advanced AI-inclined technologies therefore allows discrete collection of personal data for automated identification of behavioral changes for accurate and efficient prediction of healthcare. This improves behavioral healthcare processes and improves patients' customized healthcare, especially for the prevention of heart disease. As described in the preceding section, several AI techniques have been investigated. Success stories have been developed from the implementation of AI methods to enhance the accuracy of classification models and ultimately improve the efficiency of healthcare systems in disease prediction. More needs to be done, however, to test disease prediction systems based on multiple evaluation metrics, because the use of a single evaluation metric, such as the accuracy of model classification, does not guarantee optimum system efficiency.

Computational intelligence requires historical data for calculation, and healthcare systems generate this data, which can be leveraged to create knowledgeable primary care. The frameworks used may be in form of customized models with IoT as the basis for their operations. Various sources of medical data collecting, as well as the potential of such data to grow rapidly, necessitate high-processing capacity and performance resources and systems. Big data analytics and cloud-based frameworks as artificial intelligence approaches are thus appropriate for processing and handling medical data. Another important reason for computer intelligence's widespread adoption is that it is capable of copying and mimicking expert competence and so augmenting human specialists' abilities and minimizing the risk of clinical diagnosis and disease control errors.

10.2.3 Monitoring System

New emerging technologies, particularly the IoT, are increasingly being employed in remote health monitoring, treatment, and therapy in today's telemedicine. With an emphasis on building smart apps, this has gained significant popularity in the healthcare sector. In addition, the IoMT provides a platform for devices and sensors to communicate seamlessly in a smart environment, allowing for easy data and information transmission over the Internet. As the IoT has become more widely employed in remote health monitoring, it has gained rapid adoption in the healthcare industry, with a focus on developing smart applications. The IoT provides a platform for devices and sensors to interact seamlessly in a smart environment, allowing for easy data and information transmission through the Internet. Several wireless equipment positions have been modernized. IoT-based technology is sophisticated because it takes advantage of all the possibilities that digital technology has to offer.

The IoT-based system has gained ground especially in healthcare sectors in recent years. The IoT reshapes contemporary healthcare systems, changing the traditional ways for the medical system to a smart healthcare system. The conventional healthcare systems have gradually moved to smart healthcare systems where patients' diagnosis, monitoring, and treatments are becoming easier and effortless. With several technologies in healthcare systems, wearable body sensor networks have changed our ways of life and dramatically modified our lifestyle. The combination of wireless sensors with simulation and intelligent systems has resulted in the development of an ambient intelligence, thus helping to reduce the challenges encounter on a daily basis [3].

The IoT-based system with AI could be used to help patients get proper medical care at home when applied during any epidemic, and the healthcare policymakers and the government can make use of the robust database created for infectious disease outbreak management. Monitoring and healthcare devices such as thermometers, smart helmet, smart wristwatch, medications, protective masks, and monitoring infection kits may be purchased for people with moderate symptoms. Periodically, the health status of patients can be upload over the Internet-based IoT network to the clinical cloud storage, and their data could be forwarded to the nearest clinics or health center hospitals and the Centers for Disease Control (CDC).

Subsequently, a medical expert will provide online health consultations based on the health status of each patient, and if necessary, the policymakers and healthcare experts assign facilities and designate quarantine stations to the affected person. People may dynamically monitor their clinical diagnosis and obtain adequate medical needs using the IoT platform with AI without virus transmission to others. Hence, by minimizing the costs, alleviating the shortages of medical equipment, and providing a systemic database that could be used by physicians to track the spread of infectious diseases effectively, the supplies of relative tools become easier and enforce emergency strategies.

For example, the current COVID-19 pandemic we are fighting is increasingly suffocating the healthcare sector toward its ending levels; the hospitals and clinics are filled with reported suspected cases pending the evidence of the diagnosis. As the demands are rising, the shortage of medical diagnostic equipment and supplies is increasing, and the increase in patients that need care without adequate tools complements the upward increase in admitted patients in the hospital and places mission-critical healthcare staff at higher risk on the front lines. To mitigate this crisis, a powerful and supportive medical system is needed to save the lives of the populace.

A more robust medical framework for the fight against the COVI-19 pandemic is needed. An IoT-based system is needed to alleviate the diagnostic and monitoring problems, and this will help in enforcing stay-at-home protocols and limiting the clinical resources required. This will support the appropriate distribution of equipment and supplies by the government and private donors to clinics and various hospitals, and the approach would provide information on healthcare facilities to establish effective patient care. To save countless lives, this combined strategy can be very helpful and also safeguard strained economies and build a blueprint to tackle future threats more effectively.

IoT is an innovative way of combining healthcare gadgets and their applications to interact with human resources. The adoption of an IoT-based system with AI during the infectious outbreak provided equal rights for both rich and the poor populace in having equal access to healthcare facilities without any form of preference. Various cloud-based AiIoMT technique managements are the exchange of knowledge, report verification, investigation, diagnosis, treatment, and patient monitoring among other services provided by the system. This creates rewards to various patients with a prevailing treatment and diagnosis that are more fulfilling and creates a new working system of medical services, particularly during this outbreak. The use of an IoT-based system gives health workers full concentration on the patient by easily identifying an infected person and those that have contact with them and moving them to an isolation center. The tools provided by IoT devices can be used to curb the spread of the outbreak, such tools could be an early warning system like the geographic information system and wearable sensors embedded within the human body. Sensors like temperature and other signs might be used at airports around the world to detect people infected with any diseases.

For instance, over a two–three-day period of ongoing physiological monitoring of patients, IoT-based devices are used to recommend physiological exercises and food habits. IoT devices will continuously observe and store the health data of the patient in a cloud database during this period [42]. This allows doctors to diagnose the health condition of the patient and not only use laboratory tests but also patient health data obtained from IoT-based sensors to achieve better results. Sensor data is also most commonly used to take effective action for the recommendation of patient well-being and care, lifestyle decisions, and early diagnosis, which are important for improving the quality of patient health. Conventional computer storage approaches and mechanisms are not of enough in the areas where the volume, speed, and variety of data are increasing in above-described emerging IoT-based applications. The development of an efficient storage system for storing and processing voluminous data needs to solve this problem.

10.2.4 Personalized Treatment

Personalized care has been a remarkable field in smart healthcare systems that includes the processing and application of big data. The use of AI and data science plays prominent role in the development in this field of medical science, and the use of statistical analysis gives accurate results, especially in recent years when big data with AI-enabled technologies has been incorporated in medical devices for the process of huge data generated from IoMT-based system. The use of AI-based models and big data analytics has been used in personalized medicine for healthcare diagnosis, monitoring, and treatments of patients. For instance, the use of AI models and big data has been for complex forecasts in personalized treatment, and the result gives more accurate results and also validated clinical trials [43].

The clinical sector is divided into five key areas: first, IoT-based devices with unique integration in personalized medicine; second, the modern technology in individualized medicine; third, the treatment approaches in stratified medicine; fourth, the use of big data with segmented medicine; and, lastly, the classification from targeted the therapies. Scientists, therefore, have to function and interpret vast quantities of data that require high-level precision that enhances strategy analysis and incorporation. The combination of new high-quality big data technologies helps in generating huge amount of data, and bid data analytics has been used to provide useful interpretation. There are many possibilities in the use of AI-based models in customized healthcare, especially for data scientist and statistical analyst [44]. New approaches to advance this medical area are created by the use of AI techniques in customized medications. Together, AiIoMT techniques enable doctors to access, capture, store, and enhance the statistical analysis of the condition of patients. Based on the use of deep neural networks (DNN) [45], it suggested DeepSurv system for Cox proportional hazards analyses and survival method. The programs have customized care recommendations and built a mathematical model for the efficacy of patients' treatments.

Different experiences have been raised by the application of modern innovation for patient care, especially for patients who require greater precision during diagnosis and treatment. IoT-based monitoring systems have therefore been developed, providing high real-time efficiency. There is a healthcare monitoring model based on the intelligent IoT system, like BioSenHealth 1.0 [46]. Using thingspeak.com, this device is used to generate data and send data capture to the doctor in real time using flatforms. The prototype was used to track body temperature, heart rate, and pulse rate of patients with real-time data quantitative models and generate interactive graphs.

The truth is that Alzheimer's disease, which requires regular evaluation, is a complicated diagnosis. This method was made simpler and relaxed by IoT-based system. To track Alzheimer's disease conditions, Khan et al. [47] developed a hybrid feature vector for IoT-based capture data, and statistical analysis was used for data analysis and a three-dimensional model that resulted to a full image of the state of the patients. The testing findings reveal an average of 99.2% and 99.02% for binary and multi-class classifications when employing this novel approach. The 5G-Smart Diabetes customized care system [48] was developed based on Diabetes 1.0 and Diabetes 2.0. It combines big data approaches, wearable 2.0 technologies, and machine learning algorithms. The 5G-Smart Diabetes device is designed for diabetic patients and uses data from analytical sensors to anticipate diabetes progression.

10.3 Challenges of AiIoMT-Based System in Healthcare Industries

This section describes some of the challenges faced upon implementation of IoT-based AI models for the diagnosis, personalized treatment, prediction, and monitoring of diseases. The key objective of prediction and classification models is to build a good decision support system for domain experts.

The major cause for the shortage of standard disease datasets is that the disease may be relatively new and exclusion of data over different geographic regions. The deployment of AI models for the classification and prediction of the disease needs a vast volume of data. Also, the small sample available could be poorly biased. Consequently, developing models to analyze this small sample size is one of the main challenges in the classification and prediction of diseases. One of the solutions suggested is the use of textual descriptors to extract radiomic features from CXR and CTs.

Also, obtaining more disease data will give precise prediction in the number of deaths and infections as most ML and DL models are highly accurate with a vast amount of data [49]. The daily occurrences of many infectious diseases like COVID-19 incidences are modeled as time series problems. Modeling time series problem is one of the challenges of data mining model techniques [50]. The deployment of ML and DL methods such as Long Short-Term Memory (LSTM) and Support Vector Machine (SVM) can model the problem as a multiple time series problem simultaneously and also forecast as multistep output. ML and DL method models can forecast the daily occurrences as a simultaneous joint model of multiple target fields (cases) simultaneously to capture dependencies between them.

The COVID-19 pandemic belongs to the family of pneumonia disease which is one of its main complications. The hierarchy of pneumonia infection by different organisms is viruses, bacteria, or fungi [51], and COVID-19 cannot be regarded as a single disease or binary classification but rather as a group of different infections with different characteristics [52]. The challenge is that COVID-19 and pneumonia diseases have similar symptoms, hence the overlapping of disease symptoms. This is a class imbalance problem where one class has an extremely high number of a sample size than the other class. The problem is compounded when allied with class overlap and disjoints. This problem will cause the sub-optimal performance of models for classification [53]. This situation can be alienated using class imbalance schemes to form clear clusters for the classes, hence improving classification.

To be fully accepted clinical treatment, AI will achieve a set of high requirements to meet the demands of both patients and doctors. AI-based models have shown level of superiority when compared to other algorithms, but there is still some level of inaccuracy especially with there is limited data available for modeling. Thus, this method is not and never flawless, and this can lead to large, negative impressions [54]. Any AI-enabled system error, no matter how minor, would have a significant negative influence on any medical matter [54]; therefore, an appropriate amount of control and monitoring is critical when implementing AI into clinical practice. The cost-effectiveness of AI-based clinical efficacy must also be assessed [54, 55]. Huge investments in AI were made, analogous to robotic surgery, with the expectation of cost productivity and cost savings. However, the evidence of AI-based models reduces the expenses related to data storage, design, data curation, and maintenance and remains unproved by the researchers. The resources need to reduce expenses can be used to replace the present expenses that can successfully reduce medical prices [54, 55].

AiIoMT approaches continued to reveal the following issues in the disease outbreak system. Security is one of the healthcare issues that must be addressed promptly since it is widely accepted that security is a general challenge in various industries [55, 56]. In Europe, for instance, the patient data cannot leave the country, and researchers and most hospitals need to source for data to be used for any meaningful results from public medical database cloud. This makes it almost impossible to get huge amount of data to model AI-based systems in medical industries [56]. For instance, the latest outbreak of COVID-19 has brought the difficulty of securing personal data to a head in a transnational sense [57]. This is because COVID-19 spreads quickly as a result of persons traveling internationally [58]. The governments of various nations demanded their overseas travelers to reveal personal information, travel history, purpose of trip, and residence, among other things, and impose quarantine restrictions as a result of the outbreaks [59].

Using a genuine case where Chinese media secretly published the sensitive information of a foreign traveler, the study describes that multiple patterns for lex causae that emerged at each point of dispute-of-law analysis: (1) the EU, the United States, and China vary in characterizing the right to personal data; (2) the expanding centralized approach to relevant legislation lies in the fact that all three territories either find the law on personal information privacy to be a contractual law or follow linking factors leading to the law of the forum and (3) actively support the de-Americanization of meaningful data privacy legislation. The patterns and their mechanisms have important consequences in the application of regulations for transnational information [57]. In many cases, medical researchers find it easier to use standard application techniques to model clinical data than the complex AI-based models. The Global Data Protection Regulation (GDPR) rules, which were implemented in May 2018, will result in various new regulations that must be followed and that are not always apparent [60].

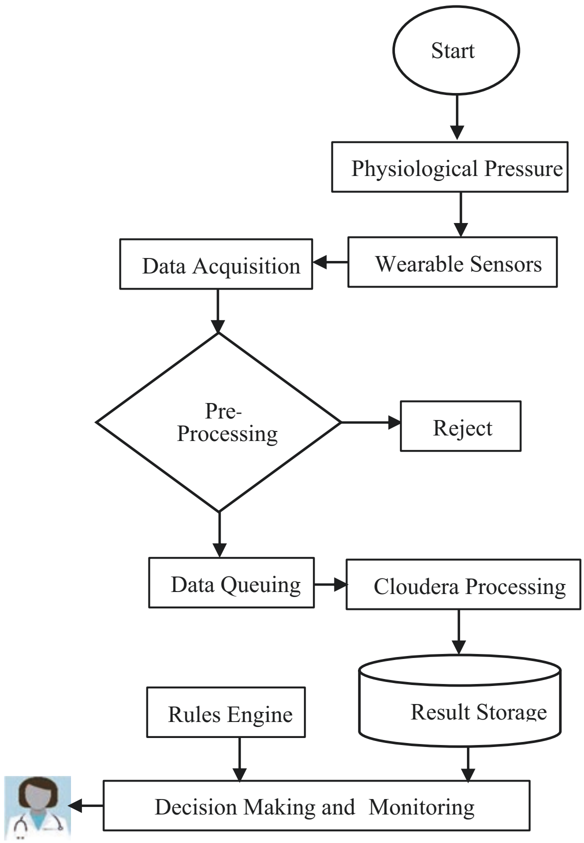
10.4 The Flowchart of the Proposed System

Three layers made up of the architecture of the AiIoMT-based system were discussed as follows.

The objective of the framework is divided into three: (i) the data capture using IoT sensors and devices from the patients that was represented by the IoT-based sensor layers, (ii) the IoT wireless devices with the gateway for the proposed system, and (iii) the decision management layer using the AI-based model after the data capture and transmitted to the cloud database for final processing. The IoT-based sensor layer was used to capture patient physiological characteristics using diverse human body sensors, stored in IoMT-based cloud database, and the Cloudera platform was used for the processing of the stored data on the cloud database based on the MapReduce instrument. Figure 10.2 displayed the flowchart of the framework.

The physiological result is acquired utilizing wearable sensors planted in the human body, and these sensors were attached to the human body. The data was collected using a data-gathering device from several sensors. To design a resourceful framework and filter the data for preprocessing by transforming, aggregating, and cleaning, the data is carefully studied and reviewed.

Fig. 10.2 Flowchart for the AiIoMT-based framework



The cloud database was used to store and hold the data generated and data extraction for data analytics, ingestion, visualization, and patient monitoring control in real time. Lastly, for decision-making and management, the AI-based model was used to process the data, and rules are used to notify the physicians, medical experts, and users. Big data is incorporated into the framework to be able to realize the analytics into smart health monitoring. This was done to provide real-time decision-making to improve the data processing efficacy.

10.4.1 The Machine Learning XGBoost Classifier

Chen and Guestrin [61] popularized XGBoost, a machine learning classifier that is both effective and scalable. The gradient enhances the decision tree first to result in an XGBoost classifier, which associations many decision trees in a boosting manner. Each new tree is created in order to lower the gradient boosting of the prior model's residual. Residual describes the differences between the real and expected values. The template has been trained until the quantity of decision trees defines the threshold. XGBoost follows the same notion of gradient boosting; to manage overfitting and enhance efficiency, it employs the quantity of spikes, training rate, subsampling ratio, and maximum tree depth that are all variables to consider. Specifically, XGBoost optimizes the function goal, tree size, and scale of the weights, all of which are governed by typical variables for normalization. With many hyper-parameters, the XGBoost provides greater efficiency in a specific search space.

Gamma $\gamma \epsilon (\theta,+\infty)$ denotes minimal loss reduction, which includes a split to render the partition on a tree's leaf node, according to the hyper-parameters. The minimum child weight $w_{mc} \epsilon (\theta,+\infty)$ is defined as the minimum instance weight overall, implying that if the graph division stage yields a tree structure with the instance weight sum less than w_{mc}, the further partition will be discarded by the tree. The early stop algorithm works to find the optimum number of epochs that correspond to other hyper-parameters given. Finally, subsampling methods and $r_c \epsilon (0, 1)$ column subsample ratio concepts were also provided by XGBoost in each tree. In the final step, to minimize the classification error, grid search is used to control the hyper-parameters.

Given $X \epsilon R^{n \times d}$ as training dataset with d features and n samples, XGBoost object function in $t - th$ is represented by the following:

$$Obj^{(t)} \simeq \sum_{i-1}^{n} \left\{ \ell\left(y_i, \tilde{y}_i^{(t-1)}\right) + g_i f_t\left(x_i\right) + \frac{1}{2} h_i f_t^2\left(x_i\right) \right\} + \Omega\left(f_t\right), \tag{10.1}$$

$$g_i = \partial_{\tilde{y}(t-1)} \ell\left(y_i, \tilde{y}_i^{(t-1)}\right), h_i = \partial_{\tilde{y}(t-1)}^2 \ell\left(y_i, \tilde{y}_i^{(t-1)}\right), \tag{10.2}$$

where the loss function ℓ is represented by the first gradient g_i, and h_i is the second gradient of ℓ. To measure the complexity of the model, the regularization $\Omega\left(f_t\right) = \gamma T + \frac{1}{2}\varphi\varphi^2$ was used, where the number of leaf nodes is represented by T.

As demonstrated in Eq. (10.3), the logistic loss ℓ of the training loss measures how well the model fits on the training data:

$$\ell\left(y_i, \tilde{y}_i^{(t-1)}\right) = y_i \ln\left(1 + e^{-\tilde{y}_i}\right) + \left(1 - y_i\right)\ln\left(1 + e^{\tilde{y}_i}\right) \tag{10.3}$$

Given the $t - th$ training sample $x_i \in R^d$ and assuming that a XGBoost model of XGB contains K trees, the corresponding prediction y_i is computed as follows:

$$\tilde{y}_i = \sum_{k=1}^{k} F_k\left(x_i\right) \tag{10.4}$$

$$s.t. F_k \in XGB, where\ XGB = \left\{F_1, F_2, F_3, \ldots, F_K\right\}. \tag{10.5}$$

R programming language was used to implement the proposed classifier, and the evaluations were done using various performance metrics. The dataset with the relevant activity monitoring recognition was used seamlessly to incorporate all characteristics.

10.4.2 Dataset Used

The proposed AiIoMT-based system was evaluated on 400 cytology images provided in Peshawar, Pakistan, by Lady Reading Hospital's pathology department. The dataset was used due to a shortage of available data and dataset on the breast cancer images and for the correctness of the proposed system.

10.5 Results and Discussion

The confusion matrix is used to examine the classifier's quality assessment. True positive (TP) represents malignant cell cases that are accurately identified as positive (malignant) in the confusion matrix, whereas false positive (FP) represents nonmalignant cell cases that are incorrectly classified as positive (malignant) called type 1 error. True negative (TN) denotes nonmalignant cell cases that are correctly categorized as negative (nonmalignant), while false negative (FN) denotes malignant cell cases that are incorrectly classified as negative (nonmalignant), also known as type 2 error.

Table 10.1 shows the results obtained from the proposed model using the performance evaluation, where the total number of cells in the image is represented by n = 29,000. The performance of the classifier was measure using factors like sensitivity, precision, F-score, specificity, and accuracy (Fig. 10.3).

Tools like big data, 5G communication, IoT, machine learning (ML) cloud infrastructure, artificial intelligence (AI), and blockchain play a crucial role in helping the world to protect and improve people and societies differently. The healthcare experts would continue to face crucial obstacles to incorporate and appreciate these optimized solutions and their advantages findings carry out elaborate regard to risk management, resources, cost, scope, and quality. Along with mobile device platforms that rely on automated hospital control services that use automated surgical technologies (e.g., ultrasound, MRI, endoscopes, electrocardiograms) and computerized patient information systems (e.g., Picture Archiving and Communication System (PACS), Organized System of Care (OSC), and Electronic Medical Record (EMR), smart healthcare technology platforms have been created.

In recent years, the deployment of the AIoMT has provided various dimensionalities in healthcare through online services. These have offered a new atmosphere for millions of individuals to learn about fresh healthcare ideas on a regular basis in order to live a healthy existence. The usage of AIoMT technology and related

Table 10.1 Proposed method evaluation

Dataset	Accuracy	Precision	Sensitivity	F-score	Specificity	Class
Images	99.7%	98.4%	99.2%	98.9%	98.9%	Benign
	100%	99.8%	99.6%	96.7%	99.8%	Malignant
Total	99.85%	99.10%	99.40%	97.80%	99.35	

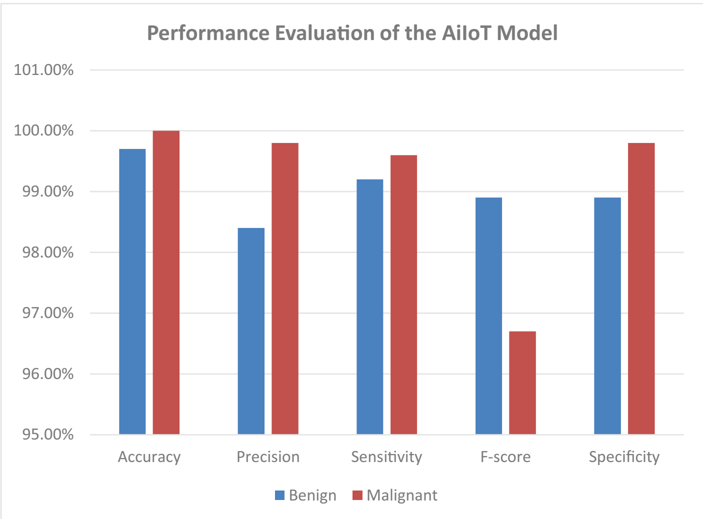


Fig. 10.3 The performance evaluation of the proposed model

devices in medical fields has grown [61–62]. It is easier to have a big number of less powerful devices, such as a wristband, air conditioner, umbrella, and fridge, than it is to have a small number of powerful computer devices, such as a laptop, tablet, or phone, thanks to the Internet of Things.

As such, geographic borders have been overcame by the smart healthcare industry and transformed into digital hospitals aimed at comprehensive patient care and the quality of high-level medical services. Different Information and Communication Technology (ICT), medical, and big data innovations are developing different services in the smart healthcare field in conjunction with wearable medical device-based AI technology, as the paradigm of patient care is moving from hospital-based therapy to customer prevention. For instance, the quantified movements used to track and retain daily personal health information, including the volume of blood glucose, heart rate, electrocardiogram, and nutritional information collected by wearable sensors or healthcare apps, have been distributed. Also, the smart healthcare industry is widening its deployment to telemedicine, mobile wellness, Electronic Health Record (HER)/EMR/Personal Health Record (PHR), cellular medical facilities, and targeted therapy through a mix of IoT technologies.

The IoT-based system with AI healthcare system has become one of the most indispensable parts of human lives; this has dramatically increased the medical information system that brings about big data. Healthcare practitioners are already adopting wearable devices based on the IoT to streamline the diagnosis, monitoring, prediction, and treatment process. The healthcare system that depends on IoT assists the individuals and aids their vital everyday life activities. Cloud computing technology has been used to handle the huge amount of data generated by IoT devices called “big data” and becomes easy to access and use. The major role played by cloud-based applications with IoT-based system can never be overlooked globally. For secured storage and easy accessibility, cloud computing can be used in medical applications. When these two innovations are combined, AiIoMT supports each other in an equal manner. The tracking system is built by integrating these two technologies to accurately track patient records, including at a remote location, that is useful to doctors. In terms of high resource usage, storage, resources, and computational capacity, IoT technology is often supported by AI to boost performance.

Machine learning and cognitive algorithms have experienced advances recently and, hence, have been used to solve many complex problems. The ML showed an outstanding performance in clairvoyance to perform accurate object recognition and in a difficult assignment that requires humanlike intelligence and outperforming the traditional based techniques. AI is ideal for the situation where no rules for performing a task are defined; instead, the rules are learned from the actual data. ML can identify and use secret structures in the data to make intelligent decisions. Big data is the core component of the AI techniques’ high performance. A huge amount of knowledge is produced by the different number of sensors in the IoT-based system, which makes it possible to integrate these cognitive skills into the IoT. It will automate the processing and interpretation of the data. This leads to more efficient and smart solutions for healthcare professionals that can save lives and time.

For continuous health tracking, AiIoMT can be implemented to enhance the well-being of patients, make the healthcare system more effective, and help respond quickly to crises. The AiIoMT can be employed to enhance the well-being of patients, make the medical system more effective, and help respond quickly to emergencies. Hence, it is possible to take advantage of the latest technical arsenal to build a new wave of smart healthcare cities that would be able to forecast widespread disease occurrences more accurately, supporting their claim. It's not quick and apparent, and, as cities become more and more integrated, many problems will still arise. Nevertheless, the negative effects of the widespread diseases can give this process the requisite boost.

Given their increasing capabilities, deep neural networks (DNN) have done badly in healthcare. The technologies are still in their infancy, and the resources required to support them are also in their infancy, with few professionals capable of dealing with the massive amounts of data and software engineering issues. In particular, in medicine, AI solutions are sometimes hampered by data shortages and poor quality. As new data is obtained, predictive models will need to be reinstructed and keeping an eye on changes in data creation methods. The data added to train the predictive model are rarely disclosed for special reason, and this reduces the data dependencies that are needed in the model for it to be able to function efficiently [55, 56, 60].

10.6 Conclusion and Future Directions

The use of modern technologies in healthcare systems has really solve global health challenges with equal access to medical services by both the poor and rich. The increases in the emergency of infectious diseases and rise in medical costs have really reduced the effectiveness of healthcare systems in developing nations. Thanks to the growth of intelligent and modern equipment, there is substantial improvement in data creation in medical sectors. The application of IoT-based systems has helped patients in receiving proper treatment in real time and created a social forum in assisting individuals. The system also creates robust repository for the government and healthcare organizations on various disease control and management. The huge data generated by IoT-based systems facilitates the use of AiIoMT for diagnosis and monitoring. The use of capture data for patient symptoms from various devices like thermometers, wearable sensors, and embedded devices can be for personalized disease infection diagnosis, monitoring, and management. The IoT and AI interaction is currently at a phase where high-frequency dispensation, storage, and analysis of massive amounts of data are required. Therefore, this chapter presents the essential principles of IoMT-based system-enabled AI-based system in medical systems. The opportunities, expectations, and challenges of using IoMT-based system-enabled AI models were also reviewed, which focused on AI technology with an emphasis on IoMT-based systems. The lack of huge data from medical fields is one of the hindrance of using AI-based models with IoMT system. The findings showed that security and privacy of patients' data are of the some major problems of using IoMT-based system-enabled AI models in healthcare systems. Oher challenges of using IoMT-based system-enabled AI models are interoperability, confidentiality, and resource management. There is an urgent need to address these problems in order to fully enjoy the benefits of AI models in IoMT-based systems. Future research will focus on the security and privacy of IoMT-based system using AI models. Also, there are pressing issues related to AiIoMT in disease diagnosis and treatment; while progress has been made in the study of the IoT-based healthcare system in customized e-healthcare, operational issues still need to be addressed. Therefore, in this case, an intelligent security model should be thoroughly investigated in order to reduce the identified risks.

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