Chapter 6
Body Sensor Networks as Emerging Trends of Technology in Health Care System: Challenges and Future

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6.1 Introduction

In today's express, digital world Information Technology is dominating every field including healthcare industry [1]. The information technologies have the potential to impact various fields such as genome analysis, medical science, and public health. The emerging field of health informatics and its associated practices offers new opportunities and it is very promising approach [2]. Storing patient's records in an electronic format has significant advantages and offers improved and affordable health care facilities [3]. The current technological developments in the healthcare can be attributed to creation of Artificial intelligence (AI), Bigdata, Internet of things (IoT), Blockchain, and Cloud-based Technology [4].

Healthcare is such a vast ecosystem and digital transformations start from personal healthcare, pharma industry, medical insurances to real-time healthcare monitoring, and healthcare building amenities. Applications of IoT in use of robotics, biosensors, smart beds, smart pills, and the various healthcare specialties are never-ending. As, the emerging healthcare sectors are producing hefty volumes of data on patient history, pathological reports, treatment planning, bills and insurance coverage, demographics – drawing the attention of clinicians and researchers towards progressive information technology.

Therefore, this chapter discusses the overview of health informatics approaches which are entwined with techniques such as AI, block chain, cloud computing, big data, and Internet of things (IoT). The next section will focus on significant role of these technologies in healthcare. It will also highlight the implementation of technologies in current pandemic outbreak, i.e., COVID-19. Further, this chapter will

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present the emerging role of bioinformatics in healthcare system. A major hurdle in adopting healthcare informatics is the hesitation associated with patient's data privacy and security. Hence, the last section emphasizes the need to recognize the advantages and challenges of implementing health informatics globally.

6.2 Technologies in Healthcare

The emerging information technologies shaping-up future of healthcare by implementing technologies such as AI, big data, block chain, IoT, machine learning, and deep learning (Fig. 6.1). Artificial Intelligence is an approach of enabling a computer system or software to think like an intelligent human being. Intelligence is defined as the capability of a system to perform tasks such as calculations, reasoning, perceiving relationships and analogies, learn from experiences, storing and retrieving data based on memory, solving problems, comprehending complex ideologies, employing natural language processes fluently and classifying, generalizing, and adapting to new states [5]. Due to its diverse nature, AI is exploited by biologists across the globe to solve complex biological problems by applying algorithms to massive biological data obtained after experimental studies [6]. From bioimaging, signal detection, sequencing analysis, protein structure folding to molecular modeling for drug discovery artificial intelligence improve the practices of computational biology to yield cheaper yet accurate solutions [7]. This chapter mainly discusses the basic aspects of the data science in public health sector. Further, it will provide an insight into the various dimensions, recent developments, and the future prospects. Machine learning (ML) is a part of AI whereas deep learning is a particular technique in machine learning. ML is considered a sub-set of Artificial Intelligence (AI), in other words it is an implementation of AI.

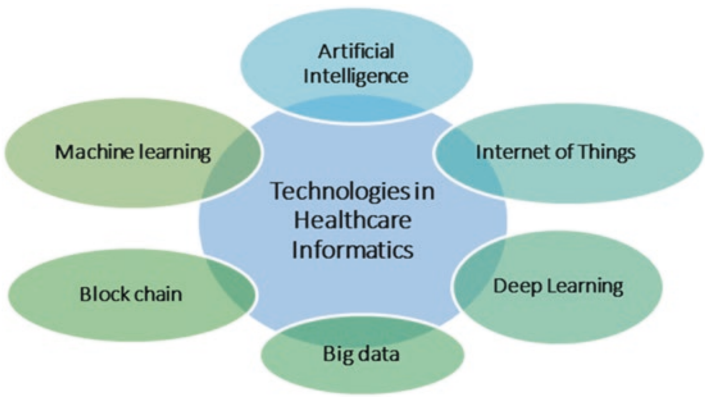


Fig. 6.1 Schematic Representation of Health informatics Components

Learning basically refers to the process of acquiring a specific skill or knowledge during a study or experience. Machine learning is an application of computer sciences, which allows a computer system to learn a specific piece of data and develop itself from this study without the need of explicit programming [8]. One can infer from this process that machine learning operates in two steps namely the training phase and testing phase [9]. A model is defined with some parameters present in a data pool where the system learns the parameters based on their relationships and inherent properties in the training phase. This model is tested on a new dataset to predict the learnt outcomes [10]. The ultimate goal of the model is to make generalized yet accurate predictions in the future, or descriptive to gain knowledge from new and large datasets, or both [11, 12].

Deep Learning is a branch of machine learning that takes inspiration from the structure and functioning of the human brain called artificial neural networks. Neural networks mimic the neuronal circuit in human brain; therefore, deep learning is a type of imitation of human brain [13]. It learns high-level abstractions and transformations in datasets by exploiting hierarchical architectures of input data thereby reducing the need for preprocessing [14]. Deep learning can be applied to modeling complex linear and nonlinear applications, moreover, they have multiple implementations especially in the field of pattern recognition for bioinformatics, medical image analysis, maintenance of healthcare data, and for drug discovery (Table 6.1) [22].

Major applications of Deep Learning in clinical imaging analyses are divided into six main groups (Fig. 6.2):

(i) Classification which involves the identification of specific features in an image;
(ii) Detection, involves locating these picked features;
(iii) Segmentation process in other words is to fragment an image into multiple chunks;
(iv) Reconstruction is the process of rebuilding the features into their original conditions;
(v) Registration is the procedure of integrating two different images into one;
(vi) Dose estimation, which is the process of estimating the right dose quantity of a substance [23].

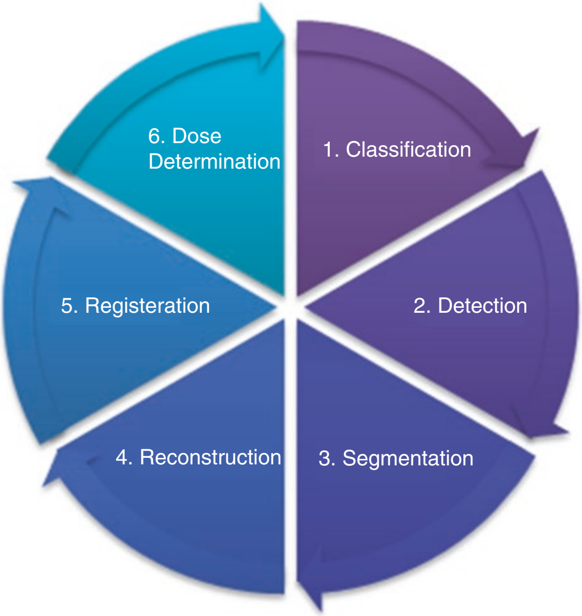
Deep Learning classification models have been extensively exploited in oncology research and clinical studies for detecting tumor type (Benign, malignant or equivocal), tumor stratification, and grading. The abstraction and exploration of quantitative features from medical imaging datasets can help in developing a better understanding of tumor characteristics, including lesion grade and staging, potentially may allow avoiding biopsies. Lesion segmentation is an important ML application in medical imaging for automatic tumor segmentation that supports planning for radiotherapy treatments. Convolutional Neural Networks (CNNs) have proved to be the most effective neural networks in image segmentation in case of gliomas, breast cancers, prostate cancer, and lung cancers [24, 25]. According to the WHO, Cardiovascular diseases are the number 1 cause of the mortality globally therefore placing paramount focus on early detection of cardiovascular diseases. Deep learn-

Table 6.1 Tools based on Deep learning for Biological Analysis

Name of Application	Description
DeepBind	DeepBind specificities can be visualized in the form of weight-based position matrices or mutation maps which specify how variations alter binding with sequence of interest [15].
CellProfiler	Identifies and measures different biological entities in images. The applications demonstrated in the study referred are counting yeast colonies and their classification, annotating cell microarrays, yeast patch assay, tumor quantification in mice, and measuring tissue topology dimensions [16].
TITER	Translation Initiation siTE detectoR is a deep learning tool aimed at predicting translation initiation sites using sequencing data. TITER identifies vital sequence signatures [17].
DeepCpG	A DNN-based computing tool that determines methylation states in single cells and detects variable sites for DNA methylation. It takes advantage of the relationship between sequence pattern and their state of DNA methylation along with the nearby CpG regions, taking into account both inter and intra cellular sites [18].
Deep-CRISPR	Deep-CRISPR is based on a hybrid deep neural network. It can be used in different Cas9 Species for single-guide RNA on-target identification and efficacy prediction and also overcomes off-target binding [19].
DeepLOC	DeepLOC uses RNN framework to process the query protein sequence and identify sites using attention mechanisms for the subcellular localization [20].
LncADeep	LncADeep is markov model-based tool for identifying and functional annotation of long noncoding RNA which uses KEGG and Reactome databases for enriching the model. For functional annotation, lncRNA's interacting proteins are predicted using deep learning networks based on sequence and structure information [21].

ing algorithms play a crucial role in rapid and efficient in analyzing images produced by diagnostic procedures such as cardiac ultrasound, angiography, and magnetic resonance imaging, and computed tomography. The analysis includes detecting edges, texture features, morphological sieving, along with the construction of shape models and template matching algorithms. Several Classification studies on angiography images and echocardiography videos to predict the onset of coronary artery disease, plaque formation, and valve calcification using Multilayer Perceptrons, Convolutional neural network or Fusion neural networks that combine the spatial and temporal data obtained by echocardiography signals. A major limitation of existing Deep Learning techniques is the use of single sets of medical imaging data, those crucial parameters like genetic factors other relevant clinical constraints. Therefore, Radiologists initially refer to nonimaging information, such as clinical history, to help diagnose the disease in people. For radiologists, it is time consuming to identify sub-anatomic structures within medical images and perform measurements in order to attain quantification for the image-based diagnosis. However, advancement in deep learning allows accurate segmentation of 3D aCNNimages (Left Ventricle, Right Ventricle, and myocardium) to estimate cardiac parameters such as cardiac ejection fraction, volume, and mass by segmentation methods [26].

Fig. 6.2 Tasks in Deep Learning



Next to cardiology, Neurology is perhaps one of the medical fields in which clinical images are extensively used both for research purposes in relation to the brain development, monitoring, and for diagnostic procedures linked to neurological disorders. CNN-based neurological models have achieved a high level of accuracy in relation to the prevention of Alzheimer's disease. In multiple sclerosis imaging, both the white and gray matter are affected, so normalization methods that depend on the brain tissue may introduce bias or remove biological changes of interest [27].

Big Data is used to define data with colossal volume or complications which cannot be handled by traditional data processing techniques. First and foremost is the volume of data that is growing rapidly in the biomedical informatics fields. The second feature is the diversity in data types and structures. The third distinctive feature of big data is velocity, refers to generating and handling data [28]. Big Data setup is a framework, which entails significant components including Hadoop (hadoop.apache.org), massively parallel processing, NoSQL databases that are used for Big Data storage, processing, and analysis [29]. Hadoop is a big data analysis platform that is highly effective for processing biologically pertinent data sizes, when we consider computing hours for both split and un-split datasets. Apache Hadoop has Packages like Cloudburst, MapReduce, Eoulsan, Crossbow, Contrail, Myrna, DistMap, and Seal that can accomplish several NGS applications, such as quality checking, de novo assembly, adapter trimming, read mapping, quantification, variant analysis, expression analysis, and annotation [30]. While debate is still on for the actual definition and limitations of Big Data and its advantages of healthcare, Big Data has been proven itself in three key aspects of healthcare- first prevention of diseases, identifying amendable risk factors in disease, and drug discovery for changing health behaviors [31].

Blockchain technology is being posited as the next frontier in healthcare sector. It is a distributed network containing public ledgers, recording transactions, and asset monitoring [32]. This technology is believed to bring significant progress in medical records management and insurance claims, aid clinical investigations and biomedical researches and progress biomedical and health care data ledgers [33]. This approach facilitates the switch from institution driven interoperability to patient-centered interoperability [34].

The basic idea behind Internet of Things is the linking of smart objects or things to Internet in a transparent manner. This allows exchanging information between all components, and conveys it to the user securely [35]. IoT-supported gadgets assist remote monitoring in the healthcare industry and enhanced patient involvement and gratification due to easy and effective communication with physicians and are commonly called as Internet of Healthcare Things (IoHT) or Internet of Medical Things (IoMT) [36].

Earlier in traditional healthcare systems, information management was paper based and later it was substituted by the Healthcare Information System (HIS). However, the HIS also seemed ineffective because of numerous concerns such as data storage volume, system integration, high expenses of operating, and system maintenance [37]. Cloud computing is a progressive and affordable approach that enables real-time data collection, data storage, and give-and-take amongst healthcare organizations. Cloud network is equipped with high-throughput and high-volume storage capacity. While conducting data computing on high population of patient's data, privacy and security are the aspects to be considered. Both are major concerns for adopting cloud-based healthcare facilities. Therefore, healthcare organizations must have electronic medical records in order to utilize the cloud networks [38].

6.3 Significant Role of Technologies in Health Care

The innovations of the digital world have revolutionized the healthcare system to attain sustainability goals by balancing the link healthcare experts and patients thereby yielding rapid, affordable, and efficacious treatments for all diseases. In healthcare, technology is progressively playing a significant part in practically all the procedures, from patient registration to record keeping, from pathology reports to personal care policies [39].

6.3.1 Artificial Intelligence (AI)

The advent of Artificial intelligence is at par with healthcare professionals and aids them to make accurate medical choices or even substitute human decisions in active zones of healthcare such as radiology. It has also shown significant potential in the healthcare marketing. AI utilization in the healthcare business is estimated to boom by 40% annually reaching a target of $6.6 Billion by 2021. Artificial Intelligence algorithms process various types of clinical data that include Diagnostic Imaging, Sequencing, Microarray, Electrodiagnosis, Monitoring, Mass screening, and Disability Evaluation [40]. AI has various applications in health informatics such as automate reminders, identifying people at high risk, and delivering personalized dosage recommendations. Google's DeepMind created an AI-based application for breast cancer analysis. The algorithm outperformed all human radiologists on pre-selected data sets to identify breast cancer, on average by 11.5% [41].

6.3.2 Blockchain and Data Security

Blockchain claims to redefine the fundamental operational strategies of colossal sectors – including digital healthcare marketing. Blockchain provides a safe yet branched database which operates without a dominant authority or proprietor. To promote legitimacy and transparency of healthcare information based on pre-existing data, from monitoring authorizations in electronic health records (EHR) to rationalizing claim and complaint processes. Data Security and privacy is one of the top priorities in the Blockchain developers [42]. A successful example of this is MedRec, a collaborative blockchain project of MIT Media Labs and Beth Israel Deaconess Medical Center. This system provides a decentralized style to manage consents, authorization, and data sharing amongst healthcare organizations. This project enables patients to monitor who can access their personal healthcare records. A key feature is that patient consents, data storage location, and audit logs are pooled on a blockchain to generate an automated method to share data for clinical and research practice, without actually storing the data in the blockchain. The healthcare information stays within EHR systems and requires additional softwares to allow interoperability [43].

6.3.3 Voice Search

Voice is the most recent target of healthcare market promotion strategies that has been on the ascent since the release of android phones and smart-speakers (with Amazon's Echo and Google Home). About 46% of adults in US households use voice assistants at home and the number is only anticipated to increase in the coming years. It is arguably one of the most compelling devices in the market today. Voice assistants are improving patient care by growing efficacy and offering a novel experience by providing a plethora of benefits. Patients can access medical records, check and deliberate healthcare-related issues, and communicate using this service. This is especially helpful for the elderly patients [44]. Hossain et al. proposed a cloud-based smart healthcare nursing system called Voice pathology detection (VPD) method which takes input as voices and an electroglottograph signal. This input instrument is linked to the Internet so that caught signals are transferred to the cloud which are further processed and categorized as normal or pathological with a confidence score. The outcome is then sent to Physicians who make the final decision and take suitable action [45].

6.3.4 Healthcare Trackers

Fitbit and jawbone have become our new fitness trainers. For people looking to improve their health, wearable fitness tracking gadgets provide an easy and real-time approach monitors one's health and to motivate them towards leading a healthy disease-free lifestyle that is driven by personal data-based understanding which is offered by such devices [46]. However multiple factors including interpersonal effect, personal creativity, individual's efficacy, attitude towards a wearable fitness tracker, well-being, and assumed cost of the device affect an individual's acceptance towards these trackers [47].

6.3.5 Chatbots

A chatbot offers users with a text-based conversation like the ones usually used on messaging applications, including SMS, social network systems, and web-based applications. Compared to the communicability of traditional interfaces, chatbots in healthcare provide a plethora of advantages and the prospect for improving patient medical record management, clinical management, aid in emergency situations, or with first aid. A major aspect of User experience is the interface that links a user and the service. In an effort to improve the human-computer interaction, engineers constantly come up with new technologies. Conversational interfaces are aimed to let users to communicate or to chat with bots by means of voice (voicebot) or text (chatbot) [48]. HOLMeS stands for Health On-Line Medical Suggestions, a medical recommendation system developed to autonomously contact with the user by understanding natural language in a chat and substituting a human physician. It is made of diverse components to deliver numerous innovative eHealth services through an instinctive chat service [49].

6.3.6 Virtual Reality (VR)

Virtual reality (VR) is improving the lives of patients and physicians alike. In the next few decades, we might watch surgeries as if we used the surgical blade on an organ or one could visit the picture-perfect Swiss Alps simply lying on their hospital bed. VR is a great tool with unrivalled engagement. VR also provides an immersive view where patients can get a virtual tour of the hospital and often helps them to cope with pain. VR is being used to train future doctors for actually carrying out surgeries. Such softwares are developed and provided by companies like Osso VR and ImmersiveTouch and are in active use with promising results. Women are being equipped with VR headsets to visualize soothing landscapes so as to help them get through labor pain. VR has been in use to reduce pain associated with surgeries, cardiac, neurological, and gastric problems in patients by distracting them from the stimulus of pain [50, 51].

6.3.7 Augmented Reality (AR)

Augmented reality varies from VR in two aspects: Here the users are in touch with reality throughout the experience and it adds information to the eyesight rapidly. These unique features have made augmented reality powerful component of future medicine; both on the healthcare experts and the patient's perspective. Using this method, medical students have access to detail and accurate, albeit virtual, and depictions of the human anatomy to study the subject without the need of real bodies [47]. Luo et al. describe the head-mounted display visualization which helps visually impaired patients instead of physicians. They utilized an optically transparent system to superimpose contour images from a camera connected for normal vision. The system was developed to assist patients with tunnel vision, mending their visual search practice [52, 53].

6.3.8 Internet of Medical Things (IoMT)

Internet of Medical Things (IoMT) plays a significant part in healthcare market to improve the accuracy, dependability, and efficiency of electronic instruments used for providing medical support to patients. Researchers from different parts of the world are coming together to develop a digitized healthcare system which links the accessible medical assets and healthcare facilities [54]. Georges Matar et al. offered a method to check patient posture by utilizing their body weight which applies pressure on specifically designed mattress; he used this measured pressure for monitoring patient posture. He validated this study using Cohen's Coefficient, where the value of the coefficient was 0.866 indicating high accuracy of prediction. According to him, the aim of this project was to cut down storage requirements along with computational costs [55].

6.3.9 Digitization of Healthcare Records

Electronic medical records or Electronic health records (HER) have created immense strides in the concentration and effectiveness of patient clinical data, it also finds use in population studies bringing in a huge cultural swing in the upcoming decades of data-driven medicine. Multiple data elements are collected in Electronic health records: daily charts, medical administration, physical assessments, on-admission nursing notes, healthcare plan, referrals, existing conditions or symptoms, medical history, life style, physical examinations, diagnosis, tests, medical procedures, treatments, medications, discharge, journals, findings, and immunization [56]. Raj Kumar et al. designed a representation of patients' complete raw EHR records on the basis of Fast Healthcare Interoperability Resources (FHIR) format. Further, this data is used with deep learning models for effectively forecasting multiple medical events from many centers without the need of integrating site-specific data [58]. Successful management of EHRs will offer key advantages just not only for patient's safety and quality of health care services but also make healthcare amenities more affordable [57].

6.3.10 Telemedicine/Telehealth

Studies reliably show the advantages of telehealth, particularly in rural areas whose access to resource are limited compared to main cities. Additionally, telemedicine centers will likewise lessen organization maintenance expenses by disposing the requirement of leaving work to go to a primary healthcare facility. Several medical labs use android devices connected to affordable telehealth equipment's, such as blood glucose monitors and electrocardiogram device [58]. Telemedicine offers clinical services linked to information technology, video imaging, and telecommunication connections to allow doctors to deliver healthcare services at a distance [59]. Teleradiology and telepsychiatry were among the earliest telemedicine applications [60]. Compared to telemedicine, which is specifically defined as the provision of medical services at a distance by a physician, telehealth is a canopy that encompasses telemedicine and a variety of nonphysician facilities, including telenursing and telepharmacy [61]. The main aim of telehealth application is to ease the burden on health care system and providing good healthcare facilities based on long-term follow-up for diagnostics and mediation strategies [62]. A few concerning clinical demerits of telehealth are poor standards of patient- physician relationships, physical examinations, and healthcare with remote appointments than physical meetings and abuse complaints [63, 64].

6.3.11 mHealth/Mobile Health

M-health provides an easy solution for an issue commonly overlooked in the clinical field: how to get to the correct data when and where it is required in highly dynamic and branched heath care systems [65]. M-health is liberating medical gadgets of wires and cords and permitting doctors and patients alike to check on medical practices on the go. Androids phones enable healthcare experts to easily access and send information. Doctors and healthcare providers can use mHealth applications for orders, documentation and just to gather adequate information when with patients. Huang et al. present WE-Care, a smart tele-1cardiological system that provides mhealth facilities in the form of wearables and mobile 7-lead ECG equipment. This application reduces the feedback time by distributing the detection process between mobile phone and the linked server so that diagnostic ability of ECG device can be utilized. The algorithm is designed to identify the aberrations in the ECG records and produces warnings if required; doctors get access to the alerts and ECG data further utilized conduct detailed analysis at the application end [64]. A randomized clinical study of a mHealth application aimed for weight loss and HbA1c reduction in Type 2 Diabetes Mellitus patients showed promising results [65]. This way mHealth changes the manner in which healthcare systems were perceived.

6.3.12 Portal Technology

Patients are gradually becoming dynamic players in their own healthcare; definition has almost shifted to personal care, and portal technology is a powerful tool in achieving these goals. Additionally, medical information accessibility is also increasing. The US portable healthcare recording systems employ a database which stores the details of the patients that can be accessed by the physicians and patients. Each patient is allotted a card with unique id and password to access this information. A doctor who is handling a particular patient's case can review and update their clinical data [66]. A different kind of application of portable technology is the use of portal UV disinfectants that prevent patients against infections acquired in the hospital environment that can be caused by pathogenic microbes such as *Clostridium difficile,* vancomycin-resistant *Enterococcus,* and methicillin-resistant *Staphylococcus aureus* [67].

6.3.13 Self-Service Kiosks

The self-service kiosk is an explicit type of Self Service Technology employed in healthcare facilities. They are generally installed on large touch screen panels or small monitors and keypad combos. (GG) Self-service kiosks can accelerate procedures like hospital registration. Patients can effectively do all procedures linked to registration in a hassle-free manner without the need to communicate with whole lot of administration. This allows cost cutting on staffs. Automated kiosks can help patients with payments, id verification, documentation, and other registration requirements [68]. Yet, Healthcare systems should be thoughtful while integrating it to make sure human to human communication is not entirely eradicated. If a person needs to communicate to the authorities, they should be able to allow such provisions. Lyu et al. designed self-service physiology-based kiosk that combines multiple biosensors and medical devices to take up user's physiological parameters such as plasma glucose, heart pulsing rate, blood oxygen, height, and weight. These measurements are vital to understand user's health condition. This system was designed with the aim to improve Human Machine Interactions and to calculate measurements accurately [69].

6.3.14 Remote Monitoring Tools

Monitoring patients' health at home can decrease costs and needless appointments to clinics. For heart patients, a cardiac cast with a pacemaker regularly transmits data to a monitoring center. So in case of emergencies, the physicians can be immediately informed and reached out for help. This technology is very helpful for people suffering with chronic disorders. Several studies have shown that remote monitoring tools have been successful in reducing emergency department or urgent hospital visits especially for patients suffering from cardiovascular diseases with implantable [70, 71].

6.3.15 Nanotechnology

Nanoparticles and nanodevices function as mini surgeons employing specialized drug delivery systems for complex diseases like cancer, Alzheimer's as a treatment tool. In 2014, researchers from the Max Planck Institute designed scallop-like microbot designed to literally swim through bodily fluids. Small, smart pills like the PillCam are already in use for colon exams in a noninvasive, patient-friendly way. In 2018, MIT researchers created an electronic pill that can be controlled wirelessly and transmit diagnostic data or drug release mediated by android phone instructions. At CES 2020, France-based Company called Grapheal demonstrated its smart patch that allows continuous monitoring of wounds and its graphene core can even stimulate wound healing. Nanotechnology has numerous applications in the field of medical science that include bioimaging, sensing, synthetic grafts, and target-specific delivery of genes, drugs, and bioactives [72].

6.3.16 Robotics

Robotics is one of the rapidly emerging and sensational technologies in healthcare. The innovations in this field are cutting-edge from robotic carts that moves equipment's at hospital to super-smart surgeon robots, pharmabots. The year 2019 was a great year for exoskeletons. It saw Europe's first exoskeleton-aided surgery and a tetraplegic man capable of controlling an exoskeleton with his brain. There are loads of other applications for these sci-fi suits from aiding nurses through lift elderly patients to helping patients with spinal cord injury. Robot companions also have their place in healthcare to help alleviate loneliness, treat mental health issues, or even help children with chronic illness. The Jibo, da Vinci Pepper, Xenex Germ-Zapping Robot, Paro, and Buddy robots are successful instances of robotics in healthcare and personal care. These robots have cameras, special sensors, and mics to communicate with its owner. For instance, ikki from an Australian startup is helping children with chronic illnesses monitor their medications, temperature, and breathing rate while keeping them company with music and stories. Another example is Cyberknife, a robotic surgery system developed in 1990s that carries out radiation therapy on tumors with supreme precision and is now being used in hospitals to treat patients with surgically complicated cancers [73].

6.3.17 3D-Printing

AI is a game changer in healthcare because when AI combined with three-dimensional (3D) printing technologies, it could increase the performance by reducing the risk of error and facilitating automated production. Nowadays, 3D printing has become an essential and potentially transformative approach to revolutionize health care rapidly. 3D-printing can bring wonders in all aspects of healthcare such as biotissues, artificial limbs, pills, and blood vessels. In November 2019, scientists at the Rensselaer Polytechnic Institute in New York developed a method to 3-Dimensional print living skin along with blood vessels. This development proves crucial for skin grafts for burn victims. Also, helping patients in need are NGOs like Refugee Open Ware and Not Impossible which 3D-print prosthetics for refugees from war-torn areas. The pharmaceutical industry is also benefiting from this technology. FDA-approved 3D-printed drugs have been a reality since 2015 and researchers are now working on 3D-printing polypills. These contain several layers of drugs so as to help patients adhere to their therapeutic plan [74].

6.3.18 Sensors and Wearable Technology

Wearable medical instruments and biosensors are efficient tools for collecting patient health information. Wearable electronic technologies integrate an electronic device into clothing, accessories, human skin, or implanted in vivo and detect biological components which are further used for body sensing, data storing, and mobile computing [75]. The advent of microelectromechanical systems has led to the development of miniaturized wearables that can be used for a range of applications [76]. A sensor can be as simple as device that sends alert to healthcare providers when the patient falls from the bed or pH bandages that can measure the skin pH and identify whether the cut or wound is infected. A wearable technology developed by Roy et al. assists in carrying out sweat analysis by measuring Na+ ion concentration using a polyvinyl chloride doped with ionophore and ion exchanger on Carbon Nanotube electrodes. Sweat Analysis is essential as its contents are biomarkers for a various disease like osteoporosis, hyponatremia, drug abuse, and cystic fibrosis [77]. One of the most developed biosensors are glucometers that have evolved from finger-prick-based blood glucose sensors to noninvasive glucometer that simply require a press of the finger on the sensing device (example: DiaMonTech, Cnoga), employs a nonperceptible electric current across the skin to extract a small quantity of analyte-glucose into a blotch positioned on the skin. These biosensors are being designed to provide astonishing features like voice readout for visually impaired patients, glucose pens that can be easily carried in the patient's pockets, and glucose sensors linked to mobile applications such as DiabetesPal, Dlife, and MyGlucoseBuddy. Table 6.2 shows the other types of sensors and their properties.

6.3.19 Wireless Communication

It is only recent that instant messaging system is being employed in hospitals instead of pagers and beeping devices. Vocera Messaging offers users to send posts like lab tests and alert signals to others using smartphones, web-based servers, or third-party clinical networks. These messaging systems can speed up the communication processes while still tracing and sorting information in a secure approach. Wireless-equipped healthcare systems can distantly and constantly observe the patients' health condition in both domestic and outdoor settings, so that the patient does not feel constricted to stay at a place. Timely finding of patients' emergency states based on wireless communications enables provision of timely first-aid and access to patients' health data in a ubiquitous method, thus refining both systems dependability and productivity [78]. CareNet is an Integrated Wireless Sensor Networking Environment for Remote Healthcare that provides dependable and secure information transfer between patients' homes and the healthcare providers [79]. Several healthcare companies such as TactioHealth sync with the modern fitness trackers like Bodymedia

Table 6.2 Common sensors used in healthcare

Type of sensor	Measurable Quantity	Functionality of sensor	Market products
Thermometer	Body temperature (°C, °F, or °K)	Measures patient's temperature at different body parts including oral, temporal, tympanic, and rectal	Pipercare, leelvis infrared, Clinitemp plastic strip thermometer
Glucometer	Plasma glucose Levels (mg/dL)	Glucometers are extensively used by diabetic patients to monitor glycemic variability.	Accu-Check lancing device, One touch Select Strips, Dr. Morepengluco One
Blood Pressure Sensor	Systolic, diastolic, and mean arterial pressure (mmHg)	Blood pressure sensors are used by patients with cardiovascular conditions	Omron Blood Pressure Monitor, BMP barometric pressure sensor, Vernier sensor
Pacemaker	Atrial, ventricular electrical pulses (bpm)	Real-time embedded sensor systems which maintain synchronized heart rates	Medtronic, Boston Scientific, Biotronik heart pacemaker
Oximeter	Blood oxygen saturation (SpO2) (%)	Measures the saturation of oxygen carried in RBCs	Accu-sure finger pulse oximeter, Newnik Pulse oximeter
Electro encephalography sensor	Voltage fluctuations (mV/s)	EEG signals evaluate the intracranial activity with electrodes placed on scalp.	Neurosky, Olimex, and sky technology neurosensor
Airflow sensors	Volumetric air flow rate is measured in "standard cubic centimeters per minute" (SCCM)	Silicon-based sensors that operate on differential air pressure and heat transfer commonly used in anesthesia delivery systems and heart pump	MQ135, Omron D6F, and Sensirion AG flow sensor

Fit, Fitbit, and Withings Pulse. It also stocks patient's glucose levels, A1c, and other important data and lets them print out detailed reports for your doctor.

6.3.20 *Medical Tricorder*

The Viatom CheckMe Pro is one such palm-sized gadget which can measure ECG, heart rate, oxygen saturation, temperature, blood pressure, and more. A smartphone application known as "Medical Tricorder" exploits android phone's inertial electro sensors when located on the human's chest, it proficiently captures the motion patterns produced by heart pumping. Through the obtained ballistocardiograph signal, the system effectively computes the heart rate in real time comparing it to the values of standard clinical grade electrocardiographs. These signals can be made readily available to clinicians for detection of heart defects at primary stage itself without involving healthcare staff [80].

6.3.21 Real-Time Locating Services

While GPS systems are successful in locating assets but they fail in indoor setting. Therefore, real-time location systems have become an essential service to solve tracking problems. Real-time locating services are of prime importance in effectively detecting emergency conditions in healthcare setting. The tracking facility can be installed in wide range of subjects-medical instruments, patients to healthcare staff. A real-time tracking system essentially consists of location sensors known as receivers or readers that receive wireless signals from the subject of interest (person/object) installed with a tag. Surveillance also has some boundaries, mainly in dynamic places like emergency units but tracing movements with real-time locating services highlight possible concerns in productivity and operations. At a fundamental level, these services make sure that equipment's and supplies are not stolen, as they are fairly expensive, also allow verification of its proper use. The same principle also applies to safeguarding of patient records as the healthcare is responsible for its security. However, the functionality of these devices must not be misinterpreted. Real-time locating system does not constantly track speed, direction, or spatial positioning of tracked assets and persons [81].

Hence, this is revolutionary time for healthcare due to development of digital health.

6.4 Potential Role of Technologies in COVID-19

The beginning of 2020 has seen the emergence of coronavirus outbreak caused by a novel virus called SARS-CoV-The sudden explosion and uncontrolled worldwide spread of COVID-19 show the limitations of existing healthcare systems to timely handle public health emergencies. In such contexts, inno-vative technologies such as blockchain and Artificial Intelligence (AI) have emerged as promising solutions for fighting coronavirus epidemic. On the one hand, blockchain can combat pandemics by enabling early detection of outbreaks, protecting user privacy, and ensuring reliable medical supply chain during the outbreak tracking. On the other hand, AI provides intelligent solutions for identifying symptoms caused by coronavirus for treatments and supporting drug manufacturing.

Today our world is trapped under an evasive pandemic called COVID 19 which has claimed upto 661k lives and still counting. COVID 19 is a highly communicable disease caused by a subfamily of a coronavirinae specifically known as SARS CoV-2 of beta coronavirus family. COVID19 has severely impacted economies, academics, transport, and politics but the worst hit is on healthcare systems [82].

The extent of clinical manifestations in this respiratory disease may be acute, moderate, or chronic depending upon the pre-existing comorbidities. So it can be treated with effective measures taken at the right time. But the sudden outburst and hysterical spread of COVID-19 globally show the overall flaws and limits of our existing healthcare facilities indicated by the inefficient handling of this public health emergency [83].

In this pandemic, nonmedical technologies such as artificial intelligence and blockchain arose to provide innovative solutions to tackle new problems emerging every day. Blockchain helps fighting the pandemic by aiding early detection of plague, guarding patient's record privacy, and warranting dependable medical services during the disease outbreak. AI offers intelligent solutions for detecting symptoms produced by the virus for effectively treating patients and aiding drug discovery and manufacture [84].

AI is a potent tool to combat the COVID19 pandemic. For example, Beck and his coworkers (2020) designed a deep learning algorithm to detect effective drugs for the drug-repurposing, i.e., identifying a swift drug using present drugs in market that can cure infected patients. This approach helps just not only in saving the expenses of drug discovery but also reduces the timeline [85].

In the situation of COVID-19, big data refers to the patient's information including admission-notes, X-Ray report, patient disease history, list of doctors, and nurses, and close contacts [82, 86]. Big data potentially provides a number of promising solutions to help combat COVID-19 epidemic. By combining with AI analytics, big data helps us to understand the COVID-19 in terms of outbreak tracking, virus structure, disease treatment, and vaccine manufacturing [87].

In USA, the George Washington University Hospital has utilized various telemedicine approaches, which include video consultation and live informative webinars to give remote medical advices to numerous people [88]. The Rush University Medical Center (USA) has adopted telemedicine platforms to assist on-demand video consultations. However, these health professionals were using such consultations not only to provide medical advices to patients but also to test them for the COVID-19 [89].

During outbreak, Infervision Company launched a coronavirus AI solution that assists front-line healthcare workers to screen and monitor the disease effectively. Similarly, during COVID-19, Ant Financial, a blockchain platform, helps to quicken the claim processes to reduce the incidences of physical meeting between patients and healthcare workers [90].

As the overall incidences of COVID-19 are rapidly increasing Machine Learning and Cloud Computing can be employed efficiently to trace the disease, hypothesize spread of the epidemic and design policies and guidelines to prevent its spread. Tuli and et al. (2020) develop Generalized Inverse Weibull distribution, a prediction framework for the growth and trends of COVID-19 pandemic using machine learning and cloud computing [91].

Andhra Pradesh and Assam (India), have executed telemedicine services to facilitate remote communication of probable COVID-19 patients with health experts [92, 93]. The Sheba Medical Center (Israel's largest hospital), several telehealth technologies were used to screen 12 Israeli passengers who were on board in the cruise quarantined in Japan for some weeks. However, the Sheba Medical Center deployed telemedicine services not only to treat these travelers remotely but also to make sure that least human contact was made while handling them within the hospital premises [94, 95]. A study compared the effectiveness of real- time location services in contact tracing for covid19 in healthcare workers of Singapore of preventing the spread of this infectious disease [96].

Wearable sensors aid in the real-time monitoring of heart rate, heart rate variability, resting heart rate, body temperature, arterial oxygen saturation (SPO2) respiration rate, and blood glucose levels for asymptomatic and mild-symptom home-based COVID-19 patients, along with specific parameters for patients with comorbidities like diabetes or chronic obstructive pulmonary disease and patients with severe symptoms in hospital intensive care units (ICU). Conventional sensors that measure heart rate and respiration rate can serve as potential markers of COVID-19 infection and are already measured by wearable devices such as the Apple Watch, Fitbit, Zephyr BioHarness, or VivaLNK Vital Scout [97, 98]. To enhance accuracy of detection of COVID-19, RT-PCR is aided by imaging informatics employed to analyze routine CT scans or X-ray images for detection and monitoring disease progression. In healthcare settings, multimodal dataset is intricately analyzed to support healthcare providers to develop better and efficacious treatments plans when managing for severe stage COVID-19 patients [99, 100]. Behavioral informatics is also being exploited to study human behavior data in the situation of self-quarantine, or community-quarantine in different countries to drive execution of better policies and laws [101]. These studies also help in providing a better grasp of human behavior by assessing patterns in the mental, emotional, and physical data so as to provide ample support to help people cope with self-quarantine, and any other potential agoraphobia post self-quarantine [102]. In rehabilitation informatics, medical data are being analyzed to comprehend the effect of the disease on affected organs like lung and heart functions post recovery in patients with varying stages of COVID-19 [103, 104]. In infectious disease modeling, epidemiological models have been built with field data to predict the rate of COVID-19 spread so as to assist policy makers in taking proper actions. The outbreak figures are analyzed for population health management and COVID-19 care resources supply chain management [105, 106].

6.5 Impact of Bioinformatics in Health Care

Bioinformatics is the integration of biology, mathematics, and computer science. It utilizes various in silico approaches and tools to predict biological information (Table 6.3). The computational tools are beneficial in analyzing metabolic disorders and genetic defects. Healthcare information includes physiological characteristics based on affected organs, cost reports, claim bills, and assessments linked to patient contentment [107].

Table 6.3 Bioinformatics Techniques and Approaches used in Health Informatics

S. No.	Bioinformatics Techniques	Approach (Tool/Database/Software)
1	Microarray analysis	GEO
2	Next gene sequencing	Strand NGS, DESeq (R package) EdgeR, TopHat/ Cufflinks
3	Pathway analysis	KEGG, Reactome, BioGRID, STRING
4	Protein modeling and docking analysis	Sequence Databases: Uniprot
		Structure Databases: PDB
		Modeling Database: SWISS-MODEL, I-TASSER, Phyre2 Server
		Structure Refinement: SAVS, RAMPAGE
		Protein-Ligand Docking: SWISSDOCK, GLIDE (Shrodinger)
		PPI-Docking: HADDOCK, CLUSPRO
5	Genetic Variation	TOOLS: NovoAlign, SAMToolsGenome Analysis ToolKit
		Variant Annotation Databases: dbSNP
6	Sequence analysis	Alignment tools: BLAST, L-Align, CLUSTALW, MUSCLE, T-COFFEE
		Sequence Databases: NCBI Entrez, Ensemble, Uniprot

The identification of biomarkers is based on omics studies, which is generally done to predict consequences in a precision medicine such as patient disease vulnerability, analysis, diagnosis, prognosis, and response to therapeutics. Hence biomarker discovery tool has been developed, i.e., BioDiscM, which is a stand-alone program based on machine learning [108]. To classify the microarray cancer data, AI techniques has been utilized in gene selection tool [109]. Other application, AI in bioinformatics is drug repurposing and classification based on imaging data [110].

6.5.1 Genome Sequencing

Biological data science is an emerging area that has complemented computational techniques and the usage of contemporary high-performance structures that include CPU clusters, clouds, GPUs, and field programmable gate arrays. Next Gen Sequencing analysis needs computing all pairwise read alignments or all pairwise read-genome mapping software's like BLAST are computationally infeasible either due to the large size of query data or the software's are not designed for that specific task [111]. This is where big data comes into play. Cloudburst is a parallel-computing model that allows sequenced genomes to be mapped by utilizing short read mapping that enhances the scalability of sequencing data [112]. Biological databases play a noteworthy role in storing big data. Biological Databases such as the virulence factor database http://www.mgc.ac.cn/VFs/ that offers comprehensive information about virulence factors of bacteria that are medically proven to be pathogenic [113].

The Big Data has revolutionized several sectors of technology; the healthcare market has however been slow and has finally reached the period where big data can fully renovate the business for the better [114]. Big Data can increase operational efficiency, aid prediction and planning response to treatment, optimize the quality of monitoring of clinical trials, and reduce healthcare expenditure at multiple levels from patients to hospitals to governments**.** Combining the efforts interdisciplinary fields such as genomics and big data empowered by machine learning algorithms that can identify disease biomarkers, predict disease diagnosis, progression stage and prognosis in critical life-threatening diseases like cancer, neurological disorders like Parkinson, Schizophrenia, and Alzheimer. Reconstructing regulatory pathways from gene expression data is another well-developed field that uses a high-throughput genome scale data. Network reading approaches can be divided into five groups based on the primary model in each instance: regression, mutual information, correlation, Boolean regulatory networks, and other methods [115]. Figure 6.3 shows major applications of big data are genomics which is expected to be the future of healthcare [116].

The other side of genomics data is the multifaceted phenotypic data with which the sequence information is being correlated. Phenotypic data come from a variety of sources such as simple and unorganized textual data from electronic health records, biological function measurements from laboratories, sensors, and electronic trackers, and bioimaging data [117].

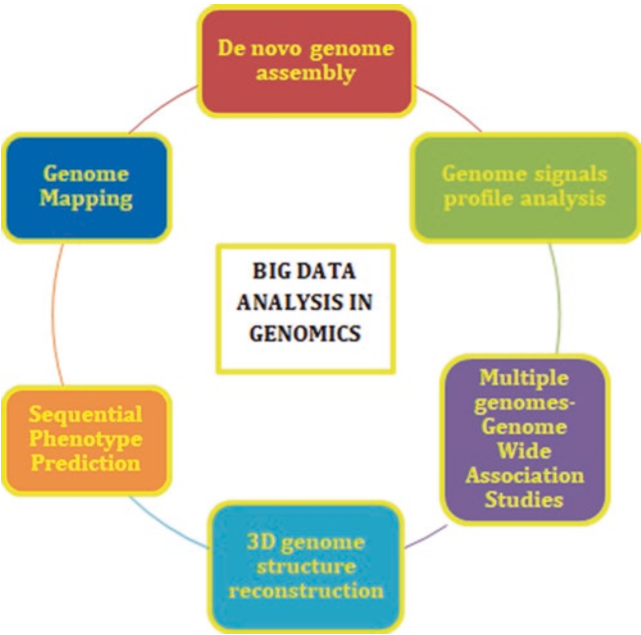


Fig. 6.3 Applications of Big DATA in genomics

6.5.2 Revolutionizing Drug Development

Drug discovery plays a key role in the pharma and biotech industries. The major objective of drug development is to create novel drugs in less time utilizing bioinformatics techniques. The drug discovery process has been reformed with the use of high-throughput technologies in biosciences that include – genomics, proteomics, metabolomics, and microbiomics. Novel trends and fast progress in drug discovery have led to success of the bioinformatics tools [118]. Cutting-edge in silico methodologies have given a remarkable opportunity to pharmaceutical corporations to identify novel drug targets which in turn quicken the success and time for conducting clinical trials for drug discovering [119]. The traditional drug discovery process was more serendipitous rather than a planned process. But today, drug discovery involves a streamlined progression from identification to optimization. Recently, companies such as Innoplexus are making it possible for pharma industries to revolutionize their drug discovery processes by harnessing AI-powered solutions. AI can help experts at various stages of drug discovery, expanding options for researchers involved in laboratory and computation-based research (in vitro, ex vivo, in silico), and facilitating translational medicine and bioinformatics.

Current drug discovery requires significantly time-consuming efforts in order to search literature such as publications and presentations to identify connections between genes, molecular targets, pathways, and drugs. Such efforts require searching through disparate databases and using search engines with inadequate understanding of the language of life sciences, leaving researchers with an incomplete picture of the connections and interactions between biological entities. This limitation makes it challenging to identify and test new methods (new targets, molecules, pathways, patient stratification, genomic sequencing, etc.) and find new indications to target. Highly advanced technology developed by Innoplexus enables researchers to have nearly all online published life science data at their fingertips and easily see connections between closely and distantly related entities [120].

6.6 Challenges and Future in Health Informatics

Healthcare modernization is led by a number of trends including increasing healthcare costs, an elderly population, and the rising occurrence of chronic disorders that necessitates long-term personal care. As technology advances and the productivity of the healthcare business have also risen, so are the number of people profiting from the healthcare industry. Moreover, the uses of devices that collect huge volumes of data are crucial for the shift to evidence based and prevention-based medications that the industry has adopted. These approaches lead to a more successful treatment for patients [121].

There are several challenges when it comes to wide scale implementation health informatics. The first and foremost challenge is providing data security and privacy during confidential transmissions of patient information that must comply with bioethical and legal agreements [122]. These guidelines are being constructed for medical websites; however, doctors and healthcare professional are yet to be trained efficiently enabling them to accurately guide and interpret the content to patients [123, 124]. Health informatics approaches are aimed to attain an ideal balance between cost efficiency and quality of service but they are often limited by the poor return investments in information management and technology [125]. AI- powered Clinical decisions support system that uses historical and current data to provide treatment plans, maximizes resource utilization, and cost procedures. Their adaptability has been fairly low due to the negligence of medical professionals, limitations in software systems and algorithms, and partly because of the effort in capturing expert knowledge. It also raises questions on the allocation of responsibility when a machine-based decision system fails to provide the correct solutions. Technologies such as robotic surgery and implantable controller devices based on artificial intelligence are yet to seek approval in several countries as their efficacy and safety in regards to human life are yet to be proved [126, 127]. To address these issues, information must be operationalized, adjusted according to clinical workflow along with generating ethical guidelines for responsibility of the data, integrating standard data models, and provision of supportive infrastructure to make sense of the collected data for patients themselves.

The future of healthcare will rest upon three sectors: a digitalization, data science, and a patient-centric approach. Information technology will be the heart of this revolution, helping in cost reduction, improving productivity, and discovering new economies of scales for better efficiency and good patient care. IT can also mess up today's organizations and fundamentally alter healthcare delivery through personalized medicine and connected care. Predictive Analytics and IoT will form the future of many businesses, including healthcare. However, before these new technologies can truly deliver value to patients such as improving survivability and life expectancy or giving predictive and prescriptive indicators for ailments, healthcare associations must first figure out their data strategies. This includes recording of data, storage of raw data, and ensuring security of data and utilizing it for greater patient insights [128].

Medical informatics is currently in the early stages of budding. Today, as an interdisciplinary field, it forms one of the bases for medicine and health care. As a consequence, considerable responsibility rests on medical informatics for refining the health of people, through its contributions to high quality, well-organized health care provisions, and to ground-breaking research in biomedicine and related health and computer sciences. Future research fields might range from seamless interactivity with automatic data capture and storage, via informatics diagnostics and therapeutics, to living labs with data analysis procedures, involving sensor-enhanced ambient environments [129].

The development in healthcare system is progressing by implementing information technology. Hence, today, health informatics is a combination with rapidly evolving technologies such as AI, big data, block chain, cloud technology, and internet of medical things which improves efficiencies and offers multiple avenues of streamlining healthcare delivery. It accelerates resource availability, boosts interoperability while lowering the costs but still there is need of better protocols, web services, and electronic medical record with better clinical decision support systems because there are few barriers in digitalized healthcare system such as security concern, system downtimes, and lack of patient data privacy. Programmers are still working on the drawbacks of these techniques and hence, the future is bright for the modern junctures between technology and healthcare.

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