Artificial Intelligence and Big Data for COVID-19 Diagnosis

Houneida Sakly, Ahmed A. Al-Sayed, Mourad Said, Chawki Loussaief, Jayne Seekins, and Rachid Sakly

Machine learning can help process medical data and give medical professionals important insights, improving health outcomes and patient experiences. (IBM)

H. Sakly (✉)
COSMOS Laboratory, National School of Computer Sciences (ENSI), University of Manouba, Manouba, Tunisia
e-mail: houneida.sakly@esiee.fr

A. A. Al-Sayed
University of California, San Francisco, Berkeley, USA
e-mail: ahmed_alsayed@berkeley.edu

M. Said
Radiology and Medical Imaging Unit, International Center Carthage Medical, Monastir, Tunisia
e-mail: mouradsaid@yahoo.fr

C. Loussaief · R. Sakly
Higher School of Health Sciences and Techniques, Monastir, Tunisia
e-mail: prchawkiloussaief@gmail.com

R. Sakly
e-mail: rchid.esstsm@gmail.com

J. Seekins
Department of Radiology, Stanford Medicine, Palo Alto, USA
e-mail: jseekins@stanford.edu

© The Author(s), under exclusive license to Springer Nature Switzerland AG 2022

H. Sakly et al. (eds.), *Trends of Artificial Intelligence and Big Data for E-Health*, Integrated Science 9, https://doi.org/10.1007/978-3-031-11199-0_6

1 Introduction

The World Health Organization (WHO) recently designated coronavirus disease 2019 (COVID-19) as an infectious pandemic.[1] Since the beginning of the epidemic, there have been over 243 million confirmed infections and over 4.9 million fatalities. Because of the rapid spread of the disease, most health institutions and hospitals are unprepared to deal with the influx of cases. With a 2–14 day incubation period, the severe acute respiratory syndrome coronavirus 2 (SARS-CoV2) is said to spread by tiny droplets and perhaps aerosols [1, 2]. COVID-19 positive persons may have symptoms such as fever, dry cough, bodily aches, shortness of breath, lack of taste and smell, sore throat, and diarrhea [3]. With such readily misconstrued symptoms and the danger of negative repercussions from a misdiagnosis, effective viral infection detection is one of the top objectives of medical organizations. Artificial Intelligence (AI) diagnostic models might relieve the burden on healthcare staff, allowing them to devote more time to patient care and vaccine research. It is vital to recognize the presence of infection early in order to provide treatment and save lives. According to a survey, symptoms may begin with a simple cold and progress to life-threatening pneumonia [4, 5]. The most prevalent form of diagnostic test is reverse transcription-polymerase chain reaction (RT-PCR) evaluation for the detection of viruses via pharyngeal swabs or blood samples. With an accuracy range of 81–96%, RT-PCR can deliver results in as little as a few hours up to two days. These tests, on the other hand, are unable to assess the degree of contamination, and their accuracy is contingent on the strength of the viral strain. Differentiating between coronavirus infections and other infections is a vital step toward appropriate diagnosis [6].

Positive individuals typically exhibit bilateral diffuse patchy opacities with some bibasilar sparing on chest X-ray images, which can assist in the diagnosis of the condition. Irritation of the lungs, and lymph adenopathy are saliant features on computed tomography (CT) scans of COVID-19 patients. Lungs involvement shows a patterned dissemination of opacities (interlobular septal thickening layered on ground-glass opacities) [7]. The prime goal of evaluating the density of these patterns is to provide a truthful diagnosis, regulate the sternness of the ailment, and offer prognosis advice. Artificial intelligence (AI) performance for detecting infections and associated radiological characteristics from medical imaging, such as chest X-rays and CT scans, has proven to be beneficial in making truthful diagnoses [8, 9]. Machine learning and deep learning may be used to solve COVID-19 identification and segmentation difficulties in a number of different ways. Medical imaging analysis aided by AI offers great potential as a primary diagnostic tool for COVID-19 detection [10, 11]. The first step in the diagnosis is to identify deep features that may be used to detect COVID-19 radiological patterns on chest X-ray and CT scans. Machine learning-based prediction techniques have the potential to be used in prognostic analyses. As a result, several studies have employed algorithms such as Support Vector Machine (SVM) and Random Forests to provide critical

[1] https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports.

insight into coronavirus infection prediction and diagnosis [12, 4]. By automating the COVID-19 diagnostic selection procedure, these automation technologies help ease the burden on healthcare workers. Early identification of infection can save time by allowing treatment to begin, while the disease is still mild, reducing the chance of consequences. The consequences of a misdiagnosis pose a major risk to the patient and can even be fatal. Automated systems face a number of challenges because of the enormous amount and velocity of data. Data cleaning and processing becomes a huge difficulty with such a large intake of cases, especially when high-resolution images are required. A consistent nursing and remote detection method for people will help in the wild trailing of suspected COVID-19 cases. Furthermore, the usage of such systems would generate a vast amount of data, presenting various opportunities for big data analytics tools to improve healthcare service quality [13, 14]. The Six V's [15] are a set of essential qualities of big data, which include value, volume, velocity, variety, veracity, and variability. The inventive definition of big data essential qualities, however, only considers three Vs: volume, velocity, and variety [16]. Big data analytics technologies are considered critical for gaining the knowledge needed to make judgments and take preventive steps [17]. As the large amount of available data on COVID-19 comes from various sources, it will be crucial to review the protagonists of big data analysis in governing COVID-19, as well as a promoter insight of the main contests and main uses of COVID-19 data prevention, as well as a number of correlated current frameworks with the goal of COVID-19 breakdown [18]. COVID-19 has been proven to benefit from big data in the battle against infectious illnesses. To combat the COVID-19 pandemic, big data may hold many intriguing possibilities. When big data is integrated with AI analytics, it helps researchers better understand the COVID-19 outbreak, viral structure, illness treatment, and vaccine manufacturing [19–21]. For instance, complex simulation models based on coronavirus data streams may be created using big data and powerful AI-based techniques to anticipate epidemics. This would allow health agencies to follow the coronavirus's progress and better plan preventative actions [31]. Because of their data aggregation capabilities, which allow them to use huge volumes of data for early detection, big data models can also assist in predicting the COVID-19 epidemic in the future. Furthermore, big data analytics as a diversity of medical sources, such as infected patients, can support the implementation of large-scale COVID-19 research and the creation of high-reliability treatment techniques [22–24].

2 COVID-19 Therapy and Health Informatics: Promises and Challenges

The worldwide health care community continues to grow to the defiance of the coronavirus complaint 2019 (COVID-19) epidemic, from combat zone caregivers to information processing experts. Clinical informatics is dependent on the relinquishment of specialized backing, which is critical for optimizing COVID-19 epidemic clinical operations. The requirement to produce a “new normal” for safe and operative care for all cases urged major advancements in data use, including the use of big data for exploration because traditional time-long studies were no longer an option, prophetic logical functionality retooled to assist prognosticate COVID-19, supersonic deployment of test attempts and trials of new drugs, development and implementation of innovative telemedicine care models, and the exponential expansion of the information technology system [25]. Loosening laws, encouraging cooperative practice between health systems and their merchandisers, and a worldwide need for answers created the ideal early slush for invention to sow at snappy rates. By keeping up with diurnal non-supervisory changes to offering day-to-day help to a tired bedside clinician, informaticists play a crucial part in a successful epidemic response strategy. Informatics are about fostering invention and advancing health care in the information age. As the new coronavirus spread throughout China and the world, informatics passed a DNA transformation to help frontline icons and discover a way to annihilate the contagion [26]. The Marvel X-MenTM conception, in which fictional characters’ transformation into icons is backed by hyper-accelerated inheritable mutation, is a good starting point for allowing the tremendous hops in informatics necessary to respond to COVID-19. Like numerous grand narratives, the speeding up of growth creates opponents as well as protagonists. The villains began as well-known data-related issues, such as a lack of an initial dataset for nursing evaluation and interventions or a lack of ICD-10 canons to register a new hazard complaint, but the pandemic quickly transformed them into major hurdles to finding answers [27, 28]. Informatics is much more than flow charts in an electronic health record (EHR). Experts in health informatics who work within a medical system handle a variety of data-related procedures in order to assist doctors in patient care. Architecting, locating the right seller, carrying backing, assuring nonsupervisory compliance, and establishing a structure similar to servers or interfaces can take months or times [29, 30]. A benchmark for classifying IT informatics solutions of the numerous activities elaborated in public health planning, replies, and retrieval was established based on this abstract model (Fig. 2). Indeed, seemingly basic procedures such as confirming that the EHR supports a new business strategy can take hundreds of hours to develop, test, educate, implement, and track compliance or effectiveness [31]. On the clinical side, IT infrastructure must be expanded to enable an increase in telehealth usage. To help preserve physician resources during a surge, all emergency departments were given the option of telehealth consultations for qualified patients who presented during the surge. The registration/check-in process now includes questions about travel and symptom screening (Fig. 1). All paperwork had to be completed in all patients treated for acute and elective treatment across the hospital and screened using the EHR by front desk personnel.

In care settings, interviews generated a predictive alert with clinical decision support to provide a suitable track for following clinical treatment, including any testing or isolation orders required, and front-line employees followed a uniform screening “script” using EHR templates as needed [26, 32].

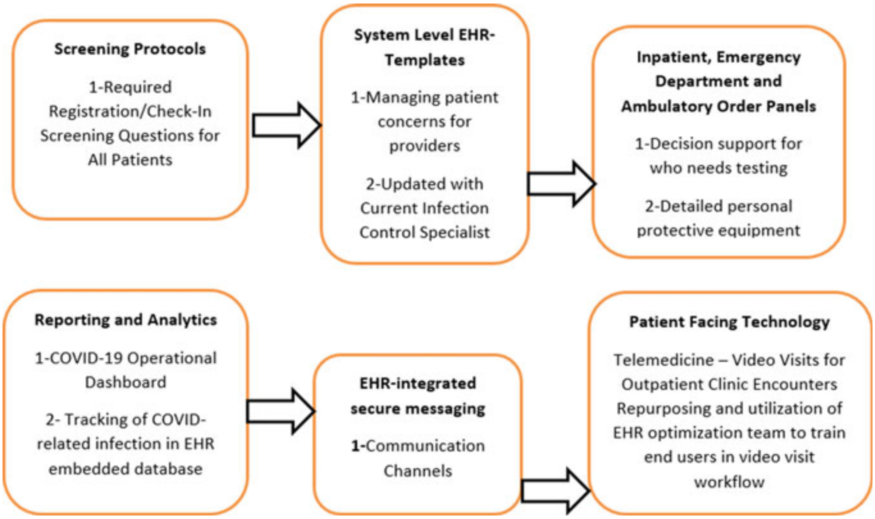

Fig. 1 Tools for managing a pandemic

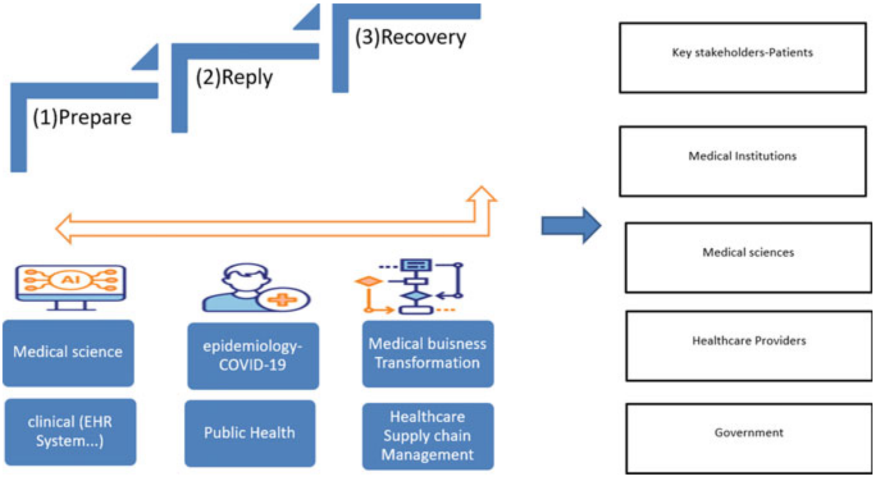

Fig. 2 Framework involved in preparing for, reacting to, and recovering from severe public health risks

At the time of ordering, clinical decision support in the form of screening criteria, specimen collection instructions, the requirement of defending equipment, and test result turnaround time estimates for simple assessment were supplied. The COVID-19 orders asked the ordering practitioner to answer a series of questions on the patient's compliance with the testing requirements.

Our build structure allowed for fast adjustments to maintain the system in line with operational expectations because screening criteria and lab handling processes often changed after the first deployment. Our occupational health department used

COVID-19 ordering practices similar to avert infections. When it comes to IT resources, there are always conflicting priorities. A crisis, such as an emerging disease danger, is necessary to bring all stakeholders together to work toward a common objective. Each category includes a variety of informatics and technology solutions that can be used at different stages of a major health problem [33]. Furthermore, each sector is influenced by a certain stakeholder group. It should be noted that the project's finance and implementation may include a large number of parties. Each category has a wide range of informatics and technology solutions that can be applied at various stages of a serious health issue [34, 35].

Clinicians in various system institutions may manage in different areas where caretakers are required, either due to universal access security requirements; they may only travel inside their own hospital or to another hospital system [36]. Personnel from surgical and procedural sectors, as well as affiliated surgery centers and clinics, were given access as part of an all-hands-on-deck plan to successfully staffing in a significant surge situation. This information is now available to respiratory therapists, pharmacists, physical therapists, and others who interact directly with patients [37]. Non-bedside clinicians, such as nurse auditors, administrative function clinicians, and IT clinicians, are also provided access. From a compliance viewpoint, lowered constraints are required for this type of access to be possible. Reports on access availability monitoring have been utilized to assist in preventing misuse [38]. Big data is being utilized in the EHR to train predictive analytic (PA) algorithms to alleviate the cognitive burden on overworked doctors. The team created a sepsis/infection risk PA tool to detect inpatients with COVID-19 symptoms after an initial emerging disease screening on arrival. When a patient is at danger for COVID, the EHR alerts clinicians, allowing the patient to be evacuated, evaluated, and treated as needed while also ensuring the safety of the crew [39]. To stay current with CDC standards, the emerging disease screen (EDS) is updated on a regular basis. Many aspects of clinical decision support (CDS) are powered by EDS, which allows busy physicians when a patient tests positive for COVID or other developmental illnesses [40]. On the clinical side, IT infrastructure must be expanded to enable an increase in telehealth usage. To help preserve physician resources during a surge, all emergency departments were given the option of telehealth consultations for qualified patients who presented during the surge. On the clinical side, IT infrastructure must be expanded to enable an increase in telehealth usage. To help preserve physician resources during a surge in demand, all emergency departments were offered the option of performing telehealth consultations for approved patients [41, 42].

3 COVID-19 Infrastructures and Technological Solutions

The epidemic has generated a rush of interest in initiatives that would utilize cutting-edge technology to mitigate COVID-19's influence on our lives. To combat the coronavirus pandemic, a number of technological advances and applications have been developed. Technology development, design, and use were all affected by the epidemic. It is critical to have a better understanding of the role that information systems and technology researchers may play in combating this global crisis [43]. The rapid adoption of telemedicine in response to the coronavirus threat reminds us that digital technologies may help with pandemic management and reduce risks both during and after the pandemic [44]. Many IT workers are helping to battle the outbreak in a variety of ways, including developing anti-virus software, tracking and forecasting the disease's growth, and protecting hospitals from cyberattacks [45]. The pandemic has consequences for manipulating information systems and implementation based on IT technology infrastructure. Researchers and practitioners in the fields of information systems and technology may assist with the analysis of COVID-19 pandemic data, such as the rate of interest in a prospective new promoter axis [44, 46].

Adapting, coping, and halting the information crisis were characterized as reforming organizations by improving crisis-driven agility and minimizing crisis-revealed fragility [47]. COVID-19's significant challenges should be assessed from the perspective of information systems and technology, with implications for further research and recommendations on COVID-19's influence on information management. It is impossible to overestimate the role of information systems and technology in civilization [48]. The pandemic of COVID-19 has emphasized the urgent need to shift the public health system from reactive to proactive, as well as to develop technology that provides restructured data for proactive decision-making. COVID-19 is unique among chronic illnesses in that it is extremely infectious, may be transmitted from person to person, and has a high mortality rate. Furthermore, since COVID-19 is a novel illness, scientific knowledge of the virus that causes it, as well as medical treatments and government and organization responses, are still in the early stages of development. COVID-19's impact on individuals and society is growing unanticipated. Because of the present pandemic situation and its ramifications, combating the COVID-19 pandemic necessitates extensive coordination of various factors [49–51].

To combat this problem, new technological solutions, such as mobile tracing COVID-19 and chatbots, have recently been exploited. These technologies may assist individuals, businesses, and society in dealing with the repercussions of the coronavirus pandemic. New technologies can aid in the detection of community-wide coronavirus propagation, monitoring of infected people's health, and treatment of COVID-19 patients [52, 53]. Machine learning, image recognition, and deep learning algorithms are examples of AI-based technologies that may be used to enable faster drug discovery and development of new therapies, as well as for early detection and diagnosis of infection [54]. A few businesses have also adopted AI systems created for other purposes to help with social distance enforcement and contract tracking [55]. During the COVID-19 outbreak, emergency 3D-printing of therapeutic items was proposed as a feasible method to alleviate shortages. In the field of crisis management, medical manufacturing and IT equipment within hospitals have been explored. Experts in health and additive manufacturing technology are anticipating this shift, but legislative reforms will be required. A 3D-printed medical case study item developed during the COVID-19 epidemic offers the design and manufacture of a suture guide for heart surgery [56].

In the field of health, big data (or massive data) corresponds to all socio-demographic and health data available from different sources that collect data for various reasons. The use of these data has many advantages for COVID-19: identification of disease risk factors, aid in diagnosis, choice and monitoring of the effectiveness of treatments, pharmacovigilance, and epidemiology. Nevertheless, this raises many technical challenges and human beings and poses many ethical questions [57]. These standards have made it easier for hospitals and healthcare organizations to gather all of the data acquired for Covid-19 into biomedical data warehouses, which researchers can query through online interfaces. Many research groups now use integrated systems to link databases and aggregate data from cohorts.

As the number of mobile applications is constantly growing, it is advisable to integrate them into the e-health quality process, that is, to test them internally using the practices and tools made available to experts. The coronavirus pandemic has shaken for the medical industry, which has proven extremely resilient, that of mobile applications. With the massive use of telecommuting, the installation of professional applications for monitoring and trapping covid-19 has increased considerably, assuming you have been diagnosed with a COVID-19-related illness. In this case, health officials may be able to use the technology to track down any mobile application in the case of a suspected case [58]. The current COVID-19 epidemic has shattered provincial, radical, intellectual, spiritual, social, and educational barriers worldwide. An Internet of Things (IoT) equipped healthcare system is useful for effective monitoring of COVID-19 patients because it uses a linked network. This technology contributes to increasing patient satisfaction and decreasing readmission rates to hospitals. The use of the Internet of Things has a favorable impact on the healthcare expenses and treatment outcomes of infected patients. As a result, the goal of this research is to investigate, evaluate, and highlight the diverse applications of the well-known IoT idea, as well as to create a road map for dealing with them [59, 60]. Blockchain technology has been employed in the fight against COVID-19 to overcome the problems and trust concerns that arise with safeguarding privacy and fulfilling public health goals, such as tracking infected persons. Blockchain based on distributed ledgers is a type of digital ledger that records online medical encrypted transactions that use a consensus technique to operate. To support the fight against the coronavirus epidemic, a solution based on mHealth, blockchain technology, and AI was created [61, 62]. The technologies listed in Table 1 require data, people, and systems to be integrated and classified based on their primary focus and initial design intent for practical use. Data-centric technologies such as machine learning/deep learning, big data analytics, IoT, and blockchain are being utilized to combat COVID-19.

Table 1 Notes of COVID-19 technological solutions

Technologies	COVID-19 solutions examples	Sample	Tools—frameworks
Machine learning/deep learning	An explainable AI COVID-19 evaluation and lesion characterization from CT images using an automated method [63]	166 CT scans	http://perceivelab.com/covid-ai
	For stock price movement prediction, COVID-19 used a hybrid and parallel deep information fusion methodology [64]	Twitter data with extended horizon market data	COVID19-HPSMP framework
	COVID-19 classification and lesion localization from chest CT using a weakly-supervised framework [65]	3D CT volumes for COVID-19	https://github.com/sydney0zq/covid-19-detection
Big data	Deep features and SVM to classify images [66]	2138 images	Deep visual words (BoDVW)
	Researchers and decision-makers are paying more attention to technological advancements and big data analytics approaches for evaluating large quantities and types of data [67]	COVID statistics: https://covid.ourworldindata.org/data/owid-covid-data.xlsx, Google. 2020. Mobility data. https://www.google.com/covid19/mobility	Big data analytics techniques
	COVID-19 is being tracked utilizing big data and big technologies via a digital Pandora's box [68]	The NHS is collaborating with a various of big tech companies, including Google, Amazon, and data-processing firm Palantir, to create a common data platform to aid with COVID-19 monitoring	Pandora's box
IOT	Testing and tracking of IoT-COVID-19 can assist to limit the virus's transmission, which is critical in the fight against the pandemic [69]	5000 subjects	IoT-enabled HVAC systems, sensor data integration for context-awareness

(continued)

Table 1 (continued)

Technologies	COVID-19 solutions examples	Sample	Tools—frameworks
	The AIoT was used in the COVID-19 pandemic prevention and control [70]	Data collected from GPS location	AI + IoT (AIoT), 5G
	CIoTVID: COVID-19: towards an open IoT-platform for infectious pandemic diseases [71]	The NGSI protocol was established by the open mobile alliance (OMA) to deal with context information. The FIWARE IoT agent, which supports MQTT and lightweight M2M protocols, will next process the data. FIWARE is an open-source platform for controlling internet of things (IoT) systems. In FIWARE, the OMA NGSI interface is a RESTful API that can be accessed over HTTP (https://knowage.readthedocs.io/en/6.1.1/user/NGSI/README/index.html)	CIoTVID platform
Blockchain	COVID-19 blockchain uses in health care [72]	A total of 85,375 articles were reviewed, with 415 full-length papers (37 of which were connected to COVID-19 and 378 which were not)	Ethereum and hyperledger platform
	Process claims and issue buyouts; develop a "digital identity" for healthy persons [73]	COVID-19 related health data	"Immunity certificates" or "immunity licenses"
Robotic applications	Robot-assisted surgery for gynecological cancer was employed during the COVID-19 outbreak [74]	Healthcare providers	Disposable surgical hat, medical protective mask (FFP3) with goggles/visor, work uniform, disposable latex gloves)
	Using four robotic arms to perform Senhance® robotic surgery at COVID-19 may reduce the risk of coronavirus infection among medical staff [75]	To date, our hospital has done 100 different types of gynaecological surgeries, 10 of which were performed utilizing four robotic arms	Senhance® robotic platform "https://www.senhance.com"

(continued)

Table 1 (continued)

Technologies	COVID-19 solutions examples	Sample	Tools—frameworks
3D printing	The effect of 3D printing on patient education, diagnosis, and treatment in medicine [76]	Copper3D NanoHack mask model, Lowell Makes mask design, and open-source non-adjustable venturi valve design, early reusable Prusa research 3D	Materialise "https://www.materialise.com/en"
	COVID-19-related supply shortages can be addressed using 3D printing technology [77]	N95 respirators masks with CAD format, Ventilator valves,	COVID-19 Specimen Collection Kit
	As part of a pandemic printing initiative, a new 3D-printed swab for detecting SARS-CoV-2 has been produced [78]	The study experiment included nasal swabs manufactured in 3D, 50 hospital staff who attended a COVID-19 clinic processing, and 2 patients with laboratory-confirmed COVID-19	3DMEDiTech "https://www.3dmeditech.com"
Mobile application	Smartphone applications for corona virus disease 2019 (COVID-19) and a quality assessment using the mobile application rating scale (MARS) [79]	18 apps were created to share up-to-date COVID-19 information, and 8 were used for contact tracing	PRISMA—mobile app
	Examine and rank the contents and features of the COVID-19 mobile applications [80]	223 COVID-19-related mobile apps, 28 in the play store	Both the android play store and the iOS app store include mHealth applications
	COVID-19, mobile health, and significant mental illness are all issues that need to be addressed [81]	With serious mental illnesses (SMI) patients	Mobile mental health

4 The Post-COVID-19 Era and e-Health

The use of the Internet for healthcare delivery is referred to as electronic health (e-Health), sometimes known as cybermedicine. Telemedicine, telesurgery, telerehabilitation, teledentistry, and ePrescribing are only a few options available [82]. Certain developments in healthcare delivery worldwide have been hastened by the epidemic. As many governments across the world struggle to curb the outbreak, eHealth has become increasingly important. While eHealth services are not new, their acceptance by many healthcare organizations throughout the world has been examined, and regulations controlling their use have been devised to speed up their deployment. eHealth has become a requirement to maximize resources, partly due to the logistical and financial demands of the COVID-19 epidemic [83].

The rate of adoption varies because of the variances in pre-existing infrastructure between countries. Ironically, while eHealth is a critical resource for delivering healthcare to places with limited access to healthcare services, the same areas frequently lack access to the requirements for eHealth. Electricity and Internet access are not commonly available in low- and middle-income nations. Furthermore, the current economic situation makes it more difficult to utilize workaround solutions to these issues, exacerbating the problem of access [84]. Even when sufficient motivation exists, eHealth is not only a distant priority, but also a costly luxury in many countries, which ironically contributes to healthcare disparity.

Beyond infrastructure and financing, the discussion of eHealth encompasses a wide range of issues. Data privacy is still a major concern and a barrier to adoption in many wealthy countries. Despite being partly helpful during the epidemic, public anxieties persist that eHealth solutions will establish a permanent governmental monitoring system. As a result, government mandates may have a negative impact on the public adoption and usage of accessible eHealth technologies [85]. Thus, citizens must be involved in policymaking. They must be informed of the shifting scene as stakeholders in continuing innovation. Individual freedoms and common goods must be carefully balanced. This delicate balancing act is critical for government preparedness for the next pandemic, which will undoubtedly occur.

Another significant challenge confronting eHealth is end-user digital literacy. While continual technical improvements make the implementation of digital solutions simpler, they may also increase the difference between those who are digitally savvy and those who are not, producing even more inequality [86]. The degree to which digital technologies are used limits the utilitarian gains that drive eHealth solutions. Digital solutions should be made as simple to use as feasible while retaining a high level of cybersecurity and data protection. Communication portals, in particular, should not be difficult to set up and should make use of existing consumer technologies, such as PCs and mobile phones.

Despite the hurdles, eHealth will continue to flourish in the post-COVID age. Although each nation and location has a unique set of issues, worldwide legislation and actions have mostly favored eHealth. As previously stated, the pandemic has accelerated the global trend toward the adoption of a plethora of digital health solutions that fall under the eHealth banner. In the post-pandemic world, many of these are still applicable [87]. Such technology solutions would undoubtedly be beneficial in integrating disparate healthcare systems and perhaps lowering ever-increasing healthcare expenses.

5 Medical Digital Transformation by the COVID-19 Pandemic

The COVID-19 pandemic served as a stimulus for the digital transformation of the healthcare industry. Opportunities to provide healthcare appeared in the middle of the pandemic's social, economic, and regulatory uncertainties. Virtual outpatient visits have increased by 50–175 times in the United States, according to healthcare professionals. Telehealth use surged 38 times since the beginning of the outbreak. According to McKinsey and Company, virtual care might account for up to $250 billion in US healthcare spending. According to their findings, Telehealth is currently used by 46% of patients to replace canceled in-person appointments, up from 11% in 2019. A similar upward trend was observed among healthcare providers, with 57% seeing telehealth in a more positive light than before the pandemic and 64% indicating that they are more comfortable using virtual solutions for healthcare delivery.

Virtual urgent care, virtual office visits, close virtual workplace visits, home health services, and tech-enabled medical supervision were highlighted as the major paths that might have the most effect. It is predicted that by using these channels to move to virtual delivery, 20% of all emergency department visits may be avoided, 24% of office visits could be virtualized, and another 9% could be managed remotely. Furthermore, virtual home health services with technology-enabled medicine administration might account for 2% of all outpatient volumes, and virtual home health attendant services could account for 35% of normal home health attendant services. However, to fully achieve the promise of delivering healthcare electronically, two key components must be prioritized: providing the correct treatment in the right location and providing a positive patient experience.

The shift to reimbursement based on outcomes as opposed to volume of service necessitates that patient must be cared for in the most appropriate setting. This means that patient populations must be segregated based on their clinical condition and based on their need for specialties with remote interactions that might be scaled up using home-based diagnostics and equipment. In addition, virtual healthcare delivery requires the development of provider competencies and the creation of incentives. Health systems must construct a sturdy infrastructure. Telehealth technology needs to be integrated with electronic health records, clinical protocols for appropriate telehealth visits must be defined, and hospital and physician practice processes must be revamped to support virtual care. Finally, measurable clinical outcomes must be tracked to quantify the value of virtual care [88, 89].

The pandemic response has forced many consumer service providers to digitize their services and offerings [88]. Limiting the spread of the virus was the aim, and convenience was the by-product. As such, patient experience, just as customer experience, is paramount for virtual healthcare delivery. Patient expectations of ease of use and equal effectiveness must be honored. Many healthcare systems have implemented "digital front-door services". Digital front doors have arisen as a patient engagement buzzword in recent years. In its most basic definition, it refers to the digital means of scheduling appointments, finding and interacting with healthcare providers, renewing medications, paying bills, and navigating the healthcare system among other services. Many healthcare systems have adopted these digital front-door services, but they remain crude. Therefore, these services will continue to improve [89].

6 Artificial Intelligence (AI) and Supply IT Infrastructure During COVID-19

With a few exceptions, most of the AI literature on COVID-19 detection is in the deep learning field. I have examined machine learning methods. Fully automated deep learning algorithms learn feature extraction directly from image data. In medical image processing, CNNs for deep feature representation and classification have demonstrated great performance, and they perform extremely well in the COVID-19 detection challenge. The ability of clinicians to diagnose patients is greatly aided by their knowledge of essential traits and patterns gained from data.

Deep neural networks are a type of learning system that layers several neuronal nodes on top of the other. They are gradient-based learners, meaning that their parameters vary in response to the model's classification/segmentation mistake. This involves employing stratified-class sampling to build up the model training, modifying the calculation of the learning rate over epochs, and performing a hyper-parameter has made significant progress in healthcare automation by providing for a variety of design alternatives that may be adjusted for significant features. Because of the computational capabilities of graphics processing units (GPUs) and distributed computing models, the proposed deep learning architectures can be taught and evaluated in clinical routine. Several studies have investigated a variety of CNN approaches, ML classifiers on deep features, capsule networks, CNN, and other methods for COVID-19 detection. This section examines a number of cutting-edge AI-based COVID-19 detection techniques. Table 2 summarizes the various classification and segmentation methods.

6.1 Classification for COVID-19

Various COVID-19 categorization research methods have been thoroughly examined. For the COVID-19 identification task, these investigations used two primary imaging modalities (chest X-ray/CT). The key takeaways from these books have been extensively examined. Chest X-ray images are considered the most reachable modality for diagnosing COVID-19 in the AI literature. The following are the several types of X-ray detection techniques: Transfer learning techniques [110–112], customized deep architectures [113–115], capsule networks and sequential CNN [116, 117], semi-supervised GAN techniques [118, 119], deep feature extraction and image processing techniques [120, 121], and CAD methodologies

Table 2 Overview of classification and segmentation methods

Techniques	Modality	Methodology	Library-API	Database
Classification				
Fine tunning/multi-class classification [90]	Chest X-ray	COVID-ResNet	rishav1122/Covid-ResNet	COVIDx (COVIDx CRX-2), "https://github.com/rishav1122/Covid-ResNet"
Cough acoustics diagnosis of COVID-19 [91]	Sound recordings	ConvNets and data augmentation	Saranga7/covid19-cough-diagnosis	DiCOVA "https://github.com/Saranga7/covid19–cough-diagnosis"
COVID-19 identification and diagnosis using a deep neural network [92]	X-ray	CoroNet	Keras, Tensorflow	Images of radiology from a variety of reliable sources (radiological society of North America) (RSNA), "https://github.com/drkhan107/CoroNet"
COVID-19 detection using a channel-shuffled dual-branched CNN architecture [93]	Chest X-rays	CNN	PyTorch	A set of 558 COVID-19
Keep track of COVID-19 positive patients' development [94]	Chest X-rays	Transfer learning	Python	"https://github.com/ieee8023/covid-chestxray-dataset"
COVID-19 disease infected patients: a deep bidirectional classification model [95]	CT	MADE-DBM model classification	MATLAB 2018b	Benchmark COVID-19 datasets
Unsupervised COVID-19 image clustering using a self-organizing feature map [96]	Chest X-ray	SOFM network	Python, OpenCV	https://github.com/king2b3/SOFM
Automated COVID-19 identification based on deep transfer learning [97]	CT	Deep transfer learning and data augmentation	MATLAB 2019a	349 positive COVID-19 CT scans from 216 individuals, as well as 397 non-COVID CT images
COVID R–CNN: a new framework for diagnosing novel coronavirus disease [98]	X-Ray	R–CNN	TensorFlow	5450 sample images

(continued)

Table 2 (continued)

Techniques	Modality	Methodology	Library-API	Database
COVID-19: contrastive cross-site learning with a redesigned net [99]	CT	Redesigned net	PyTorch	2482 CT scans were taken from 120 people, 1252 of whom tested positive for COVID-19 and 1230 of whom tested negative for COVID but had other signs of lung illness
Segmentation				
A hybrid COVID-19 detection model using a ranking-based diversity reduction strategy and an improved marine predators algorithm [100]	X-ray	A new algorithm for marine predators and a ranking-based diversity reduction	FADs algorithm	"https://github.com/ieee8023/covid-chestxray-dataset"
A noise-resilient framework for automatic COVID-19 pneumonia lession segmentation [101]	CT	(COPLE-Net), 2D CNNs	Adaptive self-ensembling CNN	"https://github.com/HiLab-git/COPLE-Net"
Inf-Net: automatic COVID-19 lung infection [102]	CT	Semi-Inf-Net + multi-class	PyTorch	"https://github.com/DengPingFan/Inf-Net"
Lung infection segmentation for COVID-19 pneumonia [103]	CT	Cascade convolutional network from	Python	"https://github.com/UCSD-AI4H/COVID-CT"
In a quantitative analytic pipeline, evaluate the effect of lung segmentation accuracy [104]	CT	CNN	3D slicer 4.10.2 (https://www.slicer.org), Pyton U-Net	55 COVID-19 patients, "https://github.com/acil-bwh/ChestImagingPlatform/blob/develop/cip_python/dcnn/projects/lung_segmenter/lung_segmenter_dcnn.py"

(continued)

Table 2 (continued)

Techniques	Modality	Methodology	Library-API	Database
COVID-19 CT image segmentation using a fuzzy entropy-based improved marine predators algorithm for multi-level thresholding [105]	CT	For multi-level thresholding, a marine predators algorithm with fuzzy entropy is used	Matlab 2021a	13 COVID-19 patients
Diagnosis of COVID-19 using four-region lung segmentation based on deep learning [106]	Chest radiography	EfficientNet v0 and v	TensorFlow	"https://github.com/younggon2/Research-Segmentation-Lung-CXR-COVID19"
Explainable artificial intelligence for the prognosis and COVID-19 lung segmentation [107]	Chest X-ray	U-Net CNN	Python	"https://github.com/lucasxteixeira/covid19-segmentation-paper"
COVID-19 lung infection: automated chest CT image segmentation [108]	Chest CT	3D U-Net	TensorFlow	"https://github.com/frankkramer-lab/covid19.MIScnn"
Assessment of semantic segmentation based in encoder-decoder pairs using COVID-19 CT's in the dark [109]	CT	Encoder–decoder pairs	Pytorch	"https://github.com/vri-ufpr/sparkinthedarklars2021"

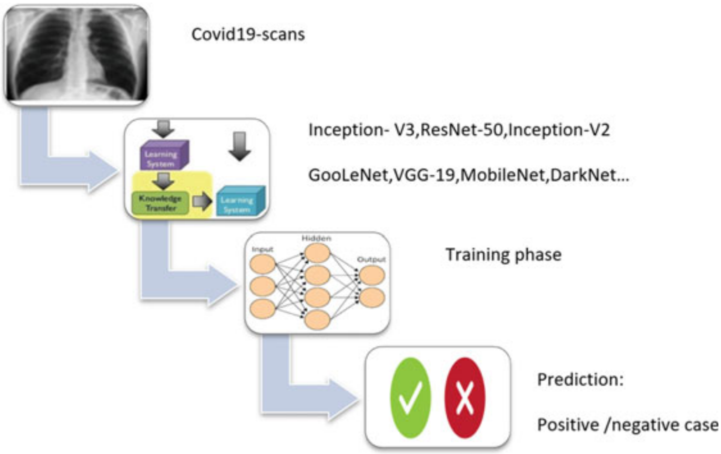

Fig. 3 Transfer learning process

and optimization algorithms [122, 123]. As shown in Fig. 3, transfer learning models apply prior experience-based knowledge to the dataset by altering or adding specialized layers to match the dataset.

In the CNN-sponsored COVID-19 study, this topic attracted a lot of attention. This field includes VGG networks, Residual networks, Inception, Xception CNNs, and a combination of architectures. Because of its ability to avoid the vanishing gradient problem, residual learning was a popular design paradigm in most CNN projects. To help in the diagnosis of COVID-19 chest X-rays, a multi-channel pre-trained ResNet architecture was presented [124]. Following that, three ResNet-based models were retrained one by one to categorize X-rays. A various method that includes pre-processing, augmentation, and crucial steps to implement transfer learning model was used to compare several networks [125]. The first stage used different ResNet topologies to recover viral pneumonia features from other pneumonia, whereas the second stage used different ResNet topologies to gain COVID from other viral pneumonia. A concatenation-based arrangement of transfer learning models was another sort of combination [126].

Deep features were extracted using the combined ResNet50V2 and Xception models to improve the classification based on feature vectors. The pretrained ResNet50 and InceptionV3 transfer learning architectures were employed with logistic regression to detect COVID-19 in a similar study [127].

Since COVID-19 has been related to airspace opacities in X-rays, the Resnet-based CNN is being used to train the task of identifying airspace opacities in chest X-rays [128]. The performance of multiple transfer learning CNNs has been compared in several different studies. For example, Minaee et al. used a custom-constructed dataset to report findings for four alternative architectures: ResNet18, ResNet50, SqueezeNet, and DenseNet-121 [89]. The performance of inception and Xception networks has been compared in several studies. Xception, ResNet50, MobileNet, and Inception V3 were used to create a "recommendation network" that included four pre-trained architectures [129]. Pre-trained deep-learning models for recognizing COVID-19 or normal X-ray images (DenseNet121, ResNet50, VGG16, and VGG19) have also been reported. ResNet, VGG16, Xception, and Inception networks, as well as modified ResNet, VGG16, Xception, and Inception networks, were adapted for COVID-19 classification. The Xception net architecture was used to construct transfer learning models to correctly identify COVID-19 from chest X-rays. A multimodal classification model with enriched input data was published and tested on eight different transfer learning architectures. Transfer knowledge from previous designs, such as the DarkNet model, which started with fewer layers and filters and subsequently increased them depending on trial results [130]. Unlike current CNN architectures, customized CNN architectures are expressly created for classification applications [131]. The class decomposition technique is used for invention-scan irregularities in its class borders. A composite of three binary decision trees, each trained using a CNN model, was characterized using an external classifier [132]. Low-level features were extracted using a bespoke deep CNN model, which was then categorized using an Xception network [133]. For the classification of COVID-19 X-rays, the feature engineering technique was utilized to choose relief features from deep features from a pre-trained AlexNet CNN. Many CNN architectures have convolutional and pooling layers stacked in a linear pattern [134]. A network was designed with a 14-layer convolutional network, and spatial pyramid pooling was created for the multi-scale classification architecture [135]. Das et al. used an approach to minimize over-fitting and model complexity, and a truncated architecture was created utilizing the transfer learning technique [136]. The simplified InceptionV3-based architecture was pre-trained on the ImageNet database using an adjustable learning rate technique. Bridge et al. proposed a generalized extreme value distribution-based activation function that may be utilized with the Inception model to improve pre-trained InceptionV3 models. On unbalanced datasets, this resulted in a better classification performance than models using typical activation methods [136]. The GreyWolf Optimizer (GWO) method was used to optimize the architecture of the CNN feature extraction and classification components [137]. Many studies have backed up the effectiveness of the capsule network. Afshar et al. developed the COVID-CAPS model, which was pre-trained using an external X-ray dataset, to investigate the performance of various capsule net topologies [138]. A capsule network-based model with five distinct convolutional layers was constructed to provide richer feature maps to better understand its contribution [139]. COVID Diagnosis-Net was built using Deep Bayes-SqueezeNet [120] to include the benefits of data enhancement and network optimization For a chest X-ray dataset, the network was developed using the SqueezeNet architecture, which was pre-trained and conducted Bayesian optimization as well as offline augmentation. A CycleGAN to enhance the sample count was developed using convolutional backbones as a feature extractor [121]. To forecast COVID-19, CT-based algorithms have used a range of feature extraction and assembly methods. Only a few studies have used the transfer learning technique for CT picture classification, in contrast to chest X-ray literature. Pathak et al. COVID-19 positive and negative CT images were detected using deep transfer learning on ResNet32 with appropriate layers [140]. A number of studies on CT-based COVID-19 detection have been based on feature extraction. Yan et al., For example, based on the multi-scale spatial pyramid, constructed a CNN with a decomposition architecture (MSSP) [141], which was able to learn multi-scale feature representations without the need for massive amounts of training data With the Enhanced kNN algorithm, Shaban et al. suggested a hybrid feature selection strategy [142], When paired with a classifier, it's a powerful combination. New heuristics were added to a standard kNN classifier, and the strategy included wrapper and filter feature selection strategies. Han et al. used a deep 3D multi-instance learning model to extract features at the instance level. To create patient-level classification, attention-based pooling of such instance labels is applied [143]. New heuristics were added to a standard kNN classifier, and the strategy included wrapper and filter feature selection strategies. Han et al. employed a deep 3d multi-instance learning model to extract features at the instance level. To produce patient-level classification, attention-based pooling of such instance labels is applied [124]. Similarly, Li et al. used a modified Rubik's cube Pro model as the backbone of the classification network to extract 3D attributes using a self-supervised technique. Wang et al. changed the network topology and learning mechanism for cosine annealing in their previously proposed pre-trained COVID-Net architecture [99]. They also showed how to deal with data heterogeneity and improve model performance using a collaborative learning technique. Ztürk et al. used a 2-stage classification model using an SVM classifier in a similar investigation [144]. The data were lightly augmented and subjected to numerous feature extraction methods before being over-sampled using the SMOTE technique. A Q-deformed entropy-based texture feature and deep CNN features to train a Bi-LSTM classifier for COVID-19 identification from CT slices was employed [145]. The combined feature collection was refined using a statistical ANOVA. Solutions provide settings for parameter adjustment based on classic CNNs. According, Pathak et al. [95] An LSTM network-based deep bidirectional classification model was proposed. A mixed density network is used in the bi-directional LSTM network, using a memetic adaptive differential evolution technique, and the hyperparameters were fine-tuned. COVID-19 traits were discovered from X-ray images using an unsupervised clustering-based technique. They used a self-organizing feature map to cluster infection incidences by analyzing each component of the image separately [96]. To develop a comparison of these networks, we used a deep CNN architecture for COVID-19 classification that used multi-objective differential evolution. It is a form of genetic algorithm that uses many rounds of mutation, crossover, and selection to improve the search for hyperparameters [146].

6.2 Segmentation for COVID-19

Singh et al. proposed a deep CNN architecture for COVID-19 classification that used multi-objective differential evolution to build a network comparison. It is a type of genetic algorithm that optimizes the search for hyperparameters through a series of mutation, crossover, and selection phases. Automatic COVID-19 diagnosis approaches employing deep learning on CT images have garnered considerable interest as a way to speed up the examination process. However, the number and type of COVID-19 diagnosis datasets that may be utilized for training are limited, and the number of initial COVID-19 samples is substantially smaller than the average, resulting in a class imbalance problem. Because some classes have a lot of data and others have a lot of data, segmentation algorithms have a hard time learning discriminative boundaries. As a result, building robust deep neural networks with skewed data is a difficult yet critical challenge in the diagnosis of COVID-19.

The issue of AI efforts for COVID-19 identification using X-ray modalities has addressed the problem of segmentation. In X-ray, only a few studies on segmenting COVID-19-affected areas have been conducted. This is because, unlike CT, X-ray characteristics for COVID-19 localization and quantification are not commonly used in clinical settings. COVID-19 CT symptoms have been extensively researched, and their characteristics are typically used to identify COVID-19-affected areas. X-rays, on the other hand, are an excellent tool for diagnosing any type of pneumonia, prompting some studies to use them to divide COVID-19 infections into subgroups. The majority of algorithms are used for optimization. Abdel-Basset et al. developed a meta-heuristic approach that combines the slime mold technique (SMA) with the whale optimization algorithm to enhance Kapur's entropy [147]. The model uses thresholding approaches to extract the regions of interest in the X-ray image. Ground-glass or consolidative pulmonary opacities can be observed in the excised areas of the image. COVID-19 can manifest itself in several ways, including X-ray findings. On chest X-rays, the performance of the integrated SMA was compared to the performance of five algorithms: WOA, FireFly algorithm FFA, HHA, Lshade algorithm, and salp swarm. Abdel-Basset et al. proposed a hybrid detection model for X-ray image segmentation based on an improved marine predator algorithm (IMPA) and a ranking-based diversity reduction (RDR) approach [100]. The test of reverse transcription polymerase chain reaction (RT-PCR) [148] is used to detect viral RNA in sputum or a nasopharyngeal swab is currently the gold standard for detecting COVID-19. The RT-PCR test falls short of its main purpose of swiftly detecting and isolating positive patients due to the time it takes to receive results, the restricted availability of the material in hospitals, and its relatively poor sensitivity. Medical imaging, such as chest radiography or computed tomography (CT) scanners, may be utilized as a rapid screening alternative [149].

6.3 COVID-19 Risk Assessment and Prognosis

Early treatment and selection of the course of follow-up treatment are aided by COVID-19 risk analysis. Some studies have examined methods for predicting the severity of a viral infection in order to aid clinical prognosis. The assessment of the regression task for lung involvement and opacity in COVID-19 was modeled with

DenseNet applied to chest X-ray scans [150]. For feature extraction, fully connected layers were exhibited for the target predictions. Li et al. developed a convolutional Siamese network algorithm that learns from chest X-rays to assess COVID-19 pulmonary disease severity [151].

DenseNet121 was trained on a CheXpert dataset with weak labels as a Siamese network. To test the influence of COVID-19 on pulmonary risk, CNN learning was switched to a smaller COVID-19 training dataset that included a random forest classifier based on patient health data and symptoms [136]. A multivariable logistic regression-based risk prediction model [152] considering the input (sex, age, symptoms, blood test results, and CXR findings) of the patient were all taken into account for medical decision making. A deep learning-based survival model that can predict the risk of COVID-19 patients acquiring critical illness based on clinical parameters at the time of admission was described [153]. For survival modeling, the researchers developed a three-layer feed-forward neural network, which was then integrated with a deep learning survival Cox model, which was used to split patients into high- and low-risk groups, using CT-segmented lung lesion sites and clinical data as input. CT segmentation was used to identify consolidation (CL), ground-glass opacity (GGO), pulmonary effusion, and pleural effusion. Research into severity assessment and criticality prediction is the next stage in the automation of COVID-19 therapeutic regimens [154].

7 Big Data Management and IT Infrastructure During COVID-19

Health big data offer great prospects for innovation and progress in the sector. The COVID-19 crisis highlighted the value of this data and its usefulness for analysis, information, and awareness.

Patients who might benefit from preventative treatment or lifestyle modifications can be identified using big data analysis techniques; the most valuable patient nursing programs can be determined by collecting and analyzing medical procedure data; and the most valuable patient nursing programs can be determined by analyzing and drug treating patients' health status can be determined by analyzing and drug treating patients' health status. Technological advances have increased the volume of health data that are available exponentially. However, the sources and types of data remain heterogeneous and compartmentalized, making their use by health actors more complex [155, 156]. As shown in Fig. 4, the implementation of these first application cases makes it possible to deal with data collection, transformation, standardization, architecture, and storage issues as they arise [157].

The fast spread of the epidemic, along with its ever-changing patterns and symptoms, makes it increasingly impossible to manage. In addition, the epidemic has wreaked havoc on health systems and medical resource availability in a number of countries throughout the world, resulting in a high fatality rate.

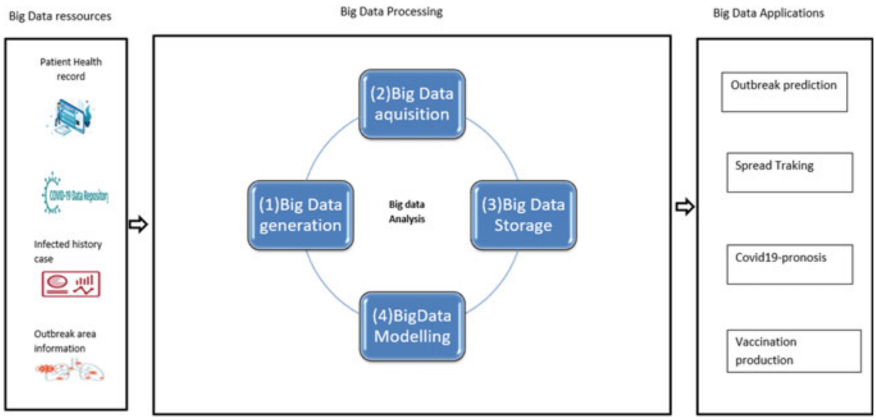

Fig. 4 Big data analytics

Individuals will be checked on a regular basis, and a remote detection device will help track suspected COVID-19 instances more quickly. Furthermore, the utilization of such systems will create a vast volume of data, opening up a variety of opportunities for big data analytics [158] to raise the level of healthcare service quality open-source software, such as the Apache project's big data components, is widely accessible [159]. Cloud computing and distributed environments are considered crucial for building efficient medical data applications. The Six V's [15] are a set of key qualities of big data, which include value, volume, velocity, variety, veracity, and variability [16]. Big data analysis methodologies are more likely to be employed to enhance the sector's services and performance because of the features of big data that apply to data obtained from the healthcare business. Because of its capacity to foresee epidemics using large-scale data analytics, big data is crucial for combatting COVID19. During local or global disease outbreaks, big data analytics is progressively becoming a vital component for modeling viral propagation, infection control, and emergency response evaluations. The topic of data quality for covid-19 patients is also a major challenge. With millions of data created every day, problems of duplicates, updates, and availability of data are frequent. Guaranteeing the reliability of data in its operation involves the setting up of data management projects (governance, roles, mapping, repositories, processes, etc.). It is essential to establish rules, roles, and iterative processes for data management to ensure its integrity in a sustainable manner [20]. The establishment of a patient data warehouse for covid-19 can occur in the context of collecting, processing, and sharing massive volumes of data. A big data application can lead to privacy issues or even storage costs [160]. The volume and heterogeneity of health data sources and formats raise real complexities in terms of data integration, processing, and analysis. Current hospital information systems are generally made up of application silos that do not allow data to be sufficiently standardized and cross-referenced [161].

Prior to the COVID-19 pandemic, infectious disease case data reports were extensively dependent on early sickness detection and monitoring, as well as improving medical institutions, information processes, and storing and gathering a large amount of medical service data. The hospital information system (HIS) is a hospital information management system [162] including: (1) laboratory information system (LIS) [163], (2) Radiation Safety Information Management System (RASIMS), (3) Picture Archive and Communication System (Pacs), and Radiology Information System (RIS) [164] are considered the main servers implemented in hospital environments for data storage and management. In medical and health departments, data on patient coordinates, historical medical records, illnesses, test results, orders, operation records, and nursing records are all recorded in the electronic medical record system (EMRS) [31, 165]. Following the outbreak, the use of big data technologies to prevent and manage COVID-19 has become a critical step in medical decision-making. To manage epidemic monitoring and analysis, viral source tracking, epidemic prevention and treatment, and resource allocation, digital technologies such as big data, AI, and cloud computing are being used.

Utilizing big data technologies, the activity patterns of verified people and close connections were evaluated, and an epidemic spread model was developed using the positioning system. There is no doubt about the predictive competence that data offers us, but this advantage is perhaps all the more decisive in the medical field. Indeed, business intelligence in healthcare aims to help physicians make data-driven decisions in seconds and improve the treatment of covid 19 patients.

This is particularly useful in patients with a complex medical history and multiple comorbidities [166]. Healthcare systems that contain features and capabilities for analyzing massive volumes of data are known as big data analytics platforms. It allows medical decision-makers to sift through huge amounts of big data for previously undiscovered connections, market trends, and pertinent data. Table 3 outline the most common big data analytics systems and data storage management platforms.

It will feasible to simplify the actions of managing covid-19 patients using big data solutions in the healthcare industry. Time-constrained medical institutions may maximize staffing while anticipating diagnostic demands by using the correct human resource analytics, therefore expediting the treatment of patients afflicted by covid19. To combat the danger of covid-19, big data and healthcare are essential. This may also aid in the prevention of degeneration. Healthcare facilities can give correct preventative care and eventually account for hospital admissions by examining information such as kind of medicine, symptoms, and frequency of medical visits, among other things. This degree of risk assessment will not only result in lower inpatient expenditure, but it will also guarantee that space and resources are accessible to individuals who need them.

Table 3 Summary of big data tools

Tools	Features	Availability
Apache Hadoop [167]	Hadoop distributed file system (HDFS) distributed parallel processing of enormous amounts of data, including MapReduce YARN data storage and distributed processing ("yet another resource negotiator")	https://hadoop.apache.org
IBM [168]	IBM big SQL, apache spark, text analytics, and data visualization are just a few of the big data tools available	https://www.ibm.com/analytics/hadoop/big-data-analytics
Amazon [169]	Data storage, data analysis systems data analytics is a term that refers to the study of apache spark, hive, presto, and other big data applications can be easily performed and scaled. scalable and easy to use apache spark, hive, presto, and other big data workloads	https://aws.amazon.com/emr/?c=a&sec=srv
Microsoft azure [170]	Using a cloud-based big data platform, you may design, assess, build, and manage applications. It offers the following goods and services: software as a service (SaaS) (SAAS). PaaS (platform as a service) is a term for infrastructure that is offered as a service	https://azure.microsoft.com/en-us/industries/healthcare/
Knime [171]	KNIME Server is corporate software that enables data scientists to collaborate, automate, manage, and deploy analytical applications and services. Non-experts may use the KNIME WebPortal or REST APIs to access data science	https://www.knime.com
Datameer [172]	Tools for data administration and modeling that are easy to use. Datameer spectrum is a non-programmable ETL++ tool and platform	https://www.datameer.com/healthcare/
Apache Cassandra [173]	Database management system with several servers and a distributed database	https://cassandra.apache.org/_/index.html
Chukwa [174]	Hadoop distributed file system (HDFS)	https://chukwa.apache.org
Rapiminer [171]	Regulatory compliance needs a thorough grasp of difficult data issues	https://rapidminer.com/industry/healthcare/
BigML [175]	BigML encrypts all connections using HTTPS, ensuring the safety of user data and discussions. The BigML team does not have access to any data in the system unless the user grants explicit permission	https://bigml.com
COVID-QF [176]	Over COVID-19, a big data-based framework for complex query execution	https://github.com/cqframework/covid-19
Apache spark [177]	Using apache spark, a multi-dimensional big data storing system for generated COVID-19 large-scale data	https://spark.apache.org

8 Conclusion

The COVID-19 outbreak has sparked great concern around the world. In a silver lining, the uproar may act as a motivation for artificial intelligence research and development to assist medical personnel in combatting the epidemic. While the advantages are clear, artificial intelligence models will never be able to completely replace doctors and radiologists. Nonetheless, in recent years, computer-assisted techniques for medical image processing have made significant progress, boosting medical research and practical applications. Recent research using deep learning and machine learning architectures has demonstrated the reliability of image-based COVID-19 diagnosis. The goal of this research is to examine how far these designs have progressed in terms of categorization and segmentation of COVID-19 symptoms using the modalities that have been used. The COVID-19 outbreak has sparked great concern around the world. In a silver lining, the uproar may act as a motivation for artificial intelligence research and development to assist medical personnel in combatting the epidemic. While the advantages are clear, artificial intelligence models will never be able to completely replace doctors and radiologists. Nonetheless, in recent years, computer-assisted techniques for medical image processing have made significant progress, boosting medical research and practical applications. The reliability of image-based COVID-19 diagnosis has been established in recent research employing deep learning and machine learning architectures. This study aims to examine the current accomplishments and progress of these architectures in the classification and segmentation of COVID-19 infection manifestations using the modalities utilized. Despite these advances, significant barriers remain, preventing future growth. Because of the urgency of this epidemic, humanity is counting scientific ingenuity to find a cure. Breakthroughs may happen quicker if medical practitioners and radiologists are engaged in the conceptualization and building of a framework for artificial intelligence models. While deep learning and machine learning have shown promise in the medical field, they also have great promise in other image-based classification and segmentation problems.

The massive amount of time and resources necessary, as well as hefty implementation costs, are now impeding this potential. Insufficient and uneven data are another difficulty for classification and segmentation algorithms, which leads to overfitting and erroneous predictions. Further advancements and innovations aimed at overcoming these limitations may significantly contribute to advances in biomedical image processing.

Controlling an epidemic requires a complete understanding of its features and behavior, which may be discovered through the collection and analysis of relevant big data. Big data analytics are critical for obtaining the data needed to make judgments and take precautionary steps. The huge volumes of data currently available pose technical challenges for their storage and operational capacities. Increasingly complex computer and statistical programs and algorithms are required.

References

1. Ejima K, Kim KS, Ludema C, Bento AI, Iwanami S, Fujita Y, Ohashi H, Koizumi Y, Watashi K, Aihara K, Nishiura H, Iwami S (2021) Estimation of the incubation period of COVID-19 using viral load data. Epidemics 35:100454. https://doi.org/10.1016/j.epidem.2021.100454
2. Zaki N, Mohamed EA (2021) The estimations of the COVID-19 incubation period: a scoping reviews of the literature. J Infect Public Health 14:638–646. https://doi.org/10.1016/j.jiph.2021.01.019
3. Teotônio IMSN, de Carvalho JL, Castro LC, Nitz N, Hagström L, Rios GG, de Fátima Rodrigues de Oliveira M, Dallago BSL, Hecht M (2021) Clinical and biochemical parameters of COVID-19 patients with prior or active dengue fever. Acta Tropica 214:105782. https://doi.org/10.1016/j.actatropica.2020.105782
4. Owais M, Yoon HS, Mahmood T, Haider A, Sultan H, Park KR (2021) Light-weighted ensemble network with multilevel activation visualization for robust diagnosis of COVID19 pneumonia from large-scale chest radiographic database. Appl Soft Comput 108:107490. https://doi.org/10.1016/j.asoc.2021.107490
5. Rosas J, Liaño FP, Cantó ML, Barea JMC, Beser AR, Rabasa JTA, Adsuar FM, Auli BV, López IF, Sainz AMG, Ramis PE, Pérez LR, Rebollo MLN, Lorido RH, Escolar LG (2020) Experience with the use of baricitinib and tocilizumab monotherapy or combined, in patients with interstitial pneumonia secondary to coronavirus COVID19: a real-world study. Reumatología Clínica. https://doi.org/10.1016/j.reuma.2020.10.009
6. Karthik R, Menaka R, Hariharan M, Kathiresan GS (2021) AI for COVID-19 detection from radiographs: incisive analysis of state of the art techniques, key challenges and future directions. IRBM. https://doi.org/10.1016/j.irbm.2021.07.002
7. Xie Y, Wang X, Yang P, Zhang S (2020) COVID-19 complicated by acute pulmonary embolism. Radiol Cardiothoracic Imaging 2:e200067. https://doi.org/10.1148/ryct.2020200067
8. Shuja J, Alanazi E, Alasmary W, Alashaikh A (2020) COVID-19 open source data sets: a comprehensive survey. Appl Intell:1–30. https://doi.org/10.1007/s10489-020-01862-6
9. Alsharif W, Qurashi A (2021) Effectiveness of COVID-19 diagnosis and management tools: a review. Radiography (Lond) 27:682–687. https://doi.org/10.1016/j.radi.2020.09.010
10. Alakus TB, Turkoglu I (2020) Comparison of deep learning approaches to predict COVID-19 infection. Chaos Solitons Fractals 140:110120. https://doi.org/10.1016/j.chaos.2020.110120
11. Sufian A, Ghosh A, Sadiq AS, Smarandache F (2020) A survey on deep transfer learning to edge computing for mitigating the COVID-19 pandemic. J Syst Architect 108:101830. https://doi.org/10.1016/j.sysarc.2020.101830
12. Singh S, Parmar KS, Makkhan SJS, Kaur J, Peshoria S, Kumar J (2020) Study of ARIMA and least square support vector machine (LS-SVM) models for the prediction of SARS-CoV-2 confirmed cases in the most affected countries. Chaos Solitons Fractals 139:110086. https://doi.org/10.1016/j.chaos.2020.110086
13. Bachhety S, Kapania S, Jain R (2021) 2—big data analytics for healthcare: theory and applications. In: Khanna A, Gupta D, Dey N (eds) Applications of big data in healthcare. Academic Press, pp 45–67
14. Renugadevi N, Saravanan S, Naga Sudha CM (2021) Revolution of smart healthcare materials in big data analytics. Mater Today Proc. https://doi.org/10.1016/j.matpr.2021.04.256
15. Andreu-Perez J, Poon CCY, Merrifield RD, Wong STC, Yang G-Z (2015) Big data for health. IEEE J Biomed Health Inform 19:1193–1208. https://doi.org/10.1109/JBHI.2015.2450362
16. Hagar Y, Albers D, Pivovarov R, Chase H, Dukic V, Elhadad N (2014) Survival analysis with electronic health record data: experiments with chronic kidney disease. Stat Anal Data Min 7:385–403. https://doi.org/10.1002/sam.11236

17. Wang L, Alexander C (2021) Chapter 2—big data in personalized healthcare. In: Moustafa AA (ed) Big data in psychiatry #x0026; neurology. Academic Press, pp 35–49
18. Chugh S, Kumaram S, Sharma DK (2021) 3—application of tools and techniques of big data analytics for healthcare system. In: Khanna A, Gupta D, Dey N (eds) Applications of big data in healthcare. Academic Press, pp 69–84
19. Chae S, Kwon S, Lee D (2018) Predicting infectious disease using deep learning and big data. Int J Environ Res Public Health 15:E1596. https://doi.org/10.3390/ijerph15081596
20. Bansal S, Chowell G, Simonsen L, Vespignani A, Viboud C (2016) Big data for infectious disease surveillance and modeling. J Infect Dis 214:S375–S379. https://doi.org/10.1093/infdis/jiw400
21. Eisenstein M (2018) Infection forecasts powered by big data. Nature 555:S2–S4. https://doi.org/10.1038/d41586-018-02473-5
22. Mangono T, Smittenaar P, Caplan Y, Huang VS, Sutermaster S, Kemp H, Sgaier SK (2021) Information-seeking patterns during the COVID-19 pandemic across the United States: longitudinal analysis of google trends data. J Med Internet Res 23:e22933. https://doi.org/10.2196/22933
23. Chen C-M, Jyan H-W, Chien S-C, Jen H-H, Hsu C-Y, Lee P-C, Lee C-F, Yang Y-T, Chen M-Y, Chen L-S, Chen H-H, Chan C-C (2020) Containing COVID-19 among 627,386 persons in contact with the diamond princess cruise ship passengers who disembarked in Taiwan: big data analytics. J Med Internet Res 22:e19540. https://doi.org/10.2196/19540
24. Zhang S, Diao M, Yu W, Pei L, Lin Z, Chen D (2020) Estimation of the reproductive number of novel coronavirus (COVID-19) and the probable outbreak size on the diamond princess cruise ship: a data-driven analysis. Int J Infect Dis 93:201–204. https://doi.org/10.1016/j.ijid.2020.02.033
25. Padden JS (2020) Informatics X-men evolution to combat COVID-19. Nurse Lead 18:557–560. https://doi.org/10.1016/j.mnl.2020.09.005
26. Reeves JJ, Hollandsworth HM, Torriani FJ, Taplitz R, Abeles S, Tai-Seale M, Millen M, Clay BJ, Longhurst CA (2020) Rapid response to COVID-19: health informatics support for outbreak management in an academic health system. J Am Med Inform Assoc 27:853–859. https://doi.org/10.1093/jamia/ocaa037
27. Werley HH, Devine EC, Zorn CR, Ryan P, Westra BL (1991) The nursing minimum data set: abstraction tool for standardized, comparable, essential data. Am J Public Health 81:421–426
28. Dixon BE (2020) Applied public health informatics: an eHealth discipline focused on populations. J Int Soc Telemed eHealth 8:e14(1–8). https://doi.org/10.29086/JISfTeH.8.e14
29. Grange ES, Neil EJ, Stoffel M, Singh AP, Tseng E, Resco-Summers K, Fellner BJ, Lynch JB, Mathias PC, Mauritz-Miller K, Sutton PR, Leu MG (2020) Responding to COVID-19: the UW medicine information technology services experience. Appl Clin Inform 11:265–275. https://doi.org/10.1055/s-0040-1709715
30. Vilendrer S, Patel B, Chadwick W, Hwa M, Asch S, Pageler N, Ramdeo R, Saliba-Gustafsson EA, Strong P, Sharp C (2020) Rapid deployment of inpatient telemedicine in response to COVID-19 across three health systems. J Am Med Inform Assoc 27:1102–1109. https://doi.org/10.1093/jamia/ocaa077
31. Huang Y, Li X, Zhang G-Q (2021) ELII: a novel inverted index for fast temporal query, with application to a large COVID-19 EHR dataset. J Biomed Inform 117:103744. https://doi.org/10.1016/j.jbi.2021.103744
32. Dagliati A, Malovini A, Tibollo V, Bellazzi R (2021) Health informatics and EHR to support clinical research in the COVID-19 pandemic: an overview. Brief Bioinform 22:812–822. https://doi.org/10.1093/bib/bbaa418
33. Moore JH, Barnett I, Boland MR, Chen Y, Demiris G, Gonzalez-Hernandez G, Herman DS, Himes BE, Hubbard RA, Kim D, Morris JS, Mowery DL, Ritchie MD, Shen L, Urbanowicz R, Holmes JH (2020) Ideas for how informaticians can get involved with COVID-19 research. BioData Mining 13:3. https://doi.org/10.1186/s13040-020-00213-y

34. Brown JS, Bastarache L, Weiner MG (2021) Aggregating electronic health record data for COVID-19 research—caveat emptor. JAMA Netw Open 4:e2117175. https://doi.org/10.1001/jamanetworkopen.2021.17175
35. Pryor R, Atkinson C, Cooper K, Doll M, Godbout E, Stevens MP, Bearman G (2020) The electronic medical record and COVID-19: is it up to the challenge? Am J Infect Control 48:966–967. https://doi.org/10.1016/j.ajic.2020.05.002
36. Bowman S (2013) Impact of electronic health record systems on information integrity: quality and safety implications. Perspect Health Inf Manage 10:1c
37. Zarour M, Alenezi M, Ansari MTJ, Pandey AK, Ahmad M, Agrawal A, Kumar R, Khan RA (2021) Ensuring data integrity of healthcare information in the era of digital health. Healthc Technol Lett 8:66–77. https://doi.org/10.1049/htl2.12008
38. Graber ML, Byrne C, Johnston D (2017) The impact of electronic health records on diagnosis. Diagnosis (Berl) 4:211–223. https://doi.org/10.1515/dx-2017-0012
39. Zahabi M, Kaber DB, Swangnetr M (2015) Usability and safety in electronic medical records interface design: a review of recent literature and guideline formulation. Hum Factors 57:805–834. https://doi.org/10.1177/0018720815576827
40. Wu G, Yang P, Xie Y, Woodruff HC, Rao X, Guiot J, Frix A-N, Louis R, Moutschen M, Li J, Li J, Yan C, Du D, Zhao S, Ding Y, Liu B, Sun W, Albarello F, D'Abramo A, Schininà V, Nicastri E, Occhipinti M, Barisione G, Barisione E, Halilaj I, Lovinfosse P, Wang X, Wu J, Lambin P (2020) Development of a clinical decision support system for severity risk prediction and triage of COVID-19 patients at hospital admission: an international multicentre study. Eur Respir J 56:2001104. https://doi.org/10.1183/13993003.01104-2020
41. Dixon BE, Grannis SJ, McAndrews C, Broyles AA, Mikels-Carrasco W, Wiensch A, Williams JL, Tachinardi U, Embi PJ (2021) Leveraging data visualization and a statewide health information exchange to support COVID-19 surveillance and response: application of public health informatics. J Am Med Inform Assoc 28:1363–1373. https://doi.org/10.1093/jamia/ocab004
42. Bookman RJ, Cimino JJ, Harle CA, Kost RG, Mooney S, Pfaff E, Rojevsky S, Tobin JN, Wilcox A, Tsinoremas NF (2021) Research informatics and the COVID-19 pandemic: challenges, innovations, lessons learned, and recommendations. J Clin Transl Sci 5.https://doi.org/10.1017/cts.2021.26
43. Sein MK (2020) The serendipitous impact of COVID-19 pandemic: a rare opportunity for research and practice. Int J Inf Manage 55:102164. https://doi.org/10.1016/j.ijinfomgt.2020.102164
44. Richter A (2020) Locked-down digital work. Int J Inf Manage 55:102157. https://doi.org/10.1016/j.ijinfomgt.2020.102157
45. Pranggono B, Arabo A (2021) COVID-19 pandemic cybersecurity issues. Internet Technol Lett 4:e247. https://doi.org/10.1002/itl2.247
46. O'Leary DE (2020) Evolving information systems and technology research issues for COVID-19 and other pandemics. J Organ Comput Electron Commer 30:1–8. https://doi.org/10.1080/10919392.2020.1755790
47. Dwivedi YK, Hughes DL, Coombs C, Constantiou I, Duan Y, Edwards JS, Gupta B, Lal B, Misra S, Prashant P, Raman R, Rana NP, Sharma SK, Upadhyay N (2020) Impact of COVID-19 pandemic on information management research and practice: transforming education, work and life. Int J Inf Manage 55:102211. https://doi.org/10.1016/j.ijinfomgt.2020.102211
48. Sharma A, Borah SB, Moses AC (2021) Responses to COVID-19: the role of governance, healthcare infrastructure, and learning from past pandemics. J Bus Res 122:597–607. https://doi.org/10.1016/j.jbusres.2020.09.011
49. Rehani B, Rodriguez JA, Nguyen JK, Patel MM, Ammanuel SG, Winford E, Dillon WP (2021) COVID-19 radiology preparedness, challenges & opportunities: responses from 18 countries. Curr Probl Diagn Radiol. https://doi.org/10.1067/j.cpradiol.2021.03.017

50. Gupta D, Bhatt S, Gupta M, Tosun AS (2021) Future smart connected communities to fight COVID-19 outbreak. Internet Things 13:100342. https://doi.org/10.1016/j.iot.2020.100342
51. Shahroz M, Ahmad F, Younis MS, Ahmad N, Kamel Boulos MN, Vinuesa R, Qadir J (2021) COVID-19 digital contact tracing applications and techniques: a review post initial deployments. Transp Eng 5:100072. https://doi.org/10.1016/j.treng.2021.100072
52. Goel I, Sharma S, Kashiramka S (2021) Effects of the COVID-19 pandemic in India: an analysis of policy and technological interventions. Health Policy Technol 10:151–164. https://doi.org/10.1016/j.hlpt.2020.12.001
53. Dodoo JE, Al-Samarraie H, Alzahrani AI (2021) Telemedicine use in sub-Saharan Africa: barriers and policy recommendations for COVID-19 and beyond. Int J Med Informatics 151:104467. https://doi.org/10.1016/j.ijmedinf.2021.104467
54. Brohi S, Zaman N, Brohi N, Brohi MN (2020) Key applications of state-of-the-art technologies to mitigate and eliminate COVID-19
55. Sipior JC (2020) Considerations for development and use of AI in response to COVID-19. Int J Inf Manage 55:102170. https://doi.org/10.1016/j.ijinfomgt.2020.102170
56. Laliève L, Adam J, Nataf P, Khonsari RH (2021) 3D-printed suture guide for thoracic and cardiovascular surgery produced during the COVID19 pandemic. Ann 3D Printed Med 1:100005. https://doi.org/10.1016/j.stlm.2020.100005
57. Bragazzi NL, Dai H, Damiani G, Behzadifar M, Martini M, Wu J (2020) How big data and artificial intelligence can help better manage the COVID-19 pandemic. Int J Environ Res Public Health 17:E3176. https://doi.org/10.3390/ijerph17093176
58. Kalgotra P, Gupta A, Sharda R (2021) Pandemic information support lifecycle: evidence from the evolution of mobile apps during COVID-19. J Bus Res 134:540–559. https://doi.org/10.1016/j.jbusres.2021.06.002
59. Singh RP, Javaid M, Haleem A, Suman R (2020) Internet of things (IoT) applications to fight against COVID-19 pandemic. Diabetes Metab Syndr 14:521–524. https://doi.org/10.1016/j.dsx.2020.04.041
60. Otoom M, Otoum N, Alzubaidi MA, Etoom Y, Banihani R (2020) An IoT-based framework for early identification and monitoring of COVID-19 cases. Biomed Signal Process Control 62:102149. https://doi.org/10.1016/j.bspc.2020.102149
61. Fusco A, Dicuonzo G, Dell'Atti V, Tatullo M (2020) Blockchain in healthcare: insights on COVID-19. Int J Environ Res Public Health 17:E7167. https://doi.org/10.3390/ijerph17197167
62. Tan L, Tivey D, Kopunic H, Babidge W, Langley S, Maddern G (2020) Part 2: blockchain technology in health care. ANZ J Surg 90:2415–2419. https://doi.org/10.1111/ans.16455
63. Pennisi M, Kavasidis I, Spampinato C, Schinina V, Palazzo S, Salanitri FP, Bellitto G, Rundo F, Aldinucci M, Cristofaro M, Campioni P, Pianura E, Di Stefano F, Petrone A, Albarello F, Ippolito G, Cuzzocrea S, Conoci S (2021) An explainable AI system for automated COVID-19 assessment and lesion categorization from CT-scans. Artif Intell Med 118:102114. https://doi.org/10.1016/j.artmed.2021.102114
64. Ronaghi F, Salimibeni M, Naderkhani F, Mohammadi A (2022) COVID19-HPSMP: COVID-19 adopted hybrid and parallel deep information fusion framework for stock price movement prediction. Expert Syst Appl 187:115879. https://doi.org/10.1016/j.eswa.2021.115879
65. Wang X, Deng X, Fu Q, Zhou Q, Feng J, Ma H, Liu W, Zheng C (2020) A weakly-supervised framework for COVID-19 classification and lesion localization from chest CT. IEEE Trans Med Imaging 39:2615–2625. https://doi.org/10.1109/TMI.2020.2995965
66. Sitaula C, Aryal S (2021) New bag of deep visual words based features to classify chest x-ray images for COVID-19 diagnosis. Health Inf Sci Syst 9:24. https://doi.org/10.1007/s13755-021-00152-w
67. Sözen ME, Sarıyer G, Ataman MG (2021) Big data analytics and COVID-19: investigating the relationship between government policies and cases in Poland, Turkey and South Korea. Health Policy Plann. https://doi.org/10.1093/heapol/czab096
68. Roberts SL. Tracking COVID-19 using big data and big tech: a digital Pandora's Box

69. Umair M, Cheema MA, Cheema O, Li H, Lu H (2021) Impact of COVID-19 on IoT adoption in healthcare, smart homes, smart buildings, smart cities. Transp Ind IoT Sensors 21:3838. https://doi.org/10.3390/s21113838
70. Chen S-W, Gu X-W, Wang J-J, Zhu H-S (2021) AIoT used for COVID-19 pandemic prevention and control. Contrast Media &#x26 Mole Imaging 2021:e3257035. https://doi.org/10.1155/2021/3257035
71. Ramallo-González AP, González-Vidal A, Skarmeta AF (2021) CIoTVID: Towards an open IoT-platform for infective pandemic diseases such as COVID-19. Sensors (Basel) 21:E484. https://doi.org/10.3390/s21020484
72. Ng WY, Tan T-E, Movva PVH, Fang AHS, Yeo K-K, Ho D, Foo FSS, Xiao Z, Sun K, Wong TY, Sia AT-H, Ting DSW (2021) Blockchain applications in health care for COVID-19 and beyond: a systematic review. Lancet Digit Health S2589–7500(21):00210–00217. https://doi.org/10.1016/S2589-7500(21)00210-7
73. Bansal A, Garg C, Padappayil RP (2020) Optimizing the implementation of COVID-19 “immunity certificates” using blockchain. J Med Syst 44:140. https://doi.org/10.1007/s10916-020-01616-4
74. Kimmig R, Verheijen RHM, Rudnicki M (2020) Robot assisted surgery during the COVID-19 pandemic, especially for gynecological cancer: a statement of the society of European robotic gynaecological surgery (SERGS). J Gynecol Oncol 31:e59. https://doi.org/10.3802/jgo.2020.31.e59
75. Samalavicius NE, Siaulys R, Janusonis V, Klimasauskiene V, Dulskas A (2020) Use of 4 robotic arms performing Senhance® robotic surgery may reduce the risk of coronavirus infection to medical professionals during COVID-19. Euro J Obstetrics Gynecol Reprod Biol 251:274–275. https://doi.org/10.1016/j.ejogrb.2020.06.014
76. Tino R, Moore R, Antoline S, Ravi P, Wake N, Ionita CN, Morris JM, Decker SJ, Sheikh A, Rybicki FJ, Chepelev LL (2020) COVID-19 and the role of 3D printing in medicine. 3D Print Med 6:11. https://doi.org/10.1186/s41205-020-00064-7
77. Ishack S, Lipner SR (2020) Applications of 3D printing technology to address COVID-19—related supply shortages. Am J Med 133:771–773. https://doi.org/10.1016/j.amjmed.2020.04.002
78. Williams E, Bond K, Isles N, Chong B, Johnson D, Druce J, Hoang T, Ballard SA, Hall V, Muhi S, Buising KL, Lim S, Strugnell D, Catton M, Irving LB, Howden BP, Bert E, Williamson DA (2020) Pandemic printing: a novel 3D-printed swab for detecting SARS-CoV-2. Med J Aust 213:276–279. https://doi.org/10.5694/mja2.50726
79. Davalbhakta S, Advani S, Kumar S, Agarwal V, Bhoyar S, Fedirko E, Misra DP, Goel A, Gupta L, Agarwal V (2020) A systematic review of smartphone applications available for corona virus disease 2019 (COVID19) and the assessment of their quality using the mobile application rating scale (MARS). J Med Syst 44:164. https://doi.org/10.1007/s10916-020-01633-3
80. Ming LC, Untong N, Aliudin NA, Osili N, Kifli N, Tan CS, Goh KW, Ng PW, Al-Worafi YM, Lee KS, Goh HP (2020) Mobile health apps on COVID-19 launched in the early days of the pandemic: content analysis and review. JMIR Mhealth Uhealth 8:e19796. https://doi.org/10.2196/19796
81. Torous J, Keshavan M (2020) COVID-19, mobile health and serious mental illness. Schizophr Res 218:36–37. https://doi.org/10.1016/j.schres.2020.04.013
82. Eysenbach G (2001) What is e-health? J Med Internet Res 3:e833. https://doi.org/10.2196/jmir.3.2.e20
83. Bitar H, Alismail S (2021) The role of eHealth, telehealth, and telemedicine for chronic disease patients during COVID-19 pandemic: a rapid systematic review. Digit Health 7:20552076211009396. https://doi.org/10.1177/20552076211009396
84. Li J, Seale H, Ray P, Rawlinson W, Lewis L, Macintyre CR (2012) Issues regarding the implementation of eHealth: preparing for future influenza pandemics. Interact J Med Res 1:e20. https://doi.org/10.2196/ijmr.2357

85. Gerli P, Arakpogun E, Elsahn Z, Olan F, Prime KS (2021) Beyond contact-tracing: the public value of ehealth application in a pandemic. Gov Inf Q 38.https://doi.org/10.1016/j.giq.2021.101581
86. Neter E, Brainin E (2012) eHealth literacy: extending the digital divide to the realm of health information. J Med Internet Res 14:e1619. https://doi.org/10.2196/jmir.1619
87. Scott RE, Mars M (2021) COVID-19 and eHealth: a promise or peril paradox? J Int Soc Telemed eHealth 9:e1(1–2). https://doi.org/10.29086/JISfTeH.9.e1
88. Palabindala V, Bharathidasan K (2021) Telemedicine in the COVID-19 era: a tricky transition. J Community Hosp Intern Med Perspect 11:302–303. https://doi.org/10.1080/20009666.2021.1899581
89. Dorn SD (2021) Backslide or forward progress? Virtual care at U.S. healthcare systems beyond the COVID-19 pandemic. NPJ Digit Med 4:6. https://doi.org/10.1038/s41746-020-00379-z
90. Farooq M, Hafeez A (2020) COVID-ResNet: a deep learning framework for screening of COVID19 from radiographs. arXiv:200314395 [cs, eess]
91. Mahanta SK, Kaushik D, Jain S, Van Truong H, Guha K (2021) COVID-19 diagnosis from cough acoustics using ConvNets and data augmentation. arXiv:211006123 [cs, eess]
92. Khan AI, Shah JL, Bhat MM (2020) CoroNet: a deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. Comput Methods Programs Biomed 196:105581. https://doi.org/10.1016/j.cmpb.2020.105581
93. Karthik R, Menaka RMH (2021) Learning distinctive filters for COVID-19 detection from chest X-ray using shuffled residual CNN. Appl Soft Comput 99:106744. https://doi.org/10.1016/j.asoc.2020.106744
94. Cohen JP, Morrison P, Dao L (2020) COVID-19 image data collection. arXiv:200311597 [cs, eess, q-bio]
95. Pathak Y, Shukla PK, Arya KV (2021) Deep bidirectional classification model for COVID-19 disease infected patients. IEEE/ACM Trans Comput Biol Bioinf 18:1234–1241. https://doi.org/10.1109/TCBB.2020.3009859
96. King B, Barve S, Ford A, Jha R (2020) Unsupervised clustering of COVID-19 chest X-ray images with a self-organizing feature map. In: 2020 IEEE 63rd international midwest symposium on circuits and systems (MWSCAS), pp 395–398
97. Ahuja S, Panigrahi BK, Dey N, Rajinikanth V, Gandhi TK (2021) Deep transfer learning-based automated detection of COVID-19 from lung CT scan slices. Appl Intell 51:571–585. https://doi.org/10.1007/s10489-020-01826-w
98. Shibly KH, Dey SK, Islam MT-U, Rahman MM (2020) COVID faster R-CNN: a novel framework to diagnose novel coronavirus disease (COVID-19) in X-ray images. Inform Med Unlocked 20:100405. https://doi.org/10.1016/j.imu.2020.100405
99. Wang Z, Liu Q, Dou Q (2020) Contrastive cross-site learning with redesigned net for COVID-19 CT classification. IEEE J Biomed Health Inform 24:2806–2813. https://doi.org/10.1109/JBHI.2020.3023246
100. Abdel-Basset M, Mohamed R, Elhoseny M, Chakrabortty RK, Ryan M (2020) A hybrid COVID-19 detection model using an improved marine predators algorithm and a ranking-based diversity reduction strategy. IEEE Access 8:79521–79540. https://doi.org/10.1109/ACCESS.2020.2990893
101. Wang G, Liu X, Li C, Xu Z, Ruan J, Zhu H, Meng T, Li K, Huang N, Zhang S (2020) A noise-robust framework for automatic segmentation of COVID-19 pneumonia lesions from CT images. IEEE Trans Med Imaging 39:2653–2663. https://doi.org/10.1109/TMI.2020.3000314
102. Fan D-P, Zhou T, Ji G-P, Zhou Y, Chen G, Fu H, Shen J, Shao L (2020) Inf-Net: automatic COVID-19 lung infection segmentation from CT images. IEEE Trans Med Imaging 39:2626–2637. https://doi.org/10.1109/TMI.2020.2996645

103. Ranjbarzadeh R, Jafarzadeh Ghoushchi S, Bendechache M, Amirabadi A, Ab Rahman MN, Baseri Saadi S, Aghamohammadi A, Kooshki Forooshani M (2021) Lung infection segmentation for COVID-19 pneumonia based on a cascade convolutional network from CT images. Biomed Res Int 2021:e5544742. https://doi.org/10.1155/2021/5544742
104. Berta L, Rizzetto F, De Mattia C, Lizio D, Felisi M, Colombo PE, Carrazza S, Gelmini S, Bianchi L, Artioli D, Travaglini F, Vanzulli A, Torresin A (2021) Automatic lung segmentation in COVID-19 patients: impact on quantitative computed tomography analysis. Phys Med 87:115–122. https://doi.org/10.1016/j.ejmp.2021.06.001
105. Elaziz MA, Ewees AA, Yousri D, Alwerfali HSN, Awad QA, Lu S, Al-Qaness MAA (2020) An improved marine predators algorithm with fuzzy entropy for multi-level thresholding: real world example of COVID-19 CT image segmentation. IEEE Access 8:125306–125330. https://doi.org/10.1109/ACCESS.2020.3007928
106. Kim Y-G, Kim K, Wu D, Ren H, Tak WY, Park SY, Lee YR, Kang MK, Park JG, Kim BS, Chung WJ, Kalra MK, Li Q (2020) deep learning-based four-region lung segmentation in chest radiography for COVID-19 diagnosis. arXiv:200912610 [cs, eess]
107. Teixeira LO, Pereira RM, Bertolini D, Oliveira LS, Nanni L, Cavalcanti GDC, Costa YMG (2021) Impact of lung segmentation on the diagnosis and explanation of COVID-19 in chest X-ray images. arXiv:200909780 [cs, eess]
108. Müller D, Rey IS, Kramer F (2020) Automated chest CT image segmentation of COVID-19 lung infection based on 3D U-Net. arXiv:200704774 [cs, eess]
109. Krinski BA, Ruiz DV, Todt E (2021) Spark in the dark: evaluating encoder-decoder pairs for COVID-19 CT's semantic segmentation. arXiv:210914818 [cs, eess]
110. Civit-Masot J, Luna-Perejón F, Domínguez Morales M, Civit A (2020) Deep learning system for COVID-19 diagnosis aid using X-ray pulmonary images. Appl Sci 10:4640. https://doi.org/10.3390/app10134640
111. Pandit MK, Banday SA (2020) SARS n-CoV2-19 detection from chest x-ray images using deep neural networks. Int J Pervasive Comput Commun 16:419–427. https://doi.org/10.1108/IJPCC-06-2020-0060
112. Makris A, Kontopoulos I, Tserpes K (2020) COVID-19 detection from chest X-ray images using deep learning and convolutional neural networks. In: 11th Hellenic conference on artificial intelligence. Association for Computing Machinery, New York, NY, USA, pp 60–66
113. Dey N, Zhang Y-D, Rajinikanth V, Pugalenthi R, Raja NSM (2021) Customized VGG19 architecture for pneumonia detection in chest X-rays. Pattern Recogn Lett 143:67–74. https://doi.org/10.1016/j.patrec.2020.12.010
114. Wang W, Yu Z, Fu C, Cai D, He X (2021) COP: customized correlation-based filter level pruning method for deep CNN compression. Neurocomputing 464:533–545. https://doi.org/10.1016/j.neucom.2021.08.098
115. Zhang Z, Lin X, Li M, Wang Y (2021) A customized deep learning approach to integrate network-scale online traffic data imputation and prediction. Transp Res Part C Emerging Technol 132:103372. https://doi.org/10.1016/j.trc.2021.103372
116. Lee K, Joe H, Lim H, Kim K, Kim S, Han CW, Kim H-G (2021) Sequential routing framework: fully capsule network-based speech recognition. Comput Speech Lang 70:101228. https://doi.org/10.1016/j.csl.2021.101228
117. Shahin I, Hindawi N, Nassif AB, Alhudhaif A, Polat K (2022) Novel dual-channel long short-term memory compressed capsule networks for emotion recognition. Expert Syst Appl 188:116080. https://doi.org/10.1016/j.eswa.2021.116080
118. Deng X, Jiang P, Zhao D, Huang R, Shen H (2021) Effective semi-supervised learning for structured data using embedding GANs. Pattern Recogn Lett 151:127–134. https://doi.org/10.1016/j.patrec.2021.07.019
119. Zhang G, Pan Y, Zhang L (2021) Semi-supervised learning with GAN for automatic defect detection from images. Autom Constr 128:103764. https://doi.org/10.1016/j.autcon.2021.103764

120. Devulapalli S, Potti A, Krishnan R, Khan MdS (2021) Experimental evaluation of unsupervised image retrieval application using hybrid feature extraction by integrating deep learning and handcrafted techniques. Mater Today Proc. https://doi.org/10.1016/j.matpr.2021.04.326
121. Popescu DM, Abramson HG, Yu R, Lai C, Shade JK, Wu KC, Maggioni M, Trayanova NA (2021) Anatomically-informed deep learning on contrast-enhanced cardiac magnetic resonance imaging for scar segmentation and clinical feature extraction. Cardiovascular Digital Health J. https://doi.org/10.1016/j.cvdhj.2021.11.007
122. Costa G, Montemurro M (2020) Eigen-frequencies and harmonic responses in topology optimisation: a CAD-compatible algorithm. Eng Struct 214:110602. https://doi.org/10.1016/j.engstruct.2020.110602
123. Laishram R, Rabidas R (2021) WDO optimized detection for mammographic masses and its diagnosis: a unified CAD system. Appl Soft Comput 110:107620. https://doi.org/10.1016/j.asoc.2021.107620
124. Misra S, Jeon S, Lee S, Managuli R, Jang I-S, Kim C (2020) Multi-channel transfer learning of chest X-ray images for screening of COVID-19. Electronics 9:1388. https://doi.org/10.3390/electronics9091388
125. Jain G, Mittal D, Thakur D, Mittal MK (2020) A deep learning approach to detect COVID-19 coronavirus with X-ray images. Biocybern Biomed Eng 40:1391–1405. https://doi.org/10.1016/j.bbe.2020.08.008
126. Rahimzadeh M, Attar A (2020) A modified deep convolutional neural network for detecting COVID-19 and pneumonia from chest X-ray images based on the concatenation of Xception and ResNet50V2. Inform Med Unlocked 19:100360. https://doi.org/10.1016/j.imu.2020.100360
127. Arora V, Ng EY-K, Leekha RS, Darshan M, Singh A (2021) Transfer learning-based approach for detecting COVID-19 ailment in lung CT scan. Comput Biol Med 135:104575. https://doi.org/10.1016/j.compbiomed.2021.104575
128. Che Azemin MZ, Hassan R, Mohd Tamrin MI, Md Ali MA (2020) COVID-19 deep learning prediction model using publicly available radiologist-adjudicated chest X-ray images as training data: preliminary findings. Int J Biomed Imaging 2020:e8828855. https://doi.org/10.1155/2020/8828855
129. Apostolopoulos ID, Mpesiana TA (2020) COVID-19: automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. Phys Eng Sci Med 43:635–640. https://doi.org/10.1007/s13246-020-00865-4
130. Manickam A, Jiang J, Zhou Y, Sagar A, Soundrapandiyan R, Dinesh Jackson Samuel R (2021) Automated pneumonia detection on chest X-ray images: a deep learning approach with different optimizers and transfer learning architectures. Measurement 184:109953. https://doi.org/10.1016/j.measurement.2021.109953
131. Abbas A, Abdelsamea MM, Gaber MM (2021) Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network. Appl Intell 51:854–864. https://doi.org/10.1007/s10489-020-01829-7
132. Yoo SH, Geng H, Chiu TL, Yu SK, Cho DC, Heo J, Choi MS, Choi IH, Van Cung C, Nhung NV, Min BJ, Lee H (2020) Deep learning-based decision-tree classifier for COVID-19 diagnosis from chest X-ray imaging. Front Med 7:427. https://doi.org/10.3389/fmed.2020.00427
133. Narayan Das N, Kumar N, Kaur M, Kumar V, Singh D (2020) Automated deep transfer learning-based approach for detection of COVID-19 infection in chest X-rays. IRBM. https://doi.org/10.1016/j.irbm.2020.07.001
134. Haque KF, Abdelgawad A (2020) A deep learning approach to detect COVID-19 patients from chest X-ray images. AI 1:418–435. https://doi.org/10.3390/ai1030027
135. Abdani SR, Zulkifley MA, Mamat M (2020) U-net with spatial pyramid pooling module for segmenting oil palm plantations. In: 2020 IEEE 2nd international conference on artificial intelligence in engineering and technology (IICAIET). pp 1–5

136. Bridge J, Meng Y, Zhao Y, Du Y, Zhao M, Sun R, Zheng Y (2020) Introducing the GEV activation function for highly unbalanced data to develop COVID-19 diagnostic models. IEEE J Biomed Health Inform 24:2776–2786. https://doi.org/10.1109/JBHI.2020.3012383
137. Goel T, Murugan R, Mirjalili S, Chakrabartty DK (2021) OptCoNet: an optimized convolutional neural network for an automatic diagnosis of COVID-19. Appl Intell 51:1351–1366. https://doi.org/10.1007/s10489-020-01904-z
138. Afshar P, Heidarian S, Naderkhani F, Oikonomou A, Plataniotis KN, Mohammadi A (2020) COVID-CAPS: a capsule network-based framework for identification of COVID-19 cases from X-ray images. Pattern Recogn Lett 138:638–643. https://doi.org/10.1016/j.patrec.2020.09.010
139. Dhaya R (2020) Deep net model for detection of COVID-19 using radiographs based on ROC analysis. J Innov Image Process 2:135–140. https://doi.org/10.36548/jiip.2020.3.003
140. Deep transfer learning based classification model for COVID-19 disease. IRBM (2020). https://doi.org/10.1016/j.irbm.2020.05.003
141. Yan T, Wong PK, Ren H, Wang H, Wang J, Li Y (2020) Automatic distinction between COVID-19 and common pneumonia using multi-scale convolutional neural network on chest CT scans. Chaos Solitons Fractals 140:110153. https://doi.org/10.1016/j.chaos.2020.110153
142. Shaban WM, Rabie AH, Saleh AI, Abo-Elsoud MA (2020) A new COVID-19 patients detection strategy (CPDS) based on hybrid feature selection and enhanced KNN classifier. Knowl-Based Syst 205:106270. https://doi.org/10.1016/j.knosys.2020.106270
143. Han Z, Wei B, Hong Y, Li T, Cong J, Zhu X, Wei H, Zhang W (2020) Accurate screening of COVID-19 using attention-based deep 3D multiple instance learning. IEEE Trans Med Imaging 39:2584–2594. https://doi.org/10.1109/TMI.2020.2996256
144. Öztürk Ş, Özkaya U, Barstuğan M (2021) Classification of coronavirus (COVID-19) from X-ray and CT images using shrunken features. Int J Imaging Syst Technol 31:5–15. https://doi.org/10.1002/ima.22469
145. Hasan AM, AL-Jawad MM, Jalab HA, Shaiba H, Ibrahim RW, AL-Shamasneh AR (2020) Classification of COVID-19 coronavirus, pneumonia and healthy lungs in CT scans using Q-deformed entropy and deep learning features. Entropy 22:517.https://doi.org/10.3390/e22050517
146. Fung DLX, Liu Q, Zammit J, Leung CK-S, Hu P (2021) Self-supervised deep learning model for COVID-19 lung CT image segmentation highlighting putative causal relationship among age, underlying disease and COVID-19. J Transl Med 19:318. https://doi.org/10.1186/s12967-021-02992-2
147. Hurt B, Kligerman S, Hsiao A (2020) Deep learning localization of pneumonia: 2019 coronavirus (COVID-19) outbreak. J Thorac Imaging 35:W87. https://doi.org/10.1097/RTI.0000000000000512
148. Xu X, Jiang X, Ma C, Du P, Li X, Lv S, Yu L, Ni Q, Chen Y, Su J, Lang G, Li Y, Zhao H, Liu J, Xu K, Ruan L, Sheng J, Qiu Y, Wu W, Liang T, Li L (2020) A deep learning system to screen novel coronavirus disease 2019 pneumonia. Engineering 6:1122–1129. https://doi.org/10.1016/j.eng.2020.04.010
149. Wang S, Kang B, Ma J, Zeng X, Xiao M, Guo J, Cai M, Yang J, Li Y, Meng X, Xu B (2021) A deep learning algorithm using CT images to screen for corona virus disease (COVID-19). Eur Radiol 31:6096–6104. https://doi.org/10.1007/s00330-021-07715-1
150. Cohen JP, Dao L, Roth K, Morrison P, Bengio Y, Abbasi AF, Shen B, Mahsa HK, Ghassemi M, Li H, Duong TQ. Predicting COVID-19 pneumonia severity on chest X-ray with deep learning. Cureus 12:e9448. https://doi.org/10.7759/cureus.9448
151. Li MD, Arun NT, Gidwani M, Chang K, Deng F, Little BP, Mendoza DP, Lang M, Lee SI, O'Shea A, Parakh A, Singh P, Kalpathy-Cramer J (2020) Automated assessment and tracking of COVID-19 pulmonary disease severity on chest radiographs using convolutional Siamese neural networks. Radiol Artif Intell 2:e200079. https://doi.org/10.1148/ryai.2020200079

152. Ng M-Y, Wan EYF, Wong HYF, Leung ST, Lee JCY, Chin TW-Y, Lo CSY, Lui MM-S, Chan EHT, Fong AH-T, Fung SY, Ching OH, Chiu KW-H, Chung TWH, Vardhanbhuti V, Lam HYS, To KKW, Chiu JLF, Lam TPW, Khong PL, Liu RWT, Chan JWM, Wu AKL, Lung K-C, Hung IFN, Lau CS, Kuo MD, Ip MS-M (2020) Development and validation of risk prediction models for COVID-19 positivity in a hospital setting. Int J Infect Dis 101:74–82. https://doi.org/10.1016/j.ijid.2020.09.022
153. Liang W, Wang H, Huang X, Zhou J, Liu W (2020) 56 Gbit/s OOK signal in C-band over 20 km dispersion-uncompensated link transmission with receiver-side EDC algorithm. IEEE Photonics J 12:1–7. https://doi.org/10.1109/JPHOT.2020.3027836
154. Zhang K, Liu X, Shen J, Li Z, Sang Y, Wu X, Zha Y, Liang W, Wang C, Wang K, Ye L, Gao M, Zhou Z, Li L, Wang J, Yang Z, Cai H, Xu J, Yang L, Cai W, Xu W, Wu S, Zhang W, Jiang S, Zheng L, Zhang X, Wang L, Lu L, Li J, Yin H, Wang W, Li O, Zhang C, Liang L, Wu T, Deng R, Wei K, Zhou Y, Chen T, Lau JY-N, Fok M, He J, Lin T, Li W, Wang G (2020) Clinically applicable AI system for accurate diagnosis, quantitative measurements, and prognosis of COVID-19 pneumonia using computed tomography. Cell 181:1423-1433.e11. https://doi.org/10.1016/j.cell.2020.04.045
155. Ginsberg J, Mohebbi MH, Patel RS, Brammer L, Smolinski MS, Brilliant L (2009) Detecting influenza epidemics using search engine query data. Nature 457:1012–1014. https://doi.org/10.1038/nature07634
156. Bragazzi NL, Dai H, Damiani G, Behzadifar M, Martini M, Wu J (2020) How big data and artificial intelligence can help better manage the COVID-19 pandemic. Int J Environ Res Public Health 17:3176. https://doi.org/10.3390/ijerph17093176
157. Garattini C, Raffle J, Aisyah DN, Sartain F, Kozlakidis Z (2019) Big data analytics, infectious diseases and associated ethical impacts. Philos Technol 32:69–85. https://doi.org/10.1007/s13347-017-0278-y
158. Ajah I, Nweke H (2019) Big data and business analytics: trends, platforms, success factors and applications. Big Data Cogn Comput 3:32. https://doi.org/10.3390/bdcc3020032
159. White T (2012) Hadoop: the definitive guide, 3rd edn. Yahoo Press, Beijing
160. Chowell G, Cleaton JM, Viboud C (2016) Elucidating transmission patterns from internet reports: ebola and middle east respiratory syndrome as case studies. J Infect Dis 214:S421–S426. https://doi.org/10.1093/infdis/jiw356
161. Salathé M (2016) Digital pharmacovigilance and disease surveillance: combining traditional and big-data systems for better public health. J Infect Dis 214:S399–S403. https://doi.org/10.1093/infdis/jiw281
162. Zhao Y, Liu L, Qi Y, Lou F, Zhang J, Ma W (2020) Evaluation and design of public health information management system for primary health care units based on medical and health information. J Infect Publ Health 13:491–496. https://doi.org/10.1016/j.jiph.2019.11.004
163. Petrides AK, Tanasijevic MJ, Goonan EM, Landman AB, Kantartjis M, Bates DW, Melanson SEF (2017) Top ten challenges when interfacing a laboratory information system to an electronic health record: experience at a large academic medical center. Int J Med Inform 106:9–16. https://doi.org/10.1016/j.ijmedinf.2017.06.008
164. Mosser H, Urban M, Dürr M, Rüger W, Hruby W (1992) Integration of radiology and hospital information systems (RIS, HIS) with PACS: requirements of the radiologist. Eur J Radiol 16:69–73. https://doi.org/10.1016/0720-048X(92)90248-8
165. EMRS adoption: exploring the effects of information security management awareness and perceived service quality. Health Policy Technol 7:365–373 (2018). https://doi.org/10.1016/j.hlpt.2018.10.012
166. Wu J, Wang J, Nicholas S, Maitland E, Fan Q (2020) Application of big data technology for COVID-19 prevention and control in China: lessons and recommendations. J Med Internet Res 22:e21980. https://doi.org/10.2196/21980
167. Rodger JA (2015) Discovery of medical big data analytics: improving the prediction of traumatic brain injury survival rates by data mining patient informatics processing software hybrid Hadoop hive. Inform Med Unlocked 1:17–26. https://doi.org/10.1016/j.imu.2016.01.002

168. Winters-Miner LA, Bolding P, Hill T, Nisbet B, Goldstein M, Hilbe JM, Walton N, Miner G, Brown EW, Kohn MS (2015) Chapter 25—IBM Watson for clinical decision support. In: Winters-Miner LA, Bolding PS, Hilbe JM, Goldstein M, Hill T, Nisbet R, Walton N, Miner GD (eds) Practical predictive analytics and decisioning systems for medicine. Academic Press, pp 1038–1040
169. Douine M, Lambert Y, Galindo MS, Mutricy L, Sanna A, Peterka C, Marchesini P, Hiwat H, Nacher M, Adenis A, Demar M, Musset L, Lazrek Y, Cairo H, Bordalo Miller J, Vreden S, Suarez-Mutis M (2021) Self-diagnosis and self-treatment of malaria in hard-to-reach and mobile populations of the Amazon: results of Malakit, an international multicentric intervention research project. Lancet Regional Health Am:100047.https://doi.org/10.1016/j.lana.2021.100047
170. Wu CH, Chiu RK, Yeh HM, Wang DW (2017) Implementation of a cloud-based electronic medical record exchange system in compliance with the integrating healthcare enterprise's cross-enterprise document sharing integration profile. Int J Med Inform 107:30–39. https://doi.org/10.1016/j.ijmedinf.2017.09.001
171. Santos-Pereira J, Gruenwald L, Bernardino J (2021) Top data mining tools for the healthcare industry. J King Saud Univ Comput Inf Sci. https://doi.org/10.1016/j.jksuci.2021.06.002
172. Mathew PS, Pillai AS (2015) Big data solutions in healthcare: problems and perspectives. In: 2015 international conference on innovations in information, embedded and communication systems (ICIIECS), pp 1–6
173. Dolezel D, McLeod A (2019) Big data analytics in healthcare: investigating the diffusion of innovation. Perspect Health Inf Manage 16:1a
174. Zhang H, Zang Z, Zhu H, Uddin MI, Amin MA (2022) Big data-assisted social media analytics for business model for business decision making system competitive analysis. Inf Process Manage 59:102762. https://doi.org/10.1016/j.ipm.2021.102762
175. Wang M, Tai C, Zhang Q, Yang Z, Li J, Shen K, Wang K (2021) Application of BigML in the classification evaluation of top coal caving. Shock Vib 2021:e8552247. https://doi.org/10.1155/2021/8552247
176. Khashan EA, Eldesouky AI, Fadel M, Elghamrawy SM (2020) A big data based framework for executing complex query over COVID-19 datasets (COVID-QF). arXiv:200512271 [cs]
177. Elmeiligy MA, Desouky AIE, Elghamrawy SM (2020) A multi-dimensional big data storing system for generated COVID-19 large-scale data using apache spark. arXiv:200505036 [cs]

Houneida Sakly is a Ph.D. and Engineer in Medical Informatics. She is a member of the research program "deep learning analysis of Radiologic Imaging" in Stanford university. Certified in Healthcare Innovation with MIT-Harvard Medical school. Her main field of research is the Data science (Artificial Intelligence, Big Data, blockchain, Internet of things…) applied in healthcare. She is a member in the Integrated Science Association (ISA) in the Universal Scientific Education and Research Network (USERN) in Tunisia. Currently, she is serving as a lead editor for various book and special issue in the field of digital Transformation and data science in Healthcare. Recently, she has won the Best Researcher Award in the International Conference on Cardiology and Cardiovascular Medicine—San Francisco, United States.