

Review

Technological Advancements and Elucidation Gadgets for Healthcare Applications: An Exhaustive Methodological Review-Part-I (AI, Big Data, Block Chain, Open-Source Technologies, and Cloud Computing)

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Abstract: In the realm of the emergence and spread of infectious diseases with pandemic potential throughout the history, plenty of pandemics (and epidemics), from the plague to AIDS (1981) and SARS (in 2003) to the bunch of COVID variants, have tormented mankind. Though plenty of technological innovations are overwhelmingly progressing to curb them—a significant number of such pandemics astounded the world, impacting billions of lives and posing uncovered challenges to healthcare organizations and clinical pathologists globally. In view of addressing these limitations, a critically exhaustive review is performed to signify the prospective role of technological advancements and highlight the implicit problems associated with rendering best quality lifesaving treatments to the patient community. The proposed review work is conducted in two parts. Part 1 is essentially focused upon discussion of advanced technologies akin to artificial intelligence, Big Data, block chain technology, open-source technology, cloud computing, etc. Research works governing applicability of these technologies in solving many uncovered healthcare issues prominently faced by doctors and surgeons in the fields of cardiology, medicine, neurology, orthopaedics, paediatrics, gynaecology, psychiatry, plastic surgery, etc., as well as their role in curtailing the spread of numerous infectious, pathological, neurotic maladies is thrown light off. Boundary conditions and implicitly associated challenges substantiated by remedies coupled with future directions are presented at the end.

Keywords: artificial intelligence; big data; block chain; cancer; cardiology; cloud computing; healthcare; hololens; robotics; open-source technology



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1. Introduction

Technology is astounding; it is completely surrounding every aspect of the 21st century human lives—indeed it is really an exciting time for healthcare and information technology (IT).

From the past few decades and centuries, different types of pulmonary (viral), bacterial, and inflammatory diseases have continuously posed challenges to clinical pathologists and technocrats—evidently exposing the limitations of existing public health practices [1]. Characteristically, the above mentioned viral diseases are an outcome of the different genetic substances (viruses) found in air, water, soil, etc.—causing diversified infectious diseases from the flu and cold to the deadly COVID-19 pandemic and its variants. On the other hand, pandemics affect the internal human immunity system, liver, and other organs, gradually damaging the healthy cells, thereby enhancing morbidity and mortality rates [2] and generating social and economic turbulences [3]. Typically, pandemics are so tricky, in that sometimes they start with meek illness and slowly affect the respiratory tract, targeting the internal immunity system and ultimately leading to multi-organ failures in most patients, ultimately followed by cardiac arrests and deaths [4–9]. The

sudden outburst of the COVID-19 pandemic uncovered the deficiencies of global healthcare systems in preparing to handle emergency public-health situations—in addition to the existing uncovered maladies in clinical microbiology, medical education, preoperative surgical planning, spine medicine, tuberculosis diagnosis, mastectomy surgical planning, orthopaedic surgery, laparoscopic surgery, surgical training, robotic surgeries, anxiety (and depression treatments), hospital navigations, etc. Therefore, the need for addressing the gaps and deficits associated with rendering best quality preventive life-saving emergency treatments to the patient community, as well as uncovering the variant number of unspoken medical issues (disorders) and ailments that serve as major hindrances in saving lives of people, has motivated authors to conduct this review work to decipher the contribution of innovative technological advancements governing healthcare applications. The proposed review work was conducted in two parts, such that contribution of technologies, such as artificial intelligence (and its subsets—machine learning and deep learning), Big Data analytics, block-chain technology, open source technologies, and cloud computing are discussed in the current PART-I manuscript, while technologies such as robotics, drones, 3D printing, IoT (Internet of things), virtual/augmented/mixed reality, and their roles played in uncovering many healthcare issues specifically targeting the manifold healthcare domain and its allied segments to mimic various healthcare trends [10] are left for discussion in Part II of the manuscript.

As many healthcare organizations are maintaining the critical patient health data in various heterogeneous systems, it is exceptionally difficult for healthcare providers to deliver superior quality healthcare services to the patients. Keeping in view all these limitations, artificial intelligence (AI) systems are deployed to ensure life-saving timely decisions [11,12] and heart failure prediction using different data modalities [13], machine learning (ML) classifiers and deep learning (DL) algorithms to interpret medical findings akin to epilepsy [14,15], nerve and muscle diseases [16,17], heart rhythms [18,19], cancer predictions [20], ill effects of virus diseases [21], and biomedical studies of other healthcare segments [22], an ML approach survey on bone-segmentation techniques in knee osteoarthritis [23], DL techniques for estimation of articular cartilage loss rate [24], 3D CNN deployment for more accurate diagnosis of knee osteoarthritis [25,26], and the prediction of knee joint kinematics from wearable sensor data [27], and radiologists deployed advanced DL algorithms and Big Data in healthcare sectors [28] to signify the prominent role of Big Data in hospital management and medical waste reduction [29]. Since AI-based DL algorithms are limited by the computing power requirements and implicit complexity levels, advancements in Big Data-based shallow network-enabled computing systems to react faster than humans in different complex situations have been exploring the role of Big Data in modeling the viral activities globally [30]. The government of France formed a worldwide AI system (Well-being Data Hub) to ensure collaborative working environment between scientists and specialists of society to provide outstanding clinical information for the society.

Today, Chatbot and virtual patient care technologies decide the order of treatment for patients (or casualties), while AI and supercomputing performances are focused upon accelerated research works to uncover the inhabitancy of pre-diagnostic requirements and surgical hindrances (and viruses and bacterial infections) occasionally challenging the clinical pathologists, surgeons, and doctors were developing therapeutics. On the other hand, investigations are under progression to innovate hypersensitive technological gadgets for assisting clinical specialists, thereby helping governments to safeguard health and lives of patient community. The rest of the manuscript is organized as follows—in Section 2—survey and review works pertaining to applicability of AI, Big Data, block chain, open-source and cloud computing technologies to healthcare applications is discussed. Section 3 provides an overview of advanced technologies with an elaborative discussion on investigative healthcare frameworks and their applicability. Further the implicit pros and cons associated with unspoken challenges with wide scope for future explorations are presented in Section 4. Section 5 brings out the concluding remarks.

2. Overview of Technological Contributions to Healthcare Sector

The past few decades witnessed multiple research works to determine the best possible ways of subjecting technological advancements to revamp the healthcare domain by continuously providing solutions to nature-thrown viruses, pandemics, and clinical issues, as well as diagnostic procedures relevant to cardiology, neurology, orthopaedics, dentistry, oncology, etc. This section of the manuscript is aimed at highlighting the survey and review works pertaining to applicability of AI, Big Data, block chain, open-source and cloud computing technologies to various healthcare issues. There are AI-based healthcare apps to measure patient health conditions, provide medication warnings, products (IBM Watson) to assist clinical pathologists in oncology, breast cancer colorectal cancer, rectal cancer, lung cancer, etc., typically highlighting the potential of AI to improve the therapeutic accuracy and clinical treatment process.

On the other hand, large amounts of clinical and patient data (Big Data) are generated at an unprecedented speed for documenting electronic health records, with many novel investigations and discoveries being published time-to-time ensuring the efficient management and interpretation of Big Data opening new avenues for modern healthcare. Now, healthcare is at an arena where regularly evolving use cases are handled by different healthcare organizations and industries through the adoption of block chain technology, such that members of the research community and practitioners typically grasping novel block chain-based healthcare applications targeting them. Rapidly developing innovations depicting the applicability of IoT technology, coupled with the variant types of sensors connecting smart devices, promoted the seamless requirement of data analysis and data storage platforms, such as cloud computing. The gradual and systematic transformation in healthcare systems to ensure highly efficient and flexible healthcare services to the patient community can be attributed to multiple investigations taken place over past few decades.

Table 1 summarizes the research findings extracted from various survey papers and review papers depicting the applicability of technologies such as AI, Big Data, block chain, and open-source and cloud computing technologies to solve clinical and healthcare issues. In the current manuscript, the authors have pooled research data pertaining to all the above five technologies, enabling readers to make them abreast of technological know-how's (relevant to healthcare sector) and providing a direction for future investigations to be carried out, thus paving way for multi-disciplinary collaborative research works.

Table 1. Past review highlights of various technologies for healthcare applications.

Year	Past Review Highlights	Reference
Artificial Intelligence		
2021	Review to summarize the application of virtual and augmented reality technologies to orthopaedic surgery training and practice aims.	[31]
2020	Review aimed to provide an overview of potential applications of AI and Big Data in the global effort to manage the COVID-19 pandemic.	[32]
2019	Evolution of research in AI in health and medicine: A bibliometric study.	[33]
2018	Literature review depicting application of machine learning techniques and methods to solve orthopedic problems (covering articles of last two decades).	[34]
2016	IBM computing system Watson for oncology with Manipal Hospitals.	[35]
2004	AI-based technologies depicting innovations in medicine and healthcare industry.	[36]
2016	Big Data application review in bioinformatics, clinical informatics, imaging informatics, and public health informatics.	[37]
2015	Cloud framework to ensure concurrent and scalable medical record retrieval.	[38]
2014	Review on facilitating big data to predict hazards of disease incidence and improve primary care.	[39]
2016	Survey on research advancements in ML for Big Data processing.	[40]
2022	Review of blockchain technology in healthcare, finance, wireless networks, IoT, and smart grids.	[41]

Table 1. *Cont.*

Year	Past Review Highlights	Reference
2021	Survey depicting various research works pertaining to deployment of block chain in Internet of Things (IoT).	[42]
2021	Comprehensive survey of emerging IoT technologies, machine learning, and blockchain for healthcare applications.	[43]
2020	Literature review of blockchain approaches for electronic health record systems.	[44]
2019	Review of block chain model implementation to existing and latest healthcare scenarios.	[45]
2020	Attempt to analyze combination of IoT and cloud computing for healthcare applications.	[46]
2019	Attempt to highlight research challenges to build a security model for EHR.	[47]
2019	Survey depicting development of IoT- and cloud computing-based healthcare applications.	[48]

3. Emerging Technologies

“Technological Advancement—a boon to Patients and Healthcare Providers”

Technological advancements deeply penetrated and significantly impacted clinical care and the healthcare industry, to such an extent that the immersion of encroaching technologies into healthcare sector witnessed exponential expansions, in conjunction with societal advancements, specifically (since last 20 years) enabling clinicians and doctors to ensure better patient care and treatments. A few breakthrough technological inventions, such as infusion pumps, haemodialysis, heart pressure monitoring valves, and MRI scanners, etc., continuously redefined the routine medicinal approaches of treatments. Keeping in view the emerging population rise and pressing demands to provide lifesaving medical treatments at higher success rates—technological advancements are diverted towards clinical research, diagnosis, treatments, surgeries, etc, thanks to the advancements of information technology (IT) resources for providing a number of online communication platforms (healthcare websites) enabling round the clock interaction of patients with medical professionals (Figure 1).

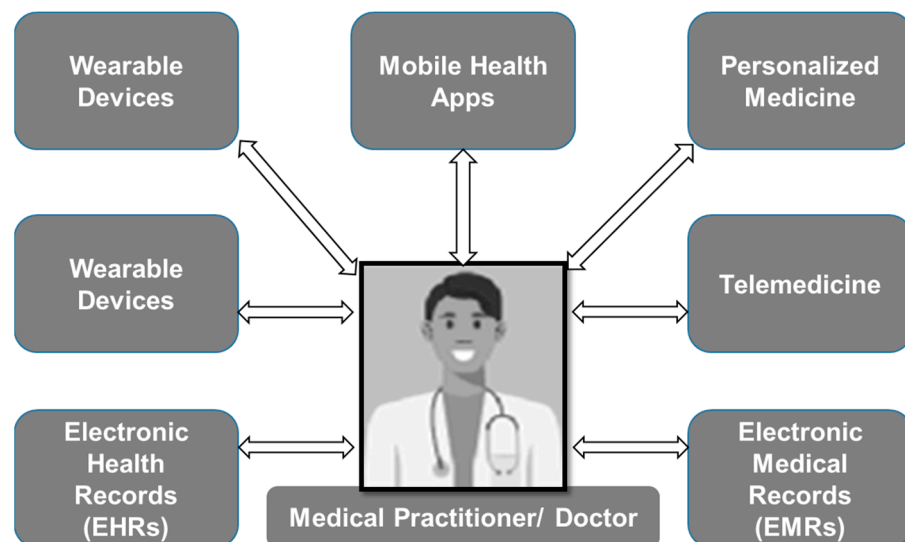


Figure 1. Digital Health Technologies.

There are many data mining and data warehousing tools at the open discretion of hospitals and healthcare organizations to manage the gigantically complex crunches of patient’s data, helping to accomplish storage resiliency in the healthcare sector because data mining in healthcare provides information on the symptoms, causes, and courses of actions under certain conditions. One cannot shrug off the impacting role of emerging

technological advancements in the healthcare sector—as they lowered the mortality rate and enhanced average life expectancy levels because “With technology early diagnosis always ensures better prognosis”.

In today’s scenario, the majority of the human community is resorting to self-medication and healing techniques, thanks to the internet—now patients are able to comfortably communicate with a nurse or doctor instantly over many healthcare websites, without even moving an inch, and they are at the disclosure of talking to likely affected symptomatic people through plenty of online social interaction forums lead by specialized doctors and medical professionals. Today, telemedicine and tele-health facilities are making use of emerging technological advancements to deliver life-giving healthcare services to people inhabiting remote areas. On the other hand, today’s healthcare system is greatly driven by the promoted utility of wearable technology gadgets, coupled with personalized treatments to aid mankind unendingly. On the contrary, social media apps, such as Facebook, Twitter, Snapchat, Instagram, etc., are greatly serving to ensure effective communication between clinicians and patients. The digitization of health records in many countries provides the ample benefits of reduced healthcare expenses, pandemics prediction, prevention of sudden deaths, development of new therapeutics (novel drugs), devising best healthcare services, etc.

In the words of the famous plastic surgeon Dr. Charlie Chen, “Technology and Medicine are handy to either—in performing various activities like Pre-operative planning, surgical planning and post-operative planning etc., to monitor the outcomes”.

3.1. Artificial Intelligence

AI is a booming technology that has impressively penetrated into healthcare domain and its allied fields, including other sectors, such as banking, agriculture, automobiles (self-driven cars), gaming consoles, business administration, marketing management (forecasting), sales management, crime detection, cyber security aspects, etc. The demand for deploying artificial intelligence (AI) in healthcare domain existed for many years, and it presumed to top level in 2018 - with wide-spread range of applications. Typically, the artificial intelligence-based ML and DL architectures comprising the 2D convolution neural network structures (CNN), recurrent neural network structures (RNN), auto encoders (AEs), DNN(deep neural networks), LSTM(linear short-term memory), AlexNet, VGG (visual geometry group) network, SqueezeNet, Inception Res-Net, CapsNet, GoogleNet, DenseNet, XceptionNet, MobileNet, GANs (generative adversarial networks), etc., have deep grass-roots in many specialized areas of healthcare, ranging from clinical diagnosis, treatments, telemedicine, endoscopy, laparoscopy, dentistry, neurology, orthopaedics, gastroenterology, paediatrics, gynaecology, radiology including disastrous COVID pandemic, the latest monkey pox virus, and many other infectious (pulmonary) diseases. Additionally multiple numbers of Hybrid DL Network architectures (CNN-RNN/AE) and cross-coupled advanced technology specimens (architectures) are deployed for utility in healthcare applications. Few such architectures include:

Standard 2D-CNN—Typical CNN architectures are comprised of convolutional layers, pooling layers, fully connected layers, and their combinations with their outputs forward propagated to the fully connected layers. CNNs are a form of deep learning models commonly employed for better outcomes to analyze visual imagery, typically CNNs and the k-nearest neighbor (KNN) ML algorithm are used for the accurate prediction of diseases, especially when deployed for early stage prediction and medical diagnosis during COVID-19 using chest X-ray and CT(computed tomography) images. Techniques such as dropout and batch normalization of networks ensure the achievement of better learning in CNNs. However, the problem of over fitting in training can be overcome with convolutional layers, while a differentiable function can also be utilized to transform the volume of conversions among different layers because of the structurally arranged sequence of layers (Figure 2).

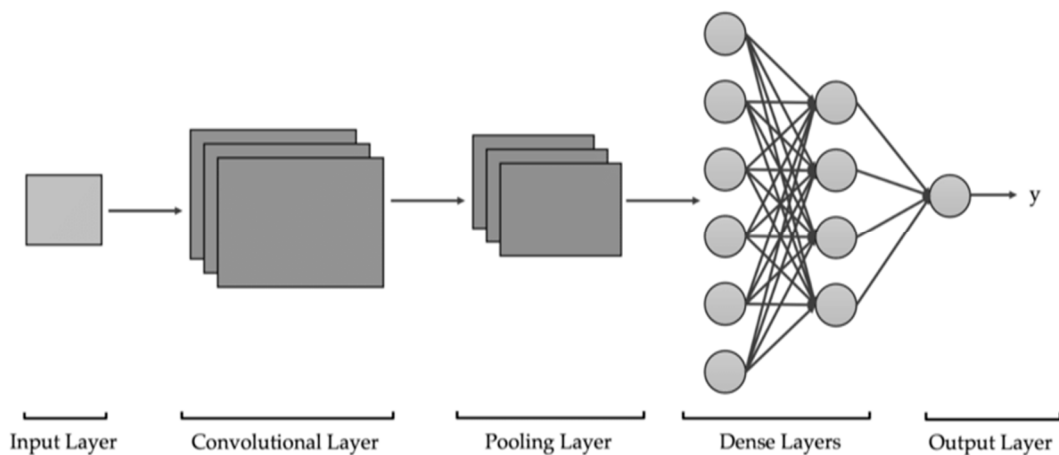


Figure 2. Standard CNN.

VGGNET—Typically *VGGNET* is a deep CNN architecture with multiple layers that include the optimum number of convolutional layers utilizing the ReLU activation function and the softmax classifier in the final layer, with variant filter sizes and strides among the convolutional layers. *VGGNET* possesses around 11, 16, and 19 layers and few other variants, respectively (Figure 3). However, most of the *VGGNET* variant architectures are comprised of three fully connected layers at the end, while the number of convolution layers count is different. *VGGNET* is one among the popular object recognition architectures.

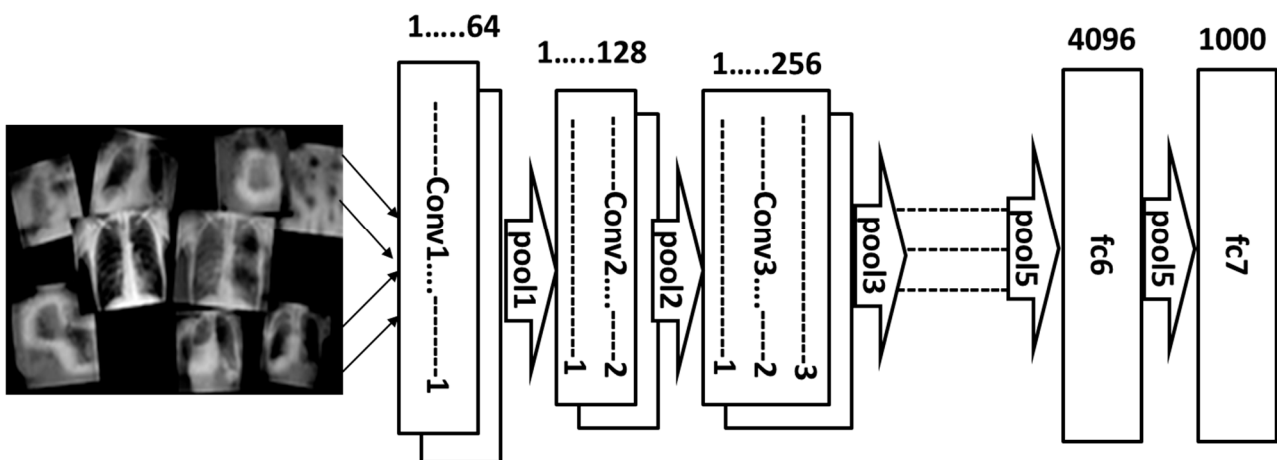


Figure 3. VGG NET.

GoogleNET—Typically, the *GoogleNET* Architecture is a 22-layer deep-convolutional neural network intended for computer vision tasks such as face recognition and detection etc. It is trained on over a million images to classify them into around 1000 categories of objects. The architecture is comprised of more than 60 million parameters, involving 650,000 neurons, such that any pre-trained *GoogleNET* may be loaded to ensure the classification of images into more than 100 object categories. However, the number of parameters in the *GoogleNET* architecture is less, in comparison to the *VGGNET* and/or *AlexNet* architectures [49–51].

On the other hand, *GoogleNET* (Figure 4) can be deployed as a pre-trained network, predominantly for imaging applications favoring the healthcare domain and allied sectors, thus aiding the appropriate diagnosis of patient data from X-rays, CT scan reports, MRI scan reports, and data from various towers, as well.

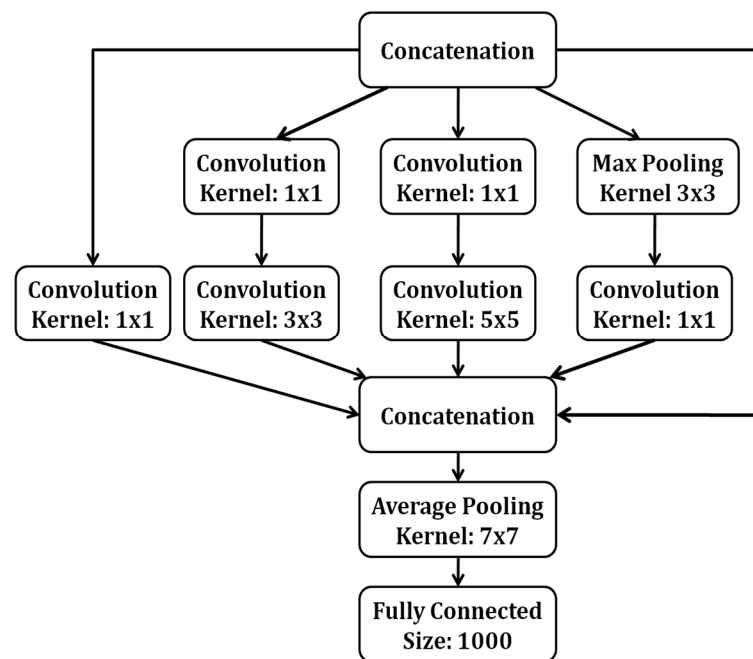


Figure 4. Google NET.

RESNET—A RESNET, or residual network, is a deep learning CNN model that is predominantly employed for many computer vision tasks and designed to support variants of 34, 50, 152, and 1202 layers. While the ResNet18 architecture is comprised of 11 million trainable parameters, with only two pooling layers, one at the beginning and the other at the end of the network, on the other hand, the popular ResNet50 is a 50-layer deep CNN architecture comprising 49 convolution layers and 1 fully connected layer at the end, such that a pre-trained version of ResNet50 trained on more than a million images can be loaded to classify images into around 1000 categories.

RESNET architectures are almost similar to the VGG architectures comprising 3×3 filters, while the pre-trained RESNET models can also be deployed in various realistic clinical applications (Figure 5). Investigations depicting utility of hybrid ML and DL architectures for addressing the healthcare issues and challenges encountered by clinical pathologists and doctors are discussed here. Alakus et al. [52], Ali Narin et al. [53], Zhang et al. [54], Alqudah et al. [55], and Medhi et al. [56] explored the utility of ResNet DL models based on KNN (k-nearest neighbor), SVM (support vector machine) algorithms, etc. Afshar et al. [57] developed a deep neural network (DNN) framework training different NN models, such as CNN, RNN, long short-term memory (LSTM), hybrid CNN-LSTM, and CNN-RNN, etc., to biomedical and healthcare applications covering various segments of health sectors. The authors in [58–60] applied machine learning techniques, decision trees, SVM classifiers, etc., to predict the clinical severity and spread of viruses, and Lalaantika Sharma [61] et al., developed a tool for heart diseases, deploying machine learning algorithms. In recent years, we have seen the applications of AI in medicine to diagnose brain tumors and multiple brain disorders from MR images [62–65], as well as breast cancer from mammographic images [66–69]. Deep learning has changed the applicability of AI in Big Data processing by mimicking the feelings of human beings, as well [70,71].

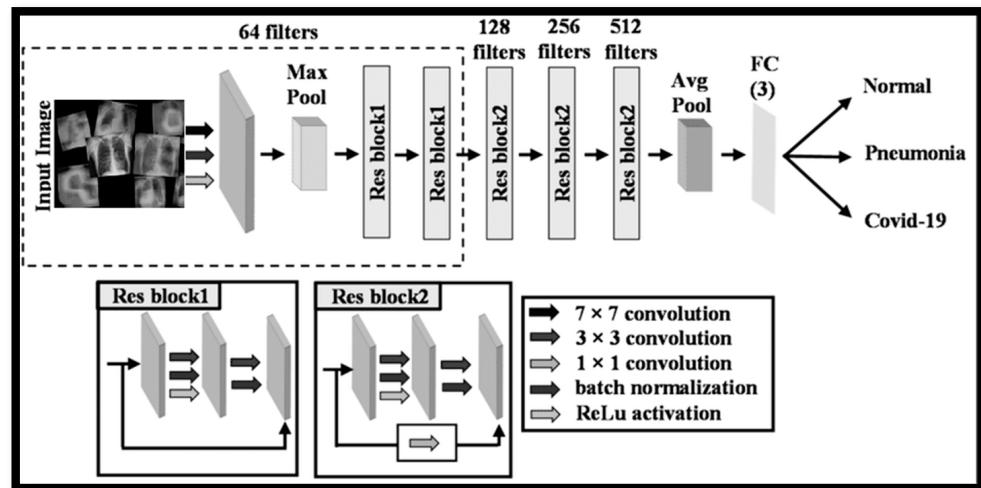


Figure 5. RESNET.

Long short-term memory (LSTM) DL networks [72–76] are proven to be highly advantageous for learning sequences and increased utility in robotic control, speech recognition, human action recognition, etc. Recurrent neural networks(RNN) [77,78] present promising results in various ML-based computer vision tasks [79–81], on the other hand, a special type of neural network—GANs (generative adversarial networks)—are deployed in a wide field of medical image computing [82–85] to perform predictive diagnostic analysis. The authors in [86–93] employed deep convolutional neural systems, ResNet-101 and Inception-v4, AlexNet, VGGNET, Google tools, etc., for clinical rescue operations and medical applications. The roles of advanced technologies such as block chain, Big Data, drones, and the Internet of Things (IoT), cannot be side-lined, especially in the prediction of pandemics [94–100] and other healthcare issues troubling the clinical pathologists. DNN algorithms, LSTM models, auto-encoder algorithms, SVM, hidden Markov chain model (HMM), etc., variants serve various diagnostic cardio-thoracic healthcare applications. A few such exploratory works are tabulated below (Table 2).

Table 2. Review of AI in Healthcare.

Sl. No	Ref.	Category of Health Segment	Application Type	Year	
1	[101–104]	AI in healthcare	Periodontal diagnosis, overview, literature review, genetic algorithm-based CNN for COVID detection	2022 2020	
2	[105–110]		CNN-based knee MRI images mapping DL for orthopedic disease	2022	
3	[111]		Anterior cruciate ligament tear detection based on deep CNN		
4	[112]		DL techniques for recognition of tropical diseases in images	2022	
5	[113]		DL-based schistosomiasis in Africa and Senegal	2022	
6	[114]		Patient diagnosis and treatment activities	2021	
7	[64,65]		ML and deep CNN for seizure detection in EEG signals	2022 2019, 2018	
8	[115]		CNN-based framework using transfer learning d	2020	
9	[116–120]		Pandemic detection and diagnosis	Auto encoder framework to model transmission dynamics, DL CT image analysis, and ML-DL models for COVID detection	2020
10	[121]		Deep generative model (CogMol) to investigate protein structure of corona virus	2020	

Table 2. Cont.

Sl. No	Ref.	Category of Health Segment	Application Type	Year
11	[95]	Pandemic data analysis	IoT, block chain, and AI models	2020
12	[66,122,123]	Breast cancer	NLP-based mammography interpretation system	2020, 2017
13	[82]	Medical imaging	Generative adversarial networks in medical imaging applications for screening	2020
14	[62,63]	Brain tumor	DNN with generative adversarial neural networks for brain tumor detection	2017, 2020
15	[124]	Home diagnosis	ML-and NLP-based personalized home care and diagnosis	2019
16	[125]	Nursing	ML-based home nurse avatar	2019
17	[126]	Oncology clinical trial	ML-, DL-,andNLP-based IBM deploying Watson AI platform	2018
18	[127]	Psychiatric diagnosis	Predicting development of psychosis in people	2018
19	[128]	Ophthalmology	ML for predicting eye diseases	2018
20	[129]	Robot-assisted surgery	Robotic prostatectomy, cardiac, oncology	2017
21	[130]	Cardiology	ML-based mobile platform on anticoagulation therapy	2017
22	[131]	Drugs distribution	ANN-based software to detect patient and drug for ingestion	2017
23	[132]	Diabetics	ML-based glucose monitoring system	2017
24	[133]	Tuberculosis	Alexa and GoogleNet CNNs for diagnosing tuberculosis	2017
25	[70]	Skin cancer detection	ANN and ML for cancer detection using skin lesions	2017, 2019
26	[134,135]	Cardiac arrest monitoring	ANN for monitoring heart conditions based on patient history	2012, 2017
27	[136–141]	COVID Pandemic Survey	AI (and Bigdata) for clinical decision support and management of COVID-19	2020, 2021
28	[142]	Health care	AI applications in health care	2021

3.2. Big Data

“Bigdata for health-care domain is an economically feasible life saver to enhance the operational efficiency of medical systems”.

Today’s healthcare industry has traversed a long way, surpassing decades of hurdles, toward the current trends of deploying Big Data in vast number of healthcare applications (Figure 6), such as the maintenance of generic patient databases, medical imaging applications, electronic health records of patients in authorized databases(portals) and government agencies, clinical employees pay records, pharma-technological inventions, search engines data, data pertaining to generic databases, smart phones and wearable gadgets, virtual tele-medical facilities, robotics deployment in medical healthcare applications, etc.

The swift development of IoT technologies keep on generating tonnes of medical data from ubiquitously variant number of sensors and wearable devices [18], and these exceptionally unparalleled volumes of data associated with data analytics of AI generate in massive volumes of Big Data from wide number of mobile devices (smart phones), IoT gadgets [143,144], etc., to predict online complaining behavior in hospital industry—substantially applying big-data analytics to perform online reviews [145]. Establishments relevant to handling such ubiquitous volumes of Big Data from various applications shall be attributed to the explorative investigations and innovations synchronizing the frameworks and mechanisms contributed by the wide scope of works by the research community. Few such applications relevant to healthcare are tabulated (Table 3) for an elaborative understanding of their findings.

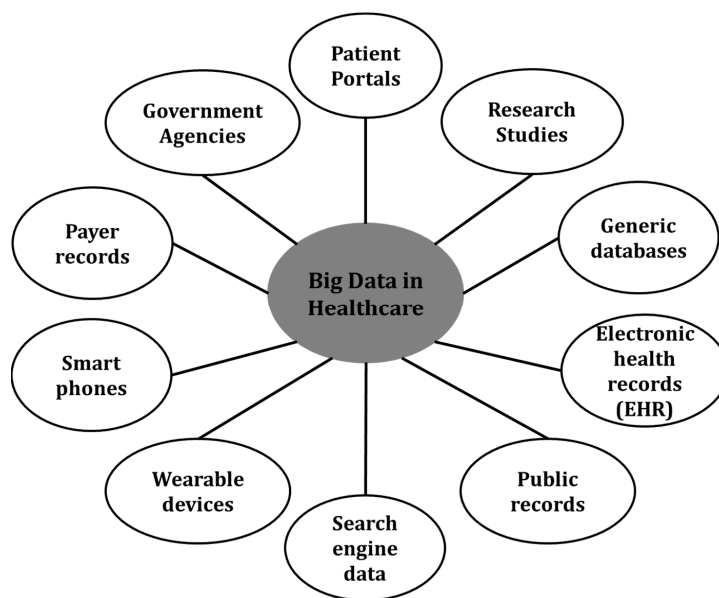


Figure 6. Big Data Applications.

Table 3. Review of Big data in Healthcare.

Sl. No	Paper	Category of Health Segment	Application Type	Year
1	[146,147]	Pandemic surveillance	Big Data analytics platform to estimate the risk of pandemic spreading and surveillance	2022,2020
2	[148]	COVID	Analysis of COVID-19 in China	2020
3	[149–153]	Infectious disease surveillance and healthcare	DL, Big Data analytics, AI, and IoT to monitor spread of bacteria, viruses, and pulmonary diseases	2018, 2016, 2020
4	[154]	Electronic health records	Big Data for risk estimation in cancer patients	2011
5	[155]	Safety and prediction	Big Data for secured healthcare	2017

According to a forecast by software giant CISCO, it was predicted that the highly diversified and heterogeneous volumes of data generated from clinicians, IoT devices/wearables, healthcare organizations, etc., are anticipated to reach a toll of around 930 exabytes (from terabytes) from 2022—the processing of this diversified text and video formatted Big Data with conventional databases is highly constrainable, compelling Big Data analysts to significantly manage, analyze, and leverage Big Data in order to merge them. Despite these challenges and limitations, plenty of progressive technological innovations continuously transform healthcare Big Data into useful and actionable information by appropriately leveraging suitable software tools, which opens doors to remarkably predictable conclusions and contributions, thus transforming every aspect of healthcare to be more economically feasible.

With the affluence of sourcing healthcare data from various resources—clinical pathologists are able to checkout optimally better medical and financial decisions well ahead of dangers, providing gifted life-saving quality care to the patient community and ensuring overwhelming professional satisfaction to the clinical community, as well as the family members of the patient community. Irrespective of the vastly applicable subjective areas of Big Data in the healthcare sector—the fullest adoption of Big Data analytics into healthcare was still lagging behind other industries, which is attributed to the associated challenges, such as privacy of healthcare information, data security concerns, budget constraints, etc. A demonstration of the Big Data analytics approach for providing aggravated patient care in hospitals and clinical arenas is summarized below:

- (A) Prediction of staffing requirements in hospitals, based on patient count.

- (B) Patients' electronic health records (EHRs) maintenance, warning them of pending lab tests in synchronization with doctor's instructions.
- (C) Provision of on-the-spot real-time medical data analysis to healthcare practitioners by continuously gathering patient's health data and pumping the same to the cloud instantly.
- (D) Enhance patient's self-health monitoring engagement using smart devices, for example, counting steps walked upon, monitoring heart beats, blood pressure levels, sugar levels, sleeping habits, etc., connecting them to physicians as, and when, required.
- (E) Promoting patients to opt for advanced medical treatments based on factors that are really discouraging them from taking up treatments.
- (F) In cancer, curing enables medical researchers to examine tumor samples and predict the interaction of certain mutations based on patient treatment records (in bio-banks) to chalk out the highest rates of recovery and success in cancer patients.
- (G) It is helpful in sequencing cancer samples genetically and deploying them to a cancer database and the global researcher's community.
- (H) Predictive analytics help doctors to arrive at life-saving conclusive treatments, in the case of patients suffering from complex ailments and disorders.
- (I) Big Data analytics promote telemedicine services to prevent the further worsening of patient's health conditions in remote areas.
- (J) Integration of Big Data analytics into medical imaging for healthcare drastically saves the time incurred by radiologists by quickly finalizing the clinical procedures to be adopted for every patient.
- (K) Big Data analytics helps healthcare institutions in preventing suicide deaths and self-harm (as globally, around eight lakhs people expiring every year due to suicides).
- (L) Big Data analytics provides end-to-end effective supply chain management solutions to hospitals and healthcare institutions by leveraging the analytics tools to arrive at accurate decisions.
- (M) Big Data analytics play a pivotal role in developing ground-breaking new drugs and forward-thinking therapies, based on gene cloning information analysis and intransigent patient predictions.

It can be compellingly said that, in the present-century healthcare scenario, Big Data is implicitly embedded with intelligent AI tools for building complex simulation monitoring mechanism models that aid clinical pathologists in various healthcare-relevant fields, in order to save the lives of the patient community (Figure 7).

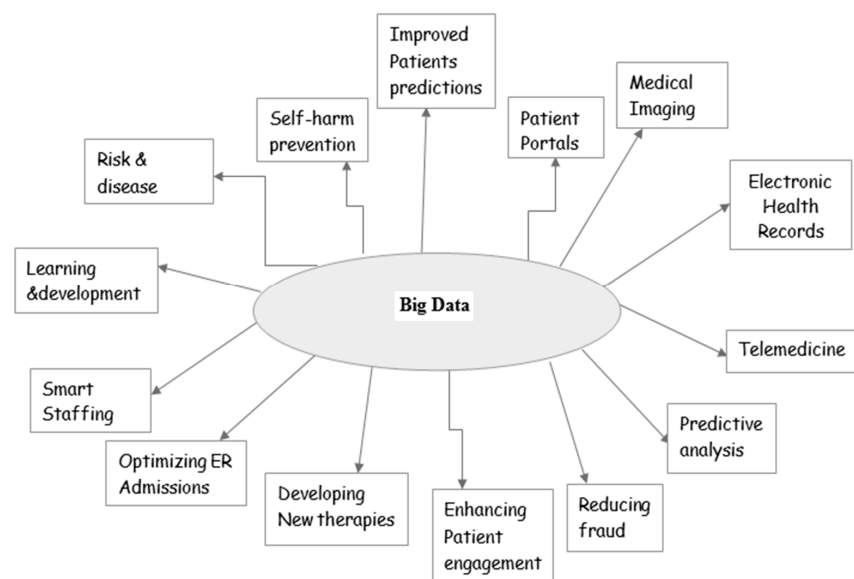


Figure 7. Big Data for Healthcare Applications.

3.3. Block Chain Technology

Block chain technology in the healthcare ecosystem typically addresses various operational compatibility challenges to conserve and swap the overall patient diagnostic information with hospitals, clinical laboratories, pharmacy industries, physicians, surgeons, etc. This technology enables a reliable, trustworthy data switch-over and workflow beyond limitations, with totally decentralized and disseminated ledger technology paving the path to novel healthcare information exchange application models. The members of the block chain technology-dispersed network are comprised of clinicians, pathologists, hospitals, laboratories, pharmaceutical companies (optional), government medical agencies, authorized healthcare and distribution companies, etc. This network enables storing all kinds of digital transactions into a pooled (shared) ledger, with each of the members having access to an identical copy preserved in the ledger, such that any modifications to the pooled ledger stands reflected over all the copies and no single member of the network holds any power to alter or modify the data, while keeping other in abeyance. Contrary to the conventional healthcare data storage-preserving mechanism of physical data, this technology provides a barter system model of healthcare information exchanges, comprising health records, documents, or images in a data repository known as a data lake, such that they are highly scalable and capable of storing wide varieties of data in various formats ranging from text, documents, and visuals, to images, etc. To ensure the confidentiality and legitimacy of the information, the entire data are preserved in the data lake after encryption, and they are digitally authenticated (signed) by the healthcare provider, i.e., whoever incorporates a medical record in the data lake.

Block chain technology is typically based on open-source software, commodity hardware, and open APIs that runs on a peer-to-peer internet-connected network of computers—all maintaining an identical copy of transaction ledger—and it offers many advantages to healthcare IT, while potentially addressing interoperability challenges with built-in fault tolerability, adversity revival mechanisms embedded with data encryption, and cryptography features throughout. It serves as a replacement to the conventional client/server distributed database management systems comprising Structured Query Language or relational inputs.

A block chain network offers vast advantages to the healthcare sector by incorporating personalized and secured real-time data accessibility permissions at the granular level and ensuring continuous accessibility to real-time data generated from wearable sensors and mobile devices, thereby enhancing the critical clinical care (CCC) and coordination among doctors in emergency situations (Figure 8). This rapidly evolving field provides fertile ground for experimentation, investment, and verification testing, henceforth paving the way for developing a new breed of SMART applications, thus aiding healthcare providers and surgeons. Research works and experimental evolutions critically elaborating the prominently applicable role of block chain technology to the medical sector and allied segments of healthcare applications are highlighted.

An innumerable number of innovations contributing to the applicability of block chain technology for healthcare applicable segments is under progression to elaborately educate the healthcare institutions and medical community. Not all, but few, are briefed for creating awareness among the future research community anticipators. Kumar and Tripathi [156] et.al, created a block chain consortium network to validate virus-related scan reports, block chain technology applications in managing electronic medical records (EMR), patient consent management [157–159], health insurance dispensation [160–162], artificial intelligence data transfer model development [163], genomics, logistics management for medical supplies, transportable healthcare and IoT [164,165], shared keys utility in the case of patient (key-holder) expiry [166], secure cloud-based EMRs [167], AI-based medical research collaboration with legitimacy [168,169], hybrid block chain solutions with medical IoT for remote patient monitoring [170], i.e., cardiac monitoring, sleep apnoea testing, etc., safety concerns of patients and medical personnel [171–175], and block chain technology-based retrieval of medical information through linking of hospitals [176–178]. The hybrid

utility of cloud and block chain technology (IBM’s medical-block chain; Al Omar et al., 2019) deployed large-size electronic health records on block chain. Though all the investigative works cannot be discussed elaborately, few such are tabulated (Table 4) to make the readers more aware of the happenings.

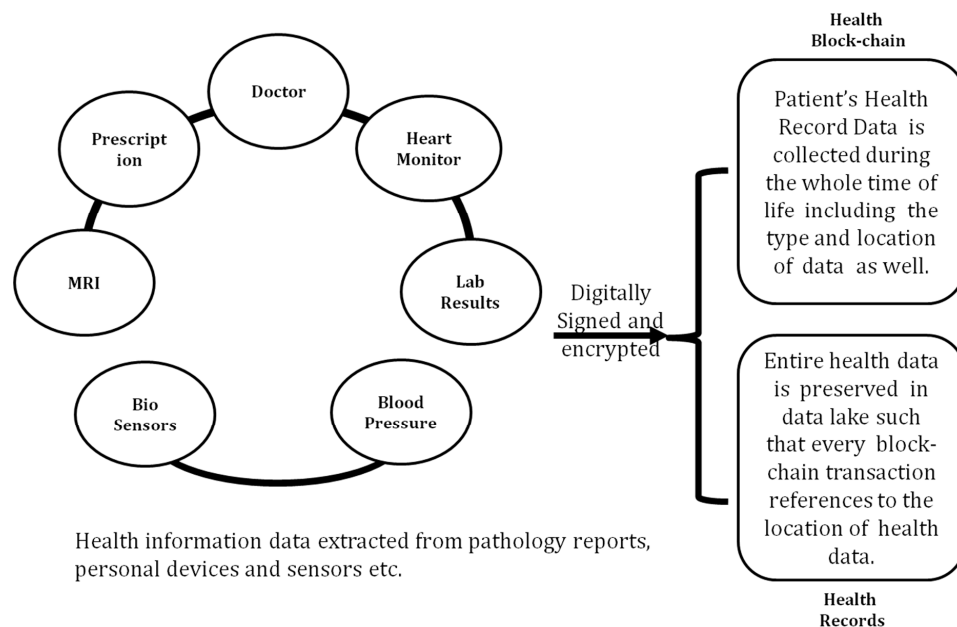


Figure 8. Block chain Technology for Healthcare Applications.

Table 4. Review of Block Chain Technology in healthcare.

Sl. No	Paper	Category of Health Segment	Application Type	Year
1	[175,179,180]	Healthcare applications	Block chain technology’s future challenges	2022, 2019
2	[181,182]	Patient Health care	Preserve patient information and data, such as blood tests, quality assessments, and estimates, in electronic health record formats	2021, 2020
3	[172,178]	Secured healthcare	Intelligent block chain framework for secured biomedical applications	2020,2019
4	[163]	Research on myopia treatment	Deep learning and block chain framework study	2021
5	[183]	Wide services to patients community	Block chain infrastructure challenges in future health care applications	2020
6	[170]	Secured healthcare	Provenance enhanced IoT and block chain framework	2020
7	[160,161,184]	Enhanced clinical trials	Block chain framework to ensure best clinical treatments, healthcare management	2020, 2018
8	[185,186]	Validation	Block chain enabling healthcare industries to obtain validated data of patients	2019
9	[157]	False content detection	Block chain ensures identification of false data to healthcare insurance companies	2018
10	[187]	Patient healthcare	Block chain and Big Data for transforming patient healthcare segments	2018
11	[162]	Medical insurance	Block chain-based genuine insurance claiming system	2018
12	[166,176]	Drugs distribution	Supply chain distribution framework for distributing drugs	2018
13	[188]	Healthcare Innovations	Block chain technology innovations for health care applications	2017

3.4. Open-Source Technologies

Over the past few decades, healthcare IT journeyed through multiple transformations from the then existing administrative perspective mechanism to the current day's constructive critical care mechanism, offering life-saving superior quality treatments to patients today, with the help of emerging technologies, such as AI, Big Data, block chain, cloud computing and IoT, amicably saving the lives of the patient community through timely healthcare facilities. This entire process of materialization shall be attributed only through the exchange of medical data across hospitals, medical institutions, patients, doctors, connected wearable (and smart) devices, electronic health (and medical) records, back-end administrative processing staff, and front-end clinical staff effectively utilizing the open-source software (Figure 9)—that leaves operational flexibility for healthcare institutions and medical centers to perform an analysis of real-time medical data, with the help of many visualization tools, thus ensuring better and timely life-giving care treatments to the patient community.

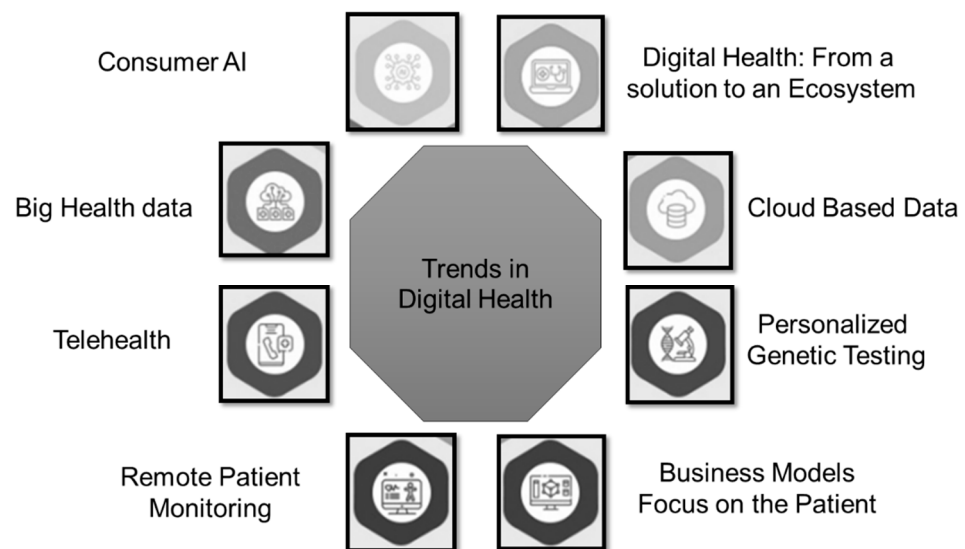


Figure 9. OST for Healthcare Applications.

The penetration of open-source tools and software into the healthcare sector is offering numerous benefits of ethical advantages, such as license-free utility, inter-operability, safe integration, etc., and promotes innovations akin to the publication of research and methods. Explorative research works that typically signify the applicability and utility of open-source software in the healthcare scenario-based segments of medication, surgeries, and treatments in various allied sectors are briefly highlighted for feasible studies and continuous evolutions by the research community. In 1990, Open GALEN (a non-profit organization) was formed to provide an open-source route for disseminating the academic research results of medical terminology and tools for future development [189]. Health information technology (IT) has its own history for adopting open-source technologies. The U.S Veterans Health Information Systems and Technology Architecture (VistA) and Mirth (an open-source software) were distributed as free source code [190,191]. In view of the easily available open software tools, healthcare IT practitioners have the flexibility to choose from licensed vendor tools, open-source tools, hybrid software environment (or in-house) tools, etc., to suit their requirements, since most of the open-source technologies are built upon the collaborative utility concepts of providing freely accessible code to all healthcare practitioners. Large open-source projects, such as Apache, Eclipse, and Mozilla, demonstrated the role of open-source technology (OST) adoption in facilitating a matured healthcare ecosystem [192]. The National Health Service (NHS) in England supported an initiative called Code4Health—an open-source platform [193–195]. Open-source health information technologies (OS-HIT) [196] are used to curb viral diseases, such as Ebola and

other pandemics [197]. Open-source software publicizes bugs, allowing sophisticated users to fix them, thereby regularly updating the codes to enhance the applicability of reusing proven code and benefitting the patient's safety. Care2X is an open-source hospital information system [198], and Open Receipt Computer Advanced is another OSS in Japan [199] that aids the patient community and clinicians.

As we are aware that proprietary vendors always insist upon standardization only, healthcare IT practitioners (and doctors being ethical) shall insist upon OST (open-source technology) to drive standardization, though they are aware of the fact that most of the open-source software runs on shared source code; hence, they are tweaked to work in synchronization with the proprietary software. Therefore, they shall trade off whether to go for stand-alone open-source programs or adopt a mix of either, in order to counter the administrative challenges. On the other hand, the flexibilities associated with open-source software users ability to adopt any desired open-source support vendor enables them to create diverse and global communities on the internet, with a motto of helping others desiring to use them [200–205], thereby helping the clinical and healthcare community as a whole.

3.5. Cloud Computing for Healthcare

Cloud healthcare is a cloud computing service for healthcare providers with internet-connected remote servers deployed for storing, maintaining, and processing personal healthcare-related patient data (PHRPD). This setup of cloud computing healthcare is in disparity, with an on-site datacenter and server mechanism of the conventional system [206]. Cloud storage healthcare mechanisms offer large volumes of secured data storage space at rescue—of course maintained by tech savvy IT professionals. Specifically, the Microsoft Azure cloud computing system provides on-demand simple access to healthcare applications and data.

Typical healthcare cloud service scenarios under utilization (Figure 10) and the associated benefits of cloud healthcare are briefly discussed, as follows:

- A. An efficient electronic medical health record (EMHR) ensures hospitals and healthcare institutions facilitate the storage of the entire patient health history, in order to provide enhanced medical services with the fullest security and privacy of data.
- B. Cloud storage machinery for the EMHR of patients paved the way for a collaborative patient caring mechanism, ensuring the easy sharing of patient's medical records with other physicians and surgeons, in order to formulate the treatment methodologies to be adopted for every patient, thereby preventing over-prescribed medications and repeated tests for the patients.
- C. Since cloud-based healthcare service providers alone handle the maintenance of cloud services, healthcare providers need not worry about the initial expenditures and can focus more upon rendering the best services to patients, except to arrange provisions for their own storage space and hardware setups.
- D. With the EMHR mechanism, healthcare providers can maintain an onsite data storage system, with IT staff totally waiving having reams of patient data physically, which is prone to theft/damage or being affected by natural disasters etc.
- E. Truly speaking, cloud healthcare paved the way for Big Data applications because the EMHR mechanism today enables physicians and doctors to predict effective treatment options for patients, based on subtle correlations in patients past medical data using, many complex computer algorithms.
- F. Cloud healthcare provides long-term financial benefits to organizations because it ensures fully scalable healthcare solutions, with provisions for the in-line expansion of the business.
- G. The cloud healthcare EMHR-based data storage mechanism promotes researchers to derive more benefits from digitized healthcare information and open access to massive, previously inaccessible data sets.

H. Cloud healthcare provides an interoperability platform to facilitate rapid data transfer between IoT-enabled devices that can interface freely, such that organizations with cloud computing capabilities can acclimatize to the changing scenario of the healthcare landscape in the future [207].

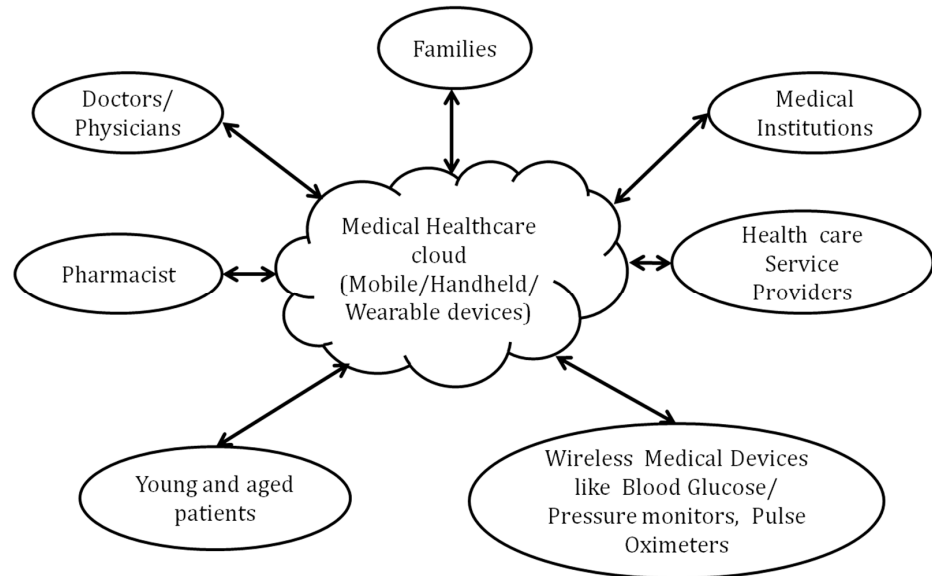


Figure 10. Healthcare cloud services.

A typical, realistic deployment of a cloud computing scenario for healthcare applications, visualizing the healthcare data information flow between cloud computing servers, patients, doctors, surgeons, health institutions, medical centers, clinical pathologists, laboratories, ambulances, and back-end data processing personnel, is depicted (Figure 11) to develop a clear, analytic view of the cloud computing-based healthcare scenario.

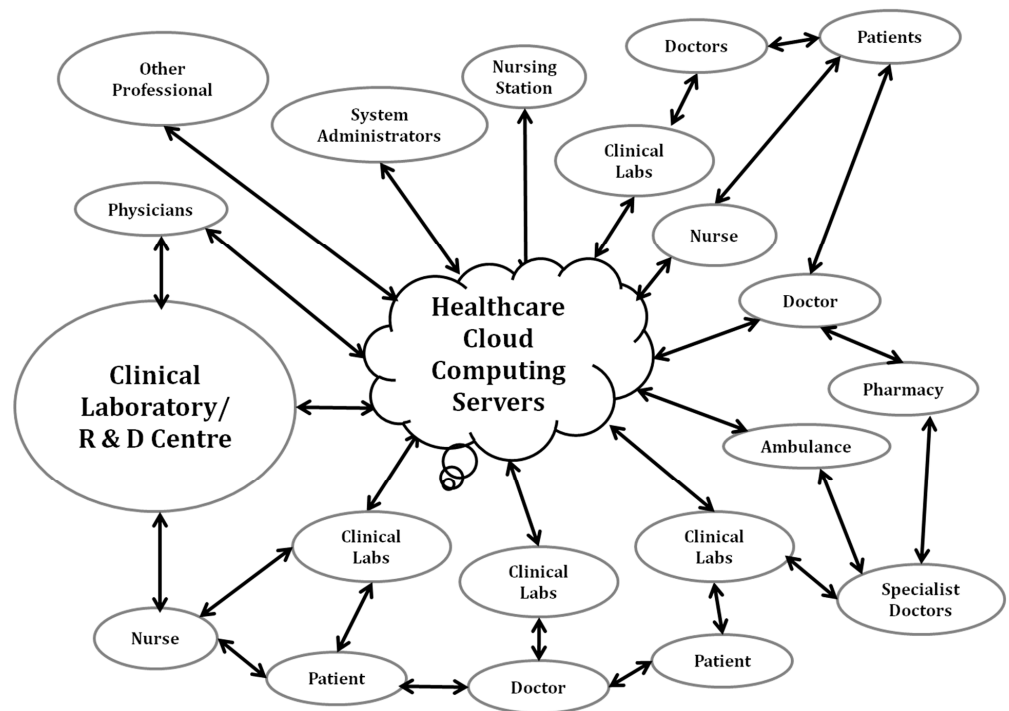


Figure 11. Cloud computing servers for Healthcare.

In India, the government of Delhi devised an integrated patient healthcare data managing system between the hospitals, with around 13.9 billion (\$18.9 million) rupees associated with IT providers (NEC Corporation, India). It is expected that the global cloud healthcare market is going to hit 35 billion Canadian dollar by 2024, with a predicted annual growth rate of 11.6%, despite the fact that around 69% of the respondents confirmed that the majority of hospitals have no plans to port their existing data centres to cloud storage.

4. Future Scope and Challenges

Though the deployment of technological advancements to the healthcare sector is no doubt a boon, there are plenty of implicit challenges associated with their practical utility for addressing many healthcare issues. Therefore, the future scope governing the deployment of technologies such as AI, Big Data, block chain, open-source software, and cloud computing, substantiated by the limitations(or challenges) adhering to practicality, are herewith outlined, inviting innovative solutions by the research community.

- Though artificial intelligence penetrated into chat bots, CAD (computer-aided detection) systems for diagnosis, and surgeries leveraging analytics, human surveillance cannot be avoided in surgeries because surgical robots can operate logically, but not empathetically - on the other hand AI applications and relevant data are not totally free from (i.e., they are susceptible to) cyber-attacks.
- With the healthcare organizations adopting Big Data in large numbers, multiple sources of Big Data include data from hospital records, patients' health records, the results of medical examinations, wearable devices, the Internet of Things (IoT), etc., and the challenges associated with handling Big Data demands adequate infrastructure to systematically analyze Big Data. On the other hand, incompetent and incompatible data systems render the interfacing of big data sets difficult, thereby posing problems to ensuring the confidentiality of patient's data.
- Though fullest deployment of block chain technology bears a potential to revolutionize healthcare sector by ensuring medical records to be well-organized and secured. Storage of patient EHR (electronic health records) on block chain is not economically viable for implementation (especially in the developing and middle-eastern countries). Further it is difficult to query data with block chain technology; data redundancy, data privacy infringement, data ownership, etc., are the additional challenges associated left for being addressed by research community.
- Though open-source technologies (OST) hold the potential to bring various healthcare service providers together, i.e., pharmaceutical vendors, medical institutions, patient communities, and researchers, and by slashing down the IT infrastructure costs, they remain agile to adopt novel IT solutions, while the shared availability of OST elevates the risk of hacking and data breaches, as well as the lack of standardization in utility, when compared with software's provided by the standard vendors.
- Cloud computing transformed the healthcare sector by hastening the migration of workloads from data centers to the cloud, significantly changing the way information systems are deployed, operated, and maintained inside a sole informative system. Cloud computing data in the healthcare sector is prone to data breaches and security issues, thereby raising concerns in protecting the privacy of real-time data; henceforth, the types and levels of security issues are left open to be taken care of.

5. Conclusions

The proposed review work outlined the prominent role of AI, Big Data, block chain technology, open-source, and cloud computing technologies in solving various healthcare ailments, from general medicine, dentistry, cardiology, neurology, orthopaedics, paediatrics, gynaecology, and psychiatry to plastic surgery, as well as curbing the different neurotic maladies, infectious pandemics, etc. Though these technologies have superseded the role of doctors (clinical pathologists) by relentlessly addressing many interoperability and platform integrity (confidentiality) issues, there exist many unspoken practical and

technical liabilities governing their implementation in the healthcare sector. It was observed that AI cannot fully replace surgeons, contrary to the probability of defective/incorrect diagnosis by robots—on the other hand, multiple data handling across multiple data systems raises concerns regarding security firewalls and confidentiality issues, stressing the need to develop a predictive analysis-based online reporting software (typically, an open-source software will do). The storage of large-scale medical data using block chain still seems inferior to the distributed database management systems (DBMS) and not economically viable. In view of these concerns, cloud chain or distributed storage options with cloud computing storage are preferred. Ultimately, open-source technologies are serving to improve the patient care manifold, with due consideration to the cyber security measures. Therefore, it is essentially required for the healthcare community to leverage the open-source technologies gaining momentum across healthcare sectors in-line with the three main goals of healthcare, i.e., accessibility, accountability, and affordability.

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