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

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10.1 Introduction

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

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

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

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

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

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

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

10.1.1 Organization of the Chapter

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

10.2 Applications of AiIoMT in Healthcare System

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

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

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

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

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

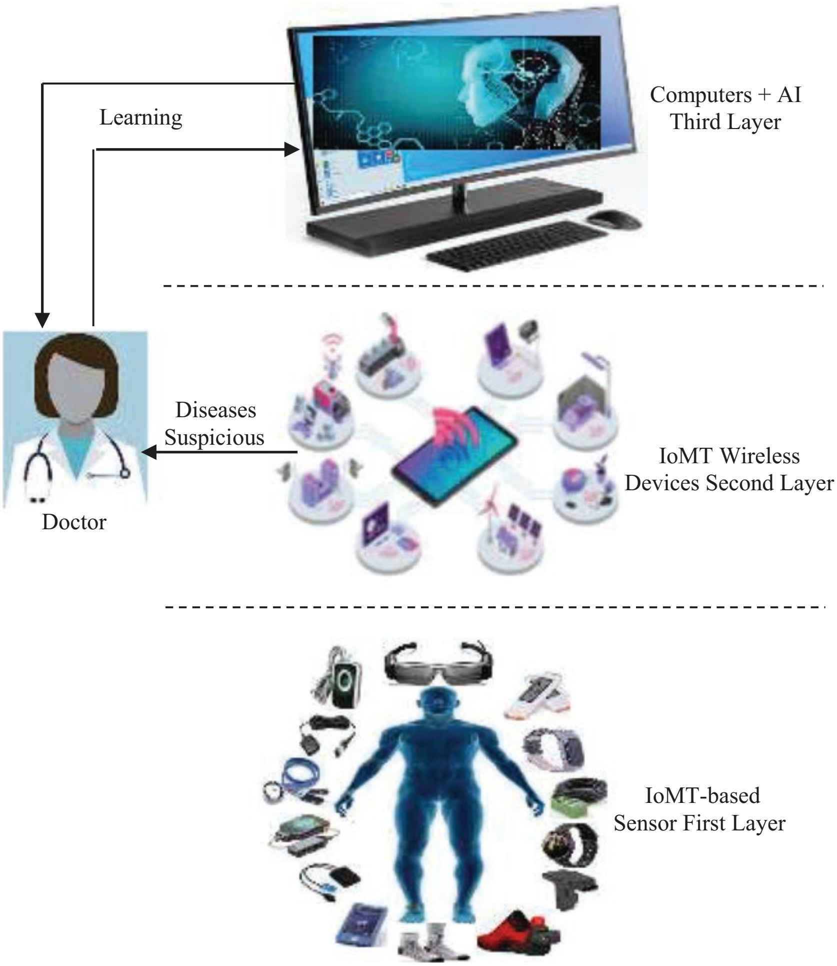


Fig. 10.1 The architecture of an AiIoMT for disease diagnosis and monitoring

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

10.2.1 Disease Diagnosis

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

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

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

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

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

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

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

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

10.2.2 Prediction and Forecasting Method

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

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

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

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

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

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

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

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

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

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

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

10.2.3 Monitoring System

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

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

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

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

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

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

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

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

10.2.4 Personalized Treatment

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

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

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

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

10.3 Challenges of AiIoMT-Based System in Healthcare Industries

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

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

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

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

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

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

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

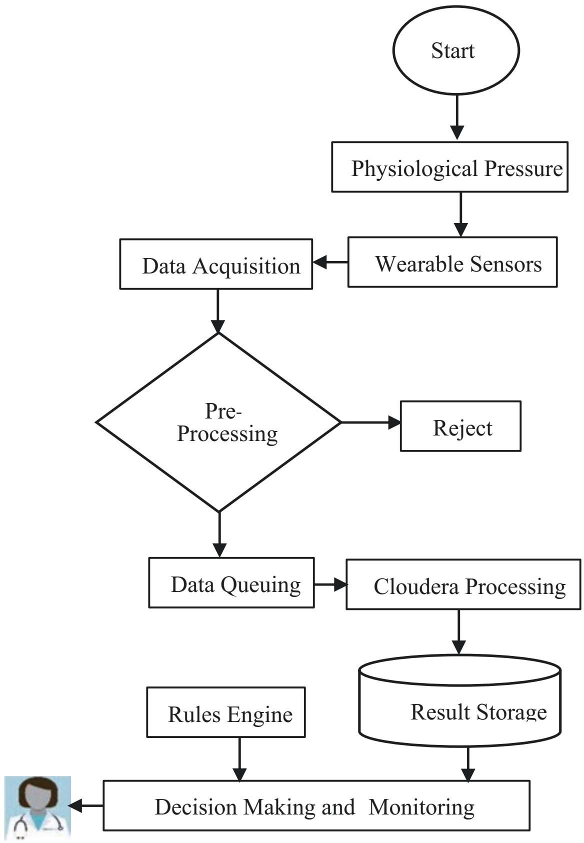
10.4 The Flowchart of the Proposed System

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

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

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

Fig. 10.2 Flowchart for the AiIoMT-based framework



The cloud database was used to store and hold the data generated and data extraction for data analytics, ingestion, visualization, and patient monitoring control in real time. Lastly, for decision-making and management, the AI-based model was used to process the data, and rules are used to notify the physicians, medical experts, and users. Big data is incorporated into the framework to be able to realize the analytics into smart health monitoring. This was done to provide real-time decision-making to improve the data processing efficacy.

10.4.1 The Machine Learning XGBoost Classifier

Chen and Guestrin [61] popularized XGBoost, a machine learning classifier that is both effective and scalable. The gradient enhances the decision tree first to result in an XGBoost classifier, which associations many decision trees in a boosting manner. Each new tree is created in order to lower the gradient boosting of the prior model's residual. Residual describes the differences between the real and expected values. The template has been trained until the quantity of decision trees defines the threshold. XGBoost follows the same notion of gradient boosting; to manage overfitting and enhance efficiency, it employs the quantity of spikes, training rate, subsampling ratio, and maximum tree depth that are all variables to consider. Specifically, XGBoost optimizes the function goal, tree size, and scale of the weights, all of which are governed by typical variables for normalization. With many hyper-parameters, the XGBoost provides greater efficiency in a specific search space.

Gamma $\gamma \in (\theta, +\infty)$ denotes minimal loss reduction, which includes a split to render the partition on a tree's leaf node, according to the hyper-parameters. The minimum child weight $w_{mc} \in (\theta, +\infty)$ is defined as the minimum instance weight overall, implying that if the graph division stage yields a tree structure with the instance weight sum less than w_{mc}, the further partition will be discarded by the tree. The early stop algorithm works to find the optimum number of epochs that correspond to other hyper-parameters given. Finally, subsampling methods and $r_c \in (0, 1)$ column subsample ratio concepts were also provided by XGBoost in each tree. In the final step, to minimize the classification error, grid search is used to control the hyper-parameters.

Given $X \in R^{n \times d}$ as training dataset with d features and n samples, XGBoost object function in $t - th$ is represented by the following:

$$Obj^{(t)} \simeq \sum_{i-1}^{n} \left\{ \ell\left(y_i, \tilde{y}_i^{(t-1)}\right) + g_i f_t\left(x_i\right) + \frac{1}{2} h_i f_t^2\left(x_i\right) \right\} + \Omega\left(f_t\right), \tag{10.1}$$

$$g_i = \partial_{\tilde{y}(t-1)} \ell\left(y_i, \tilde{y}_i^{(t-1)}\right), h_i = \partial^2_{\tilde{y}(t-1)} \ell\left(y_i, \tilde{y}_i^{(t-1)}\right), \tag{10.2}$$

where the loss function ℓ is represented by the first gradient g_i, and h_i is the second gradient of ℓ. To measure the complexity of the model, the regularization $\Omega(f_t) = \gamma T + \frac{1}{2}\varphi\varphi^2$ was used, where the number of leaf nodes is represented by T.

As demonstrated in Eq. (10.3), the logistic loss ℓ of the training loss measures how well the model fits on the training data:

$$\ell\left(y_i, \tilde{y}_i^{(t-1)}\right) = y_i \ln\left(1 + e^{-\tilde{y}_i}\right) + \left(1 - y_i\right)\ln\left(1 + e^{\tilde{y}_i}\right) \tag{10.3}$$

Given the $t - th$ training sample $x_i \epsilon R^d$ and assuming that a XGBoost model of XGB contains K trees, the corresponding prediction y_i is computed as follows:

$$\tilde{y}_i = \sum_{k=1}^{k} F_k\left(x_i\right) \tag{10.4}$$

$$s.t. F_k \epsilon\ XGB, where\ XGB = \left\{F_1, F_2, F_3, \ldots, F_K\right\}. \tag{10.5}$$

R programming language was used to implement the proposed classifier, and the evaluations were done using various performance metrics. The dataset with the relevant activity monitoring recognition was used seamlessly to incorporate all characteristics.

10.4.2 Dataset Used

The proposed AiIoMT-based system was evaluated on 400 cytology images provided in Peshawar, Pakistan, by Lady Reading Hospital's pathology department. The dataset was used due to a shortage of available data and dataset on the breast cancer images and for the correctness of the proposed system.

10.5 Results and Discussion

The confusion matrix is used to examine the classifier's quality assessment. True positive (TP) represents malignant cell cases that are accurately identified as positive (malignant) in the confusion matrix, whereas false positive (FP) represents nonmalignant cell cases that are incorrectly classified as positive (malignant) called type 1 error. True negative (TN) denotes nonmalignant cell cases that are correctly categorized as negative (nonmalignant), while false negative (FN) denotes malignant cell cases that are incorrectly classified as negative (nonmalignant), also known as type 2 error.

Table 10.1 shows the results obtained from the proposed model using the performance evaluation, where the total number of cells in the image is represented by n = 29,000. The performance of the classifier was measure using factors like sensitivity, precision, F-score, specificity, and accuracy (Fig. 10.3).

Tools like big data, 5G communication, IoT, machine learning (ML) cloud infrastructure, artificial intelligence (AI), and blockchain play a crucial role in helping the world to protect and improve people and societies differently. The healthcare experts would continue to face crucial obstacles to incorporate and appreciate these optimized solutions and their advantages findings carry out elaborate regard to risk management, resources, cost, scope, and quality. Along with mobile device platforms that rely on automated hospital control services that use automated surgical technologies (e.g., ultrasound, MRI, endoscopes, electrocardiograms) and computerized patient information systems (e.g., Picture Archiving and Communication System (PACS), Organized System of Care (OSC), and Electronic Medical Record (EMR), smart healthcare technology platforms have been created.

In recent years, the deployment of the AiIoMT has provided various dimensionalities in healthcare through online services. These have offered a new atmosphere for millions of individuals to learn about fresh healthcare ideas on a regular basis in order to live a healthy existence. The usage of AiIoMT technology and related

Table 10.1 Proposed method evaluation

Dataset	Accuracy	Precision	Sensitivity	F-score	Specificity	Class
Images	99.7%	98.4%	99.2%	98.9%	98.9%	Benign
	100%	99.8%	99.6%	96.7%	99.8%	Malignant
Total	99.85%	99.10%	99.40%	97.80%	99.35	

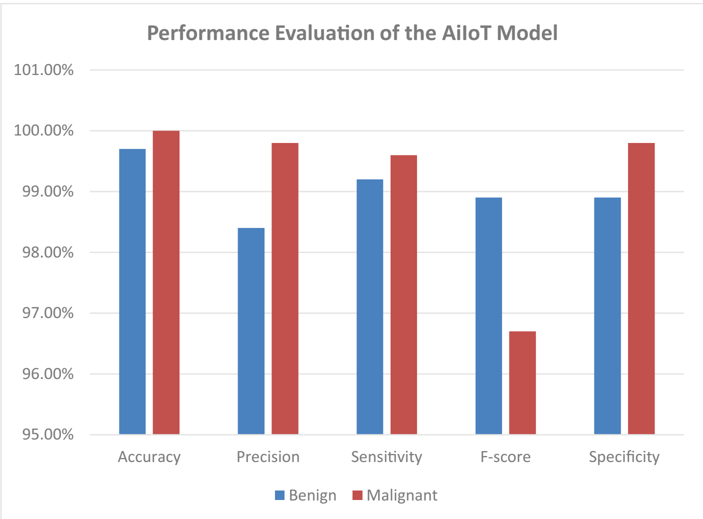


Fig. 10.3 The performance evaluation of the proposed model

devices in medical fields has grown [61–62]. It is easier to have a big number of less powerful devices, such as a wristband, air conditioner, umbrella, and fridge, than it is to have a small number of powerful computer devices, such as a laptop, tablet, or phone, thanks to the Internet of Things.

As such, geographic borders have been overcame by the smart healthcare industry and transformed into digital hospitals aimed at comprehensive patient care and the quality of high-level medical services. Different Information and Communication Technology (ICT), medical, and big data innovations are developing different services in the smart healthcare field in conjunction with wearable medical device-based AI technology, as the paradigm of patient care is moving from hospital-based therapy to customer prevention. For instance, the quantified movements used to track and retain daily personal health information, including the volume of blood glucose, heart rate, electrocardiogram, and nutritional information collected by wearable sensors or healthcare apps, have been distributed. Also, the smart healthcare industry is widening its deployment to telemedicine, mobile wellness, Electronic Health Record (HER)/EMR/Personal Health Record (PHR), cellular medical facilities, and targeted therapy through a mix of IoT technologies.

The IoT-based system with AI healthcare system has become one of the most indispensable parts of human lives; this has dramatically increased the medical information system that brings about big data. Healthcare practitioners are already adopting wearable devices based on the IoT to streamline the diagnosis, monitoring, prediction, and treatment process. The healthcare system that depends on IoT assists the individuals and aids their vital everyday life activities. Cloud computing technology has been used to handle the huge amount of data generated by IoT devices called “big data” and becomes easy to access and use. The major role played by cloud-based applications with IoT-based system can never be overlooked globally. For secured storage and easy accessibility, cloud computing can be used in medical applications. When these two innovations are combined, AiIoMT supports each other in an equal manner. The tracking system is built by integrating these two technologies to accurately track patient records, including at a remote location, that is useful to doctors. In terms of high resource usage, storage, resources, and computational capacity, IoT technology is often supported by AI to boost performance.

Machine learning and cognitive algorithms have experienced advances recently and, hence, have been used to solve many complex problems. The ML showed an outstanding performance in clairvoyance to perform accurate object recognition and in a difficult assignment that requires humanlike intelligence and outperforming the traditional based techniques. AI is ideal for the situation where no rules for performing a task are defined; instead, the rules are learned from the actual data. ML can identify and use secret structures in the data to make intelligent decisions. Big data is the core component of the AI techniques’ high performance. A huge amount of knowledge is produced by the different number of sensors in the IoT-based system, which makes it possible to integrate these cognitive skills into the IoT. It will automate the processing and interpretation of the data. This leads to more efficient and smart solutions for healthcare professionals that can save lives and time.

For continuous health tracking, AiIoMT can be implemented to enhance the well-being of patients, make the healthcare system more effective, and help respond quickly to crises. The AiIoMT can be employed to enhance the well-being of patients, make the medical system more effective, and help respond quickly to emergencies. Hence, it is possible to take advantage of the latest technical arsenal to build a new wave of smart healthcare cities that would be able to forecast widespread disease occurrences more accurately, supporting their claim. It's not quick and apparent, and, as cities become more and more integrated, many problems will still arise. Nevertheless, the negative effects of the widespread diseases can give this process the requisite boost.

Given their increasing capabilities, deep neural networks (DNN) have done badly in healthcare. The technologies are still in their infancy, and the resources required to support them are also in their infancy, with few professionals capable of dealing with the massive amounts of data and software engineering issues. In particular, in medicine, AI solutions are sometimes hampered by data shortages and poor quality. As new data is obtained, predictive models will need to be reinstructed and keeping an eye on changes in data creation methods. The data added to train the predictive model are rarely disclosed for special reason, and this reduces the data dependencies that are needed in the model for it to be able to function efficiently [55, 56, 60].

10.6 Conclusion and Future Directions

The use of modern technologies in healthcare systems has really solve global health challenges with equal access to medical services by both the poor and rich. The increases in the emergency of infectious diseases and rise in medical costs have really reduced the effectiveness of healthcare systems in developing nations. Thanks to the growth of intelligent and modern equipment, there is substantial improvement in data creation in medical sectors. The application of IoT-based systems has helped patients in receiving proper treatment in real time and created a social forum in assisting individuals. The system also creates robust repository for the government and healthcare organizations on various disease control and management. The huge data generated by IoT-based systems facilitates the use of AiIoMT for diagnosis and monitoring. The use of capture data for patient symptoms from various devices like thermometers, wearable sensors, and embedded devices can be for personalized disease infection diagnosis, monitoring, and management. The IoT and AI interaction is currently at a phase where high-frequency dispensation, storage, and analysis of massive amounts of data are required. Therefore, this chapter presents the essential principles of IoMT-based system-enabled AI-based system in medical systems. The opportunities, expectations, and challenges of using IoMT-based system-enabled AI models were also reviewed, which focused on AI technology with an emphasis on IoMT-based systems. The lack of huge data from medical fields is one of the hindrance of using AI-based models with IoMT system. The findings showed that security and privacy of patients' data are of the some major problems of using IoMT-based system-enabled AI models in healthcare systems. Oher challenges of using IoMT-based system-enabled AI models are interoperability, confidentiality, and resource management. There is an urgent need to address these problems in order to fully enjoy the benefits of AI models in IoMT-based systems. Future research will focus on the security and privacy of IoMT-based system using AI models. Also, there are pressing issues related to AiIoMT in disease diagnosis and treatment; while progress has been made in the study of the IoT-based healthcare system in customized e-healthcare, operational issues still need to be addressed. Therefore, in this case, an intelligent security model should be thoroughly investigated in order to reduce the identified risks.

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