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AI, IoMT and Blockchain in Healthcare

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Abstract

The healthcare industry is adopting new technologies such as AI, IoMT, and blockchain to enhance patient outcomes, reduce costs, and improve operational efficiencies. These technologies can revolutionize healthcare by facilitating personalized patient-focused care, improving clinical outcomes, and reducing expenses. However, the implementation of these technologies requires collaboration between healthcare providers, technology companies, and regulatory bodies to ensure patient privacy and data security. This study explores the role of AI, IoMT, and blockchain in public healthcare and their current applications, obstacles, and future research areas. It emphasizes the advantages that these technologies bring to the IoT and the difficulties involved in their implementation.

Keywords: Internet of Medical Things (IoMT), Internet of Things (IoT), Machine Learning (ML), Deep Learning (DL), Artificial Intelligence (AI), Blockchain.

1. Introduction

Though the medical advancement has begun earlier than other fields, it has progressed more slowly than the other sectors [1]. Due to the speedy development of science, technology, and economics, medical care has risen as the top concern for individuals, communities, and nations. The primitive medical pattern has flaws, for example, the difficulty in scheduling a doctor's visit, the high cost of available treatments, and limited access to healthcare knowledge. Nevertheless, ever since the concept of IoT was first presented to the public in 1999, the function of IoT has gotten progressively engaged in all sectors of the Internet of Everything (IoE) that exists in the modern day. The term Internet of Medical Things (IoMT) is an

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abbreviation for IoT-based technology applied in the medical domain, which serves as a fundamental element of the ongoing innovation and transformation within the healthcare industry. Connecting inexpensive sensors to the Internet, the IoT records events in the real world and facilitates the management of physical infrastructures. This has profound implications for human life. Personal companion, smart refrigerators, smart fire system, road signal, room temperature controls, smart watches, smart health meter, etc. are all real-world applications of IoT. This is because of the numerous advantages that its services provide to people in all walks of life. The Internet of Things (IoT) promotes time savings in routine tasks by facilitating greater connectivity; for instance, Amazon, Alexa, and Apple homepod can be used to get voice-activated responses to the inquiries without turning on the PC or using the phone. Varying sectors are adopting IoT at different rates, as evidenced by a recent poll predicting that by 2025, 41.6 billion IoT gadgets will be in use, producing 79.4 ZB of data, and a corresponding increase in IoT revenue from $5.6 billion in 2016 to $27 billion by 2024.

Improving health monitoring, management, and processes through the IoMT can have a significant impact on people's health and quality of life. Disease prevention, lower healthcare expenses, and guaranteeing a good quality of life are all bolstered by the progress of enhanced low-cost advanced healthcare infrastructure and solutions, as anticipated by WHO by the year 2030. By 2050, the world's population is expected to grow by 31 percent to 9.8 billion as a result of longer life spans. Because of the current rate of population growth, by 2050, 16% of the world's people will be 65 years of age or older.

Complex Internet of Things technologies are included in IoMT. These technologies include radio frequency recognition technology, sensor technology, and location tracking technology [3]. IoMT provides several services, including identity identification, remote monitoring of vital signs, medication administration tracking, and equipment tracking. Recently, the use of wireless medical sensors, such as pressure sensors, biosensors, and implantable sensors, has become incredibly common. The advent of 5G is expected to further progress the healthcare sector by allowing smart health applications such as distant assessment, operation instruction, emergency care vehicles, and portable medical gadget [4-8]. It is critical to process and make decisions about real-time medical data quickly, while also protecting patient privacy. The IoMT can help create a completely integrated health environment, connecting doctors and patients through various medical signals such as ultrasounds, blood pressure, glucose receptors, EEGs, and ECGs [9]. The healthcare industry has benefited greatly from the development of machine learning and deep learning, as well as the high speed provided by WLAN technologies, allowing medical professionals to deal with various formats of medical data from the same patient simultaneously, improving disease diagnosis and prediction, and ultimately improving patient outcomes [10-14].

Blockchain technology is also making significant progress in the distribution of healthcare records, and it guarantees data safety and anonymity by storing data in decentralized locations. Each member of the network has access to the same set of records, making it a distributed ledger that can also be used to speed up and automate the old procedure, and save money. In the future, a tool that combines and shows all current medical information on a person's medical condition in a secure healthcare environment could contribute to personalized healthcare that is reliable and secure [15, 16].

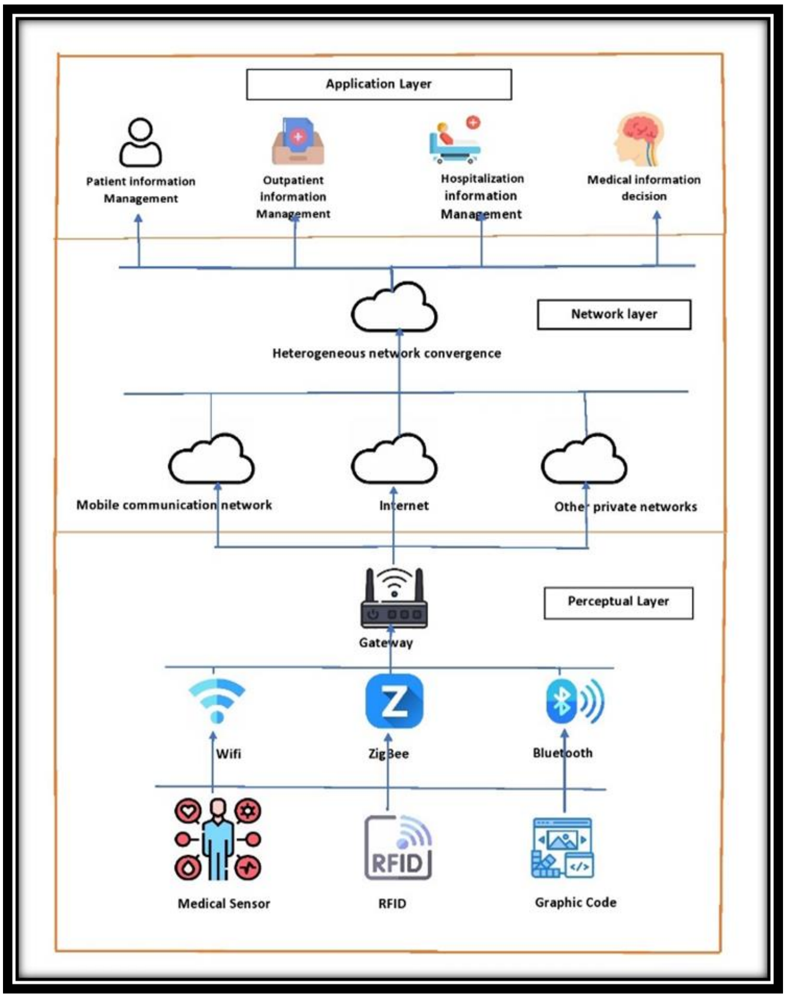

Figure 1. Layered architecture of IoMT [3]

2. IoMT

IoMT follows the typical 3-layer structure of IoT applications, which includes the perception layer, the network layer, and the transmission layer, among other things. Figure 1 illustrates the IoMT design. The network layer has two sublayers: (i) Network transmission layer, (ii) Service layer. The IoMT's network transfer layer mimics the nervous system of a person by enabling dependable, accurate, and real-time data transfer from the perception layer. The service layer unifies disparate networks, data formats, data warehouses, and other sources of information. This establishes an application support platform. This platform lets a third party construct medical apps. The application layer is subdivided into two layers: the medical information application layer and the medical information decision-making application layer [17-20].

3. IoMT-integrated technologies for building Smart Healthcare

Virtual Reality, Mixed Reality, and Augmented Reality have four primary uses: medical and therapeutic, entertainment, commercial and industrial, and education and training. Virtual reality technology creates a 3D world that can simulate reality, producing a sense of "presence". Therapeutic virtual reality involves wearing a head-mounted display that creates a realistic environment, which can treat mental health conditions, manage strokes and pain, and prevent obesity. It can also be used to monitor cancer patients' treatments, alleviating psychological symptoms caused by the malignancy, and improving the patient's emotional well-being [21]. Yahara et al. [22] reported how individuals with moderate cognitive impairment might benefit from an immersive VR experience that evoked distant recollection. It is possible that Virtual Reality can be an useful tool in providing supportive care and minimizing the negative effects of the ongoing pandemic. This can be achieved by using video chats and simulating a sense of togetherness among individuals without the need for physical travel. Augmented reality allows users to change their perception of the current world by superimposing computer pictures on their view of the world [23,24]. Augmented Reality (AR) is a useful tool for training, but it can also be useful because it helps visualize ideas that can't be seen and annotate them through navigation in a virtual environment [25].

A Virtual Reality (VR) telehealth system was created by XR-Health to help confined patients feel less stressed and anxious while also keeping them engaged in both physical and mental activities. "Immersive VR Education Company" is the company that invented the "Engage" platform for VR instruction and interaction [26]. EON Reality created a VR and AR platform for use in quarantine situations, and a VR environment for researching COVID-19.

VR also provides simulated surgical training, allowing surgeons to practice and improve techniques with haptic features. The XVision Augmedics system improved accuracy rates for spinal surgeries. Oxford Virtual Reality is used to address mental health conditions [27].

4. AI in Healthcare

AI is revolutionizing the healthcare business in a variety of ways, from medication research to clinical decision-making and patient monitoring. Medical picture analysis is one of the most crucial applications of AI. AI systems may detect patterns in medical photos that human doctors would overlook, resulting in faster and more accurate diagnosis. AI can also evaluate massive volumes of data to identify possible pharmaceutical candidates, saving time and money in drug development. AI-powered chatbots and virtual assistants serve patients by giving individualized assistance and guidance, while population health management uses AI to identify high-risk populations for preventative care. Artificial intelligence has the potential to increase healthcare efficiency, accuracy, and speed while lowering costs and human error.

4.1 AI in Breast Cancer Diagnosis

Mammography screening is used to detect breast cancer, which is a primary source of death in women. Various countries have taken various ways to screening, with some employing clinical settings and others relying on government-run initiatives. Mammograms are examined by radiologists for calcification clusters and soft tissue anomalies. It is critical to compare current and prior photos in order to discover changes and improve accuracy. Recent breakthroughs in artificial intelligence and computing have considerably improved the automated diagnosis of breast cancer, with deep learning and convolutional neural networks showing the ability to outperform traditional approaches in terms of accuracy. AI-based medical picture categorization can help doctors identify and treat patients more quickly and accurately, potentially lowering readmissions and misdiagnosed costs.

A CNN-based CAD system was developed in [28] utilizing VGG16, ResNet50, and Inception v3 on DDSM, INbreast, and BCDR database. On the DDSM database, the suggested system obtained accuracy of 97.4% and AUC of 99%, whereas on the INbreast database, it achieved accuracy of 95.5% and AUC of 97.0%; and on the BCDR database, it achieved 96.60% accuracy and 96% AUC. In [29], a deep CNN and ResNet-18 were deployed for predicting mammography breast density on 2174 images. An updated DenseNet neural network architecture, known as DenseNet II, was developed in [30] for the efficient and accurate classification of benign and malignant mammography. The DenseNet neural network model was improved, and a brand-new DenseNet-II neural network model was created to swap out the first convolutional layer with the starting structure in the DenseNet neural network model. Finally, the pre-processed mammogram datasets were combined with AlexNet, VGGNet, GoogLeNet, DenseNet, and DenseNet II neural network models. The mean accuracy of the model was 94.55%.

Improved CNN model was proposed in [31]. Hai et al. [32] recommended explicitly differentiating abnormal degrees in digital mammograms. It suggested an end-to-end learning algorithm based on the combination of hierarchical variables. At LASSO, guided logistic regression is used to extract and select low-level attributes. CNNs were created in order to extract high-level properties. A quantitative review of many classic mass detection techniques was described in [33]. The breast masses were classified, segmented, and detected from mammograms using deep learning methods. Methods based on ensemble learning were proposed in [34] to identify breast cancer. The items were classified into two classes and eight classes. An ensemble of pretrained models was offered as a solution to the classification problem of uneven distribution. It was found that 8-class classification accuracy may be as high as 98.5% in training and 89.5% in testing. Additionally, train and test accuracy of 99.1% and 98.2% were attained for 2 class classifications, respectively. Modified VGG (MVGG) approach was proposed in [35] using datasets of 2D and 3D mammography images. The suggested hybrid transfer learning model (a fusion of MVGG and ImageNet) achieved a 94.3% accuracy in experiments.

4.2 AI in PCOS Diagnosis

Several researchers have already applied various ML models to detect PCOS. When it comes to the diagnosis of PCOS in women, Bharati et al., relied on data-driven methods [36]. Machine learning algorithms were trained using data obtained from the Kaggle repository. A total of 541 women were included in the dataset, 177 of whom were diagnosed with PCOS. Data was subjected to various classification techniques, such as Random Forest (RF) and Logistic Regression (LR), as well as a combination of the two techniques (the RFLR). According to the findings, the top ten attributed factors accurately predicted the onset of PCOS. Using 40-fold cross validation on the 10 most relevant features, recall and testing accuracy of 91.01 percent and 90 percent, respectively, were achieved. Bharati et al. [37] applied two types of voting algorithm combining several ML models such as Extra Trees classifier, RF, Gaussian Naive Bayes (GNB), Light Gradient Boosting Machine (LGBM) for 5 and 10-fold cross-validation. Accuracy of 91.1243% was achieved by using Voting-1 Soft (Extra Trees Classifier, RF, GNB, LGBM) [38].

4.3 AI in Dementia Detection

A progressive neurological condition known as 'Dementia' affects millions of people globally. Early dementia detection is critical for successful treatment and management of the disease. However, dementia can be difficult to diagnose. Artificial Intelligence (AI) has shown tremendous potential in the detection of dementia. AI algorithms can examine considerable quantities of data to look for patterns that could indicate the presence of an illness. This includes analyzing medical records, brain scans, and other diagnostic tests. AI can also be used to analyze brain scans to detect changes in brain structure that may be indicative of dementia. Machine learning algorithms can identify subtle changes in brain structure and compare them to a database of scans from people with and without dementia to make a diagnosis.

Univariate feature selection was adapted by Bharati et al., as a filter-based feature selection in the MR data pre-processing step [39]. Bagged decision trees were also used to measure the most significant components in order to achieve high accuracy in categorization. Multiple ensemble learning algorithms, including Gradient Boosting (GB), Extreme Gradient Boosting (XGB), voting-based classification, and RF classification, were investigated for the diagnosis of dementia. Voting-based classifiers, such as the Extra Trees classifier, RF, GB, and XGB, were also proposed. These models were trained using an ensemble of multiple basic machine learning models [39].

Using machine learning, So et al., suggested a two-layer model based on the method used in dementia support centers to detect dementia early [40]. MMSE-KC data were first categorized into normal and abnormal in the proposed model. Using CERAD-K data, the second stage of the study was able to differentiate between moderate cognitive impairment and dementia. In order to compare the performance of each method, Precision, Recall, and F-measure were used with Naive Bayes, Bayes Network, Begging, Logistic Regression, Random Forest, SVM, and Multilayer Perceptron (MLP). With an F-measure value of 0.97 for normal, the MLP was found to be highest in F-measure values, but the SVM had an F-measure value of 0.739 for MCI and dementia [40]. In [41], a comparative study of four machine learning algorithms (J48, Naïve Bayes, Random Forest, and Multilayer Perceptron) was conducted. The researchers used CFSSubsetEval to decrease the amount of attributes. The findings indicated that, for detecting dementia, J48 outperformed all other algorithms.

4.4 AI in Spinal Disease Classification

AI has shown potential in aiding the diagnosis of spinal diseases. Researchers have used various machine learning algorithms, such as Support Vector Machines (SVM), LR, and neural networks, to develop accurate and efficient models for classifying different spinal abnormalities. In addition, feature selection and extraction techniques, such as Principal Component Analysis (PCA) and Pearson Correlation Coefficient (PCC), have been employed to enhance the performance of these models. For example, using feature selection, extraction, and machine learning techniques, spinal anomalies were diagnosed in [41]. Data pre-processing included univariate feature selection and PCA. SVM, LR, and bagging ensemble algorithms were tested for spinal abnormality diagnosis. SVM, LR, bagging SVM, and bagging LR were employed on 310 samples. Kaggle provided this dataset for free. SVM, LR, bagging SVM, and bagging LR training accuracies were 86.30%, 85.47%, 86.72%, and 85.06% when 78% of the data was used. Nonetheless, bagging SVM had the best recall and miss rate. Begum et al. [42] used the same spinal dataset to choose the best 10, 8, 6, and 5 features based on validity or measurement in the preliminary processing step. MLP, LR, SVM, and Bagging were used in the classification step.

Using AI for spinal disease diagnosis has several advantages such as, the capacity to swiftly and correctly process sizable amounts of data, providing consistent results, and potentially reducing the time and cost of diagnosis. AI models can also learn from new data and improve their performance over time. However, there are also challenges that need to be addressed, such as the need for big and varied datasets to train the models and the potential for bias in the data. Overall, AI has the potential to revolutionize spinal disease diagnosis by providing faster, more accurate, and consistent results, leading to more effective treatments and better patient outcomes. However, further research and development are needed to optimize these AI models and ensure their safety and effectiveness in clinical practice.

4.5 AI in Lung Diseases Diagnosis

Faruqui et al., developed a model called LungNet, which utilizes data from CT scans and medical IoT devices, to increase the diagnostic precision of identifying lung diseases. The model utilizes a new 22-layer Convolutional Neural Network (CNN) to combine hidden attributes acquired from CT scan pictures and MIoT data sources [43]. Article [44] proposed a deep learning model for the classification of COVID-19, pneumonia, and lung cancer using a mixture of chest x-ray and CT images. The study found that a chest CT scan is more effective in detecting abnormalities, even in the initial phases of the disease. Various machine learning algorithms were tested for detecting and diagnosing lung diseases in the human lung system. In [44], the performance of VGG19-CNN, ResNet152V2, ResNet152V2 + Gated Recurrent Unit (GRU), and ResNet152V2 + Bidirectional GRU (Bi-GRU) were tested for detecting and diagnosing lung diseases in the human lung system.

The emphasis of Podder et al.'s study [45] was the application of machine learning techniques to COVID-19 diagnosis. The diagnosis was made through data analysis using a dataset supplied by Hospital Israelita Albert Einstein in Brazil, consisting of 5644 samples with 111 variables. Standardization and processing of null values and categorical data were performed as a pre-processing step. Next, feature selection was undertaken to identify the most crucial characteristics for a COVID-19 diagnosis from the dataset. Several algorithms, like RF, LR, XGBoost, and decision tree, had their kernel parameters improved [43]. Several researchers applied different ML models for the prediction of COVID-19 patients and Intensive Care Unit (ICU) requirements [44,45,46]. Several ML models such as K means neural network, SVM learning algorithm, RF learner, Neural network, Adaboost had been executed in [47] in order to evaluate the lymphography dataset.

A modified neural architecture search network (NASNet) for COVID-19 detection using CT lung images was suggested in [48]. The research used a dataset of 3411 images and applied the NASNet-Mobile and NASNet-Large models to it. The leftover 15% of the samples were used for testing, with the remaining 85% being used for training. After 15 epochs, it was discovered that NASNet-Mobile had precision, recall, and area under the receiver operating characteristics curve (AUC) of 82.42 percent, 78.16 percent, and 91.00 percent, respectively. In contrast, the accuracy, recall, and AUC of NASNet-Large were 81.06 percent, 80.43 percent, and 89.0 percent, respectively. Bharati et al., introduced a modified DL approach for COVID-19 and lung disease called Optimized Residual Network (CO-ResNet) [49]. The suggested CO-ResNet was created by modifying the conventional ResNet 101's hyperparameters. A new dataset of 5,935 X-ray images obtained from two public datasets was subjected to CO-ResNet analysis [49]. There are also some research works where various deep learning methods are applied such as CNN [50,51], CO-IRV2 [52], VGG 16 and Xception [53].

5. Blockchain in healthcare applications

The healthcare industry has unique safety and privacy requirements, as it is responsible for safeguarding patients' medical information. With the growing use of cloud storage and mobile gadgets for data sharing, there is a higher risk of security breaches and the potential for personal information to be leaked. As people seek care from multiple providers and access health information via smart devices, there are growing concerns about the privacy and sharing of this information. The healthcare industry must adhere to specific regulations regarding authentication, data sharing, interoperability, medical record transfer, and mobile health considerations.

Blockchain technology has many features that make it suitable for use in the medical field. These capabilities are built into the system and can be used with a variety of tools and industries. This section emphasizes the features of blockchain technology that make it an appealing option for the healthcare sector, including security, authentication, and decentralized storage.

Blockchain technology's decentralized storage is a key element and the foundation for the system's improved security and authentication [54,55]. As a result of the blockchain's ledger, decentralized storage is a technique of distributing medical records among different computers, allowing for faster access and enhanced data quality and quantity for medical study [56,57,58]. Blockchain technology, for instance, can be used by IoT and cloud service providers to decentralizedly share data in a secure and discrete way. The three pillars of blockchain technology are data accuracy, immutability, and security. The decentralized ledger of the blockchain, which is private and confidential, can provide security by distributing data over multiple computers instead of depending on only one point of breakdown. It is possible to distribute a transaction around the whole blockchain network, creating a large number of redundant data sources to validate the original transaction's validity. Because of this redundancy, a malicious actor will be unable to make any changes to the network's data despite altering the data on all of the other computers in the network.

The decentralized infrastructure of the blockchain also assures the authenticity of documents and other private information recorded in blocks along the chain of blocks [59]. To begin the process of creating, altering, or reading data recorded in the blockchain, a user must have access to a unique key that is linked to a publicly available primary key [59]. It is possible to keep these keys in a Bitcoin wallet, which has a corresponding Bitcoin address. Although these software programs are mostly used for Bitcoin and cryptocurrency, the same cryptographic approach can be used to implement other authentication processes [59]. This authentication technique is being studied for identification and verification of identity in everything from public records to individual medical records.

There are a plethora of possibilities for healthcare technology in the blockchain. Blockchain-enabled healthcare applications have been tested and documented in a number of ways, with a few specific software solutions outlined below. OmniPHR is a methodology designed by Roehrs, Costa, and Righi [60] to help manage Patient Health Records (PHR) across numerous healthcare providers. The OmniPHR architecture also tackles the issue of healthcare providers having access to the most recent patient data, even if the records are stored elsewhere or changed by other healthcare providers. The distinction between Electronic Health Record (EHR) and PHR is the primary issue that OmniPHR attempts to resolve. A variety of regulatory regulations govern EHR, helping to notify the issue of standardized information guarding across state and country lines. This keeps the records as current and accurate as feasible. Unlike PHR, which are maintained by patients, these records are maintained by medical professionals without any patient participation. OmniPHR helps build a framework to solve this issue, giving patients a more complete image of their information while retaining the level of accuracy needed by doctors [60]. Medrec is a blockchain-based decentralized record management system for EMRs.

According to [61], the system of OmniPHR allows patients to access their medical records in real-time from multiple healthcare providers and clinics. The system's modular structure can connect to healthcare providers' current local data storage, enabling verification, security, reliability, and data transmission. The system enables patients and medical practitioners to communicate using blockchain technology. MedRec compensates medical stakeholders with anonymized data in exchange for maintaining and securing the blockchain network. Patients and providers can choose to share their data as metadata. The prototype is designed to test the framework's approach and implementation before field tests. Block content shared by members of a private P2P network represents shared data ownership and viewing rights. Smart contracts are used to track and regulate state transitions like adding a new record or changing viewership permissions. Patient-provider connections are logged, and viewing permissions and data retrieval instructions are provided to medical records using the Ethereum blockchain. The patient's data is encrypted and can be shared with doctors. An automatic reminder is provided to the patient to review the suggested information before accepting or declining it. A particular contract brings together all patient-provider associations, simplifying the process of updating medical records through a single reference. Public key cryptography and a DNS-like application are used to verify a current form of ID, such as a social security number, in order to authenticate the patient's identity [61]. PSN stands for Personal Sensing Network [62]. In order to fully fulfil the concept of a PSN, a component in the network must safely communicate its health information to other nodes. The researchers proposed two strategies to protect a PSN-based healthcare system [62].

6. IoMT Security by Blockchain

The design of blockchains comes in two varieties, permissionless and permissioned. Since permissionless blockchains don't need user approval, anyone is able to leave or join at any moment. Bitcoin is an example of a permissionless blockchain that can handle a large number of nodes even with low transaction throughput. In contrast, permissioned blockchains have a set of rules that must be followed to join the network. Only validated blocks by the network's miners can be added to the chain, resulting in a higher transaction throughput than permissionless blockchains. The use of blockchain and IoMTs can provide improved visibility and comfort for users. Blockchain can provide a powerful, open, distributed, and hard-to-change data structure for IoT information, while IoMT devices can collect real-time sensor data to provide a better understanding of patients' health status. These technologies can provide benefits such as data security, improved diagnosis and treatment, and tailored healthcare services.

7. Notable contributions performed by blockchain for the COVID-19 pandemic

During the COVID-19 pandemic, blockchain technology was applied in a number of sectors, including medical care, banking, politics, economics, and education. Its decentralized structure and capacity to enable safe and private data sharing have proven especially beneficial in contact tracking, patient data sharing, disaster recovery, supply chain management, migration supervision, automated monitoring, contactless delivery, and virtual learning. Blockchain-based solutions have aided in the resolution of key difficulties such as preserving data privacy, sustaining continuous supply chains, offering safe online education, and streamlining the request and authorisation procedure for financial services. Moreover, blockchain-powered drones and robots have been employed for automated delivery and tracking in high-rate transmission zones. Throughout the epidemic, the usage of blockchain technology revealed its ability to deliver efficient and effective solutions to a variety of difficulties.

8. Challenges and Future Research Directions

The use of IoT and AI-powered smart healthcare raises a number of ethical considerations, including potential health disparities and privacy concerns. Patients should be able to access and control their own health data, and adequate measures should be in place to preserve it. Regulations and standards are required to guide the development and deployment of these technologies, ensuring that they fulfil ethical, safety, and efficacy criteria while also being transparent and responsible. Therefore, while these technologies have the potential to improve healthcare outcomes significantly, resolving these problems is critical to reaching their full promise. Denial of Service (DoS) attacks can harm patients and medical groups as well. Resource replication (using numerous devices on the network) is a simple DoS avoidance approach. However, it may not be practical in healthcare because some devices are implants. New technologies and hardware problems make identifying security threats challenging. This problem will grow as more people go online. Moreover, unsecured UI access increases risk.

9. Challenges to IoMTs Privacy and Security

The stability of the IoMT ecosystem is hindered by the absence of robust authentication measures, and cryptographic approaches may not be suitable for resource-constrained IoMT devices. Lightweight cryptographic solutions that consider performance limits are necessary. The foundational components of IoMT are GPS, NFC, and RFID devices, and a versatile routing and forwarding service is required to transfer data across multiple nodes. Traditional fault-tolerance measures are ineffective compared to self-healing and self-adaptation, which are crucial for IoMT systems that support health and wellness. Fault tolerance is necessary for successful operation and fault prevention, detection, and recovery should be incorporated into IoMT security solutions.

10. Conclusion

The development of Internet of Things communication infrastructure and physical devices has resulted in significant advancements in remote health monitoring systems. Combining machine learning and deep learning techniques with advanced artificial intelligence approaches can uncover patterns that are connected to diseases and health problems. The combination of blockchain technology with machine learning models has enabled the development of IoT-connected health monitoring systems that enhance medical record management, drug traceability, and the tracking of infectious diseases. To date, cutting-edge techniques for incorporating blockchain, machine learning, and deep learning into Internet of Things applications have been developed. This paper offers a discussion of evolving Internet of Things technologies, machine learning, and blockchain for healthcare applications. Healthcare practitioners will be able to examine patients' clinical records on the blockchain, and artificial intelligence will support them by using a variety of related algorithms, decision-making tools, and a great deal of data. The medical system will benefit from the integration of the most recent technological advancements by increasing service efficiency while simultaneously lowering prices and democratizing healthcare. The blockchain permits the storing of cryptographic records, which is essential for artificial intelligence.

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