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IoMT-Enabled Smart Healthcare Models to Monitor Critical Patients Using Deep Learning Algorithms: A Review

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Abstract: A new era of healthcare transformation has begun with the combination of deep learning and the Internet of Medical Things (IoMT). In this review, we explore the transformative potential of IoMT-enabled Smart Healthcare (SHC) models for the unceasing monitoring of critical patients by leveraging the power of deep learning algorithms. The IoMT, a network of interconnected medical devices and applications has revolutionized the acquisition and transmission of real-time patient data. Simultaneously, deep learning algorithms have demonstrated exceptional proficiency in deciphering complex patterns within vast healthcare datasets. By synergizing these technologies, SHC models have emerged as a promising solution to the pressing challenges of critical patient care. This review provides an extensive insight into the latest developments and methodologies at the intersection of IoMT and deep learning in critical patient monitoring. We systematically examine existing research findings, elucidate the capabilities of IoMT-enabled SHC models, and address the challenges and opportunities inherent in their deployment.

Keywords: IoMT, SHC models, machine learning, deep learning, artificial intelligence.

1 Introduction

Despite the availability of adequate facilities and cutting-edge technologies in the current context, health-care services are neither accessible nor affordable to everyone. SHC [1] aims to assist patients by alerting them to health problems and keeping monitoring of their wellness [2, 3]. Risky patients with debilitated immune systems require consistent check-ups to keep healthy. SHC is transforming with the revolutionary technologies including big data [4], IoT [5], cloud computing [6], and Artificial Intelligence (AI) [7] to make healthcare easier and more efficient [8].

With the increasing population and the rising prevalence of chronic illnesses, the health care sector is working hard to provide patients with the optimum care available. The current medical infrastructure is not keeping up with the demand for hospital resources [9].

In order to overcome this difficulty, the IoT shows promise as a way to provide patients with access to healthcare, even in remote locations [10]. Creating a user-friendly platform that makes communication between physicians and patients easier is the main objective of integrating IoT in the medical field.

In the context of healthcare, IoT refers to a network of physical things that are connected and communicate data via the internet. Almost 10 billion IoT devices are currently connected to this network, which has grown drastically since Kevin Ashton first introduced it in 1999 [11, 12].

Around 25 billion computerized devices are expected to be connected by 2025. Hence, IoT refers to a network of interlinked computing devices, each having a unique identification (UID)[13], that can communicate data over the internet without requiring direct communication between people or between people and computers.

This technology is called the IoMT [14] when it is used in real-time with sensor nodes and clinical advancements in the healthcare industry. The landscape of healthcare is going through a revolutionary change at a time when technology breakthroughs are thought to be unprecedented.

The incorporation of cutting-edge technologies into healthcare systems has escorted in an age where patient care is not only more efficient but also progressively personalized [15]. Among these transformative technologies, the IoMT [16] stands out as a game-changing invention, offering healthcare practitioners with real-time data and insights into patient health. As the IoMT evolves, it has the ability to address some of modern healthcare's most serious issues, including effective monitoring of critical patients.

IoMT and Deep Learning (DL) present a thorough analysis of how these technologies might be used to develop a sophisticated healthcare model for monitoring crucial patients [17]. There has never been a more critical need for enhanced monitoring technologies that can improve the health of patients and alleviate the load on healthcare providers due to the rising frequency of chronic illnesses and the growing demands on healthcare services [18].

In the realm of critical patient care, the combination of these technologies offers the potential to completely change monitoring procedures in situations where prompt interventions can mean the difference between both life and death [19, 20].

The IoMT, facilitates the seamless collection, transmission, and analysis of real-time patient data [21]. In parallel, DL algorithms have demonstrated exceptional proficiency in deciphering intricate patterns within extensive datasets, including medical information.

This review embarks on an exploration of how the convergence of IoMT and DL can give rise to a SHC that not only continuously monitors critical patients but also anticipates and responds to their evolving medical needs [22, 23].

As critical patient populations grow and healthcare resources become increasingly strained, the imperative for innovative monitoring solutions intensifies [24]. This review paper contains an extensive overview of the most recent developments, methodologies, and applications at the intersection of IoMT and DL in critical patient care.

It synthesizes existing research findings, identifies gaps in current knowledge, and envisions future directions for this evolving field. Throughout this review, we aim to shed light on the transformative potential of IoMT-enabled SHC models, offering insights into their capabilities, challenges, and prospects.

By comprehensively examining the existing body of work, we seek to contribute to a deeper empathetic of how IoMT and deep learning can collectively enhance the monitoring and care of critical patients, ultimately shaping the future of healthcare delivery.

The residue of the paper is organized as follows: Section 2 provides a literature review, different applications of IoMT in SHC are described in section 3, and Section 4 talks about benefits and future challenges. The paper is concluded in Section 5 and future directions of the research.

2 Literature Survey

This work presents a comprehensive exploration of the potential applications of IoMT in the field of healthcare, specifically in the context of monitoring critical patients. The study evaluates the performance of a smart healthcare model that utilizes IoMT data and deep learning algorithms, and it compares the results with conventional machine learning techniques to showcase its effectiveness.

This review aims to contribute to a deeper understanding of how the integration of IoMT and deep learning can revolutionize critical patient care, ultimately enhancing healthcare outcomes and shaping the trajectory of healthcare delivery in the digital age. Table 1 contains a comparative details of different research works done in the literature.

A et al. [25] focused on the integration of cloud computing with wireless sensor networks to enhance monitoring systems and improve the quality of healthcare services. Patient data is collected using wearable sensor devices and biosensors, allowing for continuous monitoring without specifying the data type.

The collected data is transmitted through a gateway to an IoMT cloud repository for storage. The stored data undergoes preprocessing to refine

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Table 1. Summary of literature review

Author & Year	Advantages	Disadvantages	Dataset Used	Technologies used	Accuracy (in %)
A et al. (2023)	– Faster monitoring, prediction, and diagnose the critical patient – - Better accuracy	– Not sufficient to diagnose more critical diseases	Collecting Patients data	Feature extraction: LDA + Optimal features selection: CSA and Classification: HRGC	98
Thandapani et al. (2023)	– Providing real-time medical services for COVID-19	– May not be feasible for all healthcare institutions	Collecting patients' data(CT Scan + X-ray images)	CT Scan: Deep CNN with VGG 19 architecture	97
				X-ray: Deep CNN with ResNet-101 architecture	98
Yıldırım et al. (2023)	– Accurate predictive analysis for diabetes – Remote health monitoring by professionals	– Due risk of model inaccuracies, the continuous validation and refinement of predictive models are essential	dataset produced by WBANs	ML algorithm: SVM	89.5
				Optimization technique: fuzzy logic	64
Cinque et al. (2022)	– Identification is possible for several pathogens associated with pneumonia	– Accuracy can be improved	Kaggle x-ray dataset	DenseNet	84.46
Al-Sit et al. (2022)	– Leverages IoMT for patient monitoring - High prediction accuracy compared to existing methods.	– Difficulties with Data Analysis – Necessity of giving real-world applications adequate consideration	IoMT-based healthcare dataset from UCI repository	CNN	89.1
Ahsan et al. (2021)	– Early and accurate diagnosis – Cost-effectiveness - Efficient	– Not user friendly due to lack of integration with clinical data	Collecting Patients data	Deep CNN with VGG-16, VGG19, ResNet50, Mobile Net V2, ResNet101, and Inception ResNetV2	95(X-ray image with VGG-16)
					98.5 (CT images with MobileNetV2)

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Khan et al. (2020)	– Offers a user-friendly solution that combines medical knowledge with technology	– Accuracy can be increased	Collecting Patients data	Fuzzy Inference System	83
R. Jain et al. (2020)	– Early and cost-effective detection of COVID-19-related abnormalities in chest X-ray scans	– Important to address medical accuracy, overfitting issues, data validation, and ethical issues	Chest x-ray dataset from Kaggle repositary	Xception	97.97
Haoyu & Jianxing (2019)	– Early diagnosis, cost-effectiveness and high accurate	– Not user friendly due to lack of integration with clinical data.	Collecting patients' data	MobileNetV2	95
L. Syed et al. (2019)	– High accurate in predicting physical activities – Optimal solution for remote health monitoring of elderly populations	– Can affect patient trust/healthcare decisions due to instances of false positives or false negatives	MHEALTH dataset	Multinomial Naïve Bayes	97.10

and prepare it for further analysis. High-dimensional LDA is used for feature extraction from the preprocessed data. A reconfigured CSA is employed to select the optimal features among the extracted ones.

Abnormal and normal data are classified using a Hybrid ResNet 18 and GoogleNet classifier (HRGC). This step aims to identify potential health issues. Based on the classification results, a decision is made regarding whether to send alerts to hospitals or health care employees. Alerts are sent when abnormal data is detected. The study concludes with a performance analysis to assess the effectiveness of the proposed mechanism.

A system with multiple components, including the user interface, analytics, and cloud integration, was proposed by Thandapani et al. [26]. Initial medical data, including RT-PCR results and pulse oxygen levels, were gathered via the user interface. Oxygen levels were measured using a pulse oximeter, and COVID-19 positive is ascertained using switch test kits.

Through the user interface, this preliminary data is submitted to the system. In order to determine the severity of the disease, the system seeks CT or X-ray pictures if COVID-19 is found. Textual and image data are among the many forms of data that the system can manage.

The system's AI module is made to classify individuals with multiple diseases, including COVID-19, pneumonia, and other viral illnesses. For personalized treatment, it also evaluates the severity of the lung infection.

Various models of Deep Convolutional Neural Networks (DCNNs) are employed for classification, including ResNet-50, ResNet-100, ResNet-101, VGG 16, and VGG 19. High accuracy rates were attained by ResNet-101 and VGG-19, which performed accuracy of 97% for CT and 98% for X-ray images.

In [27], an IoMT framework was designed by the authors especially for diabetes prediction to analyse health big data produced by WBANs with fog and cloud computing. The authors used cloud computing for more involved and time-consuming analysis as well as fog computing for quick and simple data processing.

An important use case for these technologies is the diabetes prediction scenario in the IoMT framework. In order to conduct basic analysis in the fog, the research describes the use of fuzzy logic in decision-making.

For finding accuracy, ML algorithms such as SVM, RF, and ANN are employed. 89.5%, 88.4%, and 87.2% accuracy were achieved by SVM, RF, and ANN in the fog, respectively, while fuzzy logic achieves 64% accuracy in the fog.

Avola et al. [28] conducted an exploratory study focused on the application of transfer learning techniques for the classification of pneumonia. In their research, the authors utilized chest X-ray images both for training and testing purposes.

They employed two distinct datasets consisting of chest X-ray images, aiming to comprehensively evaluate the performance of 12 different pre-trained models. These datasets encompassed images of individuals with healthy lungs, viral pneumonia, and bacterial pneumonia. In total, their experimentation involved a sizable dataset of 6,330 chest X-ray images.

The research outcomes indicated that DenseNet, among the tested pre-trained models, demonstrated superior performance in pneumonia classification. Al-Sit et al. [29] proposed an innovative IoMT-driven SHC framework tailored for AAL. It leverages a Convolutional Neural Network (CNN) algorithm to swiftly analyze patients' physical activities, enhance decision-making, and support treatment. The simulation results achieved a higher prediction accuracy of 0.891.

Ahsan et al. [30] introduced an AI-driven approach for the detection of COVID-19. Their research involved the exploration of six distinct deep convolutional neural network architectures, namely VGG-16, Inception ResNetV2, Mobile Net V2, ResNet50, ResNet101, and VGG19, with the aim of achieving superior accuracy in the detection process.

To enhance their results, they employed both CT and X-ray images. Their experimental findings revealed noteworthy outcomes. Specifically, VGG 16 exhibited exceptional performance when applied to X-ray images, yielding an impressive accuracy rate of 95%. Conversely, MobileNetV2 excelled when dealing with CT images, achieving an even higher accuracy rate of 98.5%.

Khan et al. [31] developed a user-friendly solution aimed at predicting and diagnosing COVID-19 by combining medical expertise with technology, potentially increasing the accuracy of diagnosis. In this study, the authors tackled. the formidable challenge of predicting and diagnosing COVID-19 using a novel approach called the IoMTSM-HMFIS. This system assessed numerous factors directly related to COVID-19, such as fever, cough, blood count, respiratory rate, and lab test results, among others.

It employed a two-layer expert system for initial identification and in-depth analysis of these factors. The primary objective is to create an accessible smart monitoring system for individuals exposed to COVID-19. This system has evaluated their health status and advises if consultation with a specialist or quarantine is necessary. MATLAB-2019a is used for simulation, and demonstrated around 83% of accuracy.

Using chest X-ray images, R Jain et al. [32] developed a model for the study and detection of COVID-19 exposure. The model focuses on Post Anterior (PA) view X-ray images for disease classification. Jain used the ResNet, Xception, and Inception V3 models to compare model performance. There were 6,432 chest X-ray samples in the dataset; 5,467 of the samples were used for training, and 965 of the images were used for validation. The Xception model achieved an higher accuracy rate of 97.97%.

In [33], the researchers developed an affordable and highly accurate module within the IoMT framework to address obstructive sleep apnea, a sleep-related breathing disorder. This module utilizes a SpO2 sensor to continuously monitor blood oxygen levels and heart rate during sleep. The collected data is transmitted to the cloud for in-depth medical analysis. Based on the results of this analysis, a mobile app provides timely warnings to remote patients.

The effectiveness of this system is underscored by its impressive performance metrics, with an accuracy rate of 98.54% when employing the SVM as the classification method. Manimala S. et al. [34] presented a novel smart healthcare framework designed for Ambient Assisted Living (AAL), with IoMT and ML algorithms for monitoring the

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activities of aged individuals using. IoMT technology is utilized to collect data from multiple wearable sensors placed on various parts of the body, such as the right arm, left ankle, and chest. After that, the data is sent via IoMT devices to a data analytics and cloud integration layer for additional processing.

To handle large volumes of data efficiently, the paper employs Hadoop MapReduce techniques. This parallel processing approach is crucial for managing and analyzing extensive healthcare data.

An implementation of the MapReduce paradigm, the Multinomial Naïve Bayes classifier, was used in the paper. This classifier is used to identify distinct activity patterns that different body regions experience.

Through parallel processing as opposed to serial processing, it provides improved performance and scalability. With a 97.1% accuracy rate overall, the suggested framework predicts 12 distinct physical activities. This level of accuracy is considered highly effective for remotely monitoring the health conditions of elderly individuals.

3 Applications of IoMT in SHC

In a SHC, IoMT can be extremely important to the management of patients in severe condition. These are some particular ways that IoMT is being used to manage critically ill patients:

– Continuous vital signs monitoring: Essential indicators including oxygen level, cardiac activity, breathing rate and blood pressure can all be continually monitored by IoMT devices. Healthcare professionals can receive this data in real-time, allowing for quick intervention and early identification of worsening conditions.
– Smart wearables for critical patients: Specialized wearable devices designed for critical care patients can provide real-time data about their health. For example, wearable patches can monitor ECG signals, providing insights into cardiac health. These devices can trigger alarms in case of abnormalities.
– Remote ICU monitoring: Critical care patients in intensive care units (ICUs) can benefit from remote monitoring through IoMT. Healthcare providers can keep a watchful eye on patients even when physically distant, reducing the need for frequent bedside visits.
– Medication and infusion management: IoMT can help manage critical patients' medications and infusions more effectively. Smart infusion pumps can administer precise doses, and IoMT systems can alert nurses and doctors to medication errors or pump malfunctions.
– Smart alarms and alerts: IoMT can provide customizable alarms and alerts for critical patients. These systems can differentiate between critical alarms and less urgent notifications, reducing alarm fatigue among healthcare professionals while ensuring that critical issues are addressed promptly.
– Early warning systems: IoMT data can be used to create early warning systems that predict patient deterioration. Algorithms can analyze vital signs and other data to identify patients at risk of adverse events, allowing healthcare teams to intervene proactively.
– Tele-ICU services: Remote monitoring of critical care patients in ICUs by specialized tele-ICU teams is made possible through IoMT. This allows for continuous monitoring and expert consultation, especially in areas with a shortage of critical care specialists.
– Integration with Electronic Health Records (EHRs): IoMT devices can integrate with EHR systems, providing a comprehensive patient record that includes real-time data from devices. This helps clinicians make informed decisions based on the patient's complete medical history.
– Enhanced communication: IoMT facilitates better communication among healthcare professionals caring for critical patients. Real-time data sharing and communication platforms allow teams to collaborate efficiently and respond to critical situations promptly.
– Family engagement: IoMT can also provide critical patient data to family members, with appropriate consent. This transparency can help alleviate anxiety and provide families with a better understanding of their loved one's condition.
– Rehabilitation and physical therapy: IoMT devices can be used to monitor and guide physical therapy and rehabilitation exercises

for critical patients recovering from surgery or trauma, helping them regain their strength and mobility.

Hene, IoMT can improve outcomes for patients in critical condition, lower the chance of medical errors, and increase the quality medical care.

4 Benefits and Future Challenges

There are several advantages and upcoming challenges after wrapping up all the studies, which are described as follows.

4.1 Benefits

Implementing IoMT in SHC has significant benefits for identifying critically ill patients. Below are some eye-catching benefits are highlighted to enrich the glance of SHC.

Early recognition and interventions: IoMT make it possible to continuously monitor health information and vital signs. This enables rapid medical procedure and may even save lives by allowing for the early detection of serious medical disorders.

Improved patient outcomes: Critical disease outcomes can be enhanced, death rates can be decreased, and hospital stays can be shortened with early detection and timely treatment.

Cost-effective healthcare: IoMT can contribute to lower healthcare costs by preventing key incidents and consequences. Additionally, it can lessen the need for costly procedures and extensive hospitalizations.

Improved remote monitoring: IoMT allows healthcare practitioners to remotely monitor patients, and this is particularly necessary for persons who have chronic conditions or reside in rural areas. So that access to medical treatments may be made easier for them.

Optimized resource allocation: Healthcare facilities can use IoMT data to allocate resources efficiently. For example, hospitals can prioritize ICU beds for patients at higher risk of deterioration.

Minimized alarm fatigue: IoMT systems can filter and prioritize alarms, reducing the number of false alarms and mitigating alarm fatigue among healthcare professionals.

Improved data accuracy: The accuracy and real-time data provided by IoMT devices lowers the possibility of errors that come with traditional data entry and enhances the standard of clinical decision-making.

Enhanced patient experience: By allowing patients to be examined in their domiciles, IoMT can promote a more patient-centered approach to care by lowering the frequency of hospital stays.

Telemedicine integration: IoMT seamlessly integrates with telemedicine, enabling healthcare professionals to remotely assess critical patients and provide immediate guidance.

4.2 Future Challenges

After all the benefits of SHC, addressing the identified obstacles will be essential to leveraging the potential of IoMT in terms of enhancing the quality of care for patients through technology and healthcare practices.

Data safety and confidentiality: The top priority is ensuring the confidentiality and privacy of sensitive patient data. Health information about patients must be kept secure and IoMT systems must be secured from hackers.

Interoperability: It can be difficult to combine IoMT devices into a coherent system because they frequently come from different manufacturers and may employ various communication protocols.

Regulatory compliance: Compliance with regulations: It is crucial to comply with healthcare laws like the GDPR in Europe and the HIPAA in the United States. It can be challenging to navigate these rules, particularly when working with patient data.

Data fatigue: The constant flow of data from IoMT devices may cause information overload for healthcare professionals. In order to derive useful insights, data management and analytics are required.

Compatibility with EHRs: Due to variations in data formats and standards, incorporating IoMT data into EHRs can be challenging.

Ability to scale: The scalability of IoMT systems is called into question as the total amount of interconnected devices and patients increases. Systems must be able to manage multiple devices and a lot of data at once.

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Training and education: Healthcare professionals need training to effectively use IoMT systems and interpret the data generated. Additionally, patient education is crucial to ensure compliance and understanding.

Ethical concerns: The use of IoMT raises several ethical questions, such as those pertaining to patient permission, confidentiality of data, and potential flaws in algorithms.

Infrastructure and connectivity: Reliable internet connectivity are essential for IoMT systems to function properly. In regions with limited connectivity, implementation may be challenging.

Costs: Some healthcare providers may find it difficult to get behind IoMT because of the major initial expenses associated with establishing IoMT devices and infrastructure.

5 Conclusion

In this review, we explored the promising realm of an IoMT-enabled SHC model that harnesses the capabilities of DL algorithms to monitor critical patients. The fusion of IoMT with advanced DL techniques represents a groundbreaking approach in healthcare that has the potential to revolutionize critical patient care. Our analysis has highlighted the significant advantages of employing IoMT-enabled SHC systems for the monitoring of critical patients.

These systems use DL algorithms to detect relevant patterns and anomalies in medical data, resulting in more accurate forecasts and better patient outcomes.

Nonetheless, it is very important to recognize the challenges involved in IoMT-enabled SHC systems into practice. A thorough understanding of data privacy, interoperability, compliance with regulations, and legal issues is necessary to enable the sustainable and efficient use of these technologies.

To improve the precision and robustness of vital patient monitoring, research can continue to concentrate in developing more complex DL models, such as transformer-based architectures and recurrent neural networks (RNNs).

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