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An Analytical Review of IoT-Based Health Monitoring Systems Integrating CNN–LSTM for Early Disease Detection

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Abstract

The purpose of the review paper is to review the use of the IoT-based real-time health monitoring systems and CNN -LSTM deep learning models to detect diseases in their early stages. We have the intention to explore how the IoT technologies and hybrid deep-learning structures can be useful in improving the continuous patient monitoring and predictive healthcare outcomes. The study design will comprise a critical review of the literature and comparative analysis of the recent sources dedicated to the IoT-based healthcare systems, sensors and deep learning models such as CNN, LSTM, and Bi-LSTM. The literature review of the system architectures, data processing techniques, and performance measurements are analyzed. The findings demonstrate that the IoT devices can be used to obtain physiological measurements in an extremely efficient way in real time, and CNNLSTM models can extract features and recognize temporal patterns and can, therefore, be utilized to predict illnesses more efficiently as compared to traditional machine learning techniques. A number of studies document high accuracy rates with a few models recording more than 98 percent disease prediction rates. Nonetheless, other issues, including data privacy, interoperability, computational complexity, and lack of labeled datasets, are still of great concern. The review finds that incorporating IoT and hybrid deep learning models provide an exciting way to create intelligent, scalable, and patient-centered healthcare systems and that future developments will rely on edge computing, explainable AI, and secure data-sharing systems.

Keywords: IoT Healthcare, Real-Time Health Monitoring, CNN–LSTM, Deep Learning, Early Disease Detection.

I. Introduction

The blistering development of healthcare technologies has greatly changed the method of medical data collection, processing, and use to diagnose diseases and monitor patients. Iota-based real-time health monitoring systems are one of these innovations and have become a promising solution to

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round-the-clock and remotely accessed monitoring of physiological parameters to identify possible health threats early and before they develop into serious health issues. The conventional health care systems heavily rely on regular clinical visits and manual interpretation of data, which tend to result in late diagnosis and ineffective management of the disease. In contrast, in the case of Internet of Things (Iota) devices, such as wearable sensors, smart medical devices, and connected health systems, vital signs, such as heart rate, blood pressure, oxygen saturation, body temperature, and electrocardiogram (ECG) signals, can be measured in real-time [1], [2], [3]. By constantly tracking and analysing such data streams, one can gain a lot of information about the health status of a patient and detect abnormal trends that could signal the development of diseases. Nevertheless, the sheer quantity, velocity, and diversity of the health information produced by the Iota are extremely challenging when it comes to storage, processing, and correct interpretation. To address these problems, the artificial intelligence (AI) and deep learning approaches have increasingly been utilized in the healthcare systems to enhance accuracy in predictions and decision-making capabilities. In particular, the hybrid deep learning networks such as Convolution Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks have proven to have impressive abilities to analyse the complicated biomedical data [4].

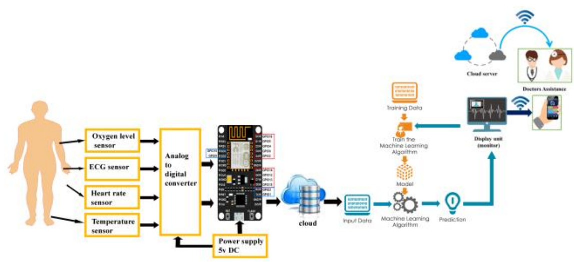

Fig. 1 Deep Learning-Based Iota System for Remote Monitoring and Early Detection of Health Issues in Real-Time[5]

CNNs are very efficient in the extraction of spatial features and the recognition of local patterns in structured and unstructured medical information, whereas LSTM networks are tailored to extracting temporal dependencies and temporal patterns. CNN + LSTM can be combined to form a potent hybrid architecture, which can learn both spatial and temporal patterns of physiological signals, and thus is very well-suited to real-time disease prediction and early diagnosis tasks [6]. When applied to the Iota-based health monitoring system, CNN-LSTM models can be used to work with data streams of sensors to detect small abnormalities that would be difficult to detect using the conventional statistical framework or single machine learning models. The skill is particularly valuable in the initial diagnosis of chronic diseases such as cardiovascular disease, diabetes, respiratory diseases, and neurological conditions, where the prompt diagnosis of the disease can significantly improve patient outcomes and reduce health care costs [7]. Moreover, Iota and deep learning enable the creation of smart healthcare systems that enable remote patient care, telehealth, and personalized care plans. This type of system not only increases the efficiency of the healthcare delivery process, but also decreases the workload of the hospitals and healthcare providers as it makes the care proactive instead of reactive. Although they have these benefits, a number of difficulties are faced in the real-world deployment of Iota-based CNN-LSTM health

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monitoring systems. Concerns like user privacy and safety, cross-platform compatibility of heterogeneous devices, wearable sensors energy usage, and large-labelled datasets are important to support widespread adoption, with real-time operation and low latency of a model being essential to critical healthcare applications. Researchers are thus working on making deep learning structures more efficient, using edge and fog computing models, and creating safe communication channels to address these shortcomings. This paper is a review article that suggests a comprehensive analysis of an Iota-based real-time health monitoring system that is based on CNN-LSTM deep learning models in order to detect early signs of the disease. It provides the fundamentals of Iota in healthcare, explains how hybrid deep learning structures can be used in the medical data analysis, and researches the existing methodologies and frameworks proposed by the existing literature. Some of the key challenges, limitations and future research directions in this area which are highlighted in the paper include the need to have scalable, secure and precise intelligent healthcare systems. The healthcare industry is on the road to becoming more proactive, data-driven and patient-cantered with the integration of Iota and more advanced methods of deep learning whereby the early-stage disease detection and continuous monitoring are the most important factors in improving the overall health outcomes and quality of life.

II. Related Work

The development of Iota-based healthcare systems has continued to adopt deep learning methods in recent times to improve real-time monitoring and disease prediction. Halifax et al. (2025) [8] highlighted the increased presence of image processing and deep learning in Iota settings, including the usefulness of CNNs, RNNs, and transfer learning to enhance real-time decision-making in any domain, including healthcare. But issues like resource limitation, latency, and security of data are still key obstacles. Similarly, Abdulkhudhur et al. (2025) [9] introduced a hybrid Deep Belief Network and neuron-fuzzy model to a 5G-enabled Iota system to enhance anomaly detection and demonstrated high accuracy, overcoming problems of interpretability. Within the framework of viable healthcare systems, Al-Qatari et al. (2025) [10] created an Iota-based medical device monitoring system based on deep neural networks to detect early signs of diseases, which proved to be scalable and low-latency. Moreover, Malherbe and Alkali (2025) [11] have demonstrated the efficacy of CNN and LSTM models in interpreting the complicated healthcare data, allowing to diagnose and treat individuals correctly. Complementing these studies, Kate et al. (2025) [12] proposed a safe Iota healthcare system based on CNN-LSTM and optimization methods, with an excellent precision of 99.43. Although these developments have been made, current studies have not yet achieved scalability, energy efficiency, and privacy of data, suggesting that more robust and integrated hybrid models are required.

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Table I. Comparative Analysis of Related Literature in Iota and AI-Based Monitoring Systems

Author / Year	**Methodology**	**Findings**	**Research Gap Identified**	**Limitations**
Nancy et al., 2023[13]	Iota devices with cloud computing and Bi-LSTM for sequential medical data analysis	Achieved high accuracy (98.86%) in heart disease prediction using real-time patient data	Limited exploration of hybrid deep learning models like CNN–LSTM for multimodal healthcare data	High dependency on labeled datasets and computational resources
Vinita et al., 2022[14]	Iota-based real-time health monitoring system for vital sign tracking during COVID-19	Enabled continuous monitoring of physiological parameters with alert-based system for abnormal conditions	Limited integration of advanced AI models for predictive disease detection	Accuracy dependent on sensor quality and network connectivity
Bolhasani et al., 2021[15]	Systematic review of deep learning applications in Iota-based healthcare systems	Highlighted increasing role of AI, big data, and Iota in healthcare transformation	Lack of standardized frameworks for deployment in real-world healthcare systems	Issues related to data privacy, Quos, and implementation complexity
Deepak et al., 2021[16]	Iota integrated with big data analytics and machine learning for healthcare monitoring	Improved clustering and classification accuracy for patient health analysis	Need for more real-time adaptive and intelligent predictive models	High computational time and reduced scalability for large datasets
Liu et al., 2020[17]	Iota-based anomaly detection using LSTM and auto encoder models	Improved detection of contextual and point anomalies in sensor-driven systems	Limited robustness in highly dynamic and heterogeneous environments	Model complexity and need for large-scale training data

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III. IoT Architecture and Sensor Technologies for Real-Time Health Monitoring Systems

The Internet of Things (Iota) has proved to be one of the back bone technologies of the modern healthcare system, as, via it, it is possible to check the health status of the patients remotely, in real time and, naturally, constantly. Iota-based health monitoring systems architecture is usually divided into multiple layers that are interconnected like the sensing layer, network layer, processing layer, and application layer. All the layers are critical to enable successful data acquisition, transmission, analysis, and utilization in healthcare decision-making [18]. The sensing layer is the heart of the system and comprises wearable, implantable and ambient biomedical sensors that sense physiological events like heart rate, blood pressure, body temperature, oxygen saturation (Sop 2), electrocardiogram (ECG) and electroencephalogram (EEG). The development of micro-electro-mechanical systems (MEMS), nanotechnology and flexible electronics has enabled non-invasive, continuous and energy-saving health data collection by these sensors. Recent research points out that the accuracy and reliability of such sensors play a key role in making sure that real-time disease monitoring and early detection systems are effective [19], [20], [21].

The role of the network layer is to pass the acquired physiological data of sensors to processing units like edge devices, gateways or cloud platforms. A range of wireless communication technologies is used to power Iota-based healthcare systems, which include: Bluetooth Low Energy (BLE), Sigsbee, WI-Fi, Lora WAN, and 5G networks. All the communication protocols have their unique advantages based on the needs of the application like energy efficiency, bandwidth, latency and range of transmission. An example of this is the application of BLE in wearable devices because it has low power consumption and 5G networks because they support high-speed, low-latency communications which can be used in critical healthcare scenarios where real-time response is needed. Trends in research show that there is increasing migration into hybrid communication architectures that combine many protocols to provide improved reliability and scalability [22].

Processing is an important component of Iota processing that involves processing, storage, and analysis of large and heterogeneous data generated by the devices. This layer is frequently based on cloud computing to deliver a scalable storage and high performance processing, and edge and fog computing paradigms are being incorporated to reduce latency and improve responsiveness in real time. Edge computing helps process the initial data closer to the data source thereby minimizing transmission delays and bandwidth usage. Recent books and articles have discussed the use of artificial intelligence (AI) with deep learning techniques on this layer as a trending topic to enable intelligent data analytics, anomaly detection, and predictive healthcare modeling.

The application layer is the user-facing part of the Iota healthcare system, which conveys the information processed to the patients, healthcare professionals, and medical institutions in the form of dashboards, mobile applications, and alert systems. The layer is used to provide real-time health visualization, remote patient monitoring, emergency notifications systems, and personalized healthcare recommendations. These systems may automatically issue alerts in case of abnormal physiological patterns and therefore allow timely medical response and possibly avoid serious health issues in critical care situations, Iota architecture in real-time health monitoring systems offers a scalable and efficient platform to continuously monitor their health and detect diseases

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early [23]. The combination of superior sensor technologies, well-developed communication systems, and sophisticated data processing systems has enhanced the functions of the contemporary healthcare systems. Nonetheless, regardless of these developments, issues of interoperability between heterogeneous devices, data security and privacy issues, short battery life of wearable sensors, and network reliability problems are critical impediments. More recent studies are concerned with overcoming these limitations using edge cloud hybrid architecture, energy efficient sensor design and secure communication protocols, which present the way to more robust and intelligent healthcare monitoring solutions.

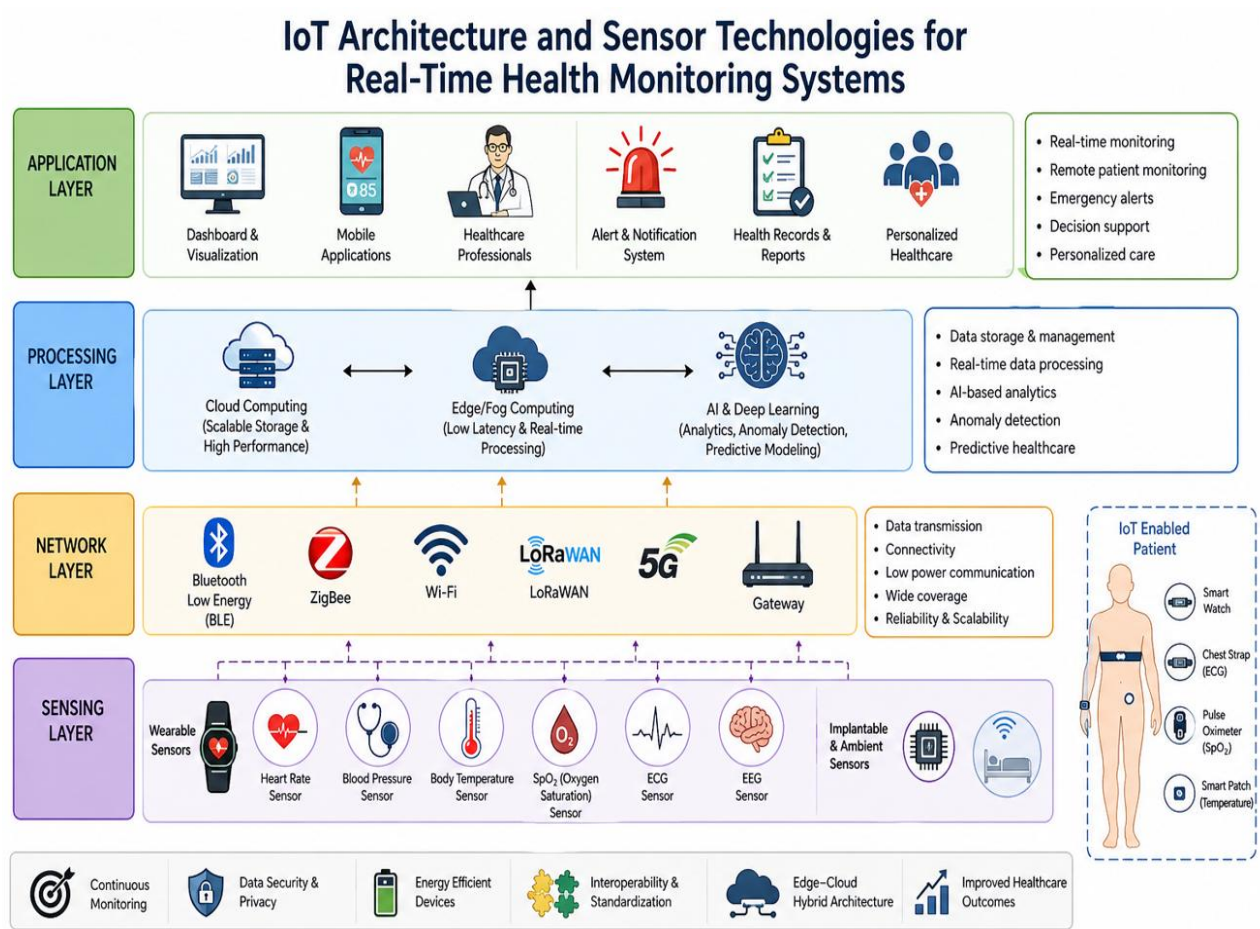

Fig. 2 Iota Architecture and Sensor Technologies

IV. CNN–LSTM Deep Learning Model for Disease Prediction and Feature Analysis in Healthcare Data

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A. **Hybrid Deep Learning Approach:** CNNLSTM is a hybrid model, which is a combination of Convolution Neural Networks (CNN) and Long Short-term Memory (LSTM) networks to effectively process complex healthcare data to predict the diseases and diagnose them early [24].

B. **Role of CNN in Feature Extraction:** CNN is mostly applicable in retrieving meaningful spatial information of a biomedical data like ECG signals, medical images, and sensor-generated physiological data to detect local patterns and concealed structures [25].

C. **Role of LSTM in Temporal Analysis:** The LSTM networks are designed to acquire time-dependent dependencies of the healthcare data sequence, and therefore can be used to analyze time-series patterns, such as heart rate variability, blood pressure patterns, and continuous glucose data [26].

D. **Sequential Learning Capability:** CNN and LSTM enable the model to capture high-level features by using CNN initially, and manipulate the features as time goes by using LSTM, which improves the understanding of dynamic health states [27].

E. **Improved Disease Prediction Accuracy:** CNN–LSTM models have demonstrated higher accuracy in making predictions about diseases like cardiovascular disorders, diabetes, and respiratory diseases better than the traditional machine learning models [28].

F. **Feature Reduction and Optimization:** The CNN layers can be used to remove redundant features and retain the necessary information, which enhances the efficiency of computations and improves model performance [29].

G. **Handling Multimodal Healthcare Data** The hybrid model can process various healthcare data, such as images, sensor signals, and electronic health records, thus it can be used in Iota-based systems [30].

H. **Real-Time Monitoring Capability:** The CNN LSTMs are able to handle real-time data, and it is essential in terms of continuous monitoring of patients and timely alert about an irregular health state [31].

I. **Anomaly Detection in Physiological Signals:** The model is effective in detecting abnormalities in physiological signals which can be indicative of illnesses or sudden health decline at its early stages [5].

J. **Integration with Iota Systems:** CNNLSTM models are used in cloud computing or edge computing systems to process sensor data in real-time to make intelligent decisions in healthcare Iota-based systems [32], [33].

K. **Reduction of Manual Intervention:** The model enhances efficiency and scalability since it automates feature extraction and classification, eliminating the need to rely on manual analysis by healthcare professionals [34].

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L. **Limitations and Computational Complexity:** Although it has its benefits, CNNLSTM models are resource-intensive and need extensive training datasets of labeled data, which can restrict their implementation in resource-intensive settings [13].

V. Challenges, Limitations, and Future Research Directions in Iota-Based Intelligent Healthcare Systems

The use of Iota-based smart healthcare systems has greatly enhanced real-time monitoring of patients and timely detection of the disease; though, a number of issues continue to constrain its extensive use and best implementation. Data security and privacy is one of the main issues to be considered because healthcare systems deal with sensitive information of patients relayed through wireless networks and stored in clouds. The need to maintain secure communication, encryption, and adherence to healthcare regulations is a critical issue. Interoperability is another significant concern, as Iota healthcare ecosystems are comprised of heterogeneous devices, sensors, and platforms that do not necessarily have standardized communication protocols and may thus be challenging to seamlessly integrate. Also, data quality and reliability is a big constraint since sensor-generated data can be prone to noise, missing values, and inaccuracies, which directly influence the predictive models performance [35].

Computational and energy constraints of wearable and edge devices are another critical limitation. Real-time monitoring needs efficient use of energy, and most Iota devices run on small batteries, limiting their long-term use [36], [37], [38]. Also, the models that are deep-learning based, such as CNN, LSTM, and hybrid models, are computationally intensive and, thus, it is hard to train them on a resource-constrained environment in real-time. System performance is also influenced by network latency and connectivity, particularly in remote or rural locations where not all locations have access to reliable internet connections. Moreover, absence of large, high-quality, annotated medical datasets limits the training and generalization of advanced AI models.

In clinical terms, it is of special concern that the model be interpretable [39]. Many deep learning models are black-box models and automated predictions are difficult to trust and understand by a healthcare professional. This makes them less acceptable when it comes to critical medical decision-making. Also, the current systems are usually dedicated to a single disease or restricted physiological parameters, without comprehensive monitoring of the health of the patient.

The emerging issues in the field of the Iota-based intelligent healthcare systems are likely to be resolved in the future with the help of a number of rather promising directions [40]. The combination of edge and fog computing and cloud infrastructure has the potential to substantially decrease the latency and enhance the efficiency of real-time processing. Long-term monitoring will be improved by development of energy efficient wearable sensors and low-power communication protocols. Moreover, explainable artificial intelligence (XAI) methods will enhance the transparency of models and clinical trust. Federated methods are also in consideration to enable collaborative training of models to avoid transfer of sensitive patient data and hence increase privacy and security, by integrating multimodal data fusion method with high-order hybrid deep learning models, like CNNLSTM, then it may be possible to potentially increase prediction accuracy by using heterogeneous data sources including physiological data, medical

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data, and electronic health records. The integration of communication technologies of 5G and higher is likely to enhance real time responsiveness and scalability of the system. Overall, the future of intelligent healthcare will move toward more secure, adaptive and patient-centric systems that can be useful to reach the correct diagnosis of early illnesses and ongoing monitoring of health.

VI. Conclusion

Concluding, the Iota based real-time health monitoring systems with CNN-LSTM deep learning networks are a big breakthrough in the current healthcare practice as it allows real-time detection of diseases and their early detection. This review underlines how Iota technologies can help to achieve smooth acquisition of data by using wearable sensors, and smart communication and computing frameworks provide efficient data transmission and processing. With the introduction of the hybrid deep learning algorithms, in particular, CNN-LSTM, the possibility to interpret spatial and temporal changes of the complex healthcare data is enhanced, leading to the enhanced predictive performance, and the early identification of the severe disease. Despite these developments, there are still other challenges such as data security, interoperability, energy and computational complexity that continue to be a barrier to large-scale implementation. Also, the lack of centralized structures and quality information limits the external validity and robustness of existing systems. Future research should undertake to develop scalable, energy-efficient and secure architectures by integrating edge-cloud computing, explainable AI and federated learning methods. In addition, data fusion in the form of multimodal data fusion and next-generation communication technologies will be embraced, which will enhance the performance of the systems even more. Overall, the convergence of Iota and deep learning is creating a new avenue to a proactive patient-centric healthcare system, in which continuous monitoring and early diagnosis can be critical in improving clinical outcomes and quality of life.

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