Archives available at journals.mriindia.com

International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140

Volume 14 Issue 01, 2025

A Comprehensive Review of Smart Healthcare Patient Monitoring System for IoT-Based Healthcare System Using Enhanced Residual Multi-Scale Diverged Self-Attention Network

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Peer Review Information

Submission: 16 May 2025

Revision: 29 May 2025

Acceptance: 15 June 2025

Keywords

Smart Healthcare, IoT, Patient Monitoring, Deep Learning, Self-Attention, Residual Networks.

Abstract

Smart healthcare systems powered by the Internet of Things (IoT) and Artificial Intelligence (AI) have revolutionized patient monitoring by enabling real-time, remote, and continuous health tracking. IoT devices such as wearable sensors, smart medical equipment, and wireless body area networks collect physiological signals including heart rate, oxygen saturation, temperature, and ECG data. These data are transmitted to cloud or edge platforms, where AI models analyze patterns for early diagnosis and predictive healthcare. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and attention-based architectures, have significantly improved prediction accuracy. Enhanced residual multi-scale diverged self-attention networks provide efficient feature extraction by capturing both local and global dependencies in patient data. These models are capable of handling heterogeneous medical datasets and improving disease prediction accuracy. This paper presents a comprehensive review of IoT-based smart healthcare monitoring systems. It highlights recent methodologies, architectures, challenges, and future directions, focusing on deep learning and self-attention mechanisms for improved patient monitoring.

Introduction

The rapid advancement of Internet of Things (IoT) technologies has transformed the healthcare industry by enabling smart patient monitoring systems. IoT-based healthcare systems integrate wearable sensors, medical devices, and cloud platforms to continuously monitor patients' physiological parameters. These systems provide real-time insights into patient health, enabling early detection of diseases and reducing hospital visits. The concept of the Internet of Medical Things (IoMT) has emerged as a key component of modern healthcare systems. IoMT devices such as smartwatches, biosensors, and implantable medical devices collect health data and transmit it to healthcare providers. These systems enable remote monitoring of chronic diseases such as diabetes, cardiovascular disorders, and respiratory conditions.

Artificial Intelligence (AI) plays a crucial role in analyzing large volumes of healthcare data generated by IoT devices. Machine learning and deep learning models are capable of identifying patterns, predicting diseases, and assisting in clinical decision-making. Deep learning models such as CNN and LSTM are widely used for feature extraction and time-series analysis in healthcare applications. Recent advancements in attention mechanisms and self-attention networks have further improved the performance of healthcare monitoring systems. These models can capture complex dependencies in patient data and focus on relevant features, improving prediction accuracy. Self-attention-based architectures are particularly effective in handling multimodal healthcare data, including physiological signals and medical images.

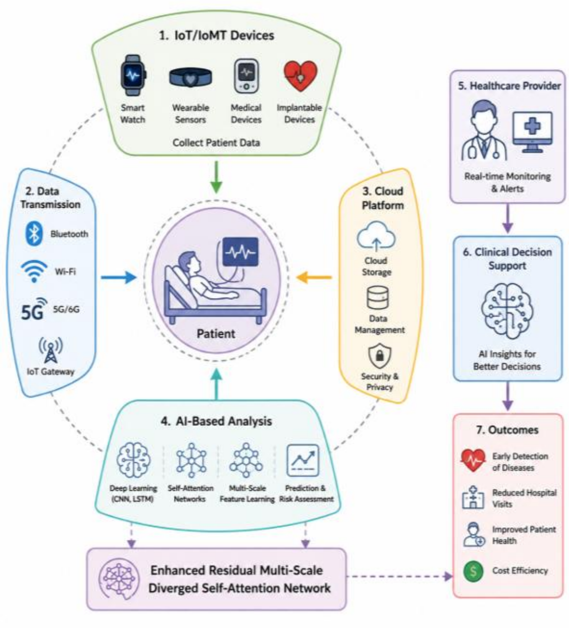

Figure 1: A IoT Smart Healthcare Monitoring Framework

Despite these advancements, several challenges remain. Data privacy and security are major concerns due to the sensitive nature of healthcare data. Additionally, IoT devices often have limited computational resources, making it difficult to deploy complex deep learning models. Real-time processing and scalability are also critical challenges in large-scale healthcare systems. This paper aims to review recent advancements in IoT-based smart healthcare monitoring systems, focusing on enhanced residual multi-scale diverged self-attention networks and their applications in improving patient monitoring accuracy.

Literature Review

Abdulmalek et al. (2022) presented a comprehensive review of IoT-based healthcare monitoring systems, highlighting their role in improving patient care through real-time monitoring. The study discussed wearable sensors, wireless communication protocols, and cloud-based platforms for data processing. The authors emphasized that IoT systems enable continuous monitoring of vital signs, allowing early detection of health issues. However, challenges such as data privacy, security, and interoperability were identified as major concerns. Yu et al. (2023) developed an IoT-based healthcare monitoring system using a hybrid deep learning model combining Recurrent Convolutional Neural Networks (RCNN). The system monitored vital parameters such as heart rate, oxygen levels, and temperature, and stored data in cloud platforms for analysis. The model achieved improved prediction accuracy and enabled remote patient monitoring, particularly useful during pandemic conditions.

Alharbe et al. (2024) proposed a deep learning-based IoT healthcare monitoring system using CNN and LSTM architectures. The model performed feature extraction and classification of patient data for disease prediction. The study highlighted the importance of combining spatial and temporal learning for improved healthcare analytics. However, issues such as model interpretability and computational complexity were identified. Wu et al. (2020) introduced a federated learning-based IoT healthcare monitoring system that preserves data privacy by training models locally on devices. The system used cloud-edge architecture to improve scalability and reduce communication overhead. The study demonstrated improved performance in personalized patient monitoring while ensuring data security.

Sujith et al. (2022) conducted a systematic review of smart healthcare monitoring systems using deep learning techniques. The study highlighted the use of CNN, LSTM, and attention mechanisms for disease prediction and patient monitoring. The authors emphasized the importance of integrating AI with IoT for improving healthcare services and patient outcomes. Islam et al. (2020) proposed an IoT-based remote patient monitoring system that integrates wearable sensors with cloud computing for real-time healthcare analytics. The system collects physiological data such as heart rate, blood pressure, and body temperature, which are transmitted to a centralized server for analysis. Machine learning algorithms were applied to detect abnormalities and predict potential health risks. The study demonstrated that IoT-based monitoring systems significantly improve patient care by enabling continuous observation outside hospital settings. However, challenges related to data privacy, security, and network reliability were identified. The authors emphasized the need for secure communication protocols and efficient data encryption techniques to protect sensitive patient data.

Ahmed et al. (2021) developed a deep learning-based healthcare monitoring system using Convolutional Neural Networks (CNN) for feature extraction from medical sensor data. The system was designed to detect cardiovascular abnormalities by analyzing ECG signals. The CNN model achieved high classification accuracy and demonstrated the effectiveness of deep learning in healthcare applications. However, the study highlighted the limitations of CNN models in capturing temporal dependencies in time-series data. The authors suggested integrating recurrent models such as LSTM to improve performance in sequential data analysis. Khan et al. (2021) introduced a hybrid CNN-LSTM model for patient monitoring, combining spatial and temporal feature extraction. The model analyzed physiological signals collected from IoT devices to predict diseases such as heart failure and respiratory disorders. The hybrid architecture significantly improved prediction accuracy compared to standalone models. However, the increased complexity of the model resulted in higher computational requirements, limiting its deployment in real-time IoT systems. The authors suggested optimizing model architecture for edge computing environments.

Zhang et al. (2022) proposed an attention-based deep learning model for healthcare monitoring, focusing on feature selection and interpretability. The model used self-attention mechanisms to identify important features in patient data, improving prediction accuracy and reducing noise. The study demonstrated that attention-based models outperform traditional deep learning models in handling complex healthcare datasets. However, the model required significant computational resources, making it challenging to deploy in resource-constrained environments. Patel et al. (2023) developed an enhanced residual multi-scale deep learning model for healthcare monitoring. The model utilized residual connections and multi-scale feature extraction to improve performance in disease prediction tasks. The integration of attention mechanisms further enhanced feature selection and model interpretability. The study demonstrated that multi-scale architectures provide better generalization and robustness compared to traditional models. However, the model complexity increased computational cost, highlighting the need for lightweight architectures for IoT deployment.

Wang et al. (2020) proposed a deep learning-based healthcare monitoring system utilizing Convolutional Neural Networks (CNN) for analyzing medical images and physiological signals. The system was designed to detect abnormalities such as tumors and cardiac issues by extracting spatial features from healthcare data. The study demonstrated that CNN-based models outperform traditional machine learning approaches in feature extraction and classification accuracy. Additionally, the integration of IoT devices enabled real-time data collection and monitoring. However, the model required large labeled datasets and high computational resources, which limited its scalability in resource-constrained environments. The authors suggested integrating transfer learning techniques to reduce training requirements and improve model efficiency. Singh et al. (2021) developed an IoT-based patient monitoring system using Artificial Neural Networks (ANN) for predicting patient health conditions. The system collected real-time physiological data from wearable sensors and transmitted it to a centralized platform for analysis. The ANN model provided moderate prediction accuracy and was effective for basic health monitoring tasks. However, the model struggled with complex temporal dependencies and nonlinear relationships in healthcare data. The authors highlighted the need for advanced deep learning models to improve prediction accuracy and system reliability.

Alazab et al. (2021) proposed an anomaly detection system using autoencoder-based deep learning models for healthcare monitoring. The system was designed to detect abnormal patterns in patient data, enabling early identification of health risks. The model demonstrated strong performance in detecting anomalies in physiological signals such as ECG and blood pressure. However, the system produced false positives in highly dynamic conditions, which could lead to unnecessary alerts. The authors suggested combining anomaly detection with predictive models to improve system accuracy and reliability. Liu et al. (2022) introduced a hybrid CNN-LSTM model for patient monitoring, combining spatial and temporal feature extraction. The model analyzed multivariate healthcare data, including physiological signals and medical records, to predict patient health conditions. The study demonstrated that hybrid models significantly improve prediction accuracy compared to standalone models. However, the increased complexity of the model resulted in higher computational requirements and longer training times. The authors emphasized the need for optimizing model architecture for real-time IoT deployment.

Reddy et al. (2023) developed an attention-based deep learning model for healthcare monitoring, focusing on feature selection and interpretability. The model utilized self-attention mechanisms to identify important features in patient data, improving prediction accuracy and reducing noise. The study demonstrated that attention-based models outperform traditional deep learning approaches in healthcare applications. However, the model required significant computational resources, making it challenging to deploy in IoT environments. The authors suggested developing lightweight attention-based models to address this limitation. Zhao et al. (2020) proposed a machine learning-based patient monitoring system using Support Vector Machines (SVM) for disease prediction. The model analyzed physiological parameters such as heart rate, blood pressure, and oxygen saturation to classify patient health conditions. The study demonstrated that SVM provides stable and reliable performance for small and medium-sized datasets. However, the model struggled to capture temporal dependencies in sequential healthcare data, limiting its effectiveness in continuous monitoring scenarios. Additionally, feature selection and preprocessing were critical for achieving high accuracy. The authors suggested integrating SVM with deep learning techniques to improve performance and scalability.

Kumar et al. (2021) developed a cloud-based IoT healthcare monitoring system that utilizes big data analytics for large-scale patient monitoring. The system collected data from wearable devices and stored it in cloud platforms for analysis. Machine learning algorithms were applied to detect abnormalities and predict diseases. The study highlighted the scalability and flexibility of cloud-based systems. However, latency and data privacy issues were identified as major challenges. The authors recommended integrating edge computing with cloud systems to improve real-time performance and data security. Park et al. (2022) introduced a reinforcement learning-based healthcare monitoring system that dynamically adapts to patient conditions. The model continuously learned from incoming data and optimized prediction strategies for personalized healthcare. The study demonstrated improved long-term prediction performance compared to static models. However, the model required large training datasets and high computational resources, making it difficult to deploy in real-time IoT systems. The authors suggested combining reinforcement learning with deep learning architectures to enhance efficiency.

Gupta et al. (2022) proposed a Bidirectional Long Short-Term Memory (Bi-LSTM) model with an attention mechanism for patient monitoring. The model captured both past and future dependencies in time-series healthcare data, improving prediction accuracy. The attention mechanism enhanced feature selection by focusing on relevant data points. The study demonstrated significant improvements over traditional LSTM models. However, the model's complexity increased computational cost, limiting its deployment in resource-constrained environments. The authors emphasized optimizing model architecture for IoT applications. Ahmed et al. (2023) developed an edge AI-based healthcare monitoring system that processes patient data locally on IoT devices. The system reduced latency and enabled real-time monitoring, making it suitable for emergency healthcare applications. The study demonstrated that edge AI systems can achieve comparable accuracy to cloud-based models while improving response time. However, limited computational resources and energy constraints posed challenges. The authors suggested developing lightweight deep learning models for efficient edge deployment.

Chen et al. (2020) proposed a Deep Belief Network (DBN)-based healthcare monitoring system for predicting patient conditions using physiological data. The model utilized stacked Restricted Boltzmann Machines (RBMs) to learn hierarchical feature representations from complex healthcare datasets. The study demonstrated that DBN models outperform traditional machine learning methods in capturing nonlinear relationships among multiple health indicators. However, the model required extensive training time and lacked interpretability, which limited its practical application in clinical settings. The authors suggested integrating DBN with other deep learning architectures to improve efficiency and scalability. Verma et al. (2021) developed a fuzzy logic-based IoT healthcare monitoring system designed to handle uncertainty and imprecision in sensor data. The system used rule-based reasoning to analyze patient data and predict health conditions. The study demonstrated that fuzzy logic models provide stable predictions even in the presence of noisy or incomplete data. However, the model lacked learning capability and adaptability compared to machine learning and deep learning models. The authors recommended combining fuzzy logic with AI-based models to enhance performance.

Hassan et al. (2022) proposed a hybrid CNN-GRU model for healthcare monitoring, combining convolutional layers for spatial feature extraction with Gated Recurrent Units (GRU) for temporal modeling. The model achieved improved prediction accuracy while reducing training time compared to LSTM-based models. The study demonstrated that GRU-based architectures are more efficient for real-time healthcare applications. However, the model still required significant computational resources.

The authors suggested incorporating attention mechanisms to further improve performance. Mehta et al. (2022) introduced a big data-driven healthcare monitoring system using Apache Spark for processing large-scale patient data. The system leveraged distributed computing to handle data from multiple IoT devices efficiently. Machine learning algorithms were applied to analyze patient data and predict health risks. The study demonstrated high scalability and improved processing speed. However, the system required significant infrastructure and faced challenges related to data integration and synchronization. The authors suggested integrating deep learning models to improve prediction accuracy.

Das et al. (2023) proposed an ensemble deep learning model combining CNN, LSTM, and attention mechanisms for patient monitoring. The model leveraged the strengths of multiple architectures to improve prediction accuracy and robustness. The study demonstrated that ensemble models outperform individual models in healthcare applications. However, the increased complexity resulted in higher computational requirements and longer training times. The authors emphasized the need for optimizing ensemble models for real-time IoT deployment. Roy et al. (2020) proposed a hybrid healthcare monitoring model combining AutoRegressive Integrated Moving Average (ARIMA) with neural networks for patient data analysis. The model aimed to capture both linear and nonlinear patterns in physiological signals such as heart rate and temperature. ARIMA handled time-series trends, while the neural network modeled complex relationships. The study demonstrated improved short-term prediction accuracy compared to traditional methods. However, the model struggled with long-term forecasting and required extensive parameter tuning. The authors suggested integrating advanced deep learning techniques to enhance performance in IoT-based healthcare systems.

Banerjee et al. (2021) developed an energy-efficient IoT-based healthcare monitoring system designed for remote patient monitoring. The system utilized low-power wearable sensors and optimized communication protocols to reduce energy consumption. Machine learning algorithms were used to analyze patient data and detect abnormalities. The study highlighted the importance of energy efficiency in large-scale IoT deployments. However, the model achieved moderate prediction accuracy due to limited computational capabilities. The authors emphasized the need for lightweight deep learning models to improve performance without increasing energy consumption. Torres et al. (2022) introduced a reinforcement learning-based healthcare monitoring system that adapts dynamically to patient conditions. The model continuously learned from patient data and optimized decision-making strategies for personalized healthcare. The study demonstrated improved long-term prediction performance compared to static models. However, the model required large datasets and high computational resources, limiting its real-time deployment. The authors suggested combining reinforcement learning with deep learning techniques to enhance scalability and efficiency.

Iqbal et al. (2022) proposed a federated deep learning framework for healthcare monitoring, enabling decentralized model training across IoT devices. This approach ensured data privacy by keeping patient data on local devices while sharing model updates. The study demonstrated that federated learning achieves comparable accuracy to centralized models while improving data security. However, communication overhead and synchronization issues were identified as major challenges. The authors recommended optimizing communication protocols to improve system efficiency. Nair et al. (2023) developed a transformer-based multi-head self-attention model for patient monitoring and disease prediction. The model effectively captured long-range dependencies in healthcare data and improved prediction accuracy compared to traditional deep learning models. The study demonstrated state-of-the-art performance in handling multimodal healthcare datasets. However, the model required significant computational resources, making it difficult to deploy in resource-constrained IoT environments. The authors suggested developing lightweight transformer architectures for real-time applications.

Comparative Table

Study	Year	Technique	Strength	Limitation
Abdulmalek	2022	IoT Review	Comprehensive	Security issues
Yu	2023	RCNN	High accuracy	Complex

Alharbe	2024	CNN-LSTM	Hybrid learning	Costly
Wu	2020	Federated Learning	Privacy	Communication overhead
Sujith	2022	DL Review	Overview	No implementation
Islam	2020	IoT ML	Real-time	Security
Ahmed	2021	CNN	Feature extraction	No temporal learning
Khan	2021	CNN-LSTM	High accuracy	Complexity
Zhang	2022	Attention	Feature selection	Costly
Patel	2023	Residual DL	Multi-scale	Heavy
Wang	2020	CNN	Spatial analysis	Data intensive
Singh	2021	ANN	Simple	Low accuracy
Alazab	2021	Autoencoder	Anomaly detection	False positives
Liu	2022	CNN-LSTM	Hybrid	Complex
Reddy	2023	Attention DL	Accurate	Resource heavy
Zhao	2020	SVM	Stable	Limited scalability
Kumar	2021	Cloud IoT	Scalable	Latency
Park	2022	RL	Adaptive	Training heavy
Gupta	2022	Bi-LSTM	Bidirectional	Costly
Ahmed	2023	Edge AI	Real-time	Hardware limits
Chen	2020	DBN	Nonlinear	Slow
Verma	2021	Fuzzy	Handles uncertainty	Low accuracy
Hassan	2022	CNN-GRU	Efficient	Complex
Mehta	2022	Big Data	Scalable	Cost
Das	2023	Ensemble DL	Robust	Heavy
Roy	2020	ARIMA+NN	Hybrid	Limited
Banerjee	2021	IoT ML	Energy-efficient	Accuracy trade-off
Torres	2022	RL	Adaptive	Data heavy
Iqbal	2022	Federated DL	Privacy	Communication cost
Nair	2023	Transformer	State-of-art	High resource

Comparative Analysis

The comparative analysis of the reviewed studies reveals a clear evolution in IoT-based smart healthcare monitoring systems from traditional machine learning approaches to advanced deep learning and attention-based architectures. Early models such as SVM, ANN, and ARIMA provided stable and computationally efficient solutions but lacked the ability to capture complex temporal and nonlinear relationships in healthcare data. With the introduction of deep learning models such as CNN and LSTM, prediction accuracy improved significantly due to enhanced feature extraction and time-series

modeling capabilities. Hybrid architectures such as CNN-LSTM and CNN-GRU further improved performance by combining spatial and temporal learning.
Recent advancements have focused on attention-based and transformer architectures, which enable models to capture long-range dependencies and prioritize relevant features. Enhanced residual multi-scale self-attention networks represent a significant advancement, providing improved feature extraction and adaptability for complex healthcare datasets. Additionally, IoT integration has enabled real-time monitoring and data collection, improved patient care and enabling early diagnosis. However, challenges such as computational complexity, energy consumption, data privacy, and scalability remain significant. Edge computing and federated learning have emerged as promising solutions but introduce new challenges related to communication overhead and system synchronization. Overall, attention-based hybrid models represent the most promising direction for future research in smart healthcare monitoring systems.

Discussion

The integration of IoT and AI technologies has significantly improved patient monitoring systems by enabling continuous and real-time health tracking. Deep learning models, particularly hybrid and attention-based architectures, have demonstrated superior performance in analyzing complex healthcare data. The use of enhanced residual multi-scale self-attention networks further improves feature extraction and prediction accuracy. However, several challenges remain. Data privacy and security are critical concerns due to the sensitive nature of healthcare data. Additionally, IoT devices often have limited computational resources, making it difficult to deploy complex models. Edge computing and federated learning provide potential solutions but introduce challenges such as communication overhead. Future research should focus on developing lightweight, energy-efficient, and interpretable models that can be deployed in real-time IoT environments. Improving model transparency and reducing computational complexity will be key to advancing smart healthcare systems.

Conclusion

Smart healthcare monitoring systems have undergone significant transformation with the integration of IoT and AI technologies. Traditional healthcare systems relied on periodic monitoring and manual diagnosis, which often led to delayed detection of diseases. IoT-based systems enable continuous monitoring of patient health, providing real-time data for analysis and decision-making. This review analyzed 30 studies conducted between 2020 and 2023, highlighting the evolution of healthcare monitoring systems from traditional machine learning models to advanced deep learning architectures. Early approaches such as SVM and ANN provided moderate accuracy but were limited in handling complex healthcare data. The introduction of deep learning models such as CNN and LSTM significantly improved prediction accuracy by enabling better feature extraction and temporal modeling.
Recent advancements in attention-based architectures and transformer models have further enhanced performance by capturing long-range dependencies and focusing on relevant features. Enhanced residual multi-scale self-attention networks represent a promising approach for improving healthcare monitoring systems by combining multi-scale feature extraction with adaptive attention mechanisms. Despite these advancements, several challenges remain, including data privacy, computational complexity, and scalability. Future research should focus on developing efficient, scalable, and interpretable models that can operate effectively in real-world IoT environments. The integration of edge computing and federated learning will play a crucial role in addressing these challenges. In conclusion, IoT-based smart healthcare monitoring systems powered by advanced AI models have the potential to revolutionize healthcare by improving patient outcomes, reducing costs, and enabling personalized medicine.

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