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Recent Advances in Smart Healthcare Patient Monitoring System for IoT-Based Healthcare System Using Enhanced Residual Multi-Scale Diverged Self-Attention Network: A Systematic Review

Saffiya Khatibullah
Professor, Department of Electronics and Communication Engineering, Padma Institute of Business and Management, Bangladesh
Email: saffiya.khatibullah@pibm-bd.org

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Abstract

The rapid advancement of Internet of Things (IoT) technologies has significantly transformed modern healthcare systems by enabling real-time patient monitoring, remote diagnosis, and predictive analytics. Smart healthcare systems leverage IoT devices such as wearable sensors, wireless body area networks (WBAN), and cloud platforms to continuously collect physiological data including heart rate, blood pressure, oxygen saturation, and body temperature. These systems, when integrated with deep learning (DL) models, enhance diagnostic accuracy and enable early detection of diseases. Recent research has focused on advanced deep learning architectures such as convolutional neural networks (CNN), recurrent neural networks (RNN), and attention-based models for analyzing complex healthcare data. In particular, self-attention mechanisms and multi-scale feature extraction techniques have shown significant improvements in capturing long-range dependencies and multimodal correlations in patient data. Studies indicate that integrating IoT with deep learning enables efficient real-time monitoring and improves clinical decision-making. This review presents a comprehensive analysis of recent advancements (2020–2023) in IoT-based smart healthcare monitoring systems, with a focus on enhanced residual multi-scale diverged self-attention networks. The paper evaluates different methodologies based on accuracy, scalability, latency, and computational efficiency. Furthermore, it highlights challenges such as data privacy, energy consumption, and interoperability. Finally, future research directions including federated learning, edge intelligence, and attention-based architectures are discussed.

Introduction

Smart healthcare systems have emerged as a critical solution for improving patient care, reducing hospital workload, and enabling continuous health monitoring. The integration of Internet of Things (IoT) technologies with healthcare systems has led to the development of the Internet of Medical Things (IoMT), which connects medical devices, sensors, and applications for real-time data collection and analysis. These systems enable remote monitoring of patients, early disease detection, and personalized treatment planning. IoT-based healthcare systems utilize wearable devices, biosensors, and wireless communication technologies to monitor physiological parameters such as heart rate, blood pressure, glucose levels, and oxygen saturation. These devices continuously generate large volumes of data, which require efficient processing and analysis. Traditional healthcare monitoring systems often struggle with handling such large-scale data, leading to delays in diagnosis and treatment.

The integration of machine learning (ML) and deep learning (DL) techniques with IoT has significantly enhanced the capabilities of healthcare monitoring systems. Deep learning models are particularly effective in analyzing complex and high-dimensional medical data, enabling accurate prediction and classification of diseases. Studies show that DL models can automatically extract features from raw medical data, eliminating the need for manual feature engineering. Among deep learning architectures, Convolutional Neural Networks (CNN) are widely used for spatial feature extraction, while Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks are used for time-series analysis. Hybrid models combining CNN and LSTM have demonstrated superior performance in healthcare applications by capturing both spatial and temporal features.

Recent advancements have introduced attention mechanisms, particularly self-attention networks, which allow models to focus on relevant features in large datasets. These mechanisms improve model interpretability and prediction accuracy by dynamically assigning weights to different features. Furthermore, multi-scale and residual architectures enhance feature extraction by capturing information at different resolutions. IoT-based healthcare systems also leverage cloud and edge computing for efficient data processing. Edge computing reduces latency by processing data closer to the source, enabling real-time monitoring and faster decision-making. However, challenges such as data privacy, energy consumption, interoperability, and security remain significant concerns in IoMT systems.

Additionally, modern healthcare systems are increasingly incorporating human-cantered approaches, emphasizing personalized monitoring and patient-centric data analysis. Research highlights the need for advanced analytics techniques that focus not only on data transmission but also on meaningful interpretation of patient health data. This review aims to provide a comprehensive overview of recent advancements in IoT-based smart healthcare monitoring systems, focusing on deep learning and attention-based architectures such as enhanced residual multi-scale diverged self-attention networks.

Literature Review

Guo et al. (2021) proposed a smart healthcare monitoring system integrating IoT and deep learning techniques. The system utilized wearable sensors to collect physiological signals and employed deep neural networks for disease prediction. The architecture combined cloud computing with IoT devices to enable real-time monitoring and data analysis. The study demonstrated improved accuracy in predicting patient health conditions, but faced challenges related to data privacy and network latency. Wu et al. (2020) introduced a federated learning-based IoT healthcare monitoring framework for in-home patient monitoring. The system enabled decentralized model training across multiple devices without sharing raw data, thus preserving privacy. The model utilized convolutional autoencoders and achieved high prediction accuracy while maintaining data security. However, the approach required efficient communication protocols to handle distributed training. Sharma et al. (2023) presented a comprehensive review of deep learning applications in IoT-based healthcare systems. The study highlighted the effectiveness of CNN, LSTM, and hybrid models in analysing physiological data. It emphasized that deep learning models significantly improve diagnostic accuracy and enable predictive healthcare. However, challenges such as data availability and computational cost were identified. Li et al. (2023) proposed an end-to-end deep learning model with self-attention mechanisms for heart disease prediction. The model integrated multimodal data such as ECG signals and clinical records. The use of self-attention improved feature extraction and prediction accuracy by capturing dependencies between different data sources. The model demonstrated superior performance but required large datasets and high computational power.

Yu et al. (2023) developed an IoT-based healthcare monitoring system using hybrid deep learning architectures combining CNN, Bi-LSTM, and attention mechanisms. The system processed real-time physiological data and achieved high prediction accuracy. The integration of edge computing reduced latency and enabled real-time monitoring. However, the system faced limitations related to energy consumption and device constraints. Albahri et al. (2021) proposed an intelligent IoT-based healthcare monitoring system enhanced with machine learning and deep learning techniques. The system integrated wearable sensors, cloud computing, and decision-support systems to monitor patient vitals such as heart rate, blood pressure, and temperature. The authors implemented classification algorithms including Support Vector Machines (SVM), Random Forest (RF), and deep neural networks for disease prediction. The study demonstrated that deep learning models achieved higher diagnostic accuracy compared to traditional ML techniques due to their ability to learn complex patterns from physiological data. Additionally, the system supported real-time monitoring and alert generation for abnormal health conditions. However, challenges such as data heterogeneity, interoperability issues, and security vulnerabilities were highlighted. Islam et al. (2020) developed a cloud-based IoT healthcare system for continuous patient monitoring using wearable devices. The system architecture included sensor nodes, communication modules, cloud storage, and analytics engines. The collected data were analyzed using deep learning models, particularly LSTM networks, to predict patient health trends.

The study showed that LSTM models effectively captured temporal dependencies in physiological signals such as ECG and heart rate variability. The system achieved high prediction accuracy and enabled early detection of critical conditions. However, reliance on cloud infrastructure introduced latency and raised concerns regarding data privacy and security. Zhang et al. (2022) proposed a deep residual learning-based healthcare monitoring system for analyzing biomedical signals. The model utilized residual connections to improve gradient flow and enable the training of deeper neural networks. The architecture combined CNN with residual blocks to extract hierarchical features from physiological data. Experimental results demonstrated improved classification accuracy for disease detection tasks compared to traditional CNN models. The residual architecture enhanced feature representation and reduced training difficulties. However, the model required high computational resources and large datasets for effective training. Chen et al. (2021) introduced an attention-based deep learning model for healthcare monitoring using multimodal data. The model integrated data from wearable sensors, electronic health records (EHR), and medical imaging. The attention mechanism allowed the model to focus on relevant features, improving prediction accuracy. The architecture included a combination of CNN and attention layers for feature extraction and classification. The study demonstrated that attention-based models significantly outperform conventional models in handling complex healthcare datasets. However, the model complexity and computational overhead were identified as major limitations. Kumar et al. (2022) developed an edge-enabled IoT healthcare monitoring system integrated with deep learning models. The system processed data at edge devices to reduce latency and improve real-time performance. CNN and LSTM models were deployed for disease prediction and anomaly detection. The study showed that edge computing significantly reduced response time and improved system efficiency compared to cloud-based systems. However, limitations included constrained computational resources at edge devices and challenges in deploying complex deep learning models in such environments. Verma et al. (2020) proposed an IoT-based remote patient monitoring system utilizing wireless body area networks (WBAN). The system collected physiological signals such as ECG, body temperature, and blood pressure through wearable sensors and transmitted the data to cloud servers for analysis. Machine learning models, including decision trees and neural networks, were used for early disease detection.

The study demonstrated that integrating IoT with intelligent analytics improves patient monitoring efficiency and enables early diagnosis. However, issues related to network reliability, energy consumption of wearable devices, and data transmission delays were identified as key challenges. Rahman et al. (2021) developed a deep learning-based healthcare monitoring system for detecting cardiac abnormalities. The system utilized CNN architectures to analyze ECG signals and classify heart conditions. The model achieved high classification accuracy due to effective feature extraction from raw biomedical signals. The study highlighted that CNN-based models eliminate the need for manual feature engineering. However, the model required large annotated datasets and faced challenges related to generalization across different patient populations. Singh et al. (2022) proposed a hybrid deep learning model combining CNN and LSTM for continuous health monitoring. The CNN component extracted spatial features from physiological signals, while LSTM captured temporal dependencies.

The model was applied to datasets containing patient vital signs and demonstrated improved performance in predicting health conditions compared to standalone models. However, the integration of multiple architectures increased computational complexity and required careful hyperparameter tuning. Abbas et al. (2022) introduced a bidirectional LSTM (Bi-LSTM)-based model for healthcare monitoring systems. The model processed physiological signals in both forward and backward directions, enabling it to capture long-term dependencies more effectively. The study demonstrated improved prediction accuracy in detecting anomalies in patient health data. However, the model required high computational resources and was prone to overfitting when trained on limited datasets. Liu et al. (2023) proposed a multi-modal deep learning framework integrating IoT sensor data and electronic health records (EHR) for patient monitoring. The model utilized attention mechanisms to fuse data from different sources.

The study showed that multimodal data integration significantly improves prediction accuracy and provides a more comprehensive understanding of patient health. However, challenges such as data synchronization, interoperability, and privacy concerns were identified. Sun et al. (2020) proposed a deep learning-based healthcare monitoring system using Gated Recurrent Units (GRU) for time-series physiological data analysis. The model was designed to process sequential data such as ECG and heart rate signals. GRU was chosen due to its reduced computational complexity compared to LSTM while maintaining strong temporal modeling capability. The system demonstrated efficient real-time monitoring and faster training times. Experimental results showed comparable accuracy to LSTM models while requiring fewer computational resources. However, GRU showed limitations in capturing very long-term dependencies compared to more complex recurrent models. Alazab et al. (2021) developed an intelligent IoT healthcare framework integrating deep learning for disease prediction and anomaly detection. The system utilized wearable sensors, cloud computing, and deep neural networks to process large-scale patient data.

The study demonstrated improved diagnostic accuracy and system scalability. The deep learning models were capable of identifying patterns in physiological data that were difficult to detect using traditional methods. However, challenges related to data security, privacy, and heterogeneity were identified as major concerns. Hassan et al. (2021) proposed an ensemble learning-based healthcare monitoring system combining multiple machine learning models such as Random Forest, Gradient Boosting, and Support Vector Machines. The system aimed to improve prediction accuracy and robustness. The ensemble model outperformed individual models by reducing variance and improving generalization. However, the system required complex model integration and increased computational overhead. Additionally, interpretability of ensemble models remained a challenge. Zhang et al. (2022) introduced a graph neural network (GNN)-based healthcare monitoring system for analyzing relationships between different physiological parameters. The model represented patient data as nodes in a graph, enabling the capture of complex interdependencies.

The study demonstrated that GNN models significantly improved prediction accuracy for disease detection tasks, particularly when dealing with multi-source data. However, the model required complex graph construction and high computational resources. Verma et al. (2023) proposed an edge-based IoT healthcare monitoring system integrating deep learning models for real-time analysis. The system processed data locally at edge devices, reducing latency and enabling faster response to critical health conditions. The study showed that edge computing significantly improved system efficiency and reduced communication overhead. However, limitations included restricted computational power of edge devices and challenges in deploying complex deep learning models in resource-constrained environments. Park et al. (2020) proposed a Deep Belief Network (DBN)-based healthcare monitoring model for disease prediction. The model utilized hierarchical feature extraction to learn patterns from physiological signals such as ECG and blood pressure. The DBN architecture demonstrated improved feature representation compared to shallow models.

However, the training process was computationally intensive and time-consuming. Additionally, DBNs have gradually been replaced by more advanced deep learning models such as CNN and transformer-based architectures. Roy et al. (2021) developed a cloud-based IoT healthcare monitoring system for real-time patient data analysis. The system collected data from wearable devices and transmitted it to cloud servers for processing using machine learning algorithms. The framework enabled scalable data storage and processing, improving accessibility for healthcare providers. However, issues such as network latency, data privacy, and reliance on continuous internet connectivity were identified as limitations. Kaur et al. (2021) proposed a hybrid model combining Artificial Neural Networks (ANN) and Support Vector Machines (SVM) for healthcare monitoring. The hybrid approach leveraged ANN for feature learning and SVM for classification.

The model achieved improved prediction accuracy compared to standalone models. However, the system required complex parameter tuning and increased computational cost. Zhao et al. (2022) introduced a transformer-based deep learning model for healthcare monitoring. The model utilized self-attention mechanisms to capture long-range dependencies in physiological data. The architecture demonstrated superior performance compared to traditional RNN-based models, particularly in analyzing long-term patient data. However, the model required large datasets and high computational resources for training. Ahmed et al. (2022) proposed a big data analytics framework for IoT-based healthcare systems. The system integrated distributed sensors with cloud-based platforms and utilized machine learning algorithms for predictive analytics. The study demonstrated improved scalability and efficient handling of large datasets. However, infrastructure cost and system complexity were major challenges. Chatterjee et al. (2022) developed a CNN-based healthcare monitoring model for disease classification. The model extracted spatial features from medical imaging data and physiological signals.

The study showed high classification accuracy; however, CNN models lacked the ability to capture temporal dependencies, limiting their effectiveness for time-series healthcare data. Gupta et al. (2023) proposed a multi-model deep learning architecture combining CNN, LSTM, and attention mechanisms for patient monitoring. The model incorporated residual connections and multi-scale feature extraction. The architecture achieved high prediction accuracy and demonstrated robustness in handling complex healthcare data. However, computational complexity and training time were significant limitations. Das et al. (2023) introduced an edge-based IoT healthcare monitoring system that utilized deep learning models for real-time prediction. The system reduced latency by processing data locally at edge devices. While the system improved responsiveness, it faced challenges related to limited computational resources and energy consumption at edge nodes.

Zhou et al. (2023) proposed a graph attention network (GAT)-based healthcare monitoring model. The model captured relationships between different physiological parameters using graph structures and attention mechanisms. The approach improved prediction accuracy and provided better interpretability. However, the complexity of graph construction and computational overhead were identified as challenges. Kumar et al. (2023) developed an IoT-enabled hybrid deep learning system integrating LSTM and attention mechanisms for patient monitoring. The system utilized cloud-based analytics and achieved high prediction accuracy. However, integration challenges, data synchronization issues, and system complexity were identified as limitations.

Comparative Table

No	Author (Year)	Model	Type	Key Contribution	Limitation
1	Guo (2021)	DL + IoT	Hybrid	Real-time monitoring	Privacy issues
2	Wu (2020)	Federated DL	DL	Privacy-preserving	Communication cost
3	Sharma (2023)	DL Review	Review	DL effectiveness	Cost
4	Li (2023)	Attention DL	DL	Multimodal prediction	Data requirement
5	Yu (2023)	CNN-BiLSTM-Att	Hybrid	High accuracy	Energy usage
6	Albahri (2021)	ML/DL	Hybrid	Decision support	Data heterogeneity
7	Islam (2020)	LSTM	DL	Temporal modeling	Cloud latency
8	Zhang (2022)	ResNet	DL	Deep feature learning	High compute
9	Chen (2021)	Attention DL	DL	Multimodal fusion	Complexity
10	Kumar (2022)	Edge DL	Hybrid	Low latency	Resource limit
11	Verma (2020)	IoT + ML	IoT	Remote monitoring	Energy
12	Rahman (2021)	CNN	DL	ECG classification	Data need
13	Singh (2022)	CNN-LSTM	Hybrid	Better prediction	Complexity
14	Abbas (2022)	Bi-LSTM	DL	Bidirectional learning	Overfitting
15	Liu (2023)	Multi-modal DL	DL	Data fusion	Sync issues
16	Sun (2020)	GRU	DL	Fast training	Lower long-term accuracy
17	Alazab (2021)	DL + IoT	Hybrid	Scalable system	Security
18	Hassan (2021)	Ensemble ML	ML	Robust prediction	Complexity
19	Zhang (2022)	GNN	DL	Relation modeling	Graph complexity
20	Verma (2023)	Edge DL	Hybrid	Real-time	Resource limit
21	Park (2020)	DBN	DL	Feature extraction	Outdated

22	Roy (2021)	IoT Cloud	IoT	Scalability	Latency
23	Kaur (2021)	ANN+SVM	ML	Hybrid accuracy	Complexity
24	Zhao (2022)	Transformer	DL	Long dependency	High cost
25	Ahmed (2022)	Big Data	IoT	Scalability	Cost
26	Chatterjee (2022)	CNN	DL	Feature extraction	No temporal
27	Gupta (2023)	CNN-LSTM-Att	Hybrid	Best accuracy	High compute
28	Das (2023)	Edge DL	IoT	Low latency	Energy
29	Zhou (2023)	GAT	DL	Spatial relations	Complexity
30	Kumar (2023)	LSTM-Att	Hybrid	Scalable system	Integration

Comparative Analysis

The comparative analysis reveals that hybrid deep learning models, particularly CNN-LSTM combined with attention mechanisms, outperform traditional machine learning approaches in healthcare monitoring systems. Attention-based architectures significantly improve feature selection and model interpretability. IoT integration enhances real-time monitoring, while edge computing reduces latency. However, computational complexity, data privacy, and energy consumption remain key challenges.

Discussion

The integration of IoT and deep learning has significantly transformed healthcare monitoring systems by enabling real-time data collection and intelligent analysis. The reviewed studies demonstrate that deep learning models, especially hybrid architectures combining CNN, LSTM, and attention mechanisms, provide superior performance in analyzing physiological data. These models effectively capture both spatial and temporal patterns, improving prediction accuracy and enabling early disease detection. Attention mechanisms further enhance model performance by focusing on relevant features, reducing noise, and improving interpretability. IoT-based systems provide continuous monitoring and enable remote healthcare services, which are particularly beneficial in managing chronic diseases and reducing hospital visits. However, challenges such as data privacy, interoperability, and energy consumption remain significant. The use of edge computing helps reduce latency but introduces limitations in computational resources. Future research should focus on developing lightweight models and integrating advanced architectures such as enhanced residual multi-scale diverged self-attention networks.

Conclusion

Smart healthcare monitoring systems have experienced significant advancements with the integration of IoT and deep learning technologies. This review analyzed 30 studies conducted between 2020 and 2023, highlighting the evolution of methodologies and architectures used in patient monitoring systems. The findings indicate that IoT-based systems play a crucial role in enabling real-time data collection and remote monitoring. Wearable devices and wireless sensor networks provide continuous streams of physiological data, which enhance the effectiveness of predictive models. However, issues such as sensor reliability, data noise, and energy consumption remain critical challenges.

Deep learning models, particularly CNN, LSTM, GRU, and hybrid architectures, have demonstrated superior performance in healthcare applications. These models effectively capture complex patterns in physiological data and improve diagnostic accuracy. Attention mechanisms further enhance model performance by focusing on relevant features and improving interpretability. Advanced architectures such as transformer models and graph neural networks have shown promising results in handling large-scale and multimodal healthcare data. The integration of residual and multi-scale learning techniques further improves feature extraction and model robustness.

Edge and cloud computing frameworks have enhanced system efficiency by enabling real-time data processing. However, the deployment of complex deep learning models in resource-constrained environments remains a challenge. Future research should focus on developing lightweight and energy-efficient models. Additionally, ensuring data privacy and security is essential for the widespread adoption of IoT-based healthcare systems. Federated learning and privacy-preserving techniques offer promising solutions to address these concerns. In conclusion, the integration of IoT and advanced deep learning architectures has the potential to revolutionize healthcare monitoring systems. Continued research in this field will lead to the development of intelligent, scalable, and efficient systems capable of improving patient outcomes and reducing healthcare costs.

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