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Artificial Intelligence Techniques for Smart Healthcare Patient Monitoring System for IoT-Based Healthcare System Using Enhanced Residual Multi-Scale Diverged Self-Attention Network: Trends and Challenges

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Abstract

The integration of Artificial Intelligence (AI) with Internet of Things (IoT)-based healthcare systems has significantly transformed patient monitoring by enabling real-time data acquisition, intelligent decision-making, and predictive diagnostics. Smart healthcare systems utilize wearable sensors, wireless body area networks (WBAN), and cloud-edge infrastructures to continuously monitor physiological parameters such as heart rate, blood pressure, oxygen saturation, and electrocardiogram (ECG) signals. These systems generate large volumes of heterogeneous data, necessitating advanced analytical techniques for efficient processing. Recent advancements in deep learning, particularly convolutional neural networks (CNN), recurrent neural networks (RNN), and attention-based architectures, have improved the accuracy and efficiency of patient monitoring systems. Self-attention mechanisms and multi-scale feature extraction techniques enhance the ability to capture complex temporal and spatial dependencies in medical data. Studies show that AI-enabled IoT healthcare systems can achieve predictive accuracies between 85% and 95%, significantly improving diagnostic performance and clinical decision-making. This paper presents a systematic review of recent developments (2020–2023) in AI-driven IoT-based healthcare monitoring systems, focusing on enhanced residual multi-scale diverged self-attention networks. The review analyses various methodologies based on accuracy, scalability, latency, and computational efficiency. Furthermore, challenges such as data privacy, energy consumption, interoperability, and security are discussed. Finally, future research directions including federated learning, edge intelligence, and attention-based architectures are highlighted.

Introduction

The rapid evolution of Internet of Things (IoT) technologies has revolutionized healthcare systems by enabling continuous and remote patient monitoring. IoT-based healthcare systems, also known as the Internet of Medical Things (IoMT), integrate wearable devices, biosensors, and communication technologies to collect and transmit physiological data in real time. These systems are particularly beneficial for monitoring chronic diseases, elderly care, and emergency situations. Traditional healthcare monitoring systems rely on periodic clinical visits and manual data collection, which often fail to provide continuous insights into patient health. In contrast, IoT-enabled systems allow real-time monitoring and early detection of abnormalities, significantly improving patient outcomes. Studies highlight that IoT-based monitoring enables secure and real-time remote healthcare services, improving quality of life and reducing hospital burden.

The integration of Artificial Intelligence (AI) with IoT has further enhanced healthcare monitoring systems by enabling intelligent data analysis and predictive modelling. AI techniques, particularly machine learning and deep learning, can analyse complex medical datasets and extract meaningful patterns for disease prediction. Deep learning models such as CNN, LSTM, and GRU are widely used for analysing physiological signals and time-series data. Recent advancements in attention-based architectures have significantly improved model performance. Self-attention mechanisms allow models to focus on relevant features within large datasets, improving both accuracy and interpretability. Multi-scale and residual learning techniques further enhance feature extraction by capturing information at different resolutions and enabling deeper network architectures.

IoT-based healthcare systems also leverage cloud and edge computing for efficient data processing. Cloud computing provides scalable storage and computational power, while edge computing reduces latency by processing data closer to the source. This combination enables real-time decision-making and improves system efficiency. Despite these advancements, several challenges remain. IoT healthcare systems generate massive amounts of heterogeneous data, making data integration and analysis complex. Additionally, issues such as data privacy, security, and interoperability pose significant challenges. The increasing use of AI also raises concerns regarding model interpretability and reliability. Recent studies emphasize the importance of human-centered healthcare monitoring, focusing on personalized data analysis and long-term health assessment. However, most existing systems prioritize data transmission over meaningful analytics, highlighting a gap in current research . This review aims to provide a comprehensive analysis of AI techniques for IoT-based healthcare monitoring systems, focusing on enhanced residual multi-scale diverged self-attention networks. It explores recent advancements, identifies key challenges, and outlines future research directions for developing intelligent and efficient healthcare monitoring systems.

Literature Review

Islam et al. (2020) presented a comprehensive survey on IoT-based healthcare systems, focusing on remote patient monitoring using wearable sensors and cloud platforms. The study highlighted that IoT enables continuous monitoring and real-time data transmission, significantly improving healthcare delivery. The authors also emphasized challenges such as data security, interoperability, and scalability. Wu et al. (2020) proposed a federated learning-based IoT healthcare monitoring framework. The model allowed decentralized training across multiple devices, ensuring data privacy by keeping patient data locally. The system achieved improved accuracy while maintaining privacy, but required efficient communication protocols for distributed learning.

Munnangi et al. (2023) reviewed deep learning techniques in IoT healthcare systems, focusing on models such as CNN, RNN, and hybrid architectures. The study highlighted that deep learning effectively captures temporal and spatial dependencies in physiological data and reduces issues such as vanishing gradients in traditional RNN models. Li et al. (2023) proposed a self-attention-based deep learning model for healthcare monitoring using multimodal data such as ECG signals and clinical records. The model improved prediction accuracy by capturing dependencies between different data sources. However, it required large datasets and high computational resources.

Yu et al. (2023) developed an IoT-based healthcare monitoring system using hybrid deep learning models (CNN + Bi-LSTM + attention). The system achieved high accuracy in predicting patient health conditions and reduced latency through edge computing integration. However, energy consumption and device constraints remained challenges. Albahri et al. (2021) presented a comprehensive framework for IoT-based smart healthcare systems integrating machine learning and deep learning techniques. The system utilized wearable sensors and cloud computing for real-time patient monitoring. Various classification models, including Support Vector Machines (SVM), Random Forest (RF), and deep neural networks, were evaluated for disease prediction.

The study demonstrated that deep learning models outperform traditional machine learning approaches due to their ability to learn complex patterns in physiological data. Additionally, the system enabled real-time alert generation for abnormal health conditions. However, issues such as data heterogeneity, interoperability, and security vulnerabilities were identified as key challenges. Rahman et al. (2021) developed a deep learning-based IoT healthcare monitoring system for detecting cardiovascular diseases. The system utilized Convolutional Neural Networks (CNN) 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 eliminates the need for manual feature engineering. However, the model required large annotated datasets and faced challenges in generalizing across diverse patient populations. Zhang et al. (2022) proposed a deep residual network (ResNet)-based model for healthcare monitoring. The architecture utilized residual connections to improve gradient flow and enable training of deeper networks.

The model demonstrated improved accuracy in disease classification tasks and better convergence compared to traditional CNN models. However, the high computational cost and lack of interpretability were identified as limitations. Chen et al. (2021) introduced an attention-based deep learning model for healthcare monitoring using multimodal data sources such as wearable sensors, electronic health records, and imaging data. The attention mechanism allowed the model to focus on relevant features, improving prediction accuracy and interpretability. The study showed that attention-based models outperform conventional deep learning models. However, increased computational complexity and training time were major challenges.

Kumar et al. (2022) proposed an edge-enabled IoT healthcare monitoring system integrated with deep learning models. The system processed data locally at edge devices to reduce latency and enable real-time monitoring. The study demonstrated improved system responsiveness and reduced communication overhead. However, the limited computational resources and energy constraints of edge devices posed challenges for deploying complex deep learning models. Verma et al. (2020) proposed an IoT-based remote patient monitoring system using Wireless Body Area Networks (WBAN). The system collected physiological data such as ECG, temperature, and blood pressure through wearable sensors and transmitted it to cloud servers for analysis. Machine learning algorithms, including decision trees and neural networks, were used for disease prediction.

The study demonstrated improved efficiency in continuous patient monitoring and early diagnosis. However, challenges such as energy consumption of wearable devices, network reliability, and data transmission delays were identified. Rahman et al. (2021) developed a CNN-based deep learning model for analyzing ECG signals in IoT healthcare systems. The model automatically extracted features from raw signals and achieved high classification accuracy in detecting cardiac abnormalities.

The study highlighted the effectiveness of deep learning in eliminating manual feature engineering. However, the model required large datasets and faced challenges in generalizing across different patient populations. Singh et al. (2022) proposed a hybrid deep learning model combining CNN and LSTM for healthcare monitoring. The CNN component extracted spatial features, while LSTM captured temporal dependencies in physiological signals. The model achieved improved prediction accuracy compared to standalone models. However, the integration of multiple architectures increased computational complexity and required careful parameter tuning.

Abbas et al. (2022) introduced a Bidirectional LSTM (Bi-LSTM)-based model for patient monitoring. The model processed data in both forward and backward directions, enabling better capture of temporal dependencies. The study demonstrated improved performance in anomaly detection and disease prediction. However, the model required high computational resources and was prone to overfitting when trained on limited datasets. Liu et al. (2023) proposed a multimodal deep learning framework integrating IoT sensor data with electronic health records (EHR). The model utilized attention mechanisms for data fusion and achieved high prediction accuracy.

The study highlighted the importance of multimodal data integration in improving healthcare monitoring systems. However, challenges such as data synchronization, interoperability, and privacy concerns were identified. Sun et al. (2020) proposed a Gated Recurrent Unit (GRU)-based deep learning model for healthcare monitoring using time-series physiological data. The model was designed to process sequential signals such as ECG and heart rate efficiently while reducing computational complexity compared to LSTM. The study demonstrated that GRU models achieved comparable accuracy to LSTM while offering faster training and reduced memory consumption. This makes GRU suitable for real-time healthcare monitoring systems. However, GRU models were less effective in capturing very long-term dependencies.

Alazab et al. (2021) developed an intelligent IoT healthcare monitoring framework integrating deep learning techniques for anomaly detection and disease prediction. The system utilized wearable sensors, cloud platforms, and deep neural networks to analyze patient data. The study showed improved diagnostic accuracy and scalability. However, issues such as data security, privacy, and heterogeneity were identified as major challenges in deploying such systems. 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 ensemble approach improved prediction accuracy and robustness by leveraging the strengths of different models. However, the system required complex integration and increased computational overhead, limiting real-time deployment. Zhang et al. (2022) introduced a Graph Neural Network (GNN)-based healthcare monitoring system for modeling relationships between physiological parameters. The model represented patient data as nodes in a graph structure, enabling the capture of complex interdependencies. The study demonstrated improved performance in disease prediction tasks, particularly for 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 data processing. The system processed data locally at edge devices, reducing latency and improving responsiveness. The study demonstrated improved system efficiency and reduced communication overhead. However, limitations included restricted computational power at edge devices and challenges in deploying complex models. Park et al. (2020) proposed a Deep Belief Network (DBN)-based healthcare monitoring model for analyzing physiological signals. The model utilized hierarchical feature extraction to improve disease prediction accuracy.

The study demonstrated improved feature learning compared to shallow models. However, DBNs are computationally expensive and have been largely replaced by modern deep learning architectures such as CNN and attention-based networks. Roy et al. (2021) developed a cloud-based IoT healthcare monitoring system for real-time patient data processing. The system utilized machine learning algorithms for predictive analysis. The framework provided scalability and efficient data management. However, issues such as network latency, data privacy, and dependency on internet connectivity were identified.

Kaur et al. (2021) proposed a hybrid ANN-SVM model for healthcare monitoring. The model combined the feature extraction capability of ANN with the classification strength of SVM. The hybrid model achieved improved accuracy compared to individual models. However, increased computational complexity and parameter tuning were major challenges. 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. However, the model required large datasets and high computational resources. Ahmed et al. (2022) proposed a big data analytics framework for IoT healthcare systems. The system integrated IoT devices with cloud platforms and utilized machine learning for predictive analytics. The study demonstrated improved scalability and data handling capabilities. However, infrastructure cost and system complexity were identified as major limitations. Chatterjee et al. (2022) developed a CNN-based healthcare monitoring system for disease classification. The model extracted spatial features from medical data and achieved high classification accuracy.

However, CNN models lack the ability to capture temporal dependencies, limiting their effectiveness in time-series healthcare data. Gupta et al. (2023) proposed a multi-model deep learning architecture combining CNN, LSTM, and attention mechanisms. The model incorporated residual connections and multi-scale feature extraction. The architecture achieved high prediction accuracy and robustness. However, computational complexity and long training time were significant challenges. Das et al. (2023) introduced an edge-based IoT healthcare monitoring system using deep learning models. The system enabled real-time prediction and reduced latency.

However, limitations included energy consumption and limited computational capacity at edge devices. Zhou et al. (2023) proposed a Graph Attention Network (GAT)-based healthcare monitoring model. The model captured relationships between physiological parameters using graph structures and attention mechanisms. The approach improved prediction accuracy and interpretability. However, graph construction complexity and computational overhead were challenges.

Kumar et al. (2023) developed a hybrid deep learning model integrating LSTM and attention mechanisms for patient monitoring. The model achieved high accuracy and scalability. However, challenges such as data synchronization, integration complexity, and system scalability were identified.

Comparative Table

No	Author (Year)	Model	Type	Key Contribution	Limitation
1	Islam (2020)	IoT Survey	Review	Remote monitoring	Security
2	Wu (2020)	Federated DL	DL	Privacy	Comm cost
3	Munnangi (2023)	DL Review	Review	DL effectiveness	Cost
4	Li (2023)	Attention DL	DL	Multimodal	Data need
5	Yu (2023)	CNN-BiLSTM-Att	Hybrid	High accuracy	Energy
6	Albahri (2021)	ML/DL	Hybrid	Decision support	Heterogeneity
7	Rahman (2021)	CNN	DL	ECG classification	Data need
8	Zhang (2022)	ResNet	DL	Deep learning	Compute
9	Chen (2021)	Attention DL	DL	Feature focus	Complexity
10	Kumar (2022)	Edge DL	Hybrid	Low latency	Resource
11	Verma (2020)	WBAN	IoT	Remote monitoring	Energy
12	Rahman (2021)	CNN	DL	ECG	Generalization
13	Singh (2022)	CNN-LSTM	Hybrid	Better prediction	Complexity
14	Abbas (2022)	Bi-LSTM	DL	Temporal learning	Overfitting
15	Liu (2023)	Multimodal DL	DL	Data fusion	Sync
16	Sun (2020)	GRU	DL	Fast training	Long-term
17	Alazab (2021)	DL	DL	Anomaly detection	Security
18	Hassan (2021)	Ensemble	ML	Robust	Complexity
19	Zhang (2022)	GNN	DL	Relation modeling	Compute
20	Verma (2023)	Edge DL	Hybrid	Real-time	Resource
21	Park (2020)	DBN	DL	Feature learning	Outdated
22	Roy (2021)	Cloud ML	IoT	Scalability	Latency
23	Kaur (2021)	ANN-SVM	ML	Accuracy	Complexity
24	Zhao (2022)	Transformer	DL	Long dependency	Cost
25	Ahmed (2022)	Big Data	IoT	Scalability	Cost
26	Chatterjee (2022)	CNN	DL	Spatial	No temporal
27	Gupta (2023)	CNN-LSTM-Att	Hybrid	Best accuracy	High compute
28	Das (2023)	Edge DL	IoT	Real-time	Energy
29	Zhou (2023)	GAT	DL	Graph attention	Complexity
30	Kumar (2023)	LSTM-Att	Hybrid	Scalable	Integration

Comparative Analysis

The comparative analysis shows that hybrid deep learning models combining CNN, LSTM, and attention mechanisms provide the highest accuracy in healthcare monitoring systems. Attention mechanisms significantly improve feature selection and model interpretability. IoT integration enables real-time monitoring, while edge computing reduces latency. However, challenges such as computational complexity, energy consumption, and data privacy remain critical issues.

Discussion

The integration of AI and IoT technologies has significantly transformed healthcare monitoring systems by enabling real-time data collection and intelligent analysis. Deep learning models, particularly hybrid architectures combining CNN, LSTM, and attention mechanisms, have demonstrated superior performance in analyzing physiological data. These models effectively capture spatial and temporal dependencies, improving prediction accuracy and enabling early disease detection. Attention-based architectures enhance model performance by focusing on relevant features, reducing noise, and improving interpretability. IoT-based systems provide continuous monitoring and support remote healthcare services, which are particularly beneficial for managing chronic diseases. However, several challenges remain, including data privacy, interoperability, and energy consumption. Edge computing offers a promising solution for reducing latency but introduces resource constraints. Future research should focus on lightweight models and advanced architectures such as enhanced residual multi-scale diverged self-attention networks.

Conclusion

The rapid advancement of IoT and AI technologies has revolutionized healthcare monitoring systems, enabling continuous, real-time patient monitoring and intelligent decision-making. This review analyzed 30 studies conducted between 2020 and 2023, focusing on AI-based IoT healthcare monitoring systems. The findings indicate that IoT-based systems play a crucial role in collecting real-time physiological data through wearable sensors and WBANs. These systems enable early detection of health abnormalities and improve patient outcomes. However, challenges such as data noise, sensor reliability, and energy consumption remain significant. Deep learning models, including 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, deploying complex deep learning models in resource-constrained environments remains challenging. 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 healthcare systems. Federated learning and privacy-preserving techniques offer promising solutions to address these concerns. In conclusion, AI-driven IoT healthcare systems have the potential to revolutionize patient monitoring by providing intelligent, scalable, and efficient solutions. Continued research in advanced architectures such as enhanced residual multi-scale diverged self-attention networks will further improve system performance and reliability.

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