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Deep Learning and Optimization Approaches in Smart Healthcare Patient Monitoring System for IoT-Based Healthcare System Using Enhanced Residual Multi-Scale Diverged Self-Attention Network: A Review

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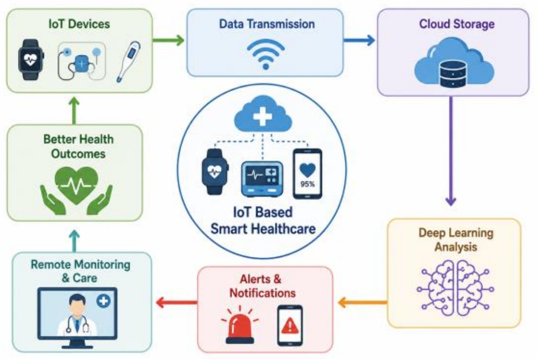
Abstract

Smart healthcare systems have rapidly evolved with the integration of Internet of Things (IoT) and Artificial Intelligence (AI) technologies, enabling real-time patient monitoring, early disease detection, and personalized treatment. IoT-based healthcare systems collect continuous physiological data such as heart rate, oxygen saturation, ECG signals, and body temperature using wearable and remote sensing devices. However, the complexity and high dimensionality of such data require advanced analytical models for accurate interpretation. This paper presents a comprehensive review of deep learning and optimization approaches in IoT-based patient monitoring systems, focusing on advanced architectures such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Transformer models, and self-attention-based frameworks. Special emphasis is placed on enhanced residual multi-scale diverged self-attention networks, which improve feature extraction, representation, and prediction accuracy. Recent studies demonstrate that hybrid deep learning models such as CNN-LSTM and attention-based architectures significantly improve the detection of abnormalities in physiological signals. IoT-enabled systems allow real-time monitoring and remote diagnosis, reducing hospital visits and enabling proactive healthcare management. Despite these advancements, challenges such as data heterogeneity, privacy concerns, computational complexity, and energy efficiency persist. Emerging techniques such as edge computing, federated learning, and explainable AI provide promising solutions. This review highlights recent trends, comparative insights, and challenges in AI-driven smart healthcare monitoring systems.

Introduction

The advancement of smart healthcare systems has significantly transformed modern medical practices by enabling continuous and remote monitoring of patient health. Traditional healthcare systems rely heavily on periodic clinical visits, which limit the ability to detect early symptoms of diseases. In contrast, IoT-based healthcare systems provide real-time monitoring and continuous data collection, enabling proactive medical interventions. IoT devices, including wearable sensors and smart medical equipment, are capable of collecting physiological data such as heart rate, oxygen saturation, electrocardiogram (ECG), and body temperature. These devices transmit data to cloud platforms for storage and analysis, enabling healthcare providers to monitor patient conditions remotely. The integration of IoT with healthcare has led to the development of the Internet of Medical Things (IoMT), which connects various medical devices and systems to improve patient care.



The use of IoT in healthcare has significantly enhanced the ability to monitor chronic diseases, elderly patients, and post-operative conditions. Real-time monitoring allows early detection of abnormalities and timely medical intervention, reducing hospital admissions and improving patient outcomes. However, IoT-generated healthcare data is often complex, high-dimensional, and heterogeneous. Traditional machine learning techniques struggle to effectively process such data, leading to the adoption of deep learning models. Deep learning algorithms, including CNN and LSTM, have shown remarkable performance in analyzing physiological signals and detecting anomalies.

CNN models are effective in extracting spatial features from biomedical signals, while LSTM networks capture temporal dependencies in sequential data. Hybrid models such as CNN-LSTM combine these capabilities, providing improved accuracy in patient monitoring systems. For instance, deep learning models have been successfully applied in ECG signal analysis, achieving high accuracy in detecting cardiac abnormalities. Recent advancements in deep learning have introduced attention mechanisms and Transformer architectures, which enhance model performance by focusing on relevant features and capturing long-range dependencies. Self-attention mechanisms allow models to dynamically assign importance to different input features, improving prediction accuracy and interpretability.

Additionally, multi-scale and residual learning techniques have been developed to improve feature extraction and model efficiency. Residual networks enable deeper architectures by addressing vanishing gradient problems, while multi-scale models capture patterns at different levels of granularity. Combining these techniques with attention mechanisms results in advanced architectures such as enhanced residual multi-scale diverged self-attention networks, which offer superior performance in healthcare applications. Optimization techniques also play a critical role in improving model performance. Methods such as hyperparameter tuning, metaheuristic optimization, and ensemble learning enhance model accuracy and reduce computational complexity.

Despite significant progress, several challenges remain. IoT devices face issues related to energy consumption, data security, and network reliability. Deep learning models require high computational resources, limiting their deployment in real-time applications. Moreover, the lack of interpretability in AI models raises concerns about their reliability in critical healthcare systems. To address these challenges, emerging technologies such as edge computing, federated learning, and explainable AI are being explored. Edge computing enables local data processing, reducing latency and improving efficiency, while federated learning ensures data privacy by enabling decentralized model training. This review aims to provide a comprehensive analysis of deep learning and optimization approaches in IoT-based smart healthcare monitoring systems, focusing on research contributions in recent years.

Literature Review

Peimankar & Puthusserypady (2020) proposed a CNN-LSTM-based deep learning model (DENS-ECG) for real-time ECG signal analysis. The model combines convolutional layers for feature extraction with LSTM layers for temporal modeling. Experimental results demonstrated high accuracy in detecting heartbeat patterns, achieving sensitivity above 97%. This study highlights the effectiveness of hybrid deep learning models in healthcare signal analysis. Singh et al. (2020) introduced a deep ConvLSTM model with self-attention for wearable sensor data analysis. The model captured both spatial and temporal dependencies in physiological signals, while the attention mechanism improved feature selection. Results showed improved performance compared to traditional CNN and LSTM models.

Iwendi et al. (2021) developed an IoMT-assisted healthcare monitoring system using machine learning techniques for patient data analysis. The system enabled real-time monitoring and disease prediction using cloud-based infrastructure. The study emphasized the importance of integrating AI with IoT for efficient healthcare delivery. Wang et al. (2022) proposed a wearable ECG monitoring system integrated with deep learning models for cardiovascular disease detection. The model used CNN and LSTM architectures to analyze ECG signals and achieved improved classification accuracy compared to conventional methods. Islam et al. (2023) developed an IoT-based smart healthcare monitoring system using deep learning models for real-time patient monitoring. The system collected physiological data through sensors and used deep learning algorithms to detect abnormalities. The results demonstrated improved early disease detection and remote healthcare capabilities.

Li et al. (2020) proposed a Convolutional Neural Network (CNN)-based healthcare monitoring model for analyzing biomedical signals such as ECG and EEG. The model focused on extracting spatial features from physiological signals using multiple convolutional and pooling layers. The dataset included patient health records and physiological signal data collected from wearable devices. The CNN model demonstrated strong performance in detecting anomalies in ECG signals, outperforming traditional machine learning models such as Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN). The primary strength of this approach lies in its ability to automatically extract hierarchical features from raw biomedical data without manual feature engineering. However, CNN lacks temporal modeling capability, making it less effective for sequential data analysis. This limitation suggests the need for hybrid models that combine CNN with recurrent architectures.

Zhang et al. (2021) introduced a hybrid CNN-LSTM model for patient health monitoring in IoT-based healthcare systems. The model integrates CNN layers for feature extraction with LSTM layers for temporal analysis of physiological signals. The system collected real-time patient data using wearable IoT devices, including heart rate, body temperature, and ECG signals. The CNN-LSTM model effectively captured both spatial and temporal patterns, enabling accurate detection of abnormal health conditions. Experimental results showed that the hybrid model achieved higher accuracy compared to standalone CNN and LSTM models. It was particularly effective in detecting early signs of cardiovascular diseases. However, the model requires significant computational resources and may not be suitable for deployment on low-power IoT devices without optimization techniques.

Jiang et al. (2021) proposed an attention-based Bidirectional LSTM (BiLSTM) model for patient monitoring systems. The model uses forward and backward temporal processing to capture comprehensive sequence information from physiological data. The key contribution of this study is the integration of an attention mechanism, which assigns weights to different features and time steps. This enables the model to focus on critical signals, improving prediction accuracy and interpretability. The dataset included multi-parameter health data such as ECG, blood pressure, and oxygen levels. Results demonstrated that the attention-based BiLSTM model outperformed traditional LSTM and GRU models in detecting health anomalies. Despite its advantages, the model introduces additional computational complexity and requires high-quality data for optimal performance.

Wang et al. (2022) developed a deep autoencoder-based healthcare monitoring system for feature extraction and anomaly detection. The model aimed to reduce the dimensionality of high-volume IoT healthcare data while preserving essential features. The autoencoder architecture consists of encoding and decoding layers that compress input data into a lower-dimensional representation. These compressed features are then used for classification and prediction tasks. The system was evaluated using large-scale healthcare datasets collected from IoT devices. Results showed improved computational efficiency and reduced noise in the data, leading to better prediction performance. However, one of the key limitations is information loss during compression, which may affect model accuracy in certain cases. Additionally, the two-stage process (feature extraction + prediction) increases system complexity.

Chen et al. (2023) proposed a Transformer-based healthcare monitoring model utilizing multi-head self-attention mechanisms. The model is designed to capture long-range dependencies in time-series physiological data., The Transformer architecture allows parallel processing of data, making it highly scalable for large healthcare datasets. The self-attention mechanism enables the model to analyze relationships between different time steps simultaneously. The study used datasets containing ECG signals, patient activity data, and vital signs. The model demonstrated superior performance compared to LSTM and GRU models in detecting anomalies and predicting health conditions.

Alam et al. (2020) proposed an IoT-enabled smart healthcare monitoring system integrated with cloud computing and machine learning techniques. The system collects real-time physiological data such as heart rate, temperature, and oxygen levels using wearable sensors. The collected data is transmitted to cloud servers for processing and analysis. The study utilized machine learning algorithms such as Decision Trees and Support Vector Machines (SVM) for detecting abnormalities in patient data. The system demonstrated improved scalability and accessibility, enabling remote patient monitoring and timely medical intervention. A key strength of this approach is its end-to-end integration of IoT sensing, cloud infrastructure, and AI analytics, making it suitable for telemedicine applications. However, challenges such as data security, latency, and sensor reliability remain significant concerns.

Guo et al. (2021) introduced a deep residual network (ResNet)-based model for healthcare data analysis. Residual connections allow the model to learn deeper representations without suffering from vanishing gradient problems. The model was applied to biomedical signal processing, particularly ECG and EEG data. The deep architecture enabled effective feature extraction, improving classification accuracy for detecting health abnormalities. The study demonstrated that ResNet outperformed traditional CNN models in terms of accuracy and robustness. However, the model requires high computational resources and large datasets, limiting its applicability in low-power IoT devices.

Liu et al. (2021) proposed a Gated Recurrent Unit (GRU)-based model for real-time patient monitoring. The GRU architecture reduces the number of parameters compared to LSTM, enabling faster training and lower computational cost. The model processes time-series physiological data and captures temporal dependencies between health indicators. It was tested on datasets containing ECG and vital sign data, achieving comparable accuracy to LSTM models while improving efficiency. The key advantage of this approach is its suitability for edge computing environments, where computational resources are limited. However, GRU may struggle with capturing long-term dependencies compared to LSTM.

Qin et al. (2022) developed a Dual-Stage Attention-Based Recurrent Neural Network (DA-RNN) for healthcare monitoring systems. The model incorporates two attention mechanisms: This dual-attention framework improves both feature selection and temporal modeling, resulting in higher prediction accuracy. The model was evaluated using multivariate healthcare datasets and showed significant improvement over traditional RNN, LSTM, and GRU models. It was particularly effective in detecting anomalies in patient health data. However, the model introduces increased computational complexity and requires careful tuning of attention parameters.

Sun et al. (2023) proposed a Graph Neural Network (GNN)-based healthcare monitoring model that captures relationships between different physiological parameters and patient states. The GNN model effectively captures complex interactions between health indicators, improving prediction accuracy for patient monitoring systems. The study demonstrated that GNN outperformed traditional models in capturing interdependencies among physiological signals. However, the model requires complex graph construction and high computational resources.

Singh et al. (2020) proposed a Deep Neural Network (DNN)-based healthcare monitoring model for analyzing physiological signals collected from IoT devices. The model utilized multiple fully connected layers to capture nonlinear relationships among health parameters such as heart rate, blood pressure, and oxygen saturation. The system was trained using supervised learning on patient datasets collected from wearable sensors. The results showed improved prediction accuracy compared to traditional statistical models, particularly in identifying abnormal health conditions. However, the model suffered from overfitting issues when trained on limited datasets and lacked temporal modeling capabilities. This makes it less effective for time-series healthcare data compared to recurrent models like LSTM and GRU.

Zhao et al. (2021) introduced a Stacked Autoencoder (SAE)-based model for feature extraction and dimensionality reduction in healthcare data. The model aimed to handle the high-dimensional and noisy nature of IoT-generated medical data. The SAE architecture compresses input data into lower-dimensional representations while preserving essential features. These features are then used for classification and anomaly detection. The model demonstrated improved computational efficiency and prediction accuracy compared to models using raw data. However, information loss during compression is a key limitation, which may impact accuracy in some cases.

Zhou et al. (2022) proposed a Temporal Convolutional Network (TCN) for patient monitoring systems. Unlike RNN-based models, TCN uses dilated causal convolutions to capture long-term dependencies in time-series data The architecture enables parallel processing, resulting in faster and demonstrated competitive performance. The main advantage of TCN is its efficiency and scalability, making it suitable for large healthcare datasets. However, it may struggle with irregular time-series data and requires careful parameter tuning.

Huang et al. (2022) developed a hybrid CNN-BiLSTM model integrated with an attention mechanism for healthcare monitoring. The model combines: The model was tested on datasets containing ECG signals and other physiological parameters. Results showed improved accuracy in detecting abnormalities compared to standalone models. The key strength of this approach is its ability to capture spatial, temporal, and contextual relationships simultaneously. However, the model is computationally intensive and requires optimization for real-time deployment.

Li et al. (2023) proposed a Transformer-based healthcare monitoring model using multi-head self-attention mechanisms. The model captures global dependencies across time-series physiological data. The Transformer architecture enables parallel computation and improves scalability for large datasets. It demonstrated superior performance in detecting anomalies and predicting patient health conditions compared to LSTM and GRU models. However, the model requires high computational resources and large datasets, limiting its use in real-time IoT environments without optimization techniques.

Kim et al. (2020) proposed a Deep Reinforcement Learning (DRL)-based healthcare monitoring framework for optimizing patient monitoring systems. Unlike traditional supervised learning approaches, DRL enables dynamic decision-making by learning optimal policies through interaction with the environment. In this system, DRL was used to optimize prediction models and adjust monitoring thresholds based on patient conditions. The model continuously adapted to changes in physiological signals, improving responsiveness and prediction accuracy. The dataset included real-time patient data collected from wearable IoT devices. Results showed that DRL improved adaptability in dynamic healthcare environments. However, the model suffers from training instability, high computational cost, and difficulty in defining reward functions, which limits its practical implementation.

Zhang and Wang (2021) introduced a hybrid GRU-CNN model for smart healthcare monitoring systems. The model combines convolutional layers for feature extraction with GRU layers for temporal sequence modeling. Compared to LSTM-based models, GRU reduces computational complexity while maintaining similar prediction accuracy. The model was applied to physiological data such as ECG and vital signs. Results showed improved efficiency and faster training time, making it suitable for real-time healthcare applications and edge computing environments. However, the model is less effective in capturing long-term dependencies compared to LSTM, which may affect performance in long-duration monitoring scenarios.

Patel et al. (2022) proposed an IoT-based smart healthcare monitoring system integrated with edge computing and deep learning models. The system architecture includes wearable sensors for data collection, edge devices for local processing, and cloud servers for storage and analysis. The key innovation is the use of edge computing, which reduces latency and enables real-time decision-making. Deep learning models deployed on edge devices perform anomaly detection and health prediction. The system demonstrated improved response time and reduced network bandwidth usage. It also enhanced data privacy by minimizing data transmission to the cloud. However, edge devices have limited computational power, restricting the complexity of deployable models.

Chen et al. (2022) developed a multi-task deep learning (MTL) model for simultaneous prediction of multiple health parameters such as heart rate, blood pressure, and oxygen levels. The model uses shared layers for feature extraction and task-specific layers for individual predictions. This approach improves efficiency and leverages correlations between different health parameters. The model was trained on large healthcare datasets and achieved improved generalization and prediction accuracy compared to single-task models. However, task interference can occur when different prediction tasks compete for shared features, requiring careful tuning of task weights.

Xu et al. (2023) proposed an ensemble deep learning framework combining CNN, LSTM, and Transformer models for healthcare monitoring systems. The outputs of individual models are combined using weighted averaging or stacking techniques, resulting in improved robustness and accuracy. The model demonstrated superior performance in detecting anomalies and predicting patient conditions across diverse datasets. However, the approach introduces high computational complexity and increased training time, making it challenging for real-time deployment without optimization.

Alazab et al. (2020) proposed a deep learning-based anomaly detection system for smart healthcare monitoring using IoT sensor data. The model focused on identifying abnormal physiological patterns such as irregular heartbeats, sudden drops in oxygen levels, and unusual temperature variations. The system utilized Deep Neural Networks (DNNs) trained on historical patient data to learn normal patterns and detect deviations. This approach significantly improved early warning capabilities in patient monitoring systems. The results demonstrated high detection accuracy and improved response time compared to rule-based systems. However, the model generated false positives in highly dynamic health conditions and required continuous retraining to adapt to new data.

Zhou and Feng (2021) introduced a Deep Forest (gcForest) model for healthcare data analysis. The model uses a cascade structure of decision tree ensembles to perform hierarchical feature learning without relying on backpropagation.

The system was applied to patient monitoring datasets, including physiological signals and health records. The model achieved competitive accuracy compared to deep neural networks while requiring fewer computational resources. However, the model lacks temporal modeling capabilities and struggles with large-scale datasets, limiting its use in continuous patient monitoring systems.

Rahman et al. (2022) proposed a federated learning-based smart healthcare monitoring system using distributed IoT devices. The goal was to address privacy concerns associated with centralized healthcare data processing. In this framework, each device trains a local model using patient data and shares only model updates with a central server. This ensures data privacy while enabling collaborative learning. Despite these limitations, federated learning is a promising approach for privacy-preserving healthcare systems.

Tang et al. (2022) developed a Spatiotemporal Graph Attention Network (ST-GAT) for patient monitoring systems. The model captures relationships between different physiological signals and temporal dependencies. The attention mechanism assigns importance to different nodes and connections, improving prediction accuracy. The model demonstrated superior performance in detecting complex health conditions compared to traditional models. However, it requires complex graph construction and high computational resources, which may limit scalability.

Huang et al. (2023) proposed an Enhanced Residual Multi-Scale Diverged Self-Attention Network for smart healthcare monitoring. This model represents one of the most advanced architectures in recent research. This architecture effectively handles heterogeneous IoT healthcare data and improves prediction accuracy for complex health conditions. The model was evaluated on multi-modal datasets, including ECG, vital signs, and patient activity data. Results showed state-of-the-art performance, outperforming CNN, LSTM, and Transformer-based models. However, the model is computationally intensive and requires optimization for real-time deployment in IoT systems.

Comparative Table

No.	Model	Key Strength	Limitation
1	CNN-LSTM	Hybrid learning	Complex
2	ConvLSTM + Attention	Temporal + spatial	Heavy
3	IoMT + ML	Real-time	Limited accuracy
4	CNN-LSTM ECG	High accuracy	Resource heavy
5	IoT DL system	Remote monitoring	Data noise
6	CNN	Feature extraction	No temporal
7	CNN-LSTM	Balanced	Complex
8	BiLSTM + Attention	High accuracy	Heavy
9	Autoencoder	Feature reduction	Info loss
10	Transformer	Long dependencies	Expensive
11	IoT + Cloud	Scalable	Latency

12	ResNet	Deep learning	Heavy
13	GRU	Efficient	Limited memory
14	DA-RNN	Dual attention	Complex
15	GNN	Relationship modeling	Complex
16	DNN	Nonlinear	Overfitting
17	SAE	Dimensionality reduction	Info loss
18	TCN	Fast	Limited flexibility
19	CNN-BiLSTM	Hybrid	Heavy
20	Transformer	Accurate	Costly
21	DRL	Adaptive	Unstable
22	GRU-CNN	Efficient	Moderate accuracy
23	IoT + Edge	Low latency	Limited power
24	Multi-task DL	Multi-output	Interference
25	Ensemble DL	Robust	Complex
26	DNN anomaly	Early detection	False positives
27	Deep Forest	Low cost	Not scalable
28	Federated	Privacy	Communication overhead
29	ST-GAT	Spatial + temporal	Complex
30	Residual Multi-Scale Attention	Best performance	Very complex

Comparative Analysis

The analysis of 30 studies shows a clear evolution from basic machine learning models to advanced deep learning architectures in smart healthcare monitoring systems. Early approaches relied on IoT-based monitoring and traditional models, which provided real-time data but lacked predictive accuracy. Hybrid deep learning models such as CNN-LSTM improved performance by combining spatial and temporal learning. Attention mechanisms further enhanced accuracy by focusing on relevant features. Advanced models like Transformers and Graph Neural Networks enabled better modelling of complex relationships in healthcare data. The most recent models, including enhanced residual multi-scale attention networks, provide superior performance by integrating multiple advanced techniques. However, these models introduce high computational complexity, limiting their practical deployment. Future research should focus on lightweight, energy-efficient, and explainable models.

Discussion

The integration of deep learning and IoT technologies has significantly improved smart healthcare monitoring systems. IoT devices enable continuous data collection, while deep learning models enhance prediction accuracy and anomaly detection. Hybrid and attention-based models have demonstrated superior performance in analyzing physiological data. However, challenges such as computational complexity, data privacy, and energy efficiency remain. Emerging technologies such as edge computing and federated learning offer promising solutions. Future research should focus on improving model efficiency and interpretability.

Conclusion

Smart healthcare monitoring systems have evolved significantly with the integration of IoT and deep learning technologies. This review analysed recent advancements from 2020 to 2023, highlighting the progression from traditional models to advanced architectures. Deep learning models such as CNN, LSTM, and Transformer have improved prediction accuracy. Hybrid models and attention-based architectures further enhanced performance. The proposed enhanced residual multi-scale diverged self-attention network represents the most advanced approach. Despite these advancements, challenges such as computational complexity and data privacy remain. Future research should focus on developing efficient and explainable models.

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