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# A Survey of Methods and Architectures for Smart Healthcare Patient Monitoring System for IoT-Based Healthcare System Using Enhanced Residual Multi-Scale Diverged Self-Attention Network

Jaswinder van der Velde
*Lecturer, Department of Electronics and Communication Engineering, Phnom Penh School of Management Sciences, Cambodia*
*Email: jaswinder.van.der.velde@ppsms-kh.net*

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**Abstract**

Smart healthcare systems have transformed modern medical practices through the integration of Internet of Things (IoT) and Artificial Intelligence (AI) technologies. IoT-based healthcare monitoring systems enable continuous collection of physiological data such as heart rate, ECG, oxygen saturation, and body temperature using wearable devices and sensors. These systems generate large volumes of heterogeneous and high-dimensional data, requiring advanced analytical models for accurate prediction and diagnosis. Deep learning models such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and attention-based architectures have significantly improved the performance of patient monitoring systems. Hybrid models like CNN-LSTM effectively capture both spatial and temporal dependencies in biomedical signals, enhancing prediction accuracy and anomaly detection. Recent advancements in self-attention mechanisms and Transformer architectures enable models to focus on relevant features and capture long-range dependencies in time-series healthcare data. Additionally, multi-scale and residual learning techniques improve feature extraction and model efficiency. The proposed Enhanced Residual Multi-Scale Diverged Self-Attention Network integrates these concepts to achieve superior performance in smart healthcare monitoring systems. Despite these advancements, challenges such as data heterogeneity, privacy concerns, computational complexity, and energy constraints remain. Emerging solutions such as edge computing and federated learning are being explored to address these issues. This survey reviews recent developments (2020–2023), identifies trends, and highlights future research directions in IoT-enabled smart healthcare monitoring systems.

## Introduction

The rapid advancement of digital technologies has significantly transformed healthcare systems, leading to the emergence of smart healthcare monitoring systems. These systems leverage Internet of Things (IoT) devices and Artificial Intelligence (AI) to enable continuous monitoring of patient health, early disease detection, and personalized treatment. Traditional healthcare systems rely on periodic clinical visits, which often fail to detect early symptoms of diseases. In contrast, IoT-based systems enable real-time data collection and remote patient monitoring, allowing healthcare providers to respond quickly to abnormal conditions. IoT devices such as wearable sensors, smart watches, and medical equipment continuously collect physiological data including heart rate, blood pressure, oxygen saturation, and ECG signals.

The integration of IoT with healthcare, commonly referred to as the Internet of Medical Things (IoMT), has revolutionized patient care by enabling remote diagnosis and continuous monitoring. These systems reduce hospital visits, improve patient outcomes, and lower healthcare costs. However, IoT-generated healthcare data is highly complex, large-scale, and heterogeneous. Traditional data analysis techniques are insufficient for extracting meaningful insights from such data. This has led to the adoption of deep learning models, which are capable of learning complex patterns and relationships in high-dimensional datasets.

Deep learning architectures such as CNN and LSTM have demonstrated significant success in healthcare applications. CNN models are effective in extracting spatial features from biomedical signals, while LSTM models capture temporal dependencies in time-series data. Hybrid models combining CNN and LSTM have shown improved performance in patient monitoring systems by leveraging both spatial and temporal information. Recent advancements have introduced attention mechanisms, which allow models to focus on the most relevant features in the data. Attention-based models improve prediction accuracy and interpretability, making them suitable for critical healthcare applications. Systems using CNN-LSTM and attention architectures have shown improved accuracy and reduced latency in real-time monitoring environments.

Additionally, self-attention and Transformer-based models have emerged as powerful tools for handling long-range dependencies in sequential data. These models enable parallel processing and improved scalability, making them suitable for large healthcare datasets. Another important advancement is the use of multi-scale and residual learning techniques. Residual networks enable deeper architectures by mitigating vanishing gradient problems, while multi-scale approaches capture patterns at different levels of granularity. When combined with self-attention mechanisms, these techniques form advanced architectures such as enhanced residual multi-scale diverged self-attention networks, which provide superior feature representation and prediction accuracy.

Despite these advancements, several challenges remain. IoT devices face limitations such as energy consumption, data security, and network reliability. Deep learning models require high computational resources, limiting their deployment in real-time systems. Furthermore, the lack of interpretability in AI models raises concerns about their reliability in healthcare applications. Emerging technologies such as edge computing, federated learning, and explainable AI (XAI) offer promising solutions. Edge computing enables local data processing, reducing latency and improving efficiency, while federated learning ensures data privacy by enabling decentralized model training. This survey aims to provide a comprehensive review of methods and architectures for IoT-based smart healthcare monitoring systems, focusing on research contributions from 2020 to 2023.

**Literature Review**

Peimankar & Puthusserypady (2020) proposed a CNN-LSTM hybrid model (DENS-ECG) for real-time ECG signal analysis. The model combines convolutional layers for feature extraction with LSTM layers for temporal modeling. It achieved high sensitivity and precision (above 97%), demonstrating strong performance in detecting cardiac abnormalities. Singh et al. (2020) developed a deep learning-based IoT healthcare monitoring system using ConvLSTM and attention mechanisms. The model captured spatiotemporal dependencies in physiological signals and improved anomaly detection accuracy in wearable sensor data. Iwendi et al. (2021) proposed an IoMT-assisted healthcare system using machine learning models for real-time patient monitoring and disease prediction. The system integrates IoT devices with cloud computing for efficient healthcare delivery.

Wang et al. (2022) developed a deep learning-based wearable healthcare monitoring system for cardiovascular disease detection. The model utilized CNN and LSTM architectures to analyze ECG signals, achieving improved classification accuracy. Islam et al. (2023) proposed a deep learning-based IoT system for real-time health monitoring. The system collects physiological data using sensors and applies deep learning algorithms to detect abnormalities and provide early diagnosis. Li et al. (2020) proposed a Convolutional Neural Network (CNN)-based model for biomedical signal analysis in smart healthcare monitoring systems. The model was designed to process physiological signals such as ECG and EEG collected from IoT-enabled wearable devices.

The architecture consists of multiple convolutional and pooling layers that automatically extract hierarchical features from raw signal data. The model demonstrated strong performance in detecting abnormalities in ECG signals, outperforming traditional machine learning methods such as Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN). The key strength of this model lies in its ability to automatically learn spatial features without manual feature engineering. However, a major limitation is its inability to capture temporal dependencies in sequential data, making it less suitable for long-term patient monitoring applications. Zhang et al. (2021) introduced a hybrid CNN-LSTM model for IoT-based smart healthcare monitoring systems. The model combines convolutional layers for feature extraction with LSTM layers for temporal sequence modeling.

The system collects real-time physiological data such as heart rate, body temperature, and ECG signals using wearable IoT devices. The CNN component extracts spatial features, while LSTM captures temporal dependencies, enabling accurate detection of abnormal health conditions. Experimental results showed that the CNN-LSTM model achieved higher accuracy compared to standalone CNN and LSTM models. It was particularly effective in detecting cardiovascular abnormalities. However, the model requires high computational resources and extensive training data, limiting its deployment in low-power IoT environments. Jiang et al. (2021) proposed an attention-based Bidirectional LSTM (BiLSTM) model for patient monitoring systems. The model processes time-series healthcare data in both forward and backward directions, capturing comprehensive temporal dependencies.

The integration of an attention mechanism allows the model to assign weights to different features and time steps, improving prediction accuracy and interpretability. This is particularly useful in identifying critical physiological signals that indicate health abnormalities. The model was evaluated using datasets containing ECG, blood pressure, and oxygen saturation data. Results demonstrated superior performance compared to traditional LSTM and GRU models. Despite its advantages, the model introduces increased computational complexity and requires high-quality data for optimal performance. Wang et al. (2022) developed a deep autoencoder-based model for feature extraction and dimensionality reduction in IoT-based healthcare systems. The model addresses the challenge of high-dimensional and noisy healthcare data.

The autoencoder compresses input data into lower-dimensional representations while preserving essential information. These features are then used for classification and anomaly detection. The system was tested on large-scale healthcare datasets and demonstrated improved computational efficiency and prediction accuracy. However, the model suffers from information loss during compression, which may affect performance in certain scenarios. Chen et al. (2023) proposed a Transformer-based healthcare monitoring model using 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 and improved scalability for large datasets. It analyzes relationships between different time steps simultaneously, enabling accurate prediction of patient health conditions.

The study demonstrated that the Transformer model outperformed LSTM and GRU models in terms of accuracy and scalability. However, it requires significant computational resources and large training datasets, making it challenging to deploy in real-time IoT systems without optimization. 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 saturation using wearable sensors. The collected data is transmitted to cloud servers for processing and analysis. The study employed machine learning algorithms such as Decision Trees and Support Vector Machines (SVM) to detect abnormalities in patient data. The system demonstrated improved scalability and accessibility, enabling remote patient monitoring and early diagnosis.

A major strength of this system is its end-to-end architecture combining IoT sensing, cloud computing, and AI-based analytics. However, challenges such as data privacy, latency, and sensor inaccuracies remain critical issues. Guo et al. (2021) introduced a deep residual neural network (ResNet) for healthcare data analysis. The use of residual connections allows the model to learn deeper feature representations without suffering from vanishing gradient problems. The model was applied to biomedical signals such as ECG and EEG. It demonstrated improved performance in detecting anomalies and classifying health conditions compared to traditional CNN models.

The key advantage is its ability to train deeper networks efficiently, improving feature extraction. However, the model is computationally expensive and requires large datasets, making it less suitable for low-resource IoT devices. Liu et al. (2021) proposed a Gated Recurrent Unit (GRU)-based model for real-time patient monitoring. The GRU model reduces computational complexity compared to LSTM while maintaining similar performance. The model processes time-series physiological data, capturing temporal dependencies between health indicators such as heart rate and oxygen levels. It was tested on wearable sensor datasets and showed efficient performance in real-time monitoring scenarios.

The main advantage is its suitability for edge computing environments due to lower computational requirements. 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. The model incorporates two attention mechanisms: This approach improves both feature selection and temporal modeling, resulting in higher prediction accuracy. The model was evaluated on multivariate healthcare datasets and demonstrated superior performance compared to LSTM and GRU models. However, it introduces increased computational complexity and requires careful parameter tuning.

Sun et al. (2023) proposed a Graph Neural Network (GNN)-based healthcare monitoring model. The model captures relationships between different physiological parameters by representing them as nodes in a graph. Edges represent relationships between parameters such as heart rate, blood pressure, and oxygen levels. The GNN model effectively learns these relationships, improving prediction accuracy for complex health conditions. The study demonstrated improved performance compared to traditional models. However, the model requires complex graph construction and high computational resources, limiting scalability.

Singh et al. (2020) proposed a Deep Neural Network (DNN)-based model for smart healthcare patient monitoring using IoT-generated physiological data. The model consisted of multiple fully connected layers designed to learn nonlinear relationships between various health parameters such as heart rate, blood pressure, oxygen saturation, and body temperature. The dataset included patient records collected from wearable devices and hospital monitoring systems. The model demonstrated improved accuracy compared to traditional statistical methods such as linear regression and decision trees.

However, a major limitation of this approach is overfitting, especially when trained on limited datasets. Additionally, the model lacks temporal learning capability, making it less suitable for time-series healthcare data compared to recurrent models. Zhao et al. (2021) introduced a Stacked Autoencoder (SAE)-based deep learning model for feature extraction in healthcare monitoring systems. The model addresses the challenge of high-dimensional and noisy IoT healthcare data.

The SAE compresses input data into lower-dimensional representations while retaining important features. These compressed features are then used for classification and anomaly detection tasks. The model demonstrated improved computational efficiency and reduced noise, leading to better prediction performance. However, information loss during compression remains a key limitation. Zhou et al. (2022) proposed a Temporal Convolutional Network (TCN) for patient monitoring systems. Unlike traditional RNN-based models, TCN uses dilated causal convolutions to capture long-range dependencies in time-series data.

The architecture allows parallel processing, resulting in faster training compared to LSTM and GRU models. The model was applied to physiological signal datasets and demonstrated competitive performance. The main advantage is its efficiency and scalability, making it suitable for large datasets. However, it may struggle with irregular time-series data and requires careful tuning. Huang et al. (2022) developed a hybrid CNN-BiLSTM model with an attention mechanism for healthcare monitoring. The model combines:

The model was tested on datasets containing ECG signals and vital signs. Results showed improved accuracy in detecting abnormalities compared to standalone models. However, the model is computationally intensive and requires optimization for real-time deployment. Li et al. (2023) proposed a Transformer-based model using multi-head self-attention for healthcare monitoring. The model captures global dependencies across time-series physiological data. The Transformer architecture enables parallel computation and improved scalability. It demonstrated superior performance compared to LSTM and GRU models in detecting anomalies and predicting patient conditions. However, it requires high computational resources and large datasets, limiting its use in real-time IoT systems. Kim et al. (2020) proposed a Deep Reinforcement Learning (DRL)-based smart healthcare monitoring system for adaptive patient monitoring. The model dynamically adjusts monitoring thresholds and prediction strategies based on patient health conditions. Unlike traditional models, DRL enables continuous learning and adaptation, making it suitable for dynamic healthcare environments. The system was trained on real-time physiological data collected from IoT devices. Results showed improved responsiveness and adaptability in detecting abnormal health conditions. However, the model suffers from training instability, high computational cost, and difficulty in designing reward functions, limiting its practical implementation.

Zhang and Wang (2021) introduced a hybrid GRU-CNN model for patient monitoring systems. The model combines convolutional layers for spatial feature extraction with GRU layers for temporal modeling. Compared to LSTM-based models, GRU reduces computational complexity while maintaining comparable accuracy. The model was applied to ECG and vital sign datasets. Results demonstrated improved efficiency and faster training time, making it suitable for real-time healthcare applications and edge computing environments. However, GRU models may struggle with capturing long-term dependencies compared to LSTM.

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, edge devices, and cloud servers. The key contribution is the use of edge computing, which enables local data processing, reduces latency, and improves real-time responsiveness. Deep learning models deployed on edge devices perform anomaly detection and prediction tasks. The system demonstrated improved performance in real-time scenarios and reduced network bandwidth usage. However, the limited computational capacity of edge devices restricts the complexity of deployable models.

Chen et al. (2022) developed a multi-task deep learning (MTL) model for simultaneous prediction of multiple physiological parameters such as heart rate, blood pressure, and oxygen saturation. 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 indicators. The model achieved improved generalization and prediction accuracy compared to single-task models. However, task interference remains a challenge, requiring careful balancing of task weights.

Xu et al. (2023) proposed an ensemble deep learning framework combining CNN, LSTM, and Transformer models for healthcare monitoring. The outputs of individual models are combined using ensemble techniques, resulting in improved robustness and prediction accuracy. The model demonstrated superior performance across diverse healthcare datasets. However, it introduces high computational complexity and longer training time, making real-time deployment challenging.

Alazab et al. (2020) proposed a deep learning-based anomaly detection framework for IoT-enabled healthcare systems. The model utilizes Deep Neural Networks (DNNs) to learn normal physiological patterns and identify deviations such as irregular heartbeats and abnormal oxygen levels. The system demonstrated improved early detection capabilities compared to rule-based systems. However, the model generates false positives in dynamic conditions and requires continuous retraining to maintain accuracy.

Zhou and Feng (2021) introduced a Deep Forest (gcForest) model for healthcare data analysis. The model uses a cascade of decision tree ensembles to perform hierarchical feature learning. It provides competitive accuracy with lower computational cost and minimal hyperparameter tuning. However, the model lacks temporal learning capability and struggles with large-scale datasets.

Rahman et al. (2022) proposed a federated learning-based healthcare monitoring system using distributed IoT devices. This approach ensures data privacy by keeping patient data local while sharing model updates. Tang et al. (2022) developed a Spatiotemporal Graph Attention Network (ST-GAT) for healthcare monitoring. The model captures relationships between physiological signals and temporal dependencies.

The attention mechanism enhances feature importance weighting, improving prediction accuracy. However, the model requires complex graph construction and high computational resources. Huang et al. (2023) proposed an Enhanced Residual Multi-Scale Diverged Self-Attention Network, representing the most advanced architecture in this domain. The model achieved state-of-the-art performance in healthcare monitoring tasks, outperforming CNN, LSTM, and Transformer models. However, it is computationally expensive and requires optimization for real-time deployment.

**Comparative Table**

| No. | Model | Key Strength | Limitation |
|---|---|---|---|
| 1 | CNN-LSTM | Hybrid learning | Complex |
| 2 | ConvLSTM + Attention | Spatiotemporal | Heavy |

| | | | |
|---|---|---|---|
| 3 | IoMT + ML | Real-time | Limited accuracy |
| 4 | CNN-LSTM ECG | High accuracy | Resource heavy |
| 5 | IoT DL | Remote monitoring | Noise |
| 6 | CNN | Feature extraction | No temporal |
| 7 | CNN-LSTM | Balanced | Complex |
| 8 | BiLSTM + Attention | High accuracy | Heavy |
| 9 | Autoencoder | Dimensionality 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 | Feature 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 |
| 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 Learning | Privacy | Communication overhead |
| 29 | ST-GAT | Spatial + temporal | Complex |
| 30 | Residual Multi-Scale Attention | Best performance | Very complex |

**Comparative Analysis**

The analysis of the 30 studies demonstrates a clear progression in smart healthcare monitoring systems from traditional machine learning models to advanced deep learning architectures. Early systems primarily focused on IoT-based data collection and basic machine learning models, which enabled real-time monitoring but lacked predictive accuracy and robustness. With the introduction of deep learning models such as CNN, LSTM, and GRU, the ability to analyze complex biomedical signals improved significantly. Hybrid models like CNN-LSTM emerged as a dominant approach due to their ability to capture both spatial and temporal dependencies. These models provided better accuracy in detecting abnormalities in physiological signals.

The integration of attention mechanisms marked a major advancement in healthcare monitoring systems. Attention-based models improved feature selection and interpretability, enabling better prediction performance. Models such as BiLSTM with attention and DA-RNN demonstrated superior accuracy compared to traditional architectures. Recent advancements have focused on more sophisticated architectures such as Transformer models, Graph Neural Networks (GNNs), and ensemble learning approaches. These models provide improved scalability, robustness, and the ability to capture complex relationships in healthcare data. Transformer models, in particular, have shown exceptional performance in handling long-term dependencies.

The most advanced approach identified in this review is the Enhanced Residual Multi-Scale Diverged Self-Attention Network, which combines residual learning, multi-scale feature extraction, and self-attention mechanisms. This architecture provides superior performance by capturing both fine-grained and global patterns in healthcare data. Despite these advancements, challenges such as computational complexity, energy consumption, data privacy, and lack of interpretability remain significant barriers to real-world deployment. Future research should focus on developing lightweight, explainable, and energy-efficient models for practical healthcare applications.

**Discussion**

The integration of IoT and deep learning technologies has significantly enhanced smart healthcare monitoring systems. IoT devices enable continuous data collection, while deep learning models improve prediction accuracy and anomaly detection. Hybrid models and attention-based architectures 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 undergone significant advancements with the integration of IoT and deep learning technologies. This survey analysed research contributions from 2020 to 2023, highlighting the evolution of models and architectures used in patient monitoring systems. Early approaches relied on IoT-based monitoring and traditional machine learning models, which provided real-time data but lacked predictive accuracy. The introduction of deep learning models such as CNN, LSTM, and GRU significantly improved the ability to analyse complex biomedical signals.

Hybrid models combining CNN and LSTM emerged as a powerful approach for capturing both spatial and temporal dependencies. Attention-based models further enhanced performance by focusing on relevant features in the data. Recent advancements such as Transformer models and Graph Neural Networks have improved scalability and accuracy in large-scale healthcare systems. The proposed Enhanced Residual Multi-Scale Diverged Self-Attention Network represents the most advanced architecture, offering superior feature extraction and prediction accuracy. However, challenges such as computational complexity, data privacy, and energy consumption remain. Future research should focus on developing lightweight, explainable, and energy-efficient models to ensure practical deployment in real-world healthcare systems.

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