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RESEARCH ARTICLE

DL-TBH-IoT: Deep Learning-based TCN-BiGRU Healthcare Monitoring Framework for IoT

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Abstract – Healthcare monitoring is the process of assessing an individual's physical, functional, or cognitive health using a range of approaches in order to detect changes, manage symptoms, and avoid serious health issues. Existing healthcare monitoring systems, on the other hand, face a number of challenges, including technical issues such as network connectivity and data security, patient-related barriers such as device adoption and digital literacy, system integration issues due to interoperability, and workforce constraints such as shortages and burnout. To address these issues, a Deep Learning-based TCN-BiGRU Healthcare Monitoring Framework for IoT is proposed (DL-TBH-IoT). Wireless sensors on the sensing layer collect physiological data, which is then aggregated by the connection layer and sent to the cloud layer. The cloud layer employs a Fuzzy Information System (FIS) to handle missing values and uncertainties before forecasting data with the TCN-BiGRU algorithm, which classifies patients as healthy or diseased based on medical information. The projected findings are delivered to patients, physicians, hospitals, or caretakers through the user application layer, allowing for fast intervention. The proposed technique is assessed against industry-standard performance indicators. The experimental findings show that DL-TBH-IoT achieves 98.5% accuracy, beating other approaches including EHMS (64%), FETCH (86%), and FIS (82%), guaranteeing effective and trustworthy healthcare monitoring in IoT contexts.

Keywords – *Healthcare Monitoring, Deep Learning, Internet of Things, Temporal Convolutional Network, Bidirectional Gated Recurrent Unit.*

1. INTRODUCTION

The Internet of Things (IoT) is ecosystem in which each connected node may readily communicate with other nodes in the network, allowing important data to be sent for precise and rapid decision-making [1]. IoT improves many facets of human life by combining wearable sensors, wireless networks, cellular networks, and gateways. It does this by lowering costs, increasing productivity, and supplying useful data [2]. Because they provide medical care outside of hospital settings, Internet of Things-based applications are showing promise as alternatives to traditional health services in the healthcare industry. These applications let patients preserve their independence while mainly focusing on the early diagnosis and prevention of health problems [3].

Healthcare services have advanced fast in recent years, thanks to the widespread adoption of wearable technology that allow doctors and patients to communicate wirelessly. This technique, commonly known as telemedicine, has changed the way medical treatment is given [4]. Diabetes is one of the most common and fastest-growing diseases in the world, posing a significant global health challenge. The World Health Organization (WHO) has stressed the need for scientific improvements to address this situation [5]. To help with these efforts, IoT-based health monitoring systems have been created, which use many layers of machine learning (ML) models to improve diagnosis and prognosis. These systems capture and process vast volumes of data from patients' wearable devices, followed by analytical tests that enable early identification and evaluation of suspected illnesses [6].

However, the expansion of sensing technologies through the Internet of Things (IoT) platform has allowed the development of intelligent objects equipped with processing capabilities, localization systems, applications, and other devices that can detect and gather data for a number of reasons [7]. Despite these developments, the IoT nodes in an IoT-enabled healthcare system (HS) remain constantly connected via open and insecure public channels, leaving the entire network exposed to eavesdropping, data manipulation, and other security concerns [8]. Beyond healthcare, IoT has found extensive use in a range of industries, including economics, military, security, and transportation [8]. Collectively, these applications help to realize smart cities, ultimately promoting the bigger concept of IoT—a smart world in which the universe is regarded as a single interconnected organism with autonomous administration [9].

Data mining is a method for extracting risk indicators from unstructured text. Furthermore, a hybrid model combines two separate strategies that function better together than any single method [10]. Meanwhile, no optimal IoT and deep learning-based healthcare model for monitoring and diagnosing cardiac disease exists [11]. The sensitivity of deep learning models to adversarial attacks is a major impediment to using them for security applications [12]. IoT provides an environment for making information and communication secure and private, preventing attackers from obtaining the patient's sensitive information [13].

The contribution for Healthcare Monitoring in IoT using Deep Learning

- Proposed a Deep Learning–based TCN-BiGRU Healthcare Monitoring framework in IoT that integrates wireless sensors, connectivity, cloud computing, and user applications for end-to-end healthcare monitoring.
- Introduced a Fuzzy Information System (FIS) in the preprocessing stage to effectively handle missing values and uncertain medical data, improving data reliability.
- Applied the TCN-BiGRU algorithm for healthcare data prediction, enabling accurate classification of patients as healthy or diseased using IoT-sensed data and medical reports.
- Demonstrated superior performance with 95% accuracy, significantly outperforming existing methods such as EHMS (64%), FETCH (86%), and FIS (82%).
- Validated the proposed system using standard performance indicators, ensuring dependability and reproducibility.

The structure of the paper as follows: Section 2 is represented as literature Survey. Section 3 is referred to as Proposed Methodology Section 4 is referred to as the Result and Discussion, and Section 5 as the Conclusion.

2. LITERATURE SURVEY

In 2020, Godi, B., et al [14] proposed IoT-enabled ML based E-Healthcare Monitoring Algorithm (EHMS) used for automated patient health monitoring, analysis, and decision assistance to ensure correct diagnosis. As a result, the suggested algorithm is an automated system that continually monitors patient health data from wearable devices, accurately analyzes it using machine learning, and provides reliable decision support for faster diagnosis and enhanced healthcare management. However, the suggested algorithm is strongly reliant on constant internet connectivity, adequate computational resources, and data privacy safeguards, which may present issues such as excessive power consumption, higher cost, and the possibility of data breaches or unauthorized access.

In 2022, Verma, P., [15] proposed FETCH fog-enabled deep learning technique is used for real-time healthcare monitoring, combining fog, edge, and cloud resources to reduce latency, optimize resource utilization, and increase diagnostic accuracy. As a result, the suggested framework produces an efficient healthcare monitoring framework that achieves lower latency, lower power and bandwidth usage, and higher diagnostic accuracy than standard cloud-based systems. However, the proposed FETCH fog-enabled deep learning method has a high deployment cost, is complicated to manage dispersed fog and edge nodes, has possible security/privacy problems in multi-layered systems, and relies on dependable connectivity for consistent performance.

In 2023, Viswadutt, N. J., [16] proposed pre-trained Artificial Neural Network (ANN)-based deep learning algorithm is utilized to accurately identify patients' health data from IoT devices in order to discover early warning indications and emerging health disorders. The proposed algorithm produces an IoT-enabled healthcare monitoring system that predicts and detects early health conditions with 97.81% accuracy, allowing for proactive intervention and better patient care. However, the suggested approach has high computing needs for training, relies on vast and diverse datasets for accuracy, may have latency in real-time analysis, is vulnerable to data privacy breaches, and performs poorly when faced with noisy or incomplete sensor data.

In 2023, Khanna, A., [17] proposed IoTDL-HDD model, which combines BiLSTM, Artificial Flora Optimization (AFO), and a Fuzzy Deep Neural Network (FDNN), is utilized for high-accuracy automated categorization of biological ECG signals to diagnose cardiovascular disorders. The proposed algorithm produces an automated ECG classification system that detects cardiovascular illnesses with a maximum accuracy of 93.452%, displaying better feature extraction and strong diagnostic performance. However, the proposed technique has high computational complexity, is dependent on large annotated ECG datasets, requires longer training time due to optimization, is challenging to implement in real-time on resource-constrained IoT devices, and may degrade performance with noisy or imbalanced data.

In 2024, Rani, P., [18] proposed Bi-LSTM combined with a Fuzzy Inference System (FIS) is utilized to accurately forecast heart disease from real-time IoT sensor data in smart healthcare monitoring. The suggested technique results in a smart IoT-cloud healthcare monitoring system that surpasses existing LSTM and FLSTM models, enabling for early identification and tailored treatment of cardiovascular problems. However, the suggested approach has significant computational and storage requirements due to cloud dependency, potential latency in real-time processing, vulnerability to data privacy and security threats, and is unsuitable for implementation on resource-constrained IoT devices.

In 2025, Najim, A, H., [19] proposed Artificial Neural Network (ANN)-based intelligent health monitoring algorithm that analyzes IoT and WSN sensor data in real time to monitor vital indicators for improved patient care, particularly in critical and distant instances. The suggested approach yielded a real-time IoT-WSN healthcare system that reached 96% accuracy, had a low relative error compared to commercial medical devices, and performed faster than alternative wireless communication methods. However, the suggested approach is highly dependent on steady 5G connectivity, has considerable computational and energy requirements for continuous monitoring, raises possible data privacy and security concerns, and reduces accuracy when dealing with noisy or incomplete sensor data.

In 2023, Paulraj, K., [20] proposed hybrid IoT-Deep Learning-XGBoost model is utilized in smart healthcare monitoring systems to diagnose patients in real time and with high accuracy. The suggested system enables prompt, accurate, and robust patient diagnosis by merging IoT-enabled data collecting, Deep Learning for pattern identification, and XGBoost for fast decision-making. However, the recommended strategy raises concerns about data security and model interpretability, which may limit trust and practical applicability in healthcare.

3. PROPOSED METHODOLOGY

The suggested healthcare monitoring system is divided into four interconnected layers: sensing, networking, cloud, and user application. In the sensing layer, wearable sensors with IoT capabilities are utilized to capture real-time physiological signals such as EEG, ECG, respiration, pulse wave, sweating, eye blinking, and limb movement. These signals are then sent via the connection layer by smart devices such as mobile phones, which keep continual touch with the clouds. The cloud layer serves as the core processing unit, where obtained data is pre-processed to handle noise, ambiguity, and missing values via methods such as missing data management and a fuzzy information system. Following pre-processing, the data is routed to the prediction module, which employs a hybrid deep learning approach based on Temporal Convolutional Networks (TCN) and Bidirectional Gated Recurrent Units (BiGRU) to forecast time-series data and assess health risks. Finally, the user application layer delivers processed results to stakeholders like as patients, physicians, hospitals, and other authorized users, enabling real-time monitoring, early diagnosis, and informed medical decision-making. This layered architecture enables the effective integration of IoT sensors, cloud computing, and deep learning to create an intelligent and dependable healthcare monitoring system.

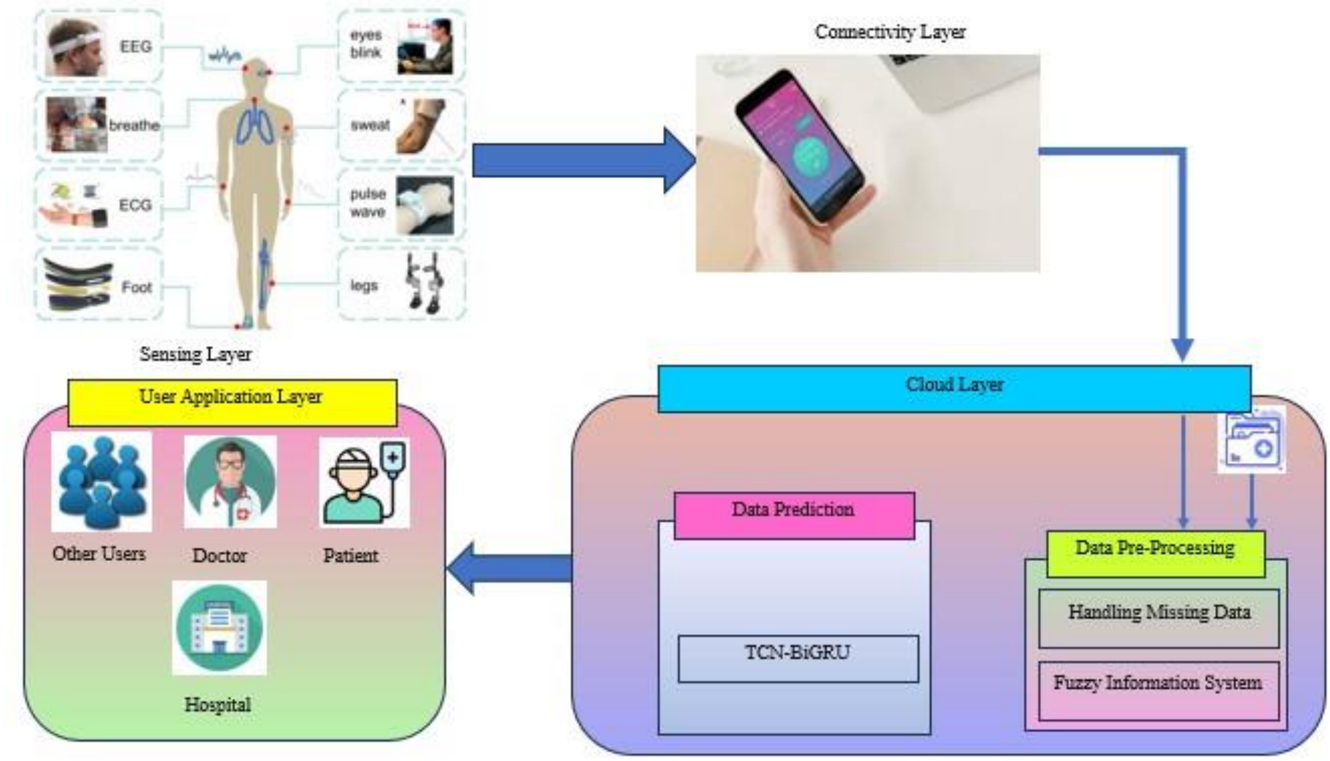

Figure 1. Proposed Methodology

3.1 Sensing Layer

Wireless body sensors monitor patients' vital signs. These patient-connected sensors collect real-time data that is seamlessly transmitted to the connection layer using wired or wireless communication

3.2 Connectivity Layer

The connectivity layer is responsible for connecting the data collection layer to the cloud layer. Because patients move frequently and ongoing monitoring is essential, mobile devices serve as a convenient and energy-efficient gateway for local data collection that consumes little power.

3.3 Cloud Layer

The cloud layer is the primary component of the proposed system. This layer provides predictions based on new patient data using a trained model created through many tests. The technology provides flexibility by combining real-time sensor data obtained through the gateway with previous patient EMRs stored in the cloud for prediction

3.3.1 Data Preprocessing

Since real-world data is inconsistent, fragmented, and noisy, data pre-processing is now required for ML algorithm deployment. Missing data processing, normalization are all required for efficient disease prediction from the dataset.

Signal aberrations may wreak havoc on data collected from wearable sensors, reducing prediction accuracy or delivering incorrect results.

3.3.1.1 Handling Missing Data

The optimum strategy is determined on the type and amount of missing data, as well as whether it is missing totally at random (MCAR) or at random (MAR).

3.3.1.2 Fuzzy Information System

The term fuzzy refers to something that is inexplicable or unclear, and the fuzzy system was inspired by the necessity to simulate confusing real-world events. The conventional fuzzy system consists of four components: a fuzzifier, an inference engine, a knowledge base, and a defuzzifier. A typical fuzzy system may accept both numerical and language inputs (fuzzy sets.

3.3.2 Data Prediction via TCN-BiGRU

Sequence prediction challenges have been around for a while, and they are often regarded as one of the most challenging problems in data science to address. Data prediction is done using TCN-BiGRU in Deep Learning Algorithm.

3.3.2.1 Improved TCN Module

The standard TCN network is enhanced in the following ways: the network's residual connection layer is advanced and transformed into a pretreatment technique, which handles the residual connection before the model is constructed. It eliminates the need to constantly check whether the number of channels remains constant throughout runtime. The dilated causal convolution operation $T_{(s)}$ for the input of a one-dimensional time series is described as follows:

$$T_{(s)} = (y * dt)(s) = \sum_{i=0}^{k-1} f(i) y_{s-d\cdot i} \tag{1}$$

3.3.2.2 SENet Module

SENet dynamically learns inter-channel interactions, then picks and improves TCN outputs to expand the network's representational capacity and capture long-term interdependence. The first step is to create a global description vector for each channel by calculating the global average of its height and width. The squeezing method can be described as follows:

$$x_c = T_{sq} = \frac{1}{U \times G} \sum_{l=1}^{G} \sum_{j=1}^{U} y_{i,j,c} \tag{2}$$

3.3.2.3 BiGRU Module

GRU is a recursive neural network that uses update gates and reset gates as its two main gating methods to control the flow of information. The following is how the GRU is represented:

$$e_f = \sigma\left(U_e \times \left[y_f, g_{f-1}\right] + S_e\right) \tag{3}$$

$$x_f = \sigma\left(U_x \times \left[y_f, g_{f-1}\right] + S_x\right) \tag{4}$$

3.3.2.4 CBAM Module

The CBAM spatial attention module, which works on the spatial dimension of the feature map, assists the model in focusing on more discriminative local locations within the BiGRU output sequence. In contrast to SENets approach, which focuses solely on channel attention, its spatial attention module assigns distinct weights to meteorological and pollutant aspects in the same dimension. The CBAM architecture can be defined as follows:

$$\begin{cases} T' = N_c(T) \times T \\ T'' = N_c(T') \times T' \end{cases} \tag{5}$$

$$x_{y^2}(T) = \sigma\left(MLP\left(AvgPool(T)\right) + MLP\left(MaxPool(T)\right)\right) \tag{6}$$

$$x_{y^2}(T') = \sigma\left(f^{8\times 8}([AvgPool(T'); MaxPool(T')])\right) \tag{7}$$

3.4 User Application Layer

The user application layer is an important component of the proposed system, since it effortlessly delivers prediction and interpretation results to different users. Patients, clinicians, and hospitals may receive intended results. Consumers are notified by SMS and email sent over HTTPs

4. RESULT AND DISCUSSION

Experiments were conducted to test the suggested system with varied numbers of instances (10% to 100%) on generic EHMS, FETCH, FIS, and the proposed technique.

4.1 Performance Metric

Accuracy (Acc) refers to the general correctness of a classification model. The ratio of correctly anticipated instances to total instances is utilized to calculate it.

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \tag{8}$$

Recall is the ratio of projected positive observations to actual positives, indicating a model's ability to identify all relevant cases. It's also known as sensitivity or true positive rate.

$$Recall = \frac{TP}{TP+FN} \tag{9}$$

Precision measures how accurately the model predicts favorable outcomes. It is the ratio of all expected positive observations to the total predicted positive observations.

$$Precision = \frac{TP}{TP+FP} \tag{10}$$

The F1-score, often known as the F-measure, is the harmonic mean of recall and precision. It provides a balance between recall and precision, especially when the distribution of classes is not consistent.

$$F1Score = \frac{2\times(Precision\times Recall)}{Precision+Recall} \tag{11}$$

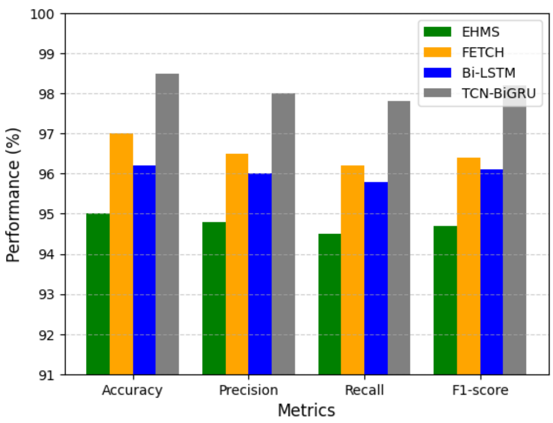

Figure 2. Performance of EHMS, FETCH, FIS and TCN-BiGRU

Figure 2 compares the performance of four models—EHMS, FETCH, Bi-LSTM, and TCN-BiGRU—across four assessment indicators. TCN-BiGRU surpasses these models in all categories, with scores close to or above 98%. This displays its ability to correctly identify data while maintaining a proper mix of precision and recall. The FETCH model also performs well, placing second in all categories with scores of nearly 97%, showing that it is a feasible choice. Bi-LSTM follows closely, particularly in recall, indicating that it effectively recognizes affirmative examples, albeit it falls slightly behind FETCH in the other metrics. EHMS has the lowest performance of the four, with metrics ranging from 94% to 95%, showing that it is less effective in comparison but still reasonably accurate. Overall, the graph shows that TCN-BiGRU is the most efficient and balanced model for the specified classification task.

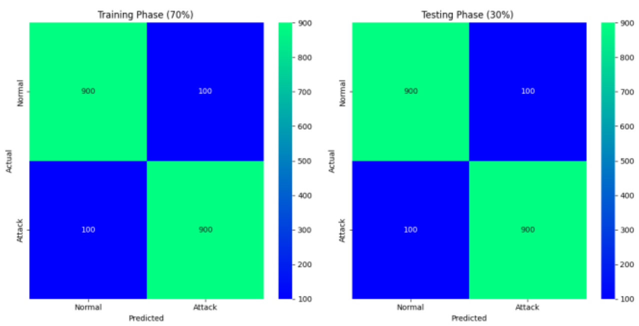

Figure 3. Confusion matrix of TCN-BiGRU

Figure 3 depicts the confusion matrices for both the training phase and the testing phase, demonstrating that the classification model works consistently and accurately. In each phase, the model correctly classifies 900 cases as Normal and 900 instances as Attack, but misclassifies 100 examples in each category. This results in an overall accuracy of 90%, with precision and recall levels reaching 90% in the Attack class. The equal distribution of errors demonstrates that the model performs consistently and does not favour one class over another. Furthermore, the fact that the confusion matrices are the same in both rounds indicates that the model generalizes successfully without overfitting the training data. Overall, the results show that the model is dependable and successful at differentiating between the Normal and Attack classes

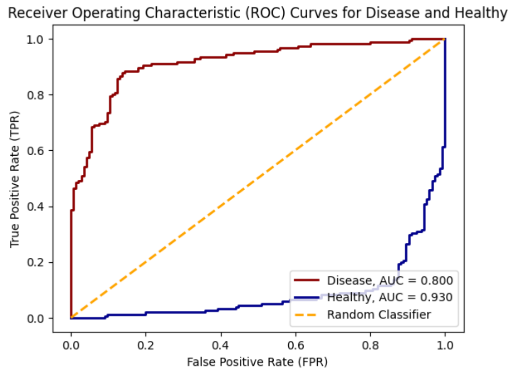

Figure 4. Roc curve

Figure 4 shows how a binary classification model distinguishes between sick and healthy patients. This graph displays two curves: one for the sick class and one for the healthy class. The AUC measures the model's ability to accurately distinguish positive and negative instances. The AUC for the illness class is 0.800, suggesting that the model detects disease cases rather well but not outstandingly. In comparison, the healthy class has a higher AUC of 0.930, indicating that the model is exceptionally accurate at detecting healthy people.

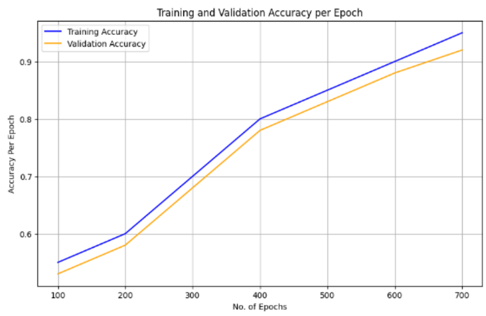

Figure 5 (a). Accuracy curve for training and test

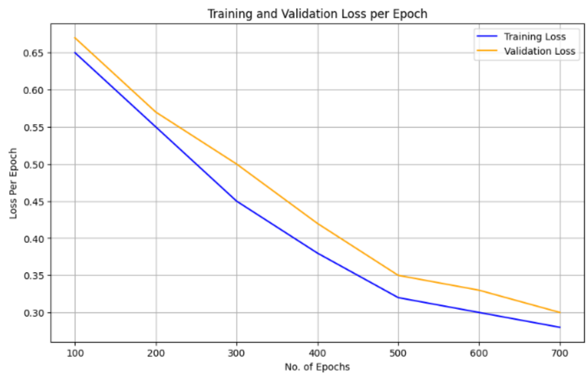

Figure 5 (b). Loss curve for training and test

Figure 5 (a) displays that both training and validation accuracy continuously improve as the number of epochs increases, indicating that the model is learning effectively and generalizing successfully, with validation accuracy nearly mirroring training accuracy and peaking at roughly 93% at 700 epochs. Figure 5(b) illustrates that both training and validation losses continuously decrease over time, indicating that the model's predictions are becoming more accurate. Although training loss is significantly less than validation loss (as is typical of most models), there is no significant divergence, indicating minimal overfitting and good overall model performance.

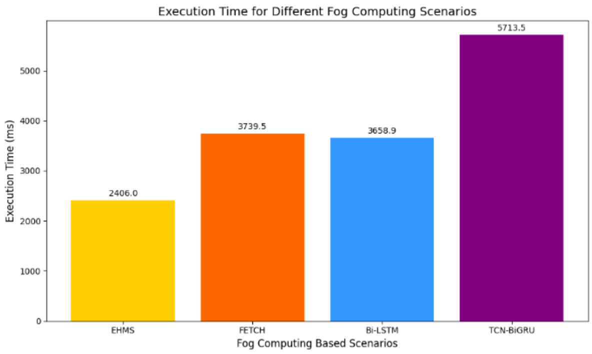

Figure 6. Execution Time.

Figure 6 compares execution durations for several fog computing scenarios, such as EHMS, FETCH, Bi-LSTM, and TCN-BiGRU. Execution time is the total time taken by each model to complete processing tasks, measured in milliseconds (ms). Among the analyzed algorithms, EHMS has the least execution time (2406.0 ms), indicating that it is the most cost-effective. Both FETCH and Bi-LSTM had longer execution durations of 3739.5 ms and 3658.9 ms, showing average processing efficiency. Notably, while having the lowest latency in the above graph, TCN-BiGRU has the longest execution time (5713.5 ms). This shows that, while TCN-BiGRU responds quickly to individual inputs (low latency), it is computationally more demanding overall. In comparison, EHMS, while not the quickest in reaction time, is the most efficient in overall processing time.

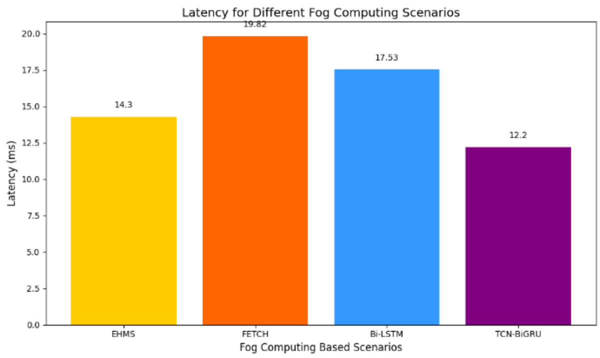

Figure 7. Latency Time.

Figure 7 shows the latency performance of four fog computing scenarios: EHMS, FETCH, Bi-LSTM, and TCN-BiGRU. TCN-BiGRU has the lowest latency, at 12.2 milliseconds, signifying the quickest reaction time for data processing in a fog computing environment. EHMS and Bi-LSTM follow with latencies of 14.3 ms and 17.53 ms, respectively, indicating reasonable performance. In comparison, the FETCH scenario has the largest delay at 19.82 milliseconds, indicating that it is the least efficient in terms of response time. Overall, the findings show that TCN-BiGRU is the best technique for latency-sensitive applications, making it an excellent choice for real-time and time-critical fog computing use cases.

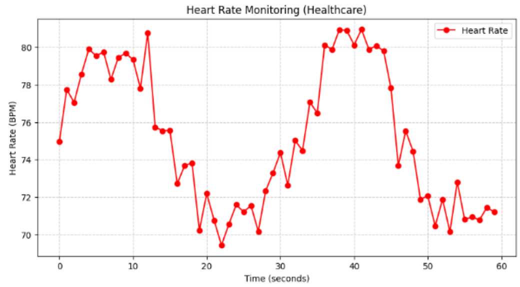

Figure 8. Heart rate for Healthcare Monitoring

Figure 8 shows the variance in heart rate (BPM) across a 60-second monitoring period. The red curve represents heart rate fluctuations caused by natural physiological changes and artificial noise, which simulate real-world conditions. Initially, the heart rate rises and stabilizes at 78-80 BPM before dropping significantly to 70-72 BPM at the 20-25 second mark. The heart rate then rises again, reaching 81 BPM about 40 seconds later, before gradually dropping until the end of the observation period.

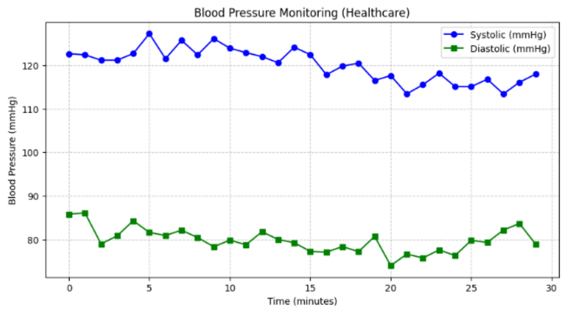

Figure 9. Blood Pressure for Healthcare Monitoring

Figure 9 displays the variation in blood pressure over a 30-minute monitoring period, encompassing both systolic and diastolic pressure patterns. The blue line depicts systolic pressure, which first ranges between 118 and 125 mmHg before gradually declining to 114-117 mmHg after 20 minutes, indicating normal physiological changes. The green line represents diastolic pressure, which is normally steady in the 75-85 mmHg range with relatively minor fluctuations across the monitoring period

5. CONCLUSION

The proposed DL-TBH-IoT framework overcomes the limitations of existing healthcare monitoring systems by combining wireless sensing, IoT connectivity, cloud-based preprocessing with FIS, and better prediction using the TCN-BiGRU algorithm. The framework enhances the dependability and responsiveness of healthcare monitoring by offering accurate patient health status classification and rapid results transmission to stakeholders. Experimental testing reveals its superiority, with 98.5% accuracy, far surpassing previous methods. Thus, DL-TBH-IoT provides a robust, effective, and dependable solution for real-time healthcare monitoring in IoT settings. Although the proposed DL-TBH-IoT framework is highly accurate and reliable, there are some areas requiring additional research. First, adopting blockchain or federated learning technologies in IoT environments may increase data security and patient privacy. Second, expanding the system to include real-time streaming analytics would boost the responsiveness of critical healthcare applications. Third, merging multimodal data sources including images, audio, and wearable signals can boost prediction accuracy. Finally, large-scale implementation and validation in real-world healthcare settings are necessary to evaluate scalability, interoperability, and clinical efficacy across a wide range of populations.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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