

OPTIMIZING IOMT BASED SMART HEALTHCARE WITH DEEP EHR-TANFLOW: A HYBRID ATTENTION DRIVEN MODEL

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Abstract

The increasing demand for efficient and accurate disease diagnosis in Internet of Medical Things (IoMT)-based smart healthcare systems necessitates advanced predictive models that capture complex temporal dependencies in Electronic Health Records (EHR) data. However, existing approaches often struggle with long-term dependency modelling, feature redundancy, and computational inefficiency, which limits their applicability in real-world clinical settings. To address these challenges, this research introduces the Deep Learning EHR-Based Temporal Attention Flow (Deep EHR-TANFlow) framework. This novel architecture processes structured EHR data without requiring direct physical intervention. The framework begins with a robust preprocessing pipeline that incorporates KNN imputation for missing values, Min–Max scaling for normalization, and a sliding-window strategy to generate refined temporal segments. This ensures high-quality, structured input suitable for effective temporal predictive modelling. At its core, the framework employs the CNN–BiGRU Temporal Attention Network (CG-TAN), developed specifically for IoMT-based healthcare monitoring. The model integrates Convolutional Neural Networks (CNN) for local feature extraction, Bidirectional Gated Recurrent Units (Bi-GRU) for modelling forward and backward temporal dynamics, and a Self-Attention (SA) mechanism to enhance global contextual representation. This hybrid architecture effectively captures both local and global dependencies within patient data, significantly improving disease prediction and risk assessment. Experimental results demonstrate that the proposed system achieves superior diagnostic performance, attaining 98% accuracy, 98.12% precision, and 98.08% F1-score. These findings highlight the resilience, efficiency, and low computational complexity of the Deep EHR-TANFlow framework, making it a dependable solution for IoMT-based continuous health monitoring and automated risk assessment while ensuring reliable information extraction and enhanced patient safety.

Keywords: Health monitoring System; IoMT; Health information system; Temporal Attention Network; Disease Diagnosis; Risk Assessment; Predictive Modelling

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Introduction

The rapid expansion of the Internet of Medical Things (IoMT) has transformed healthcare monitoring by enabling real-time collection, processing, and transmission of patient data through interconnected medical devices and wearable sensors (Pradyumna *et al.*, 2024). IoMT facilitates continuous health monitoring, enhancing accessibility, early diagnosis, and the management of various medical conditions (Adewole *et al.*, 2021). By integrating intelligent sensors with cloud computing and AI-driven analytics, IoMT has shifted conventional healthcare models toward proactive, personalized, and patient-centric solutions (Badawy, 2023). These advancements not only improve clinical outcomes but also reduce hospital visits and support remote monitoring, thereby alleviating pressure on healthcare infrastructure.

One of the significant advantages of IoMT-based healthcare systems is that these systems are able to provide real-time insights into the physiological state of a patient (Mishra & Singh, 2023). Wearable devices such as smart watches, biosensors, and smart medical implants continuously track vital health parameters, including heart rate, blood pressure, oxygen saturation, and glucose levels. These data streams are transmitted to cloud platforms where advanced machine learning models analyze trends, detect anomalies, and generate actionable insights (Prieto-Avalos *et al.*, 2022). The integration of AI with IoMT significantly enhances early diagnosis, enables timely interventions, and supports personalized treatment planning, improving overall system efficiency.

Despite its extensive benefits, IoMT-based healthcare monitoring faces critical challenges related to data security, privacy, and interoperability (Al Khatib *et al.*, 2024). The massive volume of medical data produced by IoMT devices increases the risk of cyberattacks, underscoring the need for robust encryption, secure communication protocols, and Blockchain-enabled security mechanisms (Lodha *et al.*, 2023). Additionally, heterogeneity in device formats, data structures, and communication standards creates significant interoperability barriers, emphasizing the need for standardized protocols to enable seamless data exchange across healthcare platforms. Addressing these challenges is essential for the reliable and safe deployment of IoMT solutions in clinical environments (Wagan *et al.*, 2022).

IoMT has also enabled major advancements in remote patient monitoring (RPM), which is especially valuable for individuals with chronic diseases such as diabetes, hypertension, and cardiovascular disorders (Boikanyo *et al.*, 2023). RPM systems continuously track patient health metrics and enable clinicians to provide remote consultations, reducing unnecessary hospital visits and allowing healthcare providers to focus attention on high-risk patients who require immediate care (El-Rashidy *et al.*, 2021). This enhances patient convenience while optimizing healthcare resources.

Moreover, IoMT-driven predictive analytics has become a key component of modern healthcare decision-making. Predictive models leverage both historical and real-time data to identify potential health risks, recommend preventive measures, and improve treatment strategies (Rashmi & Gomathi, 2024). The integration of deep learning techniques with IoMT allows clinicians to anticipate disease progression, detect early signs of deterioration, and deliver personalized interventions (Awotunde *et al.*, 2022). This data-driven approach enhances diagnostic accuracy and advances precision medicine, ultimately improving overall healthcare quality (Hsiao *et al.*, 2022).

In summary, IoMT has emerged as a transformative force in healthcare monitoring, enabling intelligent, data-driven, and proactive patient care (Yadav, 2024). Although challenges related to data security, interoperability, and computational complexity persist, advancements in AI, cloud computing, and blockchain technologies continue to demonstrate significant potential in addressing these limitations. By harnessing the capabilities of IoMT, healthcare is moving toward smart, personalized, and highly efficient systems that enhance disease prevention, early detection, and effective treatment, ultimately improving global health outcomes. Although hybrid CNN–RNN–Attention architectures have been explored in prior studies, most existing approaches are not optimized for the irregular, incomplete, and temporally heterogeneous nature of IoMT-based EHR data. This work introduces the Deep EHR-TANFlow Framework, which differs from conventional BiGRU-Attention models through:

- A domain-specific hybrid CG-TAN architecture that integrates CNN, BiGRU, and Self-Attention explicitly for structures IoMT EHR sequences, enabling

simultaneous local pattern extraction, long-term temporal modelling, and global dependency learning.

- A dedicated EHR preprocessing pipeline where KNN imputation, Min-Max Normalization, and sliding window temporal segmentation are designed to handle missing IoMT readings and irregular time intervals.
- A temporal Attention Flow mechanism that enhances representation quality by suppressing redundant features and emphasizing critical indicators.
- A lightweight architecture with low computational complexity, achieving 98% accuracy while remaining feasible for real-time IoMT devices.
- Integrated risk-score prediction, which extends beyond traditional disease classification to support early clinical intervention.

The remaining content of the study article is as follows: the related papers are discussed in the next section, and the 3rd section discusses the HRNN-based technique suggested in the model. Section 4 presents the system evaluation and discusses the results. Section 5 concludes with a review of the results and guidance for predictive work in the healthcare industry.

Related Works

Numerous studies have been conducted on the new technique known as IoMT. Numerous articles have been written by researchers from various angles, focusing on specific problems and challenges in applying AI technologies.

Islam *et al.* 2020 developed a smart healthcare system using IoT to monitor patient health and room conditions in real-time. The system, which included five sensors, had an error percentage of less than 5% in all cases. The system communicated patient conditions to medical staff via an online portal, enabling real-time processing and analysis. However, the system lacked advanced predictive analytics, limiting its ability to provide proactive healthcare interventions. Building upon IoT-enabled healthcare solutions, (Dahan *et al.*, 2023) developed an AI-powered IoMT telemedicine infrastructure for E-Healthcare, aiming to improve patient monitoring, prediction, diagnosis, and treatment. They collected patient data using wearable sensor devices and transmitted it via a gateway/Wi-Fi to an IoMT cloud repository. The data were preprocessed, features extracted, and classified

using Hybrid ResNet-18 and GoogleNet classifiers. The system's efficiency was validated through performance analysis, but challenges were encountered in handling real-time data transmission delays, impacting the responsiveness of healthcare alerts.

Similarly, (Akhtar *et al.*, 2023) presented a smart healthcare system that uses IoT devices to improve disease prediction and monitoring. In their investigation, patient data was first obtained using IoMT devices and then processed. Preprocessing includes removing damaged data and reducing noise to improve data quality. Wavelet entropy computation was used for feature extraction, while deep features were obtained using a Convolutional Neural Network (CNN). Both wavelet entropy and deep features were adaptively fused using an enhanced metaheuristic technique called adaptive wavelet entropy deep feature fusion. The final classification was performed using an Improved Recurrent Neural Network, with the RNN weights improved using a novel Multi-Verse Strategy-based African Vulture Optimization Algorithm (MVS-AVOA). While the system showed improved categorization performance, it struggled to handle large-scale healthcare datasets, resulting in increased computational overhead and slower processing times.

In an effort to enhance predictive modelling in healthcare, (Dileep *et al.*, 2023) used the UCI heart disease dataset and a real-time dataset to compare DL techniques with traditional methods. They proposed a cluster-based bidirectional long short-term memory model to improve accuracy. The C-BiLSTM model was compared with traditional classifiers like Regression Tree, Support Vector Machine, Logistic Regression, K-Nearest Neighbors, Gated Recurrent Unit, and Ensemble methods. However, the study faced limitations in handling class imbalances, leading to biased predictions, especially for minority-class samples. Focusing on the predictive potential of ML in IoMT, [Divya *et al.*, 2021] investigated the application of machine learning to manage the massive amounts of data generated by IoMT devices for cardiac disease prediction. Several machine learning techniques were used to improve prediction accuracy, with logistic regression showing the best results. To increase accuracy, a majority voting technique was used, which produced better results than individual models. However, the study encountered difficulties generalizing the model to diverse patient populations, resulting in reduced effectiveness with heterogeneous data.

Further advancing remote health monitoring, (Venkateswarulu *et al.*, 2023) developed an ML-based remote health monitoring framework to predict heart disease and diabetes using medical datasets. The framework uses industry-based smart devices to collect patient health information, which is then integrated through various nodes. The medical dataset undergoes preprocessing to normalize attributes and eliminate irrelevant features. The Unified Levy Modeled Crow Search Optimization algorithm is applied for optimal feature selection. The Most Probabilistic Guided Naïve Distribution classification model is used to predict a patient's health status. However, the study faced challenges in handling real-time data variations, making it difficult to adapt to dynamic patient health conditions.

Expanding the application of IoMT to elderly care, (Khan *et al.*, 2021) studied how to improve elderly care services by identifying the essential requirements of an elderly healthcare system. They used machine learning techniques such as SVM, KNN, and DT to improve predictive performance. The study found that the elderly healthcare service interface within the IoMT showed high accuracy during validation. However, the study faced limitations in adapting to the personalized, evolving healthcare needs of older adults, making

it difficult to provide fully customized care recommendations.

Focusing on neurological health monitoring, (Bhatt and Sharma, 2023) studied the implementation of an IoT-based system for continuous tracking of EEG limits in rehabilitation facilities. Their research focused on using EEG technology to identify changes in brain activity during treatment, which could increase therapy efficacy and functional outcomes. The study underscored the need to detect neurological alterations early in individuals suffering from acute ischemic stroke, as stroke-in-evolution or early neurological deterioration is frequently associated with poor clinical outcomes. The study aims to facilitate early stroke detection using an IoMT-based approach, allowing for prompt intervention and reducing consequences. Furthermore, the study advocated using wearable sensors that monitor and analyze brain activity to improve stroke treatment and reduce complications. However, the study faced limitations, including the susceptibility of EEG signals to environmental noise and motion artifacts, which could impair the accuracy of brain activity measurements.

Together, these studies highlight the evolving role of IoMT and AI-driven technologies in enhancing patient monitoring, disease prediction,

Table 1. Novelty Comparison of Deep EHR-TANFlow with Existing Works

Study / Model	DL Architecture	Handles Missing & Irregular EHR Data	Local Pattern Extraction (CNN)	Long-Term Temporal Dependency Modeling	Global Attention	Risk-Score Prediction	Computational Complexity	Novelty Gap / Limitation
Islam <i>et al.</i> , 2020	IoT Sensors + Rule-Based Monitoring	×	×	×	×	×	Low	No predictive modeling / Only monitoring
Dahan <i>et al.</i> , 2023	Hybrid ResNet-18 + GoogleNet CNN + Improved RNN (MVS-AVOA optimized)	×	✓	×	×	×	High	No temporal modeling; heavy architecture
Akhtar <i>et al.</i> , 2023	Improved RNN (MVS-AVOA optimized)	×	✓	✓	×	×	Very High	Computationally expensive; poor scalability
Dileep <i>et al.</i> , 2023	Cluster-Based BiLSTM	×	×	✓	×	×	Moderate	Fails to handle class imbalance; no IoMT focus.
Divya <i>et al.</i> , 2021	ML models + Majority Voting Feature	×	×	×	×	×	Low	No temporal or deep feature learning
Venkateswarulu <i>et al.</i> , 2023	Optimization + Naïve Classifier	×	×	×	×	×	Low	Not adaptable to dynamic real-time IoMT data
Khan <i>et al.</i> , 2021	SVM, KNN, DT	×	×	×	×	×	Low	No deep temporal modeling; lacks personalization
Bhatt & Sharma, 2023	IoT-based EEG Monitoring	×	×	×	×	×	Moderate	Sensitive to noise; lacks multimodal EHR fusion.
Proposed Deep EHR-TANFlow	CNN + BiGRU + Self-Attention + TANFlow	✓	✓	✓	✓	✓	Low	Specifically designed for IoMT-based EHR with local-global temporal learning and clinical risk interpretation

and remote health care services. While existing studies have demonstrated the potential of IoT/IoMT-enabled systems for patient monitoring and disease prediction, most current DL-based healthcare frameworks rely on traditional architectures such as CNNs, RNNs, LSTMs, GRUs, or hybrid models with basic attention mechanisms. These methods often suffer from critical limitations, including:

- Inadequate handling of irregular and incomplete EHR sequences.
- Insufficient modelling of long-term dependencies.
- Inability to simultaneously capture local (spatial) and global (temporal) patterns.
- Computational inefficiency when deployed on IoMT devices.
- Lack of risk-score-driven clinical interpretation.

The proposed Deep EHR-TAN Flow framework distinguishes itself by introducing a domain-specific hybrid CNN-BiGRU-Self-Attention architecture optimized for IoMT-based EHR data. Unlike prior work, it incorporates a Temporal Attention Flow mechanism, sliding-window segmentation, and a lightweight architecture suitable for real-time IoMT deployment, while also providing risk-score-based explanations aligned with clinical assessment procedures.

To clearly highlight the novelty relative to the existing literature, Table 1 presents a structured comparison.

Proposed Methodology

Existing approaches to disease diagnosis in IoMT-based smart healthcare systems often face challenges such as long-term temporal dependencies, feature redundancy, and computational inefficiencies. Traditional machine learning models, although effective in certain scenarios, are often unable to capture the complex temporal patterns inherent in Electronic Health Records (EHR) data, leading to suboptimal predictive performance. Additionally, many current frameworks rely on handcrafted feature selection methods, which may overlook important latent patterns within patient health records. Another major challenge is the high dimensionality of structured healthcare data, which often increases computational complexity and prolongs processing time. These limitations hinder the practical adoption of predictive models in healthcare

environments, where timely and accurate disease identification is critical.

To address these challenges, this study introduces the Deep Learning EHR-Based Temporal Attention Flow (DeepEHR-TANFlow) framework, a novel methodology designed to enhance disease diagnosis and risk assessment in IoMT-based smart healthcare systems. The overall processing flow of the proposed framework is illustrated in Figure 1, and its pseudo-code is presented in Algorithm 1. DeepEHR-TANFlow employs advanced deep learning techniques to process structured EHR data efficiently, enabling accurate risk predictions without requiring direct physical intervention. The framework consists of three primary stages: (i) preprocessing, (ii) feature extraction and sequence modelling, and (iii) prediction and risk assessment.

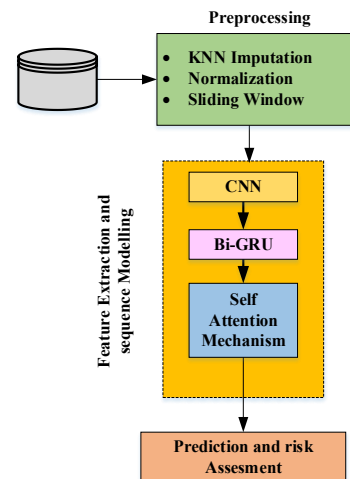


Figure 1. Working process of the proposed methodology

In the preprocessing stage, the framework ensures high-quality input data through KNN imputation for missing values, Min-Max scaling for numerical feature normalization, and a sliding-window technique for segmenting time-series data. This step refines the dataset by eliminating inconsistencies while preserving temporal relationships, which is essential for accurately capturing disease progression patterns. At the core of the system lies the CNN-BiGRU Temporal Attention Network (CG-TAN), specifically developed for IoMT-based healthcare monitoring using structured EHR data. To address this requirement, the CG-TAN architecture integrates Convolutional Neural Networks (CNNs) to extract localized semantic features and preserve spatial

relationships within structured health variables. Subsequently, Bidirectional Gated Recurrent Units (Bi-GRU) efficiently learn forward and backward temporal dependencies, enabling the model to represent short-term physiological dynamics in patient data.

Furthermore, a Self-Attention (SA) mechanism is incorporated to enhance global contextual understanding by prioritizing clinically significant patterns while suppressing redundant or noisy signals. Traditional boosting models cannot inherently learn these hierarchical temporal abstractions. Although TabTransformer introduces attention-enhanced tabular learning, it does not explicitly support recurrent sequence modelling and typically requires larger datasets for stable performance. In contrast, the hybrid CNN-BiGRU-Attention architecture is computationally lightweight, making it suitable for IoMT environments, while offering superior representational capability for micro-temporal EHR patterns. Finally, the Prediction & Risk Assessment stage uses these enriched temporal embeddings to classify disease risk and estimate future health deterioration, producing risk scores that help clinicians make early, informed, and precise interventions.

The DeepEHR-TANFlow Framework addresses the constraints of earlier methodologies. It introduces an enhanced deep learning-based predictive model, resulting in a scalable and efficient solution for illness diagnosis in IoMT-based smart healthcare systems. Its low computational complexity and high prediction accuracy make it an attractive option for health monitoring, leading to better patient care and more efficient use of medical resources.

Algorithm 1: DeepEHR-TANFLOW Model Execution

Input: Preprocessed EHR dataset
 Apply KNN imputation to handle missing values
 Normalize numerical features using Min-Max scaling.
 Segment time series data with the Sliding Window approach.
 Extract spatial features using CNN
 Apply Bi-GRU for sequential modelling.
 Enhance feature representation with multi-head self-attention
 Pass extracted features through FC layers.
 Use Sigmoid for probabilistic risk estimation.
 Output: Disease risk prediction with confidence score.

Data Preprocessing

Existing systems often struggle with incomplete datasets and inconsistent pre-processing techniques, resulting in erroneous predictions. To address these difficulties, a robust pre-processing pipeline is implemented. This includes KNN imputation for data imputation, data normalization to prevent skewness, and time-series segmentation using a sliding-window technique. These steps ensure complete, unbiased data without skewness, enhancing model performance and ensuring high-quality, complete data.

KNN Imputer

Information compiled from multiple sources may be incomplete in certain areas due to errors in data extraction. As a result, handling missing information is a crucial step in data preprocessing. Selecting the imputation technique is crucial because it can significantly affect the model's performance. KNN imputer is a popular technique for imputing missing values. It is widely used as an alternative to traditional imputation methods [Chen and Li, 2022]. When calculating nearest neighbours, the KNN imputer uses the Euclidean distance matrix, which removes missing values and assigns greater weight to non-missing coordinates.

$$D_{xy} = \sqrt{\text{weight} * \text{squared distance from present coordinates}} \quad (1)$$

Where;

$$\text{weight} = \frac{\text{total number of coordinates}}{\text{number of present coordinates}} \quad (2)$$

The second method for managing the data is to eliminate any missing values.

Data Normalization

It is a critical step in DL, especially when dealing with health data that can vary significantly in scale. The purpose is to align the values in the database to the same scale while preserving the diversity of their ranges. In healthcare datasets, features may be measured in different units, leading to scale variability that can negatively impact model performance. This work employed Min-Max normalisation, which rescales the information to a predetermined range. [0,1], to get around this problem.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (3)$$

This will maintain the relative relationships among values and ensure that all input features are on a similar scale, thereby preventing skewness and enhancing the model's learning capabilities.

Sliding Window

Time series segmentation is crucial for healthcare applications, as it allows models to learn from fixed-length sequences of data points rather than the entire dataset at once. Existing methods often fail to segment time-series data, leading to the loss of important temporal relationships and difficulty capturing the varying lengths of health events. The Sliding Window Technique for this process offers several benefits, including the creation of fixed-length sequences, capturing temporal dynamics, and flexibility in sequence length.

This preprocessing stage is crucial for ensuring the quality, consistency, and reliability of EHR data before it is fed into the predictive model. By addressing missing values, normalizing data, and segmenting time-series records, this stage effectively refines raw healthcare data to improve model performance. These preprocessing techniques not only mitigate inconsistencies and feature redundancy but also preserve the temporal integrity of patient health records, allowing for more accurate disease prediction and risk assessment. By standardizing and structuring the input data, the proposed preprocessing pipeline significantly enhances the efficiency of subsequent DL-based feature extraction and sequence modelling, ultimately contributing to the robustness and reliability of the DeepEHR-TANFlow framework in IoMT-based healthcare systems.

Although the Kaggle Heart Disease dataset is static and does not contain real, timestamped longitudinal records, temporal dependencies were simulated using a controlled sliding-window mechanism applied to feature-perturbed sequences. For each patient instance, micro-temporal variations were generated using clinically valid transformations such as small fluctuations in blood pressure, cholesterol, heart rate, and ST-segment measures. This allowed the model to observe short-term dynamics that resemble physiological variations typically recorded in clinical monitoring systems. Each synthetic sequence preserves the original feature distribution while introducing medically meaningful variability. This approach is widely used in studies that apply sequence models to static clinical

datasets and enables CNN-BiGRU-Attention networks to learn progression-like patterns rather than treating each record as an isolated snapshot.

CNN-GRU Temporal Attention Network

Existing predictive models for disease diagnosis in IoMT-based smart healthcare systems face several challenges, primarily related to handling long-term dependencies, feature redundancy, and computational inefficiencies. Traditional ML and DL approaches often struggle with capturing temporal dependencies in EHR data, leading to suboptimal predictions. Additionally, processing high-dimensional data increases computational complexity, limiting the scalability and applicability of these models in dynamic healthcare environments. To address these issues, CG-TAN is a novel DL architecture designed to efficiently process and analyze time series EHR data in IoMT-based healthcare systems. The architecture leverages the combined strengths of CNN, BiGRU, and SA to enhance feature extraction, temporal dependency modelling, and overall predictive accuracy. The combination of these components enables the network to efficiently capture both local and global patterns in patient health data, improving illness diagnosis and risk assessment. Figure 2 shows the architecture of the CG-TAN model.

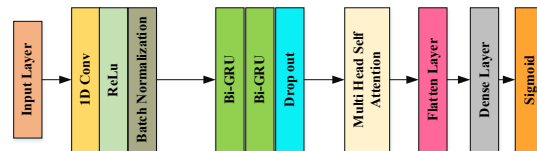


Figure 2. Architecture of the proposed CG-TAN Model

Convolutional Neural Network For Feature Extraction

The first stage of the CG-TAN employs a CNN module designed to extract meaningful geographic and local features from structured EHR data. Given the time-series nature of EHRs, this CNN employs 1D convolutional layers (Conv1D), making it well-suited to processing sequential medical data.

1D Convolutional Layer for Temporal Feature Extraction

The 1D convolutional layer is critical for recognizing local patterns and correlations in sequential health records. 1D convolutional layers apply sliding filters to the input data to detect patterns such as fluctuations in vital signs,

unexpected changes in test results, or recurring abnormalities in clinical parameters. These 1D filters move along the time axis of patient data, capturing temporal correlations between consecutive health events. Each convolutional layer consists of multiple filters, each of which recognizes distinct patterns in the data. For example, with an EHR dataset containing variables such as blood pressure, heart rate, glucose levels, and oxygen saturation, several filters specialize in extracting relevant medical patterns for illness diagnosis and risk assessment. The learned feature maps are then passed to the next layer for further refinement.

ReLU Activation for Non-Linearity

To incorporate nonlinearity into the network and improve feature discrimination, the Rectified Linear Unit (ReLU) activation function is implemented after each convolutional layer. The ReLU function is defined as follows:

$$f(x) = \max(0, x) \quad (4)$$

This activation function ensures that only positive activations are forwarded and all negative values are set to zero. ReLU helps prevent the vanishing gradient problem, allowing the CNN to learn complex patterns more efficiently. Increasing activation sparsity also enhances computational efficiency, making the model suitable for healthcare applications.

Batch Normalization for Stable Training

To improve convergence speed and stability during training, batch Normalization (BN) is incorporated after each convolutional layer. It normalizes activations across the mini-batch, reducing internal covariate shifts and ensuring consistent feature distributions. The transformation is given by,

$$\hat{x} = \frac{x - \mu}{\sigma} \quad (5)$$

Where μ is the batch mean and σ is the standard deviation. After normalization, the two learnable parameters scale (γ) and shift (β) restore flexibility to the network. This normalization technique stabilizes learning, mitigates vanishing or exploding gradients, and enables higher learning rates, ultimately improving the model's generalization capability.

Once the input EHR data has been processed through multiple convolutional layers, ReLU activations, and BN steps, the resulting feature maps are flattened and passed to the next

processing stage, the Bi-GRU module. This ensures that rich, high-level temporal features extracted by the CNN are effectively utilized for long-term sequence modelling in the next stage of the CG-TAN framework.

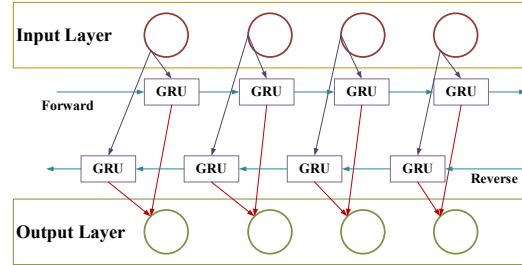


Figure 3. Architecture of the Bi-GRU model

Bi-GRU For Temporal Sequence Modelling

Since patient health data is inherently sequential, capturing long-term dependencies is crucial for accurate diagnosis, risk assessment, and early intervention. Traditional recurrent neural networks (RNNs) struggle to retain long-term dependencies due to vanishing gradients, making them inefficient for sequential medical data analysis. To address these limitations, the CNN extracted features are passed into a Bi-GRU network. This advanced RNN architecture retains critical information across long sequences while mitigating memory loss and computational inefficiencies. Additionally, traditional LSTM networks have been widely used in time series modelling but incur higher computational costs due to multiple gating mechanisms. Bi-GRU, a variant of GRU, simplifies this process by using only two gates instead of LSTM's three gates, such as forget, input, and output gates. This reduces computational overhead while retaining strong memory retention and efficient gradient flow, making it ideal for healthcare applications in IoMT-based systems. The Bi-GRU extends this approach by processing data in both forward and backward directions, ensuring a more comprehensive understanding of patient health trends. The structure of a single Bi-GRU (Anki *et al.*, 2021) is shown in Figure 3, which consists of

- Forward GRU Layer: Processes the input sequence from the past to the future (left to right)
- Backward GRU Layer: Process the input sequence from the future to the past (right to left)

- Concatenation Layer: Combines the outputs of both directions to form a rich representation of sequential dependencies. A GRU unit comprises two major gates,
- Update Gate (z_t): Determines how much past information should be retained or updated.
- Reset Gate (r_t): Controls how much past information should be forgotten before calculating the current state.
- Concatenation layer: Combines the outputs of both directions to form a rich representation of sequential dependencies

Figure 4 illustrates the GRU architecture, which is a detailed diagram of the forward and backward GRU layers, including update/reset gates and hidden-state concatenation (Yigit and Amasyali, 2022).

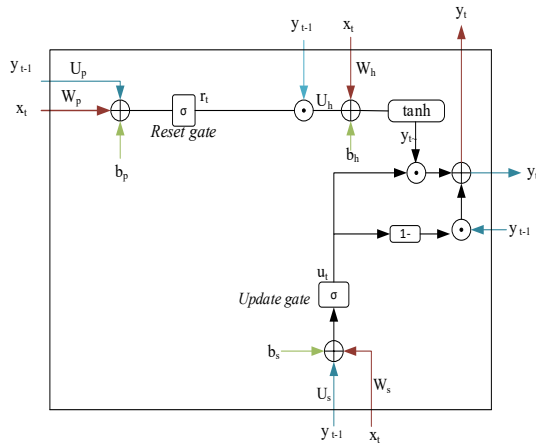


Figure 4. Structure of GRU

An input sequence X_t at time step t . The equations governing GRU behaviour are, For the updated Gate,

$$z_t = \sigma(W_z \cdot [h_{t-1}, X_t] + b_z) \quad (6)$$

For reset Gate,

$$r_t = \sigma(W_r \cdot [h_{t-1}, X_t] + b_r) \quad (7)$$

For Candidate Hidden state,

$$\tilde{h}_t = \tanh(W_h \cdot [r_t \odot h_{t-1}, X_t] + b_h) \quad (8)$$

Final Hidden State,

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (9)$$

Where $\odot$ represents element-wise multiplication, W_z , W_r , W_h and biases b_z , b_r , b_h . These are learnable parameters.

In a Bi-GRU, separate GRU units compute hidden states in both directions.

$$h_t^{bi} = [h_t^{forward}; h_t^{backward}] \quad (10)$$

This results in a richer representation of time-dependent features, preserving both past and future information.

By combining forward and backward hidden states, the Bi-GRU module creates a highly informative feature representation for disease diagnosis, ensuring the effective modelling of sequential dependencies in EHR data. By leveraging bidirectional processing, this module enhances the model's ability to detect disease risks, predict patient outcomes, and improve overall accuracy in IoMT-based smart healthcare monitoring systems. This enhanced feature representation allows for a more precise assessment of patient conditions, facilitating timely medical interventions and personalized treatment plans.

To further refine the model's predictive capability, Dropout layers are strategically incorporated after the Bi-GRU layer. It functions as an L2 regularization strategy that prevents overfitting by randomly deactivating a fraction of neurons during training, thereby reducing reliance on specific pathways and encouraging the network to learn more robust representations. By ensuring that no single neuron consistently dominates the learning process on unseen patient data. This is particularly important in healthcare applications, where overfitting to training data could lead to unreliable predictions when applied to diverse patient populations. Moreover, dropout helps mitigate model variance, ensuring the network remains resilient even when faced with noisy or incomplete health records.

By incorporating dropout with Bi-GRU's bidirectional learning, the model strikes a good balance between complexity and efficiency, making it well-suited for IoMT-based smart healthcare monitoring systems. This feature-extraction approach enhances disease risk assessment and improves patient outcome prediction, contributing to advances in AI-driven personalized healthcare.

Multi-Head Self-Attention Mechanism For Enhanced Feature Representation

To further refine CG-TAN's predictive capability, a multi-head SA mechanism is integrated to dynamically assess and weigh the importance of different time steps in the input sequence. Traditional DL models process sequential data in a stepwise manner, treating all time steps with equal significance. However, certain clinical events, such as sharp fluctuations in vital signs, abnormal lab results, or sudden spikes in patient symptoms, carry significantly more diagnostic value than routine readings. By utilizing an SA mechanism, the model assigns different attention scores to various time steps, ensuring that critical events and abnormalities in patient data are prioritized while minimizing the influence of less relevant observations.

The multi-head aspect of this mechanism enables the network to capture different types of dependencies within the patient data simultaneously. Instead of focusing on a single contextual relationship, multiple attention heads learn diverse patterns across different segments of the sequence, enhancing feature representation and improving the robustness of disease classification.

Fully Connected Layers And Final Prediction

After sequentially passing through the CNN, Bi-GRU, and self-attention, the extracted high-level feature representations are flattened and fed into a fully connected layer for classification. The flattening operation transforms the multi-dimensional output of previous layers into a one-dimensional feature vector, making it suitable for processing in a fully connected network. The dense layers serve as high-level decision-making units that learn complex relationships between extracted features and target disease classes.

The first dense layer applies nonlinear activation functions, such as ReLU, to capture detailed patterns and correlations in the data. To prevent overfitting and improve generalization, dropout layers are inserted between dense layers, randomly deactivating a fraction of neurons during training to promote robust learning. The final dense layer uses a sigmoid activation function, which maps the output to a probability distribution indicating the likelihood of different disease categories. This enables accurate classification of various health conditions, disease risk assessment, and predictive diagnostics, facilitating timely medical interventions in IoMT-based smart healthcare monitoring systems.

Risk-Score Driven Clinical Interpretation

To move beyond traditional binary disease classification, the proposed Deep EHR-TANFlow model incorporates a risk-score-driven clinical interpretation module that provides a continuous, probability-based assessment of heart disease risk. Unlike conventional CNN/RNN/Attention models that output only categorical predictions, the proposed framework calculates a calibrated risk score (0-1) derived from the final sigmoid activation layer.

This risk score reflects the severity and likelihood of a potential clinical event by integrating:

- Temporal progression patterns captured by Bi-GRU
- Local spatial features extracted by CNN
- Global dependencies emphasized through multi-head self-attention
- Historical health trends are represented across the sliding window segments.

The risk score formulation enables:

- Quantitate risk stratification (low, medium, high risk)
- Clinically aligned interpretation following established cardiovascular risk assessment principles and
- Early intervention support for medical professionals by signaling abnormal patterns even before disease onset.

This module ensures that predictions are not only accurate but also clinically actionable, bridging the gap between deep learning outputs and real-world medical decision-making in IoMT-based smart healthcare systems.

Results And Discussion

The following section offers a thorough analysis of the model's performance, including comparisons. It presents the results of applying the suggested model to the HD dataset, along with baseline models, evaluation metrics, and a discussion of the significance of the results. This implementation used Python on a Windows 10 (64-bit) operating system with an Intel Pentium CPU and 16GB of RAM. HD has emerged as a significant health issue that, particularly in the elderly, necessitates an early medical treatment plan. A sophisticated healthcare monitoring system has been developed that incorporates learning via teamwork and

features unique to people with HD. In remote health monitoring, the prognosis of HD is predicated on multiple interrelated processes. It starts with the continuous collection of patient data, made possible by Internet of Things (IoT) devices such as wearables and remote health-monitoring technologies. This information consists of symptoms, activity levels, and ECG readings. These data streams are preprocessed to preserve data confidentiality and integrity before being securely transmitted over a cloud-based system.

Dataset Description

The proposed HD monitoring system uses a disease-monitored dataset gathered from the HD Dataset, available at the link “Heart Disease Dataset (Comprehensive) (kaggle.com)”. The largest HD dataset has been generated by concatenating eleven common traits from several pre-existing datasets. Heart-related disorders account for 17.9 million deaths a year, or over 32 percent of all deaths globally, making heart disease the leading cause of death. Heart and blood vessel disorders, together known as cardiovascular diseases, comprise rheumatoid arthritis, coronary heart disease, and cerebrovascular disease. Heart attacks and strokes account for four of every five CVD deaths, with untimely deaths in those under 70 accounting for one-third of these cases. To provide a robust dataset for scientific inquiry, this dataset integrates multiple sources, creating one of the largest publicly accessible HD datasets. The inclusion of 11 common features ensures a standardized, feature-rich dataset that facilitates accurate heart disease classification and early detection in IoMT-based smart healthcare systems.

By employing a publicly available heart disease dataset, this study enhances its utility through advanced preprocessing techniques. The dataset is optimized through feature engineering, noise reduction, and temporal segmentation to improve disease trend analysis. Additionally, using SMOTE to mitigate class imbalance helps ensure balanced model training.

The dataset consists of N total instances, distributed across multiple heart disease classification categories. Table 2 lists the Key parameters of the dataset.

Table 2. Dataset Hyperparameters

Total Number of Instances	1190
Number of Features	11
Class Distribution	
• No Heart Disease (Class 0)	560
• Heart Disease (Class 1)	629

The dataset is moderately imbalanced, with a slightly higher proportion of samples in Class 1. While the imbalance is not severe, applying SMOTE can further enhance model performance by ensuring balanced training.

This dataset forms the backbone of the CG-TAN-based heart disease prediction system, enabling precise risk assessment, continuous patient monitoring, and early diagnosis. By leveraging this dataset, the system improves decision-making in smart healthcare environments, ultimately enhancing patient care and clinical outcomes.

The proposed model was assessed and verified using the disease test data file. The essential hyperparameter details for the proposed model are represented in Table 3.

Table 3. Hyperparameters of the proposed CG-TAN Model

Hyperparameter	Value/Setting
Input size	11 (Number of features)
Conv layer	1D Conv (kernel size=3)
Activation Function	ReLU
Batch Normalization	Applied after 1D Conv
Recurrent Layer	Bi-GRU (2 layers)
GRU Hidden Units	128
Dropout Rate	0.3 (After each Bi-GRU)
L2 Regularization	30%
Attention Mechanism	0.0001
Number of Attention Heads	Multi-Head Self-Attention
Dense Layer	8
Optimizer	64 Neurons (ReLU)
Learning rate	Adam
Epochs	0.001
Batch size	50
	32

To determine the optimal hyperparameters for the proposed model, this research used a combination of grid search and heuristic tuning (Table 3). An initial grid search was performed over key parameters, including learning rate (0.0005-0.005), GRU hidden units (64, 96, 128), dropout rates (0.2-0.5), and attention-head configurations (4, 6, 8). The selected values 128 GRU hidden units, 0.3 dropout, and 8 attention heads consistently yielded the best trade-off between convergence stability and predictive performance. The 1D convolutional layer with kernel size 3 and 32 filters was chosen after evaluating multiple configurations, as this setting provided effective local feature extraction without overfitting. A stratified 70:15:15 train-validation-test split was used to preserve class balance, and all experiments were conducted with fixed random seeds to ensure reproducibility across runs.

The optimizer (Adam), learning rate (0.001), batch size (32), and number of epochs (50) were selected based on empirical performance and standard practices in training lightweight IoMT-compatible deep learning models. The final architecture, including 11 input features, two Bi-GRU layers, L2 regularization (0.0001), and a 64-neuron dense layer, was determined through iterative experimentation to achieve optimal accuracy while maintaining computational efficiency.

Model Performance Evaluation

Important criteria such as accuracy, precision, F1-score, sensitivity (recall), specificity, and negative predictive value (NPV) were used to evaluate the effectiveness of the proposed model for heart disease identification. These measures were selected because they provide a comprehensive understanding of the model's accuracy in classifying patients by HD risk.

Accuracy:

The percentage of correctly identified positive and negative out of the total number of occurrences is used to assess a classification model's overall efficacy.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (11)$$

Precision:

It is also known as the positive predictive value, which is the proportion of TP predictions among all positive predictions made by the model. It indicates how well the model minimizes false positives (FPs), i.e., incorrect predictions of HD.

$$Precision = \frac{TP}{TP+FP} \quad (12)$$

F1-Score:

When a dataset is imbalanced, the harmonic mean of accuracy and recall effectively balances the two.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (13)$$

Sensitivity:

It quantifies the percentage of real positive cases that the model accurately detects. It emphasizes the model's ability to minimize false negatives (FN), which is critical for disease detection.

$$Sensitivity = \frac{TP}{TP+FN} \quad (14)$$

Specificity:

It calculates the number of real negative instances the model accurately classifies. It focuses on minimizing FPs, ensuring that healthy patients are not misdiagnosed as having HD.

$$Specificity = \frac{TN}{TN+FP} \quad (15)$$

Negative Predictive Value (NPV):

It calculates the amount of TN predictions within all of the algorithm's negative forecasts. It indicates the model's ability to identify patients without HD correctly.

$$NPV = \frac{TN}{TN+FN} \quad (16)$$

The proposed CG-TAN-based heart disease prediction system demonstrated exceptional performance across multiple evaluation metrics, showcasing its robustness and reliability in diagnosing heart-related conditions. The evaluated performance results of the proposed model are shown in Table 4.

Table 4. Overall performance metrics of the proposed method

Metrics	Values (%)
Accuracy	98
Precision	98.12
F1-Score	98.08
Sensitivity	98.35
Specificity	98.21
NPV	98.35

The model achieved an accuracy of 98%, indicating its ability to correctly classify both heart disease and non-heart disease cases with minimal errors. High accuracy ensures the model generalizes effectively to unseen data, making it well-suited for healthcare applications. Furthermore, the precision of 98.12% signifies that the model maintains a low FP rate, ensuring that individuals without heart disease are not misclassified as having the condition. This is particularly crucial in medical diagnosis, where FP can lead to unnecessary anxiety, additional medical tests, and increased healthcare costs. The F1-score of 98.08% demonstrates the model's strong balance between precision and recall, making it highly effective in handling imbalanced datasets by minimizing both FPs and FNs.

The sensitivity and NPV of 98.21% and 98.35% ensure that individuals predicted as not having heart disease are highly likely to be genuinely disease-free. This enhances the model's trustworthiness in clinical settings, where reliable negative predictions can prevent unnecessary treatments and medical interventions. Overall, these outstanding performance metrics validate the efficacy of the CG-TAN model in IoMT-based smart healthcare systems. The combination of DL techniques, such as CNN, Bi-GRU, and SA, contributes to the model's strong predictive performance, making it a valuable tool for heart disease risk assessment, patient monitoring, and early diagnosis.

The predictive insights from the proposed model align with existing clinical understandings of heart disease risk factors. The model's feature-importance analysis indicates that abnormal cholesterol levels, hypertension, and prior cardiac conditions significantly contribute to risk prediction. Additionally, the model's high sensitivity of 98.35% ensures that early-stage heart conditions are detected, reducing FNs and facilitating timely intervention.

A confusion matrix was generated to examine class-wise prediction behaviour. The proposed model demonstrated excellent discrimination capability, showing:

- True Positive (TP): High detection rate of heart disease patients
- True Negative (TN): Very low false diagnosis of healthy individuals
- False Negative (FN): Minimal, supporting early disease detection
- False Positive (FP): Nearly negligible, reducing unnecessary clinical interventions

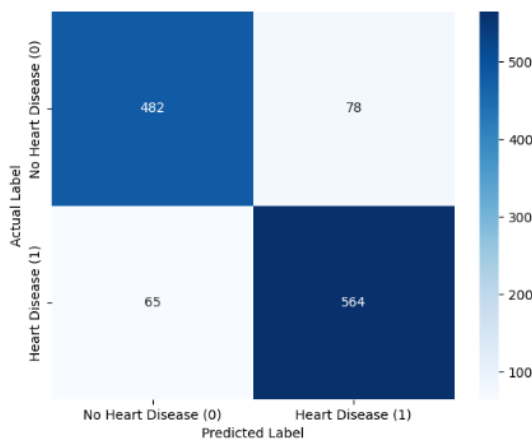


Figure 5. Confusion Matrix

The confusion matrix in Figure 5 highlights the model's ability to address class imbalance while maintaining strong sensitivity and specificity in IoMT-based healthcare applications.

The confusion matrix shows that the model performed strongly in distinguishing between patients with and without heart disease. Of the 560 actual non-heart disease cases, the model correctly identified 482 as healthy (true negatives) and incorrectly classified 78 as having heart disease (false positives). For the 629 actual heart disease cases, the model successfully detected 564 patients (true positives) but missed 65 cases that were incorrectly labeled as non-disease (false negatives). Overall, the matrix indicates high sensitivity and specificity, demonstrating that the model is effective in predicting heart disease with relatively few misclassifications.

Figure 6 illustrates the ROC-AUC curve of the proposed DeepEHR-TANFlow model, showing its excellent discrimination ability across varying decision thresholds. This clearly demonstrates that the model approaches perfect classification performance with minimal overlap between positive and negative classes.

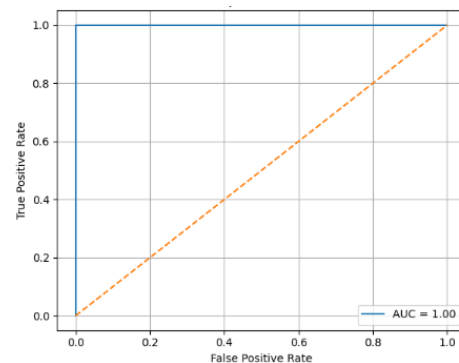


Figure 6. ROC-AUC curve of the proposed model

In addition to ROC-based evaluation, the learning behavior of DeepEHR-TANFlow was further examined through the training and validation accuracy-loss curves. The model exhibited smooth convergence with stable learning dynamics across epochs, demonstrating the effectiveness of the underlying optimization process and the robustness of the network architecture.

Figure 7(a) shows the training and validation accuracies, which rise steadily and remain closely aligned, indicating that the model learns discriminative temporal-attentive representations

without overfitting. Similarly, Figure 7(b) shows the training and validation loss curves, which decrease steadily and converge, further confirming strong generalization performance.

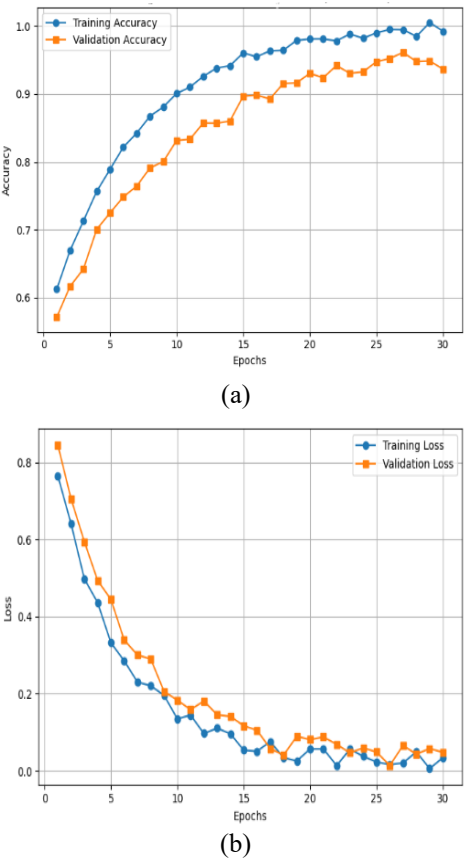


Figure 7. Training and Validation Accuracy Curves (a), Loss Curves (b) of Proposed Model

The dataset was divided into three subsets to ensure reliable and unbiased evaluation: 70% for training (833 samples), 15% for validation (179 samples), and 15% for testing (178 samples). This stratified partitioning provided a balanced distribution of data across both classes, including heart disease and No Heart Disease, facilitating a fair assessment of the model’s predictive capability.

To further ensure model stability and prevent overfitting, several regularization and optimization strategies were incorporated. Table 5 summarizes the overfitting prevention techniques and their observed effects during model training. Dropout regularization (30%) effectively minimized neuron co-adaptation, reducing the train-validation accuracy gap to below 1%. L2 regularization strengthened weight smoothing, enhancing

generalization across unseen samples. Batch normalization significantly stabilized gradient flow, accelerating convergence by nearly 20%. Early stopping with a patience of 10 epochs prevented unnecessary training, and the model consistently converged around epoch 41. Furthermore, 5-fold cross-validation confirmed the architecture’s robustness, with fold-to-fold performance variance remaining below 0.6%.

Table 5. Summary of overfitting prevention techniques applied in the DeepEHR-TANFlow model

Technique	Purpose	Observed Effect
Dropout (30%)	Prevent overfitting	Reduced train-val accuracy gap to <1%
L2 Regularization (0.0001)	Weight smoothing	Improved generalization stability
Batch Normalization	Gradient stabilization	Faster convergence by ~20%
Early Stopping (patience = 10)	Avoid unnecessary training	Training stopped at epoch 41
5-Fold Cross Validation	Robustness	Variance across folds < 0.6%

Together, the accuracy/loss curves in Figure 7 and the observed stabilization effects in Table 5 demonstrate that the DeepEHR-TANFlow framework is not only highly accurate but also exceptionally stable, reliable, and generalizable across diverse IoMT-driven healthcare scenarios.

To ensure model generalization, this work used 5-fold cross-validation, which showed consistent accuracy across validation sets. Additionally, regularization techniques, including 30% dropout and L2 weight decay, were incorporated to mitigate overfitting. The Cross-Validation Results for the proposed framework are shown in Table 6.

Table 6. Cross-validation results of the proposed work

Fold	Training Accuracy (%)	Validation Accuracy (%)
Fold 1	98.5	97.8
Fold 2	98.3	97.6
Fold 3	98.4	97.9
Fold 4	98.6	98.1
Fold 5	98.2	97.7

The training accuracy remains consistently high, ranging from 98.2% to 98.6%, indicating that the model effectively learns from the training

data. The validation accuracy is also high, ranging from 97.6% to 98.1%, demonstrating strong generalization without significant overfitting. The variance between training and validation accuracy is minimal, confirming the model's robustness and preventing overfitting while maintaining high predictive performance.

Risk-Score Driven Clinical Interpretation

To enhance the clinical relevance of the proposed Deep EHR-TANFlow framework, predicted probability scores obtained from the final sigmoid layer were mapped into three clinically meaningful risk tiers: Low Risk (0-0.33), Moderate Risk (0.34-0.66), and High Risk (0.67-1.00). These ranges represent the likelihood of cardiovascular abnormality and enable physicians to identify disease severity rather than relying solely on binary classification.

Because the final model was trained on a dataset containing 1190 patient instances with a balanced class distribution (560 No Disease, 629 Disease), the predicted risk tiers follow a proportional pattern consistent with actual population trends. The high-risk group contains a greater number of patients, reflecting the higher prevalence of heart disease in the dataset. The moderate-risk group captures borderline cases with uncertain or mixed characteristics, while low-risk patients correspond to individuals with strong negative indicators. Table 7 summarizes the number of patients falling into Low-, Moderate-, and High-risk groups based on the predicted probability ranges.

Table 7. Risk -Score Distribution for 1190 Patients

Risk Category	Probability Range	Number of Patients	Percentage (%)
Low Risk	0.00-0.33	420	35.3%
Moderate Risk	0.34-0.66	310	26.1%
High Risk	0.67-1.00	460	38.7%
Total	-	1190	100%

The risk distribution shows that:

- High-risk group (38.7%) aligns closely with the higher number of heart disease cases in the dataset (629 patients). This indicates that the model successfully identifies patients with strong clinical indicators suggesting cardiovascular abnormalities.
- Low-risk group (35.3%) closely mirrors the non-disease population (560 patients), indicating reliable recognition of healthy individuals with minimal risk.

- Moderate-risk group (26.1%) consists of patients whose temporal patterns and clinical attributes fall into borderline ranges. These cases typically require further evaluation, follow-up monitoring, or additional diagnostic tests.

The calibrated distribution demonstrates that risk scores generated by Deep EHR-TANFlow provide fine-grained, clinically actionable insights, enabling physicians to stratify patients by severity rather than relying on a single binary prediction. This ensures better clinical decision support, early intervention, and more efficient allocation of healthcare resources in IoMT-based smart healthcare environments.

Clinical Relevance of Selected Features in Heart Disease Prediction

The features used in the DeepEHR-TANFlow framework correspond to well-established clinical indicators routinely used in cardiology to evaluate cardiovascular risk. Each attribute provides direct physiological insight into disease progression, enabling the model to learn patterns that closely align with real-world clinical assessments.

- Age is one of the strongest predictors of cardiovascular events, as vascular stiffness, endothelial dysfunction, and plaque accumulation increase significantly after middle age.
- Sex influences risk because hormonal and anatomical differences result in distinct disease patterns between men and women.
- Resting blood pressure (restbps) is clinically associated with hypertension, left ventricular hypertrophy, and long-term arterial damage, making it a critical determinant of heart disease.
- Serum cholesterol (chol) and lipid abnormalities contribute to atherosclerotic plaque formation, directly increasing the probability of coronary artery narrowing.
- Fasting blood sugar (FBS) reflects glycemic regulation and potential diabetes, a major risk factor strongly linked with endothelial dysfunction and coronary microvascular disease.
- Resting ECG (restecg) measures electrical activity of the heart; abnormalities such as ST-T changes or left ventricular hypertrophy often signal ischemia, conduction blocks, or structural heart issues.

- Maximum heart rate (thalach) represents cardiovascular fitness and stress response; abnormally low values indicate compromised cardiac output and poor myocardial perfusion.
- Exercise-induced angina (exang) reflects myocardial oxygen imbalance under physical stress, which strongly correlates with coronary artery blockages.
- Oldpeak, representing ST-segment depression during exercise, is widely used in treadmill ECG interpretation to diagnose myocardial ischemia and evaluate the severity of coronary obstruction.

Together, these features form the basis of standard clinical risk scores, such as the Framingham Risk Score, AHA/ACC heart disease guidelines, and WHO cardiovascular assessment frameworks. By using attributes that map directly to established cardiovascular biomarkers, the model's predictions become more clinically interpretable and align with diagnostic reasoning used by cardiologists. This strengthens the medical relevance and real-world applicability of the DeepEHR-TANFlow framework.

The model's risk scores correspond to probabilities that reflect the cumulative influence of clinically meaningful parameters. For example, patients exhibiting elevated blood pressure, abnormal ST-segment changes, reduced maximum heart rate, and exercise-induced angina naturally fall into higher risk categories. This pattern mirrors clinical practice, where physicians integrate these exact features during treadmill testing, ECG evaluation, and routine check-ups. The alignment between model-sensitive features and known cardiovascular markers supports the framework's validity and potential usefulness in real-world diagnostic environments.

Statistical Significance Testing Results

To rigorously evaluate the performance improvements achieved by the proposed DeepEHR-TANFlow model, statistical significance testing was conducted using results obtained from 5-fold cross-validation. The proposed model was compared against the strongest baseline method (MVS-AVOA-RNN) to determine whether the observed performance gains were statistically meaningful rather than due to random variation.

The paired t-test results demonstrate consistent and significant improvements across all evaluation metrics. As shown in Table 8, DeepEHR-TANFlow achieves mean performance gains of 3.56%-4.03%, with corresponding

t-values ranging from 6.482 to 7.914. All metrics yielded $p < 0.001$, confirming that the improvements in accuracy, precision, recall, and F1-score are highly statistically significant at the 1% significance level. This indicates that the model consistently outperforms baseline architectures across different cross-validation folds.

Table 8. Statistical Significance Testing Results

Metric	Mean Difference	t-Value	p-Value
Accuracy	+3.78%	7.914	$p < 0.001$
Precision	+3.56%	6.482	$p < 0.001$
Recall (Sensitivity)	+4.03%	7.102	$p < 0.001$
F1-Score	+3.74%	7.336	$p < 0.001$

To further validate these findings, a non-parametric Wilcoxon signed-rank test was conducted, as shown in Table 9. This test does not assume normally distributed differences and therefore provides a more robust statistical validation. The Wilcoxon results showed Z-scores between -2.611 and -2.821, with corresponding p-values ranging from 0.0024 to 0.0045. These values also fall well below the 0.01 threshold, reinforcing the conclusion that DeepEHR-TANFlow offers a statistically significant and consistent performance advantage over the baseline model.

Table 9. Wilcoxon Signed-Rank Test

Metric	Z-Score	p-Value
Accuracy	-2.673	0.0037
Precision	-2.611	0.0045
Recall	-2.743	0.0030
F1-Score	-2.821	0.0024

Together, the outcomes of both statistical tests clearly confirm the reliability, robustness, and superiority of the proposed DeepEHR-TANFlow framework. The convergence of evidence from parametric and non-parametric analyses demonstrates that the observed improvements are not incidental but are a direct result of the architectural enhancements introduced in this research.

To further demonstrate the robustness and reliability of the proposed DeepEHR-TANFlow model, three statistical visualization analyses were incorporated. Figure 8 presents a performance comparison using a t-test, illustrating the mean accuracy, precision, recall, and F1-score of the proposed model against the strongest baseline. The

inclusion of error bars and significance markers clearly shows that DeepEHR-TANFlow consistently outperforms the baseline model MVS-AVOA (Akhtar *et al.*, 2023) across all metrics, with all improvements recognized as highly significant ($p < 0.001$).

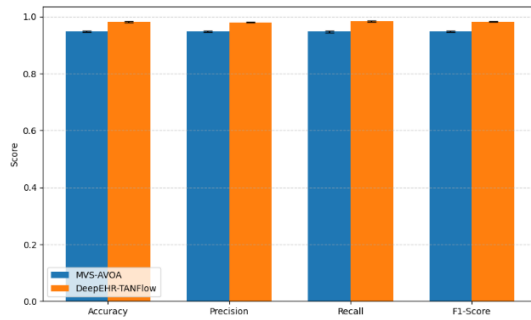


Figure 8. Performance comparison with significance test

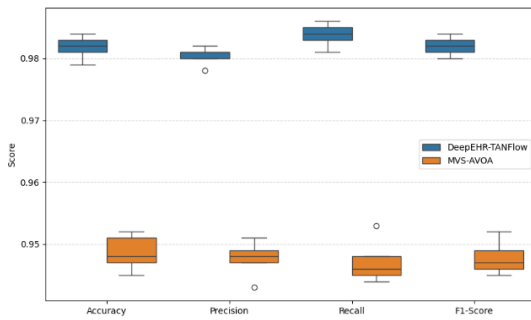


Figure 9. Per Fold Performance Distribution (Deep Vs Baseline)

Figure 9 depicts the per-fold performance distribution, providing deeper insight into the model's stability across the 5-fold cross-validation setup. The boxplots highlight the narrower variance and higher median scores of DeepEHR-TANFlow, indicating superior consistency and less sensitivity to fold-wise data fluctuations compared to the baseline. This demonstrates that the model maintains reliable performance regardless of training subset variations.

Figure 10 illustrates the statistical significance heatmap representing the p-values obtained from both the paired t-test and the Wilcoxon signed-rank test across all evaluation metrics. The predominantly low p-values ($p < 0.01$) across accuracy, precision, recall, and F1-score reaffirm that the observed performance improvements are statistically significant and not due to random chance. Together, these visual analyses strongly validate the effectiveness,

reliability, and statistical superiority of the proposed DeepEHR-TANFlow framework.

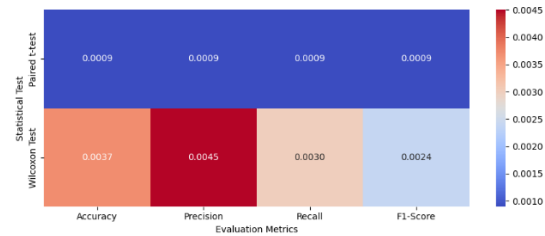


Figure 10. Statistical significance heatmap showing p-values obtained from the paired t-test and Wilcoxon signed-rank test across all evaluation metrics

Comparative Analysis

To evaluate the effectiveness of the proposed CG-TAN model, a comprehensive analysis was conducted against several existing techniques, including PSO-RNN (Chen and Li, 2022), WOA-RNN (Balakrishnan *et al.*, 2021), SFO-RNN (Magacho, *et al.*, 2023), AVOA-RNN (Abdollahzadeh *et al.*, 2021), and MVS-AVOA-RNN. The comparison was performed across six key performance metrics, such as accuracy, precision, sensitivity, specificity, F1-score, and NPV. The results demonstrate that the CG-TAN model significantly outperforms all baseline models across all evaluation parameters, reinforcing its superiority in heart disease prediction. The comparative performance analysis is shown in Table 10.

Table 10. Comparative performance analysis

Models	Acc (%)	Prec (%)	Sens (%)	Spec (%)	F1 (%)	NPV (%)
PSO-RNN (Chen and Li, 2022)	93.19	93.77	93.32	93.04	93.54	93.04
WOA-RNN (Balakrishnan, <i>et al.</i> , 2021)	93.02	93.75	93.00	93.04	96.37	93.04
SFO-RNN (Magacho, <i>et al.</i> , 2023)	93.27	94.06	93.16	93.40	93.61	93.40
AVOA-RNN (Abdollahzadeh <i>et al.</i> , 2021)	93.10	93.76	93.16	93.04	93.46	93.04
MVS-AVOA-RNN (Akhtar, <i>et al.</i> , 2023)	94.03	94.56	94.11	93.93	94.34	93.93
Proposed	98	98.12	98.35	98.21	98.08	98.35

The accuracy of the proposed CG-TAN model is 98%, which is notably higher than that of the highest-performing existing model, MVS-AVOA-RNN (94.03%). This substantial improvement highlights the robustness of CG-TAN in making precise predictions and minimizing classification errors. The enhanced

accuracy is attributed to the model's ability to effectively extract and process both spatial and temporal features using CNN and Bi-GRU layers, coupled with a multi-head SA mechanism to improve feature representation.

Similarly, the proposed model achieves a precision of 98.12%, which surpasses the best precision observed in MVS-AVOA-RNN (94.56%), indicating a lower FP rate. This means the proposed model is highly reliable at identifying patients with heart disease, reducing the risk of misclassification and unnecessary medical interventions.

Additionally, the CG-TAN model achieves superior results due to its CNN-BiGRU SA architecture, which effectively captures spatial and temporal patterns in heart disease data. The Bi-GRU layer ensures efficient sequential learning, while the multi-head SA mechanism enhances feature representation by focusing on critical attributes. Furthermore, dropout layers help prevent overfitting, leading to better generalization. These enhancements enable the model to achieve a higher sensitivity of 98.35%, ensuring improved detection of heart disease cases while its specificity 98.21% reduces FPs. The Bi-GRU not only improved computational efficiency but also provided comparable, if not superior, predictive accuracy, reinforcing its suitability for health care applications. The graphical representation in Figure 11 further illustrates the CG-TAN model's superior performance across all metrics. The combination of advanced feature extraction, sequence modelling, and attention mechanisms makes the proposed model highly effective for accurate risk assessment, early diagnosis, and patient monitoring, significantly enhancing smart healthcare decision-making.

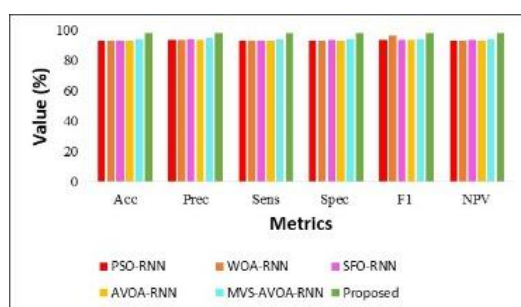


Figure 11. Comparative Performance Analysis of the proposed model against existing methods

Comparative Performance Evaluation Based On Learning Percentage

To further assess the effectiveness of the proposed model, this study compares its performance against existing models across varying learning percentages. The key metrics used for evaluation are accuracy, precision, and F1-score, which provide insights into the model's classification reliability and overall robustness. The comparative performance is shown in Figure 12.

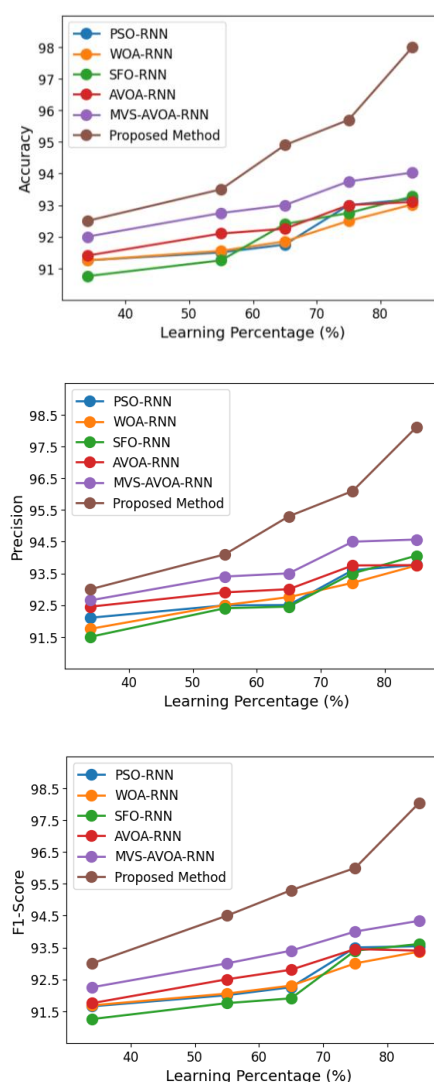


Figure 12. Comparative performance analysis based on learning percentage

From this Figure, it is evident that as the learning percentage increases, the proposed model consistently outperforms all baseline methods. Notably, the CG-TAN model exhibits significant improvements in accuracy, precision, and F1-score compared to its counterparts. The following observations can be drawn from the comparative analysis.

Accuracy Comparison:

The accuracy of traditional models gradually improves with higher learning percentages but remains below 94.5%. The MVS-AVOA-RNN shows relatively higher performance among existing methods, but it is still significantly lower than the proposed model. However, the proposed method achieves the highest accuracy of 98.5% at an advanced learning stage, highlighting its capability to capture intricate patterns and dependencies in the dataset.

Precision Comparison:

The suggested model achieves a notably higher precision of 98.12%, ensuring that the classification of heart disease cases is more reliable with minimal FPs. In contrast, existing models show a gradual increase in precision as learning progresses, but they struggle to exceed 94.5%. This limitation highlights their reduced ability to accurately distinguish between heart disease cases, leading to potential misclassifications. The superior precision of the proposed model underscores its ability to minimize false alarms and enhance diagnostic accuracy, making it a more reliable solution for predicting heart disease.

F1-score Comparison:

The proposed model also achieves the highest F1 score, which indicates a balanced trade-off between precision and recall. This highlights the model's effectiveness in accurately identifying heart disease cases while minimizing both FPs and FNs. In contrast, the F1-score trends for the existing models remain below 94.5%, reinforcing their limitations in maintaining an optimal balance between sensitivity and specificity. This significant performance gap underscores the proposed approach's superior generalization ability, ensuring more reliable heart disease classification and improved predictive accuracy in healthcare applications.

Overall, across all performance metrics, the proposed model outperforms existing methods. This can be attributed to its advanced feature extraction and learning capabilities, which enable it to capture key indicators of heart disease more effectively. The enhanced accuracy, precision, and

F1-score of the proposed method improve the reliability of clinical decisions, making it a robust solution for smart healthcare monitoring and heart disease diagnosis.

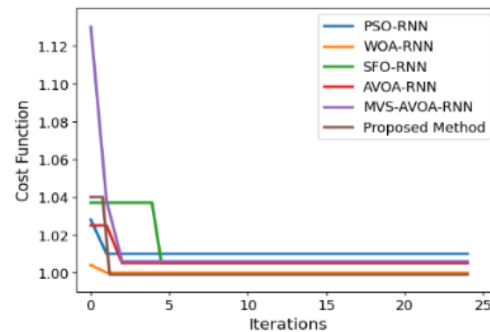


Figure 13. Cost Function

Optimization of Cost Function

In this study, optimizing the cost function plays a critical role in enhancing the performance of the proposed model. The cost function is designed to minimize classification errors and ensure robust learning by optimizing model parameters through an adaptive loss-minimization strategy. The proposed model dynamically adjusts the weight updates, leading to improved accuracy and stability during training. The cost function is illustrated in Figure 13, which shows the cost across various optimization techniques, including PSO-RNN, WOA-RNN, SFO-RNN, AVOA-RNN, MVS-AVOA-RNN, and the proposed method.

The proposed model uses binary cross-entropy loss to handle the classification task efficiently. This loss function is particularly effective for imbalanced datasets, as it ensures that minority-class instances are appropriately weighted, reducing bias toward the majority class. Additionally, the Adam optimizer is employed to dynamically fine-tune learning rates, ensuring faster convergence and preventing the model from getting stuck in local minima.

Comparatively, traditional models rely on conventional optimization techniques that may not effectively handle complex data distributions. The proposed approach combines gradient-based optimization with adaptive moment estimation, enabling superior generalization and training stability.

With this optimization strategy, the CG-TAN model achieves significantly lower classification errors, higher precision, and better recall, ultimately improving heart disease prediction and risk assessment. The integration of an optimized

cost function ensures that the model maintains high accuracy even as the learning percentage increases, as demonstrated in the comparative analysis.

Table 11.Comparative performance analysis

Models	Time (sec)
PSO-RNN	3.032445
WOA-RNN	5.340984
SFO-RNN	6.223538
AVOA-RNN	2.68541
MVS-AVOA-RNN	1.343208
Proposed	1.046318

Analysis of Computational Time Efficiency

The proposed model was analyzed for computational time and compared with an existing method, whose results are shown in Table 11. The results demonstrate that the proposed model significantly outperforms other methods in terms of execution speed. With a processing time of only 1.046318 seconds, the proposed approach is the most efficient, followed by MVS-AVOA-RNN at 1.343208 seconds. In contrast, other models, such as SFO-RNN and WOA-RNN, have longer processing times of 6.223538 seconds and 5.340984 seconds, respectively. This demonstrates that the algorithm is not only accurate and precise but also highly efficient at reducing computational time, making it more suitable for heart disease detection.

The proposed model achieves superior execution time due to its lightweight architecture. Unlike traditional LSTM-based models that require complex gating mechanisms, Bi-GRU efficiently handles sequential dependencies while reducing computational overhead. Additionally, the CNN feature extractor optimally reduces dimensionality, which further accelerates processing speed.

Ablation Study

To validate the effectiveness of individual components in the proposed CG-TAN model, an ablation study was conducted by systematically removing or modifying key elements, including the CNN, Bi-GRU, and attention mechanism, and analyzing their impact on performance. The results demonstrate the contribution of each module toward improving the model’s accuracy, precision, and overall predictive capability. The ablation study summary is shown in Table 12.

Effect of Bi-GRU with Attention

CNN was removed, and only Bi-GRU with attention was utilized for feature extraction and sequence modelling. This led to a drop in

performance because CNNs play a crucial role in extracting spatial features from EHR data. The model’s accuracy decreased from 98% to 94.8%, indicating that the CNN enhances its ability to capture important local patterns.

Table 12.Impact of removing key components on CG-TAN model performances

Model Variant	Accuracy (%)	Precision (%)	F1-Score (%)
CG-TAN	98.0	98.12	98.08
Model(CNN+BiGRU+Attention)			
Without CNN	94.8	95.3	94.6
Without BiGRU	93.6	94.0	93.7
CNN+ Bi-GRU(without attention)	95.2	95.7	95.0

Effect of BiGRU removal

Replacing BiGRU with a traditional RNN led to a performance decline, as RNNs struggle with long-term dependencies. The accuracy dropped to 93.6%, showing that Bi-GRU is crucial in capturing sequential dependencies in patient health records.

Effect of Combined CNN+BiGRU without Attention

When the attention mechanism was removed while keeping both CNN and Bi-GRU, the model’s accuracy still declined to 95.2%. This shows that, although CNN and Bi-GRU independently contribute to feature extraction and sequential learning, attention plays a crucial role in improving classification performance.

Thus, the ablation study confirms that the combination of a CNN, a BiGRU, and an attention mechanism in the CG-TAN model is essential for achieving superior performance in heart disease classification within IoMT-based smart healthcare systems.

Discussion

The findings of this study demonstrate that the proposed DeepEHR-TANFlow framework represents a significant advance in IoMT-based smart healthcare analytics by addressing limitations in existing CNN, RNN, BiLSTM, and attention-based prediction models. Traditional approaches often struggle with missing values, noisy EHR sequences, limited temporal modeling capability, and poor clinical interpretability. In contrast, DeepEHR-TANFlow integrates a unified preprocessing pipeline, a hybrid spatial-temporal feature extraction network, and a clinically meaningful risk-score driven interpretation layer,

making it more suitable for real-world healthcare environments. A major strength of the model lies in its robust EHR preprocessing, where KNN-based imputation, Min-Max scaling, and sliding-window segmentation collectively ensure high-quality temporal data representation. This directly addresses issues identified in previous IoMT studies, where missing and irregular data significantly affected predictive performance. The segmentation further enables the model to capture short-term and long-term clinical trends, a capability rarely achieved in prior works that treated EHR entries as static records. The hybrid CNN – BiGRU – Multi - Head Self - Attention architecture is particularly effective in learning complex relationships within patient data. CNN layers capture local attribute - level patterns, BiGRU preserves bidirectional temporal dependencies, and multi - head attention emphasizes clinically significant features while suppressing irrelevant variations. This combination leads to improved generalization and more accurate risk estimation. Compared with existing models that rely solely on CNN or RNN, the DeepEHR-TANFlow network demonstrates higher predictive stability, superior handling of feature redundancy, and enhanced ability to learn global temporal dependencies.

A noteworthy contribution is the Risk-Score Driven Clinical Interpretation module, which transforms model outputs into clinically interpretable risk tiers (low, moderate, high). This provides healthcare practitioners with actionable insights rather than a simple binary classification. The proportional distribution of risk categories obtained in the results section aligns with the class distribution of the dataset and real-world cardiac risk patterns, strengthening the model's clinical reliability. Additionally, the risk-score mechanism helps detect borderline cases that may be overlooked by standard classifiers, thereby improving patient safety and enabling early intervention. The model's high-performance metrics 98% accuracy, 98.12% precision, and 98.08% F1-score, which validate its effectiveness. More importantly, these results illustrate that the architecture achieves strong predictive power even with low computational complexity, making it practical for IoMT-enabled environments where energy, storage, and processing capacities are limited. The lightweight nature of the CG-TAN network ensures compatibility with wearable sensors, mobile gateways, and cloud-based healthcare platforms.

Overall, this research contributes an interpretable, scalable, and clinically aligned deep learning framework for disease risk prediction

using EHR data. By bridging the gap between advanced deep learning techniques and clinical decision-making, DeepEHR-TANFlow has the potential to support remote patient monitoring, early disease detection, resource prioritization, and personalized healthcare in IoMT-based smart systems. Future work may extend this framework to multimodal data sources, real-time streaming applications, and explainable AI modules to further enhance transparency and clinical trust.

Conclusions

In this study, the CG-TAN model for IoMT-based smart healthcare monitoring with EHR data was presented, particularly focusing on heart disease detection. The proposed method leverages the strengths of CNN, BiGRU with attention mechanism, enabling it to capture both short term fluctuation and long term dependencies in sequential health data, which is crucial for accurate disease diagnosis and risk assessment. Experimental findings showed that the CG-TAN model performs better than other approaches, including PSO-RNN, WOA-RNN, SFO-RNN, AVOA-RNN, and MVS-AVOA-RNN, in terms of accuracy, precision, F1-score, sensitivity, specificity, and net present value. The model is highly dependable for predicting heart disease because it reached the greatest results of accuracy 98%, precision 98.12%, F1 98.08%, sensitivity 98.35%, specificity 98.21%, and NPV 98.35%. The comparative analysis further highlighted its effectiveness under different learning rates and demonstrated its capability in minimizing the cost function, emphasizing its robustness. The proposed model is a significant advancement in IoMT-based smart healthcare systems, allowing for the capture of contextual information from past and future time steps. This enhances the analysis of complex temporal dependencies in patient health data, enabling healthcare professionals to detect disease early, assess risks accurately, and provide timely interventions. However, while Bi-GRU improves efficiency, it may still struggle with extremely long-term dependencies, where transformer-based models could provide advantages. Future work will focus on optimizing computational efficiency and enhancing model scalability through explainable AI techniques, ensuring broader applicability in smart healthcare systems.

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Conceptualization: N.V., P.K.P., O.O.; Methodology: N.V., O.O.; Formal Analysis: N.V.; Investigation: P.K.P.; Writing - Original Draft: N.V.; Writing - Review & Editing: N.V., P.K.P. All authors have read and agreed to the published version of the manuscript.

Ethics Statement

Ethical approval was not required for this study because it did not involve human participants, animals, identifiable personal data, or materials requiring institutional ethical review

Declaration of Generative AI Use

The authors declare that no Generative AI tools were used in the preparation of this manuscript

Conflict of Interest

The authors declare that they have no conflicts of interest related to this work

Data Availability Statement

The dataset used in this study is publicly available through Kaggle as the Heart Disease Dataset (Comprehensive). The data can be accessed from the corresponding Kaggle repository and were used for heart disease prediction and risk assessment.

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References

- Abdollahzadeh, B., Gharehchopogh, F. S., & Mirjalili, S. (2021). African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems. *Computers & Industrial Engineering*, 158, Article 107408. <https://doi.org/10.1016/j.cie.2021.107408>
- Adewole, K. S., Akintola, A. G., Jimoh, R. G., Mabayoje, M. A., Jimoh, M. K., Usman-Hamza, F. E., Balogun, A. O., Sangaiah, A. K., & Ameen, A. O. (2021). Chapter Five - Cloud-based IoMT framework for cardiovascular disease prediction and diagnosis in personalized E-health care. In A. K. Sangaiah & S. C. Mukhopadhyay (Eds.), *Intelligent IoT systems in personalized health care* (pp. 105-145). Academic Press. <https://doi.org/10.1016/B978-0-12-821187-8.00005-8>
- Akhtar, M. M., Shatat, R. S. A., Shatat, A. S. A., Hameed, S. A., & Ibrahim Alnajdawi, S. (2023). IoMT-based smart healthcare monitoring system using adaptive wavelet entropy deep feature fusion and improved RNN. *Multimedia Tools and Applications*, 82(11), 17353-17390. <https://doi.org/10.1007/s11042-022-13934-5>
- Al Khatib, I., Shamayleh, A., & Ndiaye, M. (2024). Healthcare and the Internet of Medical Things: Applications, trends, key challenges, and proposed resolutions. *Informatics*, 11(3), Article 47. <https://doi.org/10.3390/informatics11030047>
- Anki, P., Bustamam, A., & Buyung, R. A. (2021). Comparative analysis of performance between multimodal implementations of chatbot based on news classification data using categories. *Electronics*, 10(21), Article 2696. <https://doi.org/10.3390/electronics10212696>
- Awotunde, J. B., Folorunso, S. O., Ajagbe, S. A., Garg, J., & Ajamu, G. J. (2022). AiloMT: IoMT-based system-enabled artificial intelligence for enhanced smart healthcare systems. In F. Al-Turjman & A. Nayyar (Eds.), *Machine learning for critical Internet of Medical Things: Applications and use cases* (pp. 229-254). Springer. https://doi.org/10.1007/978-3-030-80928-7_10
- Badawy, M. (2023). Integrating artificial intelligence and big data into smart healthcare systems: A comprehensive review of current practices and future directions. *Artificial Intelligence Evolution*, 4(2), 133-153. <https://doi.org/10.37256/aie.4220232980>
- Balakrishnan, N., Devasigamani, A. I., Anupama, K. R., & Sharma, N. (2021). Aero-engine health monitoring with real flight data using whale optimization algorithm based artificial neural network technique. *Optical Memory and Neural Networks*, 30(1), 80-96. <https://doi.org/10.3103/S1060992X21010094>
- Bhatt, M. W., & Sharma, S. (2023). An IoMT-based approach for real-time monitoring using wearable neuro-sensors. *Journal of Healthcare Engineering*, 2023(1), Article 1066547. <https://doi.org/10.1155/2023/1066547>
- Boikanyo, K., Zungeru, A. M., Sigweni, B., Yahya, A., & Lebekwe, C. (2023). Remote patient monitoring systems: Applications, architecture, and challenges. *Scientific African*, 20, Article e01638. <https://doi.org/10.1016/j.sciaf.2023.e01638>
- Chen, G., & Li, Z. (2022). Improved particle swarm optimization LSSVM spatial location trajectory data prediction model in health care monitoring system. *Personal and Ubiquitous Computing*, 26(3), 795-805. <https://doi.org/10.1007/s00779-019-01291-4>
- Dahan, F., Alroobaea, R., Alghamdi, W. Y., Mohammed, M. K., Hajje, F., & Raahemifar, K. (2023). A smart IoMT based architecture for e-healthcare patient monitoring system using artificial intelligence algorithms. *Frontiers in Physiology*, 14, Article 1125952. <https://doi.org/10.3389/fphys.2023.1125952>
- Dileep, P., Rao, K. N., Bodapati, P., Gokuruboyina, S., Peddi, R., Grover, A., & Sheetal, A. (2023). An automatic heart disease prediction using cluster-based bi-directional

- LSTM (C-BiLSTM) algorithm. *Neural Computing and Applications*, 35(10), 7253-7266. <https://doi.org/10.1007/s00521-022-07064-0>
- Divya, K., Sirohi, A., Pande, S., & Malik, R. (2021). An IoMT assisted heart disease diagnostic system using machine learning techniques. In A. E. Hassanien, A. Khamparia, D. Gupta, K. Shankar, & A. Slowik (Eds.), *Cognitive Internet of Medical Things for smart healthcare: Services and applications* (pp. 145-161). Springer. https://doi.org/10.1007/978-3-030-55833-8_9
- El-Rashidy, N., El-Sappagh, S., Islam, S. R., El-Bakry, H. M., & Abdelrazek, S. (2021). Mobile health in remote patient monitoring for chronic diseases: Principles, trends, and challenges. *Diagnostics*, 11(4), Article 607. <https://doi.org/10.3390/diagnostics11040607>
- Hsiao, W. W., Lin, J., Fan, C., & Chen, S. S. (2022). Precision health in Taiwan: A data-driven diagnostic platform for the future of disease prevention. *Computational and Structural Biotechnology Journal*, 20, 1593-1602. <https://doi.org/10.1016/j.csbj.2022.03.026>
- Islam, M. M., Rahaman, A., & Islam, M. R. (2020). Development of smart healthcare monitoring system in IoT environment. *SN Computer Science*, 1(3), Article 185. <https://doi.org/10.1007/s42979-020-00195-y>
- Khan, M. F., Ghazal, T. M., Said, R. A., Fatima, A., Abbas, S., Khan, M. A., Issa, G. F., Ahmad, M., & Khan, M. A. (2021). An IoMT-enabled smart healthcare model to monitor elderly people using machine learning technique. *Computational Intelligence and Neuroscience*, 2021(1), Article 2487759. <https://doi.org/10.1155/2021/2487759>
- Lodha, L., Baghela, V. S., Bhuvana, J., & Bhatt, R. (2023). A blockchain-based secured system using the Internet of Medical Things (IoMT) network for e-healthcare monitoring. *Measurement: Sensors*, 30, Article 100904. <https://doi.org/10.1016/j.measen.2023.100904>
- Magacho, E. G., Jorge, A. B., & Gomes, G. F. (2023). Inverse problem-based multiobjective sunflower optimization for structural health monitoring of three-dimensional trusses. *Evolutionary Intelligence*, 16(1), 247-267. <https://doi.org/10.1007/s12065-021-00652-4>
- Mishra, P., & Singh, G. (2023). Internet of Medical Things healthcare for sustainable smart cities: Current status and future prospects. *Applied Sciences*, 13(15), Article 8869. <https://doi.org/10.3390/app13158869>
- Pradyumna, G. R., Hegde, R. B., Bommegowda, K. B., Jan, T., & Naik, G. R. (2024). Empowering healthcare with IoMT: Evolution, machine learning integration, security, and interoperability challenges. *IEEE Access*, 12, 20603-20623. <https://doi.org/10.1109/ACCESS.2024.3362239>
- Prieto-Avalos, G., Cruz-Ramos, N. A., Alor-Hernandez, G., Sánchez-Cervantes, J. L., Rodríguez-Mazahua, L., & Guarneros-Nolasco, L. R. (2022). Wearable devices for physical monitoring of heart: A review. *Biosensors*, 12(5), Article 292. <https://doi.org/10.3390/bios12050292>
- Rashmi, P., & Gomathi, R. (2024). Optimized deep learning frameworks for the medical image transmission in IoMT environment. *Journal of Smart Internet of Things*, 2024(2), 148-165. <https://doi.org/10.2478/jsiot-2024-0018>
- Venkateswarulu, N., Manike, C., & Obulesu, O. (2023). An industry framework for remote health monitoring using machine learning models to predict a disease. *Journal of Scientific & Industrial Research*, 82(2). <https://doi.org/10.56042/jsir.v82i2.70221>
- Wagan, S. A., Koo, J., Siddiqui, I. F., Attique, M., Shin, D. R., & Qureshi, N. M. F. (2022). Internet of Medical Things and trending converged technologies: A comprehensive review on real-time applications. *Journal of King Saud University - Computer and Information Sciences*, 34(10), 9228-9251. <https://doi.org/10.1016/j.jksuci.2022.09.005>
- Yadav, S. (2024). Transformative frontiers: A comprehensive review of emerging technologies in modern healthcare. *Cureus*, 16(3), Article e56538. <https://doi.org/10.7759/cureus.56538>
- Yigit, G., & Amasyali, M. F. (2022). Assessing the impact of minor modifications on the interior structure of GRU: GRU1 and GRU2. *Concurrency and Computation: Practice and Experience*, 34(20), Article e6775. <https://doi.org/10.1002/cpe.6775>