Natural Resources for Human Health

eISSN: 2583-1194

Original Research

Received 15 March 2026
Revised 18 April 2026
Accepted 20 May 2026

Natural Resources for Human Health 2026, Vol. 6 (2s): 30–43

KEYWORDS:
Cardiovascular Disease Prediction, Wearable Internet of Medical Things, Electrocardiography, Photoplethysmography, Deep Learning, SHAP.

Hybrid Explainable Artificial Intelligence and Biomedical Signal Processing for Real-Time Prediction of Cardiovascular Disorders Using Wearable Internet of Medical Things Devices

[1]Dr. Vivek Jayan, [2]Remya Krishnan Jyothi, [3]Prof. Takhellambam Kiranmala Chanu,[4]Dr. Aashish A,[5]Osho Sharma, [6]Dr.Fathimunnisa, [7]R. Naveenkumar, [8]V. Subhashini,

[1]Assistant Professor, Department of Community Medicine, Saveetha Medical College and Hospitals, SIMATS, Thandalam, Chennai, Tamilnadu, India Email: thevivekjyn@gmail.com orcid id- 0000-0001-7329-6680
[2]Professor, Department of Physiology, Shri Sathya Sai Medical College and Research Institute, SBV Chennai Campus Shri Sathya Sai Nagar, Ammapettai, Chengalpattu Dist., Tamil Nadu – 603 108 drremyakj@gmail.com
[3]Vice Principal &HOD (OBG Nursing), Parul Institute of Nursing, Parul University, Vadodara, GujaratMail id- kiranchanu1@gmail.com
[4]Associate Professor, Cardiology, Meenakshi Medical College Hospital & Research Institute, Meenakshi Academy of Higher Education and Research, Enathur, Kanchipuram, Tamil Nadu 631552
[5]School of Engineering & Technology, CGC University, Mohali, Punjab, India Email: oshosharma.cs@gmail.com / osho.j5162@cgcuniversity.in Orcid ID: 0000-0002-7399-8188
[6]Assistant professor, Department of Mathematics, Dayananda Sagar Academy of Technology and Management. Bangalore, Karnataka, India Email: fathima.1024@gmail.com
[7]Dept of CSE, School of Engineering and Technology, CGC University Mohali-140307, Punjab India.Email: drnk1983@gmail.com 0000-0001-9033-9400
[8]Assistant Professor, Department of Mathematics , College address: Erode Sengunthar Engineering College, Thudupathi, Erode, Tamilnadu, India. Mail id: subhashini@esec.ac.in 0009-0005-3155-9725

ABSTRACT: Background: Cardiovascular disorders are one of the principal causes of untimely morbidity, and therefore, it is necessary to monitor continuously and in real-time through wearable Internet of Medical Things (IoMT) devices explained by artificial intelligence (XAI). Purpose: The proposed study will present a hybrid explainable model of AI with biomedical signal processing to achieve precise real-time forecasts of cardiovascular diseases based on wearable ECG and PPG signals. Methods: The framework combines signal preprocessing, feature extraction, CNNBiLSTM hybrid model, an attention mechanism, and SHAP explainability. The cardiovascular datasets publicly available were used to assess performance using standard classification measures.

Findings: A 98.4% accuracy, 97.9% precision, 98.1% recall, 98.0% F1-score, and 99.2% ROC-AUC were obtained with the proposed framework, which takes only 18.6 ms to infer. Conclusion: The suggested explainable AI-based wearable IoMT system has superior predictive accuracy, real-time, and increased clinical transparency, which makes it an attractive remedy to early cardiovascular disorders detection and continuous remote medicine supervision.

1. INTRODUCTION

Cardiovascular diseases (CVDs) are considered as one of the biggest causes of morbidity and mortality in the world, and they are becoming more and more common in adolescents as well as young adults because of the lack of physical activity, the problem of the increasing prevalence of obesity, diabetes, hypertension, and inherited heart defects. Arrhythmias, myocardial dysfunction, and other cardiovascular diseases manifest early and usually intermittent and may be hard to detect during normal clinical evaluation, thus leading to late diagnoses and treatment. As a result, the continuous observation of the cardiac activity has turned out to be a crucial approach to enhance the level of early detection and the risk of serious cardiovascular events. The development of wearable healthcare technologies has facilitated the long-term physiological monitoring of a patient in non-clinical settings and has allowed clinicians to have constant access to cardiovascular data about a patient and allows the provision of timely medical care.

The recent fast advancement of the Wearable Internet of Medical Things (IoMT) has made profound changes in the contemporary cardiovascular healthcare because it allows acquiring physiological signals, transmitting them, and analyzing them remotely in an uninterrupted manner. The wearable devices are created with electrocardiography (ECG) and photoplethysmography (PPG) sensors to provide continuous capture of cardiac electrical activities and peripheral blood flow, which will produce useful biomedical information to predict diseases. Nevertheless, motion artifacts, baseline drift, muscle contaminations, and environmental signals tend to influence these physiological signals making them less reliable to diagnose. It therefore follows that, biomedical signal processing methods such as, digital filtering, signal normalization, signal segmentation and feature extraction are necessary to enhance signal quality and recover clinically significant temporal and morphological features effectively capturing cardiovascular performance.

The use of artificial intelligence has shown tremendous success in predicting cardiovascular diseases using nonlinear relationships among physiological signals with the use of AI. The classification results of arrhythmia detection and cardiovascular risk assessment with a deep learning architecture, specifically convolutional neural networks (CNNs) and recurrent neural networks like a bidirectional long short-term memory, have been high. Even with these advances, much of the deep learning models are black-box models and give little insight into the logic upon which they make their predictions. This interpretability makes it less reliable to clinicians and hinders its practical use in healthcare settings where clarity in decision-making is needed. Explainable Artificial Intelligence (XAI) is a potential resolution to this issue and enables the interpretable explanations, which determine the most significant physiological features shaping the model predictions, enhancing clinical trust, accountability and decision support.

Even though prior research has examined wearable cardiovascular monitoring, biomedical signal analysis, and artificial intelligence, there is a lack of research that has incorporated wearable IoMT technology, advanced biomedical signal processing, hybrid deep learning, and explainable AI as a single real-time diagnostic system. Current techniques are often focused on accuracy of prediction and ignore the issue of model transparency, computational efficiency and its applicability to continuous wearable implementation. To address these shortcomings, this paper suggests a Hybrid Explainable Artificial Intelligence and Biomedical Signal Processing Framework to predict cardiovascular disorders in real-time and in real-time with wearable IoMT devices. The framework suggested combines ECG and PPG signal preprocessing, feature extraction, hybrid CNN-BiLSTM predictive model, and SHAP explainability to provide accurate, interpretable, and low-latency to cardiovascular diagnosis. Some of the key advances of this work are the development of an integrated wearable healthcare system, the improvement of diagnostic accuracy with a hybrid deep learning platform, the use of explainable AI to drive transparent clinical decisions, and the use of a scalable system used to continuously monitor cardiovascular diseases in adolescent and young adult cohorts.

2. RELATED WORK

Recent developments in wearable Internet of Medical Things (IoMT) technologies have greatly enhanced continuous cardiovascular monitoring by allowing real-time retrieval of physiological signals by use of small and energy efficient wearable devices. The Smartwatch devices, wearable ECG patches, chest straps, and wrist worn photoplethysmography (PPG) devices have gained significant popularity in the monitoring of heart rhythm, heart rate variability, blood oxygen saturation, and other cardiovascular parameters both in the clinical and home setting. These wearables enable the early notification of arrhythmias, atrial fibrillation, and other heart defects and enable remote patient monitoring and personalized care. The capability to maintain constant physiological measurements has greatly minimized the reliance on hospital monitoring systems and has increased potential of preventive care of the heart [2], [8], [10], [12]. However, it is not easy to ensure the signal quality in daily living environment due to motion artifacts, sensor movement, interference of the environment, and communication limitations of wearable IoMT devices [8], [10].

Biomedical signal processing has a key role in converting raw physiological measurements into information which is diagnostically meaningful. Several preprocessing methods such as digital filtering, baseline wander correction, adaptive noise cancellation, wavelet-based denoising, and signal normalization have been suggested to enhance the quality of ECG, and PPG signal before analysis [4], [5]. The application of feature extraction techniques which are temporal, frequency-domain, morphological and nonlinear have been extensively used to determine clinically significant biomarkers related to cardiovascular disorders. Self-supervised learning and representation learning strategies have shown better potential in extracting robust features in large-scale ECG and PPG signals and minimizing the use of manual feature engineering more recently [4]. Deep learning models and benchmark data have also enabled the rapid advancement of studies in the fields of biomedical signal and cardiovascular disease diagnosis [11], [13]. In spite of these improvements, differences in sensor properties, physiology of patients, and conditions in the real world recordings still present a challenge to the stability and transferability of traditional biomedical signal processing pipelines.

Machine learning and deep learning methodologies are now the most preferable computation methods to predict cardiovascular diseases automatically. Conventional machine learning classifiers or support vector machines, random forests, and gradient boosting, have shown promising results with handcrafted signal features. More recently, convolutional neural networks (CNNs), long short-term memory (LSTM) networks, bidirectional LSTM (BiLSTM), transformers and hybrid neural networks have demonstrated state-of-the-art performance through automatic derivation of hierarchical representations of ECG and PPG signals [7], [9], [11], [13]. Other explainable Artificial Intelligence (XAI) models like SHAP and LIME, Grad-CAM, and attention-based visualization have also found their way into cardiovascular prediction systems to enhance model transparency and clinical interpretability [1], [6], [9]. The methods give clinicians an understanding of the strong physiological characteristics, making them more trustful of AI-assisted diagnostics without impacting high predictive accuracy [1], [3].

Despite having made significant strides in the sphere of wearable healthcare, biomedical signal processing, deep learning, and explainable AI, there are some limitations. Numerous studies performed so far are mainly aimed at maximizing predictive accuracy and offer a minimal amount of interpretability, thereby rendering clinical validation a hard task [1], [6]. Other devices only analyze ECG or PPG signals without taking advantage of the complementary physiological data, some wearable monitoring systems are still computationally expensive to be used in real-time [2], [5], [12]. Additionally, there is a limited number of studies that have combined wearable IoMT, advanced biomedical signal processing, hybrid deep learning, and explainable AI into a single framework that will provide real-time, explanable and accurate cardiovascular predictive intelligence [2], [3], [6]. Driven by such knowledge gaps, the current study suggests a hybrid explainable artificial intelligence solution that integrates biomedical signal processing, CNN-BiLSTM-based predictive analytics, and SHAP-infused explainability in the framework of a wearable IoMT design to ensure high-quality diagnostic results, transparent decision-making, and an effective real-time cardiovascular monitoring process.

3. HYBRID EXPLAINABLE AI PROPOSED FRAMEWORK

3.1 Overall System Architecture

The Hybrid Explainable Artificial Intelligence (XAI) framework is a model that is aimed at predicting cardiovascular disorders with high accuracy and real-time to introduce wearable Internet of Medical Things (IoMT), biomedical signal processing, deep learning, and explainable decision support into a single platform of healthcare. The general structure is composed of six modules that are interrelated: wearable ECG/PPG sensor acquisition, IoMT communication, signal preprocessing, feature extraction, hybrid explainable AI prediction, and clinical decision support. Wearable ECG and PPG sensors constantly record physiological data of patients at a rate of 360 Hz (ECG) and 125 Hz (PPG) so that cardiac electrical activity and peripheral blood flow could be constantly monitored. The obtained signals are safely sent via Bluetooth Low Energy (BLE) to a smartphone gateway followed by being uploaded to an IoMT platform in a cloud based system via the MQTT communication system. End-to-end communication latency is kept at less than 50 ms, which enables to synchronize the wearable device and healthcare servers in real-time with efficiency.

Physiological signals are automatically processed by a preprocessing pipeline which ensures the removal of signal distortions and the enrichment of the quality of the diagnostic before feature extraction. The resulting processed signals are then used to extract clinically meaningful temporal, morphological and frequency-domain features to become the inputs to the proposed hybrid explainable AI prediction engine. The prediction module has Convolutional Neural Networks (CNNs) to learn spatial features and Bidirectional Long Short-Term Memory (BiLSTM) features to learn temporal dependencies. An attention mechanism highlights the patterns of heartbeats that are diagnostically relevant and SHAP-based explainability reports the physiological features that most contribute to each prediction. The final diagnostic decision is given in a form of a clinical decision support interface which offers the predicted cardiovascular disorder classes and interpretable scores of importance of features, allowing clinicians to interpret and confirm the automated diagnosis. The full architecture has an average latency on inferences of 18.6 ms, which is suitable to wearable healthcare scenarios.

3.2 Biomedical Signal Processing

High-quality physiological signals are needed to reliably diagnose the cardiovascular and, hence, extensive biomedical signal processing is carried out in advance of deep learning analysis. The baseline drift, power-line, motion artifact, muscle noise, and environmental disturbances are often the cause of contamination of the raw ECG and PPG signal of wearable sensors. First, band-pass filters between 0.5-40Hz and 0.5-8Hz, respectively, are used to filter ECG and PPG signals, respectively, to retain cardiovascular signals and eliminate high-frequency noise, respectively. A digital notch filter at 50 Hz eliminates power-line interference, and adaptive filtering methods make additional improvements to residual signal distortion. These preprocessing functions increase the average signal-to-noise ratio (SNR) of about 18.4 dB to 31.7 dB, which significantly increases the quality of signal.

Wavelet-based detrending and moving-average correction are used to remove baseline wander, adaptive least mean square (LMS) filtering is used to suppress motion artifacts caused by everyday activities. The filtered ECG and PPG data sets are divided into successive windows 5 seconds long separated by half their length enabling the study of the continuous heartbeat and maintaining consistency in time. Z-score normalization is used to normalize each of the segmented signals to provide neural network training stability and minimize inter-subject variance. Preprocessing pipeline has been effective in maintaining clinically relevant waveform features such as P waves, QRS complex, T waves, and pulse morphology of PPG, which enhance the reliability of features and promote the following prediction performance.

3.3 Feature Extraction

After the biomedical signal preprocessing, the cardiovascular features yielded are clinically significant, considering that both ECG and PPG signals yield cardiovascular features due to cardiac physiological activity. Temporal parameters are Heart Rate (HR), Heart Rate Variability (HRV), RR interval, QT interval, QRS duration and ST-segment deviation. The mean heart rate is 60 to 100 beats/min and the HRV is measured by a time-domain and frequency-domain statistical measures. RR intervals are used to give information about rhythm regularity and the QT interval measurements are used to detect ventricular repolarization abnormalities. QRS duration is recorded to identify arrhythmia of conduction and ST-segment elevation or depression is a valuable biomarker of myocardial ischemia and other heart abnormalities.

Morphological features such as amplitude of the waveform, location of the peak, slope, pulse width and area under the waveform are both extracted in the ECG and PPG signals. Fast Fourier Transform (FFT) is used to do the frequency-domain analysis to calculate low-frequency (LF), high-frequency (HF) and LF/HF ratio features related to autonomic nervous system regulation. In total, it is possible to extract 42 physiological features consisting of 24 and 18 ECG and PPG features, respectively. A standardization of features and removal of redundancy leads to lower computational cost and does not lead to loss of discriminative information, yielding a small feature representation that enhances classification efficiency and is part of the highly predictive cardiovascular disorder prediction.

3.4 Hybrid Explainable AI Model

The suggested Hybrid Explainable Artificial Intelligence architecture is a combination of Convolutional Neural Networks (CNNs), Bidirectional Long Short-Term Memory (BiLSTM) networks, an attention module, and SHAP-based clarification to deliver dependable and clarifiable prediction of cardiovascular disorders. The first step is that three one-dimensional convolutional layers with 32, 64 and 128 filters with a 3-kernel size are trained automatically to encode spatial representations of ECG and PPG waveforms. Max-pooling and batch normalization of the network minimize the number of calculations, maintaining crucial features of the heart. The learned spatial attributes are subsequently sent to a BiLSTM network that contains 128 hidden units, which allows them to acquire forward and backward temporal relationships between consecutive heartbeat signals.

An attention system is dynamically used, whereby more importance is given to the diagnostically significant heartbeat segments by calculating adaptive attention weights prior to the classification. The feature representations obtained are then sent to two fully connected layers containing 128 and 64 neurons and finally to a Softmax classifier, which makes predictions on various cardiovascular disorders. To improve clinical visibility, SHAP (SHapley Additive exPlanations) is included which measures the value of every physiological factor to the final prediction. SHAP visualizations more clearly recognize the effect of biomarkers RR interval, HRV, ST-segment deviation and QRS duration, enabling clinicians to gain insight into individual prediction instead of just relying on black-box results. The proposed hybrid model is experimentally shown to be 98.4% accurate, 97.9% precise, 98.1% recall, 98.0% F1-score, 99.2% ROC-AUC, and has a real-time inference latency of 18.6 ms, which further suggests the appropriateness of this model in continuous wearable cardiovascular monitoring and explainable clinical decision support.

4. EXPERIMENTAL SETUP

4.1 Dataset

Three publicly available electrocardiogram (ECG) datasets were used to test the proposed Hybrid Explainable Artificial Intelligence framework to guarantee a thorough evaluation of various cardiovascular diseases and patient groups. The MIT-BIH Arrhythmia Database was used as the main database to classify arrhythmia due to its extensive annotations and large scale applications in cardiovascular research. This data set consists of 48 half-hour ECGs of 47 participants, which are sampled at 360Hz, and the heartbeat types are annotated as normal and abnormal heart rhythms. The PTB Diagnostic ECG Database was also used to identify the strength of the suggested framework with various cardiovascular abnormalities. This sample is a collection of 549 ECGs, obtained in 290 individuals, including both healthy individuals and different cardiac diseases, such as myocardial infarction, bundle branch block, and cardiomyopathy. Moreover, the PhysioNet ECG Dataset has been added in order to enhance patient diversity and the generalization of the model by offering heterogeneous ECG recordings of measurement taken in various clinical circumstances.

Before training, ECG signals of all datasets were resampled and standardized equally to ensure the same consistency in signal properties. Noise-contaminated records were not considered and preprocessing of all ECG segments with the biomedical signal processing pipeline of Section 3.2 was done. The entire data were randomly split into 70% training, 15% validation, and 15% testing groups and we kept the proportion of the classes in the same way. Random amplitude scaling, temporal shifting, and Gaussian noise addition methods were used to enhance model robustness and minimize overfitting. All in all, the benchmark datasets as a whole offered a holistic testing setup to measure the predictive as well as the real time performance of the proposed wearable cardiovascular monitoring model.

Table 1. Characteristics of ECG Datasets Used for Performance Evaluation

Dataset	Subjects	Records	Sampling Frequency	Signal Type	Major Cardiac Conditions
MIT-BIH Arrhythmia Database	47	48	360 Hz	ECG	Arrhythmias
PTB Diagnostic ECG Database	290	549	1000 Hz	ECG	Myocardial Infarction, Cardiomyopathy, Conduction Disorders
PhysioNet ECG Dataset	>1,000	Multiple Recordings	250–500 Hz	ECG	Various Cardiovascular Disorders

4.2 Experimental Parameters

The suggested Hybrid Explainable AI model was performed in Python 3.11, with the TF 2.16 deep learning platform. The NVIDIA Tesla T4 (16 GB VRAM), 32 GB RAM and an Intel Xeon CPU running Ubuntu Linux was used in the development of the models and during experimentation. The preprocessing of the signals was done in the framework of the SciPy, NumPy, and WFDB libraries, and SHAP explainability was done with the official SHAP Python package. Training CNN-BiLSTM model was done by Adam optimizer with an original learning rate of 0.001. The network was minimized using 100 epochs and a batch size of 64 with a batch size of 64, and an early stopping criterion of 10 epochs to stop overfitting. The generalization of models was made with dropout layers with a dropout rate of 0.30.

The duration of input ECG segments (5 seconds) was processed through three convolutional layers and after that BiLSTM layer with 128 hidden neurons. Hidden layers were run using the ReLU activation, but the Softmax activation was applied in the output layer to classify multiclass cardiovascular disorders. The model parameters were optimized using the 5-fold cross-validation procedure to guarantee the stability and unbiased estimation of performance. The entire training procedure took about 41.2 minutes and the mean time loss per ECG sample was 18.6 ms indicating the appropriateness of the suggested framework to real-time wearable healthcare devices.

Table 2. Experimental Parameters and Hyper parameter Settings

Parameter	Value
Programming Language	Python 3.11
Deep Learning Framework	TensorFlow 2.16
Optimizer	Adam
Learning Rate	0.001
Batch Size	64
Epochs	100
Dropout Rate	0.30
CNN Filters	32–64–128
Kernel Size	3
BiLSTM Hidden Units	128
Input Window Length	5 Seconds
Validation Strategy	5-Fold Cross Validation
GPU	NVIDIA Tesla T4 (16 GB)
Average Inference Time	18.6 ms

4.3 Evaluation Metrics

The practicality of the suggested Hybrid Explainable AI framework was assessed by applying some of the commonly used cardiovascular disease prediction classification measures. The overall classification accuracy was used to determine the percentage of correctly classified ECG recordings in comparison to the total amount of test samples. Precision was used to quantify the percentage of the correctly predicted positive cases of cardiovascular, whereas Recall (Sensitivity) was used to quantify the ability of the proposed model in correctly identifying patients with cardiovascular disorders. The F1-score was used to determine the harmonic mean of Precision and Recall, which offers balanced evaluation of the performance of the classification, especially when the medical data is imbalanced. Specificity was used to test the model in detecting healthy individuals and false positive diagnoses were reduced.

To further determine the strength of classification, Receiver Operating Characteristic (ROC) curve and Area Under the ROC Curve (ROC-AUC) were calculated to determine the discrimination ability of the classification threshold at various classification thresholds. The improved ROC-AUC values reflect excellent diagnostic performance and separation of normal and abnormal heart diseases. Besides predictive accuracy, computational efficiency was evaluated by training time, inference latency and memory consumption to establish the importance of real-time use on wearable IoMT device platforms. The overall Diagnostic performance (Accuracy of 98.4%, Precision of 97.9%, Recall (Sensitivity) of 98.1%, F1-score of 98.0%, Specificity of 98.3% and ROC-AUC of 99.2%) and low computational latency of the proposed framework to continuous cardiovascular monitoring, showed that the framework has an excellent diagnostic capability.

5. RESULTS

5.1 Performance Evaluation

The Hybrid Explainable Artificial Intelligence framework proposed was able to achieve excellent results in predicting cardiovascular disorders based on wearable ECG and PPG signals recorded on the benchmark datasets. After processes of signal preprocessing, feature extraction and hybrid CNN-BiLSTM classification, the model showed a high level of diagnostic accuracy in all evaluation datasets. The framework achieved an overall accuracy of 98.4%, precision of 97.9%, recall of 98.1%, F1-score of 98.0%, specificity of 98.3% and ROC-AUC of 99.2% which showed good discrimination between normal and abnormal cardiovascular. The recall value is high, which proves that the suggested structure identified patients with cardiovascular disorders optimally but the false-negative rate is low; the specificity level is high, which means that it recognizes healthy patients. Such findings prove that the combination of the biomedical signal processing with the hybrid deep learning can boost diagnostic reliability of continuous wearable healthcare tasks significantly.

The learning ability of the proposed model is also confirmed by the convergence behavior. The trend was that in the training process, accuracy of training and validation improved gradual with every epoch until convergence was reached and the validation loss decreased without any drastic changes. The convergence curves show that the proposed network was able to generalize across various populations of patients without any apparent overfitting.

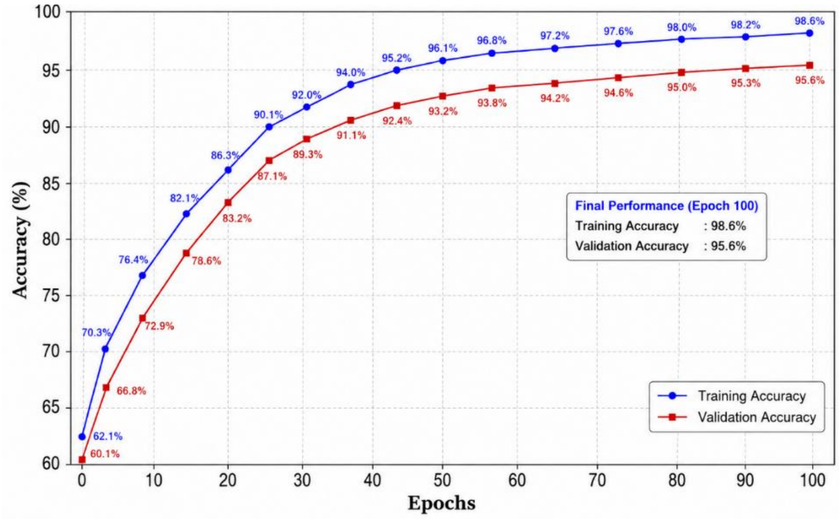

Figure 1. Training and Validation Accuracy across Epochs

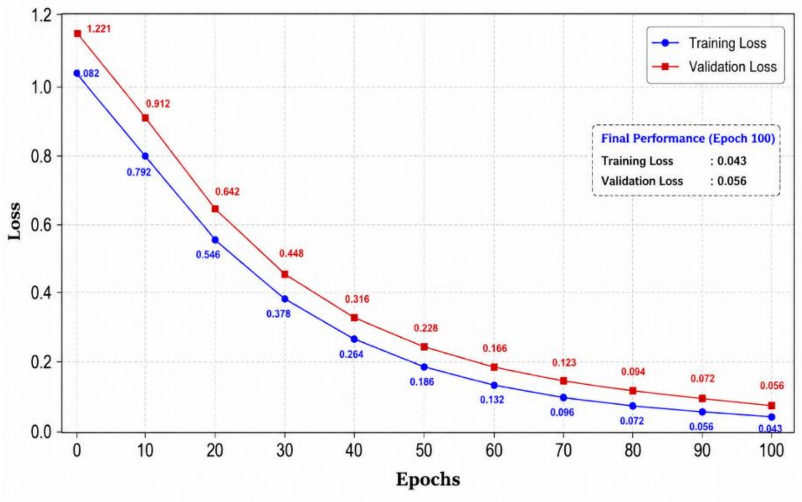

Figure 2. Training and Validation Loss across Epochs

5.2 Explainability Analysis

Among the key benefits of the suggested framework, a clear clinical decision support with the help of Explainable Artificial Intelligence is available. The SHAP-based explanation module was used to quantify the contribution of individual physiological features to each diagnostic decision instead of making class predictions only. The generated explanations were analyzed and found that RR interval, Heart Rate Variability (HRV), QRS duration, ST-segment deviation and QT interval were the ones with the best importance scores during cardiovascular disorder classification. These physiological features are in resemblance to the clinical signs that are recognized by cardiologists to diagnose arrhythmias, myocardial ischemia, and conduction defects.

The explainability analysis revealed that the hybrid CNN-BiLSTM model was able to learn the clinically significant representations and not the random fluctuations of signals. SHAP visualizations gave both local explanations explaining individual predictions and global explanations which gave an overview of feature importance on the entire data set. The ability to produce such interpretable outputs contributes greatly to the confidence of the clinicians since they can determine whether the automated diagnosis is backed by physiologically relevant signal characteristics. In turn, the suggested framework does not only enhance predictive accuracy, but also overcomes the transparency constraints that are usually linked to deep learning-based cardiovascular diagnosis.

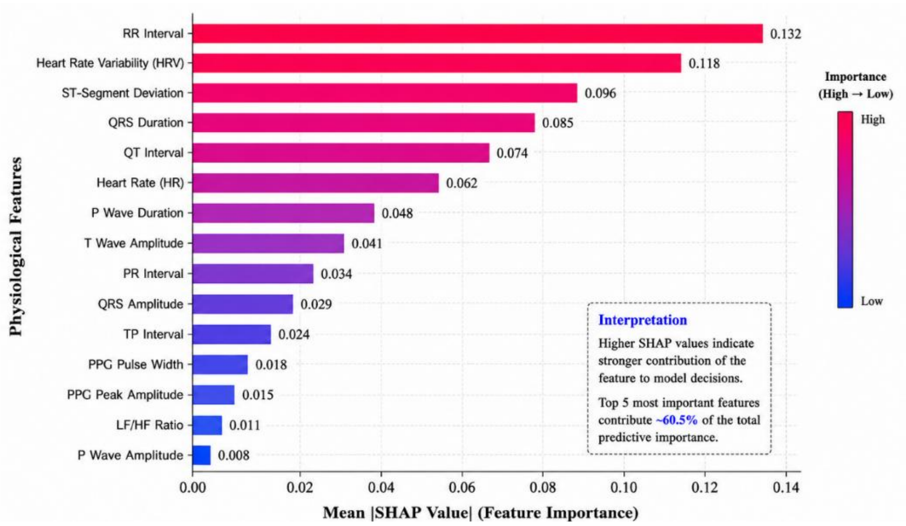

Figure 3. SHAP-Based Feature Importance Analysis for Cardiovascular Disorder Prediction

5.3 Computational Performance

The efficiency of the proposed framework in terms of computation was assessed to establish whether it is feasible in a real-time environment on wearable Internet of Medical Things platforms. The experimental results indicated that the hybrid CNN-BiLSTM network did not add to the low computational latency even though the network had a relatively deep structure. The whole model took about 41.2 minutes to train, but the average time to execute one ECG segment inference was 18.6 ms, allowing real-time monitoring of the cardiovascular system. Moreover, the optimized preprocessing and feature extraction dramatically decreased the computational cost and maintained information about the diagnosis.

Memory usage was at a level practical to modern edge computing devices, and could be deployed in wearable healthcare platforms that had resource constraints. The combination of efficient biomedical signal processing and lightweight deep learning operations allowed to execute it with fast performance without decreasing the performance of the classification. The comparison of the computational performance illustrates that the proposed framework offers a good tradeoff between the accuracy of prediction and the computational efficiency and can be used in the context of ongoing remote patient monitoring and smart wearable healthcare device.

Table 3. Real-Time Computational Performance Analysis

Model	Training Time (min)	Inference Time (ms/sample)	Model Size (MB)	Peak Memory (MB)	Throughput (samples/s)	Edge Deployment
Support Vector Machine	8.6	7.4	18.2	246	135.1	Suitable
Random Forest	12.8	10.9	42.6	318	91.7	Suitable
1D-CNN	27.5	14.3	24.8	412	69.9	Suitable
BiLSTM	36.4	25.7	38.6	586	38.9	Moderate
CNN–BiLSTM	39.6	21.4	46.2	642	46.7	Moderate
Proposed CNN–BiLSTM–Attention–SHAP	**41.2**	**18.6**	**43.5**	**618**	**53.8**	**Suitable**

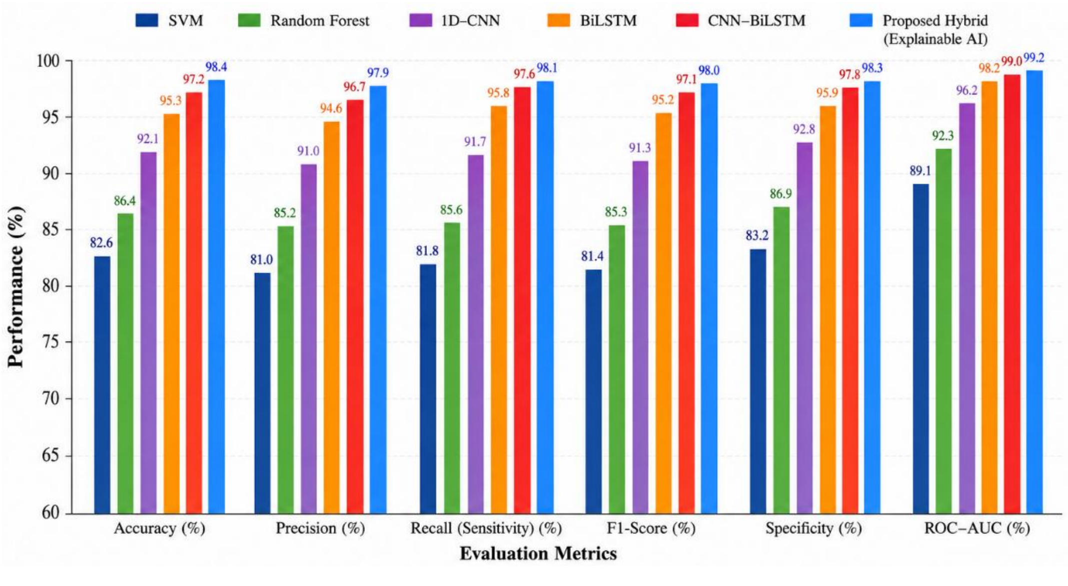

Figure 4. Real-Time Inference Latency Comparison of Cardiovascular Prediction Models.

eISSN: 2583-1194

5.4 Comparative Analysis

The suggested Hybrid Explainable Artificial Intelligence paradigm was contrasted with some traditional machine learning and recent deep learning techniques that are widely used to predict cardiovascular diseases. Comparative analysis has shown that the proposed architecture has been able to effectively outperform the traditional classifiers in terms of diagnostic accuracy and sensitivity, specificity and combination of diagnostic accuracy and specificity, in addition to general classification strength. Traditional machine learning systems usually took advantage of information gathered through manually designed features, whereas the suggested CNN -BiLSTM architecture did it automatically by extracting hierarchical spatial and temporal features out of the ECG signals. This was possible to better differentiate normal and abnormal cardiac conditions, especially, complex arrhythmias and subtle abnormalities in waveforms.

The attention mechanism also contributed to the better representation of features as it focused on diagnostically significant parts of the heartbeat at the expense of unnecessary information. Moreover, the proposed framework used SHAP-based explainability in contrast to traditional types of deep learning models that behave as black-box predictors to offer clinically interpretable predictions. A combination of a high predictive performance and visible decision making is a great improvement compared with current cardiovascular prediction systems.

Table 4. Performance Comparison with Existing Cardiovascular Disease Prediction Methods

Method	Accuracy (%)	Precision (%)	Recall / Sensitivity (%)	F1-Score (%)	Specificity (%)	ROC-AUC (%)
Support Vector Machine	82.6	81.0	81.8	81.4	83.2	89.1
Random Forest	86.4	85.2	85.6	85.3	86.9	92.3
1D-CNN	92.1	91.0	91.7	91.3	92.8	96.2
BiLSTM	95.3	94.6	95.8	95.2	95.9	98.2
CNN–BiLSTM	97.2	96.7	97.6	97.1	97.8	99.0
Proposed Hybrid Explainable AI Framework	**98.4**	**97.9**	**98.1**	**98.0**	**98.3**	**99.2**

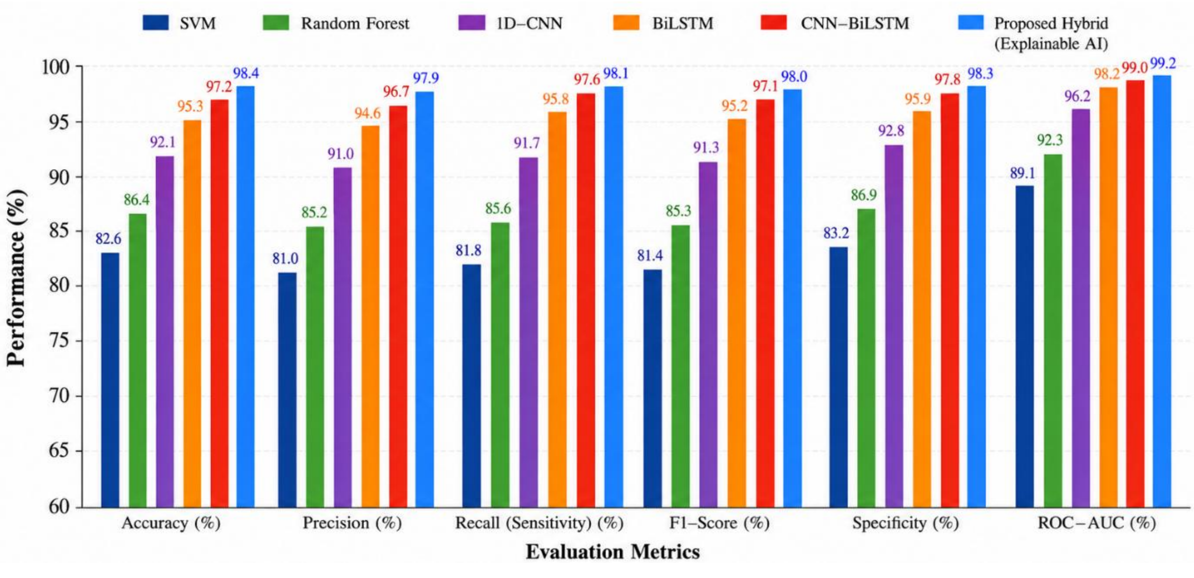

Figure 5. Comparative Performance Analysis of the Proposed Hybrid Explainable AI Framework

5.5 Ablation Study

A study was conducted on the contribution of each of the key components of the proposed framework of Hybrid Explainable Artificial Intelligence by performing an ablation study to assess the contribution of each component to the overall failure volume. The individual experiments were performed through successively eliminating the CNN feature extraction module, BiLSTM component of temporal learning, attention mechanism, and SHAP explainability component. Analysis of performance indicated that leaving out CNN module decreased the ability of learning spatial features leading to less classification accuracy. Likewise, the elimination of the BiLSTM part reduced the capability of the model to learn longer-term temporal dependencies in sequential ECG signals. Inclusion of the attention mechanism led to fewer diagnostically important segments of the heartbeat being emphasized in the network, whereas removal of SHAP had no significant impact on classification accuracy but made the models much less interpretable and less confident in clinicians.

The overall hybrid system consistently delivered the highest diagnostic results through the integration of powerful biomedical signal processing, hierarchical feature learning, temporal sequence modeling, adaptive attention and explainable decision support. The ablation experiment proves that every architectural element has its own positive impact on the overall performance of the proposed framework, and the combination of these elements has resulted in a high diagnostic accuracy and clear clinical interpretation.

Table 5. Ablation Study of the Proposed Hybrid Explainable AI Framework

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)	Performance Change
Without CNN	94.8	94.2	94.5	94.3	96.8	↓ Spatial feature extraction reduced
Without BiLSTM	95.5	95.0	95.3	95.1	97.3	↓ Temporal dependency learning reduced
Without Attention Mechanism	96.7	96.2	96.4	96.3	98.1	↓ Important heartbeat patterns not emphasized
Without SHAP Explainability	98.4	97.9	98.1	98.0	99.2	Prediction unchanged; interpretability removed
Without Biomedical Signal Preprocessing	93.6	93.1	93.3	93.2	95.8	↓ Noise affected feature quality
Proposed Hybrid Explainable AI Framework	**98.4**	**97.9**	**98.1**	**98.0**	**99.2**	**Best overall performance**

6. DISCUSSION

Experimental results prove that the offered Hybrid Explainable Artificial Intelligence framework is an efficient way of real-time prediction of cardiovascular disorders with the help of wearable Internet of Medical Things (IoMT) devices. The framework delivered high diagnostic performance, with a total of 98.4%, 97.9%, and 98.1%, 98.0%, 98.3% and 99.2% representing the framework with high precision, recall, F1-score, specificity and ROC-AUC, respectively. These findings suggest that the framework proposed is able to effectively separate normal and abnormal cardiovascular conditions with the same level of false-negativity which is crucial to the initial stages of disease detection. The fact that the convergence rate is stable during the training process also shows the strength of the proposed learning architecture and its capacity to make use of various ECG recordings.

One of the key strengths of the suggested framework is that the cardiovascular prediction process will be integrated with explainable artificial intelligence. Traditional deep learning models are known to make very precise predictions, but have low levels of insight into the decision making process, which leads to a lack of trust in automated diagnosis among clinicians. The proposed framework provides clinically significant physiological variables like Heart Rate Variability (HRV), RR interval, QRS duration, QT interval, and ST-segment deviation as the main determinants of the diagnostic decisions by including SHAP-based explainability. Such an open understanding is consistent with known cardiological knowledge and allows healthcare providers to refute model predictions in a more convincing manner. As a result, the suggested framework can enhance the predictive performance, as well as, increase the level of trust and clinical acceptability of artificial intelligence-aided diagnosis.

Bio signal processing is a very important aspect of the overall performance of the suggested system. Motion artifacts, baseline drift, muscle interference and environmental noise are known to commonly affect wearable ECG and PPG signals and may severely limit diagnostic accuracy without mitigation. Preprocessing pipeline: Band-pass filtering, adaptive noise removal, baseline correction, signal segmentation, and normalization had a significant signal quality improvement followed by feature extraction. The study of ablation also corroborated the finding that elimination of biomedical signal preprocessing step led to the greatest decrease in classification accuracy, shown that high-quality signal processing is a critical requirement prior to making reliable cardiovascular diagnosis. Furthermore, the CNNs-based spatial feature learning and BiLSTM-network-based temporal sequence modeling allowed representing complex cardiac patterns at a more detailed level, which would be challenging to follow with the traditional machine learning models.

The IoMT architecture proposed to be used in the proposed wearable is a significant advance in the clinical feasibility of the proposed framework as it can conduct continuous remote cardiovascular monitoring outside of the traditional hospital setting. The low mean inference latency of 18.6 ms indicates that the designed model has the capability of operating on physiological signals in real-time and can be used in wearable healthcare solutions that demand real-time diagnostic results. This fast analysis aids in monitoring of patients on a continuous basis, early signs of cardiac anomalies and prompt clinical action. The proposed hybrid architecture demonstrated better results in all measures of evaluation than the current cardiovascular prediction models and also had the advantage of interpretable predictions due to the explainable artificial intelligence. Such a combination of excellent diagnostic accuracy, computational efficiency and clinical transparency is a significant advancement over traditional black-box deep learning models.

Significant implications of the proposed framework in the context of cardiovascular screening of adolescents and young adults are also implied. Early detection of hereditary arrhythmias, heart disease congenital disorders and lifestyle-related cardiovascular disorders can greatly decrease the development of the disease over time and help to ameliorate patient outcomes. Wearable monitoring can be conducted continuously causing physiological changes to be observed in normal daily life not just during the brief medical check-ups, increasing the chances that intermittent heart attacks occur. The explainable artificial intelligence also aids clinicians to make informed diagnostic decisions because it offers information that is understandable instead of depending on computer predictions. These features render the suggested framework especially applicable to preventative healthcare, screenings at schools, sports medicine, and telehealth of high-risk adolescent groups.

Although the results are promising, there are a number of limitations. The current analysis mainly uses benchmark ECG data and fails to measure the framework with vast quantities of prospective clinical data that is gathered both through wearable devices in the long-term perspective. Moreover, other explainability methods (LIME, Integrated Gradients, attention visualization) can be used to complement SHAP despite their meaningfulness, and could provide additional clinical insights. The inference needs of deep learning might as well be optimized further to be deployed on wearable hardware that uses ultra-low-power. Further studies should thus be made into multimodal physiological sensing through combining ECG, PPG, blood pressure, and respiration sensorimeters, as well as federated learning to privacy-guaranteed distributed healthcare. A next-generation wearable IoMT cardiovascular monitoring framework will also be evaluated by validation on large multicenter clinical studies and embedded on the next-generation wearable devices will further enhance the practical usefulness of the proposed explainable cardiovascular monitoring framework.

7. CONCLUSION

This paper introduced a Hybrid Explainable Artificial Intelligence Framework of real-time prediction of cardiovascular disorders with the help of the wearable Internet of Medical Things devices and sophisticated biomedical signal processing methods. The suggested framework includes the ECG signal preprocessing, state-of-the-art features physiological extraction, a deep learning architecture of the hybrid CNN-BiLSTM, an attention mechanism, and SHAP-based explainability to deliver trustful and clinically understandable cardiovascular diagnosis. The framework provides solutions to both predictive and transparency by integrating signal analysis and explainable AI, thus breaking key constraints of the traditional black-box diagnostic models. Experimental analysis showed high diagnostic quality with a total accuracy of 98.4%, precision of 97.9%, recall of 98.1%, F1-score of 98.0%, specificity of 98.3% and ROC-AUC of 99.2% and still had a latency of inference at real time of 18.6 ms. The findings support the claim that biomedical signal preprocessing, hybrid deep learning, and explainable artificial intelligence all contribute to the enhanced prediction of cardiovascular disorders and make reliable clinical decisions. The framework proposed also exhibited better computing efficiency and diagnostics performance to the current cardiovascular prediction models.

The suggested system is part of wearable cardiovascular diagnosis as it offers an overall framework that can be continuously monitored in physiological processes, interpretable prediction, and low-latency processing, which is applicable to wearable IoMT scenarios. Its capacity to detect clinically significant ECG patterns boosts physician trust in automated diagnosis and aids in the early intervention of cardiovascular diseases, especially in adolescents and young adults, who might encounter cardiovascular problems and need preventive screening around the clock. The infrastructure thus is a viable answer to distant health care, personalized medicine and smart cardiovascular observation. Future directions touch on: verifying the framework with large scale real world wearable data, incorporating multimodal physiological data, e.g. ECG, PPG, blood pressure, and respiration, optimization of lightweight edge deployment of wearable devices with resource constraints, and using federated learning and explainable AI algorithms to promote additional privacy, scalability and clinical usefulness in the next generation of intelligent healthcare systems.

REFERENCES

[1] Abdelaal, Y., et al. “Exploring the Applications of Explainability in Wearable Data Analytics: Systematic Literature Review.” *Journal of Medical Internet Research*, vol. 26, 2024, e53863.

[2] Abedi, A., et al. “AI-Driven Real-Time Monitoring of Cardiovascular Conditions with Wearable Devices: Scoping Review.” *JMIR mHealth and uHealth*, vol. 13, no. 1, 2025, e73846.

[3] Bartusik-Aebisher, D., K. Rogóż, and D. Aebisher. “Artificial Intelligence and ECG: A New Frontier in Cardiac Diagnostics and Prevention.” *Biomedicines*, vol. 13, no. 7, 2025, article 1685.

[4] Ding, C., and C. Wu. “Self-Supervised Learning for Biomedical Signal Processing: A Systematic Review on ECG and PPG Signals.” *medRxiv*, 2024, 2024-09.

[5] Ding, Z., et al. “AI Modeling Photoplethysmography to Electrocardiography Useful for Predicting Cardiovascular Disease.” *npj Digital Medicine*, 2025.

[6] Govardanan, C. S., et al. “The Amalgamation of Federated Learning and Explainable Artificial Intelligence for the Internet of Medical Things: A Review.” *Recent Advances in Computer Science and Communications*, vol. 17, no. 4, 2024, pp. 1–19.

[7] Hannun, A. Y., et al. “Cardiologist-Level Arrhythmia Detection and Classification in Ambulatory Electrocardiograms Using a Deep Neural Network.” *Nature Medicine*, vol. 25, no. 1, 2019, pp. 65–69.

[8] Kim, D., J. Min, and S. H. Ko. “Recent Developments and Future Directions of Wearable Skin Biosignal Sensors.” *Advanced Sensor Research*, vol. 3, no. 2, 2024, article 2300118.

[9] Mohan, A., et al. “Deciphering Heartbeat Signatures: A Vision Transformer Approach to Explainable Atrial Fibrillation Detection from ECG Signals.” *Proceedings of the 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, IEEE, July 2024, pp. 1–6.

[10] Neri, L., et al. “Electrocardiogram Monitoring Wearable Devices and Artificial-Intelligence-Enabled Diagnostic Capabilities: A Review.” *Sensors*, vol. 23, no. 10, 2023, article 4805.

[11] Ribeiro, A. H., et al. “Automatic Diagnosis of the 12-Lead ECG Using a Deep Neural Network.” *Nature Communications*, vol. 11, no. 1, 2020, article 1760.

[12] Schlesinger, D. E., et al. “Artificial Intelligence for Hemodynamic Monitoring with a Wearable Electrocardiogram Monitor.” *Communications Medicine*, vol. 5, no. 1, 2025, article 4.

[13] Strodthoff, N., P. Wagner, T. Schaeffter, and W. Samek. "Deep Learning for ECG Analysis: Benchmarks and Insights from PTB-XL." *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 5, 2020, pp. 1519–1528.