Future Technology
Open Access Journal
ISSN 2832-0379

August 2025| Volume 04 | Issue 03 | Pages 19- 28

Journal homepage: https://fupubco.com/futech

https://doi.org/10.55670/fpll.futech.4.3.3

Future Publishing LLC

Article

# Enhanced cardiac arrhythmia classification through integration of ensemble empirical mode decomposition and heart rate variability analysis

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**ARTICLE INFO**

*Article history:*
Received 31 March 2025
Received in revised form
16 May 2025
Accepted 27 May 2025

Keywords:
Cardiac arrhythmias, Ensemble empirical mode decomposition, Heart rate variability, Support vector machine, MIT-BIH, Accuracy

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DOI: 10.55670/fpll.futech.4.3.3

**ABSTRACT**

Cardiac arrhythmias are critical conditions requiring accurate classification for effective diagnosis as well as treatment. In this investigation, we provide a novel approach for cardiac arrhythmia classification that integrates two advanced techniques for feature extraction from ECG signals: “Ensemble Empirical Mode Decomposition” (EEMD) and “Heart Rate Variability” (HRV) analysis. The proposed approach employs EEMD to decompose ECG signals into intrinsic mode functions, capturing signal features, while HRV analysis provides additional physiological insights into heart rate fluctuations. Combining two strategies, our approach leverages a comprehensive set of features to improve the accuracy and resilience of arrhythmia classification. The system's effectiveness is explained via simulated tests utilizing the MIT-BIH arrhythmia database, with performance evaluated based on recall, accuracy, and precision metrics. Our results indicate that integrating EEMD and HRV features provides a more reliable and detailed classification of cardiac arrhythmias, offering a holistic perspective on heart rhythm dynamics.

## 1. Introduction

In recent years, cardiovascular diseases (CVDs) have been found to be the leading cause of death both globally and in India. Worldwide, CVDs were accountable for roughly 17.9 million deaths in 2019, constituting 32% of all deaths, with 85% resulting from heart attacks and strokes [1]. The burden of ischemic heart disease alone accounted for 8.9 million deaths in the same year, with a significant 70% increase in CVD-related deaths since 1990, particularly affecting low- and middle-income countries [2]. In India, CVDs were responsible for 28.1% of total deaths in 2020, a leading cause of mortality, with annual deaths rising from 1.3 million in 1990 to 1.7 million in 2016. The age-standardized death rate for CVDs in India was 272 per 100,000 population in 2019, higher than the global rate of 243 per 100,000 [3]. Contributing factors in India include increasing rates of hypertension, diabetes, smoking, and obesity, with concerning rises in CVD incidents among younger populations. Accurate diagnosis and early detection are essential for reducing their impact and improving patient outcomes. “Electrocardiography” (ECG), a non-invasive and widely accessible tool, is essential to initial diagnosis and ongoing management of several cardiac illnesses. ECG has become one of the crucial tools for investigating the heart’s structure and function because of its affordability, simplicity, efficiency, and non-invasive nature. ECG captures electrophysiological activity related to repolarization and depolarization of heart muscles throughout every heartbeat, providing critical insights into cardiac health. "Arrhythmia" describes deviations from the normal sequence of electrical impulses in the heart, resulting in irregular heart rhythms [4]. These may range from benign to life-threatening, potentially leading to conditions like tachycardia or even sudden cardiac arrest. In arrhythmia investigation, ECG-based heartbeat classification has emerged as a potential technique for early detection and warning of arrhythmias. Traditional ECG interpretation [5, 6], however, relies heavily on the expertise of trained clinicians, leading to variability in diagnostic accuracy and delayed clinical decision-making. In addition, ECG signals can exhibit significant variability across different individuals. Morphologies and rhythms associated with similar arrhythmic symptoms can vary under different circumstances. Experienced cardiologists might readily distinguish abnormal heartbeats from normal sinus rhythms by examining ECG, but this remains a difficult task for automated systems due to variability in ECG signals and differences in recording environments.

**Abbreviation**

| | |
|---|---|
| CVD | cardiovascular diseases |
| ECG | Electrocardiography |
| SVM | Support Vector Machines |
| RF | Random Forests |
| K-NN | k-Nearest Neighbors |
| CNN | Convolutional Neural Networks |
| RNN | Recurrent Neural Networks |
| AS | asystole |
| VF | ventricular fibrillation |
| PEA | pulseless electrical activity |
| VT | Ventricular tachycardia |
| PR | pulse-generating rhythm |
| ANN | artificial neural networks |
| LSTM | long short-term memory |
| FFT | Fast Fourier Transform |
| ANFIS | Adaptive neuro-fuzzy inference system |
| MRR | multi-resolution representation |
| CIE | computer-interpreted ECG |
| LSSVM | Least Square Support Vector Machine |
| BLSTM | Bidirectional Long Short-Term Memory neural network |
| HRV | Heart Rate Variability |
| SDNNI | Standard Deviation of NN Intervals |
| RMSSD | Root Mean Square of Successive Differences |
| SNS | Sympathetic Nervous System |
| PNS | Parasympathetic Nervous System |
| LPF | Low-Power Frequency |
| HPF | High-Power Frequency |
| AMI | Advancement of Medical Instrumentation |
| TP | True Positives |
| FP | False Positives |
| TN | True Negatives |
| FN | False Negatives |
| MSVM | Modified SVM |
| EMD | Empirical Mode Decomposition |
| TT | Thresholding Technique |
| EMLPT | Ensemble based Multiscale Local Polynomial Transform |

Even for healthy individuals, ECG morphology and rhythm might show substantial variation over short periods. Various methods [7-9] were developed for generic heartbeat classification utilizing ECG signals on the basis of diverse technologies. Arrhythmia classification using ECG signals encompasses various methods, each leveraging distinct techniques to enhance diagnostic accuracy. Traditional approaches often rely on feature extraction approaches like time-domain [10], frequency-domain [11], and morphological analysis [12] to identify critical signal characteristics related to different types of arrhythmias. These features are then fed into ML algorithms, like Support Vector Machines (SVMs) [13], Random Forests, and k-Nearest Neighbors (k-NN), Neural Networks [14], which classify heartbeats based on learned patterns. However, Time domain features can be sensitive to noise and artifacts present in ECG signals. In addition, Time domain features typically capture basic properties such as amplitude, duration, and intervals between peaks (e.g., RR intervals). They may not fully capture complex temporal patterns or subtle variations in ECG signals that are critical for distinguishing certain arrhythmias. On the other hand, Frequency domain analysis involves transforming the signal, which in turn leads to a loss of temporal information. Further, Frequency domain features provide information about signal components at different frequencies, but interpreting these components in relation to specific arrhythmias or cardiac conditions can be complex.

Recent advancements have observed the adoption of DL models [15], including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which can automatically recognize and identify characteristics in unprocessed ECG data without manual intervention [16-18]. These models have demonstrated superior performance in capturing complex temporal and spatial relationships within the ECG signals, making them highly effective for detecting various arrhythmias. Additionally, hybrid models combining traditional feature extraction with deep learning techniques offer a balanced approach, enhancing classification accuracy and robustness. Integrating these methodologies with real-time monitoring systems holds promise for improving early detection and management of cardiac arrhythmias, thereby advancing patient care. Nevertheless, DL models frequently need much annotated data for training to achieve optimal performance. In the context of ECG signals, obtaining annotated datasets with diverse arrhythmia types and sufficient variability can be challenging. Limited or biased datasets may hinder a model's capability for extrapolating unseen, new data or for rare arrhythmias not well represented in the training set. To sort out the above-mentioned problems in the classification of cardiac arrhythmias, this paper proposes a novel methodology that integrates EEMD and HRV for feature extraction from ECG signals. Major contributions of this paper are outlined as follows.

- Innovative Classification Methodology: Developed a novel three-fold methodology for cardiac arrhythmias classification using ECG signals, which integrates both EEMD and HRV analysis.
- Advanced Feature Extraction Techniques: Utilized EEMD to break down ECG signals into IMFs, capturing detailed and nuanced features from ECG signals. Complemented this with HRV analysis to extract additional features related to heart rate fluctuations.
- Performance Evaluation: Demonstrated efficacy of suggested approach through simulation experiments utilizing the MIT-BIH arrhythmia database, evaluating performance based on recall, accuracy, and precision metrics.

The rest of the paper is organized as follows: Section 1 presents the importance of cardiac arrhythmias as well as the motivation for developing an advanced classification method using ECG signals. Section 2 provides a comprehensive literature survey, reviewing existing techniques for ECG signal analysis and identifying gaps that the proposed method aims to fill. Section 3 details the proposed three-fold methodology, which combines EEMD and HRV analysis for feature extraction and arrhythmia classification, and presents the system architecture through a block diagram. Section 4 reports the simulation results employing the MIT-BIH arrhythmia database, evaluating the suggested approach's performance based on recall, accuracy, and precision metrics. Section 5 sums up the paper by providing a summary of the results, talking about the research's significance, and outlining possible future research possibilities.

## 2. Literature survey

In the past, a number of techniques were used to categorize various cardiovascular disorders using ECG data.

Rad AB et al. [19] suggested categorizing asystole (AS), ventricular fibrillation (VF), pulseless electrical activity (PEA), Ventricular tachycardia (VT), and pulse-generating rhythm (PR) are the five categories into which cardiac rhythms fall. For massive data sets, manually annotating rhythms is impractical and time-consuming. They suggested taking into account all 47 wavelet- and time-domain-based ECG characteristics to carry out this procedure. A feature selection architecture based on wrappers was employed to choose features. At classification, classifiers based on artificial neural networks (ANN), ensembles of k-nearest neighbors, decision trees, k-local hyperplane distance nearest neighbor, and Bayesian decision theory have been investigated. For classification of ECG beats, Huang, J. et al. [20] suggested a unique architecture that combines multiple long short-term memory (LSTM) RNNs with wavelet transform. A thorough approach to ECG sample classification was proposed by Hu Y et al. [21]. First, the continuous wavelet transform is implemented to retrieve ECG characteristics. They subsequently utilized the new lightweight context transform blocks to classify arrhythmias. Block has been suggested by enhancing the linear content transform block using linear transformation and a squeeze-and-excitation network. Lastly, the MIT-BIH arrhythmia database has been utilized to validate the suggested approach. In order to differentiate among four different kinds of arrhythmia illness that had been gathered from records, Sharma R. et al. [22] suggest using an ECG arrhythmia classification approach on the basis of Fast Fourier Transform (FFT) for feature extraction as well as an enhanced AlexNet classifier.

A method to categorize cardiac signals into atrial fibrillation, ventricular arrhythmias, atrial flutter, congestive heart failure, malignant ventricular arrhythmias, premature atrial fibrillation, and normal heartbeats was proposed by Qiu, Y. et al. [23]. Cardiac arrhythmias were detected and diagnosed using a deep learning algorithm. To improve signal classification sensitivity, they put out a novel ECG signal classification technique. They used noise reduction filters to smooth the ECG signal. ECG characteristics were extracted using a discrete wavelet transform depending on the arrhythmic database. Wavelet decomposition energy attributes, as well as computed values of PQRS morphological characteristics, were utilized to generate feature vectors. Adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN) utilize a genetic algorithm to identify input layer weights as well as minimize the feature vector.

An arrhythmia detection technique relying on multi-resolution representation (MRR) of ECG data is proposed by Silva, I. & Henriques J. [24]. In order to learn ECG vector representations, this approach uses four distinct, state-of-the-art deep neural networks as four-channel models. The downstream classification technique uses the MRR, which is created by combining hand-crafted ECG data with deep learning-based representations. NEO-CCNN, a robust method for classifying arrhythmias, was proposed by Wu, W., et al. [25] for wearables that may seem applied on a basic microcontroller. With the aid of the suggested adaptive time-dependent thresholding technique, the NEO-CCNN algorithm not only identifies QRS but also precisely locates the R-peak, increasing the sensitivity and accuracy of arrhythmia classification. Yang L. et al. [26] suggested a way to identify ECG anomalies and health alerts on the basis of 3R-TSH-L methodology and ECG Holter of PHIA. Following actions are involved in putting 3R-TSH-L approach into practice: (1) using LSTM for classification, training, and testing algorithm based on MIT-BIH dataset, and obtaining relatively optimal features as spliced normalized fusion features, like kurtosis, skewness, and RR interval time domain features, STFT-based sub-band spectrum features, and harmonic ratio features; (2) extracting combination features, like time-domain features, frequency domain features, and time-frequency domain features; and (3) obtaining 3R ECG samples utilizing Pan-Tompkins technique and employing volatility to obtain high-quality raw ECG data. Plesinger, F. et al. [27] created a deep learning (DL)-based computer-interpreted ECG (CIE) method to find the best 4-lead ECG subset for heart arrhythmia classification, with an emphasis on minimizing information loss. In order to identify corresponding optimum ECG-lead subsets, four common heart arrhythmia types (RBBB, AF, LBBB, and I-AVB) were learned utilizing the DL-based CIE model. Wang Z. et al. [28] suggest a successful system design and implementation for ECG classification utilizing (Faster R-CNN) approach depending on faster regions. In this experiment, certain ECG recordings from the MIT-BIH database are included in the original one-dimensional ECG signals, along with preprocessed patient ECG signals. In order to categorize ECG beats, Li H. et al. [29] suggested an ECG recognition system based on multi-domain feature extraction. To eliminate noise interference, an enhanced wavelet threshold technique has been employed for pre-processing ECG signals. A unique multi-domain feature extraction technique is introduced, utilizing kernel-independent component analysis for nonlinear feature extraction and the discrete wavelet transform for frequency domain feature extraction. To identify various heartbeat types, it makes use of an SVM classifier that has been optimized using a genetic approach. A self-adjusting ant colony clustering technique on the basis of a corrective system was proposed by Li N. et al. [30] for categorization of ECG arrhythmias. To lessen the impact of individual variations in ECG signal characteristics and increase the model's robustness, this approach does not differentiate between subjects when creating the dataset. After classification is complete, a correction mechanism is added to increase the model's classification accuracy by fixing outliers brought on by the accumulation of classification errors. Majeed R. R. et al. [31] suggest a new model for ECG verification that combines an LS-SVM having multi-domain characteristics. To determine the optimal set of features to separate from ECG signals, two feature types are examined. ECG signals have been processed to extract time as well as frequency domain features using an improved Triple Band filter bank. To identify the most pertinent traits and eliminate the ones that are redundant, the extracted features are examined. Three classifiers—K-means, Least Square Support Vector Machine (LS-SVM), and K-nearest—have been fed chosen features. An intelligent heartbeat classification system was proposed by Runchuan Li et al. [32] using an AdaBoost + Random Forest model and chosen optimal feature sets. The Holter allows this system to obtain ECG data, which is then sent to the cloud platform for feature extraction and preprocessing. AdaBoost + Random Forest then uses features to classify heartbeats. Tang S., et al. [33] presented CSML-Net, a unique multi-task network that combines convolutional neural networks and compressed sensing. The suggested model utilizes two task branches and shared layers to recover and classify the ECG signals simultaneously after compressing them employing a learning measurement matrix. To enhance model performance, the multi-scale feature module was created. Additionally, an enhanced classification strategy for deep compressed sensing models was proposed by Hua J. et al. [34]. Pre-processing, compression, and categorization are the four modules that make up the framework. Normalized

ECG signals have been initially adaptively compressed in 3 convolutional layers to obtain findings of four distinct ECG signal types. The classification network then receives compressed data directly. The Pan-Tompkins technique can be utilized by Fang Y. et al. [35] to extract QRS characteristics of ECG signals from the MIT-BIH ECG database. Following sample extraction, samples are screened utilizing k-means clustering, and ECG data was analyzed using an RBF neural network. Both the final classification model's classification accuracy and electrical signal characteristics are trained by the classifier. A new and portable CNN-based automatic ECG classification technique has been presented by Liu F. et al. [36]. Multi-spatial deep characteristics of heartbeats are extracted using a multi-branch network with various receptive fields. Redundant ECG characteristics are filtered using a Bidirectional Long Short-Term Memory neural network (BLSTM) module and a Channel Attention Module (CAM). Gao H et al. [37] provide a multi-resolution model that can smoothly combine global rhythm patterns with local morphological traits. They presented the parameter isolation-based ECG continual (ECG-CL) technique, enhancing the effectiveness of data utilization and promoting information transfer between tasks.

## 3. Proposed approach

The proposed method utilizes ECG signals for Cardiac Arrhythmias Classification, encompassing a three-fold methodology. The suggested approach uses two different approaches for feature extraction from ECG signals. Additional ECG data are captured using Heart Rate Variability (HRV) analysis, while detailed features have been extracted from ECG signals utilizing EEMD. The approach leverages extensive physiological data to enhance the robustness of cardiac arrhythmia classification by combining these sophisticated extraction approaches. Utilizing both EEMD and HRV features improves classification accuracy by accounting for peripheral physiological changes. Furthermore, the method offers a holistic perspective on the dynamics of heartbeat by analyzing heart rate variability, leading to more reliable and detailed Cardiac Arrhythmias classification. Figure 1 illustrates the suggested Comprehensive System Architecture.

### 3.1 Feature extraction

For feature extraction from ECG, we used two distinctive techniques, namely EED and Heart Rate Variability. The combination of EEMD and HRV analysis ensures a comprehensive assessment of ECG signals. EEMD provides a detailed frequency-based decomposition of the ECG signal, capturing intricate patterns and abnormalities. In contrast, HRV analysis offers insights into temporal variations and autonomic regulation of the heart. Together, these techniques complement each other, providing a robust feature set that enhances the classification of cardiac arrhythmias. By leveraging both detailed signal decomposition from EEMD and the autonomic insights from HRV, the proposed method achieves higher accuracy and reliability in identifying various arrhythmias, thus improving diagnostic outcomes.

#### 3.1.1 Empirical mode decomposition (EMD)

The EMD technique was created to examine time series data that is non-stationary as well as non-linear. A set of IMFs, which are simpler parts that represent various frequency bands in the original signal, is produced when a signal is broken down. Each of the iteratively filtered IMFs must meet certain requirements to be derived:

- Number of zero crossings and extremes (maxima and minima) must be identical or differ by no more than one.
- At every given position, envelopes described by local maxima and minima have an average value of zero.

A signal is decomposed by EMD into a residue and an assortment of IMFs. The general EMD decomposition formula is:

$$x(t) = \sum_{i=1}^{n} IMF_i\,(t) + r_n(t) \tag{1}$$

Where $IMF_i(t)$ are intrinsic mode functions, and $r_n(t)$ is the residue after extracting $n$ IMFs.

The EMD Sifting Process: The steps involved in this process are as follows:

- Identify all local extrema (maxima and minima) of the signal *x(t)*.
- Interpolate between local maxima to form upper envelope $e_{max}(t)$.

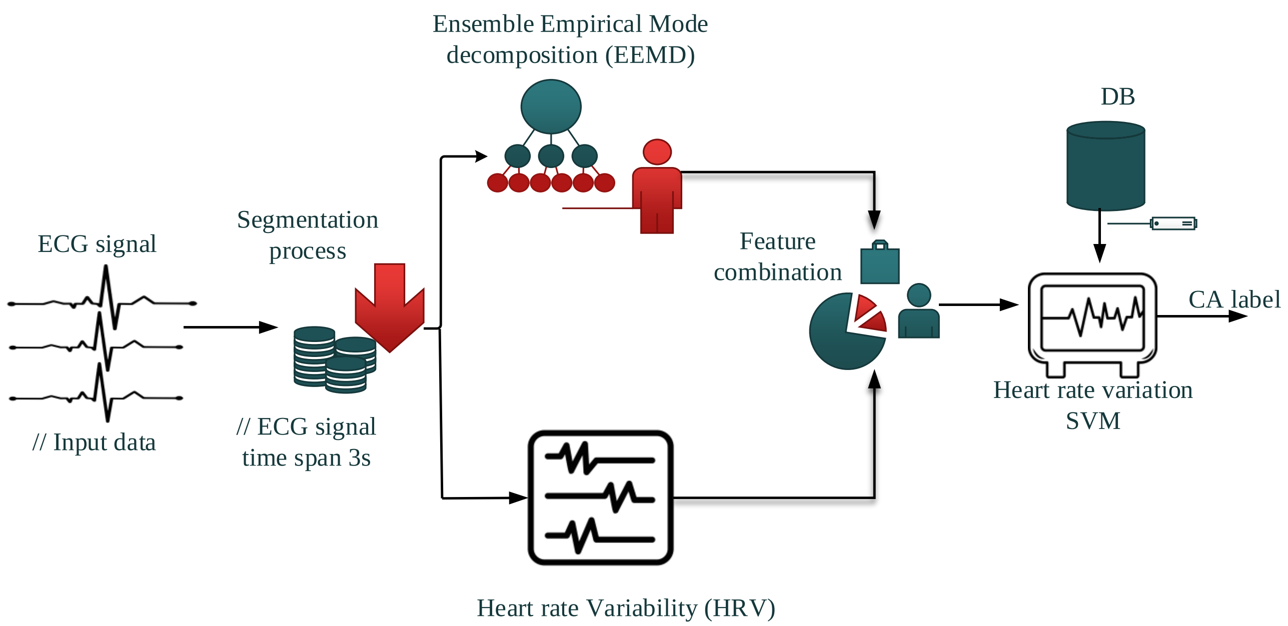


**Figure 1.** Comprehensive system architecture of the proposed model

- Interpolate between local minima to form lower envelope $e_{min}(t)$.
- Compute the mean envelope $m(t) = \frac{e_{max}(t)+e_{min}(t)}{2}$
- Extract detail $h(t)=x(t)-m(t)$.
- Iterate on $h(t)$ until it satisfies IMF conditions, then treat $h(t)$ as the first IMF.

### 3.1.2 Ensemble EMD (EEMD)

The key issue with EMD is mode mixing, where different signal components are not well-separated and multiple physical modes can exist within a single IMF. This can make the interpretation of IMFs difficult and less meaningful. EEMD is an improvement over EMD that mitigates the issue of mode mixing by introducing a noise-assisted data analysis method. It operates by first adding white noise to the original signal, then repeatedly applying EMD to the noisy signal. Major advantages of EEDM are several-fold; they are:

**Reducing Mode Mixing:** EEMD effectively reduces mode mixing, a common issue in traditional EMD where different frequency components are not well-separated. By averaging multiple noisy decompositions, EEMD ensures that each IMF represents a distinct frequency band of the ECG signal, leading to clearer and more interpretable components.

**Handling Non-Stationarity and Non-Linearity:** ECG signals are inherently non-stationary and non-linear. EEMD is well-suited for such signals because it does not assume linearity or stationarity. It adaptively decomposes the signal based on its intrinsic characteristics, allowing for accurate feature extraction that reflects the dynamic nature of brain activity.

**Improved Signal Representation:** By decomposing ECG signals into IMFs, EEMD provides multi-scale signal representation. Particularly useful in sleep studies, as different sleep stages are characterized by specific frequency bands (e.g., delta waves in deep sleep, theta waves in light sleep). EEMD allows for the isolation and analysis of these bands, improving the accuracy of sleep stage classification.

**Noise Robustness:** The noise-adding process in EEMD helps in spreading the signal's energy across different frequency scales uniformly, which enhances the separation of intrinsic modes. This makes the decomposition more robust to noise, an important consideration in ECG analysis where signal noise can be prevalent.

The procedures associated with EEMD are as follows:

**Add white noise:** Add a new realization of white noise to the original signal. This aids in evenly dispersing the energy of the signal across several frequency ranges.

$$x_k(t) = x(t) + w_k(t) \tag{2}$$

Where k varies from 1 to K, the total number of noise realizations.

**Decompose the noisy signal:** The noisy signal can be broken down into its IMFs by applying the EMD procedure.

$$x_k(t) = \sum_{i=1}^{n} IMF_{ik}(t) + r_{nk}(t) \tag{3}$$

Where $IMF_{ik}$ $(t)$ are $MF$ s of the noisy signal $x_k(t)$.

**Repeat:** To generate an ensemble of IMFs for every noisy signal, repeat the procedure several times (with varying noise realizations).

**Ensemble averaging:** Determine the related IMFs' ensemble average over all trials. This averaging procedure produces a more stable and dependable set of IMFs by eliminating the extra noise while keeping the actual signal components.

$$IMF_i(t) = \frac{1}{k}\sum_{K=1}^{K} IMF_{ik}(t) \tag{4}$$

This averaging process cancels out the added noise, retaining the true signal components.

### 3.1.3 Variability in heart rate (HRV)

The HRV is a crucial metric that is obtained from ECG readings and represents the changes in the intervals between successive heartbeats. It is frequently used to evaluate heart health and autonomic nervous system function. Time and frequency domain techniques are two categories for feature extraction from ECG signals for HRV study. Because both domains contribute significantly to the representation of sleep disorders, we took them into account in our experiment.

**A. Time domain HRV**: RR intervals are intervals of time in the ECG signal between successive R-peaks and are used to compute time domain features, which are statistical metrics. Time domain HRV features are helpful for basic HRV assessments and real-time monitoring since they are easy to calculate and comprehend. RRMean, Root Mean Square of Successive Data, and SDNN are common time domain HRV features. Differences in pNN50 and RMSSD [38]. They are described as follows;

**Mean RR Interval (RR mean):** mean duration between consecutive R-peaks.

$$RRM_{ean} = \frac{1}{N}\sum_{i=1}^{N} RR_i \tag{5}$$

**Standard Deviation of NN Intervals (SDNN):** The SD of all NN (normal-to-normal) intervals, describing overall HRV.

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RR_i - RRM_{ean})^2} \tag{6}$$

**Root Mean Square of Successive Differences (RMSSD):** Short-term HRV is indicated by RMSSD between neighboring NN intervals.

$$RMSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RR_i - RR_i)^2} \tag{7}$$

**pNN50:** Proportion of successive RR intervals that differ by < 50ms.

$$pNN50 = \frac{numberofIntervalswit\square|RR_{i+1}-RR_i|>50ms}{N} \tag{8}$$

Heart rate reflects the dynamic activities of the Parasympathetic Nervous System (PNS) as well as the Sympathetic Nervous System (SNS), correlates with RF, and offers insights into heart activity while you're asleep.

**B.HRV in the frequency Domain:** The power distribution across various frequency bands is shown by examining the RR intervals' power spectral density, which yields frequency domain properties. A deeper understanding of physiological processes and autonomic regulation is possible using frequency domain features, which is helpful for more thorough clinical investigation. The following are typical frequency domain HRV features:

**Low-Power Frequency (LF):** Low-frequency power, linked to parasympathetic & sympathetic activity, falls between 0.04- 0.15Hz.

**High-Power Frequency (HF):** In the high-frequency region (0.15- 0.4 Hz), power mostly represents parasympathetic activity ("respiratory sinus arrhythmia").

**LF/HF Ratio:** The LF to HF power ratio shows how well sympathetic and parasympathetic AC work together. Total Power: The entire spectrum's power within the frequency range, often up to 0.4 Hz.

**Total Strength:** The total strength of the spectrum within the frequency range (usually up to 0.4 Hz).

Faster periodicities in heart rate patterns are captured by Low-Power Frequency(LF)(0.04 to 0.15 Hz) as well as High-Power Frequency(HF) power (0.15 to 0.4 Hz). LF power (0.04 to 0.15 Hz) as well as HF power (0.15 to 0.4 Hz) are associated with the regulation of SNS as well as PNS, correspondingly [39]. During the shift from NREM to REM sleep, the LF/HF ratio typically rises with increased SNS activity. Utilized to evaluate changes in autonomic function between sleep stages. This ratio captures subtle changes in cardiac dynamics across different sleep stages [40].

## 4. Evaluation of EEMD and HRV for HRV analysis

This section offers a comprehensive description of the experimental assessment conducted on the developed heartbeat classification system. The experiments were performed using MATLAB 2018, along with the Signal Processing Toolbox and Wavelet Toolbox. Initially, the details of the dataset settings are discussed, providing insight into the data preparation and preprocessing steps. Following this, the section delves into the performance analysis, exploring the metrics and methodologies used to evaluate the system's effectiveness.

### 4.1 Simulation setup

The simulation setup for ECG signal-based heartbeat classification is designed to determine as well as confirm the performance of suggested classification algorithms utilizing the MIT-BIH Arrhythmia Database [41, 42]. The MIT-BIH database's collection of annotated ECG recordings is a well-known and often used resource in the fields of biomedical engineering and cardiology. It serves as a standard for creating and evaluating heartbeat classification systems. Forty-eight half-hour segments of 47 participants' two-channel ambulatory ECG recordings have been involved in the MIT-BIH Arrhythmia Database. Numerous arrhythmias are covered in these recordings, which makes the dataset perfect for classification model evaluation and training. With a 360Hz sample frequency, ECG signals are digitized to produce high-resolution data for examination. The Organization for Advancement of Medical Instrumentation (AAMI) proposed the ANSI/AAMI EC57 standard, which was introduced in 2012, and includes five categories for classifying arrhythmias. Non-ectopic beats (N), supraventricular ectopic beats (S), ventricular ectopic beats (V), fusion beats (F), as well as unknown beats (Q) are some of these classifications, which are shown in Figure 2.

**N (Non-ectopic beats):** The model has a significant amount of data to learn normal heart rhythms because these are the most prevalent normal heartbeats in both the training and testing sets.

**S (Supraventricular ectopic beats):** The ventricles are above where these beats begin. They occur less frequently than non-ectopic beats, yet they are essential for identifying anomalies.

**V (Ventricular ectopic beats):** The ventricles are the source of these beats, which are essential for spotting severe arrhythmias.

**F (Fusion beats):** These are caused by the simultaneous occurrence of an ectopic and a regular beat. Though uncommon, they are crucial for thorough classification.

**Q (Unknown beats):** These beats do not fall into the other categories and may include artifacts or unclassified rhythms.

The complete dataset is divided into 70% for training and 30% for testing, with no overlap between the two sets to ensure unbiased evaluation. Table 1 demonstrates the simulation setup of the MIT-BIH dataset with different classes. The training set includes 63,413 N beats, 1,946 S beats, 5,064 V beats, 561 F beats, & 5,628 Q beats. Testing set comprises 27,182 N beats, 835 S beats, 2,171 V beats, 241 F beats, and 2,413 Q beats. This distribution ensures a comprehensive training process by providing substantial data for each class, particularly for normal and abnormal heart rhythms. The separate test set allows for accurate performance assessment, ensuring the classification system is robust and generalizes well to unseen data.

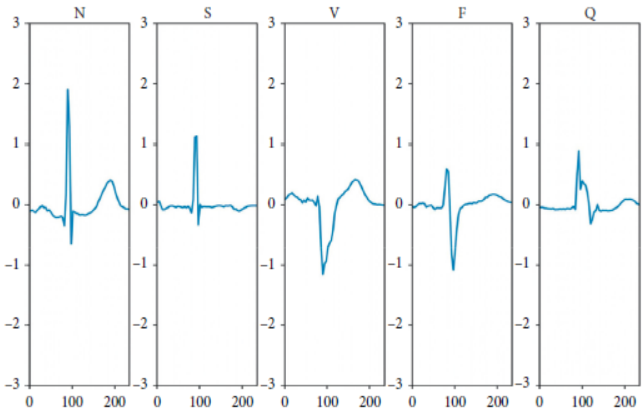


**Figure 2.** Different categories of heartbeats

**Table 1.** Simulation setup of the MIT-BIH dataset with different classes

| Class | Training | Testing | Overall |
|---|---|---|---|
| **N** | 63413 | 27182 | 90595 |
| **S** | 1946 | 835 | 2781 |
| **V** | 5064 | 2171 | 7235 |
| **F** | 561 | 241 | 802 |
| **Q** | 5628 | 2413 | 8041 |
| **Total** | **76612** | **32842** | **109454** |

### 4.2 Result observations

Further, the performance is assessed through four performance metrics, namely Recall, Precision, F1-score, and Accuracy. For a given True Positives (TPs), False Positives (FPs), True Negatives (TNs), and False Negatives (FNs), recall, precision, and F1-score are measured as follows:

$$Re\,c\,all = \frac{TP_i}{TP_i+FN_i} \tag{9}$$

$$Pr\,e\,cision = \frac{TP_i}{TP_i+FP_i} \tag{10}$$

$$F1 - Score_i = \frac{2*Re\,call_i*Pr\,ecision_i}{Re\,call_i+Pr\,ecision_i} \tag{11}$$

$$Accuracy = \frac{TP_i+TN_i}{TP_i+TN_i+FP_i+FN_i} \tag{12}$$

The provided confusion matrix in Table 2 summarizes the classification performance of an ECG heartbeat detection system across five categories: N, S, V, F, and Q. The Matrix shows that the model correctly identified 26,910 N beats, with minor misclassifications into other categories. Similarly, S beats were accurately classified 651 times but misclassified into N, V, and Q categories in a few instances. The V beats were correctly classified 2,062 times, with minor errors in other categories. F beats were correctly identified 159 times, with some misclassified as N or V beats. Lastly, Q beats were mostly correctly identified with 2,341 correct classifications, and minor misclassifications into other categories. Overall, the matrix indicates high classification accuracy, with the majority of heartbeats being correctly classified, and the total classification attempts summed up to 32,842 beats. This detailed performance evaluation highlights the robustness and reliability of the classification system in distinguishing between different types of heartbeats.

**Table 2.** Confusion matrix derived from the results

| | N | S | V | F | Q | Total |
|---|---|---|---|---|---|---|
| **N** | 26910 | 71 | 201 | 0 | 0 | 27182 |
| **S** | 100 | 651 | 10 | 0 | 74 | 835 |
| **V** | 89 | 10 | 2062 | 10 | 0 | 2171 |
| **F** | 52 | 0 | 30 | 159 | 0 | 241 |
| **Q** | 55 | 0 | 17 | 0 | 2341 | 2413 |
| **Total** | 27206 | 732 | 2320 | 169 | 2415 | 32842 |

Table 3 presents the performance metrics of an ECG heartbeat classification system across five heartbeat categories. For N beats, the system achieved a high precision of 98.9120%, a recall of 98.9993%, as well as an F1-score of 98.9556%, indicating excellent classification performance. For S beats, the recall was 77.9640%, precision 88.9344%, and the F1-Score was 83.0887%, showing moderate performance with room for improvement. V beats had a recall of 94.9792%, precision of 88.8793%, and an F1-score of 91.8281%, demonstrating strong classification accuracy. F beats had a lower recall of 65.9751%, but a high precision of 94.0828%, and an F1-Score of 77.5609%, reflecting challenges in detecting all instances correctly but substantial accuracy when identified. Q beats exhibited high performance with a recall of 97.0161%, precision 96.9358%, and F1-Score 96.9759%. Overall, the metrics indicate that the classification system performs exceptionally well for N and Q beats, robustly for V beats, and has moderate to good performance for S and F beats. Figures 3 to 6 show the accuracy, recall, precision, and F1-score rates for five heartbeat classes (N, S, V, F, Q) across four different test sets.

**Table 3.** Performance assessment of different beats

| | TP | FN | FP | Accuracy (%) | Recall (%) | Precision (%) | F1-Score (%) |
|---|---|---|---|---|---|---|---|
| **N** | 26190 | 272 | 1016 | 95.9556 | 98.9993 | 98.9120 | 98.9556 |
| **S** | 651 | 184 | 81 | 93.0887 | 77.9640 | 88.9344 | 83.0887 |
| **V** | 2062 | 109 | 258 | 93.8281 | 94.9792 | 88.8793 | 91.8281 |
| **F** | 159 | 82 | 10 | 92.5609 | 65.9751 | 94.0828 | 77.5609 |
| **Q** | 2341 | 72 | 14 | 94.9759 | 97.0161 | 96.9358 | 96.9759 |

Among the five classes, the N class has consistently high recall across all sets, while the recall for other classes varies. The Q class, represented by red bars, also shows high recall, particularly in test sets 2 and 4. The other classes (S, V, F) have more variability, with F showing the lowest recall in most sets. Figure 4 shows the precision rates for the same five heartbeat classes across the four test sets. The N class (blue bars) maintains high precision across all sets, similar to its recall performance. The Q class (red bars) also demonstrates high precision, especially in test sets 1 and 3. The precision for classes S, V, and F fluctuates more, with the F class (yellow bars) showing lower precision in several test sets. Finally, Figure 5 illustrates F1-scores for the five heartbeat classes across the four test sets. The N class (blue bars) achieves consistently high F1-scores in all sets. The Q class (red bars) follows closely with high scores as well. F1-scores for S, V, as well as F classes, are more variable, with the F class again showing the lowest scores in multiple test sets (Figure 6).

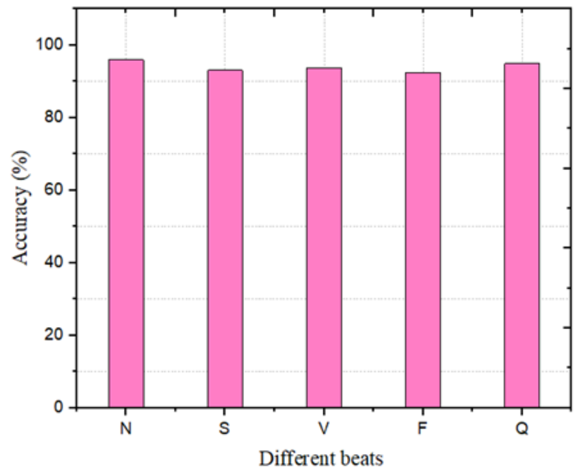


**Figure 3.** Accuracy for different classes at different test sets

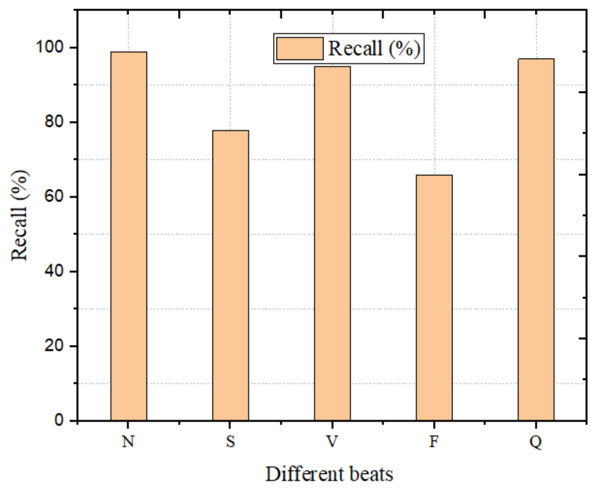


**Figure 4.** Recall for different classes at different test sets

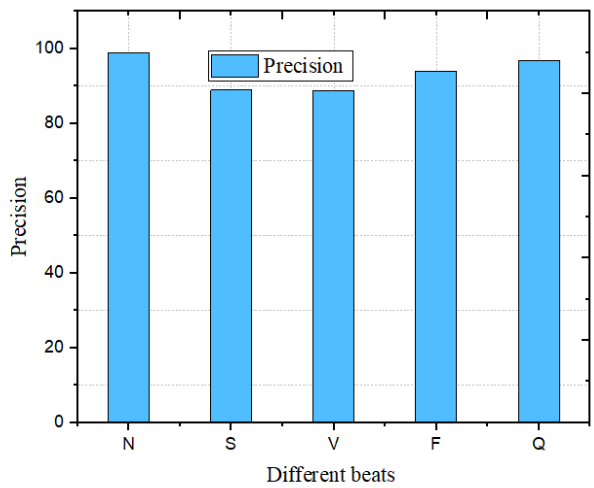


**Figure 5.** Precision for different classes at different test sets

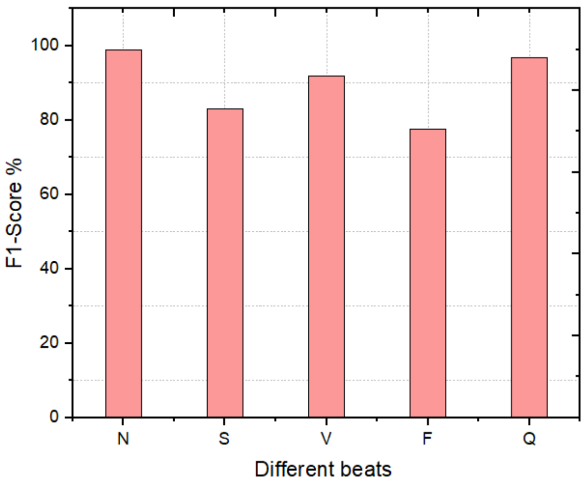


**Figure 6.** F1-Score for different classes at different test sets

On average, the recall rates are as follows: N class at 98.9%, S class at 77.96%, V class at 94.98%, F class at 65.98%, and Q class at 97.02%. The average precision rates are: N class at 98.9%, S class at 88.93%, V class at 88.88%, F class at 94.08%, and Q class at 96.94%. The average F1-scores are: N class at 98.96%, S class at 83.09%, V class at 91.83%, F class at 77.56%, and Q class at 96.98%. Across all three figures, the N class consistently demonstrates high recall, precision, and F1-scores, indicating robust classification performance. The Q class also performs well across all metrics, particularly in recall and precision. The S, V, and F classes exhibit more variability in their performance, with the F class generally having the lowest recall, precision, and F1-scores. This suggests that while the classification system is highly effective for N and Q beats, it has more difficulty accurately classifying S, V, and particularly F beats.

Table 4 compares various methods for ECG heartbeat classification, highlighting their features, classifiers, and achieved accuracy rates. Silva and Henriques [24] used a multi-resolution representation approach with a CNN, achieving 92.38% accuracy. However, the drawback of this method is that it might not fully represent the spectrum of nonlinear dynamics present in ECG signals, limiting its overall performance. Bahrami Rad et al. [19] utilized wavelet- and time-domain-based features combined with Bayesian decision theory, k-NN, and ANN, achieving a lower accuracy of 76.90%. This method's significant drawback is its relatively low accuracy, which suggests that classifiers as well as feature extraction methods used may not be sufficiently robust for effective ECG signal classification. Hu et al. [21] employed Continuous Wavelet Features with a squeeze-and-excitation network and linear transformation, achieving an accuracy of 87.77%. Despite its innovative approach, the method's lower accuracy indicates potential limitations in handling the complexities of ECG signal variations, leading to suboptimal classification performance. Anam Mustaqeem et al. [41] used wrapper-based features with Support Vector Machine (SVM) classifiers with different kernels, reaching an accuracy of 92.07%. Although the accuracy is relatively high, the method's reliance on kernel selection and feature wrapping can be computationally intensive and may not generalize well across different datasets. The suggested approach, which employs EEMD and HRV features in combination with an SVM classifier, reaches a maximum accuracy of 95.63%. Consequently, the achieved results of the developed model were outperformed by conventional models in terms of various performance metrics such as accuracy, precision, recall, and f-measure, which are demonstrated in Table 5. Moreover, the existing models are Modified SVM classifier (MSVM) [43], Empirical Mode Decomposition (EMD) [44], Thresholding Technique (TT) [45], and Ensemble-based Multiscale Local Polynomial Transform (E-MLPT) [46]. The effective combination of EEMD and HRV features provides a more comprehensive representation of ECG signal's characteristics, resulting in more precise and robust heartbeat classification, which can be attributed to this superior performance.

**Table 4.** Comparing the ECG beat categorization method with the most advanced technique

| Method | Features | Classifier | Accuracy (%) |
|---|---|---|---|
| Silva, I., & Henriques, J., [24] | multi-resolution representation | CNN | 92.3800 |
| Bahrami Rad, A., et al. [19] | wavelet- and time-domain-based features | Bayesian decision theory, k-nearest neighbor, ANN | 76.9000 |
| Hu, Y., et al. [21] | Continuous Wavelet Features | squeeze-and-excitation network and linear transformation | 87.7700 |
| Anam Mustaqeem et al. [41] | Wrapper-Based Features | SVM with different Kernels | 92.0700 |
| Proposed: Integration of EEMD and HRV for feature extraction from ECG signals | IMF, Time Domain, Frequency Domain, and Non-Linear HRV features. | SVM | 95.6320 |

**Table 5.** Comparative analysis

| Parameters | Accuracy | Precision | Recall | F-measure |
|---|---|---|---|---|
| Techniques | (%) | (%) | (%) | (%) |
| MSVM | 91.22 | 90.3 | 90.31 | 90.0032 |
| EMD | 83.88 | 90 | 77 | 87.5 |
| TT | 93.7 | 92.81 | 92 | 92.45 |
| E-MLPT | 89.21 | 88.7 | 88 | 88.4 |
| proposed | 95. | 98.9120 | 98.9993 | 98.9556 |

## 5. Conclusion

Serious health concerns are associated with cardiac arrhythmias, or abnormal heart rhythms. Timely and accurate detection is essential for successful treatment. To enhance the categorization of cardiac arrhythmias utilizing ECG signals, this study suggested a unique methodology that employs HRV analysis and EEMD. Complex ECG signals are efficiently broken down into IMFs by EEMD, a reliable signal processing method. These IMFs extract useful information from the signal by capturing minute details. HRV analysis, however, offers complementary information by shedding light on the association between heart rate and the autonomic nervous system. By combining these two techniques, suggested approach extracts comprehensive set of features that characterize both the detailed signal information and the underlying physiological mechanisms of arrhythmias. The renowned arrhythmia database of MIT-BIH was used to run thorough simulations to evaluate the efficacy of the suggested method. The approach achieved a 95.63% classification accuracy, yielding outstanding results. This significant improvement over existing techniques is attributed to the enhanced feature extraction capabilities and the holistic view of heart dynamics provided by the dual-technique approach. The proposed method offers a promising solution for reliable and detailed cardiac arrhythmia detection. Its potential applications extend to clinical diagnostics, patient monitoring, and early intervention strategies. Further investigations must concentrate on refining the feature extraction process, looking into the integration of additional physiological signals, and developing real-time implementation strategies to maximize the clinical impact of this innovative approach. Also, integrating Deep Learning (DL) and Machine Learning (ML) models can potentially achieve the finest outcomes. Moreover, energy-efficient strategies will allow monitoring device processes.

**Ethical issue**

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

**Data availability statement**

Datasets analyzed during the current study are available and can be provided upon a reasonable request from the corresponding author.

**Conflict of interest**

The authors declare no potential conflict of interest.

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