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Optimized Wavelet Neural Network for ECG Arrhythmia Detection

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Abstract

Accurate detection of cardiac arrhythmias from electrocardiogram (ECG) signals plays a vital role in computer-aided diagnosis systems. This study presents an enhanced arrhythmia classification framework based on Discrete Wavelet Transform (DWT) and Multilayer Perceptron (MLP) Neural Networks (NN). ECG recordings are decomposed into multiple frequency bands using DWT, and a set of statistical descriptors is extracted from the resulting wavelet coefficients to characterize signal behavior in both time and frequency domains. These descriptors are integrated with ECG morphological information and heartbeat interval features to construct a comprehensive feature representation. To eliminate redundant information and improve classification efficiency, a feature selection stage is employed before the classification process. The selected features are then used to train an optimized MLP classifier for distinguishing normal heartbeats from different arrhythmia types. Experiments conducted on recordings from the MIT-BIH Arrhythmia Database demonstrate that the proposed combination of wavelet-based statistical analysis, feature optimization, and neural-network classification provides reliable and accurate arrhythmia recognition performance.

Keywords: Electrocardiogram, Arrhythmia, Discrete wavelet transform, Neural network, Principal component analysis.

1 | Introduction

Cardiovascular Diseases (CVDs) continue to be one of the leading causes of death worldwide, emphasizing the need for reliable tools for early diagnosis and continuous cardiac monitoring. Among the available diagnostic techniques, the Electrocardiogram (ECG) remains the most widely used non-invasive method for

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assessing the electrical activity of the heart. The ECG waveform consists of several characteristic components, including the P wave, QRS complex, and T wave, each of which provides valuable information about cardiac function and rhythm abnormalities. Any deviation from the normal cardiac rhythm is generally referred to as an arrhythmia and may indicate the presence of potentially serious heart disorders [1].

Traditionally, arrhythmia diagnosis is performed through visual inspection of ECG recordings by experienced cardiologists. Although manual interpretation can provide an accurate clinical assessment, it becomes increasingly difficult and time-consuming when long-term recordings or large patient populations are involved. In addition, manual analysis is often influenced by observer variability and fatigue. Consequently, the development of automated ECG analysis systems has attracted significant research attention over the past two decades [2].

A typical automated arrhythmia detection system consists of two main stages: feature extraction and classification. Various ECG descriptors have been investigated in the literature, including morphological characteristics of the waveform, heartbeat interval measurements, statistical descriptors, and transform-domain features. Among these approaches, morphology-based and RR-interval-based features have demonstrated promising performance in distinguishing different heartbeat categories [3]. Artificial Neural Networks (ANNs), support vector machines, self-organizing maps, and, more recently, deep learning architectures have been extensively employed for classification tasks [4], [5].

One of the major challenges in ECG processing is the non-stationary nature of the signal. Since the frequency content of ECG recordings varies over time, conventional spectral analysis methods such as the Fourier transform are not always capable of accurately characterizing transient cardiac events. To overcome this limitation, time-frequency analysis techniques have been widely adopted. Among them, the Discrete Wavelet Transform (DWT) has proven particularly effective because it provides simultaneous temporal and frequency information at multiple resolutions. Several studies have shown that wavelet-based representations can significantly improve heartbeat classification performance by preserving clinically relevant information across different frequency bands [6], [7].

The availability of benchmark databases has further accelerated the development of automated ECG classification systems. In particular, the MIT-BIH Arrhythmia Database has become the most commonly used dataset for evaluating arrhythmia detection algorithms and remains a standard benchmark in the field [1]. Previous studies have reported encouraging classification results using wavelet-based feature extraction and Neural Network (NN) classifiers. For example, de Chazal et al. demonstrated the effectiveness of combining ECG morphology and heartbeat interval features for heartbeat classification [3]. However, many existing methods either rely on relatively limited datasets, focus on a small number of arrhythmia categories, or utilize only a subset of the information available within the wavelet decomposition coefficients [3], [6].

Recent advances in machine learning and deep learning have further improved ECG classification performance [8], [9]. Nevertheless, deep architectures often require extensive computational resources and large annotated datasets, which may limit their applicability in lightweight or real-time diagnostic systems. Therefore, developing efficient feature-based approaches that maintain competitive classification performance while reducing computational complexity remains an important research direction [8], [10].

Motivated by these observations, this study proposes an improved DWT-MLP framework for ECG arrhythmia classification. Unlike conventional wavelet-based approaches that directly utilize decomposition coefficients, the proposed method extracts statistical descriptors from multiple wavelet sub-bands and integrates them with morphological and heartbeat interval features. Furthermore, a feature selection stage is employed to eliminate redundant information and enhance class separability before classification. The resulting feature vector is then used to train an optimized Multilayer Perceptron (MLP) neural network for the recognition of normal heartbeats and five clinically significant arrhythmia classes, namely Right Bundle Branch Block (RBBB), Left Bundle Branch Block (LBBB), Premature Ventricular Contraction (PVC), Paced Beat (PB), and Atrial Premature Beat (APB).

The main contributions of this work can be summarized as follows:

I. Extraction of discriminative statistical features from DWT sub-band coefficients.

II. Integration of wavelet-domain, morphological, and heartbeat interval features within a unified representation framework.

III. Application of feature selection to reduce redundancy and improve classification efficiency.

IV. Development of an optimized MLP-based arrhythmia classifier capable of recognizing multiple clinically important heartbeat categories while maintaining low computational complexity.

2 | ECG Arrhythmias Classification Method

Fig. 1 illustrates the overall architecture of the proposed ECG arrhythmia classification framework. The proposed method consists of four main stages: 1) preprocessing, 2) heartbeat segmentation, 3) feature extraction and selection, and 4) classification.

As shown in *Fig. 1*, the acquired ECG signal is first processed in the preprocessing stage, where baseline wander and high-frequency noise components are removed using moving average filtering and wavelet-based denoising techniques. The denoised ECG signal is subsequently passed to the heartbeat segmentation stage, where individual heartbeats are identified based on the detected R-peaks.

In the feature extraction stage, two complementary groups of features are generated. The first group consists of statistical features extracted from the DWT coefficients, including energy, mean, variance, and entropy measures. The second group includes morphological and temporal features derived directly from the ECG waveform, such as QRS-related characteristics and RR interval information. The extracted features are then combined through a feature fusion process and normalized to ensure consistent scaling.

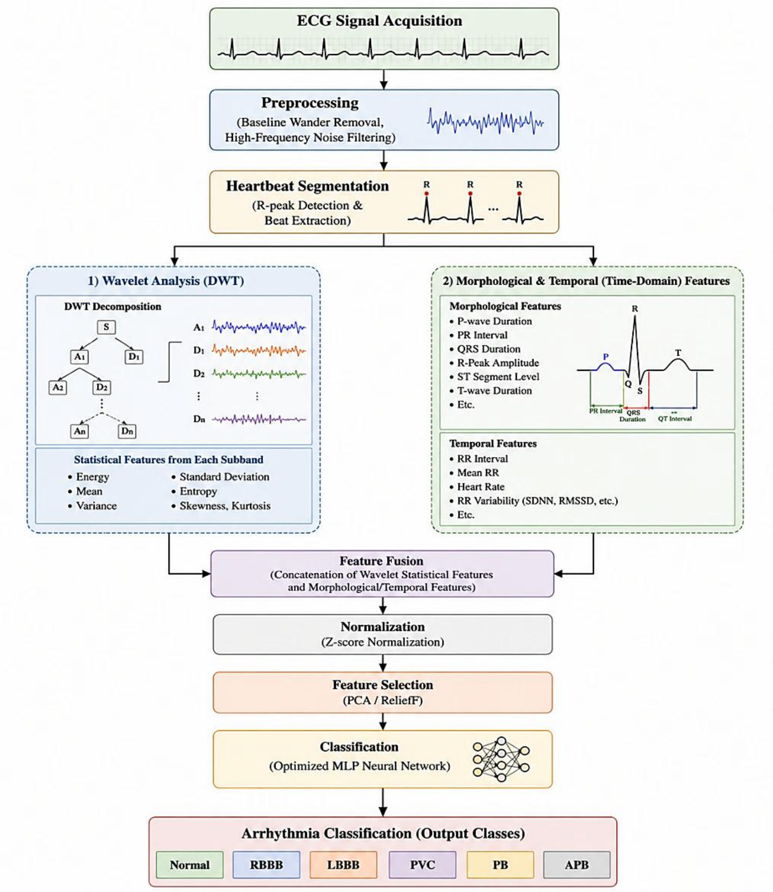


Fig. 1. Block diagram of the proposed method.

To improve the discriminative capability of the feature vector and eliminate redundant information, a feature selection stage is applied before classification. Finally, the selected features are provided to an optimized MLP neural network, which performs the classification of ECG beats into six categories: Normal, RBBB, LBBB, PVC, PB, and APB.

2.1 | Preprocessing Stage

ECG signals acquired from body-surface electrodes are frequently contaminated by various types of noise and artifacts that may adversely affect feature extraction and classification performance. Common sources of interference include baseline wander caused by respiration, electrode-skin impedance variations, body movements, and thermal drift of electronic components. In addition, power-line interference (50/60 Hz) and high-frequency noise originating from surrounding electronic devices and fluorescent lighting can significantly distort the ECG waveform. Therefore, an effective preprocessing stage is required before feature extraction.

In this study, a two-stage preprocessing strategy is employed to improve the quality of the recorded ECG signals. First, baseline wander is removed using a moving average filter. The moving average filter is a simple and computationally efficient smoothing technique that replaces each sample with the average value of its neighboring samples. This operation effectively suppresses low-frequency fluctuations while preserving the major characteristics of the ECG waveform. The filtered signal can be expressed as:

$$y(i) = \frac{1}{2N+1}(x(i+N) + x(i+N-1) + \ldots + x(i-N)), \quad \textbf{(1)}$$

where (x(i)) denotes the input ECG signal, (y(i)) represents the filtered output signal, and (2N+1) defines the averaging window length.

After baseline correction, wavelet-based denoising is applied to suppress the remaining noise components. Owing to its ability to analyze non-stationary signals in both time and frequency domains, the DWT has become one of the most effective tools for ECG denoising. The wavelet denoising procedure consists of three consecutive steps:

Step 1 (wavelet decomposition). The preprocessed ECG signal is decomposed into multiple frequency sub-bands using DWT. A suitable mother wavelet and decomposition level are selected to capture the essential characteristics of the ECG waveform while separating noise components from useful cardiac information [11].

Step 2 (thresholding of detail coefficients). Noise reduction is achieved by applying thresholding to the detail coefficients obtained at each decomposition level. In this work, soft-thresholding is employed because it provides smoother signal reconstruction and reduces abrupt discontinuities. For comparison, the hard-thresholding and soft-thresholding functions are defined as:

$$Y_H = \begin{cases} Y, & |Y| \geq T, \\ 0, & |Y| < T, \end{cases} \quad \textbf{(2)}$$

$$Y_S = \begin{cases} \text{sign}(Y)(|Y| - T), & |Y| \geq T, \\ 0, & |Y| < T, \end{cases} \quad \textbf{(3)}$$

where (Y) denotes the original wavelet coefficient, (T) is the threshold value, (Y_H) is the hard-thresholded coefficient, and (Y_S) is the soft-thresholded coefficient [12].

Step 3 (signal reconstruction). Finally, the denoised ECG signal is reconstructed by performing the Inverse Discrete Wavelet Transform (IDWT) using the modified approximation and detail coefficients. The resulting signal preserves the significant morphological characteristics of the ECG waveform while substantially reducing baseline drift and high-frequency noise.

The output of the preprocessing stage is a clean ECG signal that is subsequently used for heartbeat segmentation, wavelet-based statistical feature extraction, and morphological-temporal feature analysis.

2.2 | Heartbeat Segmentation

The denoised ECG signal is subsequently subjected to heartbeat segmentation, where R-peaks are identified, and fixed-length windows centered on each R-peak are extracted to represent individual cardiac cycles. These heartbeat segments constitute the input for the subsequent feature extraction stage.

2.3 | Feature Extraction and Selection Stage

Feature extraction is one of the most important stages in the development of a neural-network-based pattern recognition system. The primary objective of feature extraction is to obtain the most informative characteristics from the ECG signal while minimizing redundant and irrelevant information. An effective feature representation should maximize the discrimination between heartbeat classes and improve the generalization capability of the classifier.

In the proposed framework, two complementary groups of features are extracted from the segmented ECG beats. The first group is derived from the time-frequency representation of the signal using the DWT, while the second group consists of morphological and temporal characteristics extracted directly from the ECG waveform. These features are subsequently fused and processed through a feature selection stage before being supplied to the classifier.

2.3.1 | Wavelet-based statistical features

The DWT has become a widely used tool for ECG analysis because of its ability to simultaneously represent signal information in both time and frequency domains. Unlike conventional Fourier-based methods, DWT is particularly suitable for analyzing non-stationary biomedical signals such as ECG recordings.

The DWT decomposes the ECG signal into a set of approximation and detail coefficients at multiple resolution levels through successive low-pass and high-pass filtering operations. At each decomposition level, the approximation coefficients represent the low-frequency components of the signal, whereas the detail coefficients contain high-frequency information associated with rapid waveform changes.

In this work, the denoised heartbeat segments are decomposed using DWT to obtain a multi-resolution representation of the ECG signal. Instead of directly using the wavelet coefficients, a set of statistical descriptors is extracted from each sub-band. These descriptors provide a compact representation of the signal while preserving discriminative information relevant to heartbeat classification.

The extracted wavelet statistical features include:

I. Mean value.

II. Variance.

III. Energy.

IV. Entropy.

These features effectively characterize the distribution and complexity of ECG signals across different frequency bands.

2.3.2 | Morphological and temporal features

In addition to wavelet-based descriptors, several morphological and temporal features are extracted directly from the ECG waveform. Morphological features describe the geometric characteristics of the heartbeat, while temporal features provide information about the timing relationship between successive cardiac cycles.

The extracted features include:

I. R-peak amplitude.

II. QRS complex duration.

III. RR interval.

IV. Mean RR interval.

V. Heart Rate Variability (HRV)-related measurements.

These features have been extensively used in ECG analysis because they contain clinically relevant information for distinguishing different arrhythmia categories.

2.4 | Feature Fusion and Selection

After feature extraction, the wavelet statistical features and morphological-temporal features are combined to form a unified feature vector. Since the extracted feature set may contain redundant or highly correlated information, a feature selection stage is employed to improve classification efficiency and reduce computational complexity.

Feature selection aims to retain the most discriminative attributes while eliminating irrelevant features. The resulting optimized feature vector is then normalized and used as the input of the classification stage.

2.4.1 | ReliefF-based feature ranking

After feature fusion, the resulting feature vector may contain redundant and less informative attributes that can negatively affect classification performance. To address this issue, the ReliefF algorithm is employed as a feature ranking technique. ReliefF estimates the importance of each feature according to its ability to distinguish between neighboring samples belonging to different classes.

For each training instance, the algorithm identifies the nearest samples from the same class (nearest hits) and from different classes (nearest misses). Feature weights are then updated based on their contribution to class discrimination. Features with higher weights are considered more relevant for classification and are retained for subsequent processing.

The use of ReliefF improves the discriminative power of the feature set while reducing the influence of irrelevant attributes. As a result, the dimensionality of the feature space is reduced before applying further optimization procedures [13].

2.4.2 | Principal component analysis

Principal Component Analysis (PCA) is one of the techniques for feature extraction and dimensionality reduction. In some situations, the dimension of the input vector is large, but the components of the vectors are highly correlated (redundant). It is useful in this situation to reduce the dimension of the input vectors. An effective procedure for performing this operation is PCA. This technique has three effects: it orthogonalizes the components of the input vectors (so that they are uncorrelated with each other), it orders the resulting orthogonal components (principal components) so that those with the largest variation come first, and it eliminates those components that contribute the least to the variation in the data set.

The steps for the PCA algorithm are given below:

I. Consider the input data as X.

II. Calculate $\bar{X}$ that $\bar{X}$ is the mean of X.

III. Calculate the covariance matrix using *Eq. (4)*.

$$\mathrm{cov} = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(X_i - \bar{X})}{n-1}, \tag{4}$$

I. Calculate the eigenvectors and eigenvalues of the covariance matrix.

II. Arrange eigenvectors based on eigenvalues and form a matrix (E).

III. Calculate the final features matrix (P) using *Eq. (5)*.

$$P = E^{T}(x - \overline{x}), \tag{5}$$

where E^{T} is the transpose of E [14].

2.5 | Classification Stage

ANNs have been widely employed in biomedical signal classification due to their capability to model complex nonlinear relationships and generalize effectively to unseen data. Among various ANN architectures, the MLP, as shown in *Fig. 2,* is one of the most commonly used classifiers because of its simple implementation and strong classification performance.

In this study, an optimized MLP neural network is employed for ECG arrhythmia classification. The input layer receives the reduced feature vector generated after the feature fusion, ReliefF feature ranking, and PCA dimensionality reduction stages. The output layer consists of six neurons corresponding to the target classes, namely Normal, RBBB, LBBB, PVC, PB, and APB.

To improve classification performance, several MLP architectures were investigated by varying the number of hidden layers and hidden neurons. Different network configurations were trained and evaluated using the training dataset. The architecture yielding the highest validation accuracy and the lowest classification error was selected as the final classifier. This optimization process enables the network to achieve a suitable balance between learning capability and generalization performance while avoiding overfitting.

The MLP network was trained using the backpropagation learning algorithm. During training, the network weights were iteratively adjusted to minimize the Mean Squared Error (MSE) between the predicted outputs and the target labels. The training process continued until either the predefined error threshold was achieved or the maximum number of training epochs was reached.

The optimization procedure can be summarized as follows:

I. Train multiple MLP architectures with different numbers of hidden neurons.

II. Evaluate the performance of each architecture using the validation dataset.

III. Select the architecture with the highest classification accuracy and lowest validation error.

IV. Use the selected network for final testing and arrhythmia classification.

The optimized MLP classifier learns the nonlinear relationships among the extracted ECG features and provides reliable discrimination between normal and abnormal heartbeats. The combination of wavelet-based statistical features, morphological-temporal descriptors, ReliefF feature ranking, PCA dimensionality reduction, and MLP optimization contributes to improving the overall classification performance of the proposed framework.

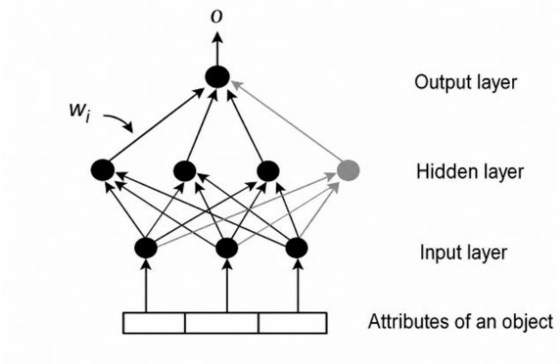


Fig. 2. An example of a neural network with an adaptive structure, when a neuron is added to the hidden layer (in gray), the links are updated, and all weights are initialized randomly.

Here, we have employed an MLP neural network for classification, as shown in "*Fig. 2*". The MLP neural network consists of an input layer (parameters characterizing an object), one or two hidden layers, and an output layer providing the class of the object. We choose to use an architecture of NNs to receive better performance in classification.

3 | Experiments and Simulation Results

In this study, the MIT-BIH Arrhythmia Database was used to evaluate the performance of the proposed arrhythmia classification framework. This database contains 48 annotated ECG recordings, each consisting of approximately 30 minutes of two-channel ambulatory ECG data selected from 24-hour Holter recordings. All signals were sampled at a frequency of 360 Hz and have been widely adopted as a benchmark dataset for ECG arrhythmia analysis.

To ensure a fair comparison with previous studies, 26 ECG records from the MIT-BIH Arrhythmia Database were selected for experimentation. The selected records are listed in *Table 1* and include normal heartbeats as well as several clinically important arrhythmia classes.

Before feature extraction, all ECG recordings were processed using the preprocessing procedure described in Section 2.1. The objective of this stage was to suppress baseline wander and high-frequency noise components that could negatively influence heartbeat segmentation and feature extraction. Effective noise reduction improves the quality of the extracted wavelet, morphological, and temporal features, ultimately enhancing the classification performance of the proposed system.

Fig. 3 presents an example of a raw ECG signal contaminated by baseline drift and high-frequency interference. After applying the moving-average filter, baseline fluctuations were significantly reduced while preserving the main morphological characteristics of the ECG waveform, as illustrated in *Fig. 4*. Subsequently, wavelet-based denoising was employed to remove the remaining high-frequency noise components. The resulting denoised ECG signal is shown in *Fig. 5*.

Following preprocessing, heartbeat segmentation was performed by detecting R-peaks and extracting individual cardiac cycles. The segmented beats were then used to generate wavelet-based statistical features and morphological-temporal descriptors. After feature fusion, ReliefF feature ranking and PCA-based dimensionality reduction were applied before the optimized MLP classifier was trained and evaluated.

Table1. ECG records from the MIT-BIH Arrhythmia.

Class	Record Numbers
NORMAL	100-101-103-112-115-117-121-123-202-234
PVC	200-208-213-233
RBBB	212-118-124
LBBB	109-111
PB	104-107-217
APB	209-220-222-223

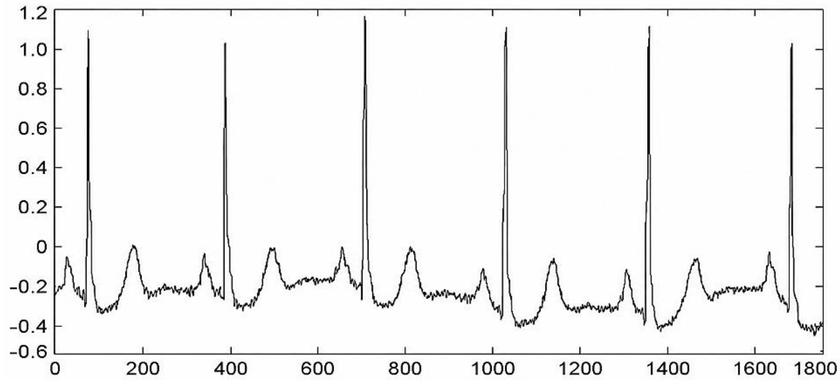


Fig. 3. Original ECG signal with baseline and high-frequency noises.

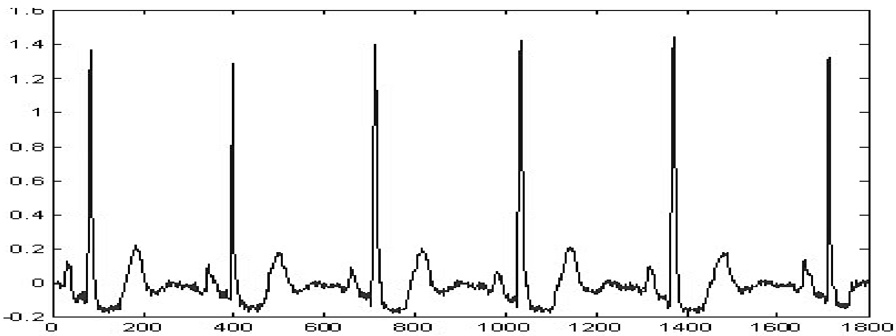


Fig. 4. Baseline eliminated ECG signal.

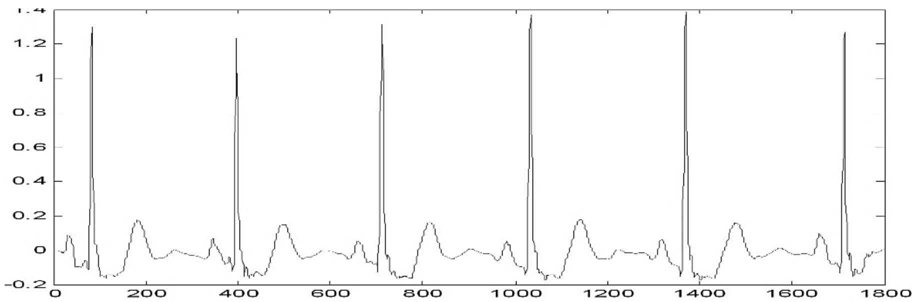


Fig. 5. Baseline and other high-frequency noises eliminated from the ECG signal.

Following the preprocessing and heartbeat segmentation stages, feature extraction was performed to obtain a compact and discriminative representation of each ECG beat. Since both time-frequency characteristics and waveform morphology contain valuable information for arrhythmia recognition, a combination of wavelet-based statistical features and morphological-temporal descriptors was employed.

The segmented ECG beats were first analyzed using an 8-level DWT based on the Daubechies 6 (db6) mother wavelet. The db6 wavelet was selected because its shape closely resembles the morphology of ECG waveforms, particularly the QRS complex, making it suitable for cardiac signal analysis. The decomposition process generated eight detail sub-bands (D1–D8) together with the final approximation coefficients obtained at the eighth decomposition level, providing a multi-resolution representation of the ECG signal.

To reduce the dimensionality of the wavelet coefficients while preserving the most informative characteristics, statistical measures were extracted from each sub-band. Specifically, the mean, variance, energy, and entropy were computed for the approximation and detail coefficients. As a result, a total of 36 wavelet-based statistical features were obtained from the sub-bands.

In addition to the wavelet features, several morphological and temporal descriptors were extracted directly from the reconstructed ECG signal. These included the R-peak amplitude, QRS complex duration, RR interval, mean RR interval, and heart-rate-variability-related measurements. These features provide clinically meaningful information regarding both the shape of the cardiac cycle and the temporal relationship between consecutive heartbeats.

The wavelet statistical features and morphological-temporal descriptors were then combined through a feature fusion process to form a unified feature vector. Consequently, each heartbeat was represented by an initial feature vector containing 41 features. Prior to feature selection, all features were normalized to the range of [-1,1] in order to eliminate scale differences and improve the stability of the learning process.

Because the fused feature vector may contain redundant and less informative attributes, the ReliefF algorithm was employed to rank the extracted features according to their discriminative capability. Based on the obtained feature weights, the 25 most relevant features were retained for further analysis.

Subsequently, PCA was applied to the selected features in order to remove residual correlations and further reduce the dimensionality of the feature space. PCA transforms the original feature set into a new set of orthogonal variables called principal components while preserving most of the information contained in the data. In this study, the first 15 principal components, accounting for more than 95% of the total variance, were selected as the final feature representation.

The resulting 15-dimensional feature vector was then used as the input to the optimized MLP classifier for ECG arrhythmia classification.

An optimized MLP neural network was employed as the classifier to distinguish between six heartbeat categories: Normal, RBBB, LBBB, PVC, PB, and APB.

The input to the MLP consists of the 15-dimensional feature vector obtained after feature fusion, ReliefF-based ranking, and PCA dimensionality reduction. The proposed network architecture is as follows:

I. Input layer: 15 neurons, corresponding to the principal components.

II. First hidden layer: 64 neurons with ReLU activation function.

III. Second hidden layer: 32 neurons with ReLU activation function.

IV. Output layer: 6 neurons with softmax activation function, representing the probability distribution over the six heartbeat classes.

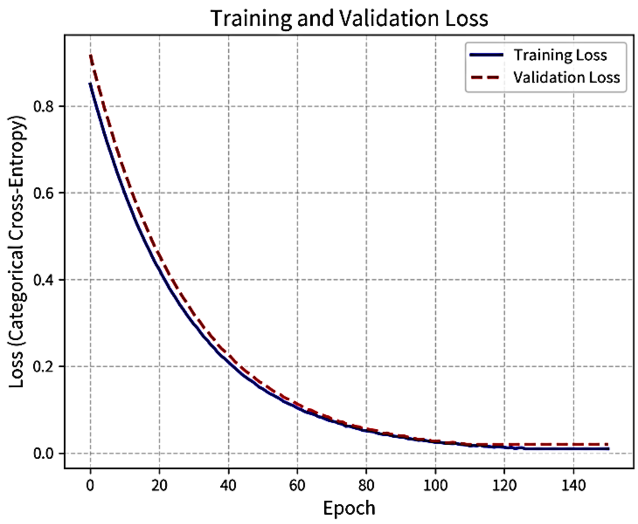
This architecture was determined through systematic trial-and-error experiments by varying the number of hidden layers and neurons while monitoring validation performance to achieve an optimal balance between model capacity and generalization ability.

To train the network, a total of 17,100 annotated heartbeats were used for training, 4,200 heartbeats for validation, and 8,000 heartbeats for final testing. These beats were carefully extracted from 26 selected records of the MIT-BIH Arrhythmia Database, ensuring sufficient representation of both normal and pathological cases. The significantly larger dataset compared to previous studies enables more robust learning of complex patterns in the feature space.

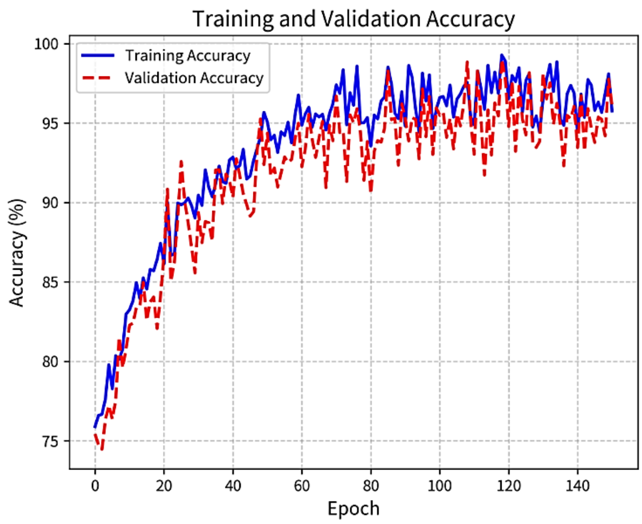
The network was trained using the Adam optimizer with a learning rate of 0.001, $\beta_1 = 0.9$, and $\beta_2 = 0.999$. Adam was chosen due to its adaptive learning rate mechanism, fast convergence properties, and excellent performance in non-stationary problems with noisy gradients, which are common in biomedical signal classification tasks. Categorical cross-entropy was used as the loss function. Training was performed with a batch size of 128, for a maximum of 300 epochs. To prevent overfitting, early stopping (with patience of 20 epochs based on validation loss) and dropout (rate = 0.25) in the hidden layers were applied. All input features were normalized to the range [-1, 1] prior to training.

The trained MLP model demonstrated strong discriminative capability by effectively learning the nonlinear relationships within the combined wavelet statistical, morphological, and temporal features. Performance evaluation on the independent test set is presented in the following sec.

The training curve for the third structure is shown in *Fig. 6*.



a.



b.

Fig. 6. Training and validation curves of the proposed MLP classifier using the Adam optimizer; a. loss curves (categorical cross-entropy), and b. accuracy curves.

The classification results achieved by the proposed method are summarized in *Table 2*. As shown in this table, the model was trained using 17,100 heartbeats and tested on 8,000 heartbeats extracted from 26 records of the MIT-BIH Arrhythmia Database. The overall accuracy reached 97.30%, with strong performance across all six classes. The highest per-class accuracy belongs to the Normal category (98.80%), while the model maintained robust sensitivity and specificity even for less frequent arrhythmia types such as APB and PB. These results demonstrate the effectiveness of combining wavelet-based statistical features, morphological and temporal characteristics, followed by ReliefF and PCA dimensionality reduction, when fed into the optimized MLP classifier with the Adam optimizer.

Table 2. The simulation results obtained using the MLP neural network.

Classification Classes	N0. of Training Data Patterns	N0. of Testing Data Patterns	No. of Miss-Classified Patterns	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
NORMAL	3500	1500	18	98.8	98.6	99.2	98.9
PVC	3000	1400	45	96.79	96.4	98.1	97.3
RBBB	2800	1300	48	96.31	95.9	97.8	96.8
LBBB	2700	1300	35	97.31	97	98.5	97.6
PB	2500	1200	42	96.50	96.2	98	97
APB	2600	1200	28	97.67	97.4	98.7	97.9
Total	17100	8000	216	97.3	97.0	98.4	97.6

To further evaluate the effectiveness of the proposed method, a comparative analysis was conducted against several recent studies in the field of ECG arrhythmia classification. *Table 3* summarizes the performance of the proposed approach in comparison with both non-deep learning and deep learning-based methods published between 2018 and 2024, all evaluated on the MIT-BIH Arrhythmia Database. The comparison focuses primarily on overall classification accuracy.

Table 3. Performance comparison of the proposed method with recent studies (2018–2024) on the MIT-BIH Arrhythmia Database.

Reference	Year	Method	Number of Classes	Accuracy (%)
[15]	2018	SVM + Wavelet Features	5	95.20
[8]	2019	Random Forest + Statistical Features	5	96.10
[10]	2021	MLP + DWT + ReliefF	5	96.45
[16]	2024	XGBoost	5	97.7
[17]	2023	1D-CNN	5	98.56
[18]	2024	CNN-LSTM Hybrid	6	98.92
Proposed method			**6**	**97.30**

As presented in *Table 3*, the proposed method achieves a competitive accuracy of 97.30% while utilizing only traditional machine learning techniques (a carefully optimized MLP neural network) combined with hand-crafted features. This performance is particularly noteworthy when compared to other non-deep learning approaches. For instance, it outperforms the SVM-based method [15] by more than 2%, the Random Forest approach [16], and even a more recent XGBoost model [18] in terms of overall accuracy, despite employing fewer classes in some competing studies.

Although deep learning models such as 1D-CNN [17] and CNN-LSTM [18] report slightly higher accuracies (98.56% and 98.92%, respectively), these methods generally require significantly larger computational resources, more complex architectures, and substantially greater training data. In contrast, the proposed DWT-based feature extraction combined with ReliefF, PCA, and a simple MLP classifier offers a highly efficient and interpretable solution that maintains excellent performance without relying on deep neural networks. These advantages make the proposed approach especially suitable for real-time clinical applications and embedded systems where computational cost and model transparency are critical considerations.

The results confirm that a well-designed feature engineering pipeline with classical NNs can still achieve state-of-the-art comparable performance in ECG arrhythmia classification, providing a favorable trade-off between accuracy and practical applicability.

4 | Conclusion

This study presented an efficient and accurate framework for automatic classification of cardiac arrhythmias from ECG signals using a combination of DWT-based statistical features, morphological characteristics, and temporal features. After effective preprocessing and heartbeat segmentation, a comprehensive feature vector was constructed and optimized through ReliefF feature ranking and PCA, resulting in a compact 15-dimensional representation. This optimized feature set was then fed into a carefully designed MLP neural network trained with the Adam optimizer.

Experimental results on a substantial dataset comprising 17,100 training, 4,200 validation, and 8,000 testing heartbeats extracted from 26 records of the MIT-BIH Arrhythmia Database demonstrated that the proposed method achieves a high overall classification accuracy of 97.30% across six heartbeat categories (Normal, RBBB, LBBB, PVC, PB, and APB). The model exhibited strong and balanced performance across all classes, with per-class accuracies ranging from 96.31% to 98.80%, along with excellent sensitivity, specificity, and F1-scores.

Comparative analysis with recent state-of-the-art methods (2018–2024) revealed that the proposed approach delivers competitive performance compared to both traditional machine learning and deep learning techniques, while maintaining significantly lower computational complexity and higher interpretability. Unlike many deep learning models that require extensive computational resources and large-scale training data, the current method offers an effective trade-off between accuracy and practical applicability, making it particularly suitable for real-time monitoring systems and resource-constrained clinical environments.

The main contributions of this work include the effective integration of multi-domain features, robust dimensionality reduction, and the successful application of an optimized classical NN that rivals more complex architectures. Future work will focus on validating the proposed framework on larger multi-center datasets, exploring patient-specific adaptation, and implementing the algorithm on embedded hardware for real-world wearable ECG monitoring applications.

In conclusion, the results of this study confirm that a well-engineered feature extraction and selection pipeline combined with a simple yet powerful MLP classifier can provide reliable, accurate, and clinically applicable solutions for ECG arrhythmia detection.

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Data Availability

All data are included in the text.

Conflicts of Interest

The authors declare no conflict of interest.

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