

High-Performance ECG Beat Analysis Using Wavelet-Based Features And Memetic Redundancy-Optimized ROCNN

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Abstract

Cardiovascular diseases are increasingly prevalent across all age groups, affecting both young and elderly populations. Early and accurate detection of cardiac abnormalities is therefore essential for timely medical intervention. This research proposes an advanced automated classification system to determine whether an Electrocardiogram (ECG) signal corresponds to a normal condition or an arrhythmia case. The key contribution of this work lies in the integration of efficient preprocessing techniques with an optimized feature selection strategy. Frequency-domain features extracted from ECG signals using wavelet lifting schemes were refined through the Memetic Redundancy (MR) approach, which effectively removes irrelevant and redundant features while preserving discriminative information. The proposed framework was evaluated using 65,448 ECG records from the MIT-BIH Arrhythmia Database and achieved a high classification accuracy of 99.75%, demonstrating its robustness and reliability for arrhythmia detection.

Keywords: ECG Classification; Arrhythmia; Approximate Entropy; Sample Entropy; Lifting Wavelets; Support Vector Machine; Feature Selection.

1. Introduction

The human heart generates electrical impulses that propagate through cardiac tissues and can be measured as voltage signals. Although these electrical activities originate within the heart, direct invasive measurement is not feasible for routine clinical practice. Therefore, Electrocardiogram (ECG) signals are non-invasively acquired from the surface of the human body. During acquisition and amplification, ECG signals are often contaminated by various types of noise, including baseline wander, muscle artifacts, and power-line interference (typically at 50 Hz). Because ECG signals generally have low amplitude, such noise can significantly distort or even mask clinically relevant information.

Numerous studies on arrhythmia classification have highlighted the adverse impact of noise on diagnostic accuracy. As a result, improving denoising techniques has become a critical research focus. In addition to noise removal, effective feature extraction and feature selection strategies are essential to ensure reliable automated classification. Designing an intelligent ECG classification system is therefore a challenging task, where maximizing accuracy while maintaining computational efficiency remains the primary objective.

Earlier research predominantly focused on extracting time-domain features for arrhythmia detection [1]–[3]. Although these approaches demonstrated promising results, many lacked advanced preprocessing mechanisms. Transforming ECG signals into alternative domains can reveal hidden characteristics that are not easily observable in the time domain. Consequently, frequency-domain feature extraction methods were introduced to enhance discriminative capability [4]. Later studies demonstrated that combining time- and frequency-domain features could further improve classification performance [5]–[7]. Additionally, statistical measures were incorporated to increase

robustness and reliability [8]–[10]. Beyond feature engineering, a wide range of classification algorithms-including traditional machine learning and neural network-based approaches-have been explored in the literature [11]–[14]. Figure 1 illustrates the typical framework employed for ECG abnormality detection.

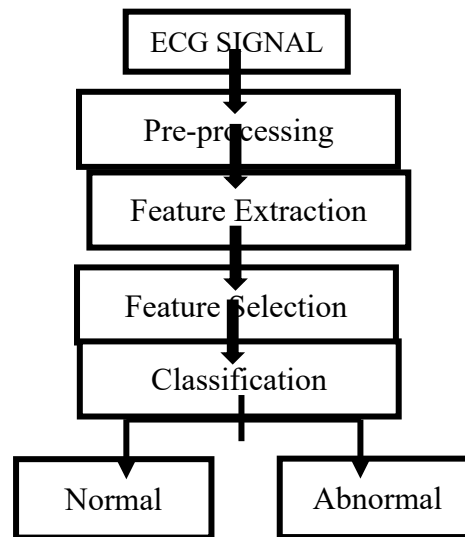


Fig. 1. Typical ECG Classification

In the modern era, cardiovascular diseases remain a leading cause of mortality, largely influenced by sedentary lifestyles, dietary habits, and genetic predispositions. Hence, automated ECG-based diagnostic systems have gained significant importance in assisting clinicians with early detection and accurate diagnosis of cardiac abnormalities.

Conventional classification approaches often experience performance degradation when applied to large-scale datasets. To address this limitation, recent studies emphasize advanced preprocessing techniques and optimized feature selection algorithms. Feature selection not only enhances classification accuracy but also reduces computational complexity by eliminating redundant and irrelevant features. Since ECG waveforms vary across individuals due to morphological and temporal differences, achieving a universal representation is inherently difficult. Nevertheless, clinical experts have categorized ECG beats into standard classes. In this work, a four-class classification problem is considered: Normal (NOR), Atrial Premature Contraction (APC), Ventricular Escape Beat (VE), and Unclassifiable Beat (UN), as summarized in Table 1.

Research initially concentrated on binary classification (normal versus abnormal), but later evolved toward multi-class classification frameworks. For instance, chaos-based feature extraction was employed in [15] to classify Premature Ventricular Contraction (PVC) beats and distinguish them from Normal (N), Premature Atrial Contractions (PAC), and Right Bundle Branch Block (RBBB) beats using the MIT-BIH database, achieving an accuracy of 99.1%. Furthermore, ECG analysis has been extended to detect other physiological disorders such as sleep apnea [16].

In [17], frequency-domain features combined with R–R interval features were utilized to differentiate normal subjects from sleep apnoea patients. Classification was performed using Support Vector Machines (SVM) with a Radial Basis Function (RBF) kernel and a Spline Activated Feed-Forward Neural Network (SAFFNN), achieving an accuracy of 90.85%. Since the R–R interval is a clinically significant parameter, geometric

methods based on the Pythagorean theorem have also been applied to detect abnormalities in R–R interval patterns [18]. Such features can be effectively combined with statistical and frequency-domain attributes for improved classification performance.

A comprehensive review of previous studies indicates that preprocessing plays a pivotal role in determining overall classification accuracy [19], [20]. Motivated by this observation, the proposed work incorporates an advanced preprocessing stage using Common Averaging Singular Value Referencing (CASVR) to enhance signal quality. Subsequently, an optimized feature selection strategy based on the Memetic Redundancy (MR) method is employed to eliminate redundant features while preserving discriminative information. Finally, classification is carried out using a Reactive Optimized Convolutional Neural Network (ROCNN), enabling robust multi-class ECG beat classification with improved accuracy and computational efficiency.

2. Materials and Methods

2.1 MIT-BIH Arrhythmia Database

For this study, the MIT-BIH Arrhythmia Database [21] was utilized, which is a widely recognized benchmark dataset for ECG analysis and arrhythmia classification. The database consists of 48 half-hour recordings collected from 47 subjects, with each recording containing two-channel ECG signals sampled at 360 Hz and digitized with 11-bit resolution over a 10-mV range. Expert cardiologists provided detailed beat-by-beat annotations for each recording, enabling accurate labelling of various heartbeat types.

As the focus of this research is on a four-class classification problem, only the ECG beats corresponding to the selected classes—Normal (NOR), Atrial Premature Contraction (APC), Ventricular Escape Beat (VE), and Unclassifiable Beat (UN)—were included in the analysis. Table 1 summarizes the distribution of these classes within the dataset, showing the number of heartbeats available for each category. This selection ensures that the classification model is trained and evaluated on the relevant subset of arrhythmia types while maintaining sufficient data representation for each class.

Table 1. Distribution of ECG Heartbeat Classes from the MIT-BIH Arrhythmia Database

ECG Signal Type	Annotation	Total Beats	Training Set	Test Set
Normal (NOR)	N	75,017	11,253	63,764
Atrial Premature Contraction (APC)	A	2,546	891	1,655
Ventricular Escape Beat (VE)	E	106	53	53
Unclassifiable Beat (UN)	Q	33	17	16
Total	—	77,702	12,214	65,488

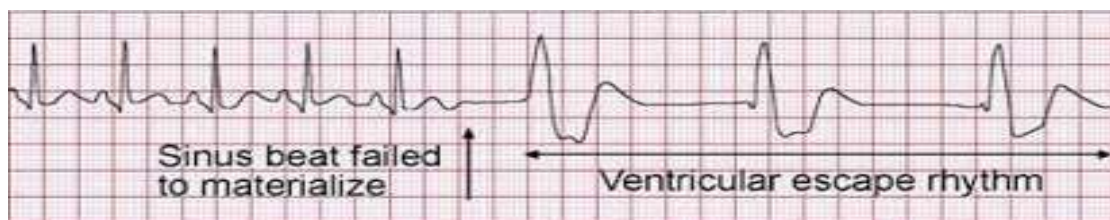


Fig. 2. Ventricular Escape rhythm

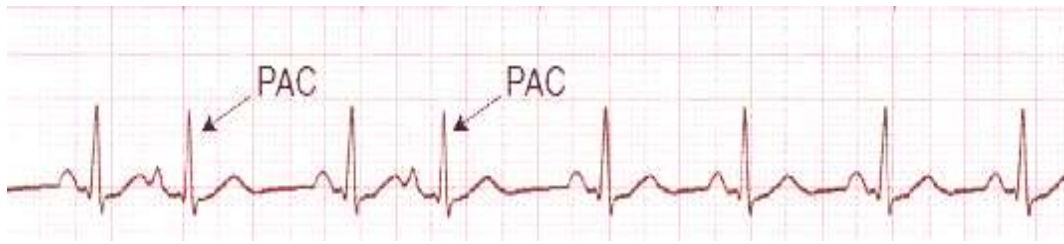


Fig. 3. Atrial premature contraction (PAC)

A total of 77,702 ECG beats, sampled at 360 Hz, were utilized in this study. The ground truth annotations provided in the MIT-BIH Arrhythmia Database served as the benchmark for class labels to evaluate the proposed method's performance. For the Normal (NOR) class, 11,253 beats were assigned for training, while 63,764 beats were reserved for testing. Similarly, the Atrial Premature Contraction (APC) class included 891 training beats and 1,655 testing beats. Due to the limited number of samples in the Ventricular Escape (VE) class, the dataset was evenly split, with 53 beats used for training and 53 for testing. The same 50-50 split was applied to the Unclassifiable Beat (UN) class, with 17 beats allocated for training and 16 for testing from a total of 33 beats. This relatively small training set—approximately 15.72% of the entire dataset—demonstrates the efficiency and robustness of the proposed classification system compared to state-of-the-art approaches.

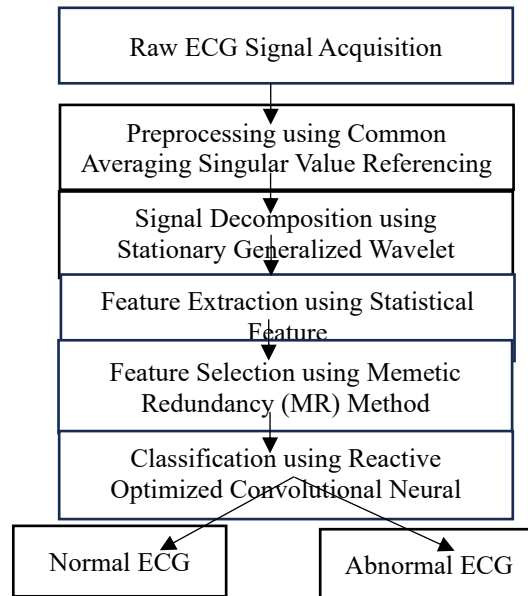


Fig.4. Proposed ECG Signal Processing and Classification

2.2 Noise Removal

Noise in ECG recordings adversely affects classification accuracy [22]. To mitigate this, the proposed preprocessing employs the Common Averaging Singular Value Referencing (CASVR) technique. Initially, common referencing is applied by subtracting the mean signal across all electrodes to enhance the signal-to-noise ratio (SNR) and reduce common-mode noise. Following this, Singular Value Decomposition (SVD) is performed on the denoised ECG data arranged in an $m \times n$ matrix M , decomposing it as:

$$M = U\Sigma V^* \quad (1)$$

where:

- $U \in \mathbb{R}^{m \times m}$ is the orthogonal matrix of left singular vectors $U = [u_1, u_2, \dots, u_m]$,
- $\Sigma \in \mathbb{R}^{m \times n}$ is a diagonal matrix containing the singular values $\sigma_i \geq 0$,
- $V^* \in \mathbb{R}^{n \times n}$ is the conjugate transpose of the orthogonal matrix $V = [v_1, v_2, \dots, v_n]$ of right singular vectors.

The covariance matrices of M satisfy the following relations:

$$MM^T = U\Sigma^2U^T \quad (2)$$

$$M^TM = V\Sigma^2V^T \quad (3)$$

Here, MM^T and M^TM are symmetric matrices whose eigenvectors correspond to U and V , respectively, and Σ^2 contains the eigenvalues as squares of the singular values.

The diagonal matrix of singular values is expressed as:

$$\Sigma = \text{diag}(\sigma_1, \sigma_2, \dots, \sigma_r) \quad (4)$$

where $r = \min(m, n)$ is the rank of M .

By reconstructing the signal using only the dominant singular values and their corresponding vectors, noise components associated with smaller singular values are effectively suppressed, improving signal quality for downstream ECG analysis and classification.

2.3 Feature Extraction

The feature extraction process employs the Stationary Generalized Wavelet Transform (SGWT), a signal decomposition method rooted in Fourier domain techniques as described in [23]. SGWT utilizes a lifting scheme that provides an efficient, invertible, and adaptive framework for analysing ECG signals.

Let f denote the input ECG signal. The signal is first separated into its odd-indexed samples γ_1 and even-indexed samples λ_1 through downsampling and shifting operations. The detail coefficients γ_2 are then computed by subtracting the predicted values derived from the even samples using the prediction operator P :

$$\gamma_2 = \gamma_1 - P(\lambda_1) \quad (5)$$

Subsequently, the approximation coefficients λ_2 are obtained by updating the even samples with a correction term generated by applying the update operator U to the detail coefficients:

$$\lambda_2 = \lambda_1 + U(\gamma_2) \quad (6)$$

This decomposition effectively separates the signal into detail components capturing high-frequency features and approximation components representing low-frequency trends, facilitating robust feature extraction from ECG signals.

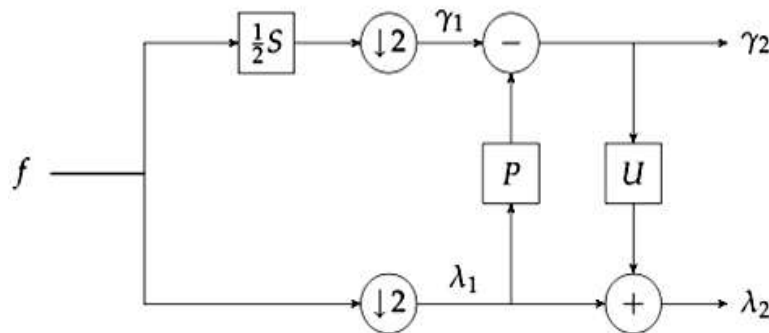


Fig. 5. SGWT representation

Fig. 5. Schematic representation of the SGWT decomposition process, illustrating the partitioning of the input signal f into odd and even samples, followed by the computation of detail and approximation coefficients via the prediction (P) and update (U) operators.

2.4 Feature Selection Process

The proposed system employs the Memetic Redundancy (MR) approach for optimal feature selection [24]. The MR method is a multi-level redundancy control technique that aims to select features with high discriminative power while eliminating redundant and irrelevant information. This process enhances classification accuracy and reduces computational complexity.

Feature selection is performed by evaluating two important criteria: relevance and redundancy. Relevance measures the dependency between each feature and the target class, whereas redundancy quantifies the similarity among selected features. Both criteria are estimated using Mutual Information (MI).

The average relevance of a selected feature subset S with respect to the class label C is defined as:

$$D(S, C) = \frac{1}{|S|} \sum_{f_i \in S} I(f_i, C) \quad (7)$$

where:

- $|S|$ is the number of features in subset S ,
- $I(f_i, C)$ represents the mutual information between feature f_i and the class label C .

A higher value of $D(S, C)$ indicates stronger discriminative capability of the selected features.

To control redundancy among features, the average mutual information between feature pairs is computed as:

$$R(S) = \frac{1}{|S|^2} \sum_{f_i, f_j \in S} I(f_i, f_j) \quad (8)$$

where $I(f_i, f_j)$ measures the similarity or shared information between features f_i and f_j .

A larger value of $R(S)$ indicates higher redundancy within the feature subset.

The MR approach aims to select the optimal subset of features by maximizing relevance while minimizing redundancy. Thus, the objective function is defined as:

$$\max[D(S, C) - R(S)]$$

By optimizing this criterion, the selected feature set maintains strong correlation with the class labels while ensuring minimal inter-feature dependency. This balanced selection strategy improves classification performance and enhances the robustness of the proposed ECG arrhythmia detection system.

2.5 Kurtosis

Kurtosis is a fourth-order statistical moment that measures the degree of peakiness or tail heaviness of a distribution relative to a normal distribution [25]. In ECG signal analysis, kurtosis is particularly useful for detecting sharp spikes and transient abnormalities within a selected signal window, which are indicative of arrhythmic events. For a windowed ECG segment consisting of n samples, the unbiased sample kurtosis is computed as:

$$K = \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_{i=1}^n \left(\frac{X_i - X_{\text{avg}}}{s} \right)^4 - \frac{3(n-1)^2}{(n-2)(n-3)} \quad (9)$$

where:

- n denotes the number of samples in the selected window,
- X_i represents the i^{th} ECG sample,
- X_{avg} is the mean of the samples,
- s is the sample standard deviation.

The sample standard deviation is calculated as:

$$s = \sqrt{\frac{\sum_{i=1}^n (X_i - X_{avg})^2}{n - 1}} \quad (10)$$

A kurtosis value greater than that of a normal distribution (i.e., positive excess kurtosis) indicates the presence of sharp peaks and heavy tails, while a lower value suggests a flatter distribution. Since abnormal ECG beats often exhibit sudden morphological deviations, kurtosis serves as an effective statistical descriptor for distinguishing normal and arrhythmic heartbeats in the proposed classification framework.

2.6 Skewness

Skewness is a statistical measure that quantifies the asymmetry of a probability distribution around its mean [25]. In ECG signal analysis, skewness helps determine whether the waveform distribution is symmetrically balanced or biased toward either the positive or negative side. Since abnormal cardiac events often introduce asymmetry in ECG morphology, skewness serves as a discriminative feature in arrhythmia classification.

For a windowed ECG segment consisting of n samples, the unbiased sample skewness is computed as:

$$S = \frac{n}{(n - 1)(n - 2)} \frac{\sum_{i=1}^n (X_i - X_{avg})^3}{s^3} \quad (11)$$

where:

- n denotes the sample size,
- X_i represents the i^{th} ECG sample,
- X_{avg} is the sample mean,
- s is the sample standard deviation.

A positive skewness value indicates that the distribution has a longer right tail, whereas a negative value indicates a longer left tail. A value close to zero suggests a nearly symmetric distribution. In the context of ECG signal processing, deviations in skewness can highlight abnormal waveform characteristics, thereby improving the discriminative capability of the proposed classification system.

2.7 R-R Interval Features

The R-R interval represents the time duration between two successive R-peaks in an ECG signal and serves as a fundamental indicator of cardiac rhythm. Variations in the R-R interval reflect changes in heart rate and rhythm, and significant irregularities are often associated with different types of arrhythmias. However, analysing a single R-R interval may not sufficiently capture the dynamic behaviour of cardiac activity. Therefore, multiple R-R interval-based features are extracted to characterize both instantaneous and temporal variations in heart rhythm.

In the proposed framework, four distinct R-R interval features are computed:

1. **Pre R-R Interval:** The time difference between the current R-peak and the immediately preceding R-peak.
2. **Post R-R Interval:** The time difference between the current R-peak and the immediately succeeding R-peak.

3. **Local R-R Interval:** The mean R-R interval calculated over a short-term window of 8 seconds, capturing short-term heart rate variability.
4. **Average R-R Interval:** The mean R-R interval computed over a longer duration of 3 minutes, representing long-term heart rate characteristics.

To further enhance discriminative capability, higher-order statistical measures—kurtosis and skewness—are computed from the extracted R-R interval sequences. These statistical descriptors quantify the peakiness and asymmetry of interval distributions, thereby highlighting rhythm irregularities and subtle abnormalities.

Finally, all dynamic features are concatenated to form a hybrid feature vector. In total, six features—four R-R interval features and two statistical descriptors—are used as inputs to the Reactive Optimized Convolutional Neural Network (ROCNN) for classification. The features are prioritized and organized based on their clinical significance and contribution to classification performance, ensuring a robust and computationally efficient arrhythmia detection system.

2.8 ROCNN Classification

The classification stage of the proposed framework is implemented using a Reactive Optimized Convolutional Neural Network (ROCNN). The ROCNN architecture is composed of multiple layers, including convolutional layers, activation layers, pooling layers, and fully connected layers, designed to learn complex nonlinear relationships among the selected features. The convolutional layer serves as the primary feature learning component. It processes the input feature vector using a set of learnable filters characterized by kernel size, depth (number of filters), and zero-padding parameters. The convolution operation extracts meaningful feature representations by sliding the kernels across the input and generating corresponding feature maps.

The output of the convolutional layer is passed through a Rectified Linear Unit (ReLU) activation function, defined as:

$$\text{ReLU}(x) = \max(0, x)$$

which introduces non-linearity into the network and accelerates convergence during training.

Subsequently, a max-pooling layer is applied to reduce the dimensionality of the feature maps while retaining the most significant activations. This step reduces computational complexity and mitigates overfitting by providing translational invariance.

The pooled features are then flattened and fed into the fully connected layer, where classification is performed. The net input to a neuron in the fully connected layer is computed as:

$$\text{Net Output} = \sum_{i=1}^N x_i w_i + b \quad (13)$$

where:

- x_i represents the i^{th} input feature,
- w_i denotes the corresponding weight,
- b is the bias term,
- N is the number of input features.

During training, the network parameters (weights and biases) are optimized to minimize the classification error. In the proposed ROCNN, parameter updates are governed by a reactive optimization strategy, which adaptively adjusts learning dynamics to reduce the overall system error efficiently. The optimization objective can be expressed as a multi-objective function:

$$f(x) = (f_1(x), f_2(x), \dots, f_k(x))^T \quad (12)$$

where each $f_k(x)$ represents an objective component contributing to improved convergence and classification accuracy.

Finally, an activation function such as sigmoid or SoftMax is applied at the output layer to produce class probabilities. Through reactive optimization and hierarchical feature learning, the ROCNN effectively classifies ECG signals into the defined arrhythmia categories with enhanced accuracy and robustness.

3. Performance Analysis

3.1 Evaluated Parameters

The performance of the proposed ROCNN-based classification system is evaluated using standard metrics widely employed in biomedical signal analysis, including sensitivity (Se), precision (Pp), specificity, accuracy, and error rate.

In the context of arrhythmia detection:

- **True Positive (TP):** Arrhythmic beats correctly classified as abnormal.
- **True Negative (TN):** Normal beats correctly classified as normal.
- **False Positive (FP):** Normal beats incorrectly classified as abnormal.
- **False Negative (FN):** Abnormal beats incorrectly classified as normal.

The primary evaluation metrics are defined as:

$$\text{Sensitivity (Se)} = \frac{TP}{TP + FN} \times 100 \quad (14)$$

$$\text{Precision (Pp)} = \frac{TP}{TP + FP} \times 100 \quad (15)$$

The overall **classification accuracy** and **error rate** are computed as:

$$\text{Accuracy (\%)} = \frac{\text{Total correctly classified samples}}{\text{Total number of samples}} \times 100 \quad (16)$$

$$\text{Error (\%)} = \frac{\text{Total misclassified samples}}{\text{Total number of samples}} \times 100 \quad (17)$$

These metrics collectively provide a comprehensive assessment of the classifier's capability to distinguish between normal and arrhythmic ECG beats.

Simulation experiments were conducted in MATLAB R2018a on a system with an AMD E1-2100 processor and 4 GB of RAM. Ground truth annotations from the MIT-BIH Arrhythmia Database were used as the reference to verify classification performance. As summarized in Table 1, four ECG beat categories—Normal (NOR), Atrial Premature Contraction (APC), Ventricular Escape Beat (VE), and Unclassifiable Beat (UN)—were used for both training and testing.

3.2 Results and Analysis

The performance of the proposed ROCNN-based classification framework was evaluated using the MIT-BIH Arrhythmia Database, following the workflow illustrated in Figure 4. The evaluation focused on the four ECG beat categories described in previous sections: Normal (NOR), Atrial Premature Contraction (APC), Ventricular Escape Beat (VE), and Unclassifiable Beat (UN).

Classification was performed on the training dataset summarized in Table 1, and the ability of the classifier to correctly identify each individual arrhythmia class was assessed. The prediction outcomes are presented in the form of a confusion matrix (Table 2), which clearly illustrates the distribution of true positives, false positives, and misclassifications for each class. It is noteworthy that only 15.72% of the total 65,488

beats were used for training. Despite this relatively small training set, the proposed ROCNN framework achieved high classification accuracy, demonstrating strong generalization capability and robustness. Using a reduced number of training samples also offers the advantage of lower computational time, making the proposed approach more efficient for large-scale ECG datasets and potential real-time applications. The results confirm that the combination of R-R interval features and higher-order statistical descriptors, when processed through the ROCNN, provides reliable and precise arrhythmia classification even with minimal training data.

3.3 Confusion Matrix

The confusion matrix is an essential tool for evaluating the performance of the proposed ROCNN-based classification system, as it provides a detailed view of how well each ECG beat category is classified. The confusion matrix for this study is presented in Table 2.

The diagonal entries, highlighted in bold, represent the correctly classified instances, referred to as True Positives (TP). For instance, in the first row corresponding to the Normal (NOR) class, 63,609 beats are correctly classified as normal out of 63,764 total beats, indicating a high accuracy for this category. The off-diagonal entries indicate misclassified instances. These are considered False Positives (FP) when normal beats are misclassified as arrhythmic, or False Negatives (FN) when arrhythmic beats are misclassified as normal. In the first row, 95, 27, and 33 beats from APC, VE, and UN classes, respectively, are incorrectly identified as normal. The same interpretation applies to the remaining rows, showing misclassification patterns for APC, VE, and UN categories.

Using the confusion matrix, the overall classification accuracy can be computed as:

$$\text{Accuracy (\%)} = \frac{\text{Total correctly classified beats}}{\text{Total beats tested}} \times 100$$

In this study, 65,324 beats out of 65,488 total test beats are correctly classified, demonstrating the high performance and reliability of the proposed ROCNN framework. The confusion matrix not only validates the overall accuracy but also provides class-wise insights, enabling identification of potential misclassification trends and ensuring a comprehensive evaluation of the classification system.

Table 2. Confusion Matrix for ROCNN model

Correctly classified instances: 65324, Misclassified instances: 164 Error: 0.25%, Accuracy: 99.75%						
Ground Truth						
Class		N	A	E	Q	Total
Normal (NOR)	N	63609	95	27	33	63764
Atrial premature contraction (APC)	A	1	1650	2	2	1655
Ventricular escape beat (VE)	E	1	2	50	0	53
Unclassifiable beat (UN)	Q	1	0	0	15	16
Total		63612	1747	79	50	65488

Table 3. Performance on single Class of ECG

ECG class	Trained beats	Test beats	F _N	T _P	F _P	S _e (%)	P _P (%)	Accuracy (%)
N	11253	63764	155	63609	3	99.75	99.99	99.75
A	891	1655	5	1650	97	99.70	94.45	99.70
E	53	53	3	50	29	94.34	63.29	94.34
Q	17	16	1	15	35	93.75	30.00	93.75
Total	23996	65488	164	65324	164	99.75	99.75	99.75

Table 4. Comparison with State of Art algorithms

Literature	Approach	Classes	Accuracy (%)
Melgani [8]	Morphology + PCA + SVM	6	91.67
Li et.al [26]	PCA + k-ICA + SVM	5	97.78
Martis et. al [27]	PCA + LS-SVM	5	93.48
Proposed method	Statistical metrics + RR + Memetic redundancy + ROCNN	4	99.75

From the experimental results, a total of 164 misclassified instances were observed, yielding an overall error rate of 0.25% and a classification accuracy of 99.75%, calculated using Equations (15) and (16). This high performance is achieved through the combination of the CASVR-based noise removal and Memetic Redundancy feature selection within the proposed ROCNN framework.

Figure 6 shows the class-wise accuracy of the proposed method, corresponding to the results presented in Table 3. Among the four classes, the 'Q' (Unclassifiable Beat) category exhibits the lowest accuracy of 93.75%, while the other classes demonstrate higher accuracy, reflecting the robustness of the proposed approach across different ECG beat types. The graphical representation provides a clearer visualization of individual class performance.

Figure 7 presents a comparison of the proposed method with existing state-of-the-art (SOTA) approaches. The proposed methodology achieves an average sensitivity and positive predictivity of 99.75%, as shown in Table 3. When compared with previous studies (Table 4), the proposed approach outperforms them in terms of overall classification accuracy for four ECG classes, achieving 99.75%.

It is well understood that as the number of classes increases, classification accuracy typically decreases due to the larger sample space and increased complexity. Nevertheless, the proposed method demonstrates superior performance while requiring a relatively small number of training samples, highlighting its efficiency, robustness, and suitability for automated ECG arrhythmia detection.

4. Conclusion

This study introduces a robust ECG arrhythmia classification framework that combines advanced preprocessing, multi-resolution wavelet lifting analysis, and optimized feature selection to achieve a high accuracy of 99.75%. Discriminative features were derived from statistical measures (kurtosis and skewness) and four R-R interval types—pre-R-R, post-R-R, local R-R, and average R-R—forming six hybrid descriptors. Eigenvalue-based selection identified the most dominant features, while the Memetic Redundancy-Based Feature Selection method eliminated irrelevant and redundant attributes, improving both accuracy and computational efficiency. The proposed method demonstrates strong reliability for automated arrhythmia detection and offers promising

potential for validation on larger, real-time ECG datasets and extended arrhythmia categories.

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