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A Shallow Neural Network Approach for ECG Arrhythmia Detection Using Feature-Based Classification

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ABSTRACT: The process of Electrocardiogram (ECG) arrhythmia detection provide an important role in the detection of heart diseases at an early stage. In the proposed work, a Shallow Neural Network (SNN) is used for ECG arrhythmia detection. During the data preprocessing stage, raw ECG signals undergo noise removal, followed by the application of Band Pass Filter (BPF), Wavelet denoising to enhance the quality of the signal, Z-score normalization is used for normalizing the amplitude of the signal, R-peak detection method is performed to accurately identify the locations of R-peaks. In the segmentation stage, the detected R-peaks are used to perform fixed-window segmentation and segments the continuous ECG into individual cardiac segments of equal length. The segmented ECG signals are used as direct input to the SNN during the classification stage, where it learns the signal pattern characteristics and classifies them as normal or arrhythmic patterns, resulting in an automated ECG arrhythmia detection framework. ECG arrhythmia classification dataset is used and this system is implemented in Python software and achieves accuracy of 98.88%, 98.84% precision, 98.88% recall and 98.84% F1-score.

Keywords: Arrhythmia detection, wavelet denoising, Z-score normalization, segmentation, Shallow neural network.

1. Introduction

ECG is considered a standard instrument for the measurement and classification of diseases related to the cardiovascular systems. ECG develops information on the electrical activity of the heart and therefore it is used for the identification of cardiovascular pathologies [1]. ECG is not very reliable in terms of identification of different pathologies but is still capable of providing certain important information about the condition of heart [2]. ECG is particularly used for diagnosing ischemic heart disease/coronary artery disease, myocardial infarction, arrhythmias and cardiomyopathy. The ECG helps in the identification of arrhythmia, which develops because of the malfunctions of the electrical system of the heart [3]. The ECG process is non-invasive and thus poses discomfort to patients because of the possibility of repetition. In addition, ECG systems and Holter monitors are very common and inexpensive pieces of diagnostic equipment, which makes them widely accessible [4]. All these apparatuses quickly collect a great amount of information such as heart rate, rhythm, and other signals of the possible diseases.

While ECG offers great benefits for identifying and classifying arrhythmias, it requires some limitations [5]. The typical method of electrocardiographic analysis tends to rely on the attentiveness of skilled physicians. This causes inconsistencies in results since they are prone to interpretation [6]. Additionally, typical ECG devices require low sensitivity and not able to recognize irregularities if they do not occur in the recording time [7]. There is also an issue with the electrodes and physical points of contact, which create discomfort for the patient and affect the result of the recordings, thus prompting the use of automatic low-cost systems based on Machine Learning (ML) technology. SVM [8] achieve great accuracy in patterns identified in ECG data using kernel functions, and is capable of resolving difficulties associated with high-dimensional feature datasets. However, SVM is computationally intensive and requires substantial time for processing big data.

Naive Bayes [9] technique is easy to use, fast, and computationally efficient for ECG arrhythmia classification. Naive Bayes method needs less training data and simple to execute. But, the use of Naive Bayes method result in low accuracy since ECG features are related with each another leading to inaccurate outcomes. AdaBoost [10] is based on effective training on weak classifiers to create a powerful classifier. Nevertheless, AdaBoost has significant problems because it require careful hyperparameter tuning.

In order to address the challenges mentioned above, this paper proposes the application of SNN for ECG arrhythmia detection. The current research utilizing the ECG preprocessing techniques, R-peak detection, fixed-window segmentation, and a SNN to classify arrhythmias. Thus, offering an alternative approach that is superior to traditional ML systems. The main objectives of this research includes,

- Preprocessing methods including eliminating noise, filtering on a specific band of frequencies, denoising, normalizing the Z-score and recognizing R-peak are utilized to refine the quality of ECG signal and identify the cardiac beats location.
- The segmentation of ECG data into fixed windows allows for the generation of standardized segments.
- A SNN is applied for classification and assessment of both normal and irregular types of ECG signals.

2. Recent Works

Table 1: *Related works of existing method.*

Author/Year	**Methods**	**Merits**	**Demerits**
Paul *et al* [2023]	Random Forest (RF)[11]	RF is capable of providing steady accuracy concerning classification and managing nonlinear links in ECG features.	RF requires lot of memory and other computing resources.
Zavadjil *et al* [2024]	Decision Tree (DT) [12]	It is able to work with nonlinear ECG patterns without pre-processing data significantly.	The decision tree is quite prone to overfitting. .
Farell *et al* [2024]	K-Nearest Neighbour (KNN) [13]	KNN does not need complicated training and classify ECG patterns by comparing their similarities with neighboring samples.	In terms of computation during the prediction process, this algorithm can be costly.
Asmawati *et al* [2024]	Extreme Gradient Boosting (XGBoost) [14]	XGBoost achieve high classification accuracy to capture complicated non-linear correlations in ECG data.	The method converge slower in large datasets.
Manivannan *et al* [2024]	Logistic Regression (LR) [15]	It is robust to overfitting and provide probabilistic prediction.	In requires careful hyperparameter tuning.

Nonetheless, the current techniques have their shortcomings, which are primarily high computation time, poor classification accuracy, and their sensitivity to ECG signals. Hence, there is a need for a novel technique that improves the quality of the ECG signal and classifies it effectively to discriminate between normal and abnormal patterns in the data.

3. Proposed Methodology

The proposed method is an ECG arrhythmia detection technique based on a SNN. The framework of the proposed work is shown in figure 1. Firstly, the input signal of ECG is processed through different preprocessing steps such as noise extraction, bandpass filter which removes noise and retains valuable information regarding heart activity. Wavelet denoising is used for better quality of signal and Z-score normalization is utilized to standardize ECG signal. After that R-peak detection is executed to find the R-peaks in each cycle of ECG. With the help of detected R-peaks, Fixed window segmentation is used to segment ECG into single heartbeats of fixed length. The ECG features are then extracted from these beats and delivered into SNN which learns the difference between normal and abnormal heart rhythms.

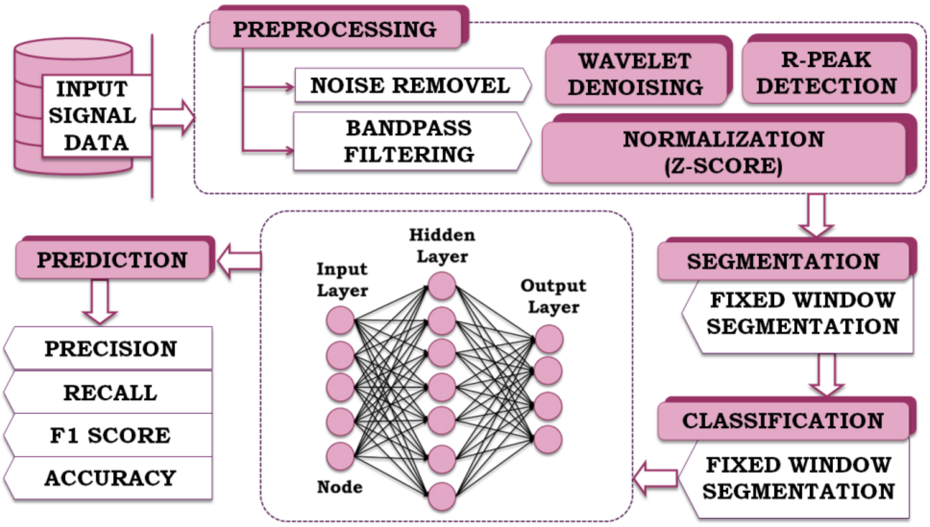

Figure 1: *Proposed framework*

The trained network ultimately detects arrhythmia, which is the effective and efficient method of ECG arrhythmia detection.

3.1 Preprocessing

3.1.1 Noise Removal and Band Pass Filtering

Noise removal is used to improve ECG signal quality for removing unwanted noises such as baseline drift, power line interference, and muscle noise and motion artifacts. To eliminate undesirable frequency component, a BPF is employed. The BPF is able to maintain important characteristics of the ECG such as the P wave, QRS complex, and T wave while minimizing the acute frequency noise. The BPF is constructed through the combination of a low pass filter and a high pass filter. A Chebyshev filter is used to provide better frequency response with minimal computation. The gain of this low pass filter is given as,

$$H_n(j\omega) = \frac{1}{\sqrt{1+r^2 T_n^2\left(\frac{\omega}{\omega_0}\right)}} \tag{1}$$

Here, r represents the ripple factor, T_n is the n^{th} Chebyshev polynomial, and ω_0 is the cutoff frequency. The Chebyshev polynomial is given through the recursive function as,

$$\begin{cases} T_0(x) = 1 \\ T_1(x) = x \\ T_{n+2}(x) = 2xT_{n+1}(x) - T_n(x), n > 0 \end{cases} \tag{2}$$

Where, n is the order of the filter and $T_n(x)$ is the n^{th} Chebyshev polynomial. $T_0(x)$ and $T_1(x)$ are the Chebyshev polynomials for the recursive calculation. Hence, the BPF eliminate the ECG related fluctuations while maintaining the morphology of the ECG signal, and help with the ECG arrhythmia detection.

3.1.2 Wavelet Denoising

Wavelet denoising is used for eliminating noise from ECG signals while maintaining essential heart features. Noisy ECG signal is modelled as follows,

$$y = x + \eta \quad (3)$$

Where, y is the noisy ECG signal, x is a normal ECG signal, and η is noise. Wavelet decomposition provide ECG in terms of approximations and details at every level. Approximations contain relevant ECG information while details consist of high frequency noise and interference. The process requires applying appropriate thresholding to detail. The level of noise is calculated by the following equation,

$$\sigma_j = median(|cD_j|) \quad (4)$$

Here, cD_j are detail coefficients on j^{th} level and σ_j is calculated noise level. Thus wavelet denoising reduces noise while preserving P wave, QRS complex, and T wave clear for arrhythmia detection.

3.1.3 Z-Score Normalization

Z-score normalization is a preprocessing method employed to standardize ECG signal according to their mean and standard deviation. It help in minimizing amplitude variations in ECG signals and giving a constant range of values to the arrhythmia detection model. The normalized ECG value are then calculated according to this formula as,

$$\frac{v\prime=(v-\mu)}{\sigma} \quad (5)$$

In this formula, v' is the calculated value of ECG signal normalized using Z-score normalization, v is the original value of the ECG feature, μ is the mean value of the ECG feature, and σ is the standard deviation of the ECG feature. Using Z-score normalization provide ECG features that are consistent and help to improve the reliability of ECG arrhythmia detection systems.

3.1.4 R-peak Detection

R-peak detection is a significant role in ECG arrhythmia detection since R-peaks are essential point of the QRS complex and the respective signal ensures relevance in determining heart rate and rhythm irregularities. Since noise in the system affect the R-peak amplitude, both amplitude information and waveform characteristics are used in R-peak detection. The processed ECG signal is utilized to amplify the signal due to R-wave while concealing other characteristics of ECG. The amplitude threshold T_c is applied to determine the R-peak candidate set:

$$S_c = \{w_j | v_j > T_c, j = 1,2,3, \ldots, N + M\} \quad (6)$$

Where, S_c is prior to R-peak candidate set, w_j is the certain position, v_j is the generated amplitude of the signal, and T_c refers to amplitude threshold. Candidate peaks are subsequently evaluated based on amplitude, kurtosis, and RR-interval information to identify actual R-peaks. Hence, R-peak is used for efficient ECG arrhythmia detection and classification.

3.2 Segmentation- Fixed Window

In fixed window segmentation, the continuous ECG signal is gathered into discrete windows of fixed window duration and processed separately for the purpose of extracting relevant ECG features and identifying arrhythmia patterns. This technique allows preserving the size of inputs to the detection model consistent while improving the processing of lengthy ECG signals. The overlapping ECG windows is defined as,

$$threshold = |T_t| * \tau \tag{7}$$

Where, T_t is the ECG signal corresponding to the considered time step and τ is the mapped parameter that controls the minimum similarity between two adjacent windows. The use of overlapping windows allows minimizing the chances of losing valuable ECG characteristics at the segment borders and enabling uninterrupted tracing of the detected arrhythmia.

3.3 Classification- Shallow Neural Network

The SNN is utilized for the classification of arrhythmia from ECG signals by examining the connection of known ECG signals and their respective classes of arrhythmia. The SNN inherently has fewer hidden layers and therefore it is easier to analyze and train. The network is represented in the following manner,

$$\mathcal{F}(s) = \Omega\left(v\big(\psi(s)\big)\right) \tag{8}$$

Where, the term s denotes the input ECG features, ψ and v are the hidden layers that perform nonlinear representation of the features, and Ω is the output layer that provides the arrhythmia output. The structure of SNN is shown in figure 2.

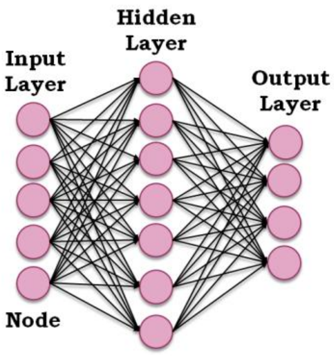

Figure 2: *SNN structure*

The hidden layer is mathematically denoted by,

$$z^{\psi} = \psi(S) = R\left(W^{\psi}S + b^{\psi}\right) \tag{9}$$

$$z^{v} = v(z^{\psi}) = R\left(W^{v}z^{\psi} + b^{v}\right) \tag{10}$$

Here, the weight matrix is denoted by W, b denote biasing terms, and $R(\cdot)$ is the activation function. A widely used activation function is ReLU which is given as,

$$R(z) = max(z, 0) \tag{11}$$

In this equation, $R(z)$ shows the result of the ReLU activation function and z represents the input to the activation function. Finally, the output layer converts the data into respective classes of arrhythmia. The method involve batch normalization and dropout techniques to enhance the stability of the training and decrease overfitting. Thus, SNN is an efficient approach to ECG feature learning and classification of arrhythmia.

4. Results and Discussion

The detection of ECG arrhythmia is examined with the proposed method of SNN and the classification strategies based on the use of selected features. The description of dataset is shown in Table 2.

Table 2: *Dataset description*

Dataset Name	ECG Arrhythmia Classification Dataset
Original dataset	INCART 2-lead Arrhythmia Database.csv, MIT-BIH Arrhythmia Database.csv, MIT-BIH Supraventricular Arrhythmia Database.csv, Sudden Cardiac Death Holter Database.csv
Combined dataset	ECG_Arrhythmia_Cleaned.csv
Combined dataset size	1,774,874 samples
Total Columns	34
Additional Identifier	1 (record)
Number of Input Features X	32
Number of Target Variable Y	1
Y Label	type
Train Split	80%
Test Split	20%

The dataset of ECG comprises 1,774,874 samples with 32 input parameters as well as one target variable. The input parameters include RR intervals, ECG peak values, along with waveform interval and morphology parameters. The target variable is used to denote the arrhythmia class.

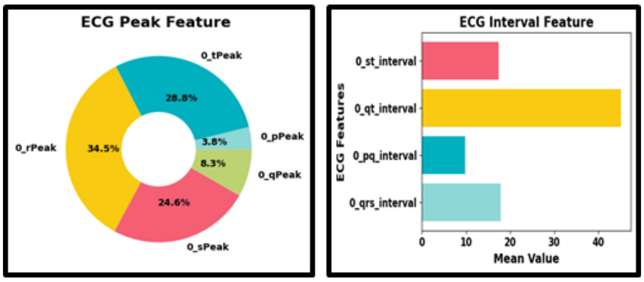

Figure 3*: Distribution of extracted ECG features*

Figure 3 provides that O_rPeak (34.5%) rate is the highest and the second position is the O_tPeak (28.8%) as well as final is the O_sPeak (24.6%). In comparison with the other interval usage, the O_qt_interval requires the mean maximum value.

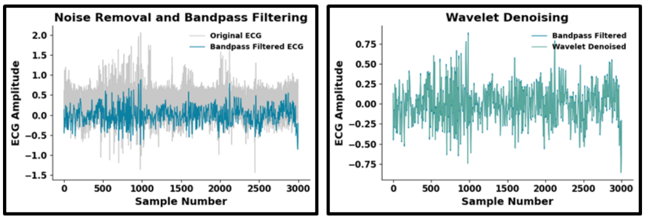

Figure 4: *Noise removal, BPF and Wavelet denoising*

In Figure 4, the noise removal from the ECG signal from −1.5 to 2.0 amplitude of the original signal to the noise-free filter. After wavelet denoising it is notable that the amplitude ranges from −0.75 to 0.75; that illustrates efficiency in noise removal process.

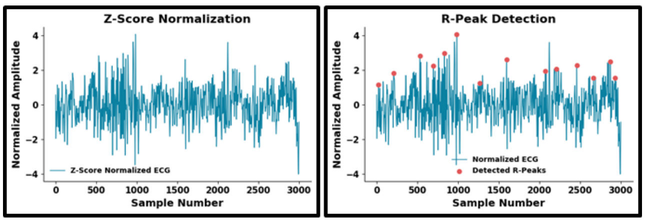

Figure 5: *Z-Score and R-Peak detection*

In figure 5, the Z-scores normalized signal shows the ECG signals amplitude from −4.0 to +4.0 with the center value of 0. As for the R-peak detection, it is visible that the majority of the peaks are mainly located in the area of 0.0-4.0 normalized amplitude and shown as the red dots in the ECG signal during the range of approximately 0 to 3000 samples.

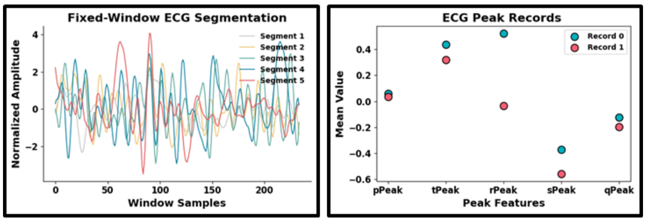

Figure 6: *Fixed-window segmentation and ECG peak record*

In Figure 6, the segments of the ECG vary from approximately −4 to +4 normalized amplitude over 0 to 220 samples. The mean values of the peak signals ranged from around −0.4 to +0.5 but tPeak provide the highest of 0.45.

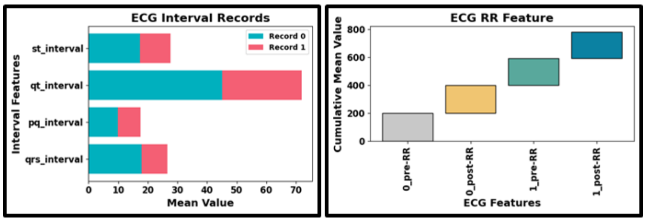

Figure 7: *Distribution of ECG RR- interval features*

Figure 7 shows that the total features of the RR intervals increased from more than 200 (Q_pre-RR) to 750 (Q_post-RR), which is the longer post-RR intervals.

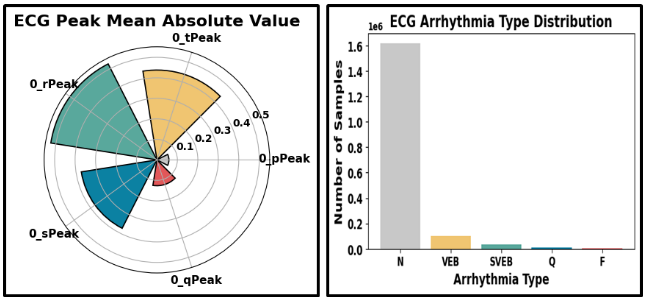

Figure 8: *ECG feature and class distribution*

Figure 8 indicates that Normal (N) beats are dominant in the ECG dataset and the number of samples is significantly higher than any other arrhythmia types. In terms of ECG peak characteristics, two features such as Q_Peak and

S_Peak require the highest average absolute values, while Q_TPeak and Q_qPeak provide lower averages.

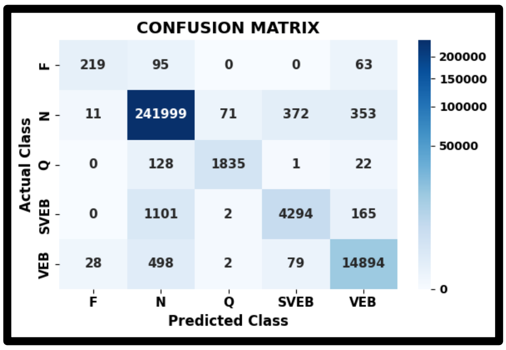

Figure 9*: Confusion matrix*

The confusion matrix in figure 9 suggests best results with 241,999 samples of Normal, 14,894 samples of VEB, 4,294 samples of SVEB, 1,835 samples of Q, and 219 F samples.

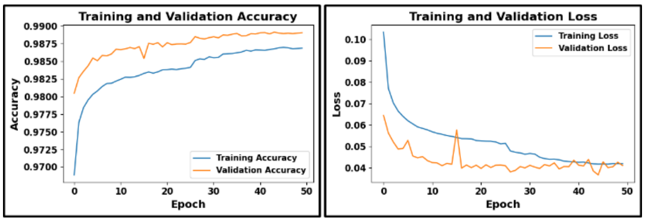

Figure 10: *Training and validation accuracy and loss*

Figure 10 improves its training and validation accuracy over time, reaching approximately 98.7% and 98.9%. The training/validation loss drops to approximately 0.04.

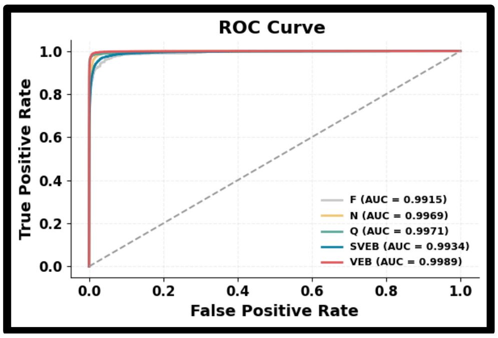

Figure 11: *ROC curve*

ROC curve in Figure 11 shows that all models performed efficiently, with AUC ranging from 0.9669 to 0.9974. The SVEB model is the best with AUC equal to 0.9974 and the N model is the lowest.

Table 3: *Performance evaluation*

Methods	Accuracy	Precision	Recall	F1-score
RF [11]	90.91%	90.96%	90.91%	90.87%
DT [12]	84%	82%	84%	82%
Proposed	98.88%	98.84%	98.88%	98.84%

Table 3 shows the performance of three methods with accuracy, precision, recall, and F1-score. The proposed method provides the best overall performance with 98.88% accuracy, 98.84% precision, 98.88% recall, and 98.84% F1-score, surpassing both RF [11] and DT [12] methods.

5. Conclusion

This paper described SNN-based approach incorporating features-based classification to perform ECG arrhythmia detection, which is demonstrated using an ECG arrhythmia classification dataset. The first step in the process is Pre-processing of ECG signals, which included applying noise removal techniques as well as band pass filtering to achieve better quality of the ECG signals, followed by wavelet denoising. After that, Z-score normalization is used to standardize ECG signals for further ECG signal processing. For further analysis, the R-peaks of the ECG signal are detected. The fixed-window segmentation process then segmented the ECG signal. SNN classification method is used to classify them as normal or arrhythmic patterns. This system is implemented in Python software and the results clearly demonstrated that the proposed SNN-based approach provides superior performance in terms of classification and prediction accuracy of arrhythmia classes. The final results achieved by the proposed approach are 98.88% of accuracy, 98.84% precision, 98.88% recall and 98.84% F1-score. In future studies, the same approach is tested against more complex and wider range of ECG signal samples and real ECGs.

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