Optimized Wavelet Scattering Network and CNN for ECG Heartbeat Classification from MIT–BIH Arrhythmia Database

Mohamed Elmehdi AIT BOURKHA[1]*, Anas HATIM[2], Dounia NASIR[3], Said EL BEID[4]
Research Laboratory in Innovative and Sustainable Technologies (LaRTID),
National School of Applied Sciences (ENSA) of Marrakech, Cadi Ayyad University (UCA), 40000, Marrakech, Morocco[1, 2, 3]
Control and Computing for Smart Systems and Green Energy (CISIEV),
ENSA of Marrakech, UCA, 40000, Marrakech, Morocco[4]

***Abstract*—Early detection of cardiovascular diseases is vital, especially considering the alarming number of deaths worldwide caused by heart attacks, as highlighted by the world health organization. This emphasizes the urgent need to develop automated systems that can ensure timely and accurate identification of cardiovascular conditions, potentially saving countless lives. This paper presents a novel approach for heartbeats classification, aiming to enhance both accuracy and prediction speed in classification tasks. The model is based on two distinct types of features. First, morphological features that obtained by applying wavelet scattering network to each ECG heartbeat, and the maximum relevance minimum redundancy algorithm was also applied to reduce the computational cost. Second, dynamic features, which capture the duration of two pre R–R intervals and one post R–R interval within the analyzed heartbeat. The feature fusion technique is applied to combine both morphological and dynamic features, and employ a convolutional neural network for the classification of 15 different ECG heartbeat classes. Our proposed method demonstrates an overall accuracy of 98.50% when tested on the Massachusetts institute of Technology -Boston's Beth Israel hospital arrhythmia database. The results obtained from our approach highlight its superior performance compared to existing automated heartbeat classification models.**

Keywords*—Electrocardiogram (ECG); Convolutional Neural Network (CNN); Arrhythmia Rhythm (ARR); Maximum Relevance Minimum Redundancy (MRMR); Wavelet Scattering Network (WSN)

I. INTRODUCTION

The cardiac conduction system ensures an electrical impulse from pacemaker cells in the Sinoatrial (SA) node travels through atria and ventricles, causing a coordinated and timely muscle contraction [1]. Components include SA node, Atrioventricular (AV) node, bundle of His, bundle branches, and Purkinje network.

Einthoven pioneered visualizing heart electrical activity using vectors in an equilateral triangle [2]. Six standard leads: I, II, III, aV_R, aV_L, and aV_F provide a frontal view, while combining them gives a biplanar view of the 3D heart. ECG records instant heart electrical activity on the surface.

ECG signals are commonly employed for the diagnosis of Cardiovascular Diseases (CVD) [3]. Advances in digital tech and cost-effective miniaturized acquisition units have led to the digital acquisition and processing of ECG signals.

Studying Electrocardiogram (ECG) signals could greatly improve early detection of CVD, a major cause of mortality globally [4]. More than that coronary heart disease contributes to premature deaths, disabilities, and a cycle of poverty and ill health [5]. Manual CVD analysis is a time-consuming, an error-prone, especially with large datasets, and requires extensive training due to the signal's complexity, as referred in [6-7-8, 9]. Mistakes in ECG analysis can lead to incorrect diagnoses and treatment. hence, the automatic classification of arrhythmias in ECG signals can be very useful as it can not only offer an impartial diagnosis, but it also has the potential to reduce the workload of medical professionals. As a result, the identification and categorization of ECG hold substantial importance in this field [10], facilitating advancements in CVD research.

Cardiac ARR, termed abnormal cardiac rhythms, arise from irregular initiation or propagation of cardiac excitation waves [11]. They are categorized into ventricular such as Ventricular Premature Complex (VPC), couplets, and triplets, and into supraventricular such as Supraventricular Tachycardia (SVT) and Atrial Fibrillation (AF) types [12]. Ventricular Arrhythmia Rhythm (ARR) stemming from heart's lower chambers, heighten the risk of sudden cardiac death, causing around 450,000 annual US fatalities. Most deaths result from ventricular tachycardia progressing to fatal ventricular fibrillation [13], necessitating prompt defibrillation.

The rest of the paper begins with the related work in Section II, where automated arrhythmia detection methods are discussed in-depth. This is followed by the ECG heartbeat classification in Section III, which starts with a detailed description of the dataset. Next, the feature extraction section provides an in-depth explanation of feature extraction using WSN. The MRMR section then presents a comprehensive overview of dimensionality reduction and the optimization of scattering paths within the scattering network. The subsequent section describes the proposed CNN model for the classification task. Finally, the results in Section IV presents the various outcomes achieved in terms of evaluation metrics and optimization results, while the discussion in Section V compares the findings of this research with state-of-the-art models. Finally, the paper is concluded in Section VI.

II. Related Works

In the last ten years, significant advancements have occurred in automatic ECG classification algorithms that employs classical machine learning models such as decision trees [18], linear discriminants [19], and logistic regression [20] for diagnosing cardiac arrhythmias [14-15-16, 17]. Techniques like Naïve Bayes, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) have also been utilized in this context [21-22, 23]. Artificial Neural Networks (ANN) have emerged also as a powerful tool [24-25, 26], capable of real-time arrhythmia detection through the recognition of intricate patterns and correlations in ECG signals. Other approaches combine feature extraction with machine learning, including time domain features [26], frequency domain features [27], and combinations of both [28]. Wavelet analysis has also proven effective [29-30].

Recently, deep learning has become a promising approach for analyzing ECG signals, outperforming traditional machine learning methods. Models like Convolutional Neural Networks (CNN) [31-32], Recurrent Neural Networks (RNN) [33], and Long-Short Term Memory (LSTM) neural networks [34] excel due to their automatic feature extraction from raw ECG data. GPU and TPU, integral to high-performance computing, have significantly bolstered deep learning in ECG analysis by efficiently processing extensive data.

Noteworthy datasets like PhysioNet [35] and PTB Diagnostic ECG database have further advanced deep learning in this field. These datasets encompass diverse ECG signals with varying abnormalities, facilitating improved learning and generalization of deep learning models. Moreover, deep learning has proven effective in vital tasks such as denoising [36], segmentation, and reconstruction of ECG signals. Recent advancements in ECG have enhanced the diagnosis and treatment of CVD, a leading global cause of mortality [37-38].

Past research has concentrated on categorizing ECG signals into broader groups like Normal Sinus Rhythm (NSR), ARR, and Congestive Heart Failure (CHF) [39-40]. Some researchers have also suggested interpreting ECG heartbeats based on the Association for the Advancement of Medical Instrumentation (AAMI) classes: non-ectopic beats (N), supraventricular ectopic beats (S), ventricular ectopic beats (V), fusion beats (F), and unknown beats (Q) [41-42]. Some other works used the annotations from the American Heart Association (AHA) that has proposed a set of 15 classes for arrhythmia classification based on the MIT–BIH arrhythmia Database.

Osowski et al. [43] proposed a method to classify ECG heartbeats from the MIT–BIH arrhythmia database with 13 classes. They combined features extracted using Higher-Order Statistics (HOS) and Hermite characterization of the QRS complex, feeding them into an SVM classifier.

Rodriguez et al. [44] describe their approach to creating a classification algorithm for a variety of 14 ECG heartbeat classes using the MIT–BIH arrhythmia database. Their reported outcomes demonstrate significant accuracy. Furthermore, they highlight the algorithm's integration potential with Personal Digital Assistants (PDA).

Chen et al. [45] proposed an innovative method for categorizing ECG beats. Their approach combines projected and dynamic features. The projected features involve a random projection matrix, normalized columns, and row-wise Discrete Cosine Transform (DCT). The dynamic features include 3 weighted R–R intervals. The SVM classifier is employed for the categorization of heartbeats into either 15 or 5 distinct classes.

Ihasanto et al. [46] present the Ensemble Multilayer Perceptron (MLP) method, streamlining ECG beat classification by integrating feature extraction and classification into one step. This eliminates the need for a separate preprocessing stage, potentially reducing computational requirements. The technique achieves over 97% accuracy, even with 10 ECG heartbeat classes.

Melgani et al. [47] demonstrated SVM effective generalization in classifying sets of 10 ECG beats. They introduced an innovative approach, combining Particle Swarm Optimization (PSO) with SVM, to enhance the performance.

Alqudah et al. [48] introduced an innovative deep learning technique aimed at arrhythmia classification through ECG analysis, utilizing iris spectrograms. Their method demonstrated remarkable recognition performance accuracy rates of 99.13%, 98.223%, and 97.494% for 13, 15, and 17 distinct categories, respectively. These results were obtained using a dataset comprising 744 ECG from 45 individuals.

Alqudah et al. [49] compared spectrogram representations in various CNN architectures using a dataset of 10,502 heartbeats from MIT–BIH arrhythmia database, covering 6 classes. They explored Log/Mel-Scale spectrograms, Bi-Spectrum, and third-order cumulant in models like AOCT-NET, Mobile-Net, Squeeze-Net, and Shuffle-Net.

Rajkumar et al. [50] devised an intelligent approach employing CNN for the automated classification of ECG signals. Their methodology obviates the need for manual feature extraction, potentially enhancing the efficiency of cardiac patient screening for cardiologists. Demonstrating its effectiveness, the CNN adeptly categorized seven distinct ARR classes sourced from the MIT–BIH database.

Shaker et al. [51] improved deep learning on the MIT–BIH arrhythmia dataset with GAN-based data augmentation. They used two CNN based approaches to avoid manual feature engineering.

Ramkumar et al. [52] used ECG data from MIT–BIH arrhythmia database to classify normal, atrial premature, and ventricular escape heartbeats. They employed wavelet transform for preprocessing, independent component analysis for feature extraction, and MLP for classification.

Arslan et al. [53] simultaneously trained an autoencoder and classifier, allowing the network to reduce overall error while accurately reconstructing the input and extracting key features useful for classification. Their work focused on classifying six types of ECG heartbeats, including normal beats, left and right bundle branch block beats, premature ventricular contractions, atrial premature beats, and paced beats, using data from the MIT–BIH dataset. They achieved a classification accuracy of 99.99% by employing a convolutional autoencoder with an integrated classifier.

Vavekanand et al. [54] used deep CNN to classify ECG beats as either normal or abnormal. They applied transfer learning, first training a generic model on ECG data from the MIT–BIH, then fine-tuning the model for specific patients. They compared the performance of these fine-tuned models of individual models trained only on a single patient's data. Both approaches performed well, with individual classifiers achieving an average balanced accuracy of 94.6% on the test set, while the fine-tuned models had a slightly lower accuracy of 93.5%.

Zhou et al. [55] transformed ECG signals into different types of images using techniques like Recurrence Plot (RP), Gramian Angular Field (GAF), and Markov Transition Field (MTF), which they then fed into their classification model. To better retain important details, they developed a CNN based model with FCA for handling multiple types of ECG tasks. Their model achieved an accuracy of 99.6% when classifying five types of heartbeats using data from the MIT–BIH arrhythmia database.

Although the previous proposed approaches successfully classify ECG heartbeats, most state-of-the-art methods tend to focus on specific types of heartbeats rather than addressing all 15 types. When attempting to classify all heartbeat types, the proposed methods show lower performances compared to those works that limit their scope to just a few types. Additionally, many existing studies on heartbeat classification fail to analyze the computational complexity of their models, which makes them impractical for real-world applications. The importance of this new research lies in addressing the challenge of low classification performance in ECG heartbeat analysis, especially when dealing with a large number of classes. To overcome this issue, it proposes a novel approach to optimize the WSN and CNN, both of which have demonstrated effectiveness in classification tasks, particularly in arrhythmia detection. The main objective of this research paper is to develop an advanced heartbeat classification model that achieves high accuracy. Additionally, the proposed model is optimized to ensure its applicability in clinical settings.

Based on these observations, the contributions of this study can be summarized as follows:

- Develop a new method for detecting arrhythmias from ECG heartbeats with high accuracy.
- Optimize the Wavelet Scattering Network (WSN) for feature extraction to make the proposed approach suitable for clinical use.

III. ECG HEARTBEAT CLASSIFICATION

A. Data Acquisition

The research utilizes publicly available data from PhysioNet in .mat format [56], sourced from MIT–BIH arrhythmia database [57] a collection of ECG recordings.

Our research used data from the MIT–BIH arrhythmia database, including 48 labeled ECG signals taken over 30 minutes from 47 individuals. Lead II ECG signals are used in this study due to their sensitivity to heart rhythm, crucial for ARR detection. Sampling frequency was 360 Hz to capture detailed heart activity.

Our study aims to categorize ECG heartbeats into 15 distinct types as outlined in Table I. The sequential procedure outlined in Fig. 1 shows different steps of our proposed approach. Initially, to detect QRS complexes in each ECG signal, the Pan-Tompkins algorithm [58] is employed, which is a well-known method commonly used for QRS detection in ECG signals. This algorithm is tailored for accurate identification of QRS complexes in ECG signals.

By applying the Pan-Tompkins algorithm, the majority of R peaks in ECG signals were successfully detected, ensuring comprehensive coverage of the QRS complex. A window of 300 samples before and 500 samples after the R peak was used, resulting in 801 sample ECG heartbeats at 360 Hz sampling frequency. This approach captured P waves, QRS complexes, and T waves, enabling accurate arrhythmias identification. Fig. 2 presents normal ECG heartbeat detected by pan-Tompkins algorithm. Dynamic features like post R–R interval, pre R–R interval, pre-pre R–R interval, and the (post R–R)-(pre R–R) interval difference were computed, aiding arrhythmia diagnosis based on heart rate variability.

B. Data Preprocessing

In this research, the data was utilized in its original raw, unprocessed state without applying any data cleaning techniques. Afterwards, the dataset was split into two segments, one for training and the other for testing. The hold-out validation technique was employed, incorporating stratification to ensure an equal representation from each class. Specifically, 80% of samples from each class were allocated for training, while the remaining samples were designated for testing. The distribution of the training and testing data are illustrated in Table II.

TABLE I. ECG HEARTBEATS DISTRIBUTION

Symbols	Types of ECG Heartbeats	No. of Heartbeats
N	Normal beat	11000
L	Left bundle branch block beat	8059
R	Right bundle branch block beat	7235
A	Atrial premature beat	1769
E	Ventricular escape beat	106
V	Premature ventricular contraction	6178
/ (P)	Paced beat	7017
F	Fusion of ventricular and normal beat	801
Q	Unknown beat	33
!	Ventricular flutter wave	472
a	Aberrated atrial premature beat	150
e	Atrial escape beat	16
f	Fusion of paced and normal beat	982
j	Nodal (junctional)escape beat	229
x	Non-conducted P wave (Blocked APB)	193

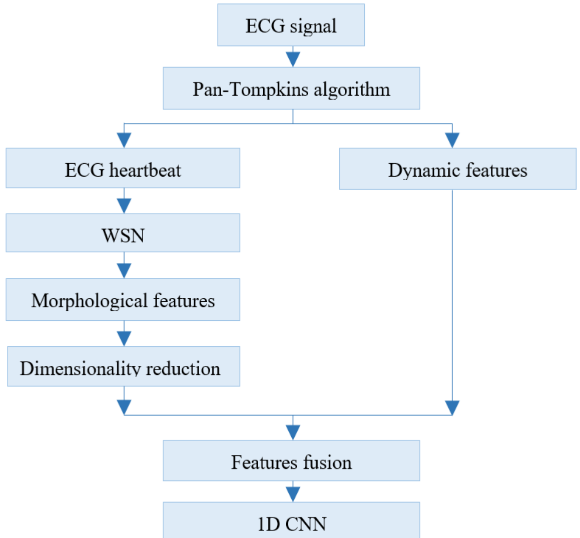


Fig. 1. Different steps of ECG heartbeat classification.

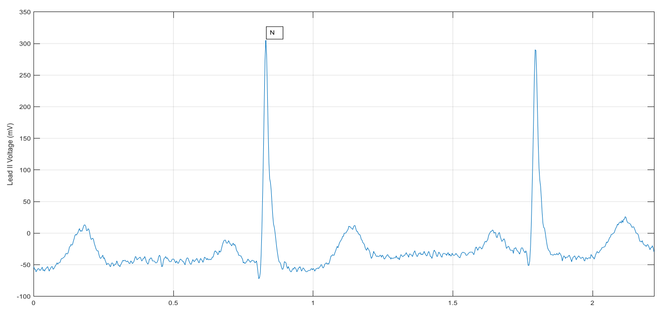


Fig. 2. Normal ECG heartbeat.

TABLE II. HEARTBEAT DISTRIBUTION FOR TRAINING AND TESTING

Symbols	Training Instances	Testing Instances
N	8800	2200
L	6448	1611
R	5788	1447
A	1416	353
E	85	21
V	4943	1235
/ (P)	5614	1403
F	641	160
Q	27	6
!	378	94
a	120	30
e	13	3
f	786	196
j	184	45
x	155	38

The dataset used for training shows an imbalance in class distribution, which lead to biased predictions and reduced model performance. To address this, the Synthetic Minority Oversampling Technique (SMOTE) [59] is employed.

C. Feature Extraction

Our research aimed to classify ECG heartbeats into 15 classes to detect ARR. Accurate predictions relied on extracting key features, split into time domain for capturing signal variations, and frequency domain for understanding spectral characteristics. Time domain features reflect changes, while frequency domain features reveal signal frequencies. The WSN was utilized as a powerful technique, for efficient feature extraction from ECG signals. This method capitalizes on wavelet transforms unique properties to capture local and global ECG waveform variations.

The WST is a mathematical method rooted in wavelets, allowing efficient signal analysis. Its strengths include translation and rotation invariances, suitable for image and audio analysis, stable features for denoising, and dimensionality reduction for enhanced accuracy [60]. This versatile technique finds use various domains such as audio, image, biomedical signals, speech, computer vision, and finance, excelling in classification and signal processing [61].

Fig. 3 illustrates the WSN with multiple layers, each applying a WST consisting of 3 stages. In the first stage, convolution uses a scale-specific wavelet ψ, to gauge similarity between the wavelet and the signal. The second stage introduces nonlinearity via modulus operations to retain signal magnitude and diminish redundant details like noise. The final stage involves low-pass filter convolution Φ , for dimensionality reduction enhancing signal representation.

The Gabor complex wavelet offers valuable traits beyond its time-frequency focus, including selective transmission of low-frequency components through its modulus acting as a low pass filter. By representing signal envelopes, it's adept at tasks like denoising and feature extraction [62].

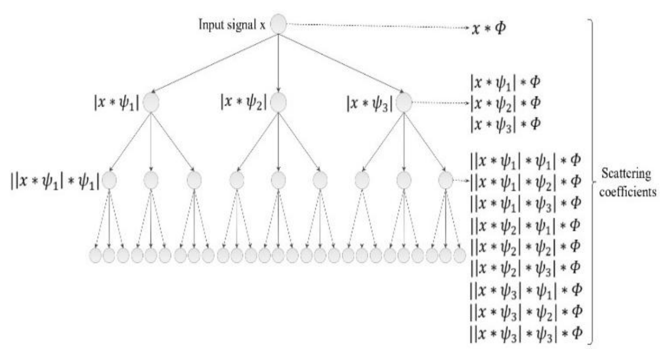


Fig. 3. Wavelet scattering network.

A Gabor wavelet in Eq. (1) is defined as the product of a Gaussian function and a complex exponential function.

$$\psi(t) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-t^2}{2\sigma^2}} e^{i\omega t} \tag{1}$$

Where t is the time, and σ is the standard deviation of the Gaussian function. In $\omega = 2\pi f$, f is the center frequency of ψ, and i is the imaginary unit. The envelope of the Gabor complex wavelet represents the low-pass filter, denoted as Φ.

$$\Phi(t) = |\psi(t)| \tag{2}$$

The scale parameter σ in Gabor wavelet analysis is denoted as the standard deviation of the Gaussian envelope. It shapes the wavelet window. Larger σ means a wider Gaussian envelope for a broader wavelet, while smaller σ leads to a more localized wavelet. In ECG analysis, Gabor wavelets suit the QRS complex detection due to its resemblance to the QRS waveform, making it suitable for arrhythmia detections.

Fig. 4 outlines the Gabor complex wavelet with its real and imaginary parts, with 0.5 second invariance scale. Fig. 5 displays frequency bands for different scaling functions used.

$$S_1 x(t) = |x * \psi_{\sigma_1}| * \Phi \tag{3}$$

In the initial stage, the signal undergoes convolution with a low pass filter Φ in Eq. (4), offering high time resolution but limited frequency accuracy. Progressing to the first order in Eq. (3), 29 paths using various Gabor wavelets capture fast variations, yet some high-frequency details are lost due to a final convolution with this filter Φ. The second order in Eq. (5) employs 10 paths with different wavelets, enhancing frequency resolution. The resulting coefficients of all stages are summarized in matrix S presented in Eq. (6), providing a comprehensive multi-scale description of signal variations.

$$S_0 x(t) = x(t) * \Phi \tag{4}$$

$$S_2 x(t) = ||x * \psi_{\sigma_1}| * \psi_{\sigma_2}| * \Phi \tag{5}$$

$$Sx(t) = \{S_0, S_1, \ldots, S_n\} \tag{6}$$

The study used a second order WSN to maintain 99% of signal energy. This choice prevented data loss and excessive computation. Two filter banks were employed, $Q_1 = 8$ and $Q_2 = 1$, ensuring accurate and efficient signal analysis.

One ECG heartbeat represented as a feature matrix of 40x26. The training dataset grows to 145,250 instances using the SMOTE technique. To handle this, the matrix becomes 40x26x145,250. Down-sampling with low pass filter reduces scattering coefficients, creating 26–time windows for 40 paths. Each tensor entry represents a path and time window.

Fig. 6(a) outlines the scattering coefficients of the first filter bank. The scattergram depicts time on the x–axis and frequency on the y–axis, and their amplitudes on the z–axis.

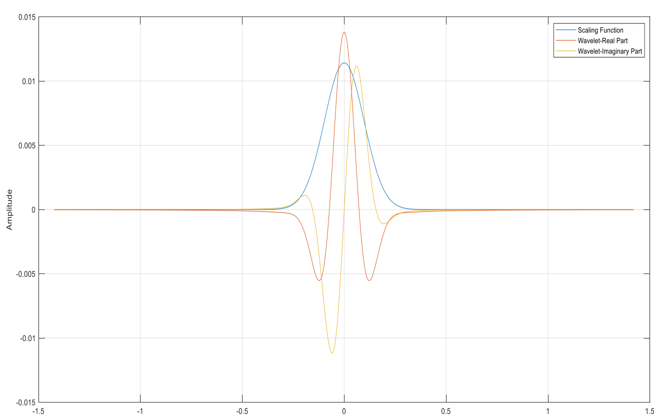


Fig. 4. Real part, imaginary part and low pass filter of Gabor wavelet.

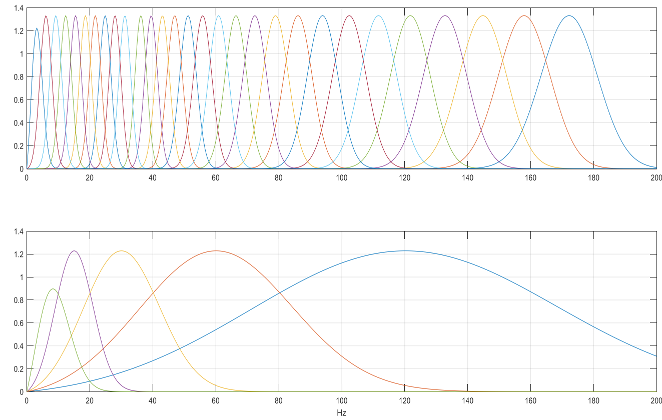
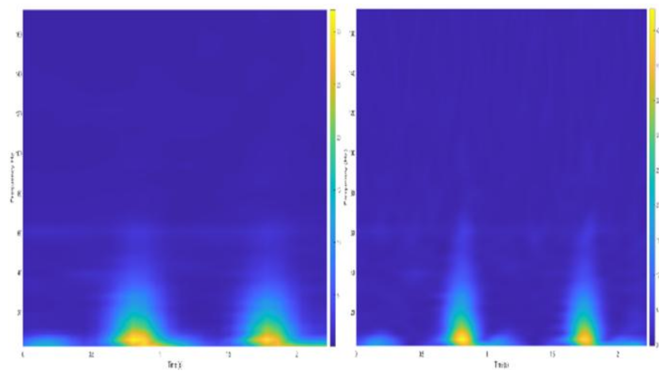


Fig. 5. Bandwidths of the first and the second filter banks.



(a) (b)

Fig. 6. Scattergram of the first filter bank. (a) Scattering coefficients, (b) Scalogram coefficients.

Fig. 6(b) displays the scalogram of the first filter bank, which effectively captures distinct high frequency details of the ECG signals. The dynamic features are oversampled 40 times, resulting in 40x4 tensor. After fusion, the tensor size becomes 40x30 for one ECG heartbeat.

D. *Maximum Relevance Minimum Redundancy (MRMR)*

To tackle high computational costs and enhance testing accuracy while avoiding overfitting, the MRMR feature selection technique is employed to reduce the dimensionality. The MRMR algorithm incorporates various parameters, among which are entropy, joint entropy, and mutual information.

Entropy is a measure of uncertainty in a random variable. It helps gauge information within it. To find entropy, the probabilities of outcomes was used in a sequence $\{X_1, X_2, \ldots, X_n\}$, denoted as X. This indicates the information required for prediction.

$$H(X) = -\sum_{i=1}^{n} p(x_i). log\, p(x_i) \tag{7}$$

Joint entropy gauges the uncertainty within a group of random variables, reflecting their unpredictability when interconnected. It evaluates the information content between two variables X and Y, expressing their correlation.

$$H(X:Y) = -\sum_{x,y} p(x,y). \log(p(x,y)) \tag{8}$$

Where $p(x,y)$ represents the joint probability.

Mutual information serves as a metric to uncover the degree of knowledge sharing between two or more random variables. It gauges their similarity and correlation, shedding light on their interdependencies [64]. During mutual information calculation, the focus lies on shared information and the robustness of their relationship.

A mutual information of zero implies independence between variables, while a higher value indicates a strong relationship and valuable information exchange.

$$I(X;Y) = H(X) - H(X:Y) = \sum_{x,y} p(x,y) log \frac{p(x,y)}{p(x).p(y)} \quad (9)$$

Where $H(X:Y)$ is the uncertainty left about X after knowing Y.

Common dimensionality reduction methods like Principal Component Analysis (PCA) and Linear Discriminate Analysis (LDA) often focus solely on feature category relationships, overlooking mutual information between features and targets. In contrast, the MRMR algorithm considers both, resulting in enhanced feature selection, predictive accuracy, and interpretability, offering a superior approach to dimensionality reduction. The MRMR algorithm measures the mutual information between features and the class label. A higher value indicates strong correlation, making a feature significant for classification. So, high mutual information between a feature X and class label C implies its importance in classification.

$$V_s = \frac{1}{|S|} \sum_{x \,\varepsilon\, S} I(x;C) \quad (10)$$

The concept of maximal relevance V_s involves identifying features that have the highest mutual information, represented by max V_s, with the target class label C. And $|S|$ which is the number of subset features in S.

Minimal redundancy evaluates the shared information between two features. High shared information implies redundancy. If two features convey the same data, one can be chosen for selection, reducing dimensions. Lower redundancy means better feature selection. So, the aim is to find features with low shared data. Let's set S as subset features, and X and Y are the features. The redundancy computes as follows:

$$W_s = \frac{1}{|S|^2} \sum_{x,y \,\varepsilon\, S} I\,(x;y) \quad (11)$$

The objective is to identify features with minimum redundancies by minimizing the function W_s , where $|S|$ represents the number of subset features in S, and $I(X;Y)$ denotes the mutual information between features X and Y.

The MRMR algorithm aims to discover a subset of features that display high relevance and low redundancy. It considers both the interdependencies among features and their connections to the target variable. It aims to maximize a specific function to find features with the highest relevance V_s to the target variable, while minimizing redundancy W_s among themselves [63]. The main goal is to achieve a balance between feature importance and mutual information, resulting in the selection of an optimal set of features.

$$\max(\beta)\,, \beta = \frac{V_S}{W_S} \quad (12)$$

Our study focuses on scoring features in subset features S. These scores stem from computing the mutual information between the target and the feature in question. This value is then divided by the mean mutual information between the previously chosen feature and the current one.

$$Score_i(x) = \frac{I(x;C)}{\sum_{S \varepsilon\, i-1\, selecled\, features} \frac{I(x;S)}{m}} \quad (13)$$

Where m is the number of features in the subset S.

The MRMR algorithm evaluates scores of the 40 scattering paths in the scattering network as illustrated in Fig. 7. These scores indicate feature significance in classifying 15 ECG heartbeats. Higher scores highlight critical roles while lower scores mean less important features that can be replaced without accuracy loss.

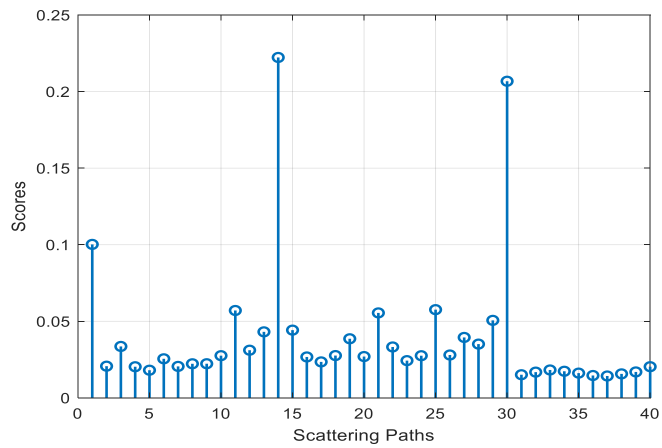


Fig. 7. Scores of different paths in wavelet scattering network.

E. Heartbeat Classification Using CNN

CNN is a specialized model designed specifically for processing 1-dimensional sequential data. Its key component is the convolutional layer, which employs filters to detect local patterns and dependencies within the input sequence. CNN chosen as a classifier to detect 15 heartbeat classes for efficiency. This minimizes computational costs compared to a 2D CNN. Our decision considers available resources and the need to process large data quickly.

In this research, a CNN with 14 hidden layers was used for classification as depicted in Table III. These layers include convolution, ReLU, normalization, global average pooling, fully connected, and SoftMax. They collectively differentiate the 15 ECG heartbeat classes. The convolutional layer involves sliding filters for computation as in Eq. (14).

$$y_t = b + \sum_{i=1}^{k} \omega_i . x_{t-i+1} \quad (14)$$

To ensure causality in the feature map, the output y_t is determined by the current input and the past samples at each time step t. This means that for a given feature vector x and a filter kernel ω, the mathematical formula for convolution can be expressed by taking into account both the current feature and previous inputs, meaning that a model only has access to past inputs to keep the causal nature of the process.

The ReLU function sets negatives to zero, leaving positives unaffected as presented in Eq. (15).

$$y_i = \max(0, x_i) \tag{15}$$

TABLE III. CNN LAYERS

Layer Types	Activations	Learnables	Total Learnables
Sequence Input	40	—	0
Convolution 1D Padding: [7,0] Stride: 1 No. of Filters: 16 Filter Size: 8	16	Weights: 8x40x16 Bias: 1x16	5136
ReLU	16	—	0
Layer Normalization	16	Offset: 16x1 Scale: 16x1	32
Convolution 1D Padding: [7,0] Stride: 1 No. of Filters: 32 Filter Size: 8	32	Weights: 8x16x32 Bias: 1x32	4128
ReLU	32	—	0
Layer Normalization	32	Offset: 32x1 Scale: 32x1	64
Convolution 1D Padding: [7,0] Stride: 1 No. of Filters: 64 Filter Size: 8	64	Weights: 8x32x64 Bias: 1x64	16448
ReLU	64	—	0
Layer Normalization	64	Offset: 64x1 Scale: 64x1	128
1D Global Average Pooling	64	—	0
Fully Connected Layers	15	Weights: 15x64 Bias: 15x1	975
SoftMax	15	—	0
Classification Output Loss Function: Cross-entropy	15	—	0

Normalization layers like batch normalization enhance neural network stability and convergence by standardizing prior layer outputs, ensuring suitable input ranges for downstream layers and promoting effective learning.

$$\hat{x}_i = \frac{x_i - \mu}{\sqrt{\delta^2 + \varepsilon}} \tag{16}$$

Where μ is the mean value of the features from one example, δ is the standard deviation, and the term $\varepsilon = 10^{-5}$ used to prevent division by zero, ensures numerical stability. Finally, the output y_t is scaled and shifted as follows:

$$y_i = \gamma . \hat{x}_i + \beta \tag{17}$$

Where γ and β represent the scaling and shifting learnable parameters.

Global Average Pooling layers condense the spatial dimensions of the feature maps into a single value, which reduces the computational complexity of the model. This operation calculates the average of each feature map, resulting in a fixed-length vector.

$$Y = Softmax(\sum WX + b) \tag{18}$$

The SoftMax layer is applied to produce the probability distribution over the 15 ECG heartbeat classes.

$$y_i = \frac{\exp(z_i)}{\sum_{j=1}^{n} \exp(z_j)} \tag{19}$$

The configuration, architecture and settings for each layer of the proposed CNN model, analyzing an ECG heartbeat with the WSN, are outlined in Table III.

In our study, CNN is used for analysis. Training employed the Adam optimizer with a 0.01 initial learning rate. Hyperparameters were manually tuned, like shuffling data using a mini-batch size of 64, enhancing performance, ensuring diverse pattern exposure, and preventing overfitting.

F. *Performance Metrics*

The effectiveness of our proposed model was evaluated using multiple assessment metrics like accuracy, sensitivity, specificity, precision, F1 score, negative predictive value, false positive rate, false discovery rate, false negative rate, and the Matthew Correlation Coefficient (MCC).

$$\text{Accuracy (ACC)} = \frac{TP+TN}{TP+TN+FP+FN} \tag{20}$$

$$\text{Sensitivity (SEN)} = \frac{TP}{TP+FN} \tag{21}$$

$$\text{Specificity (SPE)} = \frac{TN}{TN+FP} \tag{22}$$

$$\text{Precision (PRE)} = \frac{TP}{TP+FP} \tag{23}$$

$$\text{F1 score (F1)} = \frac{2*precision*sensitivity}{precision+sensitivity} \tag{24}$$

$$\text{Negative Predictive Value (NPV)} = \frac{TN}{TN+FN} \tag{25}$$

$$\text{False Positive Rate (FPR)} = \frac{FP}{FP+TN} \tag{26}$$

$$\text{False Discovery Rate (FDR)} = \frac{FP}{FP+TP} \tag{27}$$

$$\text{False Negative Rate (FNR)} = \frac{FN}{FN+TP} \tag{28}$$

$$\text{MCC} = \frac{(TP.TN)-(FP.FN)}{\sqrt{(TP+FP).(TP+FN).(TN+FP).(TN+FN)}} \tag{29}$$

The MATLAB Version R–2021b programming language was utilized to implement all algorithms on windows server. The system used for execution had an Intel(R) Core (TM), i5, CPU 6300U processor with a clock speed of 2.40 GHz. The RAM capacity was 12 GB, operated on a 64–bit architecture.

IV. RESULTS

The purpose of our research is to distinguish 15 types of ECG heartbeats. By integrating the MRMR algorithm, the computational challenges are reduced. Moreover, a CNN is used as a classifier to successfully identify and classify ECG heartbeats. The WSN generated a 40x26 feature matrix, and MRMR evaluated path importance by calculating scores.

The study employed dimensionality reduction through score sorting to discover optimal paths for classification as illustrated in Fig. 8. It started with the top 5 paths, used a CNN model for testing data accuracy, and gradually added 5 more paths at each step until all 40 were included. Following the approach presented in Fig. 9, the testing phase is assessed accuracy at each step. Increasing scattering paths boosted the testing accuracy as outlined in Fig. 10.

The test results indicate a remarkable accuracy of 98.50% when utilizing $K = 20$ scattering paths for ECG heartbeat classification. Adding more paths beyond the first 20 does not lead to any noticeable improvement in the overall testing accuracy. By selecting the top 20 paths based on their scores, the matrix size is reduced by half, maintaining accuracy while reducing feature dimensions by 50%. These changes include modifying the sequence input layer to 20 activations and adjusting the first convolution layer, resulting a reduction of 9.51% in parameter count. The confusion matrix of 15 ECG heartbeats presented in Fig. 11 shows a 98.50% overall accuracy, although classes "Q" and "e" had lower accuracy due to limited training data, affecting the overall score.

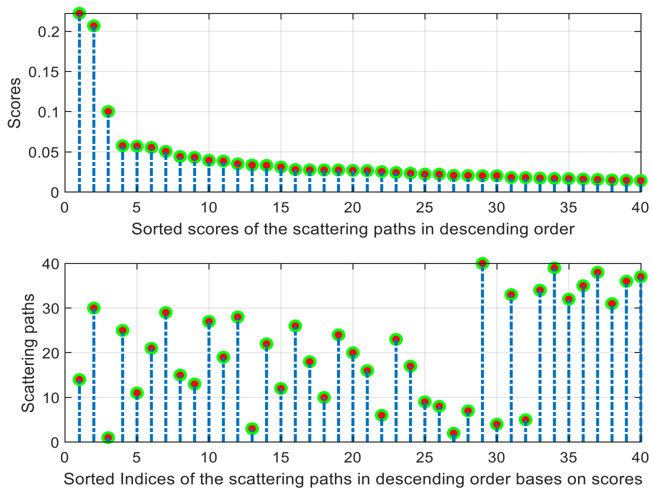


Fig. 8. Sorted scores of scattering paths in descending order.

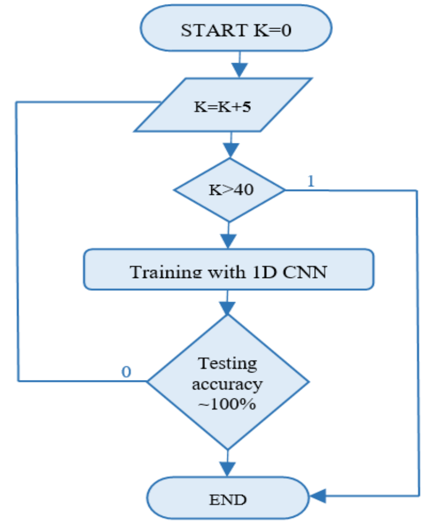


Fig. 9. Scattering paths selection algorithm.

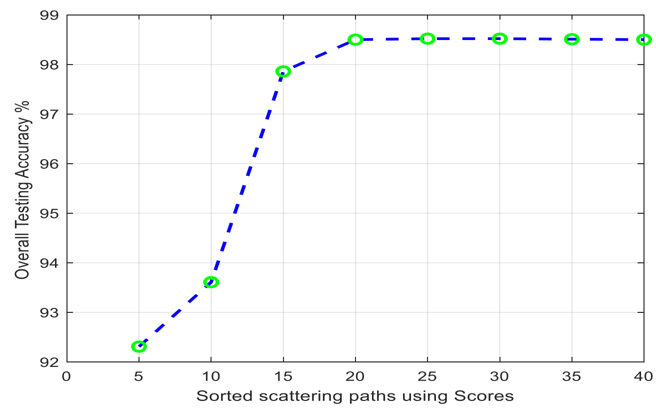


Fig. 10. Impact of adding scattering paths on testing accuracy.

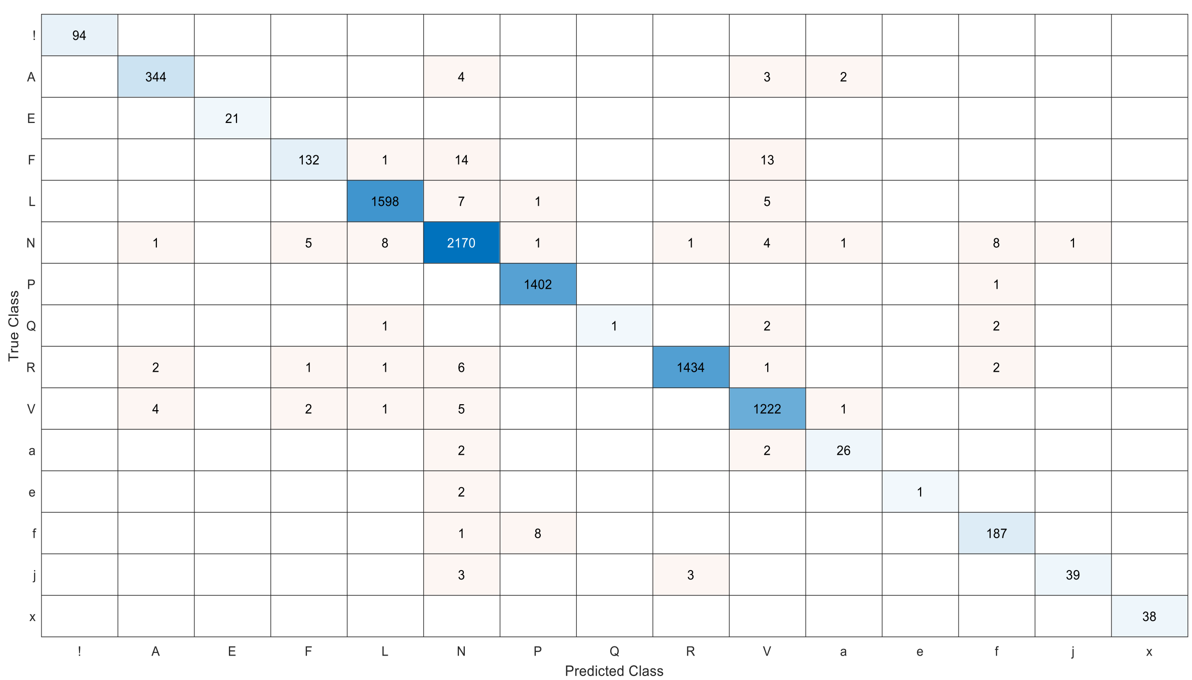


Fig. 11. Testing confusion matrix.

TABLE IV. EVALUATION METRICS OF TESTING DATA

Heartbeat Classes	PRE (%)	SEN (%)	SPE (%)	F1 (%)	NPV (%)	FPR (%)	FDR (%)	FNR (%)	MCC (%)
!	100	100	100	100	100	0	0	0	100
A	98.01	97.54	99.92	97.73	99.89	0.08	1.99	2.55	97.63
E	100	100	100	100	100	0	0	0	100
F	94.29	82.50	99.91	88.00	99.68	0.09	5.71	17.50	88.00
L	99.25	99.19	99.83	99.22	99.82	0.17	0.75	0.81	99.05
N	98.01	98.64	99.34	98.32	99.55	0.66	1.99	1.36	97.77
/	99.29	99.93	99.87	99.61	99.99	0.13	0.71	0.07	99.54
Q	100	16.67	100	28.57	99.94	0	0	83.33	40.81
R	99.72	99.10	99.95	99.41	99.82	0.05	0.28	0.90	99.30
V	97.60	98.95	99.61	98.27	99.83	0.39	2.40	1.05	98.00
A	86.67	86.67	99.95	86.67	99.95	0.05	13.33	13.33	86.62
e	100	33.33	100	50.00	99.98	0	0	66.57	57.73
F	93.50	95.41	99.85	99.44	99.90	0.15	6.50	4.59	94.32
J	97.50	86.67	99.99	91.76	99.93	0.01	2.50	13.33	91.89
x	100	100	100	100	100	0	0	0	100
Average	97.60	86.30	99.88	88.80	99.90	0.12	2.41	13.70	90.01

TABLE V. COMPLEXITY ANALYSIS OF THE PROPOSED MODEL

Execution time for feature extraction from one ECG heartbeat using WSN	14.8 ms
Prediction speed of the CNN	~3254 obs/s
Total number of learnable parameters of the CNN	24351
Memory usage after feature extraction for one ECG heartbeat	4160 bytes
Morphological feature dimensionality for one ECG heartbeat	20x26

Our innovative approach combines WSN with CNN for the classification of 15 ECG heartbeat classes. The results outlined in Table IV contain a remarkable performance metrics such as, a precision of 97.60% demonstrates precise positive predictions, a sensitivity of 86.30% signifies accurate identification of actual positives, a specificity of 99.88% reflects the model's prowess in correctly identifying negatives, a negative predictive value of 99.90% showcases minimal false negatives, a false positive rate of 0.12% indicates an extremely low occurrence of false positives, a false discovery rate of 2.41% demonstrates limited false positive predictions, a false negative rate of 13.70% portrays proficiency in classifying positive heartbeats, and a Matthew correlation coefficient of 90.01% signifies strong overall performance.

As outlined in Table V, our analysis confirms the efficiency and speed of our WSN based model using CNN for ECG heartbeat classification. The feature extraction process takes just 14.8 milliseconds per heartbeat, with a prediction speed of 3254 heartbeats per second.

The model's parameters reduced to 24351, and memory usage per heartbeat is 4160 bytes. Our model delivers swift performance, low parameter count, and minimal computational cost.

V. DISCUSSION

A comprehensive analysis was conducted to evaluate the overall accuracy of the proposed model in this research paper, and compared it with the results from previous studies. This comparison is summarized in Table VI. To ensure a fair comparison, we specifically focused on studies that also addressed the classification of 15 ECG heartbeats from the MIT–BIH arrhythmia database. These studies are referenced as [44-45-48, 51]. The obtained results clearly demonstrate that our proposed model, based on WSN combined with a CNN, outperforms the previous studies cited previously. Our model not only achieves higher accuracy in classifying heartbeats, but it also demonstrates robust performance across various types of heartbeats. It provides more accurate results and shows great potential for accurately detecting different types of heartbeats.

Our proposed method outperforms previous approaches by achieving high classification accuracy across the majority of ECG heartbeat types. Unlike existing models, our optimized technique enhances the model's performance to a level that enables clinical application. By addressing the limitations of prior methods such as suboptimal feature extraction and insufficient classification accuracy our approach ensures more reliable heartbeat classification. As a result, the proposed model surpasses state-of-the-art methods, achieving an overall accuracy of 98.50%.

In this study, the proposed approach for ECG heartbeat classification is illustrated in Fig. 12. It begins with QRS detection, using Pan-Tompkins algorithm, which identifies the dynamic features of heartbeats. These heartbeats are then fed into the WSN, where morphological characteristics are extracted. Following that, the most relevant morphological features are selected using the MRMR method combined with the proposed algorithm. After fusing the dynamic and morphological features, a feature matrix of size 20x30 is obtained. This matrix is then input into a specially designed CNN to classify the heartbeats into 15 distinct categories.

TABLE VI. COMPARISON WITH OTHER PREVIOUS WORKS

Studies	No. of Classes	Methodology	Overall Accuracy (%)
Rodriguez et al. [44]	**15**	PDA + Decision trees	96.12
Chen et al. [45]	**15**	Projection + WRR + SVM	98.46
Ihasanto et al. [46]	10	MLP	97
Melgani et al. [47]	10	PSO + SVM	89.72
Alqudah et al. [48]	13 **15** 17	Iris spectrum + CNN	99.13 98.23 97.49
Alqudah et al. [49]	6	STFT + CNN	93.8
Rajkumar et al. [50]	7	End to end CNN	93.6
Shaker et al. [51]	**15**	GAN + end to end CNN	98.0
Ramkumar et al. [52]	3	DWT + ICA + MLP	96.50
Arslan et al. [53]	6	Autoencoder + Classifier	99.99
Vavekanand et al. [54]	2	Deep CNN	94.6
Zhou et al. [55]	5	CNN model with FCA	99.4
Proposed Method	**15**	WSN + MRMR + CNN	**98.50**

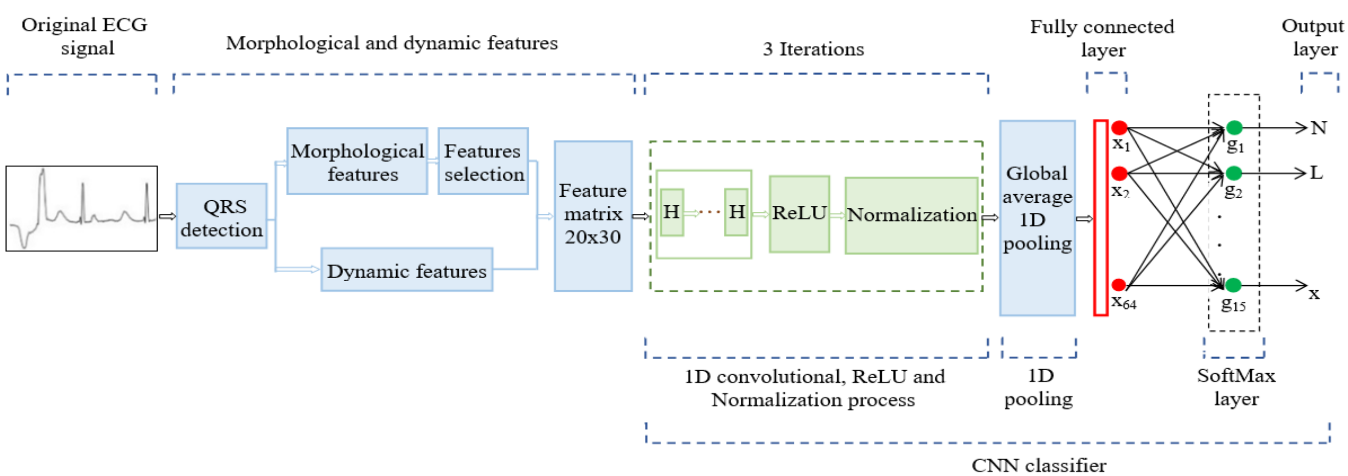


Fig. 12. Proposed framework for ECG heartbeats classification.

VI. CONCLUSION AND PROSPECTS

This study introduces an efficient approach for classifying ECG heartbeats. Our proposed model begins by detecting heartbeats in ECG signals, followed by utilizing the WSN for feature extraction. WSN is a robust technique that captures both temporal and spectral characteristics. Feature fusion is performed, and CNN employed for the classification of ECG heartbeats. Our model outperforms existing systems in terms of prediction accuracy and precision, achieving 98.50% and 97.60%, respectively, and also demonstrating low computational requirements due to the application of an innovative selection path techniques.

Although the WSN has proven effective in extracting important time and frequency domain features, it still suffers from high computational cost due to the convolution with multiple wavelets. Our approach addresses this issue by employing the MRMR technique in order to optimize the model and reduce computational costs, by selecting the most suitable wavelet for the convolution process.

The results of our proposed approach further demonstrate its effectiveness in detecting 15 types of ECG heartbeats from the MIT–BIH arrhythmia database, making it highly applicable for clinical use. This method has the potential to aid in early diagnosis and save numerous lives worldwide. Moving forward, our future work aims to enhance accuracy on testing data and further reduce computational costs to enable implementation on devices such as smartphones.

Availability of Data and Materials

ECG readings were taken from [56].

Conflict of Interest

We confirm that all authors declare no conflicts of interest.

Acknowledgment

This work was supported by the National Center for Scientific and Technical Research (CNRST), Rabat, Morocco.

References

[1] A. Kennedy,D. D. Finlay, D. Guldenring, R. Bond, K. Moran, J. McLaughlin, “The cardiac conduction system: generation and conduction of the cardiac impulse,” Critical Care Nursing Clinics, 28(3), pp. 269-79, 2016.

[2] A. D. John, L. A. Fleisher, “Electrocardiography: the ECG. Anesthesiology Clinics of North America,” 24(4), pp. 697-715, 2006.

[3] M. S. Manikandan, S. Dandapat, “Wavelet energy based diagnostic distortion measure for ECG,” Biomedical Signal Processing and Control, 2(2), pp. 80-96, 2007.

[4] E. J. Benjamin, P. Muntner, A. Alonso, M. S. Bittencourt, C. W. Callaway, A. P. Carson, A. M. Chamberlain, A. R. Chang, S. Cheng, S. R. Das, F. N. Delling, “heart disease and stroke statistics—2019 update: a report from the American Heart Association,” Circulation, 139(10), pp. 56-28, 2019.

[5] T. A. Gaziano, A. Bitton, S. Anand, S. Abrahams-Gessel, A. Murphy, “Growing epidemic of coronary heart disease in low-and middle-income countries,” Current problems in cardiology, 35(2), pp. 72-115, 2010.

[6] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, M. Adam, “Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals,” Information Sciences, 415, pp. 190-8, 2017.

[7] U. R. Acharya, H. Fujita, O. S. Lih, Y. Hagiwara, J. H. Tan, M. Adam, “Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network,” Information sciences, 405, pp. 81-90, 2017.

[8] M. Kumar, R. B. Pachori, U. R. Acharya, “Automated diagnosis of myocardial infarction ECG signals using sample entropy in flexible analytic wavelet transform framework,” Entropy, 19(9), pp. 488, 2017.

[9] J. H. Tan, Y. Hagiwara, W. Pang, I. Lim, S. L. Oh, M. Adam, R. San Tan, M. Chen, U. R. Acharya, “Application of stacked convolutional and long short-term memory network for accurate identification of CAD ECG signals,” Computers in biology and medicine, 94, pp. 19-26, 2018.

[10] S. W. Chen, S. L. Wang, X. Z. Qi, S. M. Samuri, C. Yang, “Review of ECG detection and classification based on deep learning: Coherent taxonomy, motivation, open challenges and recommendations,” Biomedical Signal Processing and Control, 74, pp. 103493, 2022.

[11] F. H. Fenton, E. M. Cherry, L. Glass, “Cardiac arrhythmia,” Scholarpedia, 3(7), pp. 1665, 2008.

[12] S. Rosara, M. Borgarelli, M. Perego, J. Häggström, G. La Rosa, A. Tarducci, R. A. Santilli, “Holter monitoring in 36 dogs with myxomatous mitral valve disease,” Australian veterinary journal, 88(10), pp. 386-92, 2010.

[13] R. Tung, N. G. Boyle, K. Shivkumar, “Catheter ablation of ventricular tachycardia,” Circulation, 122(3), pp. 389-91, 2010.

[14] S. H. Jambukia, V. K. Dabhi, H. B. Prajapati, “Classification of ECG signals using machine learning techniques: A survey,” In: Proc. International Conference on Advances in Computer Engineering and Applications, 2015.

[15] S. Celin, K. Vasanth, “ECG signal classification using various machine learning techniques,” Journal of medical systems, 42(12), pp. 241, 2018.

[16] M. G. Shankar, C. G. Babu, “An exploration of ECG signal feature selection and classification using machine learning techniques,” Int. J. Innovative Technol. Exploring Eng. Regul, 9(3), pp. 797-804, 2020.

[17] M. Alfaras, M. C. Soriano, S. Ortín, “A fast machine learning model for ECG-based heartbeat classification and arrhythmia detection,” Frontiers in Physics, pp. 103, 2019.

[18] L. Zhang, H. Peng, C. Yu, “An approach for ECG classification based on wavelet feature extraction and decision tree,” In: Proc. International conference on wireless communications & signal processing (WCSP), 2010.

[19] Y. C. Yeh, W. J. Wang, C. W. Chiou, “Cardiac arrhythmia diagnosis method using linear discriminant analysis on ECG signals,” Measurement, 42(5), pp. 778-89, 2009.

[20] M. A. Escalona-Morán, M. C. Soriano, I. Fischer, C. R. Mirasso, “Electrocardiogram classification using reservoir computing with logistic regression,” IEEE Journal of Biomedical and health Informatics, 19(3), pp. 892-8, 2014.

[21] S. Padmavathi, E. Ramanujam, “Naïve Bayes classifier for ECG abnormalities using multivariate maximal time series motif,” Procedia Computer Science, 47, pp. 222-8, 2015.

[22] R. Saini, N. Bindal, P. Bansal, “Classification of heart diseases from ECG signals using wavelet transform and kNN classifier,” In: Proc. International Conference on Computing, Communication & Automation, 2015.

[23] Q. Zhao, L. Zhang, “ECG feature extraction and classification using wavelet transform and support vector machines,” In: Proc. International Conference on Neural Networks and Brain, 2015.

[24] Y. Ozbay, B. Karlik, “A recognition of ECG arrhytihemias using artificial neural networks,” In: Proc. Conference Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2001.

[25] M. E. A. Bourkha, A. Hatim, D. Nasir, S. E. Beid, “Enhanced Atrial Fibrillation Detection-based Wavelet Scattering Transform with Time Window Selection and Neural Network Integration,” International Journal of Advanced Computer Science and Applications (IJACSA), 14(12), 2023.

[26] R. G. Afkhami, G. Azarnia, M. A. Tinati, “Cardiac arrhythmia classification using statistical and mixture modeling features of ECG signals,” Pattern Recognition Letters, 70, pp. 45-51, 2016.

[27] C. H. Lin, “Frequency-domain features for ECG beat discrimination using grey relational analysis-based classifier,” Computers & Mathematics with Applications, 55(4), pp. 680-90, 2008.

[28] M. Kropf, D. Hayn, G. Schreier, “ECG classification based on time and frequency domain features using random forests,” In: Proc. Computing in Cardiology (CinC), 2017.

[29] S. Banerjee, M. Mitra, “Application of cross wavelet transform for ECG pattern analysis and classification,” IEEE transactions on instrumentation and measurement, 63(2), pp. 326-33, 2013.

[30] T. Li, M. Zhou, “ECG classification using wavelet packet entropy and random forests,” Entropy, 18(8), pp. 285, 2016.

[31] J. Huang, B. Chen, B. Yao, W. He, “ECG arrhythmia classification using STFT-based spectrogram and convolutional neural network,” IEEE access, 7, pp. 92871-80, 2019.

[32] X. Zhai, C. Tin, “Automated ECG classification using dual heartbeat coupling based on convolutional neural network,” IEEE Access, 6, pp. 27465-72, 2018.

[33] S. Singh, S. K. Pandey, U. Pawar, R. R. Janghel, “Classification of ECG arrhythmia using recurrent neural networks,” Procedia computer science, 132, pp. 1290-7, 2018.

[34] S. Saadatnejad, M. Oveisi, M. Hashemi, “LSTM-based ECG classification for continuous monitoring on personal wearable devices,”

IEEE journal of biomedical and health informatics, 24(2), pp. 515-23, 2019.

[35] I. Silva, G. B. Moody, “An open-source toolbox for analysing and processing physionet databases in matlab and octave,” Journal of open research software, 2(1), 2014.

[36] C. T. Arsene, R. Hankins, H. Yin, “Deep learning models for denoising ECG signals,” In: Proc. 27th European Signal Processing Conference (EUSIPCO), 2019.

[37] M. A. Ozdemir, O. Guren, O. K. Cura, A. Akan, A. Onan, “Abnormal ecg beat detection based on convolutional neural networks,” In: Proc. Medical technologies congress (TIPTEKNO), 2020.

[38] L. Y. Di Marco, W. Duan, M. Bojarnejad, D. Zheng, S. King, M. Murray, P. Langley, “Evaluation of an algorithm based on single-condition decision rules for binary classification of 12-lead ambulatory ECG recording quality,” Physiological measurement, 33(9), pp. 1435, 2012.

[39] A. Çınar, S. A. Tuncer, “Classification of normal sinus rhythm, abnormal arrhythmia and congestive heart failure ECG signals using LSTM and hybrid CNN-SVM deep neural networks,” Computer methods in biomechanics and biomedical engineering, 24(2), pp. 203-14, 2021.

[40] S. Nahak, A. Pathak, G. Saha, “Evaluation of handcrafted features and learned representations for the classification of arrhythmia and congestive heart failure in ECG,” Biomedical Signal Processing and Control, 79, pp. 104230, 2023.

[41] M. E. A. Bourkha, A. Hatim, D. Nasir, S. E. Beid., & A. S. Tahiri, “A Novel Inter Patient ECG Arrhythmia Classification Approach with Deep Feature Extraction and 1D Convolutional Neural Network,” International Journal of Advanced Computer Science and Applications (IJACSA), 15(2), 2024.

[42] J. Wang, X. Qiao, C. Liu, X. Wang, Y. Liu, L. Yao, H. Zhang, “Automated ECG classification using a non-local convolutional block attention module,” Computer Methods and Programs in Biomedicine, 203, pp. 106006, 2021.

[43] S. Osowski, L. T. Hoai, T. Markiewicz, “Support vector machine-based expert system for reliable heartbeat recognition,” IEEE transactions on biomedical engineering, 51(4), pp. 582-9, 2004.

[44] J. Rodriguez, A. Goni, A. Illarramendi, “Real-time classification of ECGs on a PDA,” IEEE Transactions on information Technology in biomedicine, 9(1), pp. 23-34, 2005.

[45] S. Chen, W. Hua, Z. Li, J. Li, X. Gao, “Heartbeat classification using projected and dynamic features of ECG signal,” Biomedical Signal Processing and Control, 31, pp. 165-73, 2017.

[46] E. Ihsanto, K. Ramli, D. Sudiana, “Real-time classification for cardiac arrhythmia ECG beat,” In: Proc. 16th International Conference on Quality in Research (QIR): International Symposium on Electrical and Computer Engineering, 2019.

[47] F. Melgani, Y. Bazi, “Classification of electrocardiogram signals with support vector machines and particle swarm optimization,” IEEE transactions on information technology in biomedicine, 12(5), pp. 667-77, 2008.

[48] A. M. Alqudah, A. Alqudah, “Deep learning for single-lead ECG beat arrhythmia-type detection using novel iris spectrogram representation,” Soft Computing, 26(3), pp. 1123-39, 2022.

[49] A. M. Alqudah, S. Qazan, L. Al-Ebbini, H. Alquran, I. A. Qasmieh, “ECG heartbeat arrhythmias classification: A comparison study between different types of spectrum representation and convolutional neural networks architectures,” Journal of Ambient Intelligence and Humanized Computing, pp. 1-31, 2021.

[50] A. Rajkumar, M. Ganesan, R. Lavanya, “Arrhythmia classification on ECG using Deep Learning,” In: Proc. 5th international conference on advanced computing & communication systems (ICACCS), 2019.

[51] A. M. Shaker, M. Tantawi, H. A. Shedeed, M. F. Tolba MF, “Generalization of convolutional neural networks for ECG classification using generative adversarial networks,” IEEE access, 8, pp. 35592-605, 2020.

[52] M. Ramkumar, C. G. Babu, K. V. Kumar, D. Hepsiba, A. Manjunathan, R. S. Kumar, “ECG cardiac arrhythmias classification using DWT, ICA and MLP neural networks,” In: Proc. Journal of Physics: Conference Series, 2012.

[53] N. N. Arslan, D. Ozdemir, H. Temurtas, “ECG heartbeats classification with dilated convolutional autoencoder,” Signal, Image and Video Processing, 18(1), pp. 417-426, 2024.

[54] R. Vavekanand, K. Sam, S. Kumar, T. Kumar, “CardiacNet: A Neural Networks Based Heartbeat Classifications using ECG Signals,” Studies in Medical and Health Sciences, 1(2), pp. 1-17, 2024.

[55] F. Zhou, D. Fang, “Multimodal ECG heartbeat classification method based on a convolutional neural network embedded with FCA,” Scientific Reports, 14(1), pp. 8804, 2024.

[56] A. L. Goldberger, L. A. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C. K. Peng, H. E. Stanley, “PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals,” Circulation, 101(23), pp. 215-20, 2000.

[57] G. B. Moody, R. G. Mark, “The impact of the MIT-BIH arrhythmia database,” IEEE engineering in medicine and biology magazine, 20(3), pp. 45-50, 2001.

[58] J. Pan, W. J. Tompkins, “A real-time QRS detection algorithm,” IEEE transactions on biomedical engineering, pp. 230-6, 1985.

[59] N. V. Chawla, K. W. Bowyer, L. O. Hall, W. P. Kegelmeyer, “SMOTE: synthetic minority over-sampling technique,” Journal of artificial intelligence research, 16, pp. 321-57, 2002.

[60] J. Bruna, S. Mallat, “Invariant scattering convolution networks,” IEEE transactions on pattern analysis and machine intelligence, 35(8), pp. 1872-86, 2013.

[61] R. Leonarduzzi, H. Liu, Y. Wang, “Scattering transform and sparse linear classifiers for art authentication,” Signal Processing, 150, pp. 11-9, 2018.

[62] B. S. Manjunath, “Gabor wavelet transform and application to problems in early vision,” In: Proc. Asilomar conference on signals systems and computers, 1992.

[63] X. Jin, E. W. Ma, L. L. Cheng, M. Pecht, “Health monitoring of cooling fans based on Mahalanobis distance with mRMR feature selection,” IEEE Transactions on Instrumentation and Measurement, 61(8), pp. 2222-9, 2012.

[64] C. Ding, H. Peng, “Minimum redundancy feature selection from microarray gene expression data,” Journal of bioinformatics and computational biology, 3(02), pp. 185-205, 2005.