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An efficient ECG-based cardiac arrhythmia detection according to time–frequency information using deep learning approach

Oli Ali Abood

B.Sc. In Information Technology, Network, Master's degree in Computer/Network Engineering, Al-Mustaqbal University, Babylon

Corresponding author's email :oa108843@gmail.com

Abstract

Arrhythmia serves as a critical indicator of associated cardiovascular diseases (CVD) and is widespread globally. For prompt and efficient treatment, it is essential to precisely detect arrhythmia. The electrocardiogram (ECG) is fundamental in identifying arrhythmia. Deep learning (DL) techniques have yielded promising outcomes in the clinical field, thereby enhancing the accurate and timely detection of arrhythmia. A novel approach for the identification of cardiac arrhythmias from electrocardiogram (ECG) signals is presented in this study. Leveraging deep learning techniques, specifically convolutional neural networks (CNNs), the effectiveness of the proposed method has been demonstrated in accurately classifying various arrhythmia types. Experimental findings exhibit that the proposed approach yielded an average accuracy of 97.62% in diagnosing arrhythmia. Through the utilization of advanced algorithms and ensemble learning strategies, the suggested approach reveals robustness and efficiency in distinguishing arrhythmic patterns, thereby contributing to the advancement of automated cardiac health monitoring systems.

Key words: : electrocardiogram , cardiac arrhythmia ,deep learning ,Scalogram

الكشف الفعال عن عدم انتظام ضربات القلب القائم على تخطيط القلب وفقًا لمعلومات التردد الزمني باستخدام نـهج التعلم العميق

علا علي عبود

بكالوريوس العلوم. في شبكات تكنولوجيا المعلومات، درجة الماجستير في هندسة الحاسوب/الشبكات، جامعة المستقبل، بابل

خلاصة

يعد عدم انتظام ضربات القلب بمثابة مؤشر حاسم لأمراض القلب والأوعية الدموية المرتبطة به وهو منتشر على نطاق واسع على مستوى العالم. للحصول على علاج سريع وفعال، من الضروري الكشف بدقة عن عدم انتظام ضربات القلب. يعد مخطط كهربية القلب (ECG) أمرًا أساسيًا في تحديد عدم انتظام ضربات القلب. لقد أسفرت تقنيات التعلم العميق (DL) عن نتائج واعدة في المجال السريري، وبالتالي تعزيز الكشف الدقيق

وفي الوقت المناسب عن عدم انتظام ضربات القلب. تم تقديم طريقة جديدة لتحديد عدم انتظام ضربات القلب من إشارات مخطط كهربية القلب (ECG) في هذه الدراسة. من خلال الاستفادة من تقنيات التعلم العميق، وخاصة الشبكات العصبية التلافيفية(CNNs) ، تم إثبات فعالية الطريقة المقترحة في التصنيف الدقيق لأنواع عدم انتظام ضربات القلب المختلفة. تظهر النتائج التجريبية أن النهج المقترح حقق متوسط دقة 97.62% في تشخيص عدم انتظام ضربات القلب. من خلال استخدام الخوارزميات المتقدمة واستراتيجيات التعلم الجماعي، يكشف النهج المقترح عن المتانة والكفاءة في التمييز بين أنماط عدم انتظام ضربات القلب، مما يساهم في تطوير أنظمة مراقبة صحة القلب الآلية.

الكلمات المفتاحية:: مخطط كهربية القلب، عدم انتظام ضربات القلب، التعلم العميق، مخطط الرسم

1.Introduction

Arrhythmia, characterized by irregular heartbeat patterns, represents a serious cardiac condition that can potentially lead to cardiac arrest and fatalities [1]. Electrocardiogram (ECG) is widely utilized in the diagnosis and ongoing assessment of cardiovascular disorders [2]. Presently, Cardiovascular diseases (CVD) lead in rates of illness and death globally, posing a significant threat to public health. The World Health Organization (WHO) reports that approximately 32% of annual deaths are due to CVD [3]. Consequently, the precise and prompt diagnosis of arrhythmia is crucial to enhance treatment efficacy and patient outcomes. Timely identification of arrhythmia can remarkably decrease the likelihood of future life-threatening events [4].

Currently, several diagnostic methods are available for detecting arrhythmia, including cardiac computed tomography (CT), cardiovascular magnetic resonance imaging (MRI) and electrocardiogram (ECG). Among these, ECG is particularly valuable as it provides a precise measure of the onset, spread, and recovery of cardiac excitation. Its non-invasive nature and cost-effectiveness make ECG the most widely utilized tool for detecting arrhythmia in clinical field [5].

Electrocardiogram (ECG) recordings are often influenced by various variables, necessitating thorough preparation to improve data quality. A common step in preprocessing involves reducing noise. In this paper, we employ the discrete wavelet transform (DWT) method to achieve noise reduction in ECG data [6].

ECG diagnosis based on Machine-learning relies significantly on the extraction of features. Traditionally, processes of feature extraction have evolved to incorporate both the frequency and time domains of the ECG [7]. Extraction of time domain features mainly reflects the dynamic properties of the signal as it progresses but has limitations when analyzing non-stationary signals. On the other hand, frequency domain feature extraction exposes the frequency characteristics and spectral attributes of the ECG, yet it might fail to capture transient signal information effectively [8]. Hence, this study places emphasis on the time-frequency domain, employing visualized wavelet time-frequency diagrams to depict ECG characteristics. This hybrid method adeptly captures a wide array of time-frequency domain characteristics in ECGs, establishing a robust basis for precise classification in subsequent analyses. With the progress of Artificial Intelligence (AI), computerized ECG analysis has emerged as a prominent research field. Numerous techniques have been devised to accurately diagnose arrhythmias. Previous studies utilized conventional machine learning techniques that depended on classification through manually crafted feature extraction. In contrast, deep learning-based techniques have demonstrated significant outcomes in ECG analysis and classification.

The proposed system in this study comprises five primary stages: preprocessing, feature visualization, feature extraction, feature selection, and classification. In the preprocessing stage, artifacts within ECG signals are eliminated using discrete wavelet transform (DWT). The subsequent step involves beat segmentation to isolate individual heartbeats. Spatial features are then extracted from the visualized signals utilizing a Convolutional Neural Network (CNN) applied to scalogram transformations. To streamline data and reduce redundancy among features, an optimal subset of features is selected using the MRMR (Minimum Redundancy Maximum Relevance) algorithm. Finally, the selected features are categorized into various groups of cardiac signals using the bagging ensemble learning technique. This approach enables effective detection and classification of different types of arrhythmias. The performances of our proposed model were evaluated against state-of-the-art techniques documented in existing literature. The findings demonstrate that the presented method achieves outstanding outcomes in arrhythmias detection from ECG.

2.Related Works

In [9], the investigators integrated Wavelet Time-Frequency representations with the advanced Swin Transformer deep learning-based architecture to automate the identification of cardiac arrhythmias. Feature extraction employed the complex Morlet wavelet, generating wavelet time-frequency maps to visualize the temporal and spectral characteristics of the ECG signals. The Swin Transformer model was introduced for classifying purposes, achieving notable accuracy through its hierarchical structure and self-attention mechanisms. The experiments demonstrated high accuracies of 98.37% and 99.34% for inter-patient and intra-patient analysis, outperforming existing methodologies documented in the literature.

In [10] authors employed Support Vector Machine and Naive Bayes classifiers for predicting arrythmias using MIT-BIH dataset. For analysis, the authors utilized the data mining tool WEKA 3.8.5 to classify individuals with and without arrhythmia.

Statistical analysis was conducted using IBM SPSS version 21. Using WEKA's 10-fold cross-validation for train and test, the SVM exhibited better performance than the Naive Bayes, achieving an accuracy rate of 88.50% in classification, compared to 80.39% for NB.

In [11] authors present an advanced Ensemble Learning technique called Fine Tuned Boosting (FTBO)for arrhythmia detection leveraging multi-lead ECG data. The study introduces a novel feature extraction method that employs a sliding window sized at 5 R-peaks. The MIT-BIH arrhythmia dataset was used for experiments, concentrating on Atrial Fibrillation (AF), Atrial Premature Contraction (PAC), and Premature Ventricular Contraction (PVC). Findings showed that the presented FTBO model delivered high accuracy, sensitivity, specificity across all arrhythmia types. Remarkably, in detecting AF it achieved 100% sensitivity and specificity and 99% for PVC. Additionally, for PAC detection, the presented model attained nearly 96% specificity and sensitivity.

[12] presents a groundbreaking method by integrating LSTM, CNN and Transformer techniques. This fusion enables the extraction of long-range dependency, temporal and spatial features from ECG signals, enhancing the model's ability to capture comprehensive attributes. The extracted features are subsequently combined in an ensemble voting classifier that utilizes three conventional base learners, each leveraging deep features. The evaluation on the MIT-BIH dataset demonstrate superior performance of the proposed model compared to state-of-the-art approaches. The model achieves an impressive accuracy of 99.56%, highlighting its efficacy in improving diagnostic accuracy and reliability in arrhythmias diagnosis.

In [13], authors endeavor to develop an automated deep learning-based system designed to precisely classify ECG signals into three distinct classes: congestive heart failure (CHF), normal sinus rhythm (NSR) and cardiac arrhythmia (ARR). To accomplish this, ECG data from BIDMC and MIT-BIH datasets, underwent rigorous preprocessing and segmentation before being employed for training the models. The evaluation metrics used to assess the model's effectiveness included F-measure, recall, precision, sensitivity, specificity, and overall accuracy, derived from a multi-class confusion matrix. The results demonstrated that the proposed deep learning model achieved an impressive overall classification accuracy of 99.2%.

Authors in [14] implemented a robust deep learning model capable of diagnosing arrhythmias from a database containing 109,446 samples categorized into five classes. The research utilizes deep learning-based methodologies to automate the detection of cardiac arrhythmias, addressing bias in waveforms from the MIT-BIH arrhythmia database. The dataset's extensive ECG waveforms promise high accuracy in disease prediction. The study compares the performance of CNN and

ResNet-18 architectures in terms of accuracy. CNN achieves approximately 97.86% accuracy, while ResNet-18 improves this to 98.14%. Comparative analysis with existing techniques underscores the superiority of the proposed model.
In [15], authors aim to propose a classifier capable of accurately detecting arrhythmias in clinical patients' ECG signals. The researchers employed a Convolutional Neural Network (CNN) designed to classify five various heartbeats within ECG signals. The experiments utilized data sourced from the publicly available MIT-BIH database, with a balanced distribution across the five heartbeat classes. The proposed CNN model achieved impressive results, demonstrating an F1-score of 99.44% and an accuracy of 99.33% in the classification of heartbeats.

Authors in [16] introduce an integrated deep learning-based model called 2D-CNN-LSTM, aimed at automating the identification and classification of arrhythmias from ECG signals. For the evaluation of the suggested 2D-CNN-LSTM model, rigorous experiments were performed leveraging the MIT-BIH dataset. The outcomes demonstrate high accuracy with approximately 99%, and 99% accuracy rate.

In [17], authors have implemented a deep learning methodology that utilizes the scalogram obtained from continuous wavelet transform (CWT) to categorize ECG signals according to arrhythmia patterns. The CWT transforms the ECG recordings into scalograms, which are then applied to train a 2-D Convolutional Neural Network. In the presented framework, investigators performed training and testing on the CNN to diagnose five various heart rhythms. This method achieved impressive performance measures with an average accuracy of 99.65%.

3.Proposed Method

This section details the proposed method for detecting cardiac arrhythmias from ECG signals. The proposed system consists of five main stages: preprocessing, feature visualization, feature extraction, feature selection, and classification. The diagram of the proposed method is shown in Figure 1.

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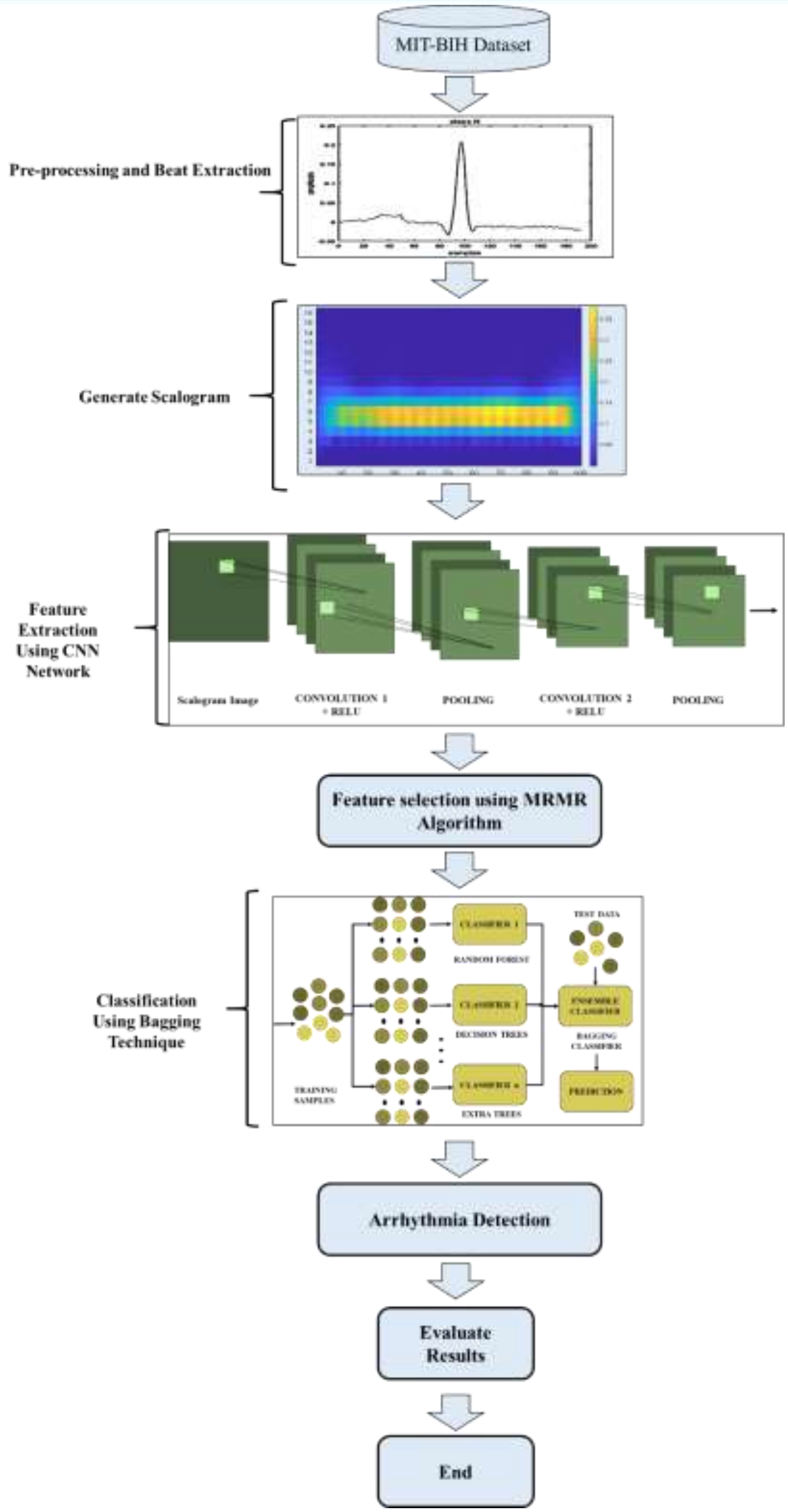

Figure 1-Diagram of the Proposed Method

In the preprocessing stage, artifacts are removed from the ECG signals utilizing Discrete Wavelet Transform (DWT). The subsequent step involves the beat segmentation. Here, the location of the R peak in each beat of the ECG signal is identified, which serves as the reference point for beat segmentation. The beats are then segmented based on the location of these R peaks. Subsequently, these signals are visualized for the extraction of time-frequency features of ECG signals. Spatial features are then extracted from the visualized signals using a CNN (Convolutional Neural Network) applied to scalogram transformations.

Following this, to reduce data dimensionality and eliminate redundancy among features, an optimal subset of features is selected using the MRMR (Minimum Redundancy Maximum Relevance) algorithm. Finally, the selected features are classified into different groups of cardiac signals employing the bagging method, allowing detection of different types of arrhythmias. The following sections detail the steps of the proposed method.

3.1. Preprocessing

Various types of noise in the cardiac signal reduce the signal-to-noise ratio (SNR). In the preprocessing stage, noise and artifacts are removed from the ECG signal as much as possible to increase the SNR. This stage is crucial for the optimal performance of the arrhythmia classification system.

Different types of disturbances and artifacts are present in the ECG signal. Examples of considered noise include muscle artifacts, baseline wander, power line interference, contact noise, electrode motion artifacts and electromyographic artifacts. The preprocessing method in this work is divided into two sections. The first phase uses discrete wavelet transform (DWT) to reduce noise in the ECG signal. The subsequent phase involves ECG signal segmentation, with each phase detailed in the following sections.

3.1.1. ECG Segmentation

Since each recorded ECG signal comprises numerous beats, these beats must first be identified and separated so that each beat can be classified into a specific class during the classification stage. After noise removal, the R peaks in each beat of the ECG signal are identified as reference points for beat segmentation. To segment a beat, 100 samples to the left of the R peak and 99 samples to the right are extracted. By selecting 100 samples to the left and 99 samples to the right of the R peak, respectively, along with the R peak itself, a beat comprising 200 samples is obtained. The figure 2 shows an example of a normal beat from an electrocardiogram signal.

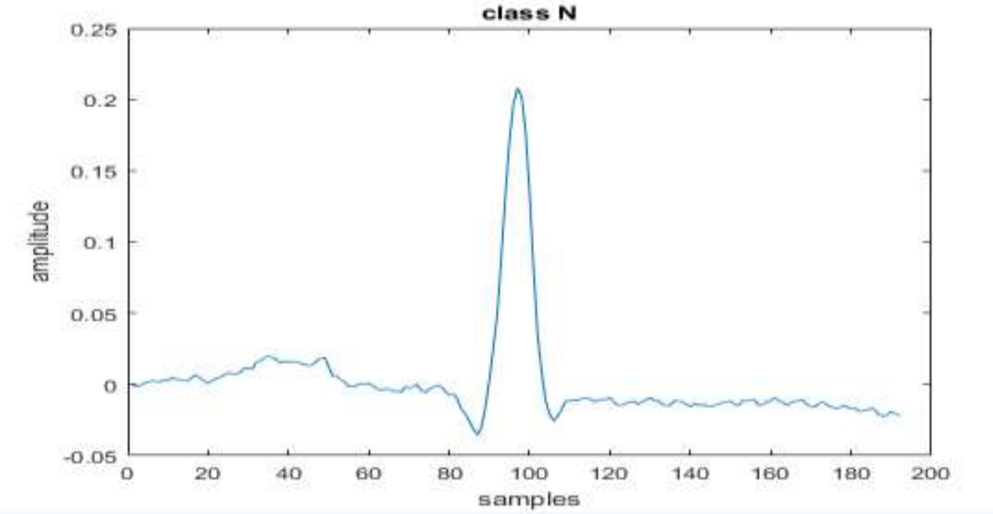

Figure 2-A Normal Beat from an Electrocardiogram Signal

3.1.2. DWT-based Noise Reduction

Since DWT is a useful tool for analyzing non-stationary signals, it is employed in this research to remove noise from the ECG signal. Wavelet transform enables the representation of a signal at multiple scales and provides simultaneous time-frequency localization. The input signal is decomposed at each stage using low-pass and high-pass filters, followed by downsampling. The high-pass filter output gives the detail coefficients D1, while the low-pass filter output gives the approximation coefficients A1. In this study, the ECG signal is decomposed into four wavelet levels using the db6 wavelet basis function. During the signal reconstruction phase, the first and second level detail coefficients are discarded, as most ECG signal noise manifests at these frequencies. The db6 wavelet is chosen for its morphological resemblance to the QRS complex of the ECG signal. The figure 3 shows an example of a denoised signal using this method.

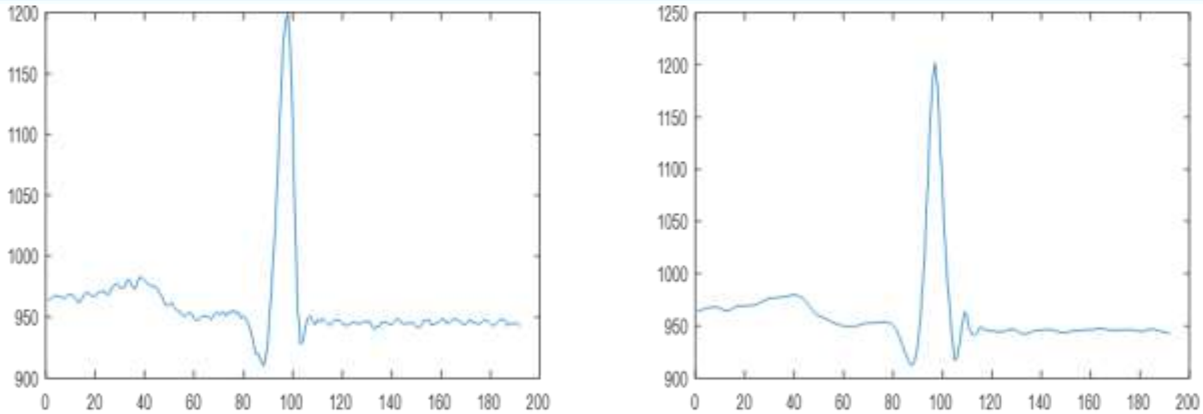

Figure 3- Example of an Extracted Beat - Left: Without Noise Removal - Right: With Noise Removal

3.2.CWT-Based Time Frequency Information Visualization

Scalogram visually represents the time-frequency characteristics of a signal, used for analysis and visualization through Continuous Wavelet Transform (CWT). This method allows us to observe how different frequencies of a signal change over time, which is particularly useful for analyzing non-stationary signals like ECG, where frequencies vary significantly with time.

The Continuous Wavelet Transform (CWT) for a signal is defined in the following equation:

$$Z(a.b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} s(t)\psi^{*}\left(\frac{t-b}{a}\right) dt \quad (1)$$

In the above equation, (t) denotes a signal of finite energy, $\psi*$ represents the complex conjugate for initial CWT function, also the parameters a and b control the scaling and translation operations applied to the CWT.

CWT is calculated by adjusting the parameters a and b continuously, thus enabling analysis over different lengths and scales of the signal. CWT exceeds the STFT in terms of time and frequency resolution. This is accomplished by employing analysis windows of different sizes at various frequencies. Figure 4 demonstrates an instance of an ECG signal alongside its corresponding scalogram.

العدد 14 آب 2024
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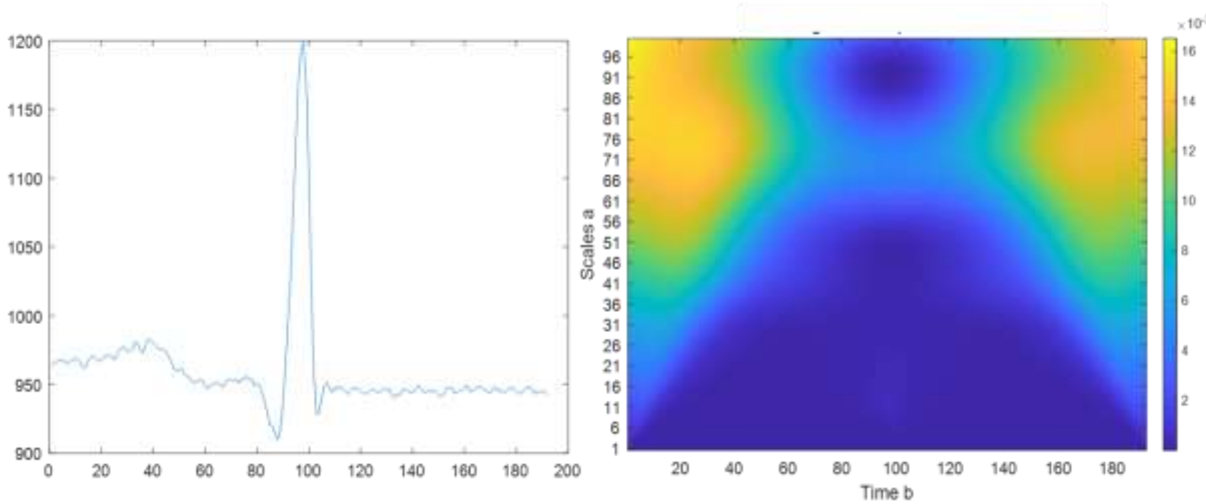

Figure 4: An illustration of a ECG signal alongside its corresponding scalogram

Also Figure 3 shows an example of scalogram images for each F, N, S, U and V classes.

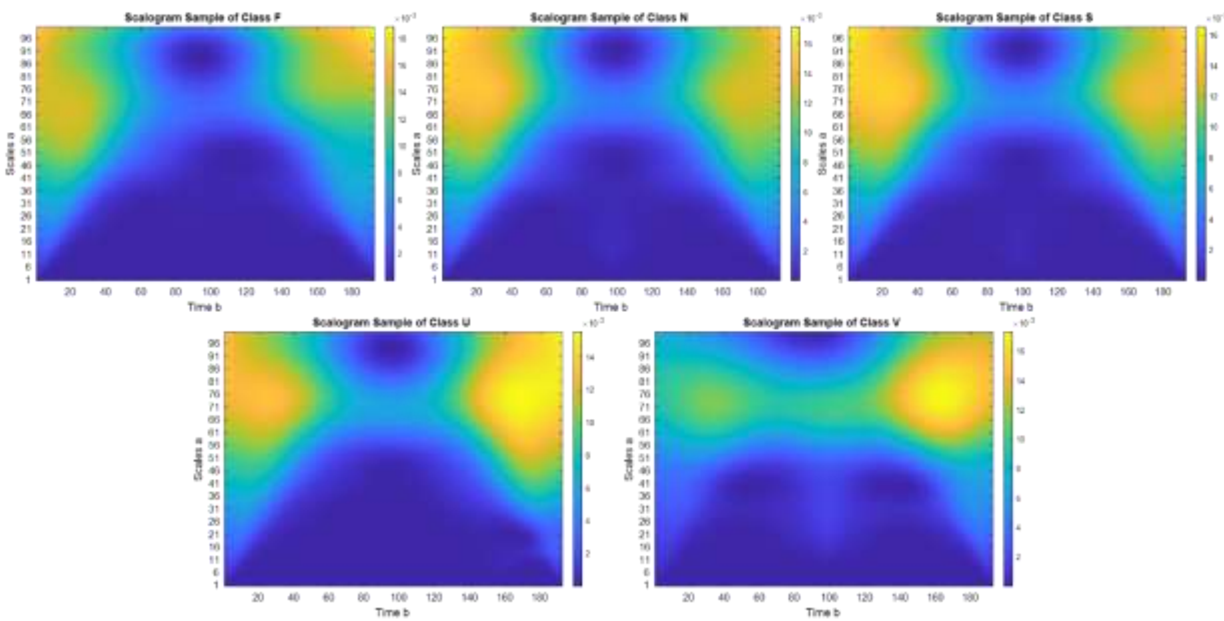

Figure 5. example of scalogram images for V, U, S, N, F classes

3. 3. CNN-Based Feature Extraction Model

CNNs represent a widely adopted type of neural architecture. The primary distinctions between CNNs and ANNs lie in their architecture and input data.

While ANNs utilize numerical values, CNNs process images. An image I comprises pixels with dimensions d, h and w. Images are initially resized based on their depth, width, and height. The image depth depends on the color representation employed. For example, in the rgb colour representation system, that employs three colour channels, the depth of network is considered in 3D size..

The CNN architecture comprises convolutional, pooling and fully-connected layers in sequence. Convolutional layers utilize filters to extract unique features of the input images. Through convolutional filters, any pixel $I_{x,y}$ from images, Accompanied by a filter k (a $p \times p$ matrix), is subjected to an operation represented by the star symbol *. This operation is independently utilized to each coordinate (x, y).

$$k * I_{x,y} = \sum_{i=1}^{p} \sum_{j=1}^{p} k_{i,j} . I_{x+i-1,y+j-1} + b_1 \quad (2)$$

The bias b_1 is incorporated in the model. To reduce the file size of the image, pooling layers are employed. The function ω(.) is employed for assess any pixel along with its adjacent pixels, utilizing operations like average calculations, maximum or minimum. The function processes each pixel and contributes to the downsized images ω(.). This concept will be expressed for clarity as follows

$$\omega(I_{x,y}) = \max_{i,j \in \{-1,0,1\}} I_{x-i,y-j} \quad (3)$$

The formula for adjusting image dimensions is given with (w-k)/(s+1) × (h-k)/(s+1), where s represents the kernel shift. The pervious operations can be iterated multiple times before the final fully connected layer, which serves as the concluding component of the method structure. This framework is composed of an output layer along with several hidden layers

Figure 6 depicts the architectural design for the presented CNN bagging method. The structure incorporates convolutional layers, a fully connected layer and two pooling layers. Classification is performed using the outputs from the second pooling layer. When processing a scalogram image leveraging the suggested Convolutional neural network, the framework provides five possibilities, each corresponding to one of the five arrhythmia classes.

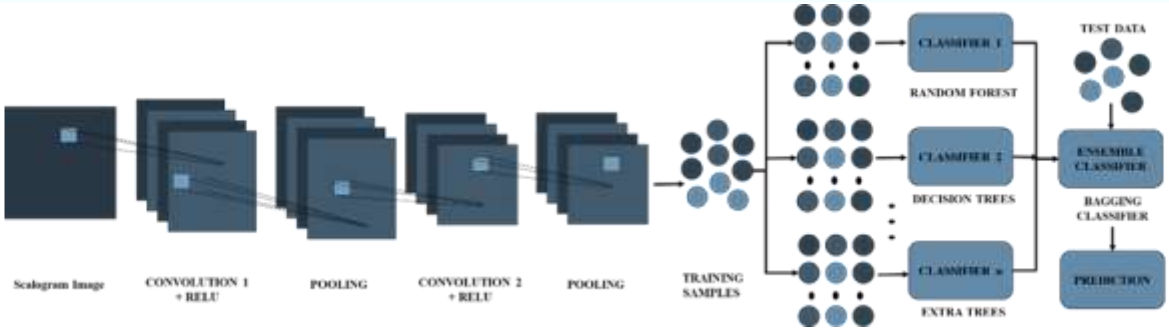

Fig. 6-The structure of the CNN-bagging technique

3.4. Feature Selection Based on MRMR Algorithm

Selecting features is the procedure of meticulously selecting a set of features from a larger dataset, aimed at removing redundant and irrelevant ones. This strategic approach not only reduces the feature's dimensions and the volume of data needed for training process but also mitigates the challenges associated with high dimensional data, thereby enhancing algorithmic effectiveness and improving generalization capabilities. Furthermore, it accelerates computational efficiency and facilitates the interpretability of models.

The primary objective of the MRMR (Maximum Relevance Minimum Redundancy) approach is to maximize the correlation between features and their corresponding class labels, while simultaneously minimizing the redundancy among features. Mutual information serves as a key metric in the MRMR method to quantify the similarity between variables. For two variables X and Y, mutual information can be computed using the following equation:

$$I(X;Y) = \sum_{x \epsilon X} \sum_{y \in Y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)} \tag{4}$$

In this relationship:

$p\,(x, y)$: Probability density function of X and Y.

- **Maximum relevancy metric**

The metric aiming to maximize the relationships among the features of every class and its corresponding label is derived from the equation below:

$$Max\ D(S,c), D = \frac{1}{|S|} \sum_{xi \epsilon S} I(xi;c) \tag{5}$$

Where:

S: features set

|S|: the size of *S*-space features set

xi: individual features

c: categorizes.

I (*xi*, *c*): mutual information for any features in specific class.

- **Minimum redundancy metric**

The metric that seeks to minimize the relationships among features as below equation:

$$Min\ R(S), R = \frac{1}{|S|^2} \sum_{xi,xj\in S} I(xi, xj) \tag{6}$$

In real-world scenarios, incremental search models are utilized for discover attributes which are nearly optimal. for identifying the optimal subset of features (with *m*-1 features), the S_{m-1} subset of features is defined using the equation below:

$$max_{xj\epsilon X - S_{m-1}} \left[I(x_i; c) - \frac{1}{m-1} \sum_{xi\,\epsilon\, S_{m-1}} I(xj; xj) \right] \tag{7}$$

3.5 Classification with Bagging Method

The bagging technique is employed for the classification and detection of cardiac arrhythmias in this work. Bagging, or bootstrap aggregating, involves sending subsets of the main dataset to every classifier. This implies that every classifier processes a segment of the dataset and constructs its system using the subset assigned to it. These subsets are selected with replacement, meaning every sample has the potential to be chosen repeatedly. Studies demonstrated that this model will enhance detection and learning capabilities with high accuracy across various data. The overall performance of this technique is illustrated in Figure 7.

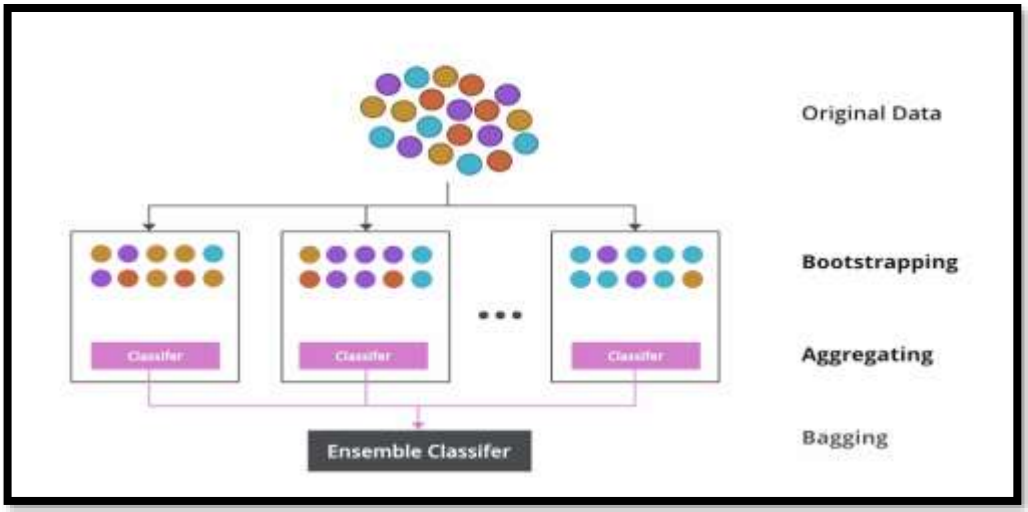

Figure 7- Classification with Bagging technique

4. Experimental Results

This segment assesses the performance of the presented approach employing established metrics and compares its effectiveness with other methods. The suggested approach was trained using MATLAB (2023a) and needs an NVIDIA graphics card with 6 GB of internal RAM. Each class contains 5000 ECG signals, resulting in the generation of 5000 scalogram images per class. Automatic cropping was used on the standard CWT images to remove any unnecessary white space. Subsequently, the resolution was diminished to 227 x 227 x 3 pixels to highlight specific regions of interest in the scalogram images.

In the simulations, 70% of the scalogram images were used for training the CNN. Specifically, a total of 17,500 scalogram images were utilized for training the CNN network, and 7,500 scalogram images were used to test the network. Each scalogram image yields 1000 features that are extracted by the CNN. Utilizing the MRMR algorithm, the dimensionality of every feature vector is then decreased to 500 dimensions. Lastly, these feature vectors are categorized using the bagging ensemble learning method.

Furthermore, the accuracy of classification is assessed through segmenting the database into ten folds. Every fold serves as a validation dataset for training and testing the method. It is worth noting that the database is segmented into training and test sets through a random procedure, and the reported outcomes are the averages of 50 program executions.

4.1 Database

This study utilizes the MIT-BIH Arrhythmia Dataset. The data in this dataset obtained through electrocardiogram recordings from 25 males ranging in age from 32 to 89 years, and 22 females aged between 23 and 89 years., approximately 60% of whom were inpatients. Due to the anatomical differences among individuals, two distinct lead channels, V and II, were used for the ECG signals recording. The sampling rate of these signals is 360 Hz and were recorded over 24 hours from 47 individuals. The database includes 48 half-hour ECG recordings. It features R-peak annotations, interpretations of most beats, and classifications of their types. Approximately 110,000 beats were analyzed in this dataset. Table 1-5 shows the different classes in this database.

Table 1- five different classes in MIT-BIH database

Classes number	Description	Abbreviation
1	Fusion of ventricular and normal	F
2	Normal	N
3	Supraventricular premature	S
4	Unclassifiable	U
5	Ventricular escape	V

4.2. Evaluation Metrics

In this work, F-score, Precision, Accuracy and Recall are utilized to assess the efficacy of the presented approach. The metrics are computed as follows:

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{5}$$

Precision (*P*) is calculated as the number of related samples correctly identified to the total count of samples predicted as positive. It can be calculated based on below equation:

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

Recall (*R*) is the ratio of related items correctly identified out of all the items that are actually relevant. R can be calculated utilizing the following equation:

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

2024 آب العدد 14
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The F1 score is widely adopted as an evaluating metric because it balances the trade-off between recall (R) and precision (P) metrics. It is calculated by determining the harmonically average of precision and recall, as shown in the below formula:

$$F1-score = \frac{2PR}{(P+R)} \quad (8)$$

In the above equations:

True Positive (TP): Indicates correctly identified positive instances.

False Positive (FP): Represents incorrectly identified positive instances.

False Negative (FN): Indicates incorrectly identified negative instances.

True Negative (TN): Represents correctly identified negative instances.

4.3 Evaluating the Training Process

The accuracy and loss learning curves throughout the 400 epochs of training, are depicted in Figures 8 and 9 respectively. Figure 5 demonstrates that the accuracy curve increases progressively, indicating the presented system improves with experience (learning). Additionally, the loss curve represents the model's error. Loss minimization is the primary goal of the proposed method, which is yielded through techniques such as gradient descent. Thus, a lower loss indicates better model performance. To quantify the loss, the cost function is computed. Figure 9 exhibits the findings related to the learning phase. According to figure, the loss curve decreases as the model trains, indicating that the suggested method is effectively learning. Despite slight variations in the learning curves, the loss decreases over the long term, and accuracy increases, demonstrating that the model is learning effectively.

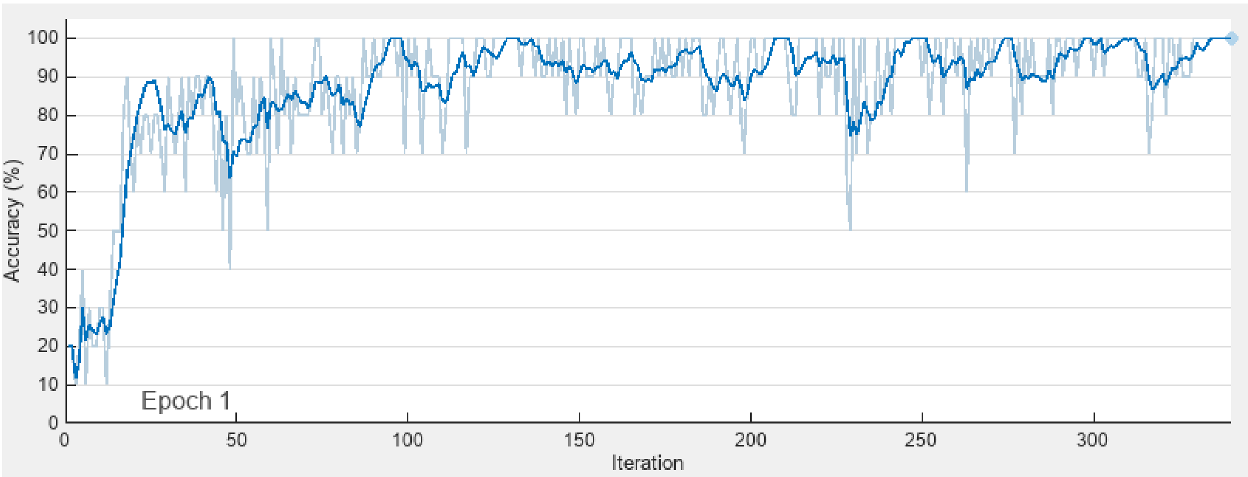

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Figure 8- diagram illustrating the improvement in the proposed model's accuracy through training

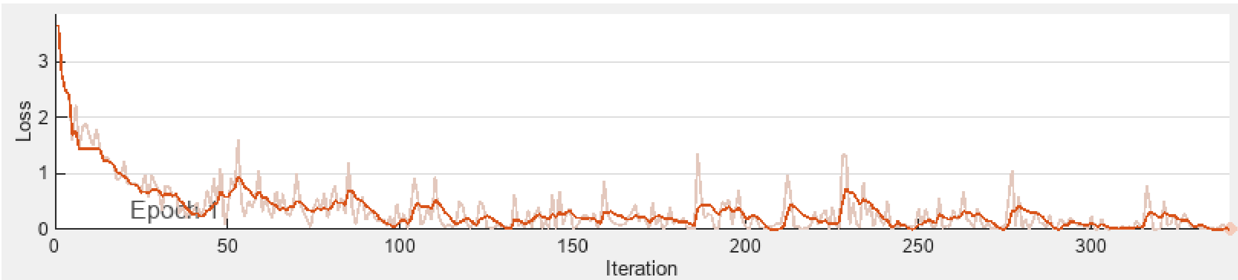

Figure 9- diagram depicting the decrease in the presented method’s loss through training

4.4 Evaluation and Result Comparison

In order to evaluate the effectiveness of the arrhythmia detection method, a confusion matrix was used, as shown in figure 10. The outcomes of classification for each class are displayed in the confusion matrix. This matrix indicates that the suggested method classification function is commendable.

Confusion Matrix

True Class \ Predicted Class	F	N	S	U	V		
F	1516	6	8	4	2	98.7%	1.3%
N	52	1465	16	2		95.4%	4.6%
S		2	1382	8	8	98.7%	1.3%
U	10	4	18	1542	2	97.8%	2.2%
V			26	10	1417	97.5%	2.5%
	96.1%	99.2%	95.3%	98.5%	99.2%		
	3.9%	0.8%	4.7%	1.5%	0.8%		

Figure 10- the presented model confusion matrix

Figure 11 shows the ROC curve of the proposed method in detecting cardiac arrhythmias. This curve is obtained by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR), demonstrating the balance between those measurements for the model. An optimal model is located towards the top-left section of the ROC curve, signifying a high true positive rate (TPR) and a low false positive rate (FPR). On the other hand, a suboptimal model is situated towards the bottom-right corner of the ROC curve, indicating a low true positive rate and a high false positive rate. An indiscriminate classifier would align along the diagonal line in the ROC diagram, where the true positive rate (TPR) equals the false positive rate (FPR). As shown in Figure 11, the ROC curve of the proposed method exhibits a higher TPR and a lower FPR, with its breaking point near the upper left-hand section. Therefore, it could be inferred that the suggested system is highly accurate in classifying cardiac arrhythmias.

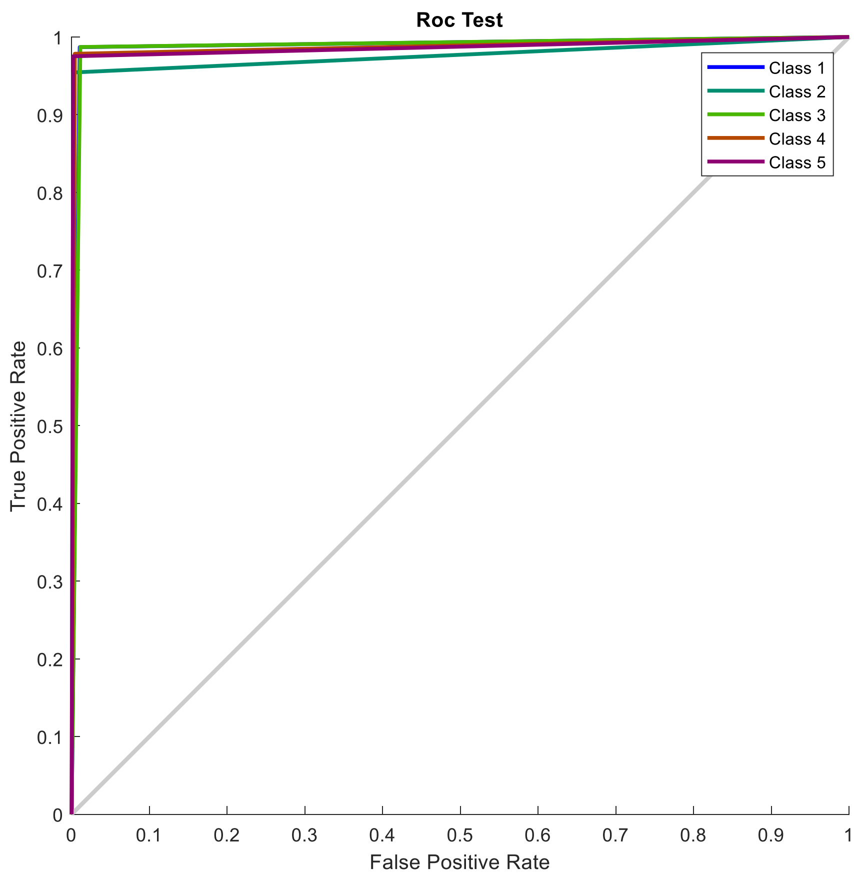

Figure 11- The ROC Curve Generated by the presented method

Additionally, a comparison of Precision, Recall, and F-score metrics is presented in Figure 12. Since F-score is a metric that balances Precision and Recall, it holds greater importance in demonstrating the performance of each method. As observed in Figure 12, the F-score for the presented method is 97.62. In contrast, the highest F-score after the proposed method belongs to the CNN [21] method with a value of 95.19. These findings exhibit the presented method's superiority compared to other methods.

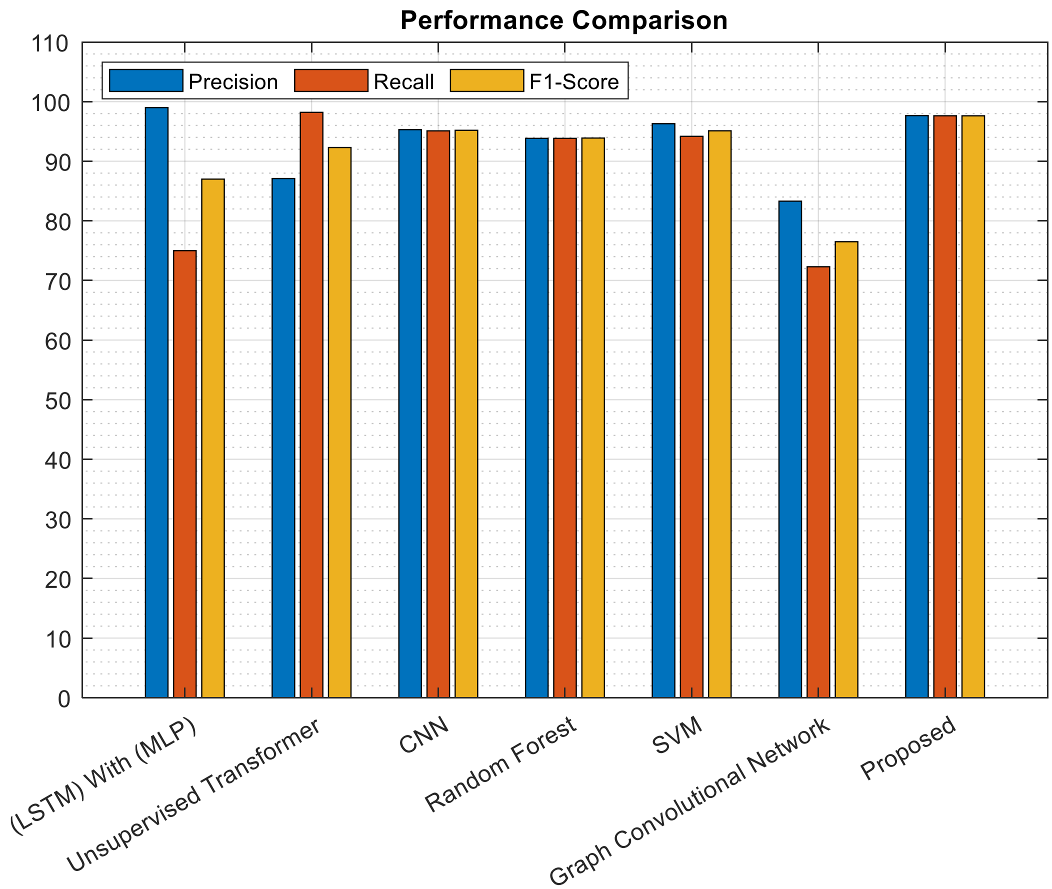

Figure 12-The Results Comparison In Terms Of Precision, Recall And F-Score

The accuracy of cardiac arrhythmia detection has been compared for the proposed approach and several existing models in Table 2. Results for the suggested system are obtained by averaging results over 30 repetitions of experiments. As shown in Table 2, the accuracy metrics for models (LSTM) with (MLP) [19], Unsupervised Transformer [20], CNN [21], Random Forest [22], SVM [22], and Graph Convolutional Network [23] are 95.0, 89.5, 90.8, 93.8, 96.2, and 96.9 respectively. Furthermore, the accuracy of the proposed method is 97.6. These table results indicate the efficacy of the presented approach based on accuracy compared to other algorithms.

Table 2- Comparison of the presented approach with other techniques.

Author	Methodology	Accuracy
Sivapalan et al. [19]	(LSTM) with (MLP)	95.00
Alamr A et.al. [20]	Unsupervised Transformer	89.50
Cao M et.al. [21]	CNN	90.80
Gour A et.al. [22]	Random forest	93.80
Gour A et.al. [22]	SVM	96.20
He Z. et.al. [23]	Graph Convolutional Network	96.90
Proposed	CWT CNN	97.62

5.Conclusion

In conclusion, the research conducted on efficient ECG-based cardiac arrhythmia detection using deep learning has yielded promising results in the realm of automated arrhythmia classification. The proposed method, leveraging convolutional neural networks and ensemble learning techniques, has demonstrated exceptional performance in accurately identifying various types of arrhythmias. Through extensive experimentation and evaluation, the proposed approach achieved an impressive accuracy of 97.62%, showcasing the method's ability to effectively detect and classify arrhythmia in electrocardiogram signals. The results highlight the superiority of the presented approach compared to other state-of-the-art techniques.

The utilization of advanced algorithms, such as convolutional neural networks trained on a comprehensive dataset of ECG signals, coupled with ensemble learning strategies like bagging algorithm, has significantly enhanced the efficiency and accuracy of arrhythmia detection. By leveraging the power of deep learning and ensemble techniques, the proposed method has paved the way for more reliable and timely identification of cardiac arrhythmias, ultimately contributing to the advancement of automated cardiac health monitoring systems.

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