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Efficient ECG Beats Classification Techniques for The Cardiac Arrhythmia Detection Based on Wavelet Transformation

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Abstract: Arrhythmia is one of the cardiovascular disease types that affect humans and often leads to death. generally, ECG signals uses to diagnose the patient's heart state where the ECG illustrates the electrical activities and physiological state of the heart. This paper proposes ECG classification model to classify four types of heartbeats for the early detection of Arrhythmia. Detail wavelet coefficients of ECG were extracted using discrete wavelet transform (DWT) to produce new datasets of ECG with for the dimensions and processed information to ensure the efficiency of proposed classification techniques. In addition, power spectral density (PSD) has been calculated for approximate wavelet coefficients of ECG to extract more relevant features that improve the performance of the classifier. The two classifier models use, the convolution neural network (CNN) utilizes for deep learning networks with artificial neural network (ANN) and the Random forest ensemble method. The experiments and results show that, the proposed model with RF archives 98.5% classification accuracy considering all decomposition levels of DWT. Additionally, the solution with CNN-ANN achieves 96% classification accuracy at the third decomposition level. Therefore, the results show the impact of the proposed solution with high efficiency in terms of fewer dimensions and high accuracy.

Keywords: Arrhythmia, Electrocardiogram (ECG) signal, Discrete wavelet transform (DWT), Convolution neural network (CNN), Random forest.

1. Introduction

Arrhythmia is a term referring to a heart rhythm that differs from normal sinus rhythm; occurs when the electrical signals that coordinate the heartbeat do not work properly. The fault signal causes tachycardia (heart beat too fast), bradycardia (too slow) or irregular. The arrhythmia may look like a racing heart or a fluttering and may be harmless. However, some arrhythmias can cause unpleasant signs and symptoms and may be life-threatening [1].

Sometimes, it is not always an irregular heart activity where it is normal for a person to have a fast or slow heart rate. For example, your heart rate may increase with exercise or slow down during sleep [1].

As a result, work on finding fast and accurate automatic methods for early detection of this disease has become a necessary task to save the lives of patients affected by it due to the problem of low diagnosis accuracy of large and complex ECG signal records the cardiologist faces it.

Most researches focus on identifying and detecting the different types of Arrhythmias by classifying different types of heartbeats, especially premature ventricular contractions (PVCs), considered the most dangerous and important essential that causes fatal arrhythmias [2].

Analyzing ECG signal to extract relevant information is the essential step in designing artificially intelligent based Arrhythmia detection techniques. Many researches produced different feature extraction methods based on analysis different characteristics of ECG signal including morphological and time domain analysis [3], feature domain analysis, time-frequency domain [4, 5], and statistical methods [6].

There are many factors affect the performance of classification model-based machine learning, one of these factors is size and dimensionality of dataset and importance and relevance of features. So, the feature reduction is an important and essential step required to improve the performance of classification model in terms of decreasing the complexity and increasing accuracy. Different approaches are used to reduce dimensionality of extracted features, most common methods are generalized discriminant analysis (GDA), principal component analysis (PCA), and independent component analysis (ICA) [7-9].

In literature, many different researches based on wavelet transform (WT) as one of time-frequency domain feature extraction methods, where the features extracted using WT are more relevant and improve the efficiency of classification model [10-13].

Most recent feature extraction techniques based on convolutional neural network since it extracts more relevant features and avoids manual approaches [14].

Support vector machine and random Forest methods play essential roles in constructing machine learning classification methods with high accuracy by combining the work of this method with other techniques such as correlation technique [15] and entropy method [10]. These techniques increased the classification accuracy and robustness against the unbalancing problem.

1.1 Problem statement

Electrocardiography (ECG) are signals have short intervals of characteristic oscillation, so the extraction methods that capture global information such as method based on the Fourier transform (FT) where the frequency information over entire signal are extracted, will not serve ECG signal classification.

the solution to this problem is to use Wavelet transform (WT). Using WT, the signal is decomposed into a set of wavelets so the discriminable features can be captured as an identification identity for each signal that can distinguish it from the rest of the signals

1.2 Motivations

In considering the problem of classification heartbeats of ECG to detect and predict the heart diseases such as Arrhythmias, a more efficient technique with less dimensionality of a dataset is required to be implemented on wearable devices and produce high performance in terms of less complexity and high accuracy.

Improving the performance of traditional learning methods by decreasing the commutation and memory requirement will increase the classification model's efficiency and accuracy. It can be a robust model used in sensitive fields such as medical applications.

In this context, we produced new strategy that increases the performance of CNN (with only six layers) in terms of less complexity by reducing the dimension of original datasets and improving the classification accuracy since it focuses on significant information localized in wavelet coefficients.

1.3 Contribution

Based on wavelet transformation that considers the most common feature extraction and dimension reduction method with aim of reducing computation complexity and processed information, this work produces two efficient classification techniques: deep network and machine learning.

The convolution neural network (CNN) was designed with three convolution layers and three max-pooling layers for deep learning networks with the single layer artificial neural network (ANN). On the other hand, the random forest ensemble method is used to produce an efficient classification technique based on the wavelet details coefficient of ECG data combined with power spectral density (PSD) for approximate wavelet coefficients of the capture level as input to the proposed model for the four decomposition levels.

These two proposed models were implemented on MIT/BIH arrhythmia database to classify four types of heartbeats: normal beat (N), supraventricular ectopic beat (S), ventricular ectopic beat (V), and fusion beats (F). Then the models were evaluated using MIT-BIH Supraventricular Arrhythmia databases (SVDB) to classify three types of heartbeats: normal beat (N), supraventricular ectopic beat (S), and ventricular ectopic beat (V).

1.4 Evaluation strategies

In order to evaluate the performance of proposed work two standard MIT/BIH database are used: MIT/BIH arrhythmia database and MIT-BIH Supraventricular Arrhythmia databases. Four measures are used to evaluate the classification accuracy for each class, accuracy, fi-score, recall, and precision. The proposed model is compared with recent works in terms of above four measures as well as number of parameters needed to build the model.

1.5 Paper layout

The rest of this paper is organized as follows. First, the related work is described in section 2. Section 3 Explains the proposed methodology. Section 4 discusses the results and analysis of the proposed techniques. Finally, the conclusions are presented in section 5.

2. Related work

Most researchers utilized the wavelet transform as a noise removal method since it decomposes the signal into two different categories of coefficients: approximation and details coefficients. The details coefficients can be removed to remove high band noise. According to the decomposition process, some proposed classification methodology as feature extraction[16].

Dewangan and Shukla [5] classified five types of heartbeats using artificial neural networks (ANN) and discrete wavelet transformation (DWT). The authors concluded that using the wavelet coefficient and morphological features increased ANN's performance in terms of accuracy, achieving 87 % accuracy. This accuracy grew by increasing the number of neurons in the hidden layer.

Jha and Kolekar[17] have developed an efficient classification technique to classify seven types of ECG beats based on 12 approximation coefficients extracted using the tunable Q-wavelet of ECG beats obtained from a different record from the MIT-BIH database. These extracted features were obtained from six decomposition levels of the ECG beat as input to the support vector machine classifier, achieving 99.27% average classification accuracy for eight types of ECG.

Based on a one-dimensional convolutional neural network (CNN) constructed from 12-layers, researchers in [18] proposed an efficient classification technique for classifying five types of heartbeats after denoising them using the threshold denoising method. As a result, this technique achieved a classification accuracy of 97.41%.

Five machine learning algorithms, including Random Forest, were used to classify four types of heartbeats acquired from different datasets in [19]. In this study, wavelet decomposition and frequency content-based sub-band coefficient was used to reduce the dimensionality of the dataset and enhance the performance of the proposed classification technique. The result of this work shows that classification accuracy achieved by RF is up to 97%.

The Discrete wavelet transform (DWT) combined with principal component analysis (PCA) was proposed by [20]as a feature selection method. The SVM and the RF were utilized as machine learning classifiers for the generalization performance of the proposed model. Moreover, the proposed model has been applied to four different datasets where the classification accuracy achieved by the RF classifier was up to 98%.

Although these related researches produced significant techniques for Arrhythmias classification, they have some drawbacks in terms of computation complexity, complex architecture of network designing, number of features extracted, and the number of epochs needed to converge the results, and some of them not manipulated or forced the imbalance problem. In addition, some of these works achieve small accuracy with low generalization performance. In this work all these drawbacks are overcome by designing a classifier technique based on less relevant number of extracted features using WT, a smaller number of epochs, and classifiers with less complexity as well as high accuracy with less computation complexity.

3. Methodology

3.1 Dataset description

The freely available benchmark ECG signals from the MIT/BIH arrhythmia database is used to test this proposal. The database contains 48 half-hour excerpts of two-channel ambulatory ECG recording files obtained from 47 patients. The recordings were digitized with a sampling frequency of 360 Hz and acquired with 11-bit resolution over a ten-mV range [21]. This work used 44 files from the database among the recordings where according to AAMI, 4 with paced beats are excluded recommendations. AAMI recommendations categorize the 18 types of heartbeats into five groups: nontectonic beat (N), supraventricular ectopic beat (S), ventricular ectopic beat (V), fusion beats (F), and unknown beat type (Q). Unknown beat (Q) group is excluded due to its tiny size [22].

The second MIT-BIH supraventricular arrhythmia databases is used to evaluate the generalization of proposed technique. The database contains 78 half-hour including the samples of supraventricular arrhythmias [23].

3.2 Data segmentation

Each record in the first database is segmented into beats; each beat is a one-dimensional signal vector and comprises 252 samples as in the following steps using tools of (WFDB) software:

Algorithm 1: ECG heartbeat extraction (ECG segmentation)

***Input**: ECG record for each patient*
***Output**: extracted heartbeats of each patient record*

for *each ECG record* **do:**
  data ← wfdb. rdsamp(record)
  index$_{time_instance}$←annotation. Samples(record)
  label$_{R_beak}$←annotation. Symbols(record)
  LEN ← length(index$_{time_instance}$)
  data$_{beat}$ ← zero (LEN,252)
  for *i:1* **to** *length (LEN)* **do:**
    N ← index$_{time_instance}$[i]
    data$_{beat}$[i,:]←data[n-108:n+144,0]
  end
  beats$_{record}$ ← concatenate (data$_{beat}$, label$_{R_beak}$)
end
Return *beats$_{record}$*

1- Using annotation file in the MIT-BIH Arrhythmia database to
   a- Detect the R-peaks samples and saving their corresponding time index
   b- Save the vector of beat-labels corresponding to each R-peak detected in step (a)
2- To extract each ECG beat a window of -300 ms to 400 ms around the R-wave is choosing, which equals 108 samples to 144 samples as in the Eq. (1):

$$T = NT_s = N/f_s \rightarrow N = Tf_s \qquad (1)$$

Where T is time in seconds, N is the number of samples, f is sampling frequency =360

$$N\ corresponding\ to\ T = 300\ ms = 0.3\ s \rightarrow N = Tf_s = 0.3 * 360 = 108$$
$$N\ corresponding\ to\ T = 400\ ms = 0.4\ s \rightarrow N = Tf_s = 0.4 * 360 = 144$$

Bellow pseudocode illustrates the segmentation procedure of ECG signal to extract heart beats in it.

The second database is segmented into beats; each beat is a one-dimensional signal vector and comprises 150 samples with the same procedure of the first database segmentation using window of 150 samples around the R-wave.

Data Pre-processing

Pre-processing is carried out in three steps:

1- Z-score normalization reduces DC offset and magnitude variant scaling among different files.
2- Discrete wavelet transform (DWT) was used to filter ECG signals from high-frequency noise, power line interference, and baseline wander without changing the morphology of ECG as compared with other denoising filters.
3- The database was split into a training set and a testing set as a rule of thumb, where the ratio of the training set to the testing set was 7:3. Then, the training set was divided into a training set and validation set with the 8:2 ratio.
4- Data augmentation using Synthetic Minority Over-sampling Technique (SMOTE) method was used to solve the imbalance problem in the dataset after down-sampling majority class randomly to 20000 samples.

3.3 Proposed classification model

In this work, two proposed classification models were developed based on wavelet transform as a feature selection method and a feature reduction method simultaneously. Fig. 1 explains the overall steps of the proposed framework. After the data pre-processing stage, the feature extraction method based on WT is used to extract detail coefficients from four decomposition levels instead of using the entire original ECG signal to overcome overfitting and reduce the computation complexity, then in the third stage, two classifiers are constructed: convolution neural network (CNN) and Random Forest. The fourth stage including classification performance evaluation and analysis in terms of four metrics: accuracy, recall, precision, and f1-score.

3.1.1. Discrete wavelet transforms (DWT)

The first stage of designing the architectures of two classification models is to calculate the detail coefficients of input heartbeats using wavelet transformation with four decompositions level; this procedure is carried out to extract important discriminate features with less dimension as compared with original data.

The mathematical formulation of wavelet transform can be expressed by Eq. (2)[24]:

$$W_x^{\psi}(t,s) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x(\tau)\psi^*\left(\frac{\tau - t}{s}\right) d\tau \qquad (2)$$

Where: τ is a time shift, s is scale(dilation), $\psi(t)$ is mother wavelet, and ψ^* is ψ complex conjugate. There is more than one example of mother wavelet, in this work Haar wavelet was used which is formulated by Eq. (3):

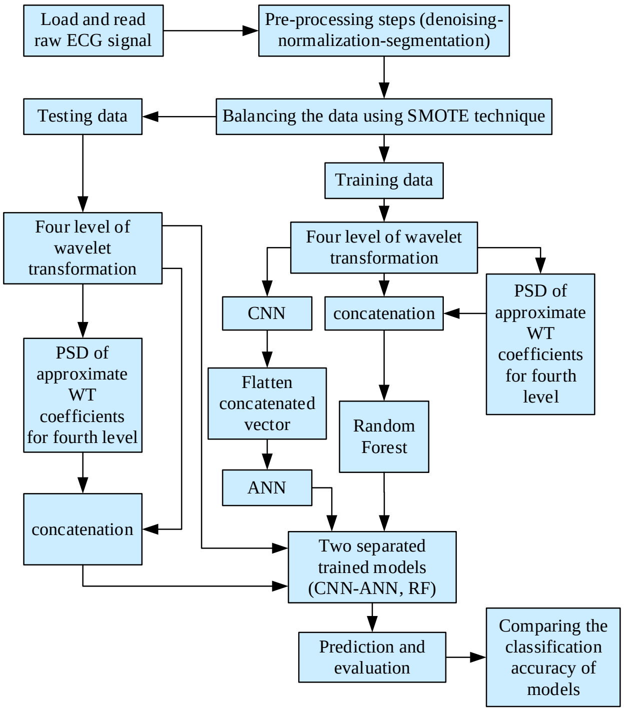

Figure. 1 General framework of proposed classification methodology

$$\psi(t) = \begin{cases} 1 & 0 \le t \le 0.5 \\ -1 & 0.5 < t < 1 \\ 0 & elsewhere \end{cases}$$
$$\overset{FT}{\leftrightarrow} \Psi(f) = je^{-j\pi f} \sin(\pi f/2).\, sinc(\pi f/2) \qquad (3)$$

Discrete wavelet transform (DWT) should be used with digital signal (with binary nature) hence it compatible with digital computer. Based on dyadic sampling discretizing scale and time shift, DWT can be designed with all discrete variables. Using DWT high-pass filters analyzed high frequencies of signal which is passed to them, and low-pass filters analyzed low frequencies[24]. The resultant coefficients of analyses process are Approximate coefficients are denoted by A_m (from the low-pass filter) and detail coefficients are denoted by D_m (from the high-pass filter), according to Eqs. (4-7)of convolution between signal and filter[25].

$$A_m[m] = \sum_{k=-\infty}^{\infty} x[k] g[2m-k] \qquad (4)$$

$$A_m[m] = (x * g) \downarrow 2 \qquad (5)$$

$$D_m[m] = \sum_{k=-\infty}^{\infty} x[k] h[2m-k] \qquad (6)$$

$$D_m[m] = (x * h) \downarrow 2 \qquad (7)$$

Where: g and h is low-pass filter and high-pass filter respectively, $x(k)$ is the ECG signal, m is refer to coefficient at each level, in this work since there are four decomposition levels then $m \in \{1,2,3,4\}, \downarrow$ is down sampling operator, $*$ is convolution process.

Since each output from convolution process as in Eq. (5) and (7) has half the frequency band of input signal where only half of each filter output characterizes the signal, so WT is significant features selection and reduction method by selecting specific coefficients only instead of entire signal will be sufficient to ECG classification. In this paper the detail coefficients for four decomposition levels have been extracted and selected as input to classifiers.

3.1.2. Power spectral density (PSD)

Fourier transform is a good and useful tool for analyses and reveals information from stationary signal, but with nonstationary signal the time-frequency and time-scale methods are needed since the Fourier transform not suitable with nonstationary signal[26].

Boashash (2015) explained the time and frequency distribution TFDs denoted by $\rho(t,f)$ using the two variables t and f denoting time and frequency respectively, not alternately, but present together. The representation of the TFD is central at t and f, so the cross section of the constant TFD t must represent the frequency or frequencies present at time t, and the constant cross section f must show the time or times in which the frequency f is present[27]

The periodogram is a nonparametric method to calculate the power spectral density (PSD) of a wide-sense stationary random process. The periodogram is the Fourier transform of the autocorrelation signal [28]

For a signal x_n sampled at f_s samples per unit time, the periodogram is defined as in the Eq. (8):

$$\hat{P}(F) = \frac{\Delta t}{N} \left| \sum_{n=0}^{N-1} x_n e^{-i2\pi f \Delta t n} \right|^2, \quad -1/2\Delta t < f < 1/2\Delta t \qquad (8)$$

where Δt is the sampling interval. For a one-sided periodogram, the values at all frequencies except 0 and the Nyquist, $1/2\Delta t$, are multiplied by 2 so that the total power is conserved.

3.1.3. CNN proposed architecture

Convolutional neural networks consider as class of artificial neural network (ANN) which simulates the operation of visual cortex for human brain and used as feature engineering instead of manual feature extraction. CNN handles the signal directly by applying a filter on it to produce number of feature maps equal to number of filters (array of weights called kernel)[29]. The mechanism of the works of CNN can be illustrated in below steps:

1- Input layer which represents the direct data of signal or image.
2- Convolution layer: in this layer the convolution operation applies on input using number of filters to produce feature maps.
3- Applying rectified linear activation function (ReLU) activation function on resultant feature maps to process them as in ordinary deep neural network.
4- Reducing the dimension of feature maps using mean or max operation in MaxPooling layer. The benefit of this layer is reducing the computational load as well as reducing overfitting.
5- Converting the result from 2D to 1D Flatten vector that passes to artificial neural network which works as classifier. Usually this fully connected network (ANN) consist of from three layers, input layers, hidden layer, and output layer. Fig. 4 explain the main architecture of CNN.

In this work, the resultant detail coefficients enter to classifier models. Two models are CNN-ANN as deep learning model and Random Forest as machine learning model. CNN is used to extract deeper features then ANN used the resultant flatten vector from CNN to classify four types of ECG heartbeat.

Table 1. Summary table of proposed CNN architecture

Layer types	**Forth level (input size=16)**	
	Output shape	**# Parameters**
convolution	(None, 16, 16)	64
Max- pooling	(None, 8, 16)	0
convolution	(None, 8, 32)	1568
Max- pooling	(None, 4, 32)	0
convolution	(None, 4, 64)	6208
Max- pooling	(None, 2, 64)	0
Flatten	(None, 128)	0
output	(None, 4)	516

Table 2. Summary table of training parameters for input detail coefficients at first decomposition level of DWT and each layer in the proposed CNN architecture

Layer types	**Number of filters**	**Kernel size**	**Activation function**
convolution	16	1*3	Leaky_Relu
Max- pooling	-	1*2	-
convolution	32	1*3	Leaky_Relu
Max- pooling	-	1*2	-
convolution	64	1*3	Leaky_Relu
Max- pooling	-	1*2	-
Flatten	-		-
output	-	1*4	SoftMax

Table 3. Summary table of training parameters for input detail coefficients at second decomposition level of DWT and each layer in the proposed CNN architecture

Layer types	**First level (input size=126)**	
	Output shape	**# Parameters**
convolution	(None, 126, 16)	64
Max- pooling	(None, 63, 16)	0
convolution	(None, 63, 32)	1568
Max- pooling	(None, 31, 32)	0
convolution	(None, 31, 64)	6208
Max- pooling	(None, 15, 64)	0
Flatten	(None, 960)	0
output	(None, 4)	3844

Table 4. Summary table of training parameters for input detail coefficients at third decomposition level of DWT and each layer in the proposed CNN architecture

Layer types	**Second level (input size=63)**	
	Output shape	**# Parameters**
convolution	(None, 63, 16)	64
Max- pooling	(None, 31, 16)	0
convolution	(None, 31, 32)	1568
Max- pooling	(None, 15, 32)	0
convolution	(None, 15, 64)	6208
Max- pooling	(None, 7, 64)	0
Flatten	(None, 448)	0
output	(None, 4)	1796

Table 5. Summary table of training parameters for input detail coefficients at fourth decomposition level of DWT and each layer in the proposed CNN architecture

Layer types	**Third level (input size=32)**	
	Output shape	**# Parameters**
convolution	(None, 32, 16)	64
Max- pooling	(None, 16, 16)	0
convolution	(None, 16, 32)	1568
Max- pooling	(None, 8, 32)	0
convolution	(None, 8, 64)	6208
Max- pooling	(None, 4, 64)	0
Flatten	(None, 256)	0
output	(None, 4)	1028

CNN consists of three convolution layers with filter of (3*3) size, followed by three Max-Pooling layers as it clear in Tables 1-5 of CNN architecture. The parameters the used 1D-CNN train with are: 10 epochs, Adam optimizer, and loss function is categorical cross entropy.

3.1.4. Random forest RF

It is one of the most common used classification methods which is uses ensemble learning techniques. This technique solves the complex problems by constructing multiple classifiers and applies them on multiple pieces of data set then the output class

Table 6. The classification accuracy of CNN at each DWT decomposition level

Level number	Number of coefficients	Overall Accuracy	Trainable parameters
1	126	96%	11,684
2	631	95%	9,636
3	32	96%	8,868
4	16	94%	8,356

decided by maximum voting of the resultant output class label from all classifiers[30]. according to this ensemble technique, RF built multiple and individual decision trees implements on multiple subsets from original dataset during the training stage. At the testing stage, the output class labels of all decision trees enter to voting process, finally the predicted output class is the class with maximum votes. The benefits of using random forest are the utilizing of its advantages and its superior performance compared with other machine learning methods in avoiding and preventing overfitting by using multiple trees, as well as giving accurate and precise results[31].

The second proposed model is constructed using Random Forest. The parameters used to build the RF classifier were selected after implementing the Grid search hyperparameters tuning method. These parameters are: The number of trees in the forest are 50 trees, and the function to measure the quality of a split is the Gini index.

3.1.5. Analysis on computational complexity

Denoting $\boldsymbol{d}$ as the number of features (dimensions) in dataset, $\boldsymbol{n}$ as the number of training ECG records, and $\boldsymbol{Ntrees}$ as number of trees, the training computational complexity of Random Forest is: $\boldsymbol{O}(\boldsymbol{d} * \boldsymbol{Ntrees} * \boldsymbol{nlogn})$ and the testing computational complexity of random forest is: $\boldsymbol{O}(\boldsymbol{d} * \boldsymbol{Ntrees})$ [32].

Using Random Forest in conventional technique with whole ECG record length equal 252, the training computational complexity is $(\boldsymbol{252} * \boldsymbol{Ntrees} * \boldsymbol{nlogn})$. In our proposed technique using WT as features selection and reduction where the number of used features is reduced to 25 only so, the training computational complexity of Random Forest is $(\boldsymbol{25} * \boldsymbol{Ntrees} * \boldsymbol{nlogn})$.

On the other hand, the testing computational complexity is $(\boldsymbol{252} * \boldsymbol{Ntrees})$. In our proposed technique the testing computational complexity of Random Forest is $(\boldsymbol{25} * \boldsymbol{Ntrees})$. As a result, the complexity is reduced by 99.2% from original value for same $\boldsymbol{Ntrees}$.

In addition, the $\boldsymbol{Ntrees}$ work on small number of features (25) is less than $\boldsymbol{Ntrees}$ work on 252 features, so, the space complexity of random forest which is $\boldsymbol{O}(\boldsymbol{depth\ of\ tree} * \boldsymbol{Ntrees})$ certainly reduced with significant ratio.

The computation complexity of CNN can be calculated using two measurements: number of parameters and multiply-accumulate operations (MAC) at each convolution layer. Denoting $\boldsymbol{K_C}$ as number of filters(kernel) in current layer, $\boldsymbol{K_p}$ as number of filters in previous layer, $\boldsymbol{M}$ is the kernel size, $\boldsymbol{m}$ is input size, $\boldsymbol{O_M}$ is the output size, p is the amount of zero padding, and $\boldsymbol{s}$ is the stride, so the (MAC) is calculated as following[33]:

$$\boldsymbol{O_M} = \frac{(\boldsymbol{m}-\boldsymbol{M}+\boldsymbol{2p})}{\boldsymbol{s}} + \boldsymbol{1} \tag{9}$$

$$\boldsymbol{MAC} = \boldsymbol{K_p} * \boldsymbol{M} * \boldsymbol{K_c} * \boldsymbol{O_M} \tag{10}$$

It is clear that the size of input signal $\boldsymbol{m}$ plays a significant role in calculating the value of MAC, so the decreasing of input ECG record will impact on decreasing the complexity of CNN according to the Eqs. (9) and (10).

The number of total parameters as in Tables 1-5 show the clear impact of input size. Thereby the technique in this paper with using input size of 25 features only instead of 252 will decrease the number of parameters and multiply-accumulate operations (MAC) by high ratio which leads to decreasing the complexity of proposed CNN architecture.

4. Results and discussion

4.1 Experimental results

The results are presented for performance evaluation of two proposed classification models where the training and test sets were selected randomly as a 70:30 thumb rule.

The classification models were trained, and their performance was evaluated after each DWT level of decomposition, where the size of the data entering the model is different at each level and equal to the number of wavelet detail coefficients at each level.

The result of evaluating the performance of CNN-ANN in terms of accuracy, as illustrated in Table 6, where the size of the input layer, which is equal to the number of wavelet detail coefficients and the number of trainable parameters at each level, was presented. Fig. 2 illustrates the performance results graphically in terms of validation loss, validation accuracy, training loss, and training accuracy; it is clear from the curve of these measures that there is non-obvious overfitting there is no gap between the angle of validation and training accuracy.

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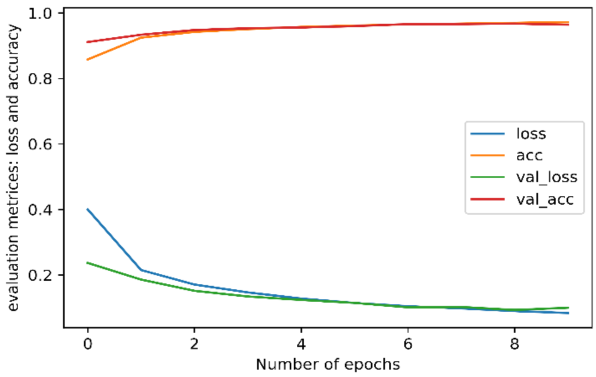

Figure. 2 The performance of CNN in terms of loss and accuracy with input layer size =32

Table 7. Performance results of CNN classifier for each class

Class	Evaluation measure	1st level (%)	2nd level (%)	3rd level (%)	4th level (%)
N	Precision	99	99	99	99
	Recall	97	95	96	94
	F1-score	98	97	98	97
S	Precision	53	52	59	50
	Recall	77	91	86	90
	F1-score	63	66	70	64
V	Precision	94	91	86	84
	Recall	91	95	95	96
	F1-score	93	93	90	90
F	Precision	65	25	40	29
	Recall	74	84	84	83
	F1-score	69	39	54	43

Table 8. Performance evaluation results of RF classifier

Class	Evaluation measure	1st level (%)	2nd level (%)	3rd level (%)	4th level (%)
N	Precision	99	99	99	99
	Recall	98	98	98	98
	F1-score	99	99	99	99
S	Precision	77	75	70	75
	Recall	72	78	83	88
	F1-score	74	77	76	81
V	Precision	90	90	92	90
	Recall	95	96	96	97
	F1-score	92	93	94	94
F	Precision	80	79	68	52
	Recall	69	71	72	75
	F1-score	74	75	70	62

From the results in a Table 6, it is clear that the number of trainable parameters and the dimensions of the data (size of input layers) represented by the number of DWT detail coefficients decreases with the increasing of the number of DWT decomposition levels with a not noticeable variation in the percentage of accuracy. As a result, the best performance of the model was at the third level with the highest classification accuracy and less trainable parameter; this is the goal of the work to achieve efficiency in terms of reducing the complexity of model designing terms of reducing the dimensions of processed data while maintaining accuracy.

The result of CNN -ANN classification performance for each class in terms of three evaluation measures: precision, recall, and f1-score, were illustrated in the Table 7. These results show the imbalance problem's impact on the classification model's performance on minority classes even after the SMOTE augmentation method. The minority classes S and F achieved less value of precision, recall, f1-score evaluation measures compared with types N and V. On the other hand, the best results for each type were conducted at different DWT decomposition levels; for classes N and S, the highest values of precision, recall, and f1-score were obtained at the third level; in contrast, for classes V and F where the highest values of precision, recall, and f1-score were obtained at second and first level respectively.

Similarly, the performance of the RF classifier was evaluated using three evaluation measures: precision, recall, and f1-score as in Table 8. It is clear that the problem of imbalance caused the same impact on minority classes as in the CNN-ANN classifier. For classes N, S, and V, the highest values of precision, recall, and f1-score were obtained at the fourth level with a smaller number of details coefficients (smallest input layer size), hence these results were compatible with the aim of this research in producing the model with the highest efficiency. In contrast, for class F, the highest values of precision, recall, f1-score, and accuracy at the second level.

From all the above evaluation results, it can be noticeable that for the classes with the minor size the feature reduction doesn’t work, hence it is necessary to find and increase relevant features and increase the training data size (number of ECG heartbeats) of these classes as well as training the classifier model to have variety in the training sample of these minority classes. the combination of nine features extracted from PSD of approximate WT coefficients at fourth decomposition level with detail WT coefficients in aim of increasing the relevant features are significant argument for these outcomes since it has clear impact on increasing the performance of RF as in Table 9, where the highest values of precision, recall, and f1-score for all classes, were obtained at the fourth level. Generally, the performance of RF has been increased for all classes as comparison between results in Tables 8 and 9

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Table 9. Performance evaluation results of RF classifier using PSD

Class	Evaluation measure	1st level (%)	2nd level (%)	3rd level (%)	4th level (%)
N	Precision	98	99	99	99
	Recall	99	99	99	99
	F1-score	99	99	99	99
S	Precision	87	85	85	90
	Recall	70	75	81	85
	F1-score	77	80	83	88
V	Precision	96	94	95	95
	Recall	95	96	96	97
	F1-score	95	95	96	96
F	Precision	92	88	86	77
	Recall	63	65	66	72
	F1-score	75	75	74	74

Table 10. Classification accuracy at each DWT decomposition level using two classification models

Level	WT coefficients	WT coefficients +PSD	Overall accuracy		
			WT-RF	WT-PSD-RF	WT-CNN
1	126	135	97%	97.9%	96%
2	63	72	97%	98%	95%
3	32	41	97%	98.2%	96%
4	16	25	97%	98.5%	94%

Table 11. Performance evaluation results of RF classifier using PSD implemented on MIT-BIH supraventricular arrhythmia database (SVDB)

Class	Evaluation measure	1st level (%)	2nd level (%)	3rd level (%)	4th level (%)
N	Precision	98	99	99	99
	Recall	96	97	97	97
	F1-score	97	98	98	98
S	Precision	69	72	74	74
	Recall	80	84	88	85
	F1-score	74	77	80	79
V	Precision	76	79	81	79
	Recall	91	92	92	92
	F1-score	83	85	86	85
Average accuracy		95	95	96	95.7

Finally, after analyzing the performance evaluation results of the two proposed classification models, a comparative study was illustrated in the Table 10. The results show that the accuracy achieved by RF is highest than the accuracy achieved by CNN for each DWT decomposition level which is up to 98%.

So, the RF classifier will candidate the best classifier based on DWT to develop an efficient classification technique. Generally, using DWT improved the performance of CNN-ANN classifier where the accuracy achieves using this classifier without using DWT as feature reduction was 90% and these results come true with the results achieved by[34].

To evaluate the best model-based RF performance and its generalization, the model is implemented on MIT-BIH Supraventricular Arrhythmia databases as in Table 11.

4.2 Comparison study of proposed classification framework with previous works

The comparative study between our proposed classification technique and related previous works of ECG beats classification to predict Arrhythmia disease has been produced and explained in terms of the resultant classification accuracy, classifier and its architecture, and number of extracted features as in the Table 12.

It is clear that the proposed classification technique has superior performance in terms of accuracy and efficiency, where its classifier has architecture with less complexity as compared with classifier of other works. In addition, it achieves higher accuracy with a smaller number of coefficients and less computation complexity.

As compared with classification technique in reference [17], it achieves accuracy higher than the accuracy achieved in our proposed technique, but it not robust against unbalancing problem since it chose only 14,878 ECG beats in balancing way to all classes so the classification technique in this work, was not confronted the unbalancing problem as in our proposed technique. As a results, the proposed technique is superior to this technique in terms of generality.

In reference [5] the accuracy was small as compare with the accuracy achieved in proposed technique in this paper, as well as the number of epochs required in this reference were 5000 epochs whereas in our technique, the maximum number of epochs required for the results to be converged are 10 epochs only as in Fig. 1.

The proposed architecture of CNN is constructed using only seven layers conversely, the CNN in references [18] and [14] constructed from 12 layers, so the proposed CNN architecture in our work overcomes the CNN complexity in these references.

Although, the classifiers used in references [19] and [20] is RF as in our work but the number of extracted features (input dimensions) are 62 and 356 respectively which is more than the number of features extracted in our work using WT which were

Table 12. The comparison between the proposed classification technique and previous works

Reference	Classifier	Dataset	Number of extracted features	Evaluation metrices		
				Accuracy	**Sensitivity (recall)**	**Specificity (Precision)**
[5]	Neural network (Three layers, one hidden layer with 300 hidden neuron)	MIT-BIH arrhythmia database	12(8 WT coafficienr+4 morphology features)	87%	65.54	92.25
[14]	CNN (12 layers) and nonlinear regression	MIT-BIH arrhythmia database	temporal and frequential properties (R–R intervals, cardiac frequencies)	91.7%	-	-
[18]	CNN with 12 layers	MIT-BIH arrhythmia database	360	97.4%	97.05	99.35
[19]	RF	MIT-BIH arrhythmia database	62 WT coefficient	97.35%	-	-
[20]	RF	MIT-BIH arrhythmia database	8 level of DWT and PCA (356 features)	98.8%	60.00	98.29
[17]	SVM	MIT-BIH arrhythmia database	12 Approximate coefficients at the sixth level	99.2%	96.22	99.58
Proposed work	**RF**	MIT-BIH arrhythmia database	**25(16 detail coefficients at the fourth level+9 PSD coefficients)**	**98.5%**	**98.5%**	**98.5%**
	CNN with 6 layers	MIT-BIH arrhythmia database	**32 detail coefficients at the third level**	**96%**	**95%**	**96%**

25 coefficients only after fourth decomposition level only. So the complexity of RF in our proposed technique is less than the complexity of RF in references [19] and [20] as in section 3.4.5.

5. Conclusion

This work aims to develop an efficient Arrhythmia classification model-based features extracted using Discrete wavelet transform with two classifier models: CNN-ANN and RF. The heartbeats are extracted by segmenting the ECG records. Additionally, the preprocessed and details coefficients for four decomposition levels of wavelet transform were extracted. Next, the details coefficient for each level enters as an input to each classifier for classifying the four types of ECG heartbeats. Finally, the arrhythmia was detected and predicted for each heartbeat type of test dataset, then, evaluates the performance of two classifiers. In terms of four evaluation measures, accuracy, recall, precision and f1-score the performance of RF was better than CNN-ANN for all decomposition wavelet levels. This model achieved high accuracy approach of 98.5% with only 16 wavelet detail coefficients and 9 features from PSD of approximate WT coefficients of ECG beats at fourth decomposition level which ensures the efficiency in terms of less processed information. These results ensure that the proposed classification technique can be used as an efficient and automatic model for arrhythmia classification, which can be implemented on wearable devices in realistic application.

Conflicts of interest

The authors declare no conflict of interest

Author contributions

Author 1: Conceptualization, analysis, methodology and coding, project administration, data curation, writing original draft, writing review and editing. Author 2: The supervision, visualization, Conceptualization, review, writing review and editing. Author 3: Supervision, validation, formal analysis, review, writing review and editing.

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