Implementation of Neural Network and Feature Extraction to Classify ECG Signals

R. Karthik, Dhruv Tyagi, Amogh Raut, Soumya Saxena, K. P. Bharath and M. Rajesh Kumar

Abstract This paper presents an efficient approach for distinguishing ECG signals based on certain diseases by implementing Pan Tompkins algorithm and neural networks. Pan Tompkins algorithm is used for feature extraction on electrocardiography (ECG) signals, while neural networks help in detection and classification of the signal into four cardiac diseases: Sleep Apnea, Arrhythmia, Supraventricular Arrhythmia and Long-Term Atrial Fibrillation (AF) and normal heart beat. The paper also presents a new approach towards signal classification using the existing neural networks classifiers.

Keywords Pan tompkins algorithm · Pattern net · Fit net · Cascaded net Feedforward net and ECG classification

1 Introduction

Electrocardiography (ECG) is a technique used to record the electrical activity of the heart and observe the heart variation and abnormalities over a period of time using electrodes placed on the skin. ECG signal can be divided into phases of

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depolarization and repolarization of the muscle fibers which make up the heart [1]. These phases consist of P-waves, QRS-complexes, and T-waves which provide fundamental information about the electrical activities of the heart [2]. ECG signal processing can be used to detect diseases like Arrhythmia, Supraventricular Arrhythmia, Sleep Apnea, Normal Sinus Rhythm and Long-Term Atrial fibrillation [3]. Sleep apnea is a sleep disorder characterized by cessations of breathing during sleep. There are three types of sleep apnea: Central Sleep Apnea (CSA), Obstructive Sleep Apnea (OSA) and mixed. An arrhythmia occurs due to factors like Coronary artery disease, electrolyte imbalances in blood, changes in heart muscle etc. Supraventricular Arrhythmia is a type of arrhythmia causing an abnormally fast heart rhythm due to unsuitable electrical activity in the heart. It begins in the areas above the heart's lower chambers, such as the upper chambers (the atria) or the atrial conduction pathways. This disorder can result from rheumatic heart disease or an overactive thyroid gland. Long-Term Atrial fibrillation (AF) involves the occurrence of an irregular heartbeat where the atria fail to contract in a strong manner. The clinical risk factors for AF include advancing age, diabetes, hypertension, congestive heart failure, rheumatic and non-rheumatic valve disease, and myocardial infarction. The echocardiographic risk factors for non-rheumatic AF includes left atrial enlargement, increased left ventricular wall thickness, and reduced left ventricular fractional shortening. ECG signals available from Physionet library provide a standard dataset for performing all tests. ECG signal processing is used to convert the raw data into a form which can be used for feature extraction (Fig. 1).

Discrete Wavelet Transform provides a method for feature extraction in which the choice of the wavelet selected lies upon the application and the user. Wavelet families include Biorthogonal, Coiflet, Harr, Symmlet, Daubechies [5] wavelets [6, 7]. Wavelet techniques are the ones most commonly used but are complex and time-consuming. Hence, other techniques like Pan Tompkins algorithm can be used for preprocessing and feature extraction, as it provides a higher level of decomposition and is comparatively less time-consuming [8, 9]. Fast Fourier transform and other techniques are used for preprocessing of the signal in order to remove noise and baseline wandering [10]. Several classification techniques can be used for ECG classification like Support Vector Machines (SVM), decision tree, neural network, nearest neighbors, etc. [11]. The linear discriminant analysis is a linear classifier that minimizes the interclass variance and maximizes the mean values of the two classes to find a line in the lower dimension of feature space [12]. They do not take into

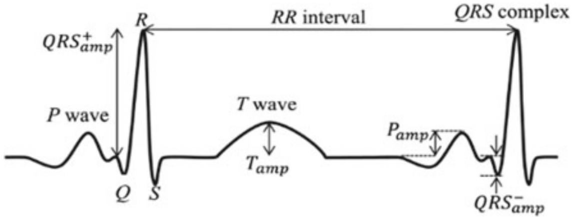

Fig. 1 Normal ECG heart beat [4]

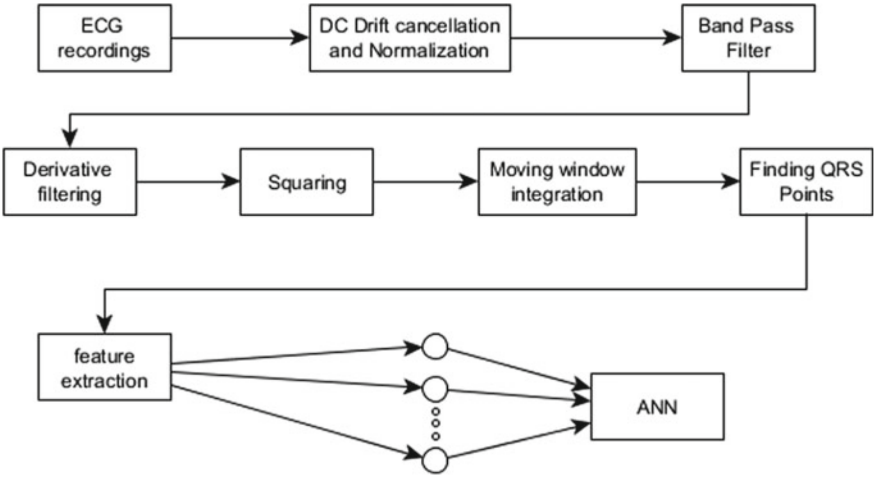

Fig. 2 Block diagram for pan tompkins algorithm to derive features used as ANN inputs

account the difference between adjacent sample points. Support Vector Machines (SVM) on the other hand uses adjacent sample points to draw a discriminatory line which is used for classification [12]. SVM is considered to give higher accuracies and hence is preferable. Artificial Neural Networks (ANN) classifiers can be fed by various parameters, some of which are spectral entropy, Poincare plot geometry, and largest Lyapunov exponent (LPE) [1] (Fig. 2).

2 Feature Extractions

The raw ECG signal is processed to filter out the noise and extract the RR interval using Pan Tompkins algorithm [9], which is further used to extract fifteen features out of each signal. The extracted features are fed into four different neural networks for training and are then validated using various test signals. The accuracy is calculated for each neural network and each disease. The same process is performed for the classification technique proposed below as well and the results are compared. ECG signal includes noise as a part of the signal which needs to be removed before it is processed for feature extraction. Pan-Tompkins algorithm is a real-time algorithm for detection of the QRS complex in ECG signals, developed by Jambukia et al. [9]. It reliably recognizes QRS-complexes on the basis of digital analysis of slope, amplitude, and width. In this algorithm, a special digital bandpass filter reduces false detections which can be caused due to various types of interferences present in ECG signals. This filtering allows the use of low thresholds and hence helps in increasing the detection sensitivity. Stepwise signal processing of raw signals of each disease is graphically depicted in Figs. 3, 4, and 5

Feature extraction was done using Heart Rate Variability (HRV). HRV can be defined as the interval between successive R peaks.

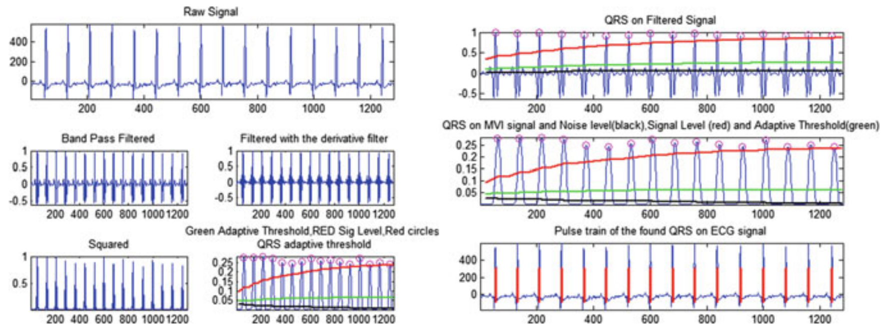

Fig. 3 Signal processing of normal raw ECG signal

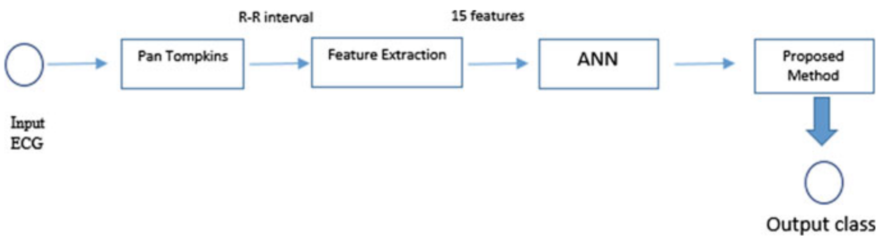

Fig. 4 Proposed block diagram

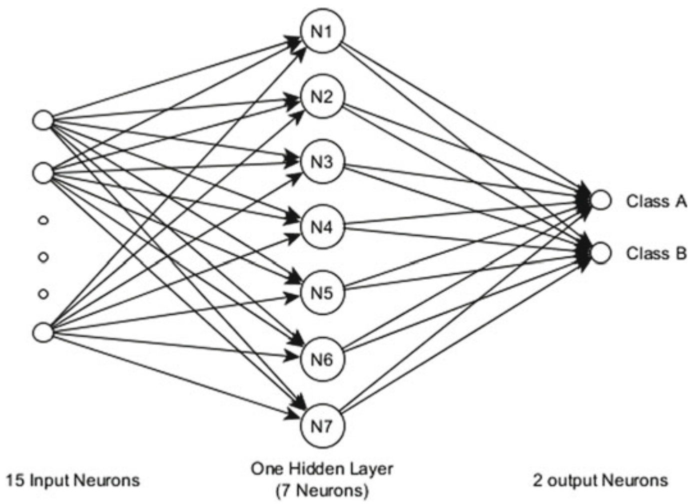

Fig. 5 ANN structure with 5 input neurons, 7 neurons in 1 hidden layer and 2 output classes

$$rr(i) = r(i+1) - r(i); 1, 2, \ldots, m-1 \quad (1)$$

where r(i) is the R peak time for *i*th wave [3]. The extracted RR interval from each data segment was used to extract a total of 15 features [3].

3 Artificial Neural Networks Classifier

Artificial Neural Networks (ANN) is a computing system which draws a parallel from neurons in the human body and causes changes in the flow path based on the information received. It can be used as a tool for classification, pattern recognition and in other aspects of machine learning. ANN can be used as a powerful tool for diagnosing diseases and forms an integral part of machine learning. This technique makes use of Scaled Conjugate Grading (SCG), which is a supervised machine learning algorithm for feedforward neural networks [13, 14]. This work involves the use of four neural networks-feedforward network, fit network [15, 16], pattern network [17] and cascade forward network [18]. Feedforward network consists of layers of neurons with hidden neurons interconnected to each other. A fit network is a specialized form of Feedforward network [15] which uses a Genetic algorithm to govern the learning parameter. Pattern networks are derived from feedforward networks that can be trained to classify a dataset based on target classes [17] and are mainly used to identify patterns in the data. Cascade forward networks are derived from feedforward network and include connection of input nodes and all the previous layer nodes to the following layers [18]. The network is responsible for classification of the ECG signal into one of the five possible categories (Normal heartbeat or any one of the four diseases). Comparison between all the algorithms used in our work is shown with the best accuracy obtained.

4 Proposed Method

The neural network is trained with 70% of total samples in each case and each sample consist of 15 features by keeping the base as RR intervals. In our proposed method, we trained 10 networks named Net1–Net10 (Table 1). Each Net consists of trained features of two diseases and accuracy of each Net case has been projected in Table 2 (excluding normal case). Since four diseases have been taken and one normal case, the total number of combinations formed by combining two cases at once will be ten and each disease will repeat four times in this process (refer Table 1). By using ten Nets, a condition Table (Table 1) is formed which clearly explains the parameters that need to be considered during post-classification from NN output.

Table 1 Condition table taking two signal classes at a time

Networks		A	B	C	D	E
Net 1	AB	1	2	0	0	0
Net 2	AC	1	0	2	0	0
Net 3	AD	1	0	0	2	0
Net 4	AE	1	0	0	0	2
Net 5	BC	0	1	2	0	0
Net 6	BD	0	1	0	2	0
Net 7	BE	0	1	0	0	2
Net 8	CD	0	0	1	2	0
Net 9	CE	0	0	1	0	2
Net 10	DE	0	0	0	1	2

Table 2 Classification performance in terms of accuracy with 2 classes at a time, *denotes test file used

Signal classes	Cascade Net	Feed forward Net	Fit Net	Pattern Net
Arrhythmia*, Lang Term AT	66.67	93.33	93.33	80
Arrhythmia, Long-Term AF*	96	100	100	96
Long-Term AF*, Sleep Apnea	100	100	100	92
Lens Term AF, Sbrep Apnea*	62.5	70.83	70.83	75
Lens Term AF, Supraventricular Arrkvthmia	100	100	100	100
Lens Term AF, Supravenlricuhir Arrhvthmin*	100	100	100	100
Sleep Apnea Supraventricular Arrhythmia	45.83	70.83	45.83	62.5
Sleep Apnea, Supraventricular Arrkvthmia*	93.61	100	97.87	100
Arrhythmia*, Sleep Apnea	66.67	73.33	46.66	13.33
Arrhythmia, Sleep Apnea*	100	79.16	79.16	83.33
Arrhythmic* Supraventricular Arrhyrkmia	<1	20	<1	20
Arrhythmia Supraventricular Arrhythmia*	100	95.74	93.62	95.74

$$X_{train} = \begin{bmatrix} x_{11} & x_{21} & x_{31} & \cdots & x_{1\,15} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2\,15} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & x_{n3} & \cdots & x_{n15} \end{bmatrix} X_{testing} = \begin{bmatrix} x_{11} & x_{21} & x_{31} & \cdots & x_{1\,15} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2\,15} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & x_{m3} & \cdots & x_{m15} \end{bmatrix} \quad (2)$$

Each ECG signal is used to extract 15 features represented by {x_1, x2, x3… x15}, used to form the matrices given above with "n" as the number of samples used for training and "m" as the number of samples used for validation. From each classifier, we get two outputs which describes which out of the two classes the sample belongs to. If the probability of obtaining the first (A) neuron as output is high, then the sample is considered to belong to class 1 (winning class). Otherwise, it belongs to class 2 (winning class). In Table 1, each Net has two outputs- either the output belongs to class A or class B. In Table 1, the last five columns A–E are the four disease and one normal ECG case. The second column depicts the cases that are chosen for testing and first column with Net (trained network varies from 1–10) respectively. The number "0", "1" and "2" are used in the table to denote the winning class as explained above. For example, in the case of Net1, if two diseases sampled from A and B are used to train the network, then "1" denotes that the sample belongs to disease A, while "2" denotes that the sample belongs to disease B and "0" implies not applicable diseases. In our proposed method, we trained 10 combinations of the five classes and dedicated 10 networks and their accuracy is presented in Table 1. Using these trained networks, the following process has been carried out. The condition table is used to find the value of flag variables FA to FE.

For coding convenience, we use "1" for NetX and "2" for NetX'. Either NetX or NetX' will be high according to the condition table which is used to determine the value of flag variables FA, FB, FC, FD and FE, the values ranging from 0 to 4.

Flag variables are defined as

FA = Sum (Net1, Net2, Net3, Net4); FB = Sum (Net1', Net5, Net6, Net); FC = Sum (Net2', Net5', Net8, Net9)

FD = Sum (Net3', Net6', Net8', Net10); FE = Sum (Net4', Net7', Net9', Net10')

Finally, Maximum of FA, FB, FC, FD, and FE will take as the output.

5 Results

For signal processing (feature extraction), the database of all the required samples was collected from physionet.org. The database of the following diseases was collected from the MIT-BIH database [2, 19]:

- Sleep Apnea
- Normal Sinus Rhythm
- Long-term Atrial fibrillation
- Arrhythmia
- Supraventricular Arrhythmia.

Each file was downloaded as a Matlab file and used for further processing. 70% of the sample was taken for training and rest 30% was used for testing. Taking 2 diseases at a time, the ANN was trained and tested with test files of both classes and its accuracy was calculated (Table 2). *denotes that the particular case's test signal was used while testing. For more clarity, accuracy of each trained network has been presented in two rows with four columns which include Cascade Net, Feedforward Net, Fit Net and Pattern Net. As observed from Table 2, maximum accuracy is obtained on training the network with Long-Term AF and Supraventricular Arrhythmia and least accuracy is obtained with classes Arrhythmia and Supraventricular Arrhythmia. Amongst all networks, normal Feedforward network which uses SCG algorithm yields the best result. Amongst Arrhythmia and Long-Term AF, Feedforward and Fit Net produce the best result. Similarly, amongst long-term AF and Sleep Apnea, Feedforward and Fit Net produce the best result. But in the case of sleep Apnea and Supraventricular Arrhythmia, Feedforward and pattern Net produce the best result and in the case of Arrhythmia and sleep apnea, cascade and Feedforward produce average results.

Since the samples from Arrhythmia, Supraventricular Arrhythmia are similar because of similarity in the disease, accuracy can be improved by providing more samples for training. DNN can be used to extract features more accurately. In terms of networks, for cascaded Net, Long-term AF and Supraventricular Arrhythmia produce 100% accuracy while Arrhythmia and supraventricular produces < 51% accuracy. Similarly, for other three networks, Long-term AF and Supraventricular Arrhythmia produce 100% accuracy.

To compare the results obtained through our method, all four networks were trained using all test samples which resulted in five classes and results of the multiclass network are shown in Table 3. It also shows the results obtained from the proposed method using the dual classifier (binary classifier). Results are obtained for all four diseases and the normal case.

From Table 3, it can be inferred that in most of the cases, the proposed method produces better results and better results are obtained while classifying Long-Term AF, like with cascade net, the accuracy has been increased to more than 87%. In case of normal disease samples, accuracy of three amongst four networks increased by 9.09%. Similarly, accuracy of the proposed method in classifying Arrhythmia with Cascade net increased by 27.579%. With FeedForward network, accuracy of Arrhyth-

Table 3 Classification performance comparison between normal and proposed classification method with 5 classes take at a time

Signal classes	Cascade Net		Feed Forward Net		Fit Net		Pattern Net	
	Normal	Proposed	Normal	Proposed	Normal	Proposed	Normal	Proposed
Arrhythmia	13.33	40.909	<1	63.636	<1	54.54	<1	50
Normal	<1	<1	<1	9.09	<1	9.09	<1	9.09
Long-Term AF	<1	88	100	100	100	100	100	100
Sleep Apnea	4.16	88	33.33	40	45.83	32	62.5	37.73
Supra Arrhythmia	78.72	4	91.49	60	91.48	80	87.23	95.83

mia classification increased by approximately 63%, while with Fit net, Arrhythmia classification accuracy increased by 54.54%. With Pattern net, arrhythmia classification accuracy increased by 50%.

6 Conclusion

The network was trained with multiple sets of neurons and gave the best result with seven neurons in one input layer. FeedForward net and Fit net performed best while classifying between arrhythmia with long-term AF, and long-term AF with sleep apnea. All the four networks performed equally well while classifying between long-term AF and supraventricular arrhythmia. FeedForward net performed best while classifying between sleep apnea with supraventricular arrhythmia. Cascade net provides the best performance when classifying between Arrhythmia and sleep apnea. Table 3 compares the performance of the normal network multi-classification and the proposed post-classification on binary classification respectively. The proposed method performs better than the multi-classification network in all the cases of Arrhythmia, normal sinus rhythm and long-term AF. Moreover it produces superior results than the multi-classification network when used with cascade and feed Forward net in case of sleep apnea. It also performs better in case of supraventricular arrhythmia when used with pattern net. Hence, it can be concluded that the proposed method provides a comparatively efficient way to classify ECG signals among the 5 classes taken. It can also be concluded that feedforward net provides the best solution in most cases when comparing the above diseases taken 2 at a time.

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