

# Identification and Classification of Cardiac Arrhythmia using Neural Network

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## Abstract

This paper proposes a Neural Network classifier model for the automatic identification of cardiac arrhythmias. Our main aim is to have a better classification rate in a minimum time with simple algorithms in their implementation. The wavelet transform is used to extract the parameters which characterize different arrhythmic pathologies and thus constitute the bases of learning and generalization of the networks of neurons. A pre-processing by filtering adapted by the Butterworth Filter is applied to the signals before the extraction. Classification is done using Neural Network classifier further dimension reduction to reduce the overhead of the training is performed by PCA. The ECG signals used in this study are taken from the internationally known MIT-BIH Arrhythmia Database. The results obtained are satisfactory with average recognition rates of 95.7% in NN and 97.1 % for PCA-NN.

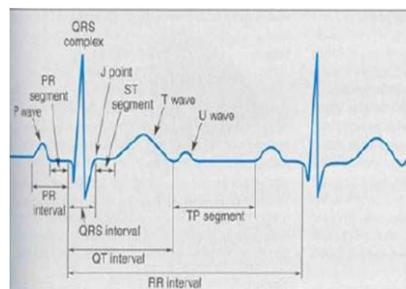
**Keywords:** Cardiac arrhythmias, DWT, MIT-BIH, Neural Network, QRS.

## 1. INTRODUCTION

Irregular beats form two groups: the first comprises fibrillation and ventricular tachycardia which are dangerous and the ECG signal represents the electrical activity of the need for immediate therapy with a heart, is probably the diagnostic technique of the defibrillator; the second group concerns the most common cardiac pathologies. ECG is non-hazardous arrhythmias but which require a non-stationary randomized signal, structured preventive therapy of other problem. These disorders (Figure 1) by the succession of wave and cardiac forms are also classified according to the frequency and the interval of the (P, Q, R, S, and T). Any rhythm modification described by the number of cycles or morphological or temporal contractions of its events (or ventricular (depolarization of the ventricles) by chronic) constitutes a cardiac pathology. The minutes, marked on the ECG by the number of changes concerning the complex rhythm or frequency QRS are cardiac arrhythmias (fatal diseases). A number of works [1], [2], [3], [4], [5], [6], and [7] have been successfully performed for clinical and technological problem highlighting arrhythmias, but they defy by (means and approaches). They are

varied and the choice of types and number of parameters to approach them are also varied, significant that characterize the arrhythmia in question. It is possible to define the premature ventricles) in cardiac arrhythmias by the irregularity of the beats [6] [8] with cardiac arrhythmias or as a group of different parameters, approaches and results.

On the other hand, several classification methods have been proposed in the literature to classify the arrhythmic beats in normal or abnormal (arrhythmic) beats for some and others according to different rhythms (TV and BV) [4], [9] and [10] compares three different procedures to characterize the rhythms to be classified by an LVQ network. But in most cases the essential parameters are measured around the QRS complex (width, shape and amplitude) and more particularly the detection of the R wave which is a dominant parameter [4], [6], [9]. Especially for atrial arrhythmias (atrial fibrillation) the P wave and the PR interval are privileged.



**Figure 1: Characteristics of a heartbeat**

This varied study allowed us to establish a number of significant parameters to classify the arrhythmias present in the QRS complex.

Inspired by several works cited, we propose an approach of automatic recognition to detect several arrhythmias. It involves methods of non-linear analysis by neural networks and tools of non-stationary analysis by the wavelet transform (WT) which have very interesting adaptation properties. Currently the wavelet method has become a technique, par excellence, very effective to extract the parameters that characterize the arrhythmia in its various forms. Many works using wavelets have been successfully carried out, in particular the articles [11], [12] and [13] have amply demonstrated the contribution of the ECG signal. It makes it

possible to produce the start and end times of waves and intervals and to filter the signal.

Nonlinear array analysis of artificial neurons (ANN) seems promising to provide indicators relevant to the identification of pathologies Heart disease. The literature is rich in works that have exploited the advantages of ANN to automatically detect or classify cardiac arrhythmias such as [4], [6] [14], [15], [16], [17], [18] and [19] where different classification approaches were discussed. But a classifier can be effective for an ECG and fail with another ECG or other pathology. This justifies the large number of works in this field. There will always be investigations because the slightest hope of improving performance saves a life. Previously Nath et al. [20] shown that for a particular study it is often difficult to identify the best classifier for lack of proper guide. Many comparative studies of classifiers are conducted. The combination of different approaches can be a powerful tool to improve the quality of classification algorithms. In particular, methods that take into account the a priori knowledge of the data have been more successful. This is why we propose vector quantization (VQ) learning algorithms whose essential tool is the codebook. By constructing the codebook, the VQ takes into account the specificities of the given application and thus makes it possible to exploit the information a priori. This is the combination of the SOM-LVQ algorithms and that of the RBF network. Each network (ANN) having learned the key characteristics of each arrhythmia, receives as input, in the test phase, a vector of parameters (defining a heartbeat) coming from the WT, discriminates in two or more classes of arrhythmias.

Our results are evaluated on the ECG recordings of MIT-BIH Data Arrhythmias, well known by ECG users, for detecting the following pathologies: Extra ventricular (V), Extra supraventricular systolic (S), Fibrillation Ventricular flutter (V), ventricular

tachycardia (VT) and ventricular bradycardia (Br), which we will classify according to the rhythm and the frequency, the symbols are those used in MIT-BIH annotation.

## 2. Methodology

### 2.1 Flow chart of Detection

We summarize the essence of the procedure established in the flowchart of Figure 2. Because our goal is to automatically detect and classify arrhythmias, the performance of the classifier depends on the choice of significant parameters to discriminate the normal beats of pathological beats. The performance of an ANN are strongly related to the quality of extraction of disease indicators. Therefore, pre-processing of the ECG signal is necessary before these parameters can be extracted accurately. Here, pre-processing involves baseline correction and noise suppression.

### 2.2 Pre - Processing

**Correction of the ECG Signal:** Pre-processing involves making the signal clean without artifacts. Before correcting the noise, it is first necessary to correct the signal, this correction is made by a median filter in order to straighten the baseline and return the signal to a standard mark. This operation is represented by equations (1), (2) and (3).

$$Y_{ecg_2}(n) = Y_{ecg_1}(n) * f_1(n) \tag{1}$$

$$Y_{ecg_3}(n) = Y_{ecg_2}(n) * f_2(n) \tag{2}$$

$$Y_{corrected}(n) = Y_{ecg_1}(n) - Y_{ecg_3}(n) \tag{3}$$

The median filter is an effective tool for correcting the signal without loss of information. It is a classic nonlinear filter, its principle is the following:

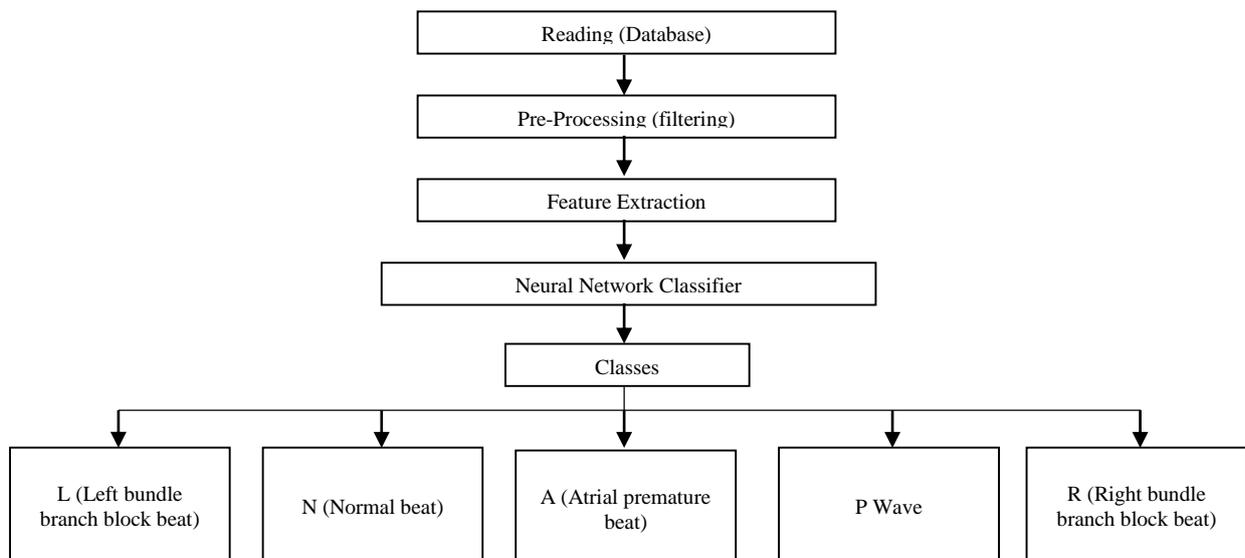


Figure 2. Flow diagram of the procedure adopted

For each sample of the signal, the neighbouring samples included in the window are classified by increasing values. The median value of the classified samples is taken and assigned to the current sample. The correction process is designed so as to eliminate the P wave and the QRS complex from the original signal  $Y_{ecg_1}(n)$  by a first filter ( $N$ ) of a width of 150 milliseconds, and then eliminating the T wave from the signal  $Y_{ecg_2}(n)$  resulting from the first filtering by a second median filter having a width of 50 milliseconds. The signal  $Y_{ecg_3}(n)$  resulting from the second operation therefore contains only the baseline. The corrected signal  $Y_{corrected}(n)$  is then obtained by a subtraction between the original signal  $Y_{ecg_1}(n)$  and the signal  $Y_{ecg_3}(n)$  resulting from the two filtering operations.

**Signal Filtering using Butterworth Filter:** ECG measures electrical potentials on the body surface via contact electrodes. Conditions such as movement of the patient, breathing, and interaction between the electrodes and skin cause baseline wandering of the ECG signal. In this stage a method of signal filtering is applied to remove baseline wandering of the ECG signal. Here we have used Butterworth filter.

The Butterworth signal processing filter is a pass band filter that has a flat frequency response. According to the characteristics of an ideal filter, the filter should eradicate vague frequencies along with uniform sensitivity for required frequencies. Butterworth filter is not ideal but close in nature that has increasing number of filter elements for desired spectrum. In process of filtering the substantial ripple in pass band and component values of required choice was interactive in nature. This filter proved that a low pass filter with cut-off frequency 1 radian per second can be designed with frequency response:

$$g\Omega = \sqrt{\frac{1}{1+\Omega^{2n}}} \tag{4}$$

Here,  $g$  is the Butterworth gain,  $n$  is the order of filter and  $\Omega$  depicts normalized frequency. The gain will be unity or null then filtered output is given as:

$$F_{out}(k) = X(k) \times g\Omega \tag{5}$$

Depending upon gain value, the filtered output will be  $F_{out}(k)$  for unity gain and flipped for null gain. The inverse Fast Fourier Transform is the conversion of frequency domain components to time-space domain for signal regeneration. The EEG components after cleaning are reverted by following expression:

$$x(t) = \left(\frac{1}{N}\right) \sum_{k=1}^N F_{out}(k) e^{\frac{(2\pi i)}{N}(t-1)(k-1)} \tag{6}$$

### 2.3 Feature extraction using DWT

Let  $x(t)$  be the signal (ECG) to be analyzed, the mother wavelet  $\psi(t)$  is chosen to serve as a prototype for all the windows. All the windows that are used (daughter wavelets) are dilated (or compressed) and offset versions of the mother wavelet.

The DWT is a function of two parameters  $\tau$  and  $s$  which is the coefficient of the (WT) of the signal  $x(t)$  using the parent ocean of analysis  $\psi(\cdot)$ :

$$DWT_X^\psi(\tau, s) = \psi_X^\psi(\tau, s) = \int_{-\infty}^{\infty} X(t) \psi_{\tau,s}^* \tag{7}$$

Once the mother wavelet is chosen, the calculation begins with  $s = 1$ . This first value of  $s$  corresponds to the most compressed wavelet, the DWT is calculated for all the values of  $s < 1$  and  $s > 1$ . Then the Two parameters  $\tau$  and  $s$  are increased by a sufficiently small step. This corresponds to the sampling of the time scale plan. When the process is completed for all desired values of  $\tau = 12$  and  $s = 6$ , in this case the SWT of the signal is calculated.

### 2.4 Dimensionality Reduction using Principal Component Analysis

An enormous measure of information is not effective to perform a pattern recognition process. Therefore, the PCA is applied to reduce the dimensionality.

Assuming  $R$  is the number of data samples be in the training set and each sample  $X_i$  is a 2-dimensional array having feature values of size  $m \times n$ . A sample  $X_i$  may be transformed into a vector of  $D$  ( $D = m \times n$ ) features.

$$X_i = (x_{i1}, x_{i2}, \dots, x_{iD}) \tag{8}$$

Vector formation is performed using the rows of features of the data sample.

Training set of  $R$  data samples is defined by:

$$X = (X_1, X_2, \dots, X_R) \subset \mathcal{R}^{D \times R} \tag{9}$$

Also, the covariance matrix ( $\Gamma$ ) is given by:

$$\begin{aligned} \text{con}(X, Y) &= \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{(n-1)} \\ &= \phi\phi^T \end{aligned} \tag{10}$$

Where,

$$\phi = (\phi_1, \phi_2, \dots, \phi_R) \subset \mathcal{R}^{D \times R} \tag{11}$$

And the mean of training set is represented by:

$$\bar{X} = \frac{1}{(n-1)} \sum_{i=1}^n X_i \tag{12}$$

Covariance matrix is used to calculate the eigenvectors and Eigen values. Then suppose:

$$Q = (Q_1, Q_2, \dots, Q_R) \subset \mathcal{R}^{D \times R} (r < R) \tag{13}$$

Here the  $r$  eigenvectors analogous to  $r$  leading non-zero Eigen values. Now, each of the data samples of the training set  $X_i$  is estimated into the eigenvector

to achieve its equivalent feature  $Z_i \in \mathcal{R}^{D \times R}$  which is represented as:

$$Z_i = Q^T Y_i, i = 1, 2, \dots, R \tag{14}$$

Where,  $Y_i$  is the reduced dimension of  $X_i$ .

**Classification using Neural Network Classifier**

The goal is to automatically classify the heartbeat. The choice of the classifier is very important, it constitutes the decision element in a system of recognition of forms. The neuronal connectionist approach retains the idea of computation Recursive, parallel and fast during the learning phase. When the classes are presented with very complex separation surfaces, the supervised networks are more appropriate because of their local learning. The ANN are generally associated with an algorithm called "learning" capable of modifying more or less automatically the processing performed of a given task.

Back Propagation Neural Network (BPNN) generates complex decision boundaries in feature space. BPNN in specific circumstances resembles Bayesian Posterior Probabilities at its output. These conditions are essential to achieve low error performance for given set of features along with selection of parameters such as training samples, hidden layer nodes and learning rate. In else case, the performance of BPNN could not be evaluated. For  $W$  number of weights and  $N$  number of nodes, numbers of samples ( $m$ ) are depicted to correctly classify future samples in following manner:

$$m \geq O \left( \frac{W}{\epsilon} \log \frac{N}{\epsilon} \right) \tag{15}$$

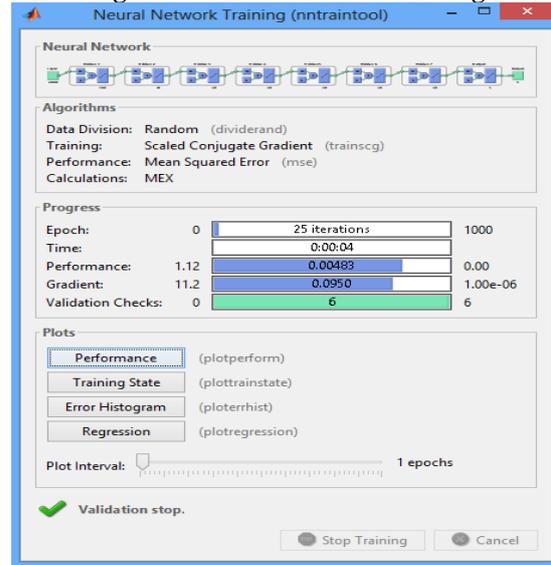
The theoretical computation of number of hidden nodes is not a specific process for hidden layers. Testing method is commonly entertained for selection of these followed in the constrained environment of performance [20].

**3. RESULT ANALYSIS**

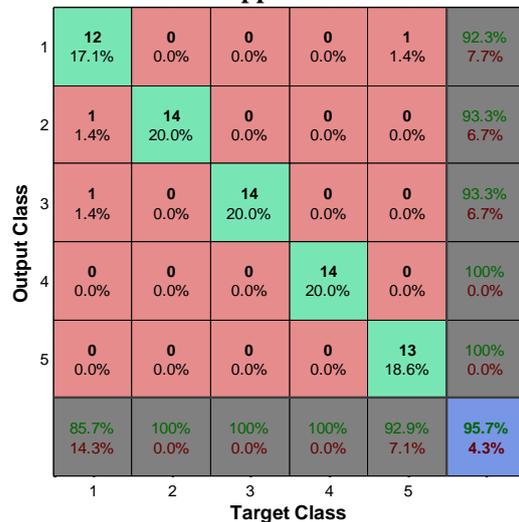
Proposed approach is simulated on MATLAB R2014a. Performance of the proposed research work is carried out using certain evaluation parameters, namely; Accuracy, Recall, Precision, F-Score, Sensitivity and Specificity.

The row and column are the class of ECG samples, taken from the database. There are 5 set of classes and each class having 14 ECG samples of with different classes of beats i.e. L (Left bundle branch block beat), N (Normal beat), A (Atrial premature beat), P and R (Right bundle branch block beat). The confusion matrix plot indicates the accuracy i.e. 95.7% for the proposed Neural Network based approach.

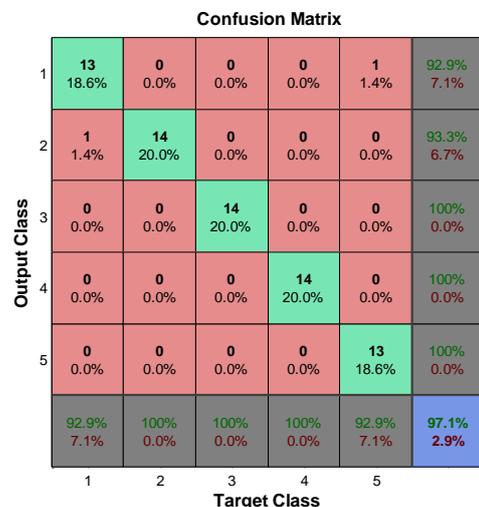
**Figure 3: Neural Network training**



**Figure 4: Confusion Matrix plot for NN approach**



**Figure 5: Confusion Matrix plot for PCA-NN approach**



**Table 1. Accuracy with training overhead reduction**

Methods	Accuracy	Training overhead
Neural-Network	95.7%	1000x150
PCA-Neural-Network	97.1%	1000x118

**CONCLUSION**

The purpose of our work is to automatically classify detected cardiac arrhythmias on real ECG signals from the MIT-BIH database. The choice of nonlinear classification by artificial neural networks gives good performances because of their separation power from complex situations such as supraventricular arrhythmias. The performance of ANN also strongly depends on the quality of QRS extraction. The work that improved the extraction of the characteristics has had high results. The detection of the wavelet start and end of wavelets has been very effective for the QRS complex. This has guided our choice of approach. It is found that the efficiency of detection is nearly around 95.7% as the data is compared with MIT-BIH database.

The slightest improvement provided by the algorithms is a good result because it involves saving a life. We can say that our procedure also has important potentialities, but in order to be able to be the subject of a method of aid to the diagnosis (applicable clinically) one must first treat more ECGs, in particular for the rhythm, to do Vary the database and treat other cardiac pathologies. Theoretically, neural networks are optimum when the database is very large. It is necessary to find explanations for the contradictory results between the two networks.

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