

Performance Analysis of Artificial Neural Networks for Cardiac Arrhythmia Detection

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Abstract- In this paper an effective and most reliable method for appropriate classification of cardiac arrhythmia using automated based Artificial Neural Network (ANN) has been proposed. The results are encouraging and are found to have produced a very confident and efficient arrhythmia classification, which is easily applicable in diagnostic decision support system. In this paper the authors have employed 3 neural network classifiers to classify three types of beats of ECG signal, namely Normal (N), and two abnormal beats Right Bundle Branch Block (RBBB) and Premature Ventricular Contraction (PVC). The classifiers used in this paper are K-Nearest Neighbor (KNN), Naive Bayes Classifier (NBC) and Multi-Class Support Vector Machine (MSVM). The performance of the classifiers is evaluated using 5 parametric measures namely Sensitivity (Se), Specificity (Sp), Precision (Pr), Bit Error Rate (BER) and Accuracy (A). Hence MSVM classifier using Crammers method is very effective for proper ECG beat classification.

Index Terms: Accuracy, Classification, ECG, KNN, MSVM, NBC, Precision and Sensitivity.

I. INTRODUCTION

In ECG signals processing we have noticed an increasing tremendous improvement. The most important diagnosis tool for assessing proper functioning of heart is a bio-electric signal called as Electrocardiogram (ECG), which represents the electrical activity of heart. The origin and propagation of electrical potential through cardiac muscles can be recorded by an ECG signal. It provides important and useful information about the rhythm and proper functioning of heart. These ECG records are formed of six peaks or six valley points represented by P wave; QRS complex; T wave; R wave and U wave (Fig 1).

The main characteristic features which are inspected in the normal beat phases of a heart include the duration, the shape, P wave, QRS complex, T wave and RR interval. The classification of these beats is an important task in the coronary care unit and can be considered as an essential non-invasive tool for proper diagnosis of heart diseases. The recording of ECG signal is taken by placing electrodes on the surface of the body i.e. arms, legs and chest [2]. Any variation in these parameters indicates the heart illness which may occur by any reason. Any type of irregularity in the beat phases of the heart can be called as arrhythmia. Early detection of arrhythmia provides the information about heart abnormalities and increases the life of human and enhances the quality of living [3].

A patient may have different ECG waveforms, and in a single ECG, different types of unlike beats may occur resulting in arrhythmia [4]. The beats can be classified as normal or abnormal. The abnormal beats include Premature Ventricular Contraction (PVC), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Atrial Premature Beat (APB), and Paced Beat (PB). The interpretation of this ECG signals is one of the applications of pattern recognition,

which automatically categorizes into one of the class (normal or abnormal) given a number of different classes. Hence there is a need of a system that could properly analyze ECG signal with high accuracy so that early treatment could be started. To achieve this type of system many works have been done in the field of Digital Signal Processing, Image Processing, Biomedical Digital Signal Processing etc. and the one which is found to be the most prominent among them is Artificial Neural Network (ANN) with promising results to complex problems [5]. Given a complex dataset, identifying the correct pattern can be considered as one of the major goal in medicine. ANN's can not only detect pattern but also differentiate between different patterns which are not apparent to human analysis.

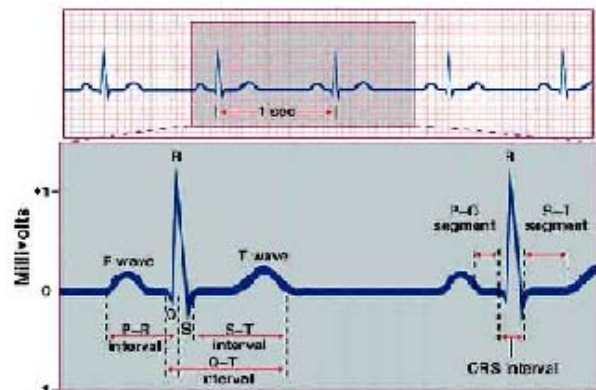


Fig 1. A Typical ECG waveform [1]

Numerous related literature works with heart disease diagnosis using ANN were demonstrated. Mitra and Chaudary [6] proposed the three stage technique for detection of heart diseases. This proposed method consists of three modules, denoising module (using stationary wavelet transform), feature extraction module and ANN classification module. A novel pruning approach is used to classify ECG arrhythmia and classification accuracy is reported as 68.47% in [7]. Zuo et. al [8] used Kernel differential weighted KNN classifier and showed an accuracy of about 70.66%. In [9] arrhythmia classification using serial fusion of SVM was done with an accuracy of about 76.1 %. Multilayer neural network has been used to classify arrhythmia QRS complexes and for ischemia detection [10].

The main objective of this paper is to easily analyze fusion beats of a particular patient for accurate diagnosis of heart problems in less time so that the cardiologist has the primary information about the ailment and could start the treatment as early as possible. Here two types of abnormalities considered, Right Bundle Branch Block (RBBB-widened QRS width i.e. > 0.10 Sec) and Premature Ventricular Contraction (PVC-shorter R-R interval). The total duration of ventricular tissue depolarization can be measured using QRS interval (normal QRS interval lies between 0.06 Secs – 0.10 Secs in adults). Due to automated determination of heart rate using QRS interval, it

can be served as a basis for different classification schemes for diagnosis of cardiac diseases. Thus, the fundamental reference for all automated ECG analysis algorithms is the detected QRS wave. These QRS detected complex features are set as input to neural network classifier for appropriate diagnosis. The different ANNN classifiers used in this paper will be presented in the next section.

II. METHODOLOGY

The proposed method is depicted in block diagram for detection and classification of arrhythmias for a given ECG signal (Fig 2).

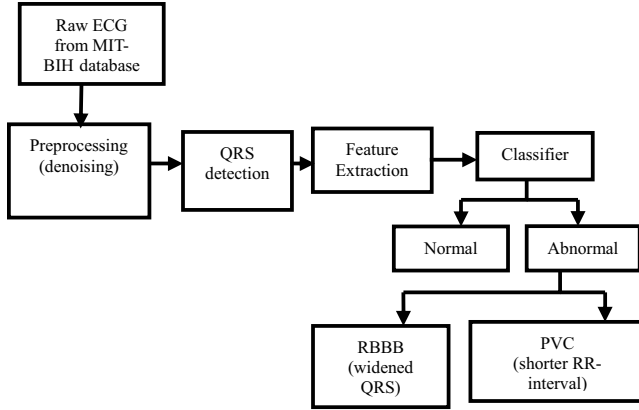


Fig 2. Block diagram of ANN classifier

The first step in the block diagram consists of loading of raw ECG signal from MIT-BIH arrhythmia database [11]. A wide range of ECG signal collection including different abnormalities were collected from the MIT-BIH arrhythmia database, which contains 48 recordings with each record containing 30 minutes ECG lead signal sampled at 360 Hz with 11 bit resolution. These 48 recordings cover all 16 different types of heart beats including Normal beat. In this paper a total of 20 ECG records are used to collect different types of beats. We have extracted 8 beats from each ECG signal sampled at 2223 samples per second and classified these beats under the following classes as normal sinus rhythm (N), Right Bundle Branch Block (RBBB), or Premature Ventricular Contraction (PVC)

The second step contains signal preprocessing which is denoising of loaded raw ECG signal. To gain better efficiency of a signal preprocessing of the signal is mandatory. As ECG signals are non stationary signals they are easily corrupted by noise and interference. Some of the prominent sources of noise in ECG signal are Power Line Interference (PLI) caused by fluctuations in power constituted by 50 Hz harmonics, Electromyography (EMG) caused by human muscle tension, Base Line Drift (BLD) caused by low frequency (<1 Hz) interference like human breathing. A Band Pass Filter (BPF) is used for denoising of ECG signal with a cascaded LPF and HPF. The reason for selection of BPF for denoising is it provides high SNR, simple in implementation and requires minimum coefficients compared to other denoising methods [12-13]. A LPF eliminates EMG and PLI with a cut-off frequency 10 Hz and HPF eliminates motion artifacts with cut-off frequency 0.5 Hz.

The third step involves detection of QRS waves from the preprocessed signal. The most important step for the analysis of heart rate variability is accurate QRS detection. In this paper we have used Pan-Tompkins algorithm for QRS complex wave detection [14]. Though many techniques exist for QRS detection, first derivative based method is often used for large dataset. One of the most popular first derivative method is Pan-Tompkins algorithm which uses a

patient specific threshold for QRS peak detection and have accuracy of about 99.68% than other real time algorithms [15].

The fourth step involves feature extraction from QRS detected ECG signal. The characteristic features of an ECG signal are divided as statistical and morphological features. To feed the classification process the three temporal features that were adopted where QRS complex duration, RR interval and RR interval averaged over 8 beats. Setting these characteristic features as input, three types of ANN classifiers: K-Nearest Neighbor (KNN), Naive Bayes Classifier (NBC) and Multiclass Support Vector Machine (MSVM) are implemented. Performance analysis of these three classifiers is evaluated using some metrics that are Sensitivity, Specificity, Precision, Bit Error Rate and Accuracy.

A. K-Nearest Neighbor Classifier

This algorithm is considered as one of the simplest non-parametric pattern recognition method which is used for classification as well as regression [16]. To perform classification, KNN finds the nearest distance from the training data and compare the corresponding predefined values of different heart disorders with sampled data. The given input data consist of K closest training examples, where K represents the number of neighbors which is small positive integer. If K=1, then the class is simply assigned to the class of its nearest neighbor. This statistical classification algorithm which is considered as an instance based learning method is used to store all available data points and classifies new data points based on a similarity measure. Whenever a new point is to be classified, its K-nearest neighbors are found from the training data. The idea behind this method is to assign new unclassified data points to the class to which the majority of its K nearest neighbors belongs. The advantage of KNN over other supervised learning methods such as neural networks, decision tree, logistic regression, Support Vector Machine is that , it can classify the given ECG signal when the class size is more than two [17]. The classification accuracy of KNN largely depends not only on the value of K, but also on the type of distance metric used to compute nearest distance [18]. A small value of K results in high influence of noise and interference, whereas large value of K makes it more complex. Taking these two conditions into consideration, an attempt has been made using four fold cross validation method to find optimal value of K (K=1, 3, 5, 7) and also the type of distance metric (Euclidean distance) to be used. Highest classification accuracy is achieved using Euclidean distance for K=5. The classification is performed by finding the minimum distance from given ECG dataset which contains the training data (input) and reference values. The parameter with highest accuracy is chosen to define a classifier. In this paper K=5 and Euclidean distance metric is proposed for KNN classification. The Euclidean distance is calculated by using:

$$d(x, y) = \sqrt{\sum_{i=1}^N (x_i - y_i)^2} \quad (1)$$

where x, y are true and measured values respectively, and N= number of values taken (2223 samples per second).

B. Naive Bayes Classifier

Naive Bayes is one of the simple and supervised machine learning classification method which is based on Bayes theorem with good results in classification problem [19]. It is a family of simple probabilistic classifiers with enhanced independent assumption between the given features. Given the instance, this classifier conditionally computes the probabilities of the class (normal or abnormal) and picks the class with highest priority or highest

posterior. The probabilities of unknown attributes are skipped, nominal attributes are estimated by counts and continuous attributes are estimated by normal distribution [20]. The probability model for

Naive Bayes classifier is a conditional model given as $P\left(\frac{K}{O_1 \dots O_n}\right)$,

where K are dependent class variables on $\{O_i\}_{i=1 \dots n}$ and O_1, O_2, \dots, O_n are feature variables. In this paper, $n=3$ which represent 3 feature variables i.e. QRS complex duration, RR interval and RR interval averaged over 8 beats.

As applied to medical context, a conditional probability is the likelihood of some conclusion K, given some evidence or observation O where a dependence relation exists between K and O. This probability is denoted as

$$P\left(\frac{K}{O}\right) = \frac{P\left(\frac{O}{K}\right)P(K)}{P(O)} \quad (2)$$

Using Bayes theorem, it can be rewritten as

$$P\left(\frac{O}{K}\right) = \frac{P\left(\frac{K}{O}\right) \cdot P(O)}{P(K)} = \frac{P(K, O)}{P(K)} \quad (3)$$

Eq. (3) represents a conditional relationship to gain probably information about K or O. Given an evidence set as $O = \{O_1, O_2, \dots, O_n\}$, the numerator in the above Eq. (3), $P(K, O)$ can be expanded using conditional probability to $P(K, O_1, \dots, O_n) = P(K) \cdot P(O_1, \dots, O_n / K)$ (4)

$$= P(K) \cdot P(O_1 / K) \cdot P(O_2, \dots, O_n / K_1 O_1) \\ = P(K) \cdot P(O_1 / K) \cdot P(O_2 / K) \cdot P(O_3 / K) \dots \dots \dots \text{Therefore}$$

$$P(K, O_1 \dots O_n) = P(K) \cdot \prod_{i=1}^n P(O_i / K) \quad (5)$$

Where n = number of binary features used for classification, and

$P\left(\frac{O_i}{K}\right)$ is the independent probability distribution. The probability of the class of interest can be computed using Eq. (5). If there are N classes, each $P\left(\frac{O_i}{K}\right)$ can be expressed in terms of r parameters then

the Naive Bayes model has $(N-1)+nrN$ parameters. In this paper $N=3$, and $r=1$ (Bernoulli variable as a feature) are common, so number of parameters of NBC is $3n+2$, where n is the number of binary features used for classification.

C. Multi-class Support Vector Machine Classifiers

In a multi-class classification, when each training point belongs to one of N different classes, then there is a need to construct a function which easily predicts the class to which the new data point belongs to [21]. A simple SVM is a binary classifier which classifies only two classes [22]. Where as a multi class SVM solves N -class classification ($N=3$; 1-normal and 2-abnormal) by constructing a set of binary classifiers f^1, f^2, \dots, f^N , each trained to separate class from rest.

Here two methods are employed for multi-class SVM classification, One-against-all SVM method and Crammers SVM method. Comparing the performance accuracy, Crammers SVM shows highest accuracy and is preferred.

(i). One-against-all

The principle behind this approach is to construct a SVM for each class by discriminating that particular class against the remaining classes ($N-1$). The number of SVM's used here is 3 ($N=3$). A text pattern 'x' is classified by assigning the class with maximum value of discriminate function $f(x)$. If the m^{th} binary classifier is trained using a set of data then the desired output is (x_i, y_i) , where y_i is the desired output of x_i . When $y_i=+1$, the desired outputs are called as positive examples and when $y_i=-1$, the remaining ($N-1$) classes are called as negative examples. Though this method is considered as the earliest implementation for SVM classification, a major problem of one-against-all is that the training set is imbalanced [23].

(ii). Crammers MSVM

The extension of binary SVM classifier to more than two classes was done by [24]. Here a SVM classifier is trained for minimizing Eq. (6), by solving the primal optimization problem given as

$$\min_{w_c} \frac{1}{2} \sum_{c=1}^d \langle w_c^T w_c \rangle + k \sum_{n=1}^l \xi_n \quad (6)$$

where d is the decision function ($d=3$), ξ_n is a non-negative slack variable which measures degree of misclassification of signal x , and k is a constant ($k=1$).

By separating training vectors of class 'c' from other classes, there exist a decision function 'd'.

Eq. (6) is subjected to the constraints

$$w_{y_n}^T \phi(x_n) - w_c^T \phi(x_n) \geq e_n^c - \xi_n \quad (7)$$

for $n=1, 2, \dots, l$.

$$\text{Where } e_n^c = 1 - \delta_{y_n, c} \quad (8)$$

$$\text{Where } \delta_{i,j} = \begin{cases} \text{Kronecker Delta Function} \\ 1 & \text{for } i=j \\ 0 & \text{otherwise} \end{cases}$$

The decision function is given as

$$f_c(x) = \arg \max_c (w_c^T \phi(x)) \quad (9)$$

III. RESULTS AND DISCUSSION

The simulation results of the QRS detected ECG signal for record number 100 is depicted in figure below (Fig 3, 4, 5, 6). We have evaluated the performance of all three classifiers using five metrics, Sensitivity, Specificity, Precision, Bit Error Rate and Accuracy (Table. 1). These metrics are defined using True Positive (TP), true Negative (TN), False Positive (FP) and False Negative (FN). When the classifier decision of arrhythmia detection coincides with cardiologist decision then TP occurs. When the classifier decision of absence of arrhythmia coincides with cardiologist decision then TN occurs.

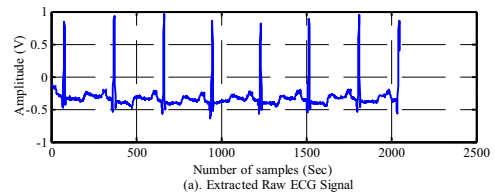


Fig 3. Extracted raw ECG signal of record no. 100

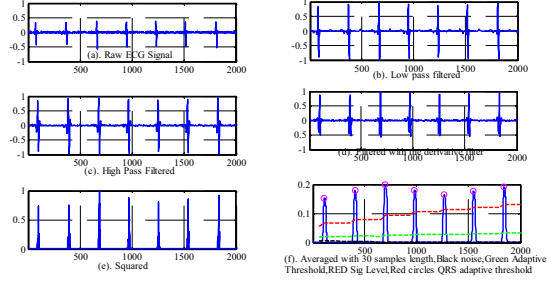


Fig 4. Pan-Tompkins algorithm applied to record 100

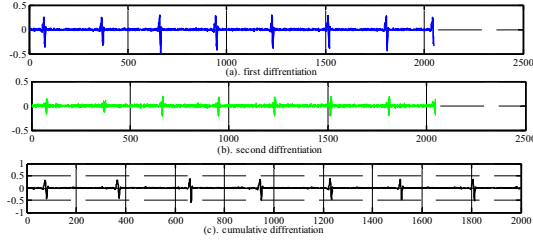


Fig 5. (a). First Differentiation (b). Second Differentiation (c). Cumulative Differentiation

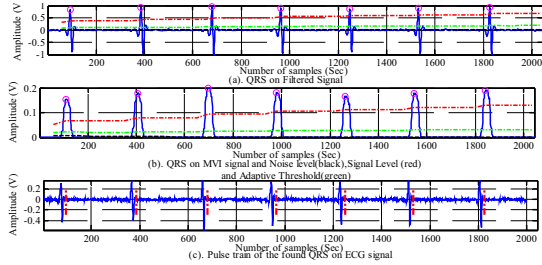


Fig 6. Detected QRS complex of record no. 100

Fig 3. represents the extracted raw ECG signal of record number 100 from MIT-BIH database. The first step involved in QRS detection using Pan-Tompkins algorithm is Band Pass Filtering the signal which is a combination of LPF and HPF as shown in Fig (4). Second step involves differentiation (Fig (5)), which overcomes the base line drift. To attenuate low and emphasize high frequency components, the differentiated signal is squared as shown if Fig 4(e). The squared signal is fed to a moving average filter and a total of 7 ECG beats are extracted from each record as shown in Fig 6 (b). These extracted ECG beats are fed to classifiers..

When a normal ECG is classified as abnormal then FP occurs and finally when an abnormal ECG is labelled as normal FN occurs. The performance of each classifier is governed by these operation parameters. Sensitivity refers to the true positive rate which is calculated using Eq. (10). It refers to the rate of correctly classified normal signals.

$$Se(\%) = \frac{TP}{TP + FN} \quad (10)$$

Sensitivity of MSVM classifier using Crammers method is calculated as 81%, which means 81% of normal signals are correctly classified as normal and the rest 19% are misclassified as abnormal. Whereas, $Se(\%)$ is calculated as 70%, 71%, 70%, 75% for 3NN, 5NN, NBC and MSVM One-against-all method respectively.

Specificity refers to false positive rate calculated using Eq. (11). It

refers to the rate of correctly classified abnormal signals.

$$Sp(\%) = \frac{TN}{FP + TN} \quad (11)$$

Specificity of MSVM using Crammers method is calculated as 84%, which means 84% of abnormal ECG signals are correctly classified as abnormal and the rest 16% of the signals are misclassified as normal. $Sp(\%)$ for 3NN, 5NN, NBC and MSVM using one-against-all is calculated as 78%, 79%, 72% and 81% respectively.

Precision represents the degree of closeness of two or more classified signals which is calculated using Eq. (12).

$$Pr(\%) = \frac{TP}{Tp + FP} \quad (12)$$

Accuracy is defined as the ratio of the number of correctly classified ECG beats divided by the number of input signals and is calculated using Eq. (13).

$$A(\%) = \frac{TP + TN}{N} \quad (13)$$

The overall accuracy of MSVM classifier using Crammers method is maximum i.e. 86%, compared to other classifiers.

Bit Error rate calculated using Eq. (14) is defined as the percentage of ECG beats that have errors related to total number of input signals.

$$BER = 1 - (Accuracy) \quad (14)$$

The tabular analysis indicate that the ECG signal classification by MSVM classifier using Crammers method shows highest Accuracy (86 %), highest Sensitivity (81%), maximum Specificity (84%), high Precision (87%) and minimum BER (0.102).

Table 1. Overall performance of KNN, NBC and MSVM

S.No	Method		Se (%)	Sp (%)	Pr (%)	BER	A (%)
1	KNN	3NN	70	78	82	0.27	79
		5NN	71	79	83	0.22	83
2	Naïve Bayes Classifier		70	72	81	0.29	77
3	MSVM	one-against-all	75	81	86	0.18	82
		Crammers Method	81	84	87	0.102	86

IV. CONCLUSION

The accuracy of KNN classifier with $K=3$ and $K=5$ is calculated as 79% and 83% respectively. Accuracy for NBC is calculated as 77%, whereas for MSVM it is calculated as 82% using One-against-All method and 86% using Crammers method. BER reduced to 0.102 with MSVM Crammers classifier. Classification of ECG beats using Multiclass SVM classifier showed higher accuracy compared to other classifiers which makes the system highly efficient. The analysis of five different performance parameters Sensitivity, Specificity, Precision, Accuracy and Bit Error Rate reveal that MSVM classifier using Crammers method is more appreciable for ECG classification. The Pan-Tompkins algorithm for ECG feature extraction has performed effectively to project the detected QRS complex from original ECG signal. Further application of MSVM classifier by increasing hidden layer size or by increasing the number of neurons can be done to increase the accuracy.

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