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Classification of Atrial Arrhythmias using Neural Networks

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ABSTRACT

Electrocardiogram (ECG) is an important tool used by clinicians for successful diagnosis and detection of Arrhythmias, like Atrial Fibrillation (AF) and Atrial Flutter (AFL). In this manuscript, an efficient technique of classifying atrial arrhythmias from Normal Sinus Rhythm (NSR) has been presented. Autoregressive Modelling has been used to capture the features of the ECG signal, which are then fed as inputs to the neural network for classification. The standard database available at Physionet Bank repository has been used for training, validation and testing of the model. Exhaustive experimental study has been carried out by extracting ECG samples of duration of 5 seconds, 10 seconds and 20 seconds. It provides an accuracy of 99% and 94.3% on training and test set respectively for 5 sec recordings. In 10 sec and 20 sec samples it shows 100% accuracy. Thus, the proposed method can be used to detect the arrhythmias in a small duration recordings with a fairly high accuracy.

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1. INTRODUCTION

Electrocardiogram or ECG is used to record the electrical activity of the heart over a certain time period. Any abnormality or deviation from normal ECG can prove to be fatal for patients. Mostly, these abnormalities are observed by the naked eyes of the doctor and have considerable chances of being undetected. Two of the most common life threatening Arrhythmias are Atrial Fibrillation and Atrial Flutter [1-6]. Atrial fibrillation involves irregular heartbeat. It has no visible symptoms and is termed as a 'Silent Disease', making its diagnosis extremely difficult. If remain undetected, it can lead to stroke, heart failure or even sudden deaths [7]. Statistics suggest that approximately 33.7 million people worldwide have atrial fibrillation, with the majority constituting developed nations [8]. Atrial flutter is the abnormality in the beating rate of the heart due to an abnormal conduction circuit developing inside right atrium. This reduces the blood pumping capacity of the heart and can lead to major heart diseases like stroke, congestive heart failure and heart attack [9]. Various signal processing techniques have been used in an attempt to detect and classify atrial fibrillation and atrial flutter. Time Frequency analysis, RR interval irregularity, Hidden Markov Models are few of the past techniques used for separation of AF and AFL from normal sinus rhythm.

However, they all suffered from inherent disadvantages due to quick changing rhythms of ECG signals [10-15]. Different techniques have been used in an attempt to classify the ECG signals with a maximum possible accuracy [16-20]. An accuracy of 93% have been reported in a manuscript using a feature extraction technique based on the product of the pulse duration, pulse area and pulse slope of the filtered ambulatory ECG signal [21]. Furthermore, a manuscript using Artificial Neural Network (ANN), reports an accuracy of 82% in arrhythmia classification [22]. Another paper using deep Convolutional Neural Network (CNN) as the learning algorithm reports an accuracy of 97% [1]. Another manuscript uses a Support Vector Machine (SVM) classifier to report an accuracy of 97% [7].

In this manuscript, a neural network based efficient model has been proposed to improve the detection and classification of arrhythmiasfrom normal sinus rhythm. Firstly, the features of the ECG signals are extracted using Autoregressive modelling and then, these features are fed into a neural network to classify the arrhythmias. This paper is divided into 4 sections. Section 2 gives the methodology involved in designing the efficient classification model of 5 sec, 10 sec and 20 sec duration arrhythmias samples. Section 3 describes the artificial neural network used to obtain the results. Section 4 gives the final results, followed by the overall conclusion of the work in Section 5.

2. METHODOLOGY

2.1. Database

The existing standard database available at Physionet bank archive has been used for training and testing of the model. The MIT/BIH atrial fibrillation database [23] comprised of 23 atrial flutter ECG recordings, sampled at the rate of 1250 Hz. The MIT/BIH Normal sinus rhythm database [24] had 18 normal sinus rhythm recorded and sampled at 128 Hz. The MIT/ BIH arrhythmia database [25] consisted of 3 records of atrial flutter, at the sampling frequency of 360 Hz. Out of the obtained samples, the training and testing of the samples have been done by extracting signals of 5 sec duration, 10 sec duration and 20 second duration. The number of training and test samples for each of atrial fibrillation, flutter and normal sinus rhythm for the three sample duration has been presented in Table 1. It can be seen from Table 1 that the total samples are divided in the ratio of 4:1 as training set and test set.

Table 1. Number of samples for arrhythmias detection

Sample Duration	Atrial Fibrillation			Atrial Flutter			Normal Sinus Rhythm		
	Training samples	Testing Samples	Total	Training samples	Testing Samples	Total	Training samples	Testing Samples	Total
5 sec	240	60	300	77	20	97	172	44	216
10 sec	202	50	252	37	9	46	172	44	216
20 sec	112	28	140	17	5	22	172	44	216

2.2. Autoregressive modelling

In autoregressive model the present output of any time series is predicted from the past outputs. Basically, it fits an optimized curve to the existing data points. It has been used successfully in various fields such as speech processing[26], pattern recognition[27] and biomedical signal processing[28]. Let's assume a time series Y (n) with samples y1, y2, y3, etc. The autoregressive model (AR (p)), having order *p*, is defined as

$$\mathrm{Y(n)} = \sum_{k=1}^{p} \alpha_p(k) Y(n-k) + \epsilon(n) \tag{1}$$

Here, the p is the order of the model, ε (n) is zero mean white noise sequence with a variance of σ. The AR model parameters α_p has been calculated using Burg's method, based on the principles of minimization of forward and backward linear prediction errors by selecting appropriate prediction coefficients subject to the condition that they must satisfy the Levinson-Durbin recursive algorithm. These coefficients obtained from the AR modelling of the ECG signal are used as features to the artificial neural network.

2.3. Artificial Neural Network

Artificial neural networks (ANN) are a mimic of the biological neurons present in human brain. They are used to provide thinking capability to the machines, making them smart[29]. For our application, a neural network having a single hidden layer, comprising of 7 neurons has been used. The features obtained from the AR model are used as inputs to the ANN. The output layer consisting of 3 neurons has been used to successfully classify and distinguish between normal Sinus rhythms, AF and AFL.

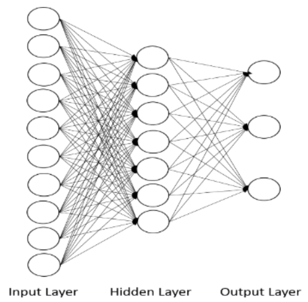

Figure 1. Structural Artificial Neural Network

Scaled conjugate gradient back propagation algorithm has been used to obtain the correct value of synaptic weights and hence minimize the mean square error function. In this method, the learning rate is adjusted at each iteration. A search is made along the conjugate gradient direction to determine the learning rate, which minimizes the performance function along that line.

3. RESULTS AND DISCUSSION

An artificial neural network, having a single hidden layer is used to differentiate between fibrillation, flutter and normal sinus ECG signal. The performance of the network is evaluated by calculating parameters like specificity, sensitivity and accuracy. All the metrics are based the parameters, true positive (TP),
false positive (FP), true negative (TN) and false negative (FN).
Sensitivity is the number of correctly identified positive instances.

$$sensitivity = \frac{TP}{TP+FN} \quad (2)$$

Specificity is the number of correctly identified negative instances.

$$specificity = \frac{TN}{TN+FP} \quad (3)$$

Accuracy is the correctness of the system, i.e. the closeness of the system to the actual value. These parameters are calculated from the data presented by the confusion matrix

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

The proposed methodhas been developed using MATLAB simulation environment. The system is trained using 'nnstart' GUI, by using a data set divided into training and validation set in the ratio of 4:1 and then the final results are obtained on an independent test set. The AR model is tested by varying the number of features to obtain the best fit. Table 2 shows the performance of the model in the training set with vaious AR features (p), for a 5 sec signal sample.

Table 2. Performance result of neural network model for 5 sec arrhythmias sample

p	Sensitivity			Specificity			Accuracy (%)
	AF	NSR	AFL	AF	NSR	AFL	
2	1	1	0.13	0.72	1	1	85.9
4	0.94	1	0.55	0.86	1	0.96	90.2
6	0.98	1	0.76	0.91	1	0.99	95.1
8	0.96	0.99	0.69	0.9	0.99	0.98	93.1
10	0.99	1	0.94	0.98	0.99	1	99.0
12	0.99	1	0.94	0.98	0.98	1	98.1

It is evident from Table 2 that the best optimum performance is obtained for number of features equal to 10. The performance is also evaluated for different time length of signals. Table 3 compares the performance parameters of the system for 5 sec, 10 sec and 20 sec samples on training set, keeping the number of features as 10.

Table 3. Performance of the proposed model in thetraining set of 5,10 and 20 sec duration recordings (keeping the model order as 10)

TDuration of	Sensitivity			Specificity			Accuracy (%)
sample (sec)	AF	NSR	AFL	AF	NSR	AFL	
t = 5 sec	0.99	1	0.94	0.98	0.99	1	99
t = 10 sec	1	1	0.97	0.99	1	1	99.8
t = 20 sec	1	1	1	1	1	1	100

It can be seen from Table 3 that training set accuracy is better for all three time duration samples. The accuracy ranges from 99% for a 5 sec time signal to 100% for a 20 sec time signal. The performance parameters of the independent test set for 5 sec, 10 sec and 20 sec samples are presented in Table 4. The sensitivity reaches a minimum of 0.95 and 0.79 for AF and AFL respectively for the 5 sec sample. The specificity reaches a minimum of 0.93 and 0.96 for AF and NSR respectively for the 5 sec sample. The minimum and maximum accuracy obtained are 94.3% and 100% respectively. The performance results of the test sets for the three cases of varying time sample duration are presented in Tables 5, 6, and 7. It is seen from Table 4, 5 that there are some misclassifications in all the three categories namely atrial fibrillation, atrial flutter and normal sinus rhythm, thereby limiting the accuracy to 94.3%.

Table 4. Performance results on arrhythmias independent test set

Time Duration	Sensitivity			Specificity			Accuracy (%)
of sample (sec)	AF	NSR	AFL	AF	NSR	AFL	
t = 5 sec	0.95	1	0.79	0.93	0.96	1	94.3
t = 10 sec	1	1	1	1	1	1	100
t = 20 sec	1	1	1	1	1	1	100

Table 5. Confusion matrix of theindependent test set for 5 sec arrhythmias sample

	Atrial Fibrillation	Normal Sinus Rhythm	Atrial Flutter
Atrial Fibrillation	57	0	4
Normal Sinus Rhythm	3	44	0
Atrial Flutter	0	0	16

Table 6. Independent test set matrix for 10 sec arrhythmias sample

	Atrial Fibrillation	Normal Sinus Rhythm	Atrial Flutter
Atrial Fibrillation	50	0	0
Normal Sinus Rhythm	0	44	0
Atrial Flutter	0	0	9

Table 7. Independent test set matrix for 20 sec arrhythmias sample

	Atrial Fibrillation	Normal Sinus Rhythm	Atrial Flutter
Atrial Fibrillation	28	0	0
Normal Sinus Rhythm	0	44	0
Atrial Flutter	0	0	5

Further from the results, it is evident that, there are no misclassifications in case of 10 sec and 20 sec samples, giving it an accuracy of 100%. The comparison results of different duration signals show that the proposed method is efficient in classifying the arrythimias from small duration signals.

4. CONCLUSION

In this manuscript, an accurate classification technique has been presented to successfully distinguish between Fibrillation, Flutter and normal ECG signals. Auto regressive model is used to extract relevant features from the ECG signals. Artificial neural network has been used to train the model. The performance of the model has been assessed in different length of signals such as 5 sec, 10sec and 20 sec.

The training set and test set accuracy of themethod obtained on the 5 sec arrhythmias sample is 99% and 94.3% respectively. Therefore, the system can easily be used to predict atrial arrhythmias with an ECG signal of small duration with a fairly high accuracy.

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