An Artificial Neural Network Approach for the Detection of Abnormal Heart Rhythms

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***Abstract*— Automatically classifying arrhythmias remains a fundamental measure during the diagnosis or detection of cardiac abnormalities. In this paper, we propose a method to accurately classify ECG arrhythmias based on artificial neural networks (ANNs). In particular, we analyze three different heart rhythms including: (a) normal sinus rhythm, bradycardia and tachycardia. ECG Feature extraction and time-frequency analysis have proven to be useful in identifying arrhythmias. However, the accuracy in classifying ECG signals depends significantly on a large number of features that can be extracted. In this study, we attempt to optimize the number of features that are required to successfully classify ECG signals correctly. Throughout the paper, we present results from testing our backpropagation neural network (BPNN) with the existing MIT/BIH Arrhythmia database. The overall performance of our method demonstrates a success rate of 98.70% in identifying the correct type of cardiac arrhythmias.**

***Index Terms*— arrhythmia detection, arrhythmia classification, neural networks, backpropagation, heartbeats, non-stationary ECG signals, RR-intervals, MIT/BIH**

I. Introduction

IDENTIFYING correctly and accurately the type of an electrocardiogram (ECG) signal is an active research area in biomedical engineering and require significant knowledge in signal processing. Researchers have explored numerous complex algorithms for analyzing and identifying ECG signals including power spectrum analysis [1,2], principle component analysis [3], signal analysis [4], Hilbert transform analysis [5,6], continuous and discrete wavelet transforms, and adaptive filtering [7]. Other complex techniques involving feature extraction have also been applied such as template matching [8], markov models [9], neural networks [10-15], among many other recognition algorithms [16, 25-39].

Although there have been numerous research efforts in detecting and recognizing ECG wave abnormalities [17-24, 40-42], optimizing the feature set required for detecting heartbeat abnormalities without sacrificing the accuracy and success rates has often been ignored. Hence, it would be desirable to determine this optimal set such that it can be used by neural network algorithms for the detection of heartbeat abnormalities while maintaining high accuracy and classification rates.

In an effort to solve existing research problems and limitations with the current state-of-the-art, we introduce an Artificial Neural Network (ANN) solution that is capable of detecting ECG heartbeat abnormalities that can be used in real-time for ECG monitoring systems. A fundamental factor in achieving this goal is mainly dependent on finding the correct number and types of features (or parameters) that represent the various ECG signal conditions within an acceptable discrimination capability.

The rest of the paper is organized as follows. Section II presents an overview of the methodology applied in this research work. Section III presents the results we have obtained from applying our neural-network solution using the obtained dataset. We also discuss and provide insights on the use of ANN in the detection of heartbeat abnormalities in the same section. Finally, a conclusion and future work directions are provided in Section IV.

II. Methodology

The Massachusetts Institute of Technology (MIT) and Beth Israel Hospital (MIT/BIH) Arrhythmia Database [20] is one of a handful data sources that can be used by researchers and data scientists as test material for the evaluation of arrhythmia detection and classification. We used the MIT/BIH arrhythmia database's annotated records [20] for evaluating the developed neural network classifier. The dataset included data from forty eight patients with duration of thirty minutes recordings for each patient. MIT/BIH's data collection was completed using two leads: (a) modified limb lead II and (b) modified lead VI of surface ECG [20]. According to MIT/BIH, these two leads provide an adequate representation of complex QRS waveforms, artifacts and conduction abnormalities [20].

For the purpose of our study, we have randomly selected data representing thirty three patients. The random selection of such records was influenced by the fact that we would like to choose records that represent the three main types of arrhythmia that we would like to classify using our neural network and these include: (a) normal sinus rhythm, (b) bradycardia and (c) tachycardia ECG signals. All the recordings in MIT/BIH arrhythmia database were sampled at a frequency of 360Hz. In addition, the dataset contains an annotation file representing the "truth" identification provided by two or more expert cardiologists [20]. These "truth" annotations are the labels that we can then use for training, evaluating and testing our neural network classifier.

Our methodology for classifying arrhythmia involved two main phases: (a) a preprocessing phase and (b) a classification phase. The scope of this study focuses on particular set of

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heartbeat abnormality (i.e. arrhythmia) as predetermined by the dataset and identified using the truth labels. Table I outlines the standard components (i.e. features) including waves and intervals that can be identified in a normal electrocardiogram. Our main goal for using the BPNN classification model is to optimize the number of features (i.e. wave types in this case) while maintaining high accuracy in identifying the type of heartbeat (e.g. normal, tachycardia or bradycardia).

Our BPNN's preprocessing phase analyzes an ECG signal and detects information about the QRS complexes. This includes extracting information such as Q-wave, R-wave, T-wave, U-wave, PR interval, QRS duration, among others. Once these individual elements of an ECG signal are identified, the following task is to identify the RR-interval. An RR-interval, as described in Table 1, requires examination of two ECG signals at a time since the interval spans from the R-wave of the first ECG signal to the R-wave of another (preceding or following) ECG signal. In our case, we examined a following R-wave. That is, we examine the current ECG signal, extract the R-wave and then extract the next ECG signal information, determine the R-wave and then construct or calculate the RR-interval. This RR-interval provides valuable information and is used to that enhance the accuracy of the neural network classifier.

TABLE I
COMPONENTS OF AN ECG SIGNAL

Waves, Intervals & Segments	Description
P-wave	depolarisation of atria
Q-wave	(small) negative wave preceding R-wave
R-wave	depolarisation of ventricles
T-wave	repolarisation of ventricles
U-wave	(small) positive wave following T-wave
PR interval	start of P-wave to start of QRS complex
PR segment	end of P-wave to start of QRS complex
QRS duration	start to end of QRS complex
QT interval	start of Q wave to end of T-wave
RR interval	from an R-wave to next (consecutive) R-wave

The BPNN algorithm uses this information extracted (i.e. features) from an ECG signal to then classify whether an ECG signal is normal or abnormal. In specific, the BPNN attempts to identify the type of ECG signal or classify it as either a (a) sinus rhythm, (b) bradycardia or (c) tachycardia. The features extracted during preprocessing provide valuable details that help the ANN in classifying a given heartbeat. For instance, a typical normal heartbeat (i.e. normal sinus rhythm) is determined using a threshold that is based on the number of heart beats per minute. That is, if the heartbeat is greater than or equal to sixty beats per minute (bpm) and less than or equal to one hundred, an electrocardiogram signal is said to be normal (or a sinus rhythm). Furthermore, a heartbeat rate exceeding or higher than one hundred beats per minute is often referred to as tachycardia. In addition, a heartbeat rate that is lower than sixty is often referred to as bradycardia. It is assumed that the discussed heartbeat rates are calculated when an adult patient is at rest (e.g. not walking or running). This information is vital with respect to identifying the correct type of arrhythmia.

The rate at which a heart beats provides vital information whether there are abnormalities in the heart or not. In the case of a tachycardia, for example, a heartbeat rate is greater than one hundred beat per minute which translates into having shorter or small RR-intervals. On the other hand, in the case of a bradycardia, the RR-intervals will be longer than that of a normal ECG. The neural network uses this critical information to be able to determine whether a given ECG signal, for example, is classified as normal, bradycardia or tachycardia.

Classifying heartbeats into one of the three categories: normal sinus rhythm, bradycardia, or tachycardia is the chief objective of this research study. However, to perform this process properly, the neural network classifier needs to have high accuracy and produces truthful classification. Therefore, the input data supplied to the neural network should not contain contradictory information that might confuse the classifier yielding to inaccurate classifications. In addition, increasing the robustness of the classification rates of the neural network depends on the extraction and collection of multiple hidden features from the QRS complexes. The more features translates into more accurate findings. However, it is important that this set of features is optimized such that it does not overwhelm the neural network and reduces any overheads with respect to the time it take to process the input data.

In order to properly train and test the data supplied in the MIT/BIH Arrhythmia Database, we had to perform some data preprocessing. In achieving this task, the data associated with a recording is stored as a single vector for each individual heartbeat across all of the recorded readings. As part of each record, a label identifies the correct type of the heartbeat (e.g. normal, bradycardia or tachycardia) as shown on Table II based on the AAMI's recommendations. We extracted a total of eight from the dataset provided in MIT/BIH Arrhythmia's Database. Each heartbeat is stored as a vector containing the values of the corresponding eight features (or elements). A ninth element in the vector indicates the label or truth annotation.

A conventional method for classifying a heartbeat is based on considering an R-wave for the current ECG signal and a former R-wave (e.g. the earlier heartbeat's R-wave). In an effort to maximize the efficiency of this conventional method, we extend this method by considering the relationships of the heartbeats with earlier ones but also ones that occur before earlier heartbeats (i.e. a window that spans across two

TABLE II
HEARTBEAT CLASSIFICATION BASED ON THE NUMBER OF BEATS PER MINUTE

Type	Identifier	Beats Per Minute (BPM)
Sinus Rhythm	1	sixty – one hundred
Bradycardia	2	< sixty
Tachycardia	3	> one hundred

heartbeats backward). Similarly, the relationship between the current beat and the next two beats (i.e. a window of two beats afterward) is taken into consideration. This enables the construction of the features including a wider combination of chronological RR-intervals.

The selection and extraction of the eight ECG features from the dataset provided by the MIT/BIH Arrhythmia Database include temporal (or non-stationary) and morphological properties. The temporal properties include: (a) the RR-interval between a heartbeat being examined (an existing heartbeat) and a preceding heartbeat (referred to as RR1), (b) between the preceding heartbeat and a former heartbeat (referred to as RR0), (c) between the existing heartbeat and the next heartbeat (referred to as RR2), and (d) between the next heartbeat and the subsequent heartbeat (referred to as RR3). An abnormality ratio is also generated based on the collected RR-intervals that include the (a) ratios of RR1 to RR0 and (b) RR3 to RR2. These ratios are used as indicators of heartbeat abnormalities particularly in identifying a normal heart activity (i.e. sinus rhythm), a slow heartbeat activity (i.e. bradycardia) or fast heartbeat activity (i.e. tachycardia).

The other group represents morphological properties represent. For example, an ECG signal is acquired as a point window consisting of two hundred and sixteen points in total. The label is used as an indication of the highest amplitude (or index) or the R peak in QRS complexes. A total of seventy six points preceding the R peak we considered as well as a total of one hundred and thirty nine points were used to form a template or window. All points in a given template vector are then normalized using min-max normalization presented in Equation 1. The result is a normalized vector ranging between zero and one.

$$v' = \left(\frac{v - min}{max - min}\right) \tag{1}$$

where v' represents a normalized vector, v represents an un-normalized vector, min is the smallest value in v and max is the largest value in v.

Comparing a heartbeat that is being analyzed to preceding heartbeats provides important information such as pattern similarity. To this extent, the last two values in vector v represent the correlation of a heartbeat currently being analyzed with the two preceding ones, respectively. As part of preparing the data for further analysis, the entire heartbeats included in the dataset were obtained for further analysis while ignoring the first and last heartbeat accounting for setup and calibration that may take place when attaching or detaching equipment on the patient's body.

III. Results & Discussion

The dataset used in this study is extracted from thirty three patients from the MIT/BIH Arrhythmia Database. A patient's recording spanned across thirty minute duration. The three types of arrhythmias listed in Table II were considered including Sinus Rhythm, Bradycardia and Tachycardia. A total of 74182 total ECG readings were obtained from the dataset. Each reading or sample represents a single ECH heartbeat consisting of a template vector of nine features. A class label (or truth value) is represented by the last element in this vector. We obtained the truth value (or class label) from the annotations also supplied by the data source provider. This truth value has been identified by cardiologists and is referred to as the truth annotations. We use this label to train and evaluate our BPNN solution. To determine the effectiveness of using a BPNN in classifying ECG heartbeats into one of the three classification types, we use the Equation 5 for measuring classification rate (CR).

$$Classification\ Rate\ (CR) = 100 \times \left(\frac{Correctly\ Classified}{Total\ Heartbeats}\right) \tag{5}$$

where CR represents the classification rate. We tested the BPNN which generated the results presented in Table III.

TABLE III
TESTING BPNN WITH DIFFERENT CONFIGURATIONS VARYING NUMBER OF HIDDEN NODES

Number of Nodes			CR
Input Layer	Hidden Layer	Output Layer	
9	1	1	80.565
9	2	1	83.335
9	3	1	81.781
9	4	1	83.849
9	5	1	80.645
9	6	1	82.568
9	7	1	86.319
9	8	1	83.847
9	9	1	91.019
9	10	1	86.487
9	11	1	85.295
9	12	1	91.347
9	13	1	97.745
9	**14**	**1**	**99.124**
9	15	1	96.359
9	18	1	93.891

Applying a wide variety of dissimilar network configuration, we determined that the BPNN configuration having fourteen

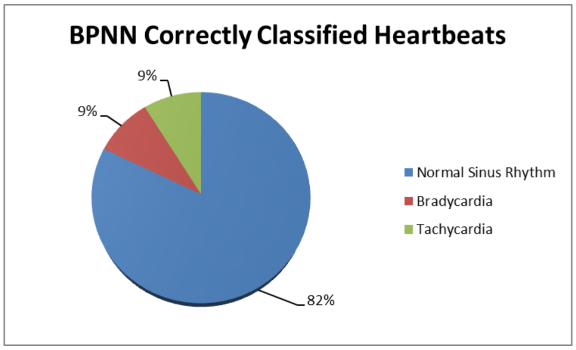

Fig. 1. Distribution of the Correctly Classified ECG Beats using BPNN

hidden nodes is one that yields the highest classification rate (CR) with 99.124%. We applied the BPNN configuration having fourteen hidden nodes to train all of the samples in the dataset, or the 74182 heartbeats (or readings). We used a subset of the readings for testing. In particular, we used 53388 readings out of the 74182 (or 72%) for testing in which a classification rate of 98.70% was achieved. A pie chart showing the distribution of the correctly and incorrectly classified

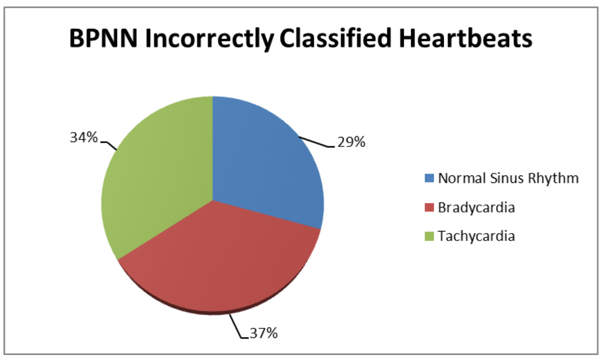

Fig. 2. Distribution of the Incorrectly Classified ECG Beats using BPNN

heartbeats based on the recommended BPNN configuration is shown in Fig. 1.

As presented in Fig.1, the total number of heartbeat readings that were correctly classified across all arrhythmia types is 52692 heartbeats of a total of 5388 heartbeats. This represents a correct classification rate of 98.70% across all types. Furthermore, it is noted that total number of correctly classified heartbeats for both tachycardia and bradycardia is equal percentage wise. A pie chart distribution chart showing the incorrectly classified heartbeats is shown in Fig. 2.

Fig. 2 shows, to a certain degree, a comparable distribution of the incorrectly classified heartbeats for both bradycardia and tachycardia with percentages being 37% and 34%, respectively. A slightly lower percentage is associated with the normal sinus rhythm. This slight variation between normal and abnormal heartbeats can be attributed to the complexity of determining normal heartbeats (i.e. normal sinus rhythm) and abnormal heartbeats (i.e. bradycardia and tachycardia).

It is important to note that the rate of occurrence in which the number of incorrect classification from normal as abnormal heartbeat is approximately twice that of abnormal as normal.

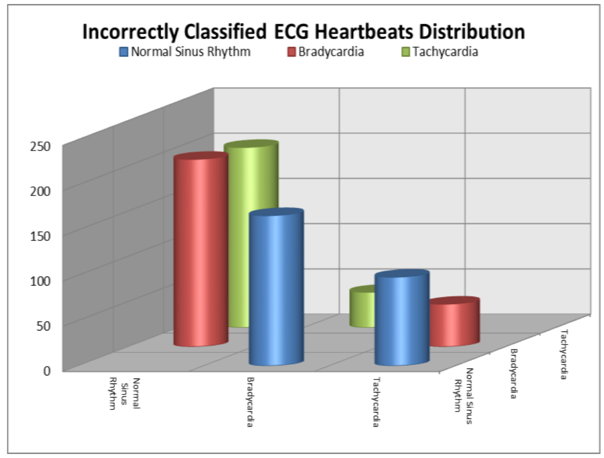

Fig. 3. Incorrectly Classified Distribution ECG Heartbeats

For example, the number of incorrectly classified beats of normal sinus rhythm as Bradycardia is 207 while the opposite is 106 beats. The same observation applies to the comparison between tachycardia and normal sinus rhythm and is illustrated in the three-dimensional graph shown on Fig. 3.

Converging of a BPNN is now always guaranteed in finding an error that is lower than the minimum during the training process. Hence, we used an acceptable error value of 1/2000. Although this may increase the time it takes for the BPNN to converge, we use this acceptable error value to achieve moderate classification rates. However, BPNN's ability to account for preceding delta of an earlier connection between the layers, the BPNN algorithm converges much quicker while taking into consideration the momentum compared to that without the momentum.

IV. CONCLUSION

In this paper, we presented a feedforward backpropagation neural network that can correctly classify abnormalities in heartbeats. In particular, this BPNN system is used for arrhythmias detection. We used MIT/BIH Arrhythmia Database as the data source. The properties obtained from this data source mainly focuses on the RR-intervals for various heartbeats. Results obtained from our testing demonstrate significant improvements in terms of the system's performance and correctly classifying ECG signals when considering heartbeats other than the current heartbeat (i.e. two previous heartbeats).

The average performance of arrhythmia classification is shown to be 98.70% and is comparable to other approaches that used the same data source. The high performance of the current system was tested against the set of features chosen and results show that the addition of features such as examining two beats ahead and prior to the current beat being examined improves the overall system performance

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