Abstract—This paper presents a comparative study of automatic classification of different types of heart beat arrhythmias. The heart beats are classified into normal, premature ventricular contraction, atrial premature, right bundle branch block and left bundle branch block classes. Different classifiers are used in this work, namely support vector machine, multilayer perceptron neural networks, and TreeBoost. We carried out several experiments using the MIT-BIH arrhythmia database and obtained promising results. The computed average accuracy, sensitivity, and specificity are 98.89%, 90.63%, and 98.71%, respectively. Results have demonstrated that TreeBoost and support vector machine have an edge over multilayer perceptron neural networks for arrhythmia classification.

Keywords-component; Arrhythmia Classification; support vector machine; multilayer perceptron; TreeBoost; ECG signals.

I. INTRODUCTION

Classification of electrocardiogram signals (ECG) is important in biomedical signal processing and is used for detection and analysis of cardiac diseases. ECG is the graphical representation of the electrical activity generated by the heart [1]. The first stage of the heart beat begins with the spontaneous depolarization of the sino-atrial (SA) node. The SA node, located in the right atrium, is the pacemaker of the heart, depolarizing at regular time intervals to insure proper rhythmicity. The SA node depolarizes at a rate that is faster than the secondary pacemakers and, therefore, is the heart’s pacemaker. The impulse is transmitted from the SA nodal tissue to the atrial muscle cells. Due to the presence of gap junctions between the muscle cells, the atrial myocardium acts as a functional syncytium. The impulse spreads throughout the atrium and into the atrio-ventricular (AV) node. The AV (His) bundle then penetrates the fibrous tissue separating the atrium from the ventricles. The AV node and bundle delay the impulse by approximately 0.12 seconds. 5-15 mm towards the apex, the AV bundle branches, at the interventricular septum, into left and right bundle branches. Each one travels on the respective side of the interventricular septum and progressively divides into smaller branches. These smaller branches course around each ventricular chamber toward the base of the heart. Therefore, the ventricular depolarization occurs from the apex to the base of the heart.

Arrhythmia refers to any disturbance of the normal rhythmic beating of the heart or myocardial contraction. Cardiac arrhythmias can be classified by abnormalities in heart rate, disorders of electrical impulse generation, or impulse conduction [2]. Impulses generated in the atrium, at sites other than the SA node, result in atrial premature beats. Atrial premature beats are commonly found during extended ECG monitoring and its incidence increases with age [3]. They should not be considered abnormal. Ventricular premature beats occur when the impulse is generated in the ventricles. Its detection is directly related to the duration of a measurement. Sobotka et al. analyzed 24-hour ambulatory ECG recordings in 50 young women without apparent heart disease. Thirty-two subjects (64%) had atrial premature beats, with only one subject (2%) having greater than 100 beats/24 hrs. Twenty-seven subjects (54%) had ventricular premature beats, with only three subjects (6%) having greater than 50 beats/24 hrs [4].

Defective conduction of the impulse through the bundle branches leads to bundle branch block. The right bundle branch travels near the subendocardial surface making it vulnerable to stretch and trauma. Right bundle branch block complicates 5% of pulmonary artery catheterizations [5]. Left Bundle Branch Block (LBBB) most often occurs due to underlying heart disease, however, it can be found in healthy individuals. Rotman and Triebwasser studied 237,000 airmen and found LBBB in 0.05% [6]. Bundle branch blocks can form a macro reentrant circuit which may progress to ventricular tachycardia.

Using DTREG [7], we explore several methods viz. support vector machine, multilayer perceptron neural networks, and TreeBoost algorithms that may be used to perform cardiac Arrhythmia classification. DTREG accepts a dataset consisting of number of rows with a column for each variable. One of the variables must be identified as a “target variable” whose value is to be modeled and predicted as a function of “predictor variables”. DTREG analyzes the data and generates a model showing how to best predict the values of the target variable based on values of the predictor variables. In addition to generating the predictive model,
DTREG can perform validation tasks like cross-validation to evaluate the quality of the models.

The rest of this paper is organized as follows. Section II discusses related work. The database we used is described in section III. In section IV, a brief description is given for the experimented algorithms. Section V describes ECG extracted features and arrhythmia classes. Experiments’ results are discussed in section VI. Finally, a conclusion is drawn in section VII.

II. RELATED WORK

Several algorithms have been proposed in the literature for classification of ECG beats. Sayadi et al. presented an algorithm for classification of premature ventricular contractions (PVCs) verses normal beats [8]. They used an extended Kalman filter in their approach [9]. The authors evaluated their algorithm using 40 records – out of 48 records – from MIT-BIH Arrhythmia Database [10]. They reported average detection accuracy of 99.10%, aggregate sensitivity of 98.77%, and aggregate positive predictivity of 97.47%.

Faezipour et al. proposed QRS complexes detection method and ECG profiling system [11]. The proposed profiling system is based on repetition-detection concept and can be used as a local ECG beat classifier. It was able to binary classify the ECG beats into normal and abnormal beats with an overall classification accuracy of 97.42% when tested against the entire MIT-BIH Arrhythmia Database [10].

Llamedo et al. proposed a heartbeat classification algorithm using quadratic discriminant, linear discriminant, and compensated linear classifiers [12]. The authors used interval and morphological features. Their algorithm identifies heart beats to be normal, supraventricular, and ventricular beats. They evaluated their approach using MIT-BIH Arrhythmia, the MIT-BIH Supraventricular Arrhythmia, and the St. Petersburg Institute of Cardiological Technics (INCART) databases. All databases are freely available on PhysioNet [13]. Forty four records of the MIT-BIH Arrhythmia Database were used. The authors reported 93% as a global accuracy rate, 95% and 98% as normal beats’ sensitivity and positive predictive value, respectively, and 77% and 39% as supraventricular beats’ sensitivity and positive predictive value, respectively.

Jadhav et al. proposed the use of Generalized Feedforward Neural Network (GFNN) classifier in the classification of cardiac arrhythmia [14]. Static backpropagation algorithm is used to train the GFNN classifier to classify arrhythmias into normal and abnormal classes. The authors evaluated their approach using the UCI cardiac arrhythmia database [15] which contains 452 normal and abnormal instances. They reported 82.35% as the best classification accuracy using 85% of data for training and the rest for testing.

The UCI database is also used in [16] for binary classification of ECG signals. Fuzzy Support Vector Machine (FSVM) is used with different membership functions. The best reported accuracy rate is 83.33% with Distance to Class Mean membership function in which representativeness of an input can be measured according to its distance to class mean.

III. MIT-BIH ARRHYTHMIA DATABASE

We conducted the experiments using ECG data from the MIT–BIH Hospital Arrhythmia Database [10] to classify different types of heart beats. The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory ECG recordings collected at Boston’s BIH Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample. The database contains approximately 109,000 beats and corresponding labels. Fig. 1 shows a typical one-cycle ECG beat and its components.

![Fig. 1. A typical one-cycle ECG beat tracing](image-url)
such as object recognition [18], handwritten character recognition [19], and bioinformatics [20]. This is because SVM offers many advantages that are typically not available in other classifiers. SVM performs well in higher dimensional spaces, copes with the problem of lacking training data, and is robust with noisy data. In this work, the SVM model is built with RBF kernel function.

A MLP is a model developed to mimic the function of neurons in a human nervous system. It is composed of layers of nodes, each of which performs a relatively simple operation using its own inputs. The first layer consists of one node for each of the components of the input data. The nodes in this layer have a transfer function of unity, and their only function is to distribute the inputs to the nodes in the second layer. The outputs of first layer are connected to the inputs of the second layer. The outputs of the second layer are, in turn, connected to the inputs of the third layer, and so on. The final layer generates the output values of the MLP. In this scheme, the layers between the first and last are not visible from outside the network, and are hence referred to as ‘hidden layers’ [21]. In this work, MLP is trained with backpropagation algorithm in which the network adjusts the weight of neurons according to the error occurred on the output layer [22]. We used three layers with one hidden layer. Deciding on how many neurons to use for the hidden layer is one of the challenges in building multilayer perceptron neural networks. However, DTREG has a choice of automatically optimizing hidden layer 1 by building multiple networks with different numbers of neurons in hidden layer 1 and evaluate how well they fit. In this experiment, DTREG is given a range from 1 to 50 neurons. The optimal size computed is 33 neurons. The logistic activation function is chosen for the hidden layer and the output layer.

TreeBoost algorithm was developed by Friedman for improving the accuracy of models built on decision trees [23]. TreeBoost is also known as Stochastic Gradient Boosting and Multiple Additive Regression Trees (MART). Its model can be described mathematically as in equation (1):

\[ V = F_0 + B_1T_1(X) + B_2T_2(X) + \ldots + B_MT_M(X) \]  

(1)

Where \( V \) is the target value, \( F_0 \) is the starting value for the series, \( X \) is a vector of “pseudo-residual” values, \( T_1(X), T_2(X) \) are trees fitted to the pseudo-residuals and \( B_1, B_2, \ldots \) are coefficients of the tree node predicted values that are computed by the TreeBoost algorithm [25].

TreeBoost consists of ensembles of many trees. The residual from the first tree is fed into the next tree which attempts to reduce the error fed by the first tree. The process is repeated through a series of successive trees. The final predicted value is formed by adding the weighted contribution of each tree. TreeBoost does not require pre-selecting or transforming predictor variables and it is robust against outliers [24]. A full TreeBoost series may consist of hundreds of trees. In this work, the series has 400 trees, and the maximum depth used for any tree in the series is 5. This work demonstrates a new application to the TreeBoost algorithm, using ECG-based arrhythmia classification.

V. ECG FEATURES AND ARRHYTHMIA CLASSES

Similar to our previous work [26], we extracted the time-domain diagnostic and morphologic features from a pre-processed data of 108,232 heartbeats. The used samples represent 99.3% of the whole data. We extracted eleven features from the ECG data records, namely, widths of PR, QRS, QT and RR waves’ intervals; the amplitude of the QRS; and the mean and standard deviation of the amplitudes in the range of the QRS complex, the QT interval and the RR interval.

In addition to the normal beats class, we classify four types of MIT-classified arrhythmias, namely, Premature Ventricular Contraction (PVC), Atrial Premature beat (APB), Right Bundle Branch Block (RBBB) and Left Bundle Branch Block (LBBB). It is worth mentioning that some samples in the data have other types of arrhythmia but they represent only a small fraction of the data. However, those samples are included and considered as outliers and they are treated as a sixth class. Table I shows the distribution of number of samples for each class. In all of the conducted experiments, only 50% of randomly chosen samples from the whole data are chosen for training the classifiers, whereas the remaining samples are used for testing.

<table>
<thead>
<tr>
<th>Class</th>
<th>Number of Samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>74385</td>
</tr>
<tr>
<td>PVC</td>
<td>6730</td>
</tr>
<tr>
<td>APB</td>
<td>2356</td>
</tr>
<tr>
<td>RBBB</td>
<td>7205</td>
</tr>
<tr>
<td>LBBB</td>
<td>8033</td>
</tr>
<tr>
<td>Other</td>
<td>9523</td>
</tr>
</tbody>
</table>

VI. RESULTS AND DISCUSSION

We used three classifiers to classify heart beats into normal beats class and five abnormal classes that include the “outliers” class. Classifiers’ performance is measured by computing the accuracy, sensitivity, and specificity. Accuracy measures the overall effectiveness of a classifier and is computed by taking the ratio of correctly classified examples to the total number of examples available. Sensitivity measures the effectiveness of a classifier to identify a desired label. Specificity is used to measure a classifier’s ability to detect negative labels [27].

For example, Table II shows the confusion matrix of the tested samples using TreeBoost classifier.

Tables III, IV, and V exhibit experiments’ results for
TABLE III
THE CONFUSION MATRIX OF THE TESTED SAMPLES USING TREEBOOST CLASSIFIER

<table>
<thead>
<tr>
<th>Actual Category</th>
<th>Predicted Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>Normal 36908 PVC 84 APB 179 RBBB 54 LBBB 284 Other 52 67 30 50 85</td>
</tr>
<tr>
<td>PVC</td>
<td>Normal 52 PVC 84 APB 179 RBBB 54 LBBB 284 Other 30 67 30 50 85</td>
</tr>
<tr>
<td>APB</td>
<td>Normal 67 PVC 84 APB 179 RBBB 54 LBBB 284 Other 7 67 30 50 85</td>
</tr>
<tr>
<td>RBBB</td>
<td>Normal 30 PVC 84 APB 179 RBBB 54 LBBB 284 Other 5 30 30 50 85</td>
</tr>
<tr>
<td>LBBB</td>
<td>Normal 50 PVC 84 APB 179 RBBB 54 LBBB 284 Other 43 50 30 50 85</td>
</tr>
<tr>
<td>Other</td>
<td>Normal 85 PVC 84 APB 179 RBBB 54 LBBB 284 Other 85 85 85 85 85</td>
</tr>
</tbody>
</table>

SVM, MLP, and TreeBoost. As we can see from these tables, TreeBoost classifier computes the best results for all classes except in 2 cases. Considering APB class, SVM and MLP compute a specificity rate of 99.86% that is higher than that of TreeBoost. For LBBB class, SVM computes a sensitivity result of 99.86% which is the highest.

Table VI shows classifiers’ overall performance with regard to accuracy, sensitivity, and specificity. It is clear from Table VI that TreeBoost achieves the highest accuracy, sensitivity, and specificity. In addition, accuracy values are comparable for all classifiers with a 98.89% average. Specificity results are close to accuracy with an average of 98.71%. Considering sensitivity, an average result of 90.63% was computed. Fig. 2 further illustrates these results.

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Table VII compares our results to the literature discussed in section II.

VII. CONCLUSION

In this paper, we have presented a comparative study of automatic classification of heart beat arrhythmias using ECG signals. Feature vectors contain time-domain diagnostic and morphologic extracted feature values. Six different classes of ECG signals are classified using the MIT-BIH Arrhythmia Database for training and testing. Average accuracy, sensitivity, and specificity of 98.89%, 90.63%, and 98.71% are obtained using three classifiers; SVM, MLP and TreeBoost algorithms, respectively. TreeBoost and SVM obtained comparable results. MLP gives the lowest sensitivity result. All things considered, these results outperform the results in [11], [12], [14] and [16], considering that we have trained and tested classifiers using data for 6 classes. Sayadi et al. reported slightly higher accuracy and sensitivity results using only two classes, namely, PVC and normal classes.

Table VI shows that Treeboost computed the best results since it considers samples that were incorrectly classified by
previously trained tree(s). This could be viewed as an advantage over the other two applied methods. However, the other methods achieved comparable results that may initiate an interest in building an SVMBoost and ANNBoost to analyze their performance over ECG signals.

Based on the obtained results, we recommend further experimentation with TreeBoost and SVM classifiers for the classification of heart beat arrhythmias.

For future work, we intend to improve the classification results by using a mutual information-based approach. Also, we will explore the effect of signals’ noise on classification results. Furthermore, we will experiment with other ECG databases and consider different classes of arrhythmias.

REFERENCES


