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Patient Specific Machine Learning Models for ECG Signal Classification

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Abstract

Arrhythmia is one of the major cause of deaths across the globe. Almost 17.9 million deaths are caused due to cardiovascular diseases. In order to reduce this much mortality rate, the cardiovascular disease should be properly identified and the proper treatment for the same should be immediately provided to the patients. In this study, a new ensemble based support vector machine (SVM) classifier was proposed to classify heartbeat into four classes from MIT-BIH arrhythmia database. The results were compared with other classifiers that are SVM, Random Forest (RF), K-Nearest Neighbours (KNN), and Long Short Term Memory network. The four features were extracted from the ECG signals that were used by the classifiers are Wavelets, high order statistics, R-R intervals and morphological features. An ensemble of SVMs obtained the best result with an overall accuracy of 94.4%.

Keywords: Arrhythmia; Electrocardiogram; ensemble; Support vector machine. ;

1. Introduction

The prime cause of deaths across the world according to the report of WHO are cardiovascular diseases (CVDs): Annually, more people die from cardiac diseases than from any other disease. In 2016, approximately 18 million people died because of cardiac-related diseases, which reflects 31% of all the deaths globally. 85% of the deaths among this 31% are due to heart attack and stroke. An approximate of three-fourths of cardiac deaths take place in low-income and middle-income countries [1]. In 2015, 82% of the 17 million premature deaths due to non- communicable diseases are in low and middle-income countries, and the rest are caused by CVDs. The leading cause of CVDs is a long-term effect of cardiac arrhythmias. When the electrical signal, to the heart that coordinate heartbeats don't work properly, Arrhythmias occur [2].

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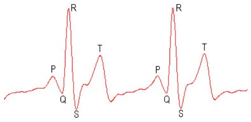

Fig. 1. Electrocardiogram heartbeat signal.

Arrhythmia is a condition in which heartbeat is either irregular, too fast or too slow. Most of the heart arrhythmias are generally not harmful; In case if they seem to be exceptionally abnormal, or result from a weak or damaged heart, arrhythmias can even cause serious and potentially fatal symptoms. The electrocardiogram (short termed as ECG) is a significant diagnostic tool that is used to assess and monitor the electrical activities and muscular functions of the human heart [3]. These heart activities result in creating some waves called P-QRS-T waves (see Fig. 1). Even though, it is a really simple test to carry on, the examination and determination of the ECG tracing require huge amounts of training. It's not mandatory to have symptoms for all the arrhythmias. Some arrhythmias do exist with no sort of symptoms. For those arrhythmias that exhibit symptoms, some of the following may be symptoms: dizziness, breathlessness and noticeably rapid, strong, or irregular heartbeat due to agitation.
There are several causes for arrhythmia, which may include diabetes, mental stress, smoking and many others. A slow heartbeat shouldn't always be considered as an indication of illness [4]. The advancement of a completely programmed framework that can order the ECG pulses has been an exploration point of high enthusiasm all through the most recent decades. Firstly, the signals were captured using the devices and the processed. This progression ordinarily incorporates the baseline removal and the cleaning of high-recurrence clamour. Next, a heartbeat division calculation is connected to part the flag at beat level. This is generally done by distinguishing the QRS-complex. At that point, a few descriptors are connected to each thump so as to separate the highlights to encourage a classifier, which at last decides the kind of heartbeat. Numerous calculations were proposed in the writing for the heartbeat segmentation [5-7], which gave an optimum result in databases like MIT-BIH [8]. The rest of the paper is arrange as : section II explain related work. Then section III is discussed about material & methods, followed by experimental results in section IV. Finally conclusion is being drawn in section V.

2. Related work

Making use of various extracted features of ECG signals and various classification methods, many researchers have reported earlier the usage of Automated Classification of Arrhythmia. To effectively detect the anomalies and addressing various problems that arise due to manual analysis of the ECG signals, several studies were explored using wide range of machine learning and deep learning techniques [9-10]. In general, ECG signal classification involves four stages namely, Preprocessing, Segmentation, Feature extraction and Classification. The major duty of the preprocessing task is to prepare the signals i.e. detection and attenuation of frequencies of artifacts related ECG signals. It also involves enhancement and normalization. Preprocessing is followed by the segmentation, in which the signal is chunked into small segments to improve the expression of electrical and muscular activities of heart [11].Classifying and the extraction of features are very significant and final stages in heartbeat detection which are generally investigated in previous researches. Highlights can be extricated directly from the morphology of the ECG signals (time area techniques) or in the wake of applying a change. R-R interval, Amplitude and term of the QRS complex are the highlights which increased real consideration in some writing [12-14]. In any case, these highlights are delicate to morphology and elements of the ECG. At that point, transforms showed up as an answer. The preferred standpoint with change based component extraction is it keeps away from the count of fiducial focuse for pulses.
According to ECG classifiers, using any multiclass classifier can be done for ECG classification. Some of the familiar classifiers include K-nearest neighbours (KNN), Support vector machine (SVM) , decision tree (DT) [15], and artificial neural network (ANN).Among all of these, the most popular one is SVM. With

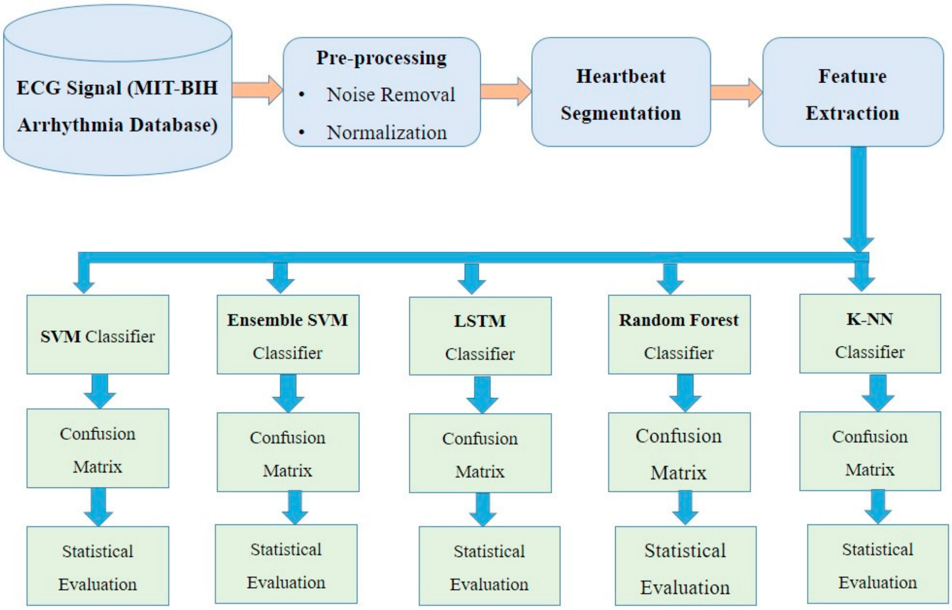

Fig. 2. Proposed patient specific arrhythmia classification system

the combination of SVM and features extracted by 2 pr-processing methods, a new approach was proposed by Osowski et al. [16] which was proved to be very advantageous and reliable, after examining the results of 13 heart rhythm types. GDA and SVM were used by Mohammadzadeh et al. for the classification of cardiac arrhythmia from the HRV signal [17]. Hierarchical SVM [18], SVM combined with particle swarm optimization (PSO) [19], weighted SVM [20] and least square SVM [21] are some of the different variations which have been applied in classification of ECG signals. Among many classifiers that are associated with ANN, probabilistic neural network (PNN) and Multi-layer perceptron (MLP) are very popular. On various feature sets, MLP was compared with other classifiers by Luz et al [11]. For extraction of various features by multi-scale PCA from the de-noised signals,autoregressive modelling is used by Alickovic and Subasi [22].

3. Material and methods

The patient-specific ECG arrhythmia recognition system is divided mainly in four parts as data pre-processing, heartbeat segmentation, feature extraction, and classification. Figure 2 shows the work flow of proposed patient specific ECG arrhythmia classification system.

3.1. Arrhythmia Database

This paper utilizes datasets from MIT-BIH [8]. It is set up by gathering the information from 47 test subjects where 48 ECG recordings are gotten. Among these, 23 of the accounts (100 to 124) were gotten from day by day schedule of the subjects. Whatever is left of 25 accounts (200 to 234) were chosen to incorporate inconsistent however clinically huge arrhythmias yet these arrhythmias are not very much spoken to in the 100 to 124 chronicles. Additionally the four records having paced beats of 102,104,107 and 217 are disposed of.

The paper focuses on the study of 200-234 recording because main ec-topic beats which are supra ventricular and ventricular ectopic are well represented in 200-234 recording.

Here the dataset has been isolated into two sections: The well known between patient plan division proposed by Chazal et al. [23], has been utilized to isolate the datasets. Each dataset contains information from 22 records with as comparative extent of beat types:

Table 1. Training and testing datasets

Train dataset	101,106, 108, 109, 112, 114, 115, 116, 118, 119, 122, 124, 201, 203, 205, 207, 208, 209, 215, 220, 223, 230.
Test dataset	100, 103, 105, 111, 113, 117, 121, 123, 200, 202, 210, 212, 213, 214, 219, 221, 222, 228, 231, 232, 233, 234

The dataset shown above is divided into two parts a) training dataset and b) testing dataset in which the training dataset is used to train the model and the testing dataset is used to evaluate the performance of the model. None of the patient is repeated for further training and testing. This paper considers only lead II to describe the morphology of the signal, since lead II is present in all the records of MIT-BIH database. Since Chazal[23] has also proved that only one lead is enough to classify the ECG cardiac arrhythmia. These records are removed from the evaluation database. Further, the heartbeats are categorized into 15 original classes of MIT-BIH Arrhythmia database are rearranged into four categories according to ANSI/AAMI standard. The relationship between AAMI standard heartbeat categories and MIT-BIH arrhythmia database classes is mentioned in table two.

Table 2. The mapping rules of ECG heartbeat labels mapped to ANSI- AAMI Labels

ANSI-AAMI Standard	Symbol	MIT- BIH heartbeat
Normal	(N)	normal(N), left(L), right(R) Bundle branch block
Supra ventricular Ectopic Beat	(SVEB)	e, A : atrial premature and escape beat S : supraventricular premature j, J : nodal premature and escape a : aberrated atrial premature
Ventricular Ectopic Beat	(VEB)	Ventricular Escape (E) , premature ventricular contraction (V)
Fusion	(F)	fusion (F)

3.2. Data Preprocessing

3.2.1. Noise Removal

Many literature works [24-25] are done prior to this, followed a sequential process of the baseline removal continued by a noise filtering of high-frequency at this step. But, here we are headed only with the baseline removal. We decided not to do noise filtering with high frequency, so that the signal is preserved in the raw form for the upcoming step of feature extraction. For computing the baseline of the signal, we consider 2 consecutive median filters of 200-ms and 600-ms that are to be applied. After this, we subtract the obtained baseline from the original signal, which results in the baseline corrected ECG signal.

3.2.2. Normalization

Normalization of the training and testing sets of heartbeats is done with the help of Z-score. Here, first we subtract the mean heart beat(μ) from the heartbeat point $x(i)$, then continue the process by dividing it by the standard deviation(σ) of the waveform. Calculation is done as:

$$Z = \frac{(x(i) - \mu)}{\sigma} \tag{1}$$

3.2.3. Heartbeat segmentation

In this step, from the annotations, we determine the R-peak position and then segment the heartbeats within window size of 180 centered at R-peak. each heartbeat signal consists of 90 points on the right of R peaks and 90 points on the left hand side.

3.3. Feature Extraction

3.3.1. Wavelets Transform

The quality that makes the wavelet transforms suitable for the description of ECG is that, they put forward the ability of allowing 'extraction of information' from time and also frequency domains. Different authors proved the usage of the wavelet transforms on ECG classification [26]. The Daubechies wavelet function (db1) has been used here in this paper.

3.3.2. High Order Statistics

Considering as a good option for describing the morphological ECG in [27], the cumulates of the 2nd, 3rd, and 4th order have been introduced. Here, each individual beat is divided into five intervals, creating a 10-dimensional feature, computing the value of skewness and kurtosis value over each one.

3.3.3. Morphological descriptor

We have proposed a morphological descriptor that depends upon a few estimations of sufficiency from the heart thumps. Our descriptor depends on the Euclidean separation between the R-peaks and four points of the beat, rather than specifically utilizing a few abundance esteems like different past works [28]. Depending on the values of amplitude over the intervals given below, the point selection is made:

- maximum(beats[0,40])
- minimum(beats[75,85])
- minimum(beats[95,105])
- maximum(beats[150,180])

3.3.4. R-R intervals

For classifying ECGs in the literature, the most employed feature is a descriptor based on these intervals[15]. Keeping aside the morphological features, we also employ the R-R intervals, that are computed from the time between consequent beats.The further intervals were extracted as:

- Pre-RR interval
- Post-RR interval
- Local-RR interva]
- Global-RR interval

3.4. Classification Techniques

3.4.1. K-Nearest Neighbour

This classification technique is supervised one with desired computational speed and is based on mathematics, simple theory. Since supervised, this classifier requires training phase, that is used for identifying the input test sample and it provides justifiable classification accuracy. KNN gives the sense that the nearest neighbours in any plane are expected that, they are of same kind i.e. they come under same class. In KNN, the class assignment is done by labelling the test sample with the majority class among the K-neighbours . K will always be greater than or equal to 1. It is a lazy learning algorithm and hence it trains only when it has some test sample to be classified [29].

3.4.2. Random Forest

Random forests, which are also known as Random Decision Forests, are learning methods for many tasks like regression, classification, etc... Random forest classifier gives performance better than a single individual tree, since it's an ensemble classifier that contains many decision trees. Regression and classification both can be performed using Random forest classifier. When Random forest is used in tasks, that involve classification, RF receives a class vote for all the trees, and at that point, it does the classification based on the majority vote [30].

3.4.3. Long short term memory network

LSTM is a method similar to Recurrent Neural Network (RNN). It is like the basic RNN which has recurrent unit to be used across time where the context value is obtained from result of the hidden node. This recurrent structure helps the network to learn the sequence of the event. Since this process is feed forwarding, the recurrent architecture uses back propagation that flows through the time. Based on the time series data, classifications, processing and prediction making are very efficiently handled by LSTM networks, as there may be chance of presence of lags of unknown duration between important events in a time series [31].

3.4.4. Support Vector Machine

The goal of the support vector machine technique is to discover a hyper plane in an N-dimensional space, that which distinctly classifies the data points. For the separation of any 2 classes of data points, we can choose many possible hyper planes. Discovering a plane with maximum margin is our aim. Maximizing the margin distance provides some reinforcement so that future data points can be classified with more confidence. Limiting only to classification of binary problems is the important drawback of support vector machines [32]. Two alternatives that can be suggested for solving the drawback of SVM are "One against all" and "One against one". These 2 can be short termed as OAA and OAO respectively. Considering N as the total no. of classes, in OAA a SVM models are constructed, i.e., one per class; where as in OAO, a SVM is constructed between each pair of classes, resulting in N(N-1) divided by 2 models. For the final decision, we need a voting system for both the alternatives. Here, in this work, we preferred the OAO approach because it is more suitable for working with imbalanced, unorganized data and training OAO requires less time than OAA, when there are large number of samples. One versus one was used in this study.

3.4.5. Ensemble Support Vector Machine

Ensembling is applied in order to improve the final prediction by combining the decisions of the individual classifiers that it is composed of .Although there are different ways of ensembling, it depends upon the desired results. For example, some of them train each individual subset with different classifiers such as Bagging or AdaBoost. The ensemble of SVMs, train each SVM with an alternate information source, essentially enhanced the outcomes in contrast with a single SVM that was train with the entire information sources. The approach applied in this paper similar to the wok of Zhang et al. [33]. where he has also used ensembling SVM for the classification of cardiac arrhythmia. This work mainly targets on evaluating the advantages of usage of ensemble of SVMs by using a combination of various SVM models that are trained with distinct features. We have employed various kinds of descriptors such as R-R intervals, HOS, wavelets, andl amplitude values. In addition to that, the combinations of different rules were extensively tested. Finally, several combination of rules were tested such as sum, product and majority rule for the final prediction.

4. Experimental Results

In all experiments, scikit-learn and tensorflow computational library of python is used for model training and evaluations. The database was normalised using Z-score normalization method. The proposed methodology's performance is evaluated for each category of ECG signal. It is found by calculating false positive$\boldsymbol{F_P}$, true positive$\boldsymbol{T_P}$, true negative $\boldsymbol{T_N}$ and false negative $\boldsymbol{F_N}$.
Sensitivity can be calculated as-

$$S_E = \frac{T_P * 100}{(T_P + F_N)} \tag{2}$$

Specificity can be calculated as-

$$S_P = \frac{T_N * 100}{(T_N + F_P)} \tag{3}$$

Accuracy can be calculated as-

$$Accuracy = \frac{(T_N + T_P) * 100}{(T_N + F_P + T_P + F_N)} \tag{4}$$

Precision can be calculated as-

$$Precision(P) = \frac{(T_P)*100}{(T_P+F_P)} \tag{5}$$

F-score can be calculated as-

$$F - score = 2 * \frac{(P*S_E)}{(P+S_E)} \tag{6}$$

4.1. Feature Evaluations

All the models were trained and test on MIT-BIH arrhythmia database. Many different parameters were used but the best ones selected are K=5 for K-nearest neighbours and 10 trees for Random Forest. SVM was applied with C = 0.001 and γ = 0.0. Here Table 3 shows all the result parameters including overall accuracy, sensitivity, specificity, precision and F-score. Among all the five classifiers the best result was obtained using ensemble of SVMs with the overall accuracy of 94.40%, sensitivity of 65.26%, specificity of 93.25%, precision of 69.11% and F-score of 66.24%. While KNN proved to be not such a strong classifier for this dataset. The overall accuracy of all classifiers can be seen that Ensemble of SVMs performed the best with 94.4% and also Random forest and LSTM per-formed good with accuracy of 93.45% and 92.16% respectively while Support vector machine and K-nearest neighbours gave the overall ac-curacy of 90.09 and 72.56 respectively.

4.2. Comparison of classification techniques

Here, our main aim is to compute whether the results of ensemble of SVMs are enhanced over the single KNN, SVM, LSTM, and RF model trained with all the features together. In case of Ensemble SVM, the 3 methods of combination, the product, the sum and the majority rule are being employed. The values of overall accuracy (Acc), the mean Sensitivity and Precision are presented in the below table.

Table 3. Comparision of results obtained from different classification techniques.

Methods	Sensitivity	Specificity	Precision	F-score	Overall Accuracy
SVM	54.42	91.12	51.26	52.82	90.09
KNN	49.09	83.96	37.58	39.16	72.56
RF	53.28	90.45	56.24	53.15	93.45
LSTM	48.09	87.95	59.81	53.31	92.16
Ensemble SVM	65.26	93.25	69.11	66.24	94.40

4.3. Comparison with Literatures

We, here, are aiming at comparison of our obtained best configuration results with some other related approaches of classification. Among some of the very well-known public databases, MIT-BIH can be included as one which can be used to refer the validating purpose of computational proposals of the issue. Table 4 includes the comparison of our best configuration of ensemble of SVMs, next to some of the best state-of-the-art methods

5. Conclusion

This paper used MIT-BIH arrhythmia patient-specific dataset to classify the heartbeats into 4 classes which include one normal beat and 3 abnormal beats i.e. SVEB, VEB and F. Data pre-processing tasks were performed which includes baseline noise removal, heartbeat segmentation which segments the heartbeats within window size of 180 centered at R-peak and normalization using Z-score. Then important features were extracted namely R-R intervals, HOS (high order statistics), Wavelets and morphological features.

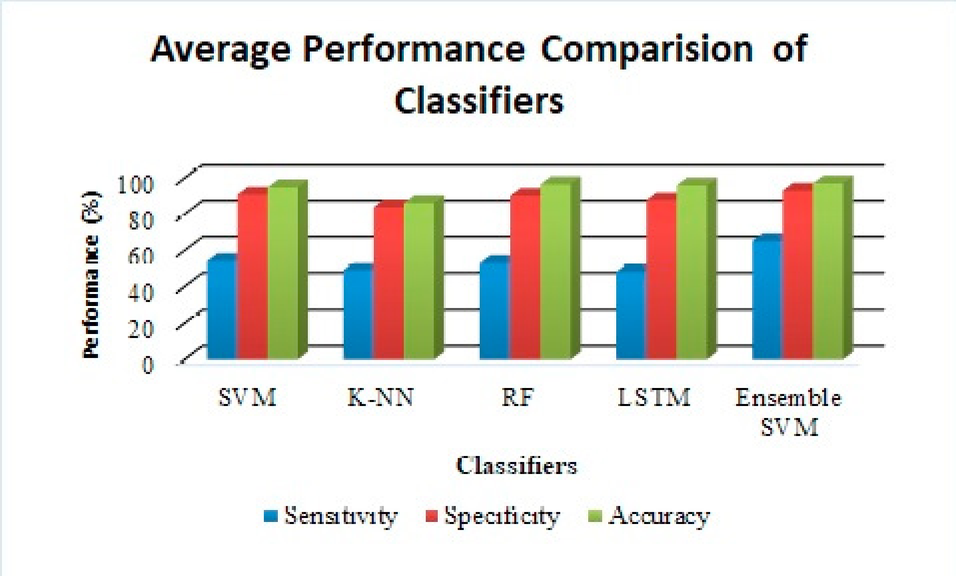

Fig. 3. Average performance on ECG signal using machine learning classifiers

Table 4. Comparision of results obtained from literatures.

Literature	Features	Classifier	Classes	Overall Accuracy
Mar et al. (2011) [26]	Wavelets, HOS	LDC, MLP	4	89.9
Martis et al. (2013) [34]	DWT, Cumulant , PCA.	LS-SVM, Neural Networks	5	94.52 (Average)
Huang et al. (2014)[35]	R-R interval, Random projection	Ensemble of SVM	5	94
Zhang et al. (2014) [36]	Morphological	SVM	4	88.83
Chen et al. (2017) [38]	Projections, Morphological	SVM	5	93.1
Kachuee et al. (2018) [39]	Morphological (MF)	Deep residual CNN	5	93.4
Proposed	Wavelet, R-R interval, HOS, Morphological	Ensemble of SVMs	4	94.4

Further, classification was done using five techniques which are Support vector machines (SVM), random forest (RF), long short term memory (LSTM), K-nearest neighbours (KNN) and ensemble of SVMs. The best result was obtained using ensemble of SVMs with overall accuracy of 94.4%, average accuracy of 97.2%, sensitivity of 65.26%, specificity of 93.35%, precision of 69.11% and F-score of 66.24%. Among the single classifiers, Random forest performed good with overall accuracy of 93.25% and mean accuracy of 96.73%. In this paper the potential of ensembling has been unwind and has been proven best among all the single classifiers.

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