Heart Rhythm Abnormality Detection from PCG Signal

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***Abstract*— Cardiovascular diseases are the major cause of mortality and PCG provides a non-invasive way to monitor the heart. In this paper, we give a unique approach to classify Normal and Abnormal heart rhythms using Machine Learning. The heart sounds are digital signals recorded from electronic stethoscope. In the initial phase Signal Quality assessment and feature extraction is done after which we explore different data models to find the relation between the features and the results, achieving poor results. In the second phase, audio files are segmented into Systolic and Diastolic phases using a Logistic Regression-HSMM These segments of systoles and diastoles are then individually analyzed and individual feature extraction is done. In the segmentation process a lot of de-noising is also done removing the background noises. This approach yields an accuracy of 79% which concludes that analyzing the heart signal at Systolic and Diastolic phase is a very essential step to solve this problem.**

Keywords— Hidden Markov Model, CNN, Segmentation, SVM, RNN.

I. INTRODUCTION

Ever since the development of smart devices and IoT, the amount of data and the type of data grew by manifolds. Smaller sensors which are easily accessible and are fairly accurate are the main benefactor of automation of such a task which requires a skilled medical practitioner. Particularly useful for remote areas where skilled workers are unavailable, secondly developing infrastructure for evaluating and recording is cheaper to achieve hence it will have a greater penetration and acceptance rate. A big development is the inclusion of ECG detectors in smart bands, although they are not very accurate hence abnormality detection is also inaccurate. Over time these devices will become more precise which calls for the development of such software.

The motivation behind this task is the growing number of human casualties due to cardiovascular diseases according to a WHO(World Health Organisation) article an estimated 17.9 million people died from Cardiovascular failures, this population accounts for 31 percent of all global deaths [1]. In poverty-stricken countries like India, where Doctor to Patient ratio is less than 1:921 [2], this high number implies that a lot of population stay untreated and queues at clinics are unending. This issue compels for the automatic detection and precise treatment procedure and precautions necessary. Since PCG is a non-invasive, cheap and accurate way of monitoring the heart, it is therefore preferred over any other signal.

The rapid evolution of machine learning algorithms put us in a position to develop multiple approaches and pick out the best one weighing the advantages and disadvantages of each. Highly advanced tools are available making the signal processing convenient, most of the signal processing comprises of noise removal algorithms and procedures. The given problem was presented in PHYSIONET challenge 2016 [3] and the paper takes into account for all the techniques that were presented as the solution. We review the techniques giving the best results and also present our own solution.

The main task is to automate the process of identification of abnormal heart rhythm. The primal step in approaching this problem is to read the audio signal and identify systolic and diastolic phases in the signal. On these segments perform feature extraction. [4]

II. LITERATURE SUMMARY

Majority of the work has been accomplished after the PHYSIONET Challenge 2016.

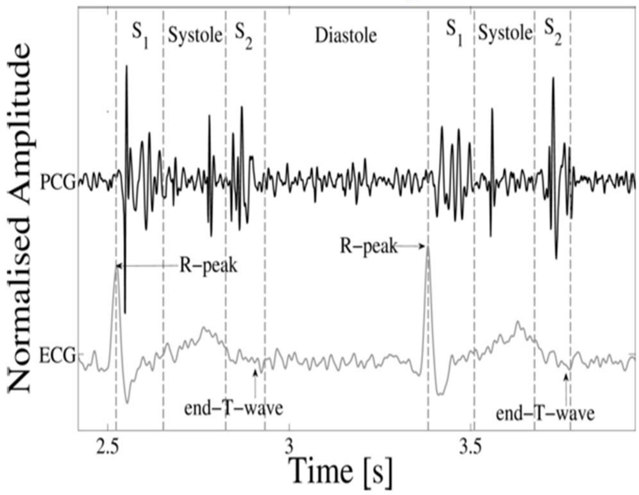

Fig. 1. PCG signal labelled with ECG. Showing states S1 phase, Systolic phase, S2 phase and Diastolic phase

Although an important part of every approach is segmenting the audio signal into states S1, Systole, S2 and Diastole.

In order to segment the audio files into four phases and detect the exact position of systole and diastole on it, HSMM

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is used. Initially the signal is processed (Homomorphic envelope, Hilbert Envelope, Power Spectral Density, Discrete wavelet transform), then it is labeled on the basis of supplied R peak and T wave locations then HSMM is trained with these three parameters which output three matrices namely transmission matrix(A), observation matrix(B) and initial state distribution(π) and p is explicitly defined as the probability of remaining in a particular state[4].

$$\lambda=(A,B,\pi,p)$$

Finally, the Viterbi Algorithm is modified to include the duration densities. Another modification was the incorporation of logistic regression model for deriving observation probability estimates instead of Gaussian distribution. Inclusion of Logistic Regression allows for better differentiation between states.

A Recurrent Neural Network based approach has been presented by [6], this paper explains that the main reason behind using RNN is the use of Neural Networks and their great success with medical application. Secondly their suitability with sequential/temporal data which may be filled with noise. The procedure is simply pre-processing data, Segment Extraction, Feature Selection and apply RNNs. Two types of RNNs are implemented namely:

- LSTM (Long Short-Term Memory)
- GRUs (Gated Recurrent Units)

In order to process the information both forwards and backwards direction so as to exploit future context. Hence a total of four models have been implemented:

- LSTM
- Bi-Directional LSTM
- GRUs
- Bi-Directional GRUs

There have been multiple approaches that make use CNN, best results are achieved by [7]. In this paper, CNN has been trained by decomposing PCG cycles into four frequency bands and further using the segmented states from Springer et al.[4] to extract cardiac cycles. Finally feeding them into a three-layered CNN: 1 input and 2 convolution layers. This approach also includes an AdaBoost-abstain classifier. The Process extracts 124 Time domain features and 88 Frequency Domain Features The boosted classifier is modeled as a generalized additive model.

Another CNN based model is implemented by [8]. CNN based tree-like feature extractor are used and 20 static state and PSD (Power Spectral Density) based features. Finally, posterior probability estimates can be obtained from the SVM model using Platt scaling or with a logistic regression model.

Artificial Neural Networks are one of the best tools to that are suitable for sequential data. [11] Implements a 15 layer fully connected NN and a random forest ensemble learner with standard procedure of segmentation and feature extraction achieving accuracy above 90 percent.

III. PRELIMINARY

Butterworth filter: a very flat response is given by this filter, thus removing noise in the form of irregularities giving us the smoothest signal possible for processing. There are different types of Butterworth filters namely low pass Butterworth filter and digital Butterworth filter. These filters are used for shaping the signal's frequency spectrum in communication systems. The corner frequency or cutoff frequency is given by equation [4]:-

$$f = \frac{1}{2\pi RC}\text{Hz}$$

Hidden Markov Model: A probabilistic / statistical model used vastly to product the next set of states, timestamps of phases in this case from existing probabilities (transition matrix) from one state to another, initial probability matrix and emission probabilities. Initial probability matrix is defined as 1/(number of states) i.e. ¼.[4]

Viterbi Algorithm: A dynamic programming(DP) algorithm used for predicting the most probable sequence of hidden states also known as the Viterbi path. In this case, Viterbi path is S1, systolic, S2, Diastolic. This paper deals with a bit modified version of the Viterbi algorithm and is coded in MATLAB along with the HMM implementation.[4]

Librosa: A python package used for analysis of audio and sound files and help in maintaining building blocks for our information retrieval systems. It also helps in extracting characteristics from the audio signals that are relevant to the problems and store them in a vector known as a feature vector which can be further used to train our different training models[9].

Support Vector Machine (SVM): A discriminative classifier which gives an optimal hyperplane for dividing classes based on the given labeled training data with the use of kernel to transform the data and then based on these transformations it finds an optimal boundary between the possible outputs. As the data points of the accumulated data seem to be in a complex order, SVM did seem to be the best option to train and classify data.

Principal Component Analysis: PCA is a technique used for dimensionality reduction by orthogonal transformations on the given dimensions and choosing the features that account for the majority of variance.

IV. METHODOLOGY

Given below in Fig. 2 is the process flow that every audio wav file goes through.

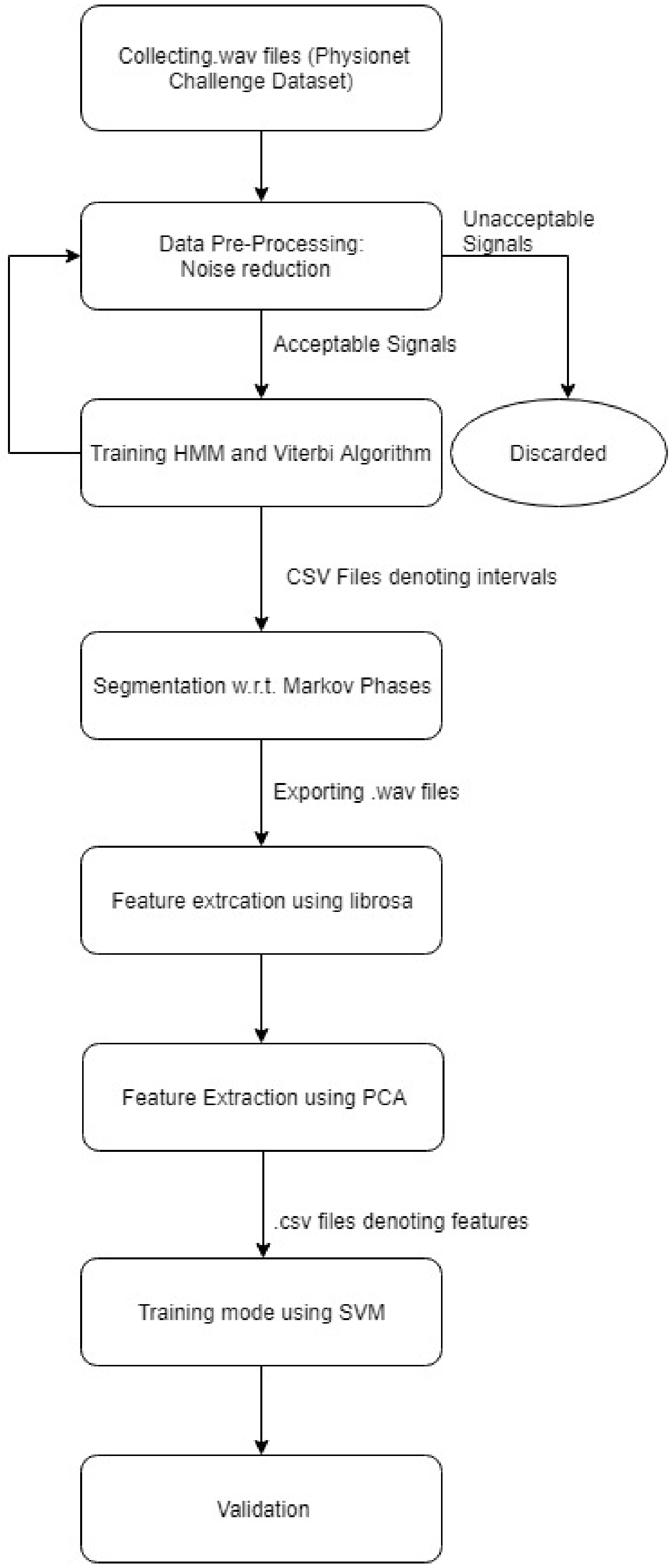

Fig. 2. Process Flow for abnormality detection.

A. Data *Gathering*

Sample data present in the .wav format of audio files on physionet.org/2016/challenge. Data comprised of 4,000 audio files having heart rhythms and csv files directing class of each audio file as normal (-1) and abnormal (1). Dataset for this problem has been provided by PHYSIONET 2016. The dataset has been collected by thoroughly going through research databases from numerous research groups. The dataset consists of 2435 recordings from 1297 patients and it is a mix of a variety of conditions whether it be a heart valve disease or coronary disease [5]

B. Removing noise from the PCG signals

PCG signals are very prone to the noise, especially in this case as sounds from internal organs and fluids inside can make it difficult to extract the features accurately for heartbeats. This was done using the Butterworth filter. This process ensures that irrelevant variations do not interrupt the training procedure and segmentation process during the Markov training. Although, some data of significance might have been lost during the process, but the trade-off was worth it, as compared to the result of the signals which didn't undergo the process of noise reduction.

C. Logistic Regression based Hidden Markov Model with modified Viterbi Algorithm

The hidden Markov model is usually used in identifying the probability of transition from one state to another, in our case there are four states S1, systole, S2 and diastole. Logistic Regression uses emission probability to segregate the states more accurately on the basis of intervals [10]. Again the initial transition probability matrix and initial state probabilities were assumed according to the previous work of [10].

D. Segmenting the data according to the intervals given by Markov Model:

The end result of Markov Model for a single wav file was a csv which stated the timestamps of intervals for the phase S1, S2, systole and diastole. The respective audio file had then to be segmented into four categories as mentioned above into different folders as to facilitate the feature extraction of all four phases of a heartbeat. Each segment was again exported as a wav file to its respective folder. Following this trend, 86,500 different segments of each type were obtained.

E. Extracting features of different phases from the heartbeat

Root mean square error (RMSE), mean spectral range and contrast of each segmented phase of audio signals were obtained using LIBROSA in python and csv for each phase along with its defined class was build. This process involved making appropriate chunks according to the intervals given by HMM. Further exporting these chunks into discrete .wav files and using librosa's functions upon them to get the specified features. Segmenting procedure ensures that no chunk of data is wasted by overlapping intervals otherwise it could have led to overfitting of the training model.

Feature Extraction using PCA : Principal Component Analysis is applied to reduce the number of features from 15 features by first *transforming* the features and then selecting the top three features contributing 83.4 % of *the variation.*

F. Training

After collecting 60,000 samples of testing data from csv files of the segmented data having parameters Soot mean square error, spectral contrast and mean spectral range. The segments were collected from the 4,000 .wav files provided in the challenge. Then these samples were trained into the SVM classifier of Sklearn. Further to compare results from the SVM, a decision tree model was also trained.

G. Validation

A total of 26,000 samples were tested against 60,000 samples of the trained data in the support vector machine (SVM). Accuracy of 79 percent was achieved as compared to 61 percent of decision tree.

V. RESULT AND DISCUSSION

Given below are the normalized values of feature calculated without using HMM for four folders (12 pitches values are not included here). All these values are for a single file from each folder.

TABLE 1 CALCULATED VALUES ALONG WITH SIGNIFICANCE EXTRACTED FROM THE WAV FILE.

Training Set	**Value Calculated**	
Folder/ Result	***FEATURE***	***Value***
a) (-1)	Contrast	0.12948
	mel_spec	0.48655
	Rmse	0.36201
b) (1)	Contrast	0.29960
	mel_spec	0.65057
	Rmse	0.31275
c) (1)	Contrast	0.23010
	mel_spec	0.54284
	Rmse	0.33712
d) (-1)	Contrast	0.19654
	mel_spec	0.38625
	Rmse	0.36253

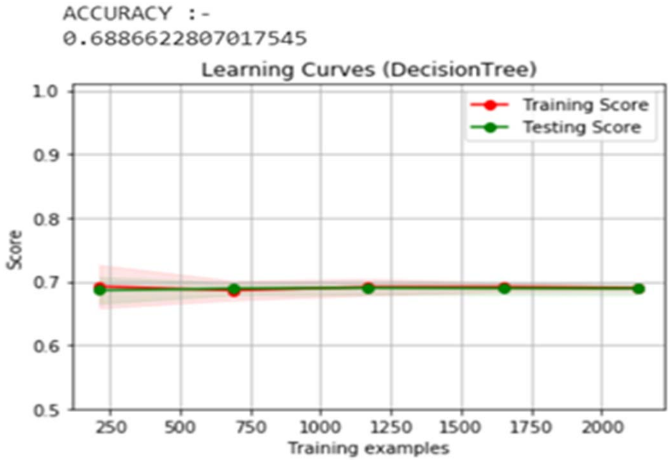

Fig.3.:DecisionTime

Fig.4.Logistic Regression with 10-fold Cross-Validation

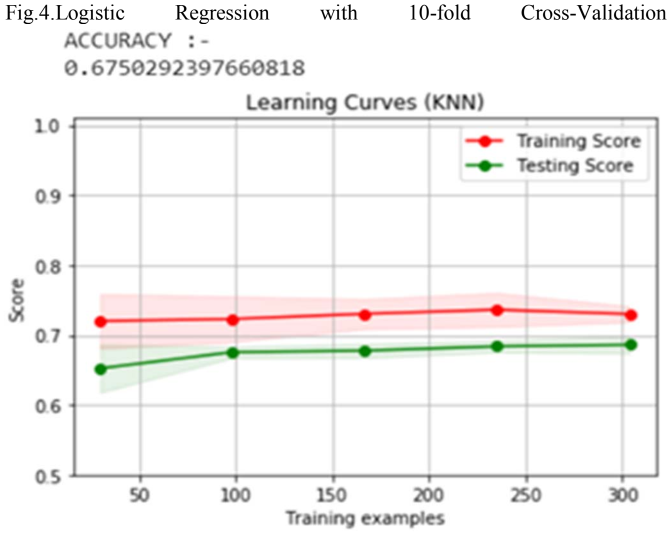

Fig. 5. K-Nearest Neighbor with 10-fold cross validation

```
data = pd.read_csv(r'E:/Major/Features/dystole_training_3.csv')

n_d = data.filter(['mel_spec','rmse','contrast'],axis=1)

target = data.filter(['class'],axis=1)

X_train, X_test, y_train, y_test = train_test_split(n_d, target, test_size=0.33, random_state=42)

clf1 = SVC(gamma = 'auto')
clf1.fit(X_train,y_train)

C:\Users\Nishant Mangla\Anaconda3\lib\site-packages\sklearn\utils\validation.py:761: DataConversionWarning: A column-vector y w
as passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)

SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)

clf1.score(X_test,y_test)

0.7970714235550249
```

Fig. 6. SVM implemented with segmented Audio file

Given below Figure 7 is comparing the accuracies calculated with all the different models with their respective features**.**

```
L.R: 0.608553  S.d:- (0.194807)
KNN: 0.621382  S.d:- (0.195485)
D.Tree: 0.609539  S.d:- (0.195199)
SVM: 0.798662  S.d:-( 0.168745 )
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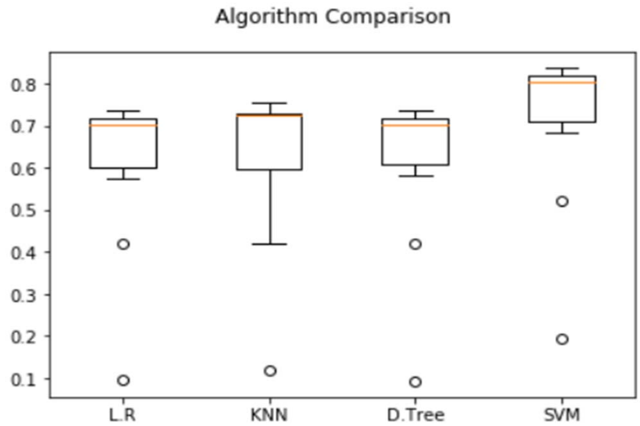

Fig. 7. Comparing all the models side by side. Logistic Regression, KNN, Decision Tree and SVM

We see that SVM implemented in conjunction with segmented heart sounds with the help of HMM results out significantly better results than others as all others where features are simply calculated without any segmentation.

Figure 3 depicts the accuracy achieved by SVM, Figure 4 depicts accuracy with Logistics Regression, Figure 5 depicts accuracy with KNN all of these are modelled without segmenting the data. Figure 6 describes SVM implemented with segmented data.

VI. CONCLUSION

The proposed algorithm does not work well with noisy signal, since numerous recordings get rejected at the time of Signal Quality Assessment. Also patients with unnatural entities such as pace makers, artificial valves etc. also create distortion. Therefore, it calls for a better de noising approach.

Secondly SVM does a multi-dimensional phase classification on the given features hence successfully classifies potentially abnormal heart beats.

This method cannot be used in the context of aperiodic sounds such as of doors, machines etc. Finally comparing the plain results with HSMM it becomes an important process.

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