Human Heart Sounds Classification using Ensemble Methods

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Abstract-Efficient diagnosis of cardiac diseases has become increasingly important because cardiac diseases are one of the main causes of decease worldwide. This article presents the research work pertaining to human heart sounds classification using ensemble techniques. In order to validate the classification results, the proposed framework was applied on publicly available standard heart sound dataset. A set of audio features is identified and used for human heart sounds classification. First, using individual classifiers, the sounds classification on the dataset is carried out. The classification results achieved using individual classifiers comes out lower as compared to the existing methods, therefore ensemble technique is applied. This technique proves to be more effective and robust as it increases the overall classification accuracy. The classification accuracies for human heart sound dataset achieved by the proposed methods are higher than the existing solutions.

Keywords-Heart Sounds Classification, Heart Signals, Ensemble Methods

I. Introduction

Cardiovascular diseases are one of the major cause of human death around the globe. The number of deaths caused by cardiac diseases is estimated to be 17.3 million and the number is expected to reach 23.3 million by 2030 [I, ii]. Enhanced procedures are in constant need to counter the flaws in persisting methods that could detect the heart disease signs to produce a substantial favorable impact on global health. This research work aims towards developing efficient solution to this problem that suggests the first level of screening of cardiac pathologies both in hospital by doctors (using digital stethoscope) and at home by the patients (using a mobile device).

The investigations involve classification of acoustic sample data in context where non-trivial discrimination between classes of concern persists. We collected data in real world environments which is subjected to frequently inherent background noise. Also, distinguishing between sounds corresponding to different heart symptoms is exceptionally challenging, and requires robust classifiers for success in the presence of aforementioned constrained parameters. To date despite its medical significance, this is a relatively unexplored area of application for machine learning.

Heart is one of the two critical organs for human life. Therefore, the heart disorder has a great significance for the human health.

In the era from 1985 to 2006, at worldwide, the death ratio reducing from the diseases of heart after brain embolisms ranked second [iii]. The heart is a hollow muscle which pumps the blood through all the body [iv]. The delivery of the blood into the circulatory system is the primary and main duty of the heart [v]. This highlights significance of the problem area and its effects on human life. The human heart performs duties in two cycles known as systole and diastole. When the heart contracts, happening of this stage is called systole, and when the heart relaxes then, occurring of this stage is called diastole. The heart sounds can be heard in the sequence as "lub, dub" occur due to the closing of the valves of the heart. The first heart sound (S_1) is known as "lub" and the second heart sound (S_2) is known as "dub". (S_3) the third number heart happens instantly after the(S_2), and it is of lower vitality than the second one. (S_4) the heart sound of number four happens before the sound S_1 having the lower size of sufficiency than alternate sounds. Also, the sounds caused by the blood flow in the vessels and heart are parts of the heart sounds. Nonetheless, indeed, how they happen is still an active topic of research [iv].

Among real heart sounds, the abnormal heart sounds like murmurs heard due to damaged valves are known as the extra heart sounds [iii]. The pathologic changes are the initial signs of murmurs occurs in valves of human heart, which can be sensed by the auscultation method in primary health care organizations [vi]. Due to the disorders of heart valve, the common diseases of the heart occur. Thus, in the disorders of the heart valve, the early diagnosis is one of the leading study area in medicine [vii].

Auscultation method is applied by the physicians as primary method to differentiate between the normal and abnormal heart sounds [viii]. Any heart disorder is then detected by the doctors after listening to these sounds using stethoscopes [ix]. With the emergence of modern and efficient methods incorporating Doppler's, echocardiography and magnetic resonance imaging

(MRI), anomalies of heart valves are effectively detected. The significance of both the conventional techniques (auscultation and phonocardiography) has declined according to expert opinion. Despite the fact that auscultation is a key method of judgment for physicians and is still employed in primary health units to suggest if the patients need to consult experts, it is subjected to objections of being cumbersome in context of time consumption, relatively costlier and inaccessible [vi].

The auscultation technique employed by expert physicians to diagnose heart disorders is prone to certain limitations. Interpretation and categorization of different heart sounds directly relates to the skills and experiences of the physicians, which are acquired after long examinations [x]. Moreover, environmental conditions may impose lack of diagnosis. Keeping in view the disadvantages associated with the auscultation method, it may rationally contribute towards solution to the problem when employed in coordination with artificial intelligence, and may not yield desirable results alone [xi]. Specifically referring to primary health units, this combination may be a great deal in terms of contribution towards diagnosis in these institutions.

Singh, Mandeep, and Amandeep Cheema have proposed a cost-effective method for the classification of normal and abnormal heart sounds. Proposed method utilizes minimum equipment and do not require Electrocardiogram (ECG) gating. For the classification of heart sounds, only 5 features have been used and obtained 93.33% of accuracy [xii, xiii]. Jia, Lijuan, et al. proposed a system for automatic analysis and heart sounds classification. The features were extracted through Normalized Average Shannon Energy and wavelet decomposition. They have focused the analysis of S1 and S2 sounds. The approach of Fuzzy Neural Network with Structure Learning (FNNSL) is designed for the prediction of heart sounds [xiv].

Sun, Shuping, et al. have proposed a diagnostic method named boundary curve model based on SVM (support vector machines) used for the diagnostic features [T_{12}, T_{11}] and [F_G, F_W]. The method was used for the purpose of diagnosing the ventricular septal defects (VSD) and three sub-classes of VSD sounds named small VSD (SVSD), moderate VSD (MVSD) and large VSD (LVSD). They have obtained 98.4% of classification accuracy for the clinical VSD sounds and 95.1%, 94.8% and 95.0% of classification accuracies respectively for SVSD, MVSD and LVSD sounds [xv]. Patidar, Shivnarayan, Ram Bilas Pachori, and U. Rajendra Acharya have designed a new method based on correntropy and tunable-Q wavelet transform (TQWT) using extracted features from heart rate signals. The method was used for the diagnosis of the coronary artery disease (CAD) patients. Also they have developed a novel CAD Risk index using a single number through significant features to detect CAD. They have achieved 99.7% of average classification accuracy, 99.6% of sensitivity, 99.8% of specificity and 0.9956 of Matthews's correlation coefficient for Q changing between 24 and 30 using morlet wavelet kernel function (MWKF) [xv].

Furthermore Papadaniil, Chrysa D., and Leontios J. Hadjileontiadis have presented an integrated efficient scheme for segmentation and extraction of heart sounds named Heart Sound Segmentation-Ensemble Empirical Mode Decomposition/Kurtosis features (HSS-EEMD/K). The proposed scheme shows promising results for detection and extraction of first heart sound S_1 and second heart sound S_2, their duration determination and heart cycle separation into its 4 components as diastole -S_1-systole -S_2. The performance of the proposed scheme was evaluated on an experimental database of clinical environment composed of 43 heart sound recordings. The HSS-EEMD/K method correctly segments the heart cycles for 83.05% of the cases and fixes the locations of the heart sounds with percentage of 94.56% [xvi].

An automatic system for heart sound classification which used a probabilistic approach that was based on Hidden Markov Models (HMM) and Mel-Frequency Cepstral Coefficients (MFCC) was discussed by Chauhan et al. [xvii]. In some other study, a prototype was developed by Reed et al. for the sounds analysis and their classification. They focused on the sounds for the wavelet transformation and used a neural network based classifier and classified different sounds of the heart [xviii]. In research work performed by Guraksin et al., a system was developed for the classification of heart sounds. They used Discrete Fourier Transform (DFT) and Artificial Neural Network (ANN). They used data containing 120 normal, mitral stenosis and pulmonary stenosis heart sounds, and obtained 91.6% of classification performance [ix]. In some other study, using the same data set, Harun Uğuz which developed a biomedical system that used Burg and Principal Component Analysis (PCA) with the ANN classifier and DFT for the classification of heart sounds, and obtained a classification performance of 95% [xix].

In our proposed work, publicly available standard heart sound dataset [ii] has been utilized to validate the classification results. Audio features have been extracted for the potential use of characterizing human heart sounds and then employed in our work. The recent study suggested that the ensemble methods are most suitable for classification due to its high accuracy rates [xi]. The ensemble method based on the idea of giving value to the predictions of individual classifiers along with accuracies. This article shows our investigations for sounds classification on well-known ensemble techniques [xx]. To our information, for such classification task, no such type of ensemble methods has been used. In classifying human heart sounds, Ensemble methods have proved effective results as compared with the results of individual classifiers. Our study also compares the results of suggested setup of ensemble methods with the existing results in [ix,xxi] and shows the substantial enhancement over them. This article is structured as follows. The proposed methodology and experimental setup are given in Section II. Section III presents the results of our experimental setup, analysis of results and comparison with the existing work. Conclusion is presented in the last section.

III. EXPERIMENTAL METHODOLOGY

Experimental methodology used for validation of the proposed framework consists of real-world human heart sound dataset, sound feature extraction and classification techniques employed for the purpose. In addition to this, experimental setup and the details of literature methods used for performance comparison are also discussed in this section.

A. Real-world Human Heart Sound Classification Dataset

One standard dataset has been employed specifically designed for human heart sounds classification task which was also used by other researchers [ix, xxi]. Here the details of human heart sounds dataset (HHSD) are mentioned below.

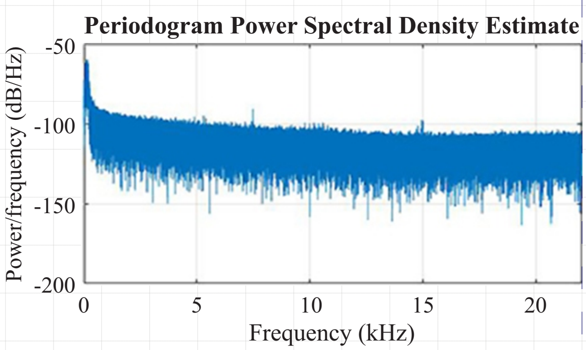

Fig. 1. Power Spectrum of Extrahls Sound

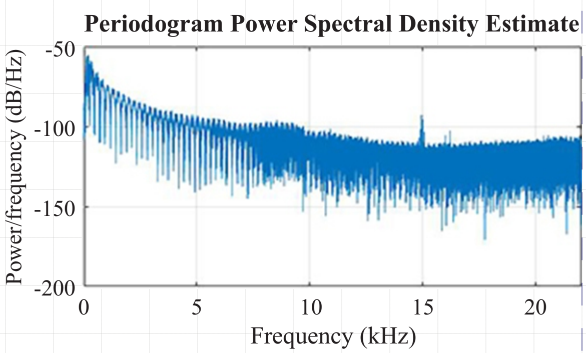

Fig. 2. Power Spectrum ofArtifact Sound

1) Heart Sound Dataset

The human heart sounds dataset contains all non speech audio files sampled at 16KHz and in WAV format. This dataset is online freely available for research purposes and the data has been collected from the public via the iStethoscope Pro iPhone app, provided in this heart sound dataset [ii]. There are 124 sound files and 4 different sound classes in the dataset. Each class containing the number of audio files with time in seconds are shown in Table I. From the dataset

TABLE I
HEART SOUND DATASET (ADAPTED FROM [i])

Sound class	No. of files	Total Duration (sec)
Normal	31	248
Murmur	34	272
Extra heart sound	19	152
Artifact	40	320

power spectrums of four sample files from each class i.e. Artifact, Extrahls, Murmur and Normal Sound is shown in Fig. 1, 2, 3 and 4.

B. Acoustic Features

In classification phase, effective feature extraction is essential for achieving higher accuracy. Dimensions reduction of the sound data is done by extracting features from sound waves. In order to perform classification task, different audio features were extracted in the existing solutions [xxii, xxiii].

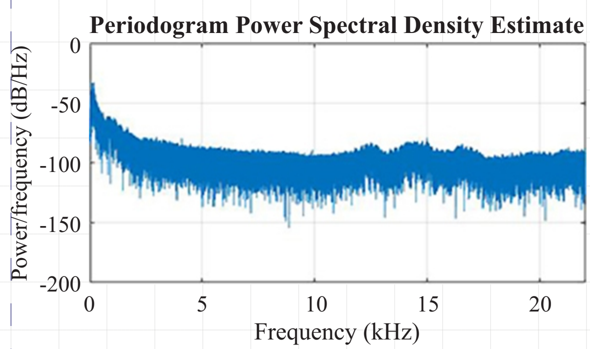

Fig. 3. Power Spectrum of Murmur Sound

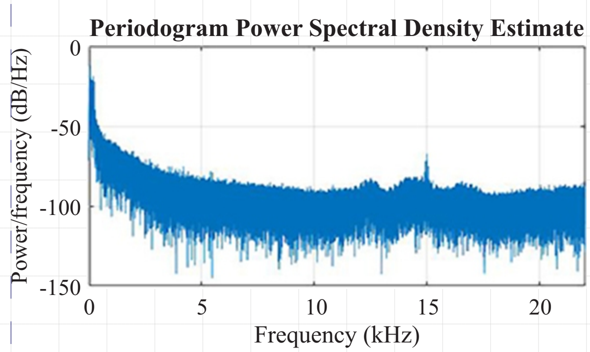

Fig. 4. Power Spectrum of Normal Sound

Comprehensive study of audio features for better classification of sound waves is conducted and set of features for potential use of classifying human heart sounds is identified and used in this work.

TABLE II
AUDIO FEATURES

Non-Spectral	**Fraction of Low Energy Windows** **Root Mean Square of Frames** **Zero Crossings** **Relative Difference Function**
MFCC	13 features
LPC	10 features

The set of audio features used for classification in our proposed framework are shown in Table II. The extracted features consist of 13 attributes of MFCC (Mel-frequency Cepstral Coefficients), 10 features of LPC (Linear Predictive Coding) and other four Non-Spectral features. The Non-Spectral features consist of fraction of low energy window, root mean square of frames, zero crossings and relative difference function [xxiv-xxvii]. These features were extracted using statistical measures such as standard deviation and mean at the utterance level. The samples window size of 512 was taken. Windows overlapping fraction was 0.5 and sound signals sample rate was set to 16 kHz, with these settings 54 total features are created and used in this research work.

C. Classification using Ensemble Methods

In proposed framework, ensemble technique is employed for classification of sound signals. Generally, the performance of combination based methods is better than individual classifier. The reason is that they weigh predicting of individual classifiers before the concluding decision is taken and also have an affinity to make progress if a single classifier fails to outperform [xxi, xxviii]. In this work, three ensemble techniques are used: Bagging, AdaboostM1 and Random Subspace. The selection of these ensemble techniques is due to their improved generalization performance on combining with low performance classifier. To our information, no such ensemble techniques were used so-far for human heart sounds classification. To show the efficiency of ensemble techniques, the baselearners are also used separately for the sounds classification. A detail description of the base classifiers and these three ensemble techniques are given below.

1) Bagging

This ensemble technique models the training set into multiple times replacement and become available into various training sets. The size of these training sets is equal to the original training set size [xxix, xxx]. It reduces variance and attempts to avoid over-fitting. The whole Bagging algorithm is shown below.

Input: *training sample S, Classifier C, iterations I*

Output: *result* C_E

Training: *for* $j = 1$ *to* I

S_j = *bootstrap sample from S*

C_j = *train a classifier on* S_j *via C*

end for

$$C_E = arg\,max_{x\in X} \sum_{j:C_j(y)=x} 1$$

2) AdaboostM1

AdaboostM1, an ensemble technique (also known as adaptive boosting) which improves the accuracy of classification of such a learning algorithm that consistently generates classifiers having better accuracy compare to a random guessing classifier [xxx]. The entire AdaboostM1 algorithm is represented below.

Input: *training sample S, Classifier C, iterations I*

Output: *result* C_E

Training:

normalize the weights and make the total weight w

S_j = *sample from S according to the distribution*

C_j = *train a classifier on* S_j *via C*

$$e_j = \frac{1}{w} \sum_{y_j \in S_j \,:\, L_j(y_j) \neq x_j} weight(y_j)$$

$$\beta_j = \frac{e_j}{1 - e_j}$$

weight (y_j) = *weight* (y_j) β_j, for all y_j *where* $C_j(y_j) = x_j$

end for

$$C_E = arg\,max_{x\in X} \sum_{j:C_j(y)=x} \log\left({}^{1}/_{\beta_j}\right)$$

3) Random Subspace

It contains various classifiers and it attempts to improve and maintain its precision when it develops to become more complicated [xxxi]. Instead of example space, it tries to modify the training set in feature space. The detail description of the Random Subspace algorithm is presented below.

Repeat for $d = 1$ *to D*

Choose an $r-$ *dimensional random subspace*

$\tilde{Y}^d$ *from the original* $q-$ *dimensional feature space Y*

Build a classifier

$L^d(Y)$ *(with a decision boundary* $L^d(Y) = 0$*) in* $\tilde{Y}^d$

Combine classifiers $L^d(Y)$,

$d = 1$ *to D by majority voting to a final decision rule*

$$\alpha(Y) = \arg max_{x\epsilon[-1,1]} \sum_{d} \delta sgn\left(L^d(Y)\right), x$$

Where $\delta_{j,k}$ *is Kronecker symbol and*

$x\epsilon[-1,1]$ *is classifier's class label (decision).*

The base learners include Random Forest, Decision Tree C4.5 and Bayes Net that are used along ensemble methods. The reason of the selection of these classifiers is that they build a model in less time and when used in combination with the ensemble methods as mentioned above, yield higher accuracy.

4) Random Forest

Random Forest can be used for regression as well as classification. It consists of multiple classifiers like decision trees like classifiers. Every tree throws its weight for a class. The algorithm picks such a class that achieves maximum votes than all other trees in the forest [xxxi].

5) Decision Tree C4.5

Decision Tree C4.5 (an ID3 algorithm extension) is a base classifier created by R. Quinlan [xxxii]. This algorithm uses training data to create decision trees by using information entropy. The support of both discrete and continuous attributes are the developments in C4.5 over ID3 algorithm. The training data which have the values of missing attributes can also be supported by C4.5. It can also handle such type of attributes which have different prunes trees and costs after they are created.

6) Bayesian Network

A Bayesian Network or Bayes Net is a network structure B_n, on a set of variables it is a directed acyclic graph while the set is; $U = \{x_1, \ldots, x_n\}$, $n \geq 1$ and a set of probability tables $B_p = \{p(u|pr(u))\ u \in U\}$ where $pr(u)$ is the parents set of u in B_n. The Bayes Net denotes a probability distribution $P(U) = \prod_{u \in U} p(u|pr(u))$ [xxxiii, xxxiv].

D. Experimental Setup

For the HHSD, we have applied the 10-fold cross validation classification scheme and compare the outcomes with [xix]. We have also applied the 50-50% training-testing approach of random partitions and compare the results with [ix]. Window size of 10ms with 50% overlapping is chosen for MFCC feature extraction scheme. Total 54 attributes have been extracted which main comprises of MFCC, LPC and other spectral features.

For classification step, we have used the three ensemble methods combined with the three base learners. Different combinations of ensemble and base learner methods were made and investigates. Afterwards, we have evaluated the performance of these six combinations of classifiers on HHSD.

III. Results and Discussion

This section presents the experimental results using the audio features given in Table II and their analysis on the HHSD. The base classifiers are used in the first attempt on the said dataset. After that the ensemble methods are applied to show the performance of these techniques in terms of results as compared to individual learners.

TABLE III
CLASSIFICATION ACCURACIES (%) OF BASE CLASSIFIERS ON HHSD RESULTS USING 10-FOLD CROSS VALIDATION

Classifiers	Classification Rates (Mean) %
Decision Stump	69.51%
Bayes Net	96.34%
NB Tree	95.73%
Uğuz's Method [xix]	95.00%

A. Results for Real-World Human Heart Sounds Dataset

The three individual classifiers, i.e. Decision Stump, Bayesian Network and Decision Tree C4.5 have been tested in the first attempt on HHSD. Table III represents the classification performance in percentage on the said dataset using 10-fold cross validation scheme and all the acoustic features. These results were compared with [xix], because they have also reported

TABLE IV
CLASSIFICATION ACCURACIES (%) OF BASE CLASSIFIERS ON HHSD RESULTS USING 50-50 TRAINING-TESTING

Classifiers	Classification Rates (Mean) %
Decision Stump	63.41%
Bayes Net	95.12%
NB Tree	91.46%
Uğuz's Method [xix]	91.60%

TABLE V
CLASSIFICATION ACCURACIES (%) OF ENSEMBLE METHODS ON HHSD USING 10-FOLD CROSS VALIDATION

Ensemble Techniques (with Base Classifiers)	Classification Rates (Mean) %
Random Subspace-Random Forest	96.95%
Random Subspace-Naïve Bayes	96.95%
AdaboostM1-Bayes Net	**98.17%**
Bagging-Random Forest	97.56%
Bagging-Bayes Net	**98.17%**
U˘guz's Method [xix]	95.00%

TABLE VI
CLASSIFICATION ACCURACIES (%) OF ENSEMBLE METHODS ON HHSD USING 50-50 TRAINING-TESTING

Ensemble Techniques with Base Classifiers	Classification Rates (Mean) %
Random Subspace-Random Forest	**98.78%**
Random Subspace-Naïve Bayes	96.34%
AdaboostM1-Random Forest	**98.78%**
AdaboostM1-Bayes Net	97.56%
Bagging-Random Forest	96.34%
Bagging-Bayes Net	96.34%
Gu¨raksın et al.'s Method [ix]	91.60%

the results on the same dataset. As we can observe that using the three base classifiers, the classification accuracies are nearly same and do not provide any improvement over existing scheme [xix]. Table IV shows the results on HHSD by applying the approach of 50-50% training-testing. Again, the results were compared with [ix] because they have used the same dataset. This time, the results are significantly improved as compared to the accuracies in [ix]. Still further enhancement is needed in accuracy, therefore the techniques based on ensemble methods are applied.

Table V presents the classification performance of six different combinations of ensemble based techniques evaluated through 10-fold cross validation.

TABLE VII
CONFUSION MATRIX OF ADABOOSTM1-BAYES NET ENSEMBLE ON HHSD USING 10-FOLD CROSS VALIDATION

Classes	a	b	c	d
a = Normal	31	0	0	0
b = Murmur	1	32	1	0
c = Extrahls	0	0	18	0
d = Artifact	0	0	0	80

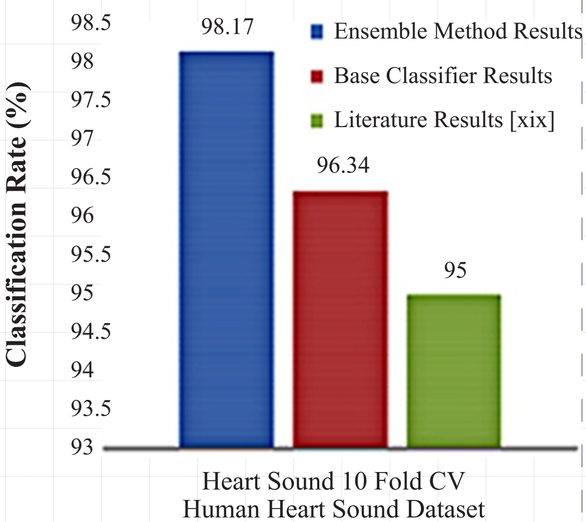

Fig. 5. Comparison of classification accuracies (%) formed by the proposed ensemble methods, Base classifiers and Uğuz's method [xix] on HHSD

Also, a comparison is made with the results in Table III. We have achieved 98.17% accuracy by using AdaboostM1 with Bayes Net as base classifier (AdaboostM1-Bayes Net). An accuracy of 98.17% was achieved when used Bagging-Bayes Net ensemble. These accuracies were compared with 96.34% of individual classifier results (Table III) and 95.00% [xix]. This shows that the combination based methods provide considerably higher results than the already reported results. Ensemble methods provides high classification performance compared to base classifiers but its training and testing time is higher on the dataset. The best classification accuracies are given in bold in Table V and in succeeding tables.

TABLE VIII
CONFUSION MATRIX OF ADABOOSTM1-RANDOM FOREST ENSEMBLE ON HHSD USING 10-FOLD CROSS VALIDATION

Classes	a	b	c	d
a = Normal	30	1	0	0
b = Murmur	1	33	0	0
c = Extrahls	0	1	17	1
d = Artifact	0	0	0	80

Next a comparison is made with the classification results [ix] by applying the method of 50-50% training-testing arbitrary partitions. The results of these combination based ensemble methods are presented in

TABLE IX
CONFUSION MATRIX OF RANDOM SUBSPACE-RANDOM FOREST ENSEMBLE ON HHSD USING 50-50 TRAINING-TESTING

Classes	a	b	c	d
a = Normal	15	0	0	0
b = Murmur	0	20	1	0
c = Extrahls	0	0	9	0
d = Artifact	0	0	0	37

Table VI. Accuracy of around 98.78% is achieved when AdaboostM1-Random Forest and Random Subspace-Random Forest ensemble methods were used with Random Forest as the base classifier as compared to 91.60% given in [ix] and 95.12% of individual classifier results mentioned in Table IV.

As shown in Table V and Table VI, the results using three type of ensemble techniques with Bayes Net and Random Forest as individual classifiers are greater than the base classifiers results. These classification accuracies are also greater as compare to the previous reported results [ix] on sound dataset.

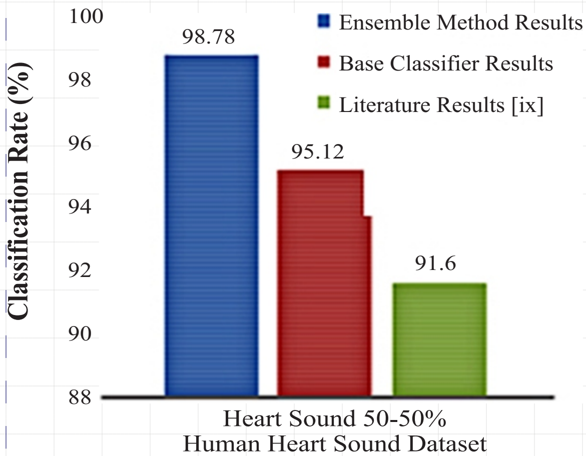

Fig. 6. Comparison of classification accuracies (%) produced by the proposed ensemble methods, Base classifiers and Guraksin et al.'s method [ix] on HHSD

Confusion matrix of AdaboostM1-Bayes Net is shown in Table VII and Table VIII shows the confusion matrix of AdaboostM1-Random Forest ensemble methods for HHSD using 10-fold cross validation approach. Results of applying Random Subspace-Random Forest algorithm are shown in confusion matrix in Table IX and the confusion matrix of AdaboostM1-Bayes Net ensemble methods for HHSD using 50-50% training-testing scheme is shown in Table I0. The results in confusion matrices are consistent with each other. This shows that our ensemble methods results are reliable and constant; and at the same time achieve greater classification rates than the earlier results [ix, xix]. Fig. 5 and Fig. 6 provides the results summary using ensemble method accomplished in terms of classification accuracies.

The best results of ensemble techniques in each scenario (highlighted in bold) are compared with the results of individual classifier and results from [ix,xix] to give an enhanced and comparative sketch.Figure 7 illustrates the comparison of the results produced by the two techniques which are applied in the proposed work (i.e.10-fold cross validation and 50-50% training-testing) on HHSD.

IV. Conclusion

In this paper, we proposed an approach of using different ensemble methods for detecting and classifying human heart sounds. In the first attempt, the base classifiers along with different audio features were used for the performance measurement of classifying human heart sounds. Subsequently, the ensemble methods were applied for the improved classification

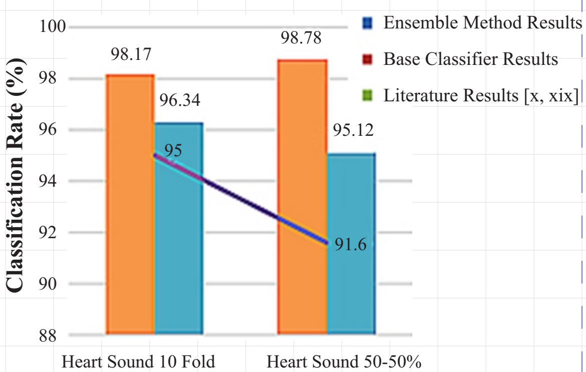

Fig. 7. Comparison of the results using two techniques i.e. 10-fold cross

of these heart sounds. The ensemble techniques provided greater sound classification accuracies than the base classifiers and two other existing approaches. Therefore, the performance accomplished by the suggested system of ensemble methods in classifying human heart sounds is greater than the existing approaches for the HHSD.

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