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Pathology Voice Detection and Classification Using Ensemble Learning

Mythili J, Vijaya MS
PSGR Krishnammal College for Women Coimbatore, India
PSGR Krishnammal College for Women Coimbatore, India
Corresponding Author: Mythili J

Abstract: *Voice disorder is a large phenomenon which is dramatically affecting a large number of people. These pathological conditions are caused due to various reasons and some of the reasons might be talking too much, screaming constantly, smoking which affects our vocal chords. Voice disorders can be treated properly when diagnosed early. The research work in this field generally splits in two stages: first, extraction of meaningful feature sets, and second, using these features for classification of speech recordings into healthy condition and different pathological cases. The objective is to use the discriminative features in the voice signals to detect the pathologically affected voices. Here Ensemble learning technique is used to find the types of disorder in voices. The first component is the extraction of feature vectors using Mel-frequency cepstral coefficients (MFCC), Linear predictive coding (LPC), Wavelet Packet Decomposition (WPD), Cepstral Analysis (CA), Jitter, Shimmer, Pulse, Pitch, Hormonicity, Intensity, Energy and entropy methods. The second is the classification of feature vectors using ensemble learning methods. The parameters from the voice signals are used to build the model. From the experimental results, it is observed that LibD3c classifier performs well in classifying the pathological voices.*

Keywords: *Acoustic voice signal, Bagging, Boosting, Ensemble learning, LibD3c*

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I. Introduction

Despite the highly developed digital technology used in acoustic analysis, there is still a significant attention has been given to the domain of voice pathology identification and monitoring. In the voice pathology treatment, patients have to frequently visit the doctor for their voice therapy. But the patients are waiting for a long time to consult; they are spending a lot of money to find the pathology because the experts have to find the problems in the vocal folds using some endoscopic instruments only. Totally it is an expensive as well as a time-consuming process. Hence such things made the patients feel discomfort. This situation paves the way for the research in finding an automated tool to identify the voice pathology. The basic purpose of this automated tool is to help the patients for identifying the pathological problems for their further progress.

Pathology voice classification model which detects the pathologically defective voice signals accurately. Implementation of statistical methods through the ensemble learning concept is used identify and predict the normal and abnormal voices precisely. The main idea of these works is to extract different features out of the voice samples using general or specific speech analysis techniques and then build a classification model on the data.

There are numerous different causes of voice disorders, and different types of voice disorders have similar symptoms. A voice disorder occurs when voice quality, pitch, and loudness differ are inappropriate for an individual's age, gender, cultural background, or geographic location. The voice disorders are categorized as follows: An organic disorder refers to a problem with the mechanisms of phonation and are classified into two categories: A structural disorder refers to a problem with the voice mechanism itself. In this case, there may be fluid in the vocal cords, polyps/cysts interfering with closure and vibration, etc. A neurogenic voice disorder refers to a disruption in the nerves controlling the larynx. Common examples of this include complete or partial vocal cord paralysis. A functional voice disorder refers to a problem with the manner in which a voice is produced and can be affected on many different levels. This is because a signal is sent from the brain that automatically results in the coordinated pattern/event that is call voicing. For various reasons, however, this pattern can become altered, resulting in behaviors that are interfering with the production of a clear voice.

II. Literature Survey

Various analogous research work are reviewed and analyzed to understand the nature and circumstances of the work. The purpose has been well studied and the need for proposed work is identified based on the literature survey on pathology voice detection is described below.

Gaganpreet Kaur et al., [1] reviewed the research done in the area of speaker recognition. The different methods used for feature extraction and feature classification had been discussed. Some techniques preferred over others such as MFCC for feature extraction had better performance rather than LPC or LPCC, because MFCC were most consistent with human hearing due to Mel scale representation. Thus, it was concluded that feature extraction of GMM performs better as they require fewer amounts of data to train the classifier. It also decreases the memory usage of the system.

Aman Ankit et al., [2] proposed ASR techniques and had put forth some of the essential information. The Speech Recognition System and various approaches used in ASR developed for various languages. Hidden Markov Model and Hidden Markov Model Toolkit (HTK) had been used in this paper. It describes the methods used and comparative study of the performance system developed. In this paper Hidden Markov Model (HMM) was used as a classifier and Mel Frequency Cepstral Coefficients (MFCC) as speech features were the most common technique. ASR implemented by using Hidden Markov Tool kit (HTK) are more efficient than the other systems implemented by using other tools.

Shweta Vijay Dhabarde et al., [3] presents LDB algorithm for audio classification. This helps to achieve high classification accuracy. LDB also uses simple dissimilarity measures for selecting the nodes and features. A database of 213 audio signals were used.LDB performs well for all signals while MFCC works well for music. Combination of MFCC and LDB also gives promising results.

Zvi Kons et al., [4] examines the performance of state-of-threat methods and investigates their weaknesses. Methods examined include features in time, frequency, perturbations, noise and spectral structure. Those features were evaluated by different machine learning techniques. The database contains samples from 719 subjects (320 male and 339 female) that were recorded at the Department of Otolaryngology, Kaunas University of Medicine, and Kaunas, Lithuania Since the glottal source extraction algorithm depends on the existence of the GCIs. Initial results show that by using - scalar quality measures against fixed thresholds and achieved 75% and 70% correct classification rates for healthy and severity-1 cases, respectively, using samples from over 100 healthy and over 50 severity-1 human subjects.

Vahid et al., [5] suggested an initial study of feature extraction and feature reduction in the task of vocal fold pathology diagnosis. A new type of feature vector, based on wavelet packet decomposition and Mel-Frequency-Cepstral-Coefficients (MFCCs), was proposed. Also, Principal Component Analysis (PCA) was used for feature reduction. An Artificial Neural Network was used as a classifier for evaluating the performance of proposed method. The database was created by specialists from the Belarusian Republican Center of Speech, Voice and Hearing Pathologies. The selected 75 pathological speeches and 55 healthy speeches randomly which are related to sustained vowel “a”. All the records were wave files in PCM format. The algorithm gives the best result of accuracy.

V.Srinivasan et al., [6] explored a method of finding the ability of acoustic parameters in discrimination of normal voices from pathological voices that were analyzed and classified. The classification of pathological voice from normal voice was implemented using support vector machine (SVM) and the classifiers were trained and tested. The dataset was recorded by speech utterances of a set of Tamil phrases containing speech samples of 10 distinct subjects (5 normal, 5 pathological children). The speech signals were analyzed and were extracted. A Genetic Algorithm (GA) based feature selection has improved the classification accuracy of this work. Support vector machine shows better performance in terms of classification accuracy.

In existing research, algorithms were implemented using same acoustic features where the predicted accuracy was less. Hence it is proposed to aggregate various features and implement using ensemble learning for better performance in terms of accuracy, precision, recall and F-measure.

III. Proposed Model

The proposed model includes four different phases such as data collection, feature extraction, model building and performance evaluation. First phase is data collection. In these four different pathology voices are collected and stored in a database such as laryngoceles, dysphonia, diplophonia, and chorditis. Second phase is an important in every classification process. In this phase various features are extracted like Mel-Frequency Cepstral Coefficients (MFCC), Linear Predictive Analysis (LPC), Wavelet Packet Decomposition (WPD), Cepstral Analysis (CA), Jitter, Shimmer, Pulse, Pitch, Harmonicity, Intensity, Energy and entropy. During third phase, normalized training dataset is used to build the pathology voice detection model based on ensemble techniques. Finally, the model is evaluated using 10-fold cross validation. The proposed framework is shown in Fig. 1.

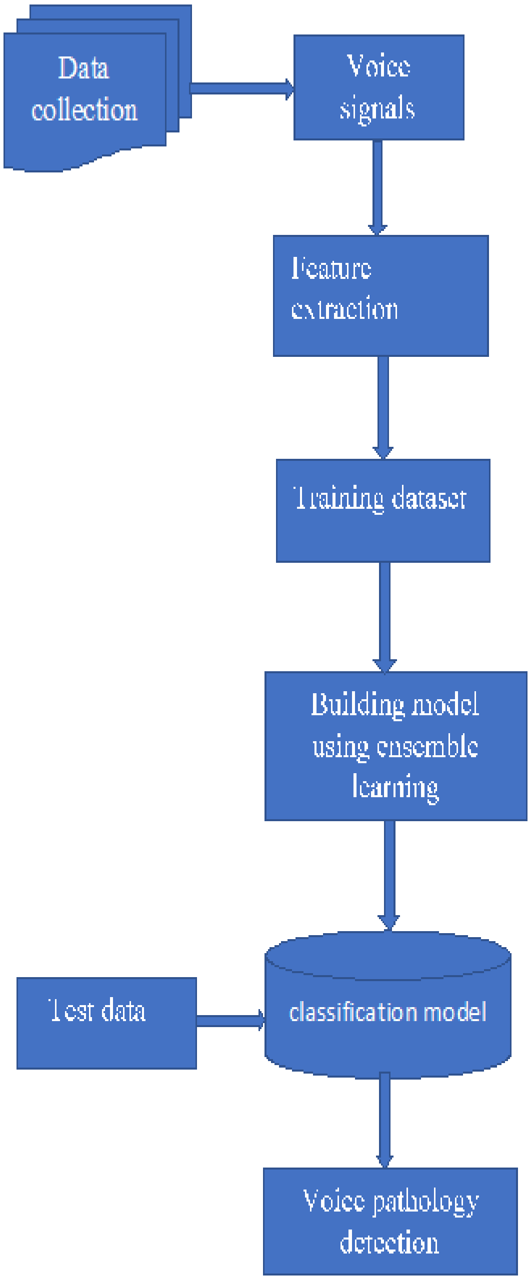

Fig. 1 Overview of proposed framework

IV. Data Collection

The voice samples are collected from the Saarbrucken voice database. This database has been made available freely online. It is a collection of voice recordings from more than 2000 persons, where a session is defined as a collection of, recordings of vowels /a/, /i/, /u/ produced at normal, high, low and low-high-low pitch. In addition, the Electro Glotto Graph (EGG) signal is also stored for each case in a separate file. The length of the audio clips with sustained vowels is 2 seconds. All recordings are sampled at 50 kHz and their resolution is 16-bit. For these experiments files with sustained vowels and people whose age in the range of 30-35 are used. Both male and female voice is taken for four different diseases like laryngoceles, dysphonia, diplophonia, and chorditis are used. A database consists of 400 voice samples such as 200 voice samples for healthy and 200 voice samples for pathology is created.

Feature Extraction

Feature extraction plays an imperative role in every process. Different types of features are extracted and differentiated as global and local features.

Local Features

Some of the local features used in this work are jitter, shimmer, pitch, intensity, pulse, harmonicity which are extracted using PRAAT tool.

Jitter

Frequency of a speaker's voice will vary from one sequence to the succeeding frequency. The random period variability= frequency perturbation or vocal jitter. Vocal jitter increases in voice disorder and is responsible for hoarse, harsh or rough voice quality. Jitter is a measurement for vocal stability a parameter used to find defects in voice. The jitter measurements are Jitter (absolute) is the cycle-to-cycle variation of fundamental frequency. Jitter (relative) is the average absolute difference between consecutive periods, divided by the average period. Jitter (rap) is defined as the Relative Average Perturbation, the average absolute difference between a period and the average of it and its two neighbors, divided by the average period. Jitter (ppq5) is the five-point Period Perturbation Quotient, computed as the average absolute difference between a period and the average of it and its four closest neighbors, divided by the average period.

Shimmer

Shimmer is same as frequency perturbation, but analogous to amplitude. Amplitude perturbation or vocal shimmer serves as an index of vocal stability. Excessive shimmer defines the perception of hoarseness. Shimmer measurements are shimmer (dB) is expressed as the variability of the peak to-peak amplitude in decibels. Shimmer (relative) is defined as the average absolute difference between the amplitudes of consecutive periods, divided by the average amplitude. Shimmer (apq3) is the three-point Amplitude Perturbation Quotient, the average absolute difference between the amplitude of a period and the average of the amplitude. Shimmer (apq5) is defined as the five-point Amplitude Perturbation Quotient, the average absolute difference between the amplitude of a period and the average of the amplitudes of it and its four closest neighbors, divided by the average amplitude. Shimmer (apq11) is expressed as the 11-point Amplitude Perturbation Quotient, the average absolute difference between the amplitude of a period and the average of the amplitudes of it and its ten closest neighbors, divided by the average amplitude.

Pitch

Pitch is an initiative property of sounds that is a frequency-related scale, pitch is the quality that evaluate sound as highs and lows in the sense associated with voice. A Pitch object represents periodicity candidates as a function of time. It is sampled into a number of frames centered around equally spaced times. Pitch is determined in the voice signal with frequency clear and stable sufficient to differentiate from noise.

Intensity

Sound pressure that is intensity is measured in decibels (loudness). Intensity defines two features. One is amount of airflow from the lungs other in amount of resistance to the airflow by the vocal folds. Every person has a baseline intensity level that characterizes his/her conversational speech which determines the voice disorder.

Harmonicity

Harmonicity is nothing but the existence of signals, superimposed on the fundamental signal, whose frequencies are integer numbers of the fundamental frequency. The presence of harmonicity in the voltage or current waveform leads to a distorted signal for voltage or current, and the signal becomes non-sinusoidal signal which causes malfunctions or damage on load.

Global Features

The global features are extracted from whole speech utterance where the local features are extracted into intervals called frames from each voice samples. Global features used in this work are Mel-Frequency Cepstral Coefficients (MFCC), Linear Predictive Analysis (LPC), Wavelet Packet Decomposition (WPD), Cepstral Analysis (CA) which are extracted using MATLAB.

Mel-Frequency Cepstral Coefficients (MFCC)

In MFCC's, the main advantage is that it uses Mel frequency scaling which is very approximate to the human auditory system. The coefficients generated by algorithm are fine representation of signal spectra with great data compression. A frame size of 20 ms and a frame shift of 10ms are used, hence, audio signals of 0 to 2 seconds have been used to generate the feature vectors. They are derived from a type of cepstral representation of the audio clip a nonlinear spectrum-of-a-spectrum. The difference between the cepstrum and the mel-frequency cepstrum is in the MFCC. The frequency bands are equally spaced on the mel scale, which approximates the human auditory system's response more closely than the linearly spaced frequency bands used in the normal cepstrum.

Mel-frequency Cepstral Coefficients (MFCC) is used for feature extraction. The speech waveform, sampled at 8 kHz is used as an input to the feature extraction module. In MATLAB, 'wavread' function reads the input wave file and returns its samples. Speech files are recorded in 'wave' format, with the following specifications: Fs = Sample rate in Hertz and n = Number of bits per sample.

Linear Predictive Analysis (LPC)

LPC is one of the good analysis techniques for extracting features and hence encoding the speech at low bit rate. LPC has capability for speech compression, synthesis and as well as identification. LPC is spectral estimation technique because it provides an estimate of the poles of the vocal tract transfer function. The LPC algorithm is a path signal is stationary within and zero outside, the analysis window. It is desirable to compress signal for efficient transmission and storage. For medium or low bit rate coder, LPC is most widely used. The LPC calculates a power spectrum of the signal. It is used for formant analysis. LPC is one of the most powerful speech analysis techniques and it has gained popularity as a formant estimation technique.

The basic idea behind LPC is that a speech sample can be approximated as a linear combination of past speech samples. In MATLAB, 'wavread' function reads the input wave file and returns its samples. Through minimizing the sum of squared differences (over a finite interval) between the actual speech samples and predicted values, a unique set of parameters or predictor coefficients can be determined. Thus 21 feature vectors are derived by using LPC.

Wavelet Packet Decomposition (WPD)

The wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis and which allows the best matched analysis to a signal. It provides level by level transformation of a signal from the time domain into the frequency domain. It is calculated using a recursion of filter-decimation operations leading to the decrease in time resolution and increase in frequency resolution. The frequency bins, unlike in wavelet transform, are of equal width, since the WPT divides not only the low, but also the high frequency sub band. In wavelet packet decomposition, each detail coefficient vector is also decomposed into two parts using the same approach as in approximation vector splitting.

In MATLAB, 'wavread' function reads the input wave file and returns its samples. The voice signal is decomposed into sub-bands using wavelet transform, approximation components contain the characteristics of a signal and high frequency components are related with noise and disturbance in a signal. Though removing the high frequency contents retain the features of the signal, sometimes it may contain useful features of the signal. So, both the high and low frequency components are decomposed in WPD. Using this method 11 feature vectors are derived.

Cepstral Analysis (CA)

Cepstral signal analysis is one out of several methods that enables to find out whether a signal contains periodic elements. The method can also be used to determine the pitch of a signal. The cepstrum analysis defined it as the power spectrum of the logarithm spectrum. The original application was to the detection of echoes in seismic signals, where it was shown to be greatly superior to the autocorrelation function because it was insensitive to the color of the signal. Cepstrum pitch determination is particularly effective because the effects of the vocal excitation (pitch) and vocal tract (formants) are additive in the logarithm of the power spectrum and thus clearly separate.

Cepstral signal analysis where the amplitude cepstrum of the signal quefrencies from 1 ms to 20 ms. The feature value of the cepstral analysis voice signal is defined using Cout=mean(C).

Feature extraction process was carried out for all the 400 voice signals such as 200 voice signals of healthy and 200 voice signals of pathology and the feature vectors are created. The class label 0 is assigned for healthy voice signals and for pathology voice signals the class label 1 is assigned. A total of 400 feature vectors are created to form a training dataset. To build models with different properties and to generate an efficient voice pathology detection model different types of features are aggregated and four different training datasets have been prepared.

The dataset LG contains both local and global features with 57 attributes. The second dataset LML consists of local, MFCC, LPC features with 45 attributes. The local features are aggregated with MFCC and CA features to develop the LMC dataset. Finally, the LMW dataset is created by pooling the local, MFCC, WPD features. The profile of training datasets is shown in Table I.

Table I

DATASET	FEATURE	NO OF ATTRIBUTES
LG	Local, MFCC, LPC, WPD, CA	57
LML	Local, MFCC, LPC	45
LMC	Local, MFCC, CA	25
LMW	Local, MFCC, WPD	35

V. Experiments and Results

Various experiments have been carried out by implementing ensemble classification algorithms namely bagging, boosting and libd3c where binary classification is done using ensemble learning technique. In bagging classifier, cart is used as base estimator and 10-fold cross validation is performed to analyze the performance. In boosting, AdaBoost classifier is used and based on cross validation score majority the best classifier for pathological voice is predicted. The performance is evaluated in terms of precision, recall, F-measure, accuracy. The results of the experiments are compared and analyzed.

Pathology Detection Using Bagging

The bagging algorithm which constructs base classifiers with inputs generated by the bootstrapping technique. The construction process of every base classifier is independent to each other. It agitates the training set repeatedly to generate multiple predictions and combines these base classifiers by simple voting (classification)or averaging (regression) so as to obtain an aggregated predictor. The multiple input data for building base classifiers is formed by bootstrapping replicates of the original learning data. Bagging performs best with algorithms that have high variance. All the four-training dataset namely LG, LML, LMC, LMW have been used to build the models. The performamce of the pathology detection models based on bagging classifier is evaluated with respect to various measures precision, recall, F-measure, accuracy and the results are shown in Table II and illustrated in Fig. 2.

Table II Results of Bagging

Dataset / Algorithm	Bagging			
	Precision	Recall	F-Measure	Accuracy
LG	0.882	0.937	0.883	0.89
LML	0.642	0.662	0.916	0.8125
LMC	0.734	0.655	0.891	0.8225
LMW	0.642	0.662	0.916	0.8125

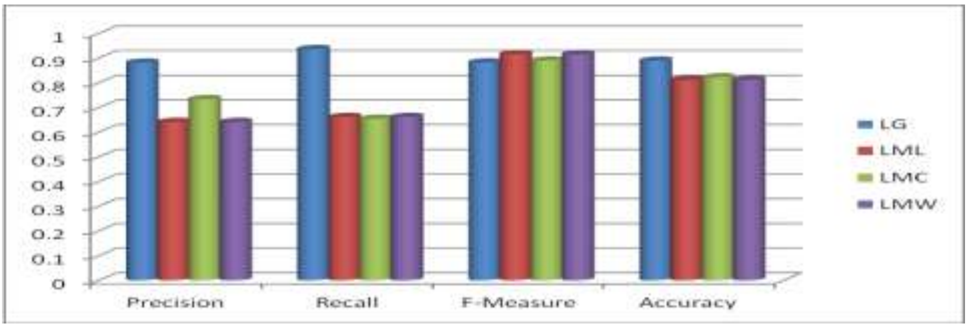

Fig. 2 Results of Bagging classifier

Pathology Detection Using Boosting

Boosting method is used to enhance the performance of a weak learning algorithm. There are lots of varieties of boosting algorithms, and AdaBoost is chosen as the boosting method in this work. Boosting adaptively re-weights the training set in a way based on an error rate of the previous base classifier. The boosting algorithm improves its behavior in reflection to the latest faults it makes. All the four-training dataset namely LG, LML, LMC, LMW have been used to build the models. The performamce of the pathology detection models based on bagging classifier is evaluated with respect to various measures precision, recall, F-measure, accuracy and the results are shown in Table III and illustrated in Fig. 3.

Table III Results of Boosting

Dataset / Algorithm	Boosting			
	Precision	Recall	F-Measure	Accuracy
LG	0.882	0.937	0.882	0.90
LML	0.667	0.701	0.709	0.735
LMC	0.75	0.678	0.694	0.745
LMW	0.666	0.701	0.709	0.735

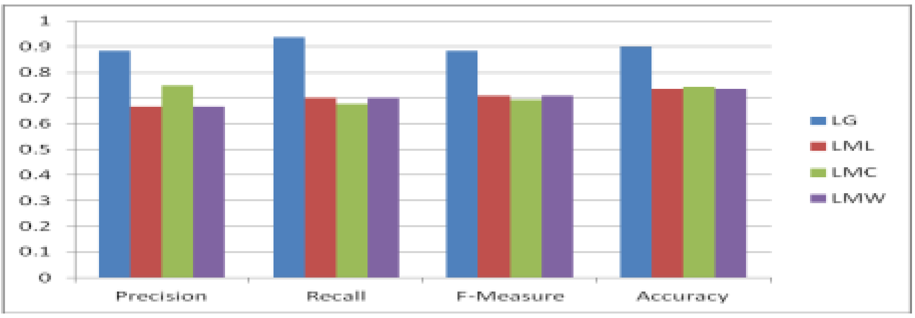

Fig. 3 Results of Boosting classifier

Pathology Detection Using LIBD3C

LibD3Cis an ensemble classifier, based on hybrid model of ensemble pruning approach. This kind of classifier is based on k-means clustering and the framework of dynamic selection and circulating in combination with a sequential search method. Ensemble classifier pruning becomes useful in some applications, where the number of independent classifiers that are needed to achieve reasonable accuracy is enormously large. The pathological voice detection is performed using LibD3c ensemble classifier. The classification task is taken as binary classification like finding healthy and pathology voices. All the four-training dataset namely LG, LML, LMC, LMW have been used to build the models. The performamce of the pathology detection models based on libd3c classifier is evaluated with respect to various measures precision, recall, F-measure, accuracy and the results are shown in Table IV and illustrated in Fig. 4.

Table IV Results of LibD3c

Dataset / Algorithm	LibD3c			
	Precision	**Recall**	**F-Measure**	**Accuracy**
LG	0.963	0.963	0.962	0.9625
LML	0.968	0.968	0.967	0.9675
LMC	0.968	0.968	0.967	0.9675
LMW	0.963	0.963	0.962	0.9625

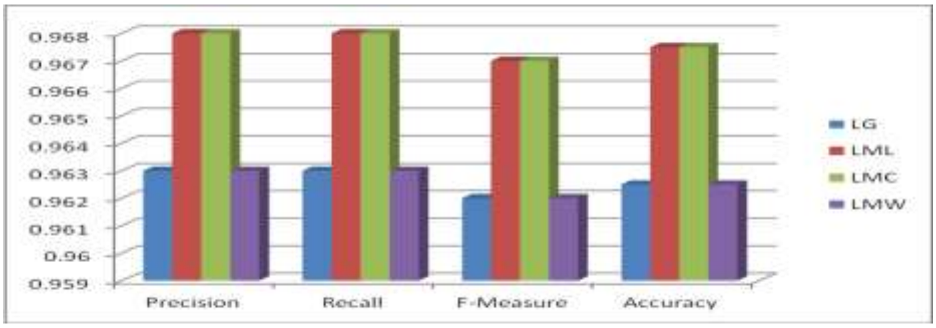

Fig. 4 Results of LibD3c classifier

Comparative Analysis

Accuracy is the most important measure used to analyze performance of classifiers. It tells about how algorithm work for given application also depends on the dataset used. In this work pathological voice dataset is used for classification. Different set of features are used to estimate the performance of classifier. Different accuracies are yield for different algorithms with different datasets. The evaluated measures such as precision, recall, F-measure and accuracy are calculated for all algorithms. The following Table V gives the accuracy comparison between algorithms and also Fig 5 shows the chart representation of algorithms.

Table V Comparative Analysis

Algorithm / Dataset	Comparative Analysis											
	Bagging				**Boosting**				**LibD3c**			
	P	**R**	**F**	**A**	**P**	**R**	**F**	**A**	**P**	**R**	**F**	**A**
LG	0.882	0.937	0.883	0.89	0.882	0.937	0.882	0.90	0.963	0.963	0.962	0.9625
LML	0.642	0.662	0.916	0.8125	0.667	0.701	0.709	0.735	0.968	0.968	0.967	0.9675
LMC	0.734	0.655	0.891	0.8225	0.75	0.678	0.694	0.745	0.968	0.968	0.967	0.9675
LMW	0.642	0.662	0.916	0.8125	0.666	0.701	0.709	0.735	0.963	0.963	0.962	0.9625

Note: P-Precision, R- Recall, F-F measure, A-Accuracy

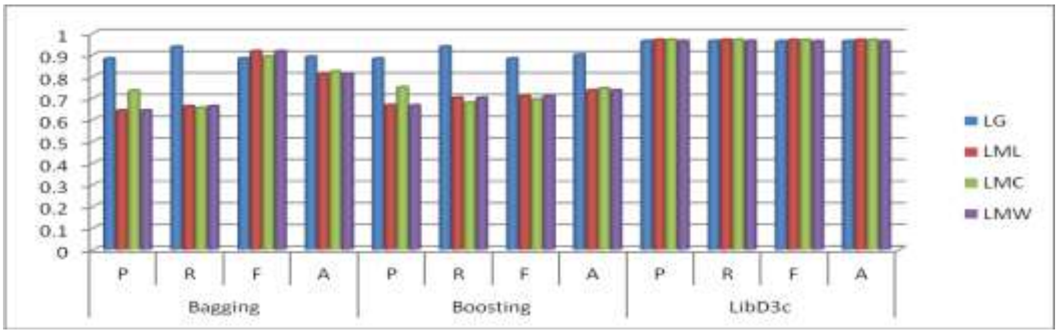

Fig. 5 Results of comparative analysis

From the above comparitive analysis it has been found that libd3c algorithm outperforms with other ensemble techniques. The classifier attains about 96% accuracy for all types of datasets but it acquires high accuracy for the dataset LML and LMC with 96.75% which shows that MFCC features are more contributive in classifying pathology voice. The measures such as precision, Recall and F score reached the maximum of 96% for the LibD3C algorithm that overcomes the measures in bagging and boosting which has the average of 75%. As the summarization of this work, LibD3c ensemble classifier performs well in classifying the pathological voice effectively.

VI. Conclusion

Acoustic analysis using proposed parameters can be a useful, objective tool for confirming the pathological changes of the glottis in the analyzed four types of voice pathology: laryngoceles, dysponia, diplophonia, and chorditis. The various types of ensemble classifiers like Bagging, Boosting and LibD3C are employed to classify the types of pathological voices. The performance of the ensemble classifiers are evaluated using 10 fold cross validation with respect to precision, recall, F-measure and accuracy and the results are compared. It is found that LibD3c outperforms well for all the type of datasets. In summary, LibD3c perform well in classifying the pathological voice. The contribution presented in this paper shows that the chosen classifying methodology is relevant to the pathology detection process.

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