Technical Journal, University of Engineering and Technology (UET) Taxila, Pakistan Vol. 24 No. 1-2019
ISSN:1813-1786 (Print) 2313-7770 (Online)

Sound Classification of Parkinsonism for Telediagnosis

[1] S.M.Adnan, [2] H.Ali, [3] S.Aziz, [4] W.Ahmad, [5] M. Obaidullah,

[1,2,4] Department of Computer Science, UET Taxila
[3] Department of Electronics Engineering, UET Taxila
[5] Department of Electrical Engineering, UET Taxila

[1] syed.adnan@uettaxila.edu.pk

Abstract- In recent years the usage of speech-based data for classification of Parkinson disease (PD) has commonly been assumed as non-invasive and effective mode of classification. As a result, an increased interest is observed in speech pattern analysis techniques appropriate for Parkinsonism with the aim of developing predictive tele-monitoring and tele-diagnosis models. In this research work a method for classification of PD patients is proposed by using different ensemble methods. For this purpose, a set of selected acoustic features, related to frequency, pulse, voice, pitch and harmonicity parameters, are extracted from PD patients' speech dataset and different classifiers (individual, ensemble and combination of ensemble methods) are applied on these 15 extracted features and achieved the overall accuracy of 97.6%. Research aims to early and accurate detection of disease in PD patients. Classification accuracies, sensitivity and specificity achieved from the proposed experimental setup of these ensemble methods are higher than the existing methods using individual classifiers.

Keywords-Parkinson disease, ensemble methods, sounds classification, feature extraction, telediagnosis, speech pattern.

I. INTRODUCTION

During the last few years, Telediagnosis is becoming a worldwide practice in medical field. Telemedicine or Telediagnosis contains a great potential to revolutionize the health care practices. The instantaneous and reliable diagnosis methodologies used in Telediagnosis incorporates interactive audios, videos, images and digital data related to the patients. This field is attracting a lot of research interest as it can deliver results in real time. Telediagnosis covers remote areas and provides assistance to physicians for diagnosing diseases with reliable accuracy. In this research work the acoustic measurement of telediagnosis for Parkinson's disease is examined.

Parkinson's disease is a neural disorder that weakens human nervous system over the time [1]. The patients suffering from this disease may face difficulty in talking, walking, thinking and completing simple day to day tasks. Mostly, older people of age above 60 years are prime victims of this disease [2]. It would be difficult for older people to visit hospitals repeatedly to get accurate medications. Telediagnosis can help in early diagnosis of Parkinson's disease by analyzing patient's data and avoiding inconvenience for older people to visit hospitals physically [3].

Parkinson's disease is considered to be the second most common degenerative neural disorder after Alzheimer [4]. This disorder affects the patients slowly as it progresses over time. Mostly, symptoms take years to develop, and patients live for years with this disease. The main cause of this disease is the lack of neurotransmitter compound 'dopamine' in brain. Dopamine is produced by neurons (nerve cells) of the brain and helps in smooth coordinated muscle movements in human body [5].

In Parkinson's disease, the nerve cells gradually stop producing dopamine. When approximately 60-80% of the dopamine producing cells are damaged, the motor symptoms of Parkinson's disease appear. Having low dopamine, an individual has low capability of regulating emotions and body movements. The victims of this disease may experience tremor, rigidity, postural instabilities and loss of body movement. Moreover, it has been observed that among all the patients affected by Parkinson's disease, 90% of them experience vocal impairments [6].

A recent study has revealed that approximately 400,000 people in Pakistan and over 6 million people all around the world are suffering from Parkinson's disease [7]. The rapid increase of this disorder all around the world and particularly in Pakistan requires immediate attention. An early diagnosis can help people to manage the disease and perform their routine activities independently. However, even for experienced doctors, it is quite difficult to diagnose Parkinson's disease at early stages with reliable accuracy. The reliability of diagnosis is affected by the fact that this disease cannot be accurately detected by simple blood or laboratory tests.

The doctors have to analyze the patient over a long duration of time to reach to their final decision [8]. This may take a long time while the disorder progresses from early stages to late stages of dopamine degeneration. Any method that can help detecting early symptoms of Parkinson's disease (PD) might thus have a substantial effect on human health. To overcome this challenge, the researchers have targeted their study towards speech pattern analysis of Parkinsonism. The speech analysis application involves voice samples of Parkinson's disease patients for constructing reliable telediagnosis models. This problem also attracted a specific interest of ML (machine learning) researchers [i] for example it includes the classification of sound sample data, where discrimination between these interested classes are non-trivial.

All the sample data is collected in real-life conditions, which commonly encompasses noises in background. The differences between Parkinson's disease patients' audios equivalent to dissimilar phases of disease indications could also be exceptionally challenging to discriminate. This type of data necessitates exceptionally robust classifiers to identify the accurate classes. Despite of medical consequence, this is a comparatively unfamiliar app for machine learning researchers.

The research objective of this study is to design and develop a conceptual architecture for classification of Parkinson's disease using ensemble methods, also present the sound dataset of patients of Parkinson's disease (PD) using different acoustic features and improve the robustness of telediagnosis techniques through ensemble techniques.

Rest of the paper is organized as follows. Section II consists of literature review of the subject. Section III consists of the proposed frame work for disease classification. In section IV experimental setup and details about dataset are discussed. Section V contains discussions about the results and comparisons. Finally, section VI sums up the conclusions of this research.

1.1. Literature Review

After Alzheimer's disease Parkinson's disease (PD) is the most usual neurodegenerative disorders and people who are aged 65 years and above are more affected by this disease. The affected people and their families are under a heavy burden because of PD [9]. Conferring to the Pakistan Parkinson's Society (PPS), the total population of PD patients is 6.5 million at present and it's going to be double in the next 10 to 20 years, in Pakistan 450,000 and in North America 1 million people alone are affected from this disease [10-11].

Parkinson disease diagnosis is very critical and hardly to accurate and there are no accurate, specific solutions and tests are available so far [9]. The reason is not known, and even though no cure is present still, there are treatment choices such as surgery or medications to meet its indications. In the last ten years the solutions and the progress made in the Parkinson disease therapies has been improved and brings some hope for the PD patients [12].

Researchers have used two different methods that are s-LOO and LOSO for k-NN classification accuracies with various numbers of adjacent neighbors that is k parameter values [13]. Experimental results showed that using the illustrations with a method of conventional LOSO cross-validation for each values of k parameter, very nearly a random prediction could be achieved. 0.3062 And 65.00% are the obtained highest MCC and overall accuracy, correspondingly, by succinct standard deviation as the dispersion metric ($k = 1$) and the data using mean as the central tendency with s-LOO technique. They perform the comparison between k-NN and SVM classifiers and found that as compare to k-NN classifier, SVM classifier produce higher accurateness. By shortening the data by means of the mean standard deviation double grouping of central tendency with s-LOO method gives the highest accuracy of 77.50%. Practically an arbitrary prediction that is MCC = 0.0006 was produced by the SVM classifier with linear kernel using LOSO method. They found the average MCC of 0.0416 which means that incomplete failure of the classifier could result by just shuffling there cording indeed as well as the originals-LOO accurateness wasn't just unintentional. They do the experimentation over thousand runs for the creation of indiscriminate pseudo-subjects beyond the entire set of soundtracks. They found very high numerical significance for the innovative accurateness of method s-LOO which is 0.006 in terms of MCC and 0.004 in terms of accurateness.

Classification is a type of predictive modeling, this is the key part in data mining and there has been significant recent research on Parkinson's disease (PD) and in speech impairment [14-15]. Many researchers have been present the research work on Parkinson's disease detection and the classification by using some known classifiers like Support Vector Machine (SVM), K-nearest neighbors (k-NN), Linear discriminant analysis (LDA), boosting, Decision Trees (DT), Quadratic discriminant analysis (QDA), Naive Bayes (NB).

There have been [11] a wide range of speech signals processing algorithms that are targeted by using speech signals to predict PD symptom severity level. There are some other ensemble learning methods for classification and regression like Random forests (RF) that operate by constructing a number of randomized decision trees at training time and predicts by averaging the results [16].

SAS based software [6] is another approach to evaluate different (DMNeural, Neural Network, Regression, and Decision tree) classifiers for identifying PD, all these classifiers are implemented with the SAS based software 9.1.3.

For automatic detection of Parkinson Disease, ParkDet 2.0 [17] a novel telemedicine technology was developed.

Neural networks and the Wavelet analysis combined to make a new class of networks that is called Wavelet networks 88]. This Wavelet Neural Network (WNN) [19] that is used for classifying Parkinson's disease data is developed via Cartesian Genetic Programming (CGP).

In recent developments and researches on Parkinson's disease (PD) diagnosis problem, there has been developed a new Hybrid diagnostic system. The proposed diagnostic system is a combination of complex-valued artificial neural network and k-means clustering-based feature weighting method which is the main novelty of this system [20].

For the purpose of detecting of Parkinson's disease (PD) another [21] CES (clinical expert system) has been proposed, the system deliberates a progressive statistical method aiming pattern recognition and extracts features from voice recordings. [22] Hybrid kernel extreme learning machine is an efficient proposed approach for the early detection of Parkinson disease (PD), the key parameters of the proposed approach including the constant parameter C, number of hidden neuron and kernel parameter γ in KELM are examined. Neural networks and the Wavelet analysis combined to make a new class of networks that is called Wavelet networks [18]. In this [23] research work researchers have used olfactory loss and the non-motor features of RBD (Rapid eye movement Behavior Disorder), together with supplementary substantial biomarkers for example dopaminergic imaging markers Cerebrospinal fluid (CSF) measurements as of 401 primary Parkinson's disease subjects as well as 183 normal healthy people which they derive from a database named as the Parkinson's Progression Markers Initiative (PPMI) for the purpose of classification of normal healthy vs the primary effected Parkinson's disease subjects by means of Support Vector Machine (SVM), Naïve Bayes, Random Forests classifiers and Boosted Trees. Research concluded that encouragement in the preclinical diagnosis of Parkinson's disease could be found by the combination of CSF, imaging markers and non-motor.

In [24] using gait analysis by means of deterministic learning theory researcher proposed a novel technique for the purpose of classification between healthy control subjects and analyzing patients with Parkinson's disease. The process of classification involves two stages, in which one is a training stage and other is a classification stage. In the first stage of training, by using the vertical ground reaction forces they derive gait features represented by the gait dynamics under the self-selected and usual paces of the subjects. By radial basis function (RBF) neural networks the gait dynamics underlying gait patterns of patients affected by Parkinson's disease and healthy controls were nearby accurately approached.

In constant RBF networks the achieved information of approached gait dynamics was stored. Now a training set was constituted by the gait patterns of PD patients and healthy controls. In the second stage of classification, for all the training gait patterns a group of dynamical estimators is created. In the estimators, previous information of gait dynamics characterized by the continuous RBF networks was enclosed. They had generated a set of classification errors by performing a comparison between test gait patterns of an assured Parkinson's disease patient with the group of estimators to be classified / diagnosed. The middling L1 standards for the inaccuracies were reserved by means of the classification measure among the dynamics of the test Parkinson's disease gait pattern and the training gait patterns dynamics rendering to the minimum error principle.

This paper [25] proposed a technique for the classification of healthy controls and idiopathic PD patients with both wavelet-based feature extraction and the gait characteristics of idiopathic PD patients. Experiment is performed on three different methods. By using wavelet transforms (WTs) they produced detail coefficients and approximation coefficients. To the neural network with weighted fuzzy membership functions (NEWFM) forty of the features are taken as inputs, and a comparison is performed between the performances of these three different methods. By using the NEWFM when classification is done between the healthy controls and idiopathic PD patients, results were specificity of 81.63%, sensitivity of 73.77% the accuracy of the 74.32% by first method, specificity of 74.67%, sensitivity of 75.24% the accuracy of the 75.18%, by 2nd method specificity of 65.48%, sensitivity of 81.10% the accuracy of the 77.33% by 3rd method.

In this research paper [26] for Parkinson's disease (PD) diagnosis an efficient and effective diagnosis system have been proposed by means of fuzzy k-nearest neighbor (FKNN). Then a comparison is performed between the support vector machines (SVM) based approaches and the proposed FKNN-based system. The efficacy of the recommended classification technique has been thoroughly projected for effected PD patient's data set in relations to the area under the receiver operating characteristic (ROC) curve (AUC), classification sensitivity, accuracy and specificity. Experimental consequences have illustrated that in the literature SVM-based approaches and other techniques are greatly outperformed by the FKNN-based system. Using a 10-fold cross validation method by the FKNN based system the best classification accuracy was found with 96.07% that could guarantee a responsible diagnostic model for recognition of Parkinson's disease.

In [27], researcher reported that to bring classifiers skilled for recognition of the movement characteristics of Parkinson's disease patients and also described how they apply evolutionary algorithms. These demonstratively appropriate designs of movement are identified to arise over numerous time scales.

In this article [28] to prevent the postponement and misdiagnosis of effected people researchers have presented improved prediction accuracy for analysis of Parkinson's disease with the help of recommended robust inference system. They proposed novel machine learning techniques, also discuss some performance comparisons of each technique on the basis of accuracy, specificity, sympathy and other determinable parameters. For the treatment of Parkinson's disease some robust methods are described that consist of rotation forest (RF) ensemble and sparse multinomial logistic regression with support vector machines(SVM), boosting methods, principal constituents analysis and artificial neural networks (ANN). Optimized by TABU search algorithm a novel ensemble method containing the Bayesian network were used as classifier in addition as projection filter HAAR wavelets were used aiming appropriate feature collection and ranking.

Using Unified Parkinson's Disease Rating Scale (UPDRS), researchers go through the standard in-clinic calculations, and used smartphones along with an Android OS (operating system) which has a smartphone application that calculate finger tapping, voice, gait, response time and posture. For the four times in a day they performed five tasks monthly [30]. One time in a researcher has visited a telemedicine (remote) with PD specialist in which a modified UPDRS (not including the calculations balance and rigidity) performed. By using the smartphone from ten healthy controls and ten patients of Parkinson's disease, 5 tasks have been recorded by statistical analyses, they search for the distinguish whether the participant suffering from Parkinson's disease as well as predict the UPDRS improved motor portion. Experimental results for distinguishing the contributors with Parkinson's disease from healthy controls, mean specificity was 96.9% and the mean sensitivity was 96.2%.

In [31] researcher has worked on different acoustic attributes to determine which one is more reliable for listener's insights of the inharmonic factor in pathologic voices. There are different seven models of the inharmonic chunk of the verbal source for copies of natural obsessive voices that were produced parametrically including jitter plus noise, jitter plus shimmer, shimmer plus noise, jitter plus shimmer plus noise, jitter only, shimmer only and noise only.

For speaker recognition, there are almost certainly numerous physical characteristics which may provide corresponding information and should have a great value. J.K. and B.R.Gerrat [32] work for a speaker verification system which focuses on the practice of jitter and shimmer. Both Jitter and Shimmer has been essentially used for detection of voice pathologies.

M. Froehlich, D. Michaelis [33] addressed two main procedural facts about jitter and shimmer dimension. One fact is about the Inspiration of the verbal zone on jitter and shimmer; commonly jitter and shimmer of a vocal sound are determined by analyzing the emitted sound stress. In 90's Kroger agreed at working of jitter which is that vocal track influence and altered at glottis that's why the glottal conditions are not reflect by the quality of voice which is by radiated sound. The synthetic vowel signals used for qualitative and quantitative explanation and measurements. The other fact is to show the accuracy of shimmer and jitter measurement. The presentation edges of the waveform corresponding algorithm used for field exposure are assessed for very low value and very high values of jitter and shimmer.

II. Materials and Methods

2.1. System Overview

Complete processing stages of proposed methodology is shown in Figure 1. It consists of six major processing stages as: data acquisition, sounds file conversion, framing, feature extraction, ensemble methods used for classification and the PD identification.

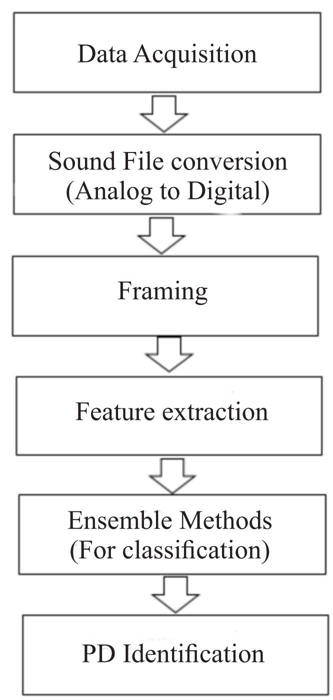

Fig. 1. Conceptual Framework

2.1.1. Feature Extraction

We used 15 acoustic features to classify our dataset as healthy and Parkinson's effected sound signals. These features have been extracted by using Praat software.

Acoustic features consist of Jitter, Number of pulses, Number of periods, Mean period, Standard deviation of period, Number of voice breaks, Degree of voice breaks, Median Pitch, Mean Pitch, Standard Deviation, Minimum Pitch, Autocorrelation, Noise-to-Harmonic and Harmonic-to-Noise with their respective groups as Frequency, Pulse, Voicing, Pitch and Harmonicity Parameters are extracted. Specifically, we used two Jitter measurements; these measurements are the acoustic characteristics of voice signal.

Jitter (absolute) is the average absolute difference between consecutive periods which is expressed as.

$$Jitter\ (absolute) = \frac{1}{M-1}\sum_{j=1}^{M-1}\left|L_j - L_{j+1}\right| \quad (1)$$

M is the total number of extracted F0 periods and the Lj are the extracted F0 period lengths.

Jitter (local) [38] is the average absolute difference between consecutive periods divided by the average period measured with the following expression

$$Jitter(local) = \frac{\frac{1}{M-1}\sum_{j=1}^{M-1}\left|L_j - L_{j+1}\right|}{\frac{1}{M}\sum_{j=1}^{M}L_j} \quad (2)$$

2.1.2. Classification of PD using ensemble methods

For classification, we have used different ensemble methods in addition to individual classifiers and compared the accuracies with existing approaches.

AdaBoost [34], abbreviated as "Adaptive Boosting", is a machine learning ensemble algorithm. To improve performance this algorithm could be used in combination with several other kinds of learning.

Algorithm: Adaboost

Training stage:

1. Initialize parameter:
   a) Set weights $wt^1 = [wt_1 ... wt_n]$, $wt_i^1 \in [0, 1]$, $\sum_{i=1}^{n} wt_i^1 = 1$
   b) Generally $wt_j^1 = 1/N$
   c) $E = \emptyset$; ensemble initialization
   d) Pick D; that is the Number of classifiers to train
2. For k=1 …D
   a) Take sample S_k from Z via the distribution wt^k.
   b) Via S_k form a classifier E_k as training set.
   c) Compute weighted ensemble error at step k by
      $\in_k = \sum_{i=}^{n} wt_i^k l_k^i$
   d) If $\in_k = 0$ or $\in_k >= 0.5$, ignore E_k, perform weights initialization again and continue.
   e) Else compute
      $\propto_k = \frac{\in_k}{1-\in_k}$ where $\in_k = 0$ or $\in_k >= 0.5$
   f) Update the weights
      $$wt_i^{k+1} = \frac{wt_i^k \propto_i^{1-l_i^k}}{\sum_{j=1}^{n} wt_j^k \propto_j^{1-l_j^k}}$$
      Where j=1…n
   g) Return E and $\propto_1 \dots \propto_D$

Classification stage:

1. On the input y run $E_1 \dots, E_L$.
2. The class which has the maximum no. of votes is elected as the label for y.

The final output of the boosted classifier is represented by a weighted sum that is the combination of all the outcomes from other kinds of learning algorithms. AdaBoost is sensitive for outliers and noisy data.

The other technique [25] used in this research work is "Bagging". It is a "bootstrap" ensemble technique in which random sampling with replacement factor is done on the training set, generating n training sets with sizes equivalent to the existing training set.

Random subspace [36] was also used for classification of PD. In machine learning the ensemble learning technique which trains estimators on random samples of features rather than the complete feature set and offers to decrease the correlation among these estimators in an ensemble is known as the random subspace technique. This technique may also call as feature bagging or attribute bagging.

Algorithm: Bagging

1. Take training set as T, inducer as I, integer as S For j=1…S {T'= a bootstrap sample taken from T i.e. sample with replacement D_i=I (S')
   }
2. $D^x(y) = (arg_{x<X} max) \sum_{j=D_{i(y)=x}} 1$
   Frequently predicted label x

Algorithm: Random Subspace

Repeat this for a = 1, 2 . . . N:

a) From the original o-dimensional feature space X Select an m-dimensional random subspace X^a.
b) Build a new classifier E^b(n) in X^a. Where a decision boundary E^b (n) = 0
c) By simply majority voting to a final decision rule, Associate classifier

E^b (n), b = 1, 2, . . ., N,

B (n) $= \underset{y\in[-1,1]}{argmax} \sum_a \delta_{sgn} (E^b$ (n)), y Where

$\delta_{i,j}$ Denotes the Kronecker symbol,
y$\in [-1,1]$ denotes a decision of the classifier.

Random Forest [36] is another algorithm for constructing the ensembles. This algorithm develops its strength from two characteristics: randomization of the algorithm for training base-level classifiers that is the decision trees and using random subsamples of the training data same as bagging technique.

Algorithm: Random Forest
Initially assign each of the labeled sample to root node i.e. M » root node with each M node do

1. Among a random subset of features with all threshold values B, Find the features A
2. Assign (A, B) to M
3. If P_{Left} left and P_{right} is too small for splitting
   a) Assign child leaf nodes C_{Left} and C_{right} to M
   b) Tag the leaves with the most present label in P_{Left} and P_{right}, respectively
4. Else
   a) Assign child nodes M_{Left} and M_{right} to M
   b) Assign P_{Left} and P_{right} to them respectively
   c) Repeat procedure for M=M_{Left} and M=M_{right}

3. Results and Discussions

3.1. Dataset

The Parkinson disease dataset contains the training and testing data of 20 Patients with Parkinson (6 female, 14 male) and 20 healthy people (10 female, 10 male) all subjects have multiple sound recordings of sustained vowels etc. The original dataset consists of stereo sounds, so dataset has been converted into mono sound using Audacity software.
The dataset is downloaded from
https://archive.ics.uci.edu/ml/datasets/parkinsons

3.2. Experimental Setup

The sound features have been extracted from the PD dataset and this feature vector is further used for classification. The implementation setup of experimentation includes Praat software and Weka on Windows operating system installed on Core i7 machine with 8 GB RAM.

Table I shows all the acoustic features extracted to classify healthy and Parkinson's effected sound signals. These features include (Jitter (local), Jitter (local, absolute), Number of pulses, Number of periods, Mean period, Standard deviation of period, Number of voice breaks, Degree of voice breaks, Median Pitch, Mean Pitch, Standard Deviation, Minimum Pitch, Autocorrelation, Noise-to-Harmonic and Harmonic-to-Noise) sound features for classification purpose and we compared our accuracies of different ensemble techniques in results section. The experimentation results have confirmed that with these smaller number of features we have achieved high accuracies as compared to other previous literatures which used more acoustic features for classification.

TABLE I: FEATURES EXTRACTED FROM VOCE SAMPLES

Group	Sound Features
Frequency Parameters	Jitter (local) Jitter (local, absolute)
Pulse Parameters	Number of pulses Number of periods Mean period Standard deviation of period
Voicing Parameters	Number of voice breaks Degree of voice breaks
Pitch Parameters	Median Pitch Mean Pitch Standard Deviation Minimum Pitch
Harmonicity Parameters	Autocorrelation Noise-to-Harmonic Harmonic-to-Noise

TABLE II: LITERATURE WORK ACCURACY

Classifier	Classification Accuracy
k-NN (LOSO AND s-LOO) [xiii]	65.00%
SVM [xiii]	85.00%
SVM [xxiii]	96.40%
Radial basis function (RBF) neural networks [xxiv]	96.39%
Wavelet Transforms (WTs) [xxv]	77.33%

Jitter is the cycle to cycle variation of fundamental frequency F0 and for sustained vowels these variations are measured [38].

TABLE III: 10-FOLD CROSS VALIDATION ON PD DATASET

Ensemble Methods with Base Learners	Accuracy	Sensitivity	Specificity
AdaBoostM1 – Bayes Net	95.2%	96.0%	93.6%
AdaBoostM1 – Random Subspace	95.2%	96.6%	92.8%
AdaBoostM1 – Random Forest	95.0%	96.8%	93.6%
Random Forest – Random Subspace	**95.6%**	**97.2%**	**94.4%**

This research work presents framework for PD dataset that is having high classification accuracy among PD patients and healthy people. We present the results of individual classifiers in comparison with ensembles method. We are using 2 validation schemes 10-fold cross validation and the 50 – 50% training-testing approach. The detailed result of comparisons and the performance analysis in terms of accuracies, sensitivity and specificity with other literature works have been shown.

We have applied three classifiers Bayes Net, Decision Stump and SVM on our PD dataset. The results in Table II show the classification accuracies after applying these classifiers. The accuracy, sensitivity and specificity of 10-fold cross validation is shown in Table III. And 50-50% training-testing approach results are in Table IV. We have used 4 ensemble methods and combination of these ensemble methods.

These results are compared with the literature results presented in Table II. AdaboostM1 and Bagging gives the 93.6%. AdaBoostM1 – Bayes Net and Random Subspace gives the same results 96.8%. Finally, by comparing the Random Forest accuracy with all of the other classifier accuracies given in Table II, Table III and in Table. IV it is seen that the RF gives overall highest 97.6% accuracy, 100% sensitivity and 95.16% specificity.

TABLE IV: 50-50% TRAINING – TESTING ON PD DATASET

Ensemble Method	Accuracy	Sensitivity	Specificity
AdaBoostM1 – Bayes Net	**96.8%**	**100%**	**93.55%**
AdaBoostM1 – Random Subspace	93.6%	98.41%	88.71%
AdaBoostM1 – Random Forest	95.2%	98.41%	91.94%
Random Forest – Random Subspace	**97.6%**	**100%**	**95.16%**

The literature work results are shown in Figure. 2. The accuracy, sensitivity and specificity of 10-fold cross validation and 50-50% scheme is shown in Figure 3 and Figure 4. The results shown in the Figure 3 and Figure 4 presents that Random Forest gives overall highest accuracy, sensitivity and specificity.

IV. CONCLUSION

The motivation for this research work is to get the higher accuracies for the prediction of Parkinson disease in patient. The presented work will give better results by using the ensemble methods classification using lesser numbers of acoustic features; both the individual and ensemble classifiers are used.

The achieved results are better with our proposed methodology as compared to previous approaches. There is a wide variety of research in sound classification domain. The future work and the main emphasis would be on the higher classification accuracy that can be achieved using efficient classification algorithms and can be enhanced by selection of best acoustic features from sound signals.

REFERENCES

[1] Behroozi, Mahnaz, and Ashkan Sami. "A multiple-classifier framework for Parkinson's disease detection based on various vocal tests." International journal of telemedicine and applications 2016 (2016).

[2] Sakar, C. Okan, and Olcay Kursun. "Telediagnosis of Parkinson's disease using measurements of dysphonia." Journal of medical systems 34.4 (2010): 591-599.

[3] Sharma, R. K., and Anil K. Gupta. "Voice Analysis for Telediagnosis of Parkinson Disease Using Artificial Neural Networks and Support Vector Machines." International Journal of Intelligent Systems and Applications 7.6 (2015): 41.

[4] De Lau, Lonneke ML, and Monique MB Breteler. "Epidemiology of Parkinson's disease." The Lancet Neurology 5.6 (2006): 525-535.

[5] Bourouhou, A., et al. "Comparison of classification methods to detect the Parkinson disease." Electrical and Information Technologies (ICEIT), 2016 International Conference on. IEEE, 2016.

[6] Ho, Aileen K., et al. "Speech impairment in a large sample of patients with Parkinson's disease." Behavioural neurology 11.3 (1999): 131-137.

[7] Imtiaz, Nida, et al. "Study of prevalence of Parkinson's disease in elderly population in Rawalpindi, Pakistan." (2016)

[8] Saloni, Saloni, Rajender K. Sharma, and Anil K. Gupta. "Human Voice Waveform Analysis for Categorization of Healthy and Parkinson Subjects." International Journal of Healthcare Information Systems and Informatics (IJHISI) 11.1 (2016): 21-35.

[9] Massano, João, and Kailash P. Bhatia. "Clinical approach to Parkinson's disease: features, diagnosis, and principles of management." Cold Spring Harbor perspectives in medicine 2.6 (2012): a008870.

[10] http://www.parkinsons.org.pk/whatis parkinsos/ what_parkinsons.html

[11] A.E. Lang, A.M. Lozano. Parkinson's disease – First of two parts, New England Journal Medicine, 339, 1044-1053, 1998

[12] Toulouse, André, and Aideen M. Sullivan. "Progress in Parkinson's disease—where do we stand?." Progress in neurobiology 85.4 (2008): 376-392.

[13] Sakar, Betul Erdogdu, et al. "Collection and analysis of a Parkinson speech dataset with

multiple types of sound recordings." Biomedical and Health Informatics, IEEE Journal of 17.4 (2013): 828-834.

[14] Das, Resul. "A comparison of multiple classification methods for diagnosis of Parkinson disease." Expert Systems with Applications 37.2 (2010): 1568-1572

[15] Tsanas, Athanasios, et al. "Novel speech signal processing algorithms for high-accuracy classification of Parkinson's disease." Biomedical Engineering, IEEE Transactions on 59.5 (2012): 1264-1271.

[16] Scornet, Erwan, Gérard Biau, and Jean-Philippe Vert. "Consistency of random forests." The Annals of Statistics 43.4 (2015): 1716-1741.

[17] Ozkan, Haydar. "A Comparison of Classification Methods for Telediagnosis of Parkinson's Disease." Entropy 18.4 (2016): 115.

[18] Alexandridis, Antonios K., and Achilleas D. Zapranis. "Wavelet neural networks: A practical guide." *Neural Networks* 42 (2013): 1-27.

[19] Khan, Maryam Mahsal, Stephan K. Chalup, and Alexandre Mendes. "Parkinson's Disease Data Classification Using Evolvable Wavelet Neural Networks." Artificial Life and Computational Intelligence. Springer International Publishing, 2016. 113-124.

[20] Gürüler, Hüseyin. "A novel diagnosis system for Parkinson's disease using complex-valued artificial neural network with k-means clustering feature weighting method." Neural Computing and Applications: 1-10.

[21] Naranjo, Lizbeth, et al. "Addressing voice recording replications for Parkinson's disease detection." Expert Systems with Applications 46 (2016): 286-292.

[22] Chen, Hui-Ling, et al. "An efficient hybrid kernel extreme learning machine approach for early diagnosis of Parkinson′ s disease." Neurocomputing(2015).

[23] Prashanth, R., et al. "High-Accuracy Detection of Early Parkinson's Disease through Multimodal Features and Machine Learning." International journal of medical informatics 90 (2016): 13-21.

[24] Fenglin Liua, Qinghui Wanga, Ying Wanga, Limin Mab, Yu Zhangb" Parkinson's disease classification using gait analysis via deterministic learning" October 2016.

[25] Lee, Sang-Hong, and Joon S. Lim. "Parkinson's disease classification using gait characteristics and wavelet-based feature extraction." Expert Systems with Applications 39.8 (2012): 7338-7344.

[26] Chen, Hui-Ling, et al. "An efficient diagnosis system for detection of Parkinson's disease using fuzzy k-nearest neighbor approach." Expert systems with applications 40.1 (2013): 263-271.

[27] Lones, Michael A., et al. "Evolving classifiers to recognize the movement characteristics of Parkinson's disease patients." IEEE Transactions on Evolutionary Computation 18.4 (2014): 559-576.

[28] Mandal, Indrajit, and N. Sairam. "New machine-learning algorithms for prediction of Parkinson's disease." International Journal of Systems Science 45.3 (2014): 647-666.

[29] Mandal, Indrajit, and N. Sairam. "Accurate telemonitoring of Parkinson's disease diagnosis using robust inference system." International journal of medical informatics 82.5 (2013): 359-377.

[30] Arora, S., et al. "Detecting and monitoring the symptoms of Parkinson's disease using smartphones: A pilot study." Parkinsonism & related disorders 21.6 (2015): 650-653.

[31] J. Kreiman, B. R. Gerratt, and B. Gabelman" Jitter, shimmer, and noise in pathological voice quality perception" Published Online: October 2002.

[32] J. Kreiman and B. R. Gerrat, "Perception of aperiodicity in pathological voice," Acoustical Society of America, vol. 117, pp. 2201-2211, 2005.

[33] D. Michaelis, M. Fröhlich, H. W. Strube, E. Kruse, B. Story, and I. R. Titze, "Some simulations concerning jitter and shimmer measurement," presented at 3rd International Workshop on Advances in Quantitative Laryngoscopy, Aachen, Germany, 1998

[34] Hu, Weiming, Wei Hu, and Steve Maybank. "Adaboost-based algorithm for network intrusion detection." IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics) 38.2 (2008): 577-583.

[35] Oza, Nikunj C. "Online bagging and boosting." Systems, man and cybernetics, 2005 IEEE international conference on. Vol. 3. IEEE, 2005.

[36] Kotsiantis, Sotiris. "Combining bagging, boosting, rotation forest and random subspace methods." Artificial Intelligence Review 35.3 (2011): 223-240.

[37] Liaw, Andy, and Matthew Wiener. "Classification and regression by randomForest." R news 2.3 (2002): 18-22.

[38] M.Farrús, J.Hernando, P.Ejarque "Jitter and Shimmer Measurements for Speaker Recognition" Dept. of Signal Theory and Communications, TALP Research Center.