Performance comparison of heterogeneous classifiers for detection of Parkinson's disease using voice disorder (dysphonia)

Conference Paper · May 2014

DOI: 10.1109/ICIEV.2014.6850849

Mohammad Islam
Case Western Reserve University

Performance Comparison of Heterogeneous Classifiers for Detection of Parkinson's Disease Using Voice Disorder (Dysphonia)

Mohammad S Islam, Imtiaz Parvez, Hai Deng
Electrical and Computer Engineering
Florida International University
Miami, FL, USA

Parijat Goswami
EEE
BUET
Dhaka, Bangladesh

***Abstract*—Speech signal processing and its recognition system have gained a lot of attention from last few years due to its widespread application. In this study, we have conducted a comparative analysis for effective detection of Parkinson's disease using various machine learning classifiers from voice disorder known as dysphonia. To investigate robust detection process, three independent classifier topologies were applied to distinguish between PD patient and healthy individual, and to make a comparison of the results. The classifiers used here are Random Tree (RT), Support Vector Machine (SVM) and Feedforward Back-propagation based Artificial Neural Network (FBANN). To validate the overall classification with acceptable error rate, a 100 times repeated 10-fold cross validation analysis has been carried out for all classifiers. With optimized statistical parameters and using selective feature set, the proposed scheme has achieved up to 97.37% recognition accuracy. FBANN classifier outperformed than the others. Considering the classification accuracy, sensitivity, specificity and the area under the receiver operating characteristic (ROC) curve, all classifiers achieved better than chance level. The proposed modality and computational process may clinically effective, viable, non-invasive, powerful technique to develop decision support system (DSS) for remote diagnosis of neurodegenerative disorders at early stage with propitious results.**

Keywords- PD; FBANN; SVM; Artificial Intelligence; Dysphonia Measurements; UPDRS; DSS

I. INTRODUCTION

Parkinson's disease (PD)is the second most common neurodegenerative disorder after Alzheimer's disease [1] which affects one in every 100 persons above the age of 65 years. It was named after James Parkinson as recognition of his work on it.

Dopamine which transmits signals within the brain to produce smooth movements of muscles is the main cause for PD. In the substantia nigra (STN's) of brain, degeneration of nerve cells occurs due to low levels of dopamine. This causes the nerve cells to fire wildly, leaving patients unable to control their movements. Even though it was believed that PD symptoms are due to dopaminergic neuron reduction in the Basal Ganglia (BG), but it is now recognized that PD is also characterized by the degeneration of numerous non dopaminergic pathways. Major symptoms are tremor, rigidity or stiffness of limbs and trunk, Bradykinesia or slowness of movement, Postural instability or impaired balance and coordination [2].

There is no permanent cure of Parkinson's disease so far [3] but there are several measures that can be used to improve patient's life. These measures include drug and surgical therapy. The other options available include making lifestyle changes, and employing physical and speech therapy. The surgical option includes Pallidotomy, Deep Brain Stimulation (DBS) etc which are risky. The major risk is bleeding in the brain that may cause a stroke. There are so many side effectsof using medicine or go through a surgical procedures with respect to huge amount of cost and life threatening side effects. Still it is not convenient and easy to restore the progression of the whole neurodegenerative process. This disease can be difficult to dia gnose accurately, particularly in the early stages of the disease when symptoms resemble other medical conditions, and misdiagnosis occur occasionally. So, to find alternating ways to detect early of PD has become a burning issue to mitigate on a large scale.

The most popular way used by medical specialist for tracking Parkinson's disease (PD) symptom progression is Unified Parkinson's Disease Rating Scale (UPDRS)[4][23]. But it is time ineffective and non-autonomous way to detect PD. Laboratory or blood testing has not very good success rate in diagnosing PD, and the prospect depends on the patient's age and symptoms. It is also based on medical history and neurological examination conducted by interviewing and observing the patient along with various signals (EEG, Speech etc.) and images (MRI, CT etc.) [5]. But this method is not so effective. So, it is really important to find an alternate solution in detecting PD and especially in early stage. About 90 percent of people with PD suffer from speech disorder, which can be the prospective or alternative method because speech signal is non-invasive, signal features can be easily identified, and less affected by other biological

This work was supported in part through FIU Graduate School Presidential Fellowship, funded by Graduate School, Florida International University, FL 33174, USA.

signals, digitally storable, remotely detectable and easy recording using modern advanced technology. An automated medical diagnosis system would enhance the accuracy of the diagnosis and reduce the cost effects. The use of Artificial Intelligent (AI) based classifier in medical diagnosis is increasing gradually [4] due to its accuracy by minimizing possible errors, more time efficient and reliability of diagnosis. Recent advances in the field of artificial intelligence have led to the emergence of expert systems [6] and Decision Support Systems (DSS) for medical applications. Despite good accuracy, these techniques converge quickly which is advantageous to apply them for real time diagnostic system conveniently. Moreover, in the last few decades computational tools have been designed to improve the experiences and abilities of doctors and medical specialists in making decisions about their patients.

In the current literature, using vocal data for detection of PD is not so abundant [8]. Resul Das has made a comparative study to detect PD using neural networks, DMNeural analysis, regression analysis and decision trees where neural networks has outperformed than others (overall classification score 92.9%) [1] . Little et al. [9] used kernel support vector machine in order to distinguish between subjects (people with PD-PWP and normal people). Although, in this study, they achieved classification accuracy of 91.4%, but it did not report single class true positive rates (TPR). M. S. Lee et al. [10] used imbalanced dataset sampling scheme conjunction with naive Bayes classifier to deal with the unbalanced data problem. Neural network based classification becoming popular due to the fact that it can perform classification of nonlinear dataset with desired upper and lower bound. Neural network conjunction with evolutionary theorem based diagnosis of Parkinson's disease using biomedical voice dataset (dysphonia) has been reported in the literature recently [11-12]. Parkinson's disease tremor overall classification rate can be improved using support vector machine over Multilayer Perception (MLP)and Radial Basis function network [13-14]. However, Neural network based design of an on-off control of human tremor of PD patient has reported in some recent literature with an overall accuracy of 75.8% and sensitivity of 92.3% [15].

The main objective is therefore, comparative study of various automated techniques which can discriminate between healthy people and people with Parkinson's (PWP) disease. This study has done using features of human voice signal that can be used as discriminatory measures to differentiate those who have the PD from those without PD. Since in many cases clinical decisions about early detection lead to unwanted biases, errors and excessive medical costs which affect the quality of services provided to patients, it is highly essential to detect accurately for treatment plan in the rest of the life. In order to achieve this, various linear and nonlinear classification methods were employed for calculating the performance, and finally performances were compared. The overall computationally effective framework can be a model of clinical trials of PD detection and telemonitoring system.

The paper organized as follows. Section II describes the framework of experimental design and data acquisition system (DAQ). Section III discussed brief overview of the classifiers. Experimental methodology is presented in section IV. Section V describes performance measures in brief. Experimental results and discussions are presented in section VI, and future direction of the work has been discussed in section VII. Finally, section VIII concludes our work.

II. Experimental Framework and Data Acquisition (DAQ) System

In this study, we had used machine learning repository to detect PD patients and data were taken from UCI [16][24]. The dataset was created by Max Little of the University of Oxford, in collaboration with the National Centre for Voice and Speech, Denver, Colorado, who recorded the speech signals [9][17]. The data consists of 195 sustained vowel phonations from 31 male and female subjects of which 23 were diagnosed with PD and eight (8) healthy persons. The diagnostic time ranges from 0-28 years and the age of the patients ranges in 65.8±9.8 years (mean ±SD). Each subject was asked to provide an average of six phonations of the vowel (there are total 147 PD phonations and total 48 healthy phonations), ranging from 1 to 36 seconds in length [17]. For detection of speech disorders, a lot of vocal tests were performed. Out of them, two are the most famous. Firstly, the person capable of pronouncing vowels tries their best to keep the bass and tremble consistent with variation of time. Secondly, disordered peoples are suggested to express a typical sentence, after that from recorded signal, useful information are registered by expert people. It should be noted that there is no missing values in the data set, and the whole features are real valued. The phonations were recorded in an IAC sound-treated booth using a head-mounted microphone (model-AKG C420) positioned at 8 cm from the lips. The voice signals were recorded directly to computer using CSL 4300B hardware (Kay Telemetric), sampled at 44.1 kHz, with 16 bit resolution.

III. Brief Overview of the Classifiers

A. *Feed forward Back propagation based Artificial Neural Network (FBANN)*

FBANN is designed to depend on the delta rule which is also known as the steepest descent training algorithm. It uses training data to form mapping of nonlinearity between input and output. It is interconnected with one input layer, one or more hidden layers and one output layer which use modifiable weights connected with numerous links [7][14]. The desired error depends on how the network learned in an efficient way and ultimately it will get optimum weights in between hidden to output layer. Feedforward neural network uses stopping criterion in conjunction with Back-propagation algorithm to obtain desired classification accuracy.

B. Support Vector Machine (SVM)

Support vector machine (SVM) [3] is common tool to detect and exploit complex patterns of features by clustering, classifying and ranking of the patterns of data. SVM performs classification task by finding decision boundary called hyper-plane. The common functions used in SVM learning methods are linear, polynomial and sigmoidal.

C. Random Tree

Random decision tree [18] [19] is a predictive model construct of multiple decision trees to obtain target value. The algorithm can be employed for classification (categorical) and regression (continuous) application. It is a collection of tree predictors also called forest. It takes the complete input feature vector and classifies it with every tree in the forest. After that, the output takes the class label if it received majority of votes.

IV. METHODOLOGY

The complete generalized flow diagram for detection of PD patient is given in figure 1.The present study implemented linear and nonlinear classifiers for binary classification (PD vs Healthy). In the prediction system, 22 attributes extracted from dysphonia measurement of people were used to identify PD patient which had provided in table I. The data is imbalanced in terms of the binary class distribution. The complete classification process was performed in the environment of WEKA (version 3.6)[20]and MATLAB R2012b.Java based API of WEKA was used from MATLAB to run the classifier.

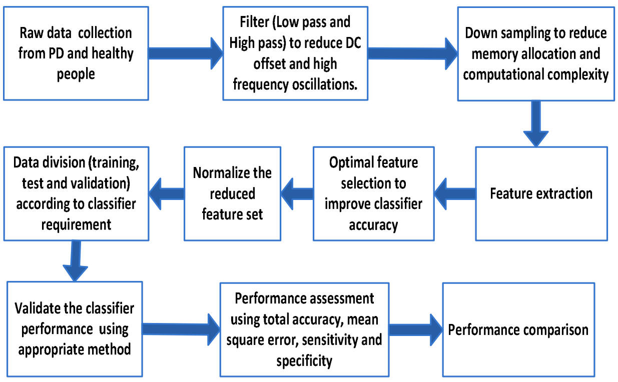

Figure 1: Generalized flow diagram of PD detection using voice disorder (dysphonia) measurement.

More details about patient description and feature extraction process can be found from reference [9].

In order to verify the effectiveness of the classification accuracy using the dataset, we have used three popular machine learning (ML) classifiers. To get robust classification result, two layered FBANN was employed comprising 22 input nodes, one hidden layer with changeable neuron to get two outputs from the output layer. Levenberg-Marquardt (LM) algorithm was used as training algorithm of FBANN which interpolates between the Gauss–Newton algorithm (GNA) and of gradient descent (GD) method [14].

TABLE I. ATTRIBUTE DETAILS FOR DIAGNOSIS OF PD PATIENT [9].

Feature #	Feature Name	Description of Feature
F1	MDVP:F0(Hz)	Average vocal fundamental frequency
F2	MDVP:Fhi(Hz)	Maximum vocal fundamental frequency
F3	MDVP:Flo(Hz)	Minimum vocal fundamental frequency
F4	MDVP:Jitter(%)	Fundamental frequency perturbation (%)
F5	MDVP:Jitter(Abs)	Variation in fundamental frequency
F6	MDVP:RAP	Relative Amplitude Perturbation
F7	MDVP:PPQ	Five-point Period Perturbation Quotient
F8	Jitter:DDP	Variation in fundamental frequency
F9	MDVP:Shimmer	Shimmer Local amplitude perturbation
F10	MDVP:Shimmer(dB)	Local amplitude perturbation (decibels)
F11	Shimmer:APQ3	3- point Amplitude Perturbation Quotient
F12	Shimmer:APQ5	Five point Amplitude Perturbation Quotient
F13	MDVP:APQ	Measures of variation in amplitude
F14	Shimmer:DDA	Measures of variation in amplitude
F15	NHR	Ratio of noise to tonal component
F16	HNR	Ratio of noise to tonal component
F17	RPDE	Nonlinear dynamical complexity measures
F18	D2	Nonlinear dynamical complexity measure
F19	DFA	Signal fractal scaling exponent
F20	Spread1	Fundamental frequency variation
F21	Spread2	Fundamental frequency variation
F22	PPE	Fundamental frequency variation

The FBANN network was provided maximum 1000 iterations to converge with minimum error goal 0.01 in every iteration. Hyperbolic tangent sigmoidal function was employed as an activation function in both hidden and output layer to get desired output. After the network has configured, initial weights and biases were chosen randomly for both hidden and output layer. The complete process of each classifier training and testing has various steps. Firstly, complete dataset was divided randomly from 195 samples into 10 training and 10 test sets. Test set dimension was 50% of training set dimension. We trained each classifier 100 times. A popular 10-fold CV method was used to evaluate the classification accuracy of all classifiers to get an unbiased estimation of the accuracy of generalization. In this 10-fold CV procedure, each time one of the 10 subsets (10% of the feature set) is used as the test set and the remaining 9 sub-sets (90% of the feature subset) are used as a training set for classifier learning and generalization. The training and test sets are independent and more reliable results were achieved from the classifier. After finalizing 10 fold cross validation, average mean square (MSE) error were computed. To evaluate more robust performance of the data set, 10-fold cross validation method was repeated of 100 independent trials and the results were averaged.

V. PERFORMANCE MEASURES IN BRIEF

Performance of the proposed three classifiers were evaluated to compare the success of prediction from the confusion matrix (Figure 2) using commonly used evaluation parameters (i.e. metrics) in pattern classification such as total overall accuracy , sensitivity , specificity, TPR, FPR and the area under the receiver operating characteristics (ROC) curve.

	Predictive Output	
Actual Output	Patients with PD	Patients without PD (Healthy)
Patients with PD	True Positive (TP)	False Negative (FN)
Patients without PD (Healthy)	False Positive (FP)	True Negative (TN)

Figure 2: Confusion matrix used to calculate overall accuracy, sensitivity and specificity of the classifier.

$$Total\ overall\ accuracy = \frac{(TP + TN)}{TP + TN + FP + FN} X100\% \quad (1)$$

$$Sensitivity = \frac{TP}{TP + FN} X100\% \quad (2)$$

$$Specificity = \frac{TN}{TN + FP} X100\% \quad (3)$$

VI. EXPERIMENTAL RESULTS & DISCUSSIONS

Various performance measures with test dataset excluding FBANN is demonstrated in figure 3. All the classifiers showed better classification performance after selecting appropriate parameters. It also shows that Random Tree classification accuracy reached 90.10% which provided highest level of certainty among them. Also, SVM detect more TN since it claims more specificity in the chart. Particularly, Random Tree has a high value of TPR with test sensitivity 93.52%. It was observed that SVM with linear kernel achieved the highest value of TP. So, it's training sensitivity reached up to 99.58%. Nevertheless, Test specificity also reached in top level which can be seen from figure 6. Although, for this dataset, Random Tree classifier managed less training accuracy, sensitivity and specificity but it has shown good testing sensitivity and specificity.

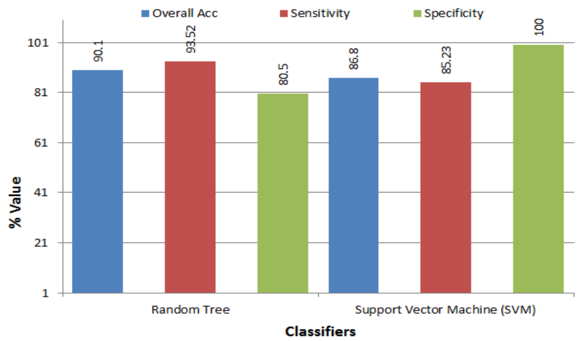

Figure 3: Comparison of performance measures in 3-D chart plot of the classifiers

It can be seen from figure 5 and 6 that SVM has more deviation in sensitivity but steady plot of specificity. In order to compare the performance of different classifiers, FBANN has implemented with same classification purpose.

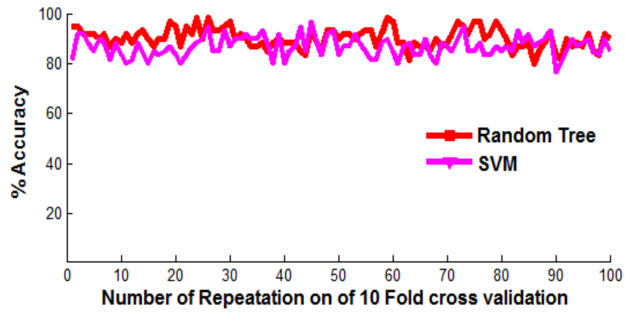

Figure 4: Overall accuracy of Random tree and SVM classifier.

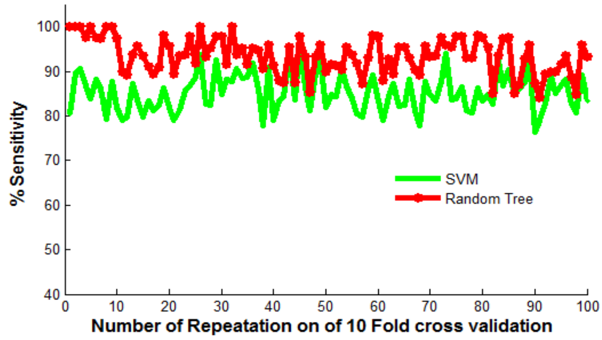

Figure 5: Comparison of different classifiers sensitivity.

Obtained accuracy, sensitivity and specificity for FBANN topology (single hidden layer with different neurons corresponding to input features) is depicted in figure 7 and table II. In this case, network was trained using Levenberg-Marquardt (trainlm) learning algorithm model. Same 10-fold CV method was also employed to evaluate the generalization performance of the FBANN model. It can be seen that with changing of hidden units in the hidden layer, accuracy and other metrics increased as long as hidden units reached forty (40), then it started to decrease. So, the optimum number of hidden units (H) of FBANN classifier was chosen forty to perform final training, test and validation.

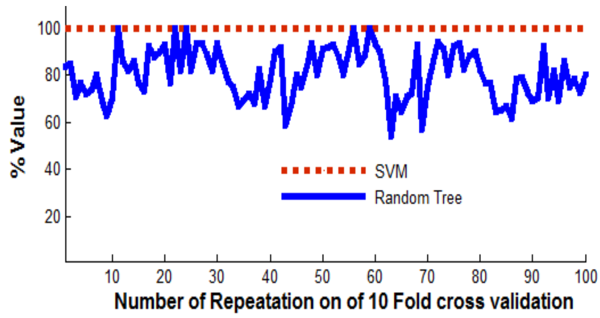

Figure 6: Comparison of different classifier's specificity.

TABLE II. PERFORMANCE DETAILS FROM FBANN CLASSIFIER (HIDDEN AND OUTPUT LAYER USED TAN-SIGMOID AS ACTIVATION FUNCTION).

No. of Hidden Layers	CA (%)	Sen	Spec	TPR	FPR	Precision	Total MSE	Training MSE	Test MSE	Validation MSE
3	91.67	95.49	79.98	95.49	20.01	0.939	0.065	0.0554	0.1330	0.080
5	93.37	96.02	85.16	96.02	14.83	0.954	0.052	0.0413	0.1198	0.077
7	94.02	96.39	86.80	96.39	13.19	0.959	0.049	0.037	0.1179	0.074
10	94.65	97.15	86.96	97.15	13.03	0.960	0.042	0.031	0.112	0.066
15	94.72	96.97	87.83	96.97	12.16	0.962	0.044	0.034	0.099	0.070
20	94.60	97.10	86.96	97.10	13.03	0.960	0.045	0.035	0.099	0.073
25	95.63	97.52	89.78	97.52	10.21	0.968	0.038	0.028	0.089	0.067
30	95.67	97.31	90.67	97.31	9.32	0.970	0.038	0.029	0.085	0.066
35	95.34	97.63	88.28	97.63	11.71	0.965	0.042	0.032	0.097	0.068
40	97.37	98.60	93.62	98.60	6.38	0.979	0.027	0.017	0.078	0.061
45	95.84	97.51	90.68	97.51	9.31	0.971	0.038	0.028	0.082	0.067
50	96.31	97.48	92.73	97.48	7.26	0.977	0.035	0.025	0.088	0.063
55	95.99	97.80	90.46	97.80	9.53	0.971	0.038	0.028	0.087	0.067

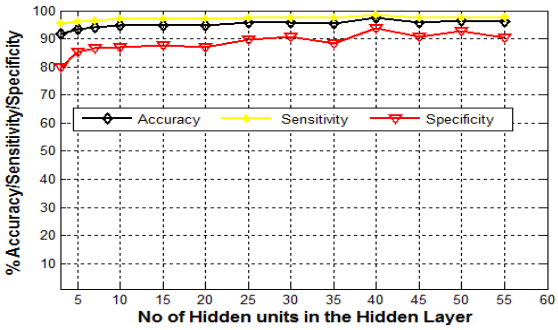

Figure 7: Variation of accuracy, sensitivity and specificity with changing of hidden units in hidden layer of FBANN classifier.

Average MSE of FBANN network is shown in figure 8 using same network configuration discussed above. It can be seen that minimum value of MSE achieved using forty hidden units in the hidden layer. While training in each iteration, a lot of samples are used to train properly the network and validation set also used. So, there was less chance of FBANN to become over fitted or overtrained. The standard deviation of training error for PD detection found more than the test error.

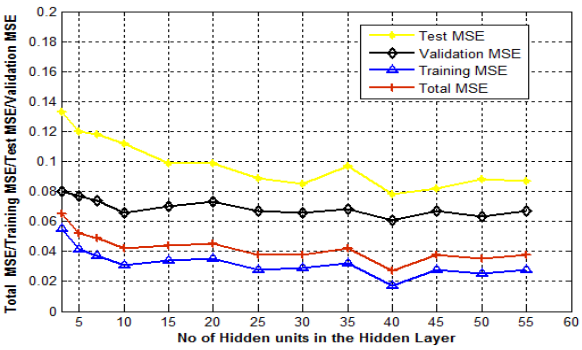

Figure 8: Variation of MSE with changing of hidden neurons in the hidden layer (Hidden and output neuron used tan sigmoid as an activation function).

It was found that with optimized neurons, FBANN topology had provided more TPR value (98.60%) with less FPR value (6.38%) (Table II). Nevertheless, Total MSE (0.027) was much less as compared to test MSE (0.078).

We achieved higher classification accuracy with lowest misclassification rate using FBANN model as compared with other classifiers. It can be seen that overall MSE value is less than test and validation error as presented in figure 9 and 10.Figure 11 is displaying overall accuracy, sensitivity and specificity of FBANN classifier using optimum number of neurons (40) in the hidden layer by varying number of repetitions of 10 fold cross validation. Although accuracy and sensitivity has smooth shape with high value in every repetition but specificity plot contain large fluctuation (i.e. average value > 90 %.)

Figure 12 has shown MSE of the FBANN network while training with Scaled Conjugate Gradient (SCG) method for updating weights and biases and log-sigmoid transfer function applied in the output layer. In this case, sensitivity was found higher in FBANN network with less execution time. Besides this, log-sigmoid activation function in conjunction with optimum number of neurons had shown faster response as compared to tansig function used earlier. Furthermore, the classification of PD using LM method attains higher classification rate as compared to SCG. This is proven from the correct detection rate as well as the lower MSE obtained.

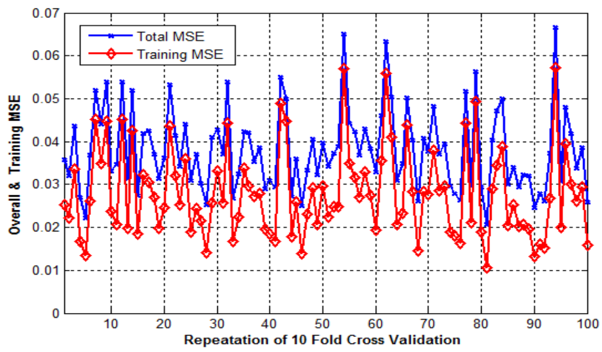

Figure 9: Overall and Training MSE of FBANN classifier using optimum number of hidden neurons in the hidden layer.

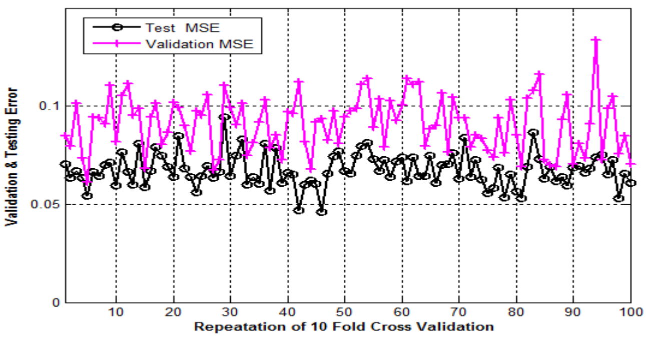

Figure 10: Validation and Test MSE of FBANN classifier using optimum number of hidden neurons in the hidden layer.

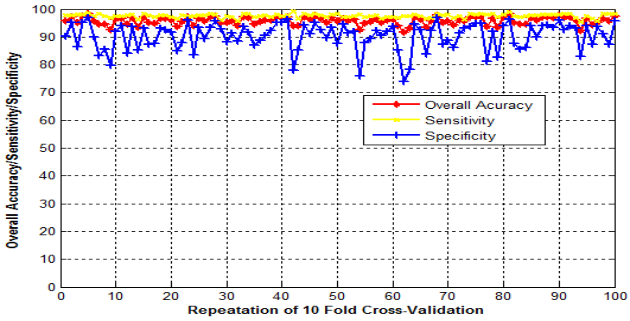

Figure 11: Overall Accuracy, Sensitivity and Specificity of FBANN classifier using optimum number of neuron in the hidden layer.

Principal component analysis (PCA) is one of the popular statistical techniques used widely in the field of image compression, face recognition to find optimal number of pattern from high dimensional dataset. We had performed PCA transformation to select optimum features. It was seen that last eight features contain high variance and ultimately more necessary information of the dataset. It was found that after transforming PCA, the reduced feature subset could not amplify recognition rate.

Receiver operating characteristics (ROC) is a very common tool used in data mining to justify classifier performance by researchers and professionals. It is a graphical plot of sensitivity (TPR) and 1-specificity (FPR) of the classifier in vertical and horizontal axis respectively which justified overall accuracy of the model. If area under the ROC curve (AUC) value indicates 1, then the dataset shows more accurate result (i.e. more samples are correctly predicted). ROC curve of FBANN classifier for randomly selected samples has been shown in figure 13 to show intuitionistic determination of performance. From the curve it was expressed that ROC plot of PD and healthy detection using FBANN classifier with all features has shown very good discrimination ability since it has high value of area (i.e. AUC > 0.9) with smooth transition in between TPR and FPR.

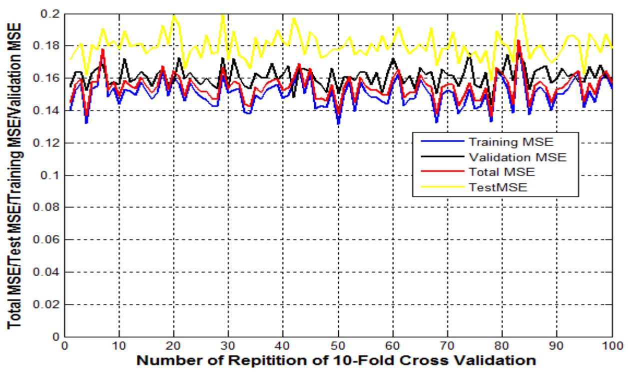

Figure 12: Different MSE while training, testing and validation of FBANN classifier with Scaled Conjugate Gradient method for updating weight and biases and log-sigmoid transfer function used in the output layer.

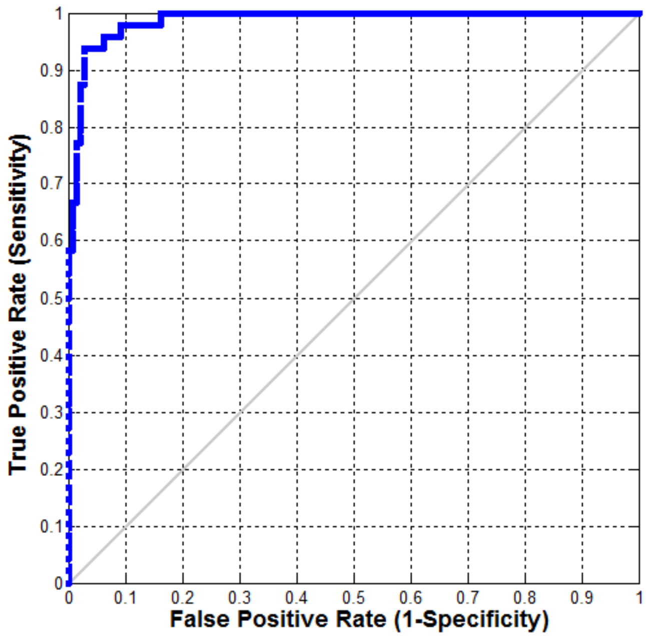

Figure 13: ROC plot of PD and healthy detection of FBANN classifier.

However, conclusion can be drawn from the average AUC values obtained from ROC plot that the developed FBANN model is quite robust and reliable since it predicted correctly both positive and negative outcomes.

With statistical parameters, FBANN classifier yields best score. The overall achieved correct recognition rate 97.37%, 98.60% sensitivity and 93.62% specificity. To best of our knowledge, these results are significantly encouraging compared to some previous results demonstrated in the literature. These results are easily comparable with support vector machine (SVM), Random Tree. More significantly, SVM had provided 100% specificity only, but it couldn't exceed the accuracy and sensitivity level as FBANN did with same features. Although SVM's generalization ability is better than multilayer neural network, but from the above results and discussions we can conclude that FBANN classifier can effectively execute the classification process of PD and healthy individual.

We have observed that the imbalanced and unevenness of classified data influenced the classification performance. The accuracy of the classifiers may be improved by eliminating a number of outliers from both the minority and majority classes, and increasing the size of the minority class to the same size of majority class.

VII. FUTURE DIRECTION OF THE STUDY

Recently significant improvement and selection in the detection algorithm has done but still their performance is not so perfect. Besides, there is no such accurate feature extraction method that can produce perfect and robust classification output. Further extensive study is necessary for the development of each algorithm to improve the overall performance of computer aided diagnosis. Considering all the facts, we aimed to optimize with evolutionary algorithm to get optimum classifier learning parameters to improve overall and reliable performance. In brief, firstly, we want to build ensemble classifier (ensemble decision fusion based system like majority voting, condorcet method, borda count, alternative voting, plurality voting, boosting, bagging etc.) for early detection of Parkinson's disease. After that, next step will be to use a clustering method also called meta-learning [22] with high dimensional real time data set obtained from many PD patients. Secondly, we want to design a model of remote diagnosis of PD using voice disorder measurement so that physically impaired, old or aged people can get better facilities for diagnosis of PD in the easiest way.

VIII. CONCLUSION

In this study, we aimed to develop predictive model for robust identification of healthy person from people with Parkinson (PWP) using voice disorder measurement. The goal is not only to establish a comparison between them but also to be benefitted from the highest accuracies of each classifier. With this system, we achieved a true recognition rate which is more than 90 % and it is encouraging. The experimental results also show that the proposed method based on neural networks is comparable to other algorithms existing in the literature and demonstrates the effectiveness and computational efficiency of the mechanism. Further research is envisioned that the proposed prediction system of PD detection explained here using numerous ML algorithms keeps a vast and promising window of opportunity for future generation to explore about effective detection of any chronic neurological disorder. However, we will provide further attention to investigate the improvement of methods for robustness and user friendly by applying different machine learning, dynamic feature extraction and selection strategy.

ACKNOWLEDGEMENT

The authors want to express high acknowledgements to Max Little of the University of Oxford, who has created the database, in collaboration with the National Centre for Voice and Speech, Denver, Colorado.

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