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ORIGINAL CONTRIBUTION

Speech-Based Parkinson's Disease Prediction Using XGBoost-Based Features Selection and the Stacked Ensemble of Classifiers

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Abstract Parkinson's disease (PD) is a neuron-related disorder due to the decrease in dopaminergic neurons present in the midbrain. For the last few decades, speech is an emerging interest in the analysis and detection of PD. In this study, a predictive machine learning framework based on extreme gradient boosting (XGBoost) features selection and a stacked ensemble approach is presented to investigate the voice tremor of people suffering from PD. The proposed framework consists of two stages: In the first stage the optimized features are obtained using XGBoost features selection, and in the second stage a PD detection system is developed using stacked ensemble classifiers. Leave one subject out (LOSO) cross-validation shows that the proposed framework gives average accuracy of up to 95.07% compared to results obtained with individual classifiers. Additionally, it was also concluded that reduced features had given the highest classification accuracy compared to the raw features set which saves training time and enhances the prediction accuracy.

Keywords Parkinson · XGboost · Ensemble · LOSO · Tremor

Introduction

Among neuro-related disorders, Parkinson's disease (PD) is most common among old age people [1]. Millions of people are affected by this disease worldwide. The main reason of this disease is a decrease in dopamine level and the severity of the disease increase as time passes. The main symptom of this disease includes uncontrollable body moments, tremor, rigidity in muscles, speech impairments, and slowness in handwriting [2]. Several clinical scales (like the unified Parkinson's disease rating scale (UPDRS) and H and Y) have been developed to measure the severity of the disease [3]. It has been found that speech impairment is one of the common conditions that appear in patients with PD and become more prominent during the progression of the disease. So, speech can be treated as an early indicator for the assessment of PD. It has been seen that people with PD suffer from less speech intelligibility, problems with regular vibration in the vocal fold, and less movement in vocal tract organs like the jaw, lip, and tongue [4]. Recent studies show that the features extracted from raw speech signals can effectively distinguish PD patients and healthy individuals. These features are obtained using various speech signal processing algorithms. According to recent studies [4–10] on speech-based PD detection, most features are based on acoustic measures that include shimmer, jitter, pitch parameters, harmonicity parameters, pitch period entropy, recurrence period entropy, and detrended fluctuation analysis. Another group of features related to dysphonia measures from sustained vowels [6]. The authors in the literature [11, 12] reported spectral and cepstral features for PD detection. These features are related to the Mel frequency cepstral coefficient (MFCC), linear prediction coefficient (LPC), linear prediction cepstral coefficient (LPCC), and cepstral separation distance (CSD) features. The authors in the researches [13] utilized the wavelet-based approach for feature extraction and used to detect the PD progression. These features are utilized to get robust model for PD detection. Gomez et al. [14] proposed articulation dynamics features for PD detection and accuracy up to 99.4%

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is reported by the author. Sakar et al. [15] presented a good comparative analysis of various signal processing technique for PD detection and shows that tunable q-factor wavelet transformation-based features show more contribution toward classification. The author in the literature [16, 17] has proposed nonlinear technique-based features using empirical and variational mode decomposition of speech signal for PD detection. The summary and characterization of the different feature are presented in Table 1.

From the literature study, it has been noticed that the robustness of the machine learning model depends upon the quality of features used. These features are fed into the different classifiers and give excellent performance. So, it is important to select appropriate features for model building and detection. In this direction number of researchers have presented their studies. The model based on speech features and seven numbers features selection algorithm is presented by Tsanas et al. [18]. The filter-based selection method such as relief and minimum redundancy maximum relevance (mRmR) is used by the author and achieved 98% accuracy only using ten optimum features. Lavalle et al. [19] have used Wrapper's selection method along with four classifiers for voice-based PD detection. 94.7% accuracy is obtained using twenty numbers of features and the Support vectors machine classifier. By the same author in [20] has reported accuracy of up to 96% using Wrappers features selection and multilayer perceptron classifier. Gunduz et al.[21] have presented filter-based feature selection and obtained 91.6% accuracy in the detection of PD using a variational autoencoder. The same author in [22] used deep learning-based architecture for PD assessment and reported 86.9% classification accuracy. Gupta et al. proposed crow search [23] and cuttlefish [24] algorithms for features selection and achieved good accuracy of 100% and 94%, respectively. From the reviewed literature, it was found that during classification task the selection of appropriate features have a great role. Different researcher has used variety of feature selection algorithm.

In this study, a new framework based on XGboost features selection and an ensemble of classifiers have been proposed for the efficient detection of PD. The proposed methodology is based on the use of four base classifiers and meta-classifier ensembles. The stacked ensemble approach gives better accuracy than the individual classifier performance.

Important Contribution of the Present Study is as Follows:

- *A new framework has been proposed for effective PD detection.*
- *The set of features obtained after feature selection saves training time and improvement in prediction accuracy.*
- *Stacked ensemble of classifiers gives better performance compared to the individual classifier.*

Table 1 Summary of features typically extracted to model pathological speech signals

Parameter	Features	Vocal fold information	Vocal tract information
Acoustic measures [4–10]	Jitter variants	✓	×
	Shimmer variants	✓	×
	Fundamental frequency	✓	×
	Harmonicity	✓	×
	Recurrence period density entropy (RPDE)	✓	×
	Detrended fluctuation analysis (DFA)	×	✓
	Pitch period entropy (PPE)	✓	×
	Formant frequency	×	✓
	Glottis quotient (GQ)	✓	×
	Glottal-to-noise excitation (GNE)	✓	×
	Vocal fold excitation ratio (VFER)	✓	×
Spectral and cepstral features [11, 12]	Mel frequency cepstral coefficient, linear prediction coefficient, linear prediction cepstral coefficient, and cepstral separation-based features	×	✓
Pitch contour based-discrete wavelet-based features [18]	Wavelet transformation-based features which quantify pitch deviation	✓	×
Tunable Q-factor wavelet-based features [15]	It quantifies the oscillatory behavior of speech articulation	×	✓
Empirical mode decomposition-based features [16]	Instantaneous energy deviation cepstral coefficients	✓	✓
Variational mode decomposition-based features [17]	These features are well defined in terms of the vocal tract information of the speakers	×	✓

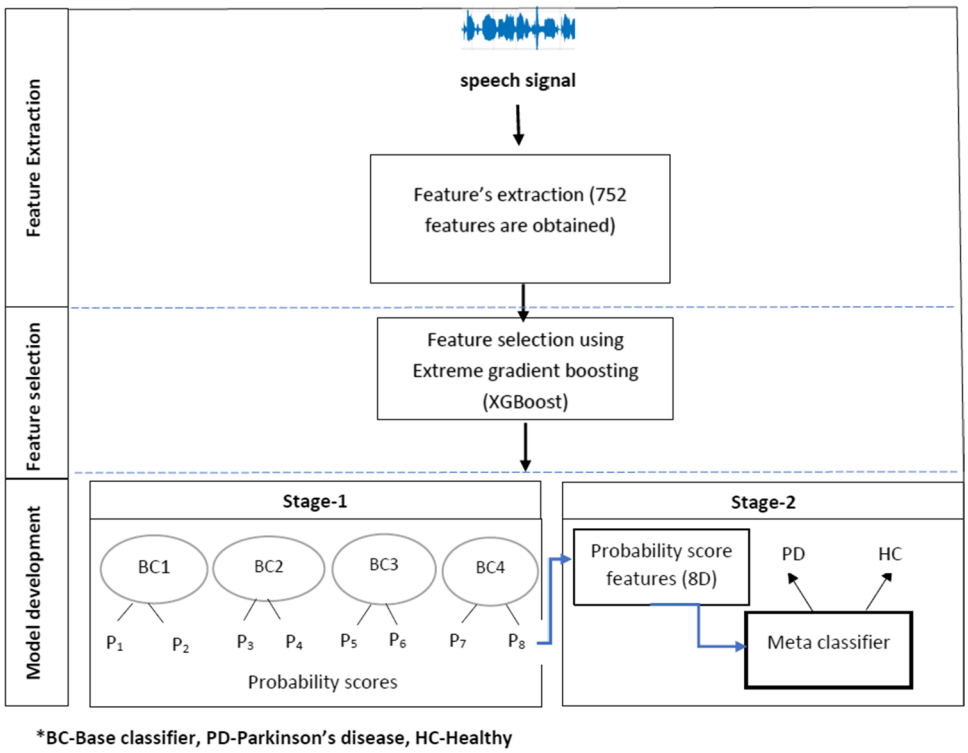

Fig. 1 Flow chart of the proposed framework

Table 2 Details of the dataset

# of subjects	188/64
Male: Female	107:81/23:41
Age (years)	65.1 ± 10.9/61.1 ± 8.9[years]
MDS-UPDRS-III scale	–

Table 3 Summary of features extracted

Sl no.	Features	# of features
1	Baseline acoustic features	54
2	MFCC features	84
3	DWT features	182
4	TQWT	432
	Total	752

Materials and Methods

The whole prediction framework is shown in Fig. 1. It consists of three major steps: The first stage consists of features extraction, the second stage consists of features selection, and the final stage consists of model development. Further model development. Consists of two substages.

Dataset Description

To check the effectiveness of the proposed framework for PD detection, Sakar et al.[15] dataset is used. The detail of the dataset is described in this section. It consists of the recording of 188 patients with PD and 64 healthy people. A total of 252 participants are involved in the generation of the datasets. Each people uttered the vowel /a/ three times. So, 756 observations are obtained within the dataset. The voice samples are recorded using a microphone with a 44.1 kHz sampling rate. The demographic information of the participants of both database is shown in Table 2.

Features Extraction

A total of 752 features are extracted from each recording using different signal processing techniques from each recording. The features are grouped under acoustic features, MFCC features, wavelet transformation-based features, and tunable Q-factor wavelet (TQWT) transformation-based features. The summary of extracted features is presented in Table 3.

Feature Selection

As mentioned earlier that the high accuracy of PD detection depends on the quality of features fed into ML models. In this study, the extreme gradient boosting (XGboost) features selection technique is implemented to get the highly informative features [25]. The importance of features is obtained by the XGboost model. The feature's important information is

sorted in descending order. The relevant features are filtered out based on different threshold values and accuracy.

Stacked Ensemble Classifier

It is the integrated method proposed by Wolpert [26] which combines many weak learners to get a strong model. The probability scores of the individual weak learners are utilized as new features vectors to minimize the prediction error. The model building is implemented in two stages. In the first stage, the relevant features are given as input to get the probability scores. So, from four base classifiers, eight-dimension (8-D) features vectors are obtained. These outputs are given as input to the classifier as a meta-classifier. Table 4 shows the pseudocode for a stacked ensemble of classifiers.

Model Development and Evaluation

In this study, the stacked ensemble approach is implemented using reduced numbers of features obtained from XGboost features selection. The proposed approach is described as follows:

Step 1: Data collection: The database of Parkinson's disease is collected from the UCI machine learning repository. The dataset is consisting of 752 features extracted from 252 subjects.

Step 2: Feature selection: XGBoost features selection is implemented by using the proper threshold value. Finally, 21 optimum features are obtained from the database.

Step 3: The optimal features are given input to the base classifier. The probability score of detecting PD and non-PD

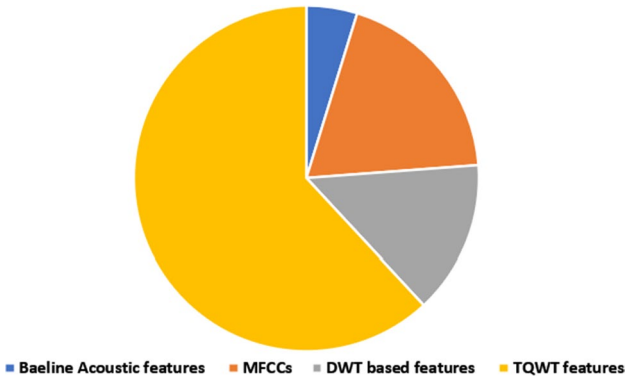

Fig. 2 Distribution of raw features in pie-chart

obtained from each base classifier is taken as input features to the meta-classifier.

Performance Evaluation

The leave one subject out (LOSO) method is applied for training the model because in both datasets each subject consists of three repeated recordings. In the training process, the model is trained with (N-1) subject and tested with one subject. This process of validation gives an unbiased and generalized model [17]. Four indicators are used to evaluate the quality of the model: Accuracy (ACC), sensitivity (SEN), specificity (SPEC), and area under the curve (AUC).

$$\mathrm{ACC} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \quad (1)$$

Table 4 Pseudocode for stacked ensemble classifier

Input: speech dataset $D = \{(S_1, L_1), (S_2, L_2), \ldots . S_m, L_m)\}$ Base classifier: $\zeta_1 = BC1, \zeta_2 = BC2, \zeta_3 = BD3, \zeta_4 = BC4$, where BC1,BC2,BC3 and BC4 are base classifier Meta classifier: $\zeta_s =$ Meta classifier
Step 1: Learn the base classifier. for i=1 2…4 Train the base classifier. $h_i = \zeta_i(D)$ End
Step 2: $D = \acute{\emptyset}$:
Step 3: for j=1,2,….m For i=1….4 Generate new set of features for each sample. $z_{ij} = h_i(x_j)$ $D' = D' \cup ((z_{j1}, z_{j2}, z_{j3}, z_{j4}), y_j)$;
Step 4: Learn the meta classifier. $h' = \zeta_5(D')$
Step 5: $H = h'(h_1(x), h_2(x), \ldots\ldots h_4(x))$
Step 6: return H

$$\text{SENS} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{SPEC} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{3}$$

where TP represents the number of PD patients correctly predicted. TN as the number of normal people correctly predicted, FN represents the number of PD predicted as normal and FP as the number of normal people predicted as PD. Additionally, the area under the ROC curve is also considered an important indicator to measure the performance of the model. The parameters of each base classifiers are as follows: (1) The number of neighbors of KNN is 10; (2) the RBF kernel is used in SVM; (3) in RF, the maximum number of a decision tree is 100; (4) the number of iteration in XGBoost is 100; (5) the number of neurons in MLP is {100, 50, and 50}. All the experiments are conducted on python 3.6.

Results

Selection of Threshold Value in Features Selection

The proper threshold is selected to obtain the optimum set of reduced numbers of features. The threshold value is varying between 0.001 and 0.02 to get the optimum number of features using the XGBoost features selector.

From Table 5 it is observed that for threshold value 0.009, 21 optimum features are obtained. These optimum features are utilized for model building using a stacked ensemble approach. The distribution of selected features is shown in Table 6. At the same time, the distribution of selected features is shown in a pie-chart.

From the pie-chart (Fig. 2), it is clearly seen that the TQWT features may more contribution toward the classification between healthy and Parkinson affected people. Next, the MFCC features are more significant. The baseline features are less significant.

Visualization of Features

The comparison of the distribution of raw features and the reduced number of features are illustrated using a t-distributed stochastic neighbor embedding (t-SNE) plot. The visualization of features is represented in two-dimensional features space shown in Figs. 3, 4.

The distribution of the original features in the two-dimensional plot is shown in Fig. 4. It is noticed that there is an obvious distinction between Parkinson and healthy samples but not clearly distinguishable because of irrelevant and noisy features.

Table 5 Threshold value for features selection

Threshold	No of features	Accuracy (%)
0.001	204	92.11
0.0015	176	93
0.002	152	91
0.0025	142	90
0.003	110	88
0.0035	94	90
0.004	85	88
0.0045	74	91
0.005	63	90
0.0055	55	90.5
0.006	50	91
0.0065	46	92
0.007	39	91.5
0.0075	34	92
0.008	31	91
0.0085	25	89
0.009	**21**	**94**
0.0095	18	88.5
0.01	16	82
0.015	12	80
0.02	10	78

The best accuracy is shown in bold letters

Table 6 Distribution of the reduced number of features obtained from XGBoost features selection

Types of features	Reduced # of features
Baseline acoustic features	1
MFCCs	4
DWT-based features	3
TQWT features	13

But in Fig. 4 it was found that in the distribution of reduced features obtained after XGboost features selection, there is a clear distinction between Parkinson's and healthy samples. So, the features obtained after feature selection can capture the difference between the two classes of samples. The proposed features selection approach effectively transforms the features from high-dimensional space to low-dimensional space which can reduce the training time and may increase the prediction accuracy. The above outcomes motivate us to utilize the reduced number of features for PD detection. This clear distinction of optimized features motivate us to conduct further experiment.

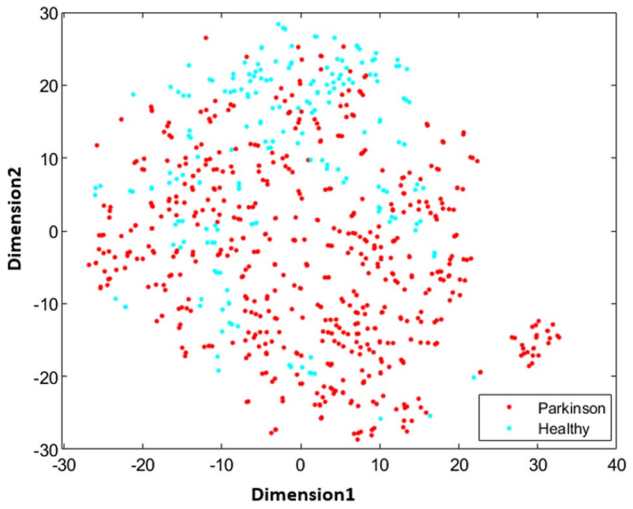

Fig. 3 t-SNE plot of the raw features in two-dimension space

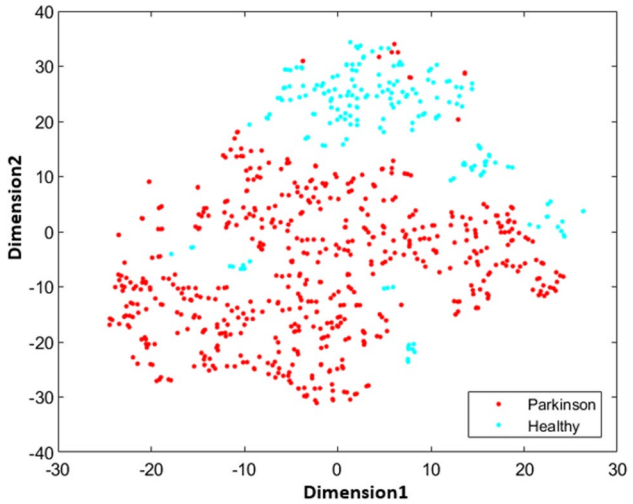

Fig. 4 t-SNE plot of optimum features in two-dimension space

Performance Evaluation

To test the performance of selected features, the 1st stage of training is performed using four base classifiers, and an eight-dimensional probability features matrix is obtained. This output probability matrix is fed into a meta-classifier for further training (Fig. 5).

From Table 7 it is observed that in case 5, the combination of four base classifiers KNN, SVM, RF, and MLP along with meta-classifier XGBoost gives the highest accuracy up to 95.07%.

Next case 3 gives the highest classification accuracy up to 91.44%. Further, the performance of stacked ensemble classifiers is represented by the region of the convergence curve with the area under curve (AUC) value in Fig. 6.

In Fig. 6, the area covered by the ROC curve of the best performing combination is illustrated. The reduced numbers of features along with the stacked ensemble classifier had given the highest area under curve (AUC) value up to 0.96 which is more than individual base classifier performance.

Statistical Analysis of Classifier Using McNemar's Hypothesis Test

McNemar's Hypothesis Test is used to compare different machine learning approaches [27]. This study uses a hypothesis test to determine how well stacked ensemble classifier performance compares to individual base classifier performance. Table 6 shows that the KNN, SVM, RF, and MLP combination with the meta-classifier XGBoost provides the maximum accuracy of up to 95.07%. To test whether the improvement in prediction is significant, each base classifier is compared with the meta-classifier XGboost shown in Table 8.

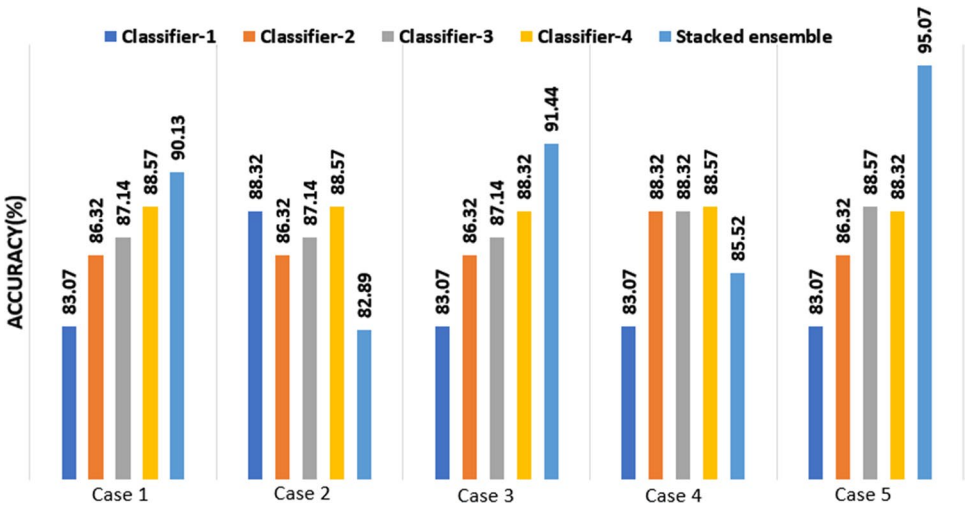

Fig. 5 Performance comparison of different cases of stacked ensemble classifier

Table 7 Performance of base classifier and different combinations of ensemble of classifiers

Case	Combination of base classifiers	Meta-classifier	Base classifier performance ACC (%)				Stacked ensemble performance		
			BS-1	BS-2	BS-3	BS-4	ACC (%)	SPEC (%)	SENS (%)
1	KNN, SVM, XGBoost, and RF	MLP	83.07	86.32	87.14	88.57	90.13	77.14	94.01
2	MLP, SVM, XGBoost, and RF	KNN	88.32	86.32	87.14	88.57	82.89	88.57	81.19
3	KNN, SVM, XGBoost, and MLP	RF	83.07	86.32	87.14	88.32	91.44	85.71	93.1
4	KNN, MLP, XGBoost, and RF	SVM	83.07	88.32	88.32	88.57	85.52	63.32	92.30
5	**KNN, SVM, RF, and MLP**	**XGboost**	**83.07**	**86.32**	**88.57**	**88.32**	**95.07**	**89.57**	**95.07**

The best accuracy is shown in bold letters

*The results are shown in terms of the average value for ten iterations

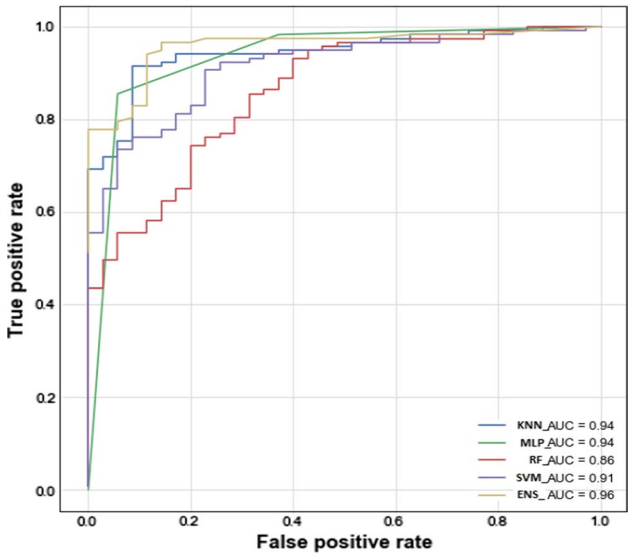

Fig. 6 ROC curve of best combination stacked ensemble of classifier (case 5)

Table 8 McNemar's Hypothesis Test of best performing stacked ensemble classifier with Case: 5

Sl no	Base classifier	Meta-classifier	*p* value
1	KNN	XGboost	4.07×10^{-2}
2	SVM	XGboost	5.979×10^{-3}
3	MLP	XGboost	9.213×10^{-4}
4	RF	XGboost	3.067×10^{-4}

From Table 8 it is inferred that the stacked ensemble of classifiers with base classifier KNN, SVM, RF, MLP, and meta-classifier XGboost is statistically significant ($p << 0.01$). The p value is agreeing with the accuracy obtained up to 95.07%.

Discussion

In this study, the authors proposed a stacked ensemble classifier approach using a reduced number of features. In the first stage, it has been removed redundant and noisy features using the XGBoost features selection approach, and finally, 21-dimensional optimal features are obtained. The t-SNE plot shows that optimum features are more separable than raw features. The stacked ensemble classifier integrated using different meta-classifiers SVM, KNN, RF, MLP, and XGBoost is used to get improved accuracy in PD prediction. The highest classification accuracy up to 95.07% is obtained using the proposed approach. Further, the proposed architecture gives better prediction accuracy compared to other reported approaches with the same database. The comparison with different approaches is illustrated in Table 9.

Sakar et al. [15] obtained 86% classification accuracy using raw features. The study in the literature [19, 20] Lavelle obtained the highest classification accuracy up to 96% using Wrapper features selection. Gunduz in [21] and [22] performed the highest accuracy up to 91.2% using deep learning architecture for PD classification. In this study, the proposed methodology obtained the highest accuracy up to 95.07% which is comparable and more than the results reported in the literature.

Limitation and future scope of present work: The proposed approach is tested with one database. Further, it can be tested with another database. Moreover, the accuracy may be improved by using different transfer learning approaches. The long-term goal is to create a smartphone application that can automatically identify Parkinson's disease. This model is prepared for usage in clinical settings. Neurological clinics in particular require a Parkinson's disease helper that is automated and intelligent. The authors wanted to aid medical professionals by creating a new cloud—and mobile-based PD speech classification assistant.

Table 9 Classification accuracy comparison performed in a different study with the same database

Serial number	Study	Methodology	Outcomes
1	Sakar et al.[15]	752 numbers of features and SVM classifier	86% classification accuracy
2	Lavelle et al.[19]	Wrapper features selection and SVM classifier	94.7% classification accuracy
3	Lavelle et al.[20]	Wrappers *features selection and multilayer perceptron classifier*	96% classification accuracy
3	Gunduz et al.[21]	Variational autoencoder and relief and Fisher ratio-based features selection along with multiple kernel SVM classifier	91.2% classification accuracy
4	Gunduz et al.[22]	Deep neural network features	85.7% classification accuracy
5	Proposed method	XGBoost features a selection and ensemble of classifiers	95.07% classification accuracy

Conclusion

The proposed framework revealed a PD detection system based on XGBoost-optimized vocal features. Further to increase the prediction accuracy the reduced numbers of features are fed into a stacked ensemble classifier. The LOSO-based cross-validation is used to develop a more reliable and unbiased model. The highest accuracy up to 95.07% is achieved using a proposed framework that outperformed the reported results with the same database. The important finding of the study is that MFCC features, and TQWT-based features have more contribution toward classification. This study inferred those features related to the vocal tract are more suitable for PD detection. The proposed framework has shown a welcome improvement in the state of art prediction model.

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Declarations

Conflict of interest None.

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