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Optimizing Support Vector Machine Performance for Parkinson's Disease Diagnosis Using GridSearchCV and PCA-Based Feature Extraction

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Abstract

Background: Parkinson's disease (PD) is a critical neurodegenerative disorder affecting the central nervous system and often causing impaired movement and cognitive function in patients. In addition, its diagnosis in the early stages requires a complex and time-consuming process because all existing tests such as electroencephalography or blood examinations lack effectiveness and accuracy. Several studies explored PD prediction using sound, with a specific focus on the development of classification models to enhance accuracy. The majority of these neglected crucial aspects including feature extraction and proper parameter tuning, leading to low accuracy.
Objective: This study aims to optimize performance of voice-based PD prediction through feature extraction, with the goal of reducing data dimensions and improving model computational efficiency. Additionally, appropriate parameters will be selected for enhancement of the ability of the model to identify both PD cases and healthy individuals.
Methods: The proposed new model applied an OpenML dataset comprising voice recordings from 31 individuals, namely 23 PD patients and 8 healthy participants. The experimental process included the initial use of the SVM algorithm, followed by implementing PCA for feature extraction to enhance machine learning accuracy. Subsequently, data balancing with SMOTE was conducted, and GridSearchCV was used to identify the best parameter combination based on the predicted model characteristics.
Result: Evaluation of the proposed model showed an impressive accuracy of 97.44%, sensitivity of 100%, and specificity of 85.71%. This excellent result was achieved with a limited dataset and a 10-fold cross-validation tuning, rendering the model sensitive to the training data.
Conclusion: This study successfully enhanced the prediction model accuracy through the SVM+PCA+GridSearchCV+CV method. However, future investigations should consider an appropriate number of folds for a small dataset, explore alternative cross-validation methods, and expand the dataset to enhance model generalizability.

Keywords: GridSearchCV, Parkinson Disaese, SVM, PCA, SMOTE, Voice/Speech

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I. INTRODUCTION

Parkinson's disease (PD) is a progressive neurodegenerative disorder affecting numerous individuals worldwide. Furthermore, it results from a small anomaly in the main processing center of the brain which directly impacts other organs [1], [2], leading to motor and nonmotor symptoms [3]. Motor symptoms often experienced are slow movements [4], tremors, impaired rapid eye movements [5], rigidity, bradykinesia [6], and postural instability caused by the loss of dopamine-producing neurons in the substantia nigra region of the brain. Nonmotor symptoms include cognitive impairment, depression, and autonomic dysfunction that significantly decrease the quality of life of those affected.

In 2020, 9.4 million individuals globally were estimated as PD patients [7], and this number was projected to rise concurrently with the increasing elderly population. PD has been identified as an incurable neurological disease [8],

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[9] with a tendency to worsen over time [10]. However, some treatments can alleviate the symptoms [11], [12], as well as certain medications that assist in inhibiting nerve impulses and regulating the motor system [13], [14].

Neurologists have previously attempted diagnosis using methods including blood tests, neuroimaging, physical examinations, and medical history of patients. However, the initial diagnosis proved inaccurate because of symptoms resemblance to those of other neurological disorders such as progressive supranuclear palsy (PSP) and multiple system atrophy (MSA) [15]. The clinical evaluation mainly relies on subjective assessments of motor symptoms and responses to dopaminergic medications, which can be confused with other movement disorders. This leads to a less efficient and time-consuming diagnosis process, particularly in the early stages, hence an accurate and rapid strategy is needed for PD detection.

In recent years, voice-based prediction of PD has become an effective and widely practiced method [16]–[19]. Patients often show signs of tremors, characterized by trembling or shaking voice during communication and speaking at a high volume. Other symptoms include 1.) bradykinesia, manifesting as a change in speech speed, resulting in slow and intermittent speech. 2.) Monotone, a situation where the voice sounds monotonous and has no variation in intonation. 3.) Slurred speech, presenting as unclear or halting sounds when talking, and the last is articulation rigidity, which means the pronunciation of words becomes less clear and limited. Analysis of the voice data of patients aims to detect and distinguish these patterns from those of healthy individuals.

Strategies for voice-based PD detection have been developed using data mining, a machine-learning method that seeks to extract valuable information [20]. This application process often incorporates various algorithm optimizations to achieve high accuracy. Classification, one of the data mining methods for predicting specific classes [21], [22], has proven effective in the early detection and accurate diagnosis of disease including glaucoma [23], [24], brain tumors [25]–[27], acute lymphoblastic leukemia [28], [29], and PD [30], [31].

Some studies perform classification by combining both preprocessing methods to address unbalanced data [32]–[37] and feature selection [38]–[43]. One of the most popular classification algorithm models is the Support Vector Machine (SVM) which separates two classes of data with a hyperplane. SVM has been widely used in various fields due to its superior capabilities in fault diagnosis [44], disease detection [45], [46], credit fraud detection [47], [48], and financial prediction [49]. Certain investigations applied PCA feature extraction method for model optimization [50] by reducing data dimensionality and computational burden, as well as expediting the classification process. SMOTE data balancing has been used to improve classification model performance on unbalanced datasets [51] Additionally, parameter-tuning was found to be capable of optimizing algorithm performance [52]–[56]. The superior abilities of these methods lead to the proposal of an SVM algorithm model with aspects including PCA-based feature extraction, SMOTE for data balancing, and GridSearchCV for parameter tuning, thereby enhancing accuracy in PD detection.

II. LITERATURE REVIEW

Several studies were previously conducted to explore PD detection based on the type of sounds produced by patients. For example, Yaman et al. detected this disease through the acoustic characteristic method by applying features with the highest weight for classification and using SVM to achieve an accuracy of 91.25% [57]. Additionally, detection through SHAP and Hard Voting Ensemble methods based on voice signals has been conducted. This incorporated Pearson's correlation coefficient to understand the relationship between features and achieve an accuracy of 85.42% [58]. A study that carried out a voice-based detection method generated accuracy rates of 95.9% in females and 100% in males. Furthermore, it showed gender-specific factors, including high-frequency voice content recommended as the most significant information for aiding PD detection in females, while low-frequency content was more effective in males [59]. PD classification was conducted using 18 feature extraction methods alongside 4 machine learning methods on continuous phonation and speech data with cardioid acoustic recording to achieve 94.55% accuracy [60]. Moreover, the intensity and spectrum of patients using 6 machine learning algorithms were examined, where the random forest (RF) algorithm showed the highest accuracy of 97% [61].

To assess the relationship among subthalamic neural activity, speech production, and intelligibility, Avantaggiato et al. [62] investigated bilateral and STN local field potentials (LFPs) in 9 PD patients chronically implanted with DBS during open reading. The spectral features of LFP in the STN were analyzed, then correlated with clinical scores and speech intelligibility levels. The results showed that during open reading, STN activity on the left side was associated with increased low beta wave activity ([12-20)Hz), while speech intelligibility level had a positive relationship with high beta wave activity ([20-30)Hz) on the right side. Additionally, speech fluency was measured using the FDBS algorithm [63] without the need for language-dependent phoneme-level segmentation. The results obtained with samples collected from Hungarian PD patients and healthy individuals yielded the highest accuracy of 89.3% based on the SVM algorithm. Deep learning was applied for diagnosis purposes by using vocal speech and the

ResNet architecture, where the audio recording spectrum was calculated and converted into an image representation [64], showing an accuracy of over 90%. Another investigation used a telemonitoring dataset [65] to predict UPDRS scores by analyzing speech signal properties essential for diagnosis. Furthermore, it incorporated ensemble learning and hybrid methods to improve the time complexity and accuracy of the PD diagnosis system, using Singular Vector Decomposition (SVD) and ensemble Adaptive Neuro-Fuzzy Inference System (ANFIS), respectively.

III. METHODS

The method applied for voice-based PD detection comprised several stages, including (1) Data Collection, (2) Pre-processing, (3) Feature Extraction, (4) Data Augmentation, (5) Model Training, and (6) Model Evaluation, as depicted in Fig. 1.

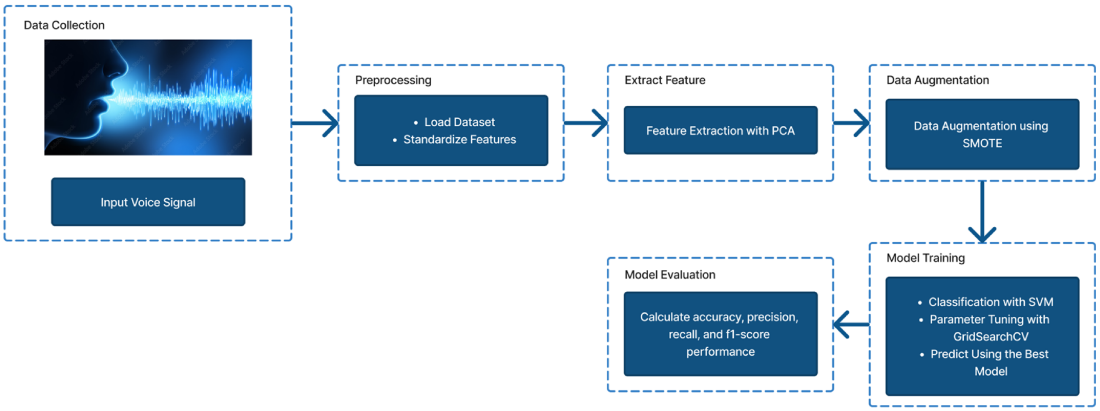


Fig. 1 Block Stages of the Proposed Method

A. Data Collection

The publicly accessible Oxford Parkinson's Disease Dataset (OPDD) created by Max Little in collaboration with the National Center for Voice and Speech, Denver, Colorado, was downloaded from the OpenML website [66]. This comprised voice recordings from 31 individuals, with an average of 6 per individual included as input audio signals in the form of text data. Out of the total number, 23 were PD patients, namely 16 males and 7 females with an average age of 67.38 and 68.71 years, respectively. Meanwhile, those in a healthy condition were 8, namely 3 males and 5 females with an average age of 64 and 58 years, respectively. From the recordings, 195 voice signal data were obtained, showing 147 affected by PD and 48 in healthy condition. The dataset consisted of 23 features, where 22 served as dependent variables, and 1 represented the target or independent variable.

The voice recordings were conducted in a sound processing room using a head-mounted microphone. Furthermore, the audio signals were sampled at a resolution of 16 bits and 44.1 kHz, recorded directly using a Computerized Speech Laboratory (CSL). The amplitude of the audio samples was digitally normalized to address variations due to differences in vocal pressure. Features of the dataset presented in Table 1 were used during PD detection, where MDVP (Kay Pentax) referred to a multidimensional voice program.

B. Preprocessing

At this stage, voice recordings in the form of numeric text were loaded into Google Colab for analysis. The datasets comprising 147 entries from patients and 48 from healthy individuals were stored in CSV files using the Pandas library. Subsequently, the separation of dependent from independent features (the target) was conducted. The target was titled 'status' with a 0 value representing healthy individuals and 1 denoting PD patients. To train and test the SVM model, the collected dataset was divided into 156 training and 39 testing data at ratios of 80% and 20%, respectively. Features of both data were normalized using SatndarScaler from Scikit-learn, leading to a conversion that generated a mean of 0 and a variance of 1 to ensure an equal influence between features with different scales in the classification process. Afterward, a heatmap was created for correlation analysis to obtain a deeper understanding of the data structure. This was used to visualize the correlation matrix, showing the degree of relationship between features, which could provide valuable insights for the development of effective classification models.

TABLE 1
FEATURES OF THE VOICE METER USED IN THE EXPERIMENT

No.	Label	Features	Description
1.	V1	MDVP:Fo (Hz)	The average fundamental frequency of sounds in vowels.
2.	V2	MDVP:Fhi (Hz)	Maximum value of fundamental frequency.
3.	V3	MDVP:Flo (Hz)	Minimum value of fundamental frequency.
4.	V4	MDVP:Jitter (%)	Describes the extent to which a sound deviates from its
5.	V5	MDVP:Jitter (Abs)	fundamental frequency, specifically higher in pathological sounds.
6.	V6	MDVP:RAP	Perturbation in relative amplitude in Kay Pentax MDVP.
7.	V7	MDVP:PPQ	Perturbation quotient in the five-point period in Kay Pentax MDVP.
8.	V8	Jitter:DDP	Mean absolute difference of variances between cycles divided by the mean period.
9.	V9	MDVP:Shimmer	The shimmer found in the data set measures the deviation of two consecutive amplitudes and is often attributed to breathing and noise, caused by changes in the resistance and mass of the vocal cords.
10.	V10	MDVP:Shimmer (dB)	Decibel measurement of local shimmer in Kay Pentax MDVP.
11.	V11	Shimmer:APQ3	Perturbation quotient based on three-point amplitude.
12.	V12	Shimmer:APQ5	Perturbation quotient based on five-point amplitude.
13.	V13	MVDP:APQ	Perturbation quotient based on eleven-point amplitude in Kay Pentax MDVP.
14.	V14	Shimmer:DDA	The mean absolute difference between consecutive variances in the amplitudes of consecutive periods.
15.	V15	NHR	Harmonic noise ratio (HNR) is also used to measure the quality of voice signals. HNR mainly reflects the noise caused by pathological changes in the vocal cords,
16.	V16	HNR	HNR values tend to be smaller in people with PD compared to healthy people.
17.	V16	RPDE	Due to the non-linear and dynamic nature of the human voice, the Recurrence Period Density Entropy (RPDE) method is used to identify periodicity in time series by measuring the recurrence in phases of the system. PD voice characteristics have higher RPDE values due to not vibrating regularly.
18.	V18	D2	The relevance dimension (D2) measures the irregularity in the reconstructed phase space of the system.
19.	V19	DFA	Detrended fluctuation analysis (DFA) is used to measure the similarity of the airflow generated by the vocal cords.
20.	V20	spread1	Three Non-Linier Measurements of Fundamental Frequency
21.	V21	spread2	Variation.
22.	V22	PPE	The entropy of pitch periods.
23.	Class	status	Health status of participants: (0) healthy, (1) Suffering from PD

C. Feature Extraction

The inherently high-dimensional nature of features in voice-based datasets increases the complexity of prediction time as well as affects model accuracy and efficiency [67]. Therefore, extraction was conducted to reduce data dimensionality, leaving behinds only the most relevant and informative features [68], [69]. This enabled the model to focus on the important information in the data and ignore noise or attributes that were less relevant for detecting PD.

In this study, principal component analysis (PCA) was implemented because it has been reported to aid the achievement of high model performance [70]–[72]. PCA operates by reducing dimensionality through the transformation of data into a new coordinate system which appears as a linear combination of the original features. This method searches for feature directions containing high variance and projects the data, thereby retrieving a smaller number of dimensions that explain most of the original data variability.

D. Data Augmentation

The applied datasets were unbalanced because PD patients had greater samples than healthy individuals, while failure to address this would lead to overfitting and performance degradation issues. Model accuracy and performance tend to be class-biased, as there is a tendency to predict the majority class for all data, without actually recognizing the minority. Data augmentation creates synthetic samples of the minority, to ensure a balance between the number of samples from both classes [73], thereby improving minority class representation and optimizing the SVM model learning process.

The Synthetic Minority Over-sampling Technique (SMOTE) [51] used in this study to address data imbalance creates synthetic representations of the minority class through interpolation. The described mode of operation includes selecting two samples from adjacent minority classes and generating a new sample between both through the incorporation of a proportion of features from each. The stages of data augmentation using SMOTE are as follows: First, a minority sample is represented as vector A = (A_1, A_2, ... A_n) and the nearest neighbor B = (B_1, B_2, B_3, …) is identified from the same class, followed by calculating the vector difference between both parameters using diff = B - A. Second, the oversampling factor α which is an integer specifying the number of synthetic samples to be generated is determined. Third, the synthetic sample A accent is generated with the following formula:

$$A' = A + \alpha \times \text{diff.} \quad (1)$$

where each element of the synthetic sample A' is calculated through the addition of alpha to A multiplied by the difference between the values of B_i and A_i. This process is repeated for other neighbors of the selected minority sample.

E. Model Training

PD detection was conducted using the SVM algorithm which operated by searching for a hyperplane capable of separating two classes with a maximum margin. This algorithm was chosen because of its ability to solve classification problems with complex feature spaces and the suitable application for the classification of high-dimensional data such as voice recordings. Additionally, SVM has a kernel capable of mapping data to a higher dimensional space in case the data are not linear and separable. Considering the good performance reported previously [57], [74], [75], significant focus is provided to improving SVM accuracy in PD diagnosis.

Parameter tuning was conducted to obtain the best combination [76] for detecting PD using the GridSearchCV method incorporating cross-validation of various predetermined values. GridSearchCV operates by training and evaluating SVM on each combination of parameters to ensure that the model developed has good generalization ability on new data.

As commonly used in SVM, this study applied three types of kernels, including linear, polynomial, and radiation basis function (RBF), that matched the voice dataset for PD detection [77]. For each kernel type, the best value of C and gamma was searched, where C served as a regulation parameter controlling the trade-off between maximum margin and the number of misclassifications in the training data. A larger C value leads to the SVM model trying harder to fit the training data correctly, but overfitting will occur when it is extremely large. Moreover, gamma is a parameter for polynomial and RBF, with a smaller value signifying a higher external influence from the training sample, and a larger value correlating to a more localized influence. The combination of parameters used in this study is comprehensively presented in Table 2.

TABLE 2
PARAMETER COMBINATION TRIAL ON SVM

Parameter: {Value}
{'C': [0.01, 0.1, 1, 10, 100], 'kernel': ['linear']}
{'C': [0.01, 0.1, 1, 10, 100], 'kernel': ['poly'], 'degree': [2, 3, 4]}
{'C': [0.01, 0.1, 1, 10, 100], 'kernel': ['rbf'], 'gamma': [0.001, 0.01, 0.1, 1]}

To prevent overfitting or underfitting and optimize SVM parameters [3], [5], this study applied a 10-fold cross-validation method which divided the data into 10 equal parts. Subsequently, the parts were used alternately for training and testing, leading to each piece being engaged as testing data only once. The 'C' and 'gamma' parameters of SVM were adjusted using 'param_grid' and the best were selected based on the greatest performance observed in cross-validation. After parameter tuning, the optimized model was used to predict the testing data, where the result and actual label were compared as an accuracy calculation. Based on this, cross-validation helps select the best parameters and results in a model that is more generalizable to new data.

F. Model Evaluation

Performance of the developed model was evaluated by its ability to classify the voice data correctly as well as the effectiveness in identifying PD patients and healthy individuals. This study used three main evaluation metrics, namely accuracy, sensitivity (recall), and specificity, selected based on the need for a comprehensive performance assessment. Accuracy provides a general overview, while sensitivity and specificity fulfill specific requirements for diagnosis by addressing false positive and false negative predictions. The metrics are computed through a confusion matrix consisting of four main components. This includes TP, which represents truly suffering from PD and correctly predicted by the model, while TN denotes truly healthy and correctly predicted. Others are FP, signifying actually healthy but wrongly classified as suffering from PD, and FN representing truly suffering from PD but wrongly classified as healthy.

1) Accuracy

This metric gauges the overall test data classification accuracy, providing insight into the extent to which the model recognizes the patients and healthy individuals, with the following formula presented in Equation (2).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

2) Sensitivity (recall)

This metric measures the ability of the model to identify positive cases (patients) from the total number of actual PD cases. Furthermore, sensitivity is crucial in healthcare applications because it minimizes false negative predictions, where patients are incorrectly classified as healthy, and the formula can be seen in Equation (3).

$$Sensitivity = \frac{TP}{TP+FN} \tag{3}$$

3) Specificity

This metric measures the accuracy of the model in identifying individuals without PD from the total number of actual non-PD cases. The focus is on minimizing false positive predictions, where individuals without PD are incorrectly classified as suffering from disease. Specificity is particularly important to maintain model reliability in identifying healthy individuals, and often calculated using Equation (4).

$$Specificity = \frac{TN}{TN+FP} \tag{4}$$

IV. Result

This section presents the result and analysis of the proposed model to enhance PD prediction in the OPDD dataset. Furthermore, the heatmap provided in Fig. 2 to observe the correlation between the dataset features, played an important role in analysis, specifically in the context of extraction using PCA. This visualization applied a correlation matrix, which showed the strength of the linear relationship between each pair of features. The depicted colors signified the degree of correlation, as red represented a positive correlation, showing the tendency of two features to increase simultaneously. Conversely, blue denoted a negative correlation, suggesting that an increase in one feature would lead to a decrease in another feature. The color intensity denoted correlation strength, with lighter colors equating to a stronger correlation, and PCA results reflected the existing relationship pattern.

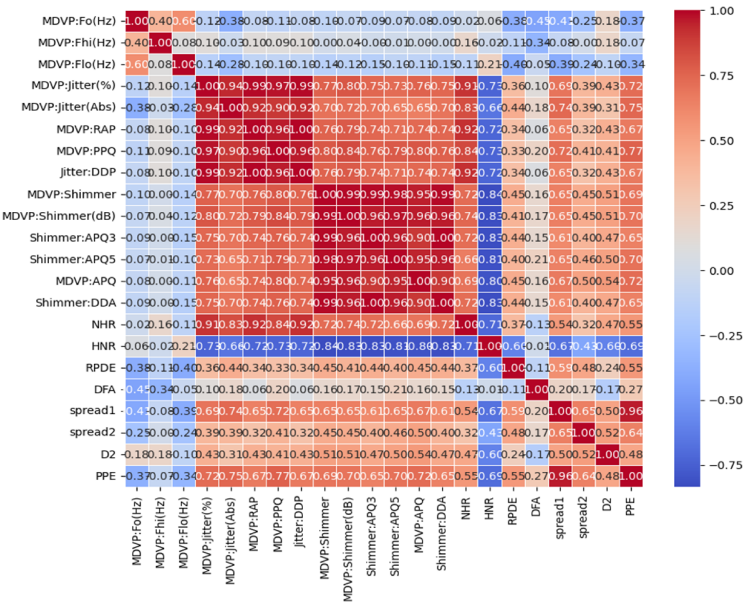


Fig. 2 Correlation between features

To gain further insight into the relationship between features in the dataset and individual health conditions, a visualization of the correlation analysis and classification targets is presented in Fig. 3. This visualization can identify features with a significant influence on distinguishing PD patients from healthy individuals.

PCA was applied in this study due to the high dimensionality of the dataset, which could result in high prediction time complexity, with a potential effect on model accuracy and efficiency. This method was used to reduce dimensionality by transforming the dataset from the original to a new coordinate system consisting of linear

combinations of the original features. The first step involved standardizing the dataset features, followed by the covariance matrix calculation using PCA. In this case, the 'n_components=0.95' setting was applied to PCA object, showing that sufficient principal components were extracted to explain 95% of the data variance. Meanwhile, the following representation in Fig. 3 provides an overview of the data before and after feature extraction.

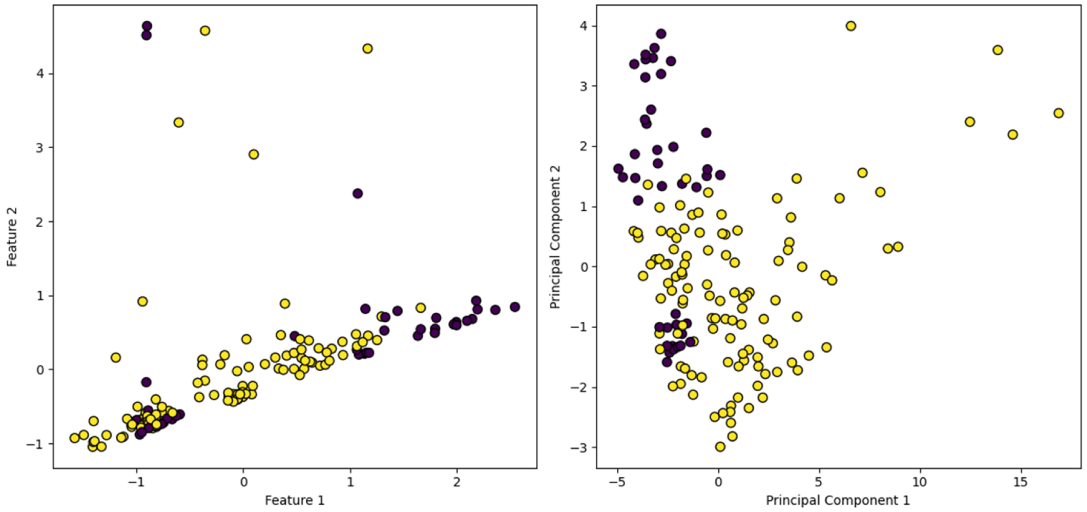


Fig. 3 (a) Data distribution before PCA and (b) Data distribution after PCA

The results showed that the data were more spread out in a lower-dimensional space after performing PCA. This occurrence could be attributed to the selected principal components (PC) being linear combinations of the original features, leading to a different distribution. Due to the 'n_components=0.95' setting, this study preserved the most important information or variation in the data despite the change in physical distribution. The 8 PC presented in Fig. 4 were generated by PCA and sorted based on the number of variances explained, with the first being the most significant in explaining data variation.

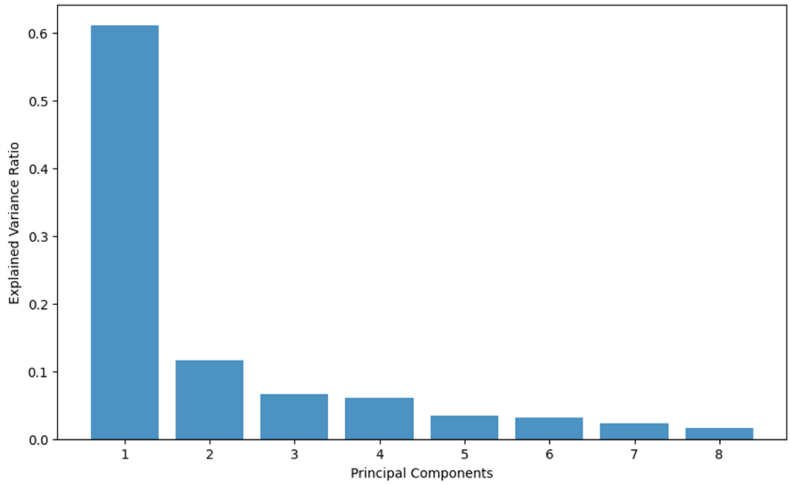
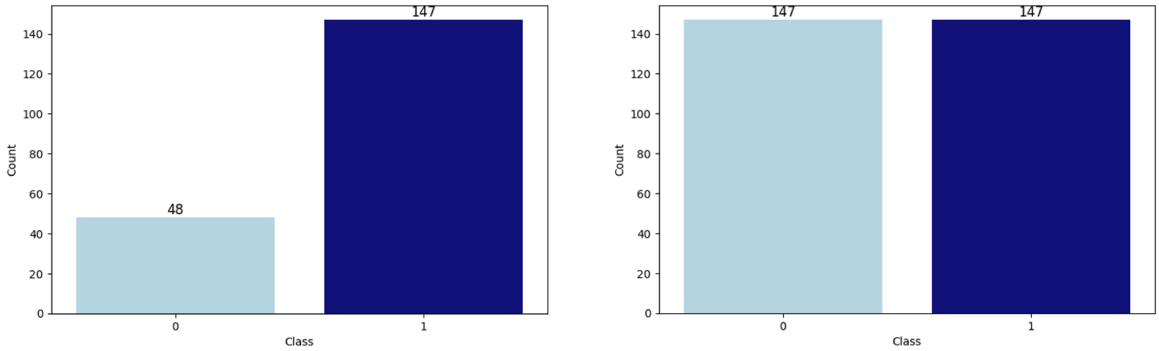


Fig. 4 Variance Explained by Principal Components

PC weights reflected the contributions provided to component formation, with the highest value measuring approximately 6.00% in PC 1 originating from feature V10, while 0.97% and 0.50% were attributed to V1 and V2, respectively. In PC 2 to 8, the most significant and lowest contributions at 15.32% and 0.33%, 9.97% and 0.44%, 12.47% and 0.33%, 12.66% and 0.17%, 22.69% and 0.08%, 18.93% and 0.03%, 16.71% and 0.15% came from V1 and V16, V21 and V22, V18 and V16, V20 and V15, V2 and V22, V21 and V5, V22 and V17, respectively.

The data used in this study had a significant imbalance between the number of patients and healthy individuals. SMOTE was applied to address the imbalance, as well as strengthen the SVM model capability in PD detection and classification, while the results could be observed from the number difference in the dataset. The results of data oversampling process can be seen in Fig. 5.



(a) (b)

Fig. 5. (a) Data Distribution Before Oversampling and (b) Data Distribution After Oversampling

Searching for the right combination of parameters according to the dataset and the proposed model was also part of the main focus of the development process. The parameter tuning using GridSearchCV showed the impact of each combination on the classification results. Several tested parameters and the degree of contribution to the model optimization can be seen in Fig. 6.

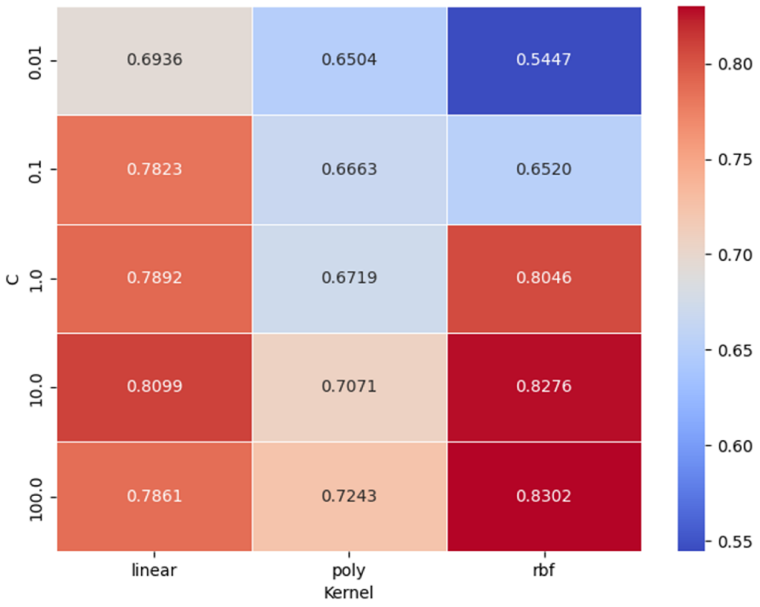


Fig. 6. Experimental results for several parameters

The best parameters for PD detection using the voice dataset and the proposed model were {'C': 100, 'gamma': 0.01, 'kernel': 'rbf'}. The k-fold cross-validation process of the SVM model is depicted in Fig. 7, with point plots showing results obtained with various kernel parameters and C values. Each point represents the average test performance for a particular combination of kernel and C-value.

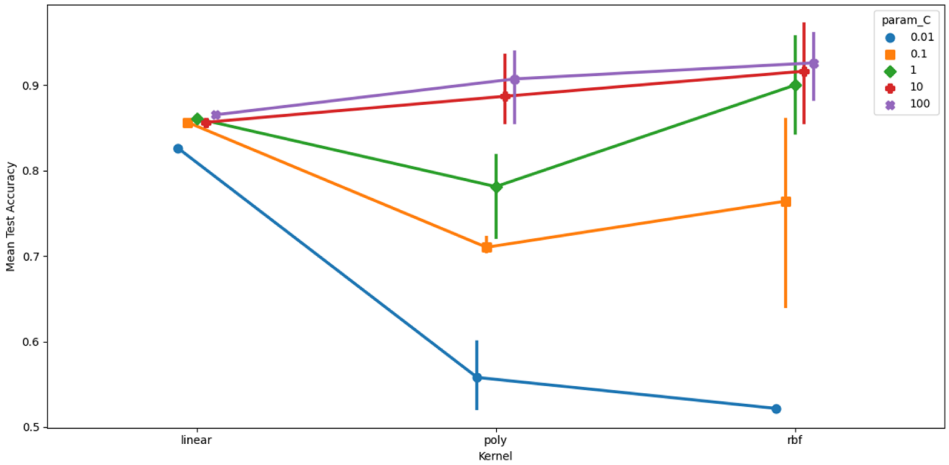


Fig. 7. Cross-Validation result

The visualization showed that the SVM model performance changed with variations in the kernel parameters and C-value. By examining the distribution of points and the trend in the visualization, the interpretation of cross-validation results and the impact of parameters on model performance can be more easily understood. Performance of all algorithms applied for PD detection was evaluated and compared, as presented in Table 3.

TABLE 3
PERFORMANCE OF EACH ALGORITHM AND METHOD

Algorithm	Accuracy	Sensitivity	Specificity
KNN	82.05%	90.62%	42.86%
SVM	84.61%	96.86%	28.57%
Logistic Regression	89.74%	100%	42.865
RF	94.87%	100%	71.43%
KNN +SMOTE+GridSearcCV	92.30%	93.75%	85.71%
LR+ SMOTE+GridSearcCV	84.61%	90.62%	57.14%
RF+ SMOTE+GridSearcCV	94.87%	100%	71.43%
SVM +SMOTE+GridSearcCV	94.87%	100%	71.43%
XGBoost+ SMOTE+GridSearcCV	94.87%	100%	71.43%
Voting Classifier (SVM+Gradient Boosting+ KNN +XGBoost)	92.30%	93.75%	85.71%
Stacking (SVM+Gradient Boosting+ KNN +XGBoost)	94.87%	100%	71.43%
SVM+PCA+SMOTE+GridSearchCV+ CV	**97.44%**	**100%**	**85.71%**

Optimal performance in PD detection was achieved by the application of algorithms including K-Nearest Neighbors (KNN), SVM, Logistic Regression (LR), RF, and XGBoost (eXtreme Gradient Boosting). The implementation of methods, such as SMOTE for class balancing, PCA for feature extraction on the same dataset, SVM with PCA feature selection, data augmentation through SMOTE, and parameter tuning using GridSearchCV, collectively contributed to the successful results. The combination forming the SVM+PCA+SMOTE+GridSearchCV model achieved the highest accuracy of 97.44%, sensitivity of 100%, and specificity of 85.71%, with superiority in diagnosis process.

V. DISCUSSION

In this study, an SVM-based learning model was proposed for PD classification using a voice database, as previous results showed that PD patients often present voice disorders [18]. Voice detection was conducted due to the potential inaccuracies of some clinical methods during diagnosis, making early detection a complex and time-consuming process [15]. Before starting training and classification, preprocessing was performed to ensure optimal data performance. PCA-based feature extraction was conducted to reduce data dimensions, thereby influencing model accuracy and efficiency. Data augmentation was used to address an imbalance between the healthy and PD samples, preventing overfitting and bias in the model. Moreover, cross-validation and GridSearchCV were applied to select the right combination of parameters capable of maximizing SVM model accuracy. The proposed model achieved a

classification accuracy of 97.44%, showing the efficacy of SVM+PCA+SMOTE+GridSearchCV in predicting the classes of PD patients and healthy individuals more accurately.

The result of the strategy implemented to yield the highest accuracy was verified by conducting experiments using various algorithms and methods on the same dataset. The models implemented in this study were KNN, SVM, LR, RF, KNN+SMOTE+GridSearchCV, LR+SMOTE+GridSearchCV, RF+SMOTE+GridSearchCV, SVM+SMOTE+ GridSearchCV, XGBoost+SMOTE+GridSearchCV, Voting Classifier (SVM+Gradient Boosting+KNN+XGBoost), and Stacking (SVM+Gradient Boosting+KNN+XGBoost). The accuracy generated included 82. 05%, 84.61%, 89.74%, 94.87%, 92.30%, 84.61%, 94.87%, 94.87%, 94.87%, 92.30%, and 94.87%, respectively. This proved that the proposed SVM+PCA+SMOTE+GridSearchCV had better accuracy with sensitivity and specificity evaluation matrices at 100% and 85.71%, respectively, showing superiority over other models. The variation of model performance with parameters and learning rate experimented, led to the generation of the greatest accuracy from {'C': 100, 'gamma': 0.01, 'kernel': 'rbf'}. To reinforce these results, comparisons were made with performance generated by previous studies as presented in Table 4.

TABLE 4
COMPARISON OF PERFORMANCE OF THE PROPOSED METHOD WITH SIMILAR EXISTING STUDIES

Related Work	Method	Performance
[78]	The ensemble method of four discretization algorithms, namely ChiMerge (ChiM), Chi2, Extended Chi2 (ExtChi2), and Modified Chi2 (ModChi2), along with stratified 10-fold cross-validation.	Accuracy: 88.03% Sensitivity: 91.84% Specificity: -
[79]	Statistical measurements of SVM + 10-fold cross-validation	Accuracy: 88.72% Sensitivity: 84.10% Specificity: 84.10%
[80]	Ensemble method + 10-fold cross-validation	Accuracy: 90.6% Sensitivity: 95.8% Specificity: 75%
[81]	Gaussian Processes + Automatic Relevance Determination (ARD) + 10-fold cross-validation	Accuracy: 96.92% Sensitivity: 90.0% Specificity: 99.29%
Proposed method	SVM+PCA+SMOTE+GridSearchCV + 10-fold cross-validation	Accuracy: 97.44% Sensitivity: 100% Specificity: 85.71%

This study conducted the selection and combination of proven effective methods, which were not previously implemented. With the used methodology, superior performance reaching 97.44% in terms of accuracy metrics was observed compared to other investigations. This result was attained with a relatively limited dataset, hence further exploration should be conducted on diverse data types and populations to ensure a more robust level of generalization.

VI. CONCLUSIONS

In conclusion, this study predicted PD using the SVM algorithm, showing effectiveness in the classification of patients and healthy individuals. Furthermore, PCA feature extraction was carried out to reduce the data dimensions, enhancing model accuracy and efficiency. SMOTE was used to address the imbalance problem, while parameter tuning was conducted to identify the optimal combination suitable for the dataset and prediction model. The evaluation results including accuracy, sensitivity, and specificity, showed the success of the developed SVM algorithm model. The best performance was achieved with an accuracy of 97.44%, sensitivity of 100%, and specificity of 85.71%, which was attributed to training the model with limited data and using a 10-fold cross-validation method. Therefore, future studies should explore more data, apply several advanced methods, and consider more suitable fold settings for a comprehensive examination.

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https://www.openml.org/search?type=data&status=active&id=1488&sort=runs

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