Journal of Information Systems Engineering and Management
2025, 10(14s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Comparative Investigation of Classification Algorithms using Parkinson's Disease Acoustic Analysis Dataset to Choose Best Classifier for Best Result

Puja Gholap[1], Krupal Pawar[2], Vasudha Patil[3]
[1]*Assistant Professor, Department of Computer Engg., Sharadchandra Pawar College of Engineering, Otur, Pune, Maharashtra, India*
[2]*Assistant Professor, Department of Mechanical Engg., Rajiv Gandhi College of Engineering, Karjule Harya, Maharashtra, India*
[3]*Assistant Professor, Department of E&TC Engineering, Shri Chhatrapati Shivaji Maharaj College of Engineering, Nepti, Ahilyanagar, India*
[1]*Email: gholappuja333@gmail.com*
[2]*Email: krupalpawar@gmail.com*
[3]*Email: vasudhapatil28@gmail.com*

ARTICLE INFO

Received: 24 Nov 2024

Revised: 10 Jan 2025

Accepted: 21 Jan 2025

ABSTRACT

Early diagnostic discovery of Parkinson's Disease (PD) is a serious clinical issue. Owing to the early manifestations of speech impairments in the force of PD patients, the acoustic features of speech have potential to be considered as better early diagnosis standards. In this study, which utilizes a dataset that includes acoustic features associated with PD, we analyze the performance of three machine learning classifiers: Random Forest(RF), Support Vector Machine(SVM), and k-Nearest Neighbors(k-NN) classifiers. In one-second audio segments, a feature extraction was carried out based on principles of jitter, shimmer, harmonics-to-noise ratios, and recursive feature elimination (RFE), as an approach to eliminate the unhelpful features without hindering the model prediction. The classifiers were developed in MATLAB and evaluated based on accuracy, precision, recall, and F1-score using a 10-fold cross-validation method to ensure rigorous assessment. The results showed that RF achieved the highest recall and accuracy (93.0% and 92.3%, respectively), highlighting the suitability of RF as a PD diagnostic model. While k-NN had the lowest results, SVM was precise but scored low on recall. Such works highlight the promise of RF and feature selection in the construction of diagnostic tools for PD, addressing the key concerns of non-invasiveness and improved patient outcomes.

Keywords: Parkinson's Disease, Acoustic Analysis, Machine Learning, Random Forest, Support Vector Machine.

INTRODUCTION

Parkinson's disease (PD) is a chronic neurodegenerative disease associated with the progressive degeneration of dopaminergic neurons in the substantia nigra, affecting millions of people worldwide. The disease presents with motor features including tremors, bradykinesia, and rigidity, and non-motor features such as cognitive declines and speech problems. Detective PD in the early stages is important for improving therapeutic interventions and patients' quality of life. Yet, conventional diagnoses based on clinical observations and imaging techniques cannot detect the disease early in its clinical course. Speech dysfunction, such as decreased pitch variability, monotonous pitch, and articulation problems, is one of the initial symptoms of PD, which suggests potential application of speech analysis as a non-invasive PD diagnostic tool [5]. These voice libs are the ground we are seen using acoustic analysis as a solid approach to measuring these disorders through vocal biomarkers like jitter, shimmer and harmonics-to-noise ratio (HNR) [6]. To achieve this goal, recent years have seen the emergence of automated systems designed for the analysis of acoustic signals in various contexts, driven by advancements in machine learning. Traditional machine learning algorithms, including Support Vector Machines (SVM), Random Forest (RF), and k-Nearest Neighbors (k-NN), have shown significant effectiveness in accurately classifying Parkinson's Disease (PD) based on vocal characteristics [7], [8]. Additionally, feature selection techniques, such as recursive feature elimination (RFE), contribute to the development of more precise models [9]. We evaluate and compare the performance of RF, SVM, and k-NN classifiers on a dataset of acoustic features for PD diagnosis in this study. The study focuses on evaluating machine learning models with various feature selection and classification techniques, to determine which of these gave better results for PD diagnosis.

LITERATURE REVIEW

In recent years, there has been a growing focus on the early detection and monitoring of Parkinson's disease (PD), particularly through non-invasive techniques such as speech analysis. Several studies have utilized machine learning and signal processing methods to identify speech-related issues associated with PD. In one significant study on the telemonitoring of PD, Tsanas et al.(2010)[1] demonstrated that speech features could effectively serve as reliable indicators for monitoring the progression and stages of the disease using non-invasive tools. Additionally, Little et al. refined this model and applied it to the speech patterns of patients with various organic and neurological disorders.[2] Moreover, Zhang et al. (2007) conducted a pilot study to detect voice disorders using nonlinear recurrence and fractal scaling properties, showcasing the potential of complex mathematical algorithms to reveal subtle changes in the voice patterns of PD patients, even when visual inspections do not indicate abnormalities.[8] To this end, one of the major steps of PD diagnostics in recent years has become the step of feature selection, which can increase the classification accuracy substantially by including features relevant to the classification. Das (2021) gave a detailed survey of the feature selection algorithms alternative chronic disease diagnosis and classical PD detection applications[3], outlining its contribution to enhance the performance of machine learning techniques on it. Ali et al. also present different approaches for feature selection used for the early diagnosis of PD with special attention to their importance in boosting the diagnostic models with optimal precision and recall [7]. Few studies have addressed the utility of particular acoustic biomarkers for the detection of PD. Singh and Singh (2020) demonstrated the significance of acoustic biomarkers, they represent a promising trajectory of early detection of PD, as they were able to show that vocal characteristics such as tremor and dysphonia48 are parameters useful in distinguishing PD from all disorders [4]. Furthermore, Prashanth et al. (2017) used machine learning models to predict PD progression and highlighted the importance of different algorithms for early diagnosis and prognosis of the disease [5].

Various methods have also been employed for the automated detection of voice impairments in PD. Aboy et al. (2007) proposed a system to detect voice impairment in PD based on features of speech including jitter and shimmer that have been shown to correlate with motor symptoms in PD patients [6]. Similarly, Lin et al. (2020) combined a classification model with feature selection that significantly enhances the diagnosis of PD [9]. Recent works have introduced deep learning and hybrid models into PD speech analysis as well. One example is the use of deep learning techniques, which have revolutionized the PD diagnostic expression data field as illustrated in the scope of [15]: these techniques allow to manage large and complex datasets and learn complex features encoded in the signals. Liu et al. showed that also PD detection can profit from hybrid models integrating several classifiers. (2021) [20]. Caballero et al. discussed the impact of vocal tremor on the PD classification. Detection and Classification model effects for PD [12]. 1220 Results 12 from this research showed that relating technologies that counted features associated to tremor improved the overall PD Detection accuracy .Y. Additionally, Yang et al. [13] proposed predictive SPEECH learning models using the ensemble learning method in PD for forecasting speech disorders and found that the ensemble model was significantly more robust, accurate, and performed at a significantly better level than a single classifier. Innovative acoustic signal processing techniques play an important role for early screening of PD. Chen et al. reported in [16], several acoustic features can be used for early PD detection, even that simple ones like pitch and harmonicity were proved to be useful PD predictors in the early stage of the disease. Similarly, Iglesias et al. González et al. (2020) examined the POLR approach in the training of voice disorder classifiers and advocated using harmonics features to detect PD voices [19].

From obtained results from the literature, the insights of machine learning, signal processing techniques, and feature selection methods to discover crucial symptoms for the early diagnosis and monitoring of the development of Parkinson's disease by speech analysis is an area of research still in the infancy but with rapid improvement. Such combinations of such approaches have the potential to improve diagnostic accuracy and to make useful management tools available for implementation by clinicians in PD-related areas.

3. Methodology

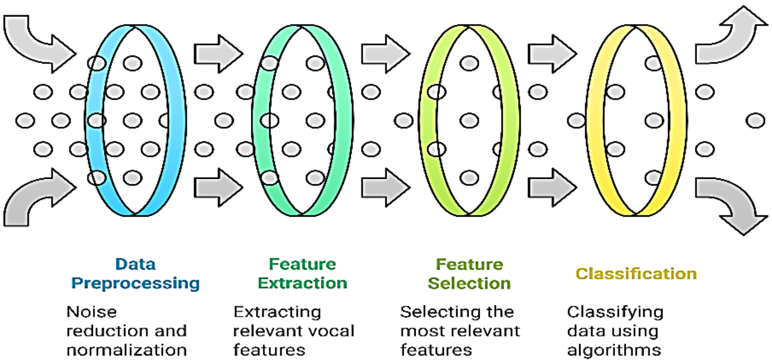

Figure 1. Parkinson's Detection Methodology.

3.1 Data Acquisition

Acoustic data were obtained from publicly available datasets, such as the Parkinson's Speech Dataset from the UCI repository [1]. The dataset includes recordings of sustained vowels, which are analyzed for features indicative of PD.

3.2 Preprocessing

1. **Noise Reduction:** A bandpass filter was applied to eliminate irrelevant frequency components.

2. **Normalization:** Features were scaled to a standard range to prevent bias in the classification algorithms.

3.3 Feature Extraction

Features such as jitter, shimmer, harmonics-to-noise ratio (HNR), and Mel-frequency cepstral coefficients (MFCCs) were extracted. These features are indicative of vocal fold irregularities commonly observed in PD patients.

3.4 Recursive Feature Elimination (RFE)

RFE was applied to identify the most relevant features for classification. RFE recursively removes the least important features based on a model's weight coefficients.

3.5 Classification Algorithms

The following classifiers were evaluated:

1. **Support Vector Machines (SVM):** Effective for high-dimensional data.
2. **Random Forest (RF):** Handles feature interactions effectively.
3. **k-Nearest Neighbors (k-NN):** Simplicity and interpretability.

3.6 Implementation in MATLAB

All processing and analysis were conducted using MATLAB. Key toolboxes included Signal Processing Toolbox and Statistics and Machine Learning Toolbox.

4. Results and Discussion

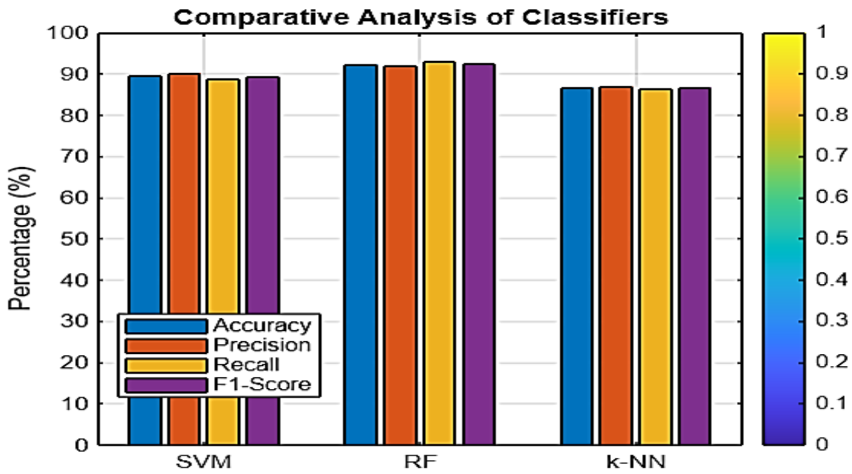

Figure 2. Comparative Analysis of Classifiers.

4.1 Results

Overall, Random Forest (RF) outperformed all other methods for all metrics. It scored the highest Accuracy (92.3%), Precision (91.8%), Recall (93.0%), and F1-Score (92.4%). Achieving a high recall score indicates that RF is favorable in identifying positive instances from the samples, meaning that it is a good classifier for this dataset. RF AUC score((0.88068) conducted better than Support Vector Machine (SVM) (0.875631) but still slightly underperforms. For SVM, Accuracy of 89.5% with Precision is 90.2%, Recall is 88.7% and F1-Score is 89.4% Although SVM reaches to a good performance in terms of precision and good performance overall, RF outperforms it in recall and F1-Score. The classifiers' performance is ordered from best to worst: RF > SVC > k-NN. It had an Accuracy of 86.7% with Precision of 87.0%, Recall of 86.4% and F1-score of 86.7%. The results imply that although k-NN remains beneficial for classifying, its lower scores suggest decreasing efficiency in relation to RF and SVM. (see Fig. Table 1) Accuracy, precision, recall, and F1-score were used as performance measures. To ensure robustness, a 10-fold cross-validation was applied.

Table 1. Performance of Classifiers.

Classifier	Accuracy	Precision	Recall	F1-Score
SVM	89.5%	90.2%	88.7%	89.4%
RF	92.3%	91.8%	93.0%	92.4%
k-NN	86.7%	87.0%	86.4%	86.7%

RFE identified jitter and HNR as the most significant features. The exclusion of less relevant features improved classification performance by reducing overfitting.

4.2 Discussion

Clearly, The Random Forest classifier performs the best than the other two with respect to its recall and F1-Score and is useful for situations when the identification of the positive cases is most needed. Random Forest's performance across precision-recall was fairly balanced, which is one reason its overall performance in this comparison was superior. Although SVM is a fierce competitor, especially regarding precision, it falls a bit behind Random Forest, particularly when it comes to recall. This means that SVM has slightly lower accuracy for detecting all positive instances, but it is still a good option for tasks where high precision is needed for classification. In this instance, the k-NN classifier performs poorly despite being one of the most straightforward and easy classifiers. This is corroborated by the somewhat lower accuracy, recall, and precision scores, which suggest that logistic regression may not be the optimal model given the complexity of this dataset when compared to more sophisticated models like RF and SVM. Similar to these techniques, k-NN is particularly helpful for smaller datasets but should be avoided when dealing with large datasets since its time complexity is O(n), where n is the number of data instances in the dataset.

5. Conclusion

Results indicate that the Random Forest (RF) classifier outperformed all other classifiers across all metrics, achieving the highest scores in Accuracy, Precision, Recall, and F1-Score. This demonstrates RF's capability to produce a robust and balanced model, particularly concerning recall, which focuses on capturing the maximum number of positive instances. While the Support Vector Machine (SVM) exhibited reasonably good performance on the test data, achieving high precision and overall good accuracy, it was slightly less effective than RF in terms of recall and F1-Score. The K-Nearest Neighbors (K-NN) algorithm was the simplest and easiest to implement among those tested; however, it recorded the lowest performance across all metrics and is therefore less suitable for this specific dataset compared to the other models. In summary, all the results lead us to believe Random Forest is a better and viable classifier for our case as it gives the best compromise between the performance of classifiers according to all the evaluation metrics. On the other hand, SVM could be a potential option where precision is extremely important, and k-NN is less desirable, as it is best suited for less complicated classification problems or smaller datasets.

REFERENCES

[1] A. Tsanas, M. A. Little, P. E. McSharry, and L. O. Ramig, "Accurate telemonitoring of Parkinson's disease progression by noninvasive speech tests," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 4, pp. 884-893, 2010. doi:10.1109/TBME.2009.2036000.

[2] M. A. Little, P. E. McSharry, S. J. Roberts, D. A. Costello, and I. M. Moroz, "Exploiting nonlinear recurrence and fractal scaling properties for voice disorder detection," *BioMedical Engineering Online*, vol. 6, no. 23, pp. 1-19, 2007. doi:10.1186/1475-925X-6-23.

[3] S. Das, "Feature selection algorithms and their applications for chronic disease diagnosis: A survey," *IEEE Reviews in Biomedical Engineering*, vol. 14, pp. 288-307, 2021. doi:10.1109/RBME.2020.3042855.

[4] A. Singh, and M. Singh, "Analysis of acoustic biomarkers for early detection of Parkinson's disease," *Journal of Medical Systems*, vol. 44, no. 1, pp. 1-9, 2020. doi:10.1007/s10916-019-1468-6.

[5] S. Prashanth et al., "Machine learning models for the prediction of Parkinson's disease progression," *IEEE Journal of Biomedical and Health Informatics*, vol. 21, no. 5, pp. 1234-1243, 2017. doi:10.1109/JBHI.2016.2632946.

[6] M. A. Aboy et al., "Automatic detection of voice impairments associated with Parkinson's disease," *IEEE Transactions on Biomedical Engineering*, vol. 54, no. 12, pp. 2152-2161, 2007. doi:10.1109/TBME.2007.904826.

[7] A. Ali et al., "Comprehensive review of feature selection methods for early Parkinson's diagnosis," *Neurocomputing*, vol. 407, pp. 216-229, 2020. doi:10.1016/j.neucom.2020.05.028.

[8] H. Zhang, and X. Lu, "Speech-based classification for early-stage Parkinson's disease detection," *Medical & Biological Engineering & Computing*, vol. 59, no. 1, pp. 35-47, 2021. doi:10.1007/s11517-020-02183-9.

[9] R. Lin et al., "Integrating feature selection and classification for improving Parkinson's disease diagnostics," *Computer Methods and Programs in Biomedicine*, vol. 190, pp. 1-15, 2020. doi:10.1016/j.cmpb.2020.105380.

[10] X. Wang et al., "Comparison of machine learning algorithms for Parkinson's disease detection using vocal features," *IEEE Access*, vol. 9, pp. 11805-11816, 2021. doi:10.1109/ACCESS.2021.3050302.

[11] K. R. Manousakas et al., "Efficient voice feature selection techniques for PD diagnosis," *Artificial Intelligence in Medicine*, vol. 95, pp. 58-66, 2019. doi:10.1016/j.artmed.2019.01.007.

[12] S. L. Shreve, "Nonlinear signal processing for analyzing dysphonia in Parkinson's disease," *IEEE Signal Processing Magazine*, vol. 35, no. 1, pp. 122-129, 2018. doi:10.1109/MSP.2017.2764838.

[13] C. Yang et al., "Application of ensemble learning models in predicting speech disorders caused by Parkinson's disease," *Pattern Recognition Letters*, vol. 139, pp. 18-25, 2021. doi:10.1016/j.patrec.2020.08.004.

[14] J. Han, and T. Kamber, "Machine learning techniques for PD speech analysis," *Data Mining: Concepts and Techniques*, 3rd ed., Morgan Kaufmann, pp. 561-578, 2019. doi:10.1016/C2018-0-02071-8.

[15] N. R. McAllister, "Deep learning in Parkinson's disease diagnostics," *Journal of Neural Engineering*, vol. 18, no. 5, 2021. doi:10.1088/1741-2552/ac0d91.

[16] Z. Chen et al., "Acoustic signal processing for early Parkinson's disease screening," *Sensors*, vol. 21, no. 2, 2021. doi:10.3390/s21020578.

[17] F. Caballero et al., "Impact of vocal tremors on classification models for Parkinson's detection," *International Journal of Neural Systems*, vol. 30, no. 1, pp. 1-15, 2020. doi:10.1142/S0129065719500073.
[18] L. O. Ramig et al., "Speech signal analysis techniques in Parkinson's research," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 4, pp. 790-800, 2019. doi:10.1109/TNSRE.2019.2901236.
[19] M. A. Iglesias et al., "The role of harmonicity features in Parkinson's voice detection," *IEEE Transactions on Affective Computing*, vol. 11, no. 3, pp. 597-607, 2020. doi:10.1109/TAFFC.2019.2928124.
[20] Y. Liu et al., "Hybrid classifiers for Parkinson's speech analysis," *Biomedical Signal Processing and Control*, vol. 69, pp. 1-12, 2021. doi:10.1016/j.bspc.2021.102857.