Computers in Biology and Medicine

Harnessing Voice Analysis and Machine Learning for Early Diagnosis of Parkinson's Disease: A Comprehensive Study Across Diverse Datasets

--Manuscript Draft--

Manuscript Number:	
Article Type:	Full Length Article
Keywords:	Parkinson's Disease (PD); machine learning; Early diagnosis; Artificial Neural networks; Voice analysis
Corresponding Author:	Osmar Pinto Neto Anhembi Morumbi University São José dos Campos, São Paulo BRAZIL
First Author:	Osmar Pinto Neto
Order of Authors:	Osmar Pinto Neto
Abstract:	Background: Early diagnosis is pivotal for the effective management of Parkinson's Disease (PD). Voice analysis emerges as a promising non-invasive method for early detection of PD, and machine learning techniques have proven adept at deciphering complex data to identify PD-indicative patterns. In this vein, we aimed to assess the efficacy of marrying voice analysis with machine learning techniques across diverse datasets to enhance early PD diagnosis. Method: Voice data were sourced from three distinct UCI Machine Learning Repository datasets. These datasets encompassed voice measurements from various PD patients and healthy individuals, characterized by different voice recording exercises and conditions and including time and spectral voice features. Machine learning models were trained and validated using these features to differentiate between PD patients and healthy subjects. Results: Our machine learning model demonstrated high diagnostic accuracy across all datasets. Specifically, the model achieved promising indicators of efficacy, including high averages across datasets of accuracy (99% ± 3.9%), sensitivity (98.8% ± 5.3%), specificity (99.1% ± 5.1%), precision (98.5% ± 4.2%), F1 score (97.9% ± 4.9%), and ROC AUC (99.3% ± 2.7%). The results were consistent across datasets, highlighting the model's robustness and adaptability. Conclusion: The integration of voice analysis with machine learning offers a promising avenue for the early diagnosis of PD. Given voice analysis's non-invasive nature and cost-efficiency, this approach could revolutionize early PD detection and monitoring. While the preliminary results are encouraging, further validation in clinical settings and larger cohorts is essential before widespread adoption.
Suggested Reviewers:	
Opposed Reviewers:	

Declaration of interests

☒The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

October 30, 2023

Estrada Dr. Altino Bondensan, 500
Eugênio de Melo, São José dos Campos - SP, 12247-016
osmarpintoneto@hotmail.com
5512981460693

Editor-in-Chief
Computers in Biology and Medicine

Dear Editor-in-Chief

I am writing to submit our manuscript entitled "Harnessing Voice Analysis and Machine Learning for Early Diagnosis of Parkinson's Disease: A Comprehensive Study Across Diverse Datasets" for consideration for publication in the Journal of Biomedical Informatics.

My study delves into the potential of linear and spectral voice analysis, combined with machine learning techniques, as a novel approach to early diagnosis of Parkinson's Disease (PD). By analyzing voice data from diverse datasets, we have demonstrated the robustness and reliability of our model in distinguishing PD patients from healthy individuals. The findings align with previous research and contribute significantly by examining voice impairments in a more extensive and clinically well-defined cohort of PD patients.

The Journal of Biomedical Informatics is a leading platform for high-quality research in biomedical informatics, and we believe our study would be a valuable addition to the journal's esteemed collection. Our research bridges the interdisciplinary gap between voice analysis, machine learning, and medical diagnosis, making it a fitting candidate for your diverse readership.

I confirm that this work is original, has not been published elsewhere, and is currently under consideration for publication elsewhere. I appreciate your time and care in reviewing our submission. I am eager to receive feedback and fully commit to any revisions or changes you deem necessary.

Thank you for considering my work. I look forward to the possibility of our research being a part of your esteemed journal.

Sincerely,

Osmar Pinto Neto.

Submitted to Computers in Biology and Medicine, October 30, 2023

Harnessing Voice Analysis and Machine Learning for Early Diagnosis of Parkinson's Disease: A Comprehensive Study Across Diverse Datasets

Osmar Pinto Neto

Center of Innovation, Technology and Education (CITE) at Anhembi Morumbi University – Anima Institute, São José dos Campos, Brazil

Arena235 Research Lab, São José dos Campos, Brazil.

Adress:

Estrada Dr. Altino Bondensan, 500

Eugênio de Melo, São José dos Campos - SP, 12247-016

e-mail: osmarpintoneto@hotmail.com

Phone: 5512981460693

Abstract

Background: Early diagnosis is pivotal for the effective management of Parkinson's Disease (PD). Voice analysis emerges as a promising non-invasive method for early detection of PD, and machine learning techniques have proven adept at deciphering complex data to identify PD-indicative patterns. In this vein, we aimed to assess the efficacy of marrying voice analysis with machine learning techniques across diverse datasets to enhance early PD diagnosis. Method: Voice data were sourced from three distinct UCI Machine Learning Repository datasets. These datasets encompassed voice measurements from various PD patients and healthy individuals, characterized by different voice recording exercises and conditions and including time and spectral voice features. Machine learning models were trained and validated using these features to differentiate between PD patients and healthy subjects.
Results: Our machine learning model demonstrated high diagnostic accuracy across all datasets. Specifically, the model achieved promising indicators of efficacy, including high averages across datasets of accuracy (99% ± 3.9%), sensitivity (98.8% ± 5.3%), specificity (99.1% ± 5.1%), precision (98.5% ± 4.2%), F1 score (97.9% ± 4.9%), and ROC AUC (99.3% ± 2.7%). The results were consistent across datasets, highlighting the model's robustness and adaptability.
Conclusion: The integration of voice analysis with machine learning offers a promising avenue for the early diagnosis of PD. Given voice analysis's non-invasive nature and cost-efficiency, this approach could revolutionize early PD detection and monitoring. While the preliminary results are encouraging, further validation in clinical settings and larger cohorts is essential before widespread adoption.

Keywords: Parkinson's Disease (PD); voice analysis; Machine learning; Early diagnosis; Artificial Neural networks

1. Introduction

Parkinson's Disease (PD) is a progressive neurodegenerative disorder with a global prevalence affecting millions, warranting timely diagnosis for effective management and therapeutic interventions (1). Traditional diagnostic modalities predominantly hinge on physical symptomatology, which often remains elusive until substantial disease progression (2,3). This diagnostic problem necessitates innovative strategies capable of early PD detection, where machine learning (ML) techniques have emerged as a promising frontier.

The application of ML in PD diagnostics has witnessed a significant evolution over the years (4). Early endeavors, such as those by Lafunte et al. (1997), utilized Artificial Neural Networks (ANNs) to differentiate individuals based on lower limb arthritis with an accuracy of 80% (5), while Barton and Lee (1997) applied kinematic analysis to discern gait patterns, achieving 83.33% accuracy (6). These seminal works laid the groundwork for further explorations into ML applications. However, a comprehensive examination of subsequent studies reveals a gradual refinement in methodologies and a broader scope of ML techniques employed. For instance, Begg and Kamruzzaman (2006) and Indira R. et al. (2014) delved into various ML techniques, marking accuracies between 68.04% and 83.3% (7,8).

A significant area of interest within ML applications in PD diagnosis hinges on voice analysis. PD patients often exhibit a range of voice impairments such as hypophonia, mono-pitch, and mono-loudness speech, collectively termed hypokinetic dysarthria (2,5–8). These vocal alterations often manifest early in the disease's trajectory, intensifying with disease progression (1,2). Despite their

clinical significance, current evaluation techniques remain largely qualitative (9), underscoring the necessity for objective evaluation modalities.

The rationale behind veering towards voice analysis-based ML stems from the early manifestation of vocal alterations in PD, often occurring even during its prodromal phase (2,5–8). Recent works have underscored the potential of voice analysis coupled with ML in early PD diagnosis (4,5,8). For instance, A. Tsanas et al. (2011) leveraged support vector machines and random forests with dysphonia features, marking a remarkable 99% accuracy (10). Additionally, Yuan et al. (2023) and Thanoun et al. (2021) have demonstrated diagnostic accuracies up to 95% and 96.52%, respectively, using machine learning algorithms on speech signal data (11,12). The methodological approaches vary, with some studies employing Support Vector Machines, Deep Neural Networks, and ensemble learning methods, often coupled with feature extraction and balancing techniques to improve classification accuracy. Nevertheless, this transition from general ML to voice analysis-based ML showcases a deliberate attempt to harness the early indicative vocal alterations in PD for diagnostic purposes.

Our investigation builds upon this evolving narrative by uniquely amalgamating data from four diverse datasets to enhance the robustness and generalizability of our findings. Additionally, we delve into a nuanced methodology employing a neural network architecture with dual hidden layers and a sigmoid activation function in the terminal layer, which is elucidated further in the subsequent sections. This approach aims to leverage the burgeoning capabilities of ANNs in medical diagnostics, paving the way for a more nuanced and effective diagnostic paradigm in PD (13).

Statement of Significance table

Problem or Issue	What is Already Known	What this Paper Adds
Early diagnosis of Parkinson's Disease (PD) is crucial for effective management yet remains challenging due to the subtle onset of symptoms.	Voice analysis has been identified as a potential non-invasive method for early PD detection. Machine learning techniques have shown promise in analyzing complex data to detect patterns indicative of PD.	This paper aligns with previous research pinpointing vocal alterations as early precursors of PD yet demonstrates superior accuracy in PD diagnosis through voice analysis integrated with machine learning across diverse datasets. The rigorous statistical validation underscores our findings' reliability, delineating this study from earlier endeavors. The model's robust performance across different voice recording conditions reinforces its potential for early, cost-effective PD diagnosis, advocating for further validation in clinical settings.

2. Material and Methods

2.1 Data Acquisition

The datasets leveraged in this investigation were meticulously curated from the UCI Machine Learning Repository, embodying four distinct collections. The selection rationale was predicated on the datasets' comprehensive and varied voice data and a minimum number of subjects (n) of 40, which is pivotal for enhancing the validation of our machine learning model across diverse data sources. These datasets are recurrently employed in analogous studies, underscoring their pertinence and reliability (11,12,14–19).

- Parkinson's Disease Classification (20,21): This dataset, originating from the Department of Neurology at Cerrahpaşa Faculty of Medicine, Istanbul University, contains voice measurements from 188 PD patients (107 males and 81 females) aged between 33 and 87 and 64 controls. Patients were instructed to vocalize the vowel "a" thrice, from which both linear and time-frequency-based features were extracted. Notably, this dataset exhibits an imbalanced class distribution.
- Parkinson Speech Dataset with Multiple Types of Sound Recordings (22,23): Curated from speaking exercises tailored for Parkinson's patients, this dataset amalgamates various voice samples, including sustained vowels, words, and sentences. It features recordings from 20 PD patients and 20 healthy subjects. The voice samples were chosen by neurologists aimed to elicit a more powerful sound from PD patients. Recording was conducted using a Trust MC-1500 microphone set at specific parameters, and subjects were instructed to read or repeat specified texts.
- Parkinson Dataset with Replicated Acoustic Features (24): This dataset lists acoustic features derived from three voice recording replications of the sustained /a/ phonation from 80 subjects, half diagnosed with Parkinson's Disease. Replications were averaged for everyone in our analysis.

Together, these datasets provide a comprehensive and varied collection of voice data with linear and spectral parameters with a total n of 372 subjects with 248 PD patients, bolstering the validation of our machine learning model across a range of data sources.

2.2 Machine Learning Analysis

Our ML endeavor was orchestrated using the Keras library in Python. Before the data influx into the neural network, standardization was executed employing the "StandardScaler" from the "sklearn.preprocessing" package, alongside one-hot encoding on the gender column in specific datasets. This preprocessing stage is indispensable for ensuring an equitable contribution from all features.

Our neural network architecture comprises an input layer, two hidden layers, and an output layer (Figure 1). The model compilation was done with Adam optimizer and binary cross-entropy loss. The choice of 64 units in the hidden layers, a dropout rate of 0.5 for regularization, and the employment of ReLU and sigmoid activation functions were predicated on literature precedents and preliminary testing, demonstrating optimal performance with these parameters. The dataset was bifurcated into training (80%) and testing (20%) subsets, a standard split ratio that balances training and validation needs, with K-Fold cross-validation employed for model validation (70% and 30% was tested and yielded similar results).

1. Network Parameters:
    - Epochs for model training: 50
    - Training batch size: 16
    - Regularization dropout rate: 0.5
    - Units in the hidden layers: 64
2. Data Splitting and Cross-Validation:
    - K = 10 for the inaugural dataset
    - K = 4 for the subsequent dataset

2.3 Parameter Tuning

An exhaustive parameter tuning was executed to optimize the neural network's performance. A range of values were tested for different parameters:

- Epochs: Values ranged from 50 to 100.
- Batch Size: Values ranged from 8 to 32.
- Dropout Rate: Values ranged from 0.1 to 0.5.
- Hidden Units: Values ranged from 32 to 128.

Additionally, multiple activation functions, including sigmoid, tanh, relu, and swish, were evaluated for their efficacy in the model.

2.4 Model's Efficacy Variables

The performance metrics selected to gauge our model's efficacy in diagnosing Parkinson's Disease were benchmarked against analogous studies to ensure a robust evaluation.

- Accuracy: This metric represents the proportion of correct predictions (both true positives and true negatives) out of the total predictions made. It provides a general measure of the model's performance.
- Sensitivity (Recall): It measures the proportion of actual positive cases (in this context, PD patients) that the model correctly identifies. It is crucial to understand how well the model detects the presence of the disease.
- Specificity: This metric gauges the proportion of actual negative cases (healthy individuals) that the model correctly identifies. High specificity indicates that the model is adept at avoiding false alarms.

- Precision: Precision assesses the proportion of positive identifications (predicted PD patients) that were correct. A model with high precision will have fewer false positives.
- F1 Score: The F1 score is the harmonic mean of precision and sensitivity. It balances the two metrics, especially when the class distribution is imbalanced. A higher F1 score indicates better overall model performance.
- ROC AUC: AUC (Area Under the Curve) measures the entire two-dimensional area underneath the Receiver Operating Characteristic (ROC) curve. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) at various threshold settings. It is a graphical representation of the model's diagnostic ability. A model with perfect discriminatory power will have an ROC AUC of 1, while a model with no discriminatory power will have an ROC AUC of 0.5. A higher ROC AUC indicates better model performance.

These metrics collectively furnish a comprehensive understanding of the model's strengths and potential areas for enhancement.

2.5 Statistical Analysis

In addition to reporting the mean and standard deviation of our model's performance metrics across multiple data-splitting and K-Fold cross-validation runs (40 total), we performed bootstrapping to estimate the confidence intervals around these metrics. Bootstrapping was used to resample our data, with replacement, and draw samples of 20 values from the data; metrics of interest were calculated on each sample. The process was repeated 1000 times or

iterations, creating a distribution of the metric values. From this distribution, the 95% confidence interval was estimated, which provides a range within which we can be 95% confident that the true value of the metric lies. This analysis gives us a better understanding of the variability and reliability of our model's performance.

We explored the impact of varying the number of splits in our cross-validation process and the value of K in our K-Fold CV to optimize the robustness of our estimates. Increasing the number of partitions and the value of K provided more data points for our bootstrapping procedure, aiding in a more robust estimation of confidence intervals. However, we balanced this with the computational resources and time available, settling on a configuration that provided robust estimates while being computationally feasible.

3. Results

The machine learning model was evaluated across four distinct datasets, yielding the following outcomes:

3.1 Parkinson's Disease Classification:

The model, comprised of 68545 parameters, exhibited an average accuracy of 99.17% ± 3.56% (CI 97.5% - 100%), sensitivity of 99.40% ± 2.61% (CI 98.0% - 100%), specificity of 98.49% ± 6.42% (CI 95.1% - 100%), precision of 99.46% ± 2.27% (CI 98.4% - 100%), F1 score of 99.43% ± 2.42% (CI 98.1% - 100%), and a ROC AUC of 99.35% ± 2.99% (CI 97.8% - 100%).

3.2 Parkinson Speech Dataset with Multiple Types of Sound Recordings:

The model, with a total of 6017 parameters, achieved an average accuracy of 98.51% ± 4.85% (CI 96.3% - 100%), sensitivity of 97.29% ± 8.41% (CI 92.9% - 100%), specificity of 99.50% ± 3.12% (CI 98.0% - 100%), precision of 99.17%

± 5.20% (CI 96.7% - 100%), F1 score of 98.08% ± 6.42% (CI 95.0% - 100%), and a ROC AUC of 99.06% ± 3.33% (CI 97.3% - 100%).

3.3 Parkinson Dataset with Replicated Acoustic Features:

In this dataset, the model, having 12161 parameters, attained an average accuracy of 99.38% ± 3.06% (CI 97.8% - 100%), sensitivity of 99.58% ± 2.60% (CI 98.3% - 100%), specificity of 99.17% ± 5.20% (CI 96.7% - 100%), precision of 99.25% ± 4.68% (CI 97.0% - 100%), F1 score of 96.20% ± 4.90% (CI 97.8% - 100%), and a ROC AUC of 99.63% ± 1.60% (CI 98.9% - 100%).

On average, across datasets, our ML model displayed promising indicators of efficacy, including high accuracy (99.0% ± 3.9%), sensitivity (98.8% ± 5.3%), specificity (99.1% ± 5.1%), precision (98.5% ± 4.2%), F1 score (97.9% ± 4.9%), and ROC AUC (99.3% ± 2.7%). These results underscore the proficiency of our machine learning model in diagnosing Parkinson's disease through time domain and spectral analysis of voice metrics.

4. Discussion

The results of our investigation underscore the potential of harnessing time and spectral voice analysis in tandem with machine learning techniques for the early diagnosis of Parkinson's Disease (PD). A salient finding of our study is the remarkable accuracy, sensitivity, specificity, precision, F1 score, and ROC AUC achieved across diverse datasets, underscoring the robustness and reliability of our model in discerning subtle vocal alterations indicative of PD. This achievement is accentuated when contextualized within the broader spectrum of existing studies.

Our findings align with previous research that pinpointed vocal alterations as early precursors of PD, yet the superior accuracy and other metrics achieved herein delineate our study of earlier endeavors. For instance, in dataset 1 (Parkinson's Disease Classification), our model's accuracy of 99.17% surpasses the 95%, 96.52%, and 92.2% reported by Yuan, Liu & Feng (2023), Thanoun et al. (2021) and Thanoun & Yaseena (2021), respectively (11,12,14). In dataset 2 (Parkinson Dataset with Replicated Acoustic Features), our model's accuracy of 98.51% is notably higher compared to the maximum accuracy of 70% reported by Ali et al. (2019) and 91% reported by Liu et al. (2023) (18,19). In dataset 3 (Parkinson Dataset with Replicated Acoustic Features), our model achieved an accuracy of 99.38%, again demonstrating superior performance compared to the 94.93%, 89.46%, and 90.3% reported by Yasar et al. (2019), Polat & Nour (2020), and Mittal & Sharma (2021), respectively (15–17). The rigorous statistical validation, including bootstrapping to estimate confidence intervals, further accentuates the reliability of our findings, presenting a robust methodological framework seldom observed in previous works.

By leveraging machine learning to discern these subtle vocal changes, we could effectively distinguish between PD patients and healthy counterparts. Our results reinforce the growing consensus in the scientific community that voice analysis, given its non-invasive and cost-effective nature, might be a cornerstone for early PD detection (6–8,25,26). While the nexus between machine learning and PD voice analysis has been touched upon in earlier studies, they often revolved around smaller and clinically varied patient groups (27–29). Our research fills this gap by delving into voice impairments within a more expansive and clinically well-defined cohort of PD patients.

The commendable generalizability of our model, underscored by the diverse data sourced from varied geographical locales and linguistic backgrounds, hints at a broader global applicability. However, the linguistic and cultural variances might present unforeseen challenges in model accuracy and applicability, necessitating further investigation into these facets to fortify the global relevance of our results.

However, our study has its limitations. Our dependence on pre-existing voice recordings, while facilitating the accumulation of a vast dataset, also introduced potential inconsistencies in recording quality and conditions. Mitigation strategies employed within our study, such as rigorous statistical validation, provide a blueprint for addressing similar limitations in future research. Prospective endeavors may benefit from a standardized voice recording protocol to foster data uniformity.

Moreover, while our results are encouraging, they should be viewed through the lens of certain constraints. The datasets, albeit more expansive than those in preceding studies (27,28), were still relatively confined regarding participant numbers, and more extensive and varied cohorts are indispensable.

The promising vista of machine learning-augmented voice analysis in clinical decision-making and telemedicine is broached within our discussion. However, a deeper delve into the real-world implications, foreseeable challenges, and integration into existing healthcare frameworks is warranted. Nevertheless, machine learning models for the diagnosis of Parkinson's Disease are being continuously refined and have shown high potential for adaptation in clinical decision-making (1,26,30). This could lead to an increasingly systematic, informed diagnosis of PD.

Moreover, the robustness of our model across diverse datasets and demographic subsets augurs well for its adaptation in varied real-world scenarios, thus holding a substantial promise for systematic, informed PD diagnosis. The potential of our methodology transcends mere diagnosis; it could also pivotally contribute to tracking disease progression and evaluating therapeutic responses.

In conclusion, our study unveils a novel methodology in PD diagnosis, blending voice analysis with machine learning to foster high diagnostic precision. The heartening initial findings, however, necessitate meticulous validation and real-world trials before broad-scale implementation. As we forge ahead in refining and validating this methodology, its transformative potential for early PD diagnosis and holistic management burgeons heralding a new epoch in PD research and clinical practice.

Declaration of Competing Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Generative AI and AI-assisted technologies in the writing process

While preparing this work, the author used OpenAI's GPT-4 architecture to improve readability and language. After using this service, the author reviewed and edited the content as needed and takes full responsibility for the publication's content.

References

1. Suppa A, Costantini G, Asci F, Di Leo P, Al-Wardat MS, Di Lazzaro G, et al. Voice in Parkinson's Disease: A Machine Learning Study. Front Neurol [Internet]. 2022 [citado 27 de outubro de 2023];13. Disponível em: https://www.frontiersin.org/articles/10.3389/fneur.2022.831428

2. Voice Analysis for Diagnosis and Monitoring Parkinson's Disease | SpringerLink [Internet]. [citado 27 de outubro de 2023]. Disponível em: https://link.springer.com/chapter/10.1007/978-981-16-3056-9_8

3. The Diagnostic Process - Improving Diagnosis in Health Care - NCBI Bookshelf [Internet]. [citado 27 de outubro de 2023]. Disponível em: https://www.ncbi.nlm.nih.gov/books/NBK338593/

4. Bherav UK. Computer Science and Engineering.

5. A Review of Artificial Intelligence's Neural Networks (Deep Learning) Applications in Medical Diagnosis and Prediction | IEEE Journals & Magazine | IEEE Xplore [Internet]. [citado 27 de outubro de 2023]. Disponível em: https://ieeexplore.ieee.org/document/9464112

6. An application of neural networks for distinguishing gait patterns on the basis of hip-knee joint angle diagrams - ScienceDirect [Internet]. [citado 27 de outubro de 2023]. Disponível em: https://www.sciencedirect.com/science/article/abs/pii/S0966636296010703

7. Neural networks for detection and classification of walking pattern changes due to ageing | SpringerLink [Internet]. [citado 27 de outubro de 2023]. Disponível em: https://link.springer.com/article/10.1007/BF03178892

8. Rustempasic I, Can M. Diagnosis of Parkinson's Disease using Fuzzy C-Means Clustering and Pattern Recognition. SOUTHEAST Eur J SOFT Comput. 1º de março de 2013;2.

9. Hendricks RM, Khasawneh MT. An Investigation into the Use and Meaning of Parkinson's Disease Clinical Scale Scores. Park Dis [Internet]. 2021 [citado 27 de outubro de 2023];2021. Disponível em: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8179766/

10. Tsanas A, Little MA, McSharry PE, Spielman J, Ramig LO. Novel speech signal processing algorithms for high-accuracy classification of Parkinsons disease. IEEE Trans Biomed Eng. maio de 2012;59(5):1264–71.

11. Yuan L, Liu Y, Feng HM. Parkinson disease prediction using machine learning-based features from speech signal. Serv Oriented Comput Appl [Internet]. 27 de junho de 2023 [citado 28 de outubro de 2023]; Disponível em: https://doi.org/10.1007/s11761-023-00372-w

12. Thanoun M, Yaseen M, Aleesa A. Development of Intelligent Parkinson Disease Detection System Based on Machine Learning Techniques Using Speech Signal. Int J Adv Sci Eng Inf Technol. 28 de fevereiro de 2021;11.

13. Fukuoka Y. Artificial Neural Networks in Medical Diagnosis. Em: Schmitt M, Teodorescu HN, Jain A, Jain A, Jain S, Jain LC, organizadores. Computational Intelligence Processing in Medical Diagnosis [Internet]. Heidelberg: Physica-Verlag HD; 2002 [citado 27 de outubro de 2023]. p. 197–228. (Studies in Fuzziness and Soft Computing). Disponível em: https://doi.org/10.1007/978-3-7908-1788-1_8

14. Younis Thanoun M, T. YASEEN M. A Comparative Study of Parkinson Disease Diagnosis in Machine Learning. Em: Proceedings of the 4th International Conference on Advances in Artificial Intelligence [Internet]. New York, NY, USA: Association for Computing Machinery; 2021 [citado 28 de outubro de 2023]. p. 23–8. (ICAAI' 20). Disponível em: https://doi.org/10.1145/3441417.3441425

15. Polat K, Nour M. Parkinson disease classification using one against all based data sampling with the acoustic features from the speech signals. Med Hypotheses. 1º de julho de 2020;140:109678.

16. Mittal V, Sharma RK. Machine learning approach for classification of Parkinson disease using acoustic features. J Reliab Intell Environ. 1º de setembro de 2021;7(3):233–9.

17. Yasar A, Saritas I, Sahman MA, Cinar AC. Classification of Parkinson disease data with artificial neural networks. IOP Conf Ser Mater Sci Eng. novembro de 2019;675(1):012031.

18. Liu W, Liu J, Peng T, Wang G, Balas VE, Geman O, et al. Prediction of Parkinson's disease based on artificial neural networks using speech datasets. J Ambient Intell Humaniz Comput. 1º de outubro de 2023;14(10):13571–84.

19. Ali L, Khan SU, Arshad M, Ali S, Anwar M. A Multi-model Framework for Evaluating Type of Speech Samples having Complementary Information about Parkinson's Disease. Em: 2019 International Conference on Electrical, Communication, and Computer Engineering (ICECCE) [Internet]. 2019 [citado 28 de outubro de 2023]. p. 1–5. Disponível em: https://ieeexplore.ieee.org/abstract/document/8940696

20. Sakar,C., Serbes,Gorkem, Gunduz,Aysegul, Nizam,Hatice, and Sakar,Betul. Parkinson's Disease Classification. UCI Machine Learning Repository. 2018.

21. A comparative analysis of speech signal processing algorithms for Parkinson's disease classification and the use of the tunable Q-factor wavelet transform - ScienceDirect [Internet]. [citado 28 de outubro de 2023]. Disponível em: https://www.sciencedirect.com/science/article/abs/pii/S1568494618305799?via%3Dihub

22. Kursun,Olcay, Sakar,Betul, Isenkul,M., Sakar,C., Sertbas,Ahmet, and Gurgen,Fikret. Parkinson Speech Dataset with Multiple Types of Sound Recordings. UCI Machine Learning Repository. 2014.

23. Sakar BE, Isenkul ME, Sakar CO, Sertbas A, Gurgen F, Delil S, et al. Collection and analysis of a Parkinson speech dataset with multiple types of sound recordings. IEEE J Biomed Health Inform. julho de 2013;17(4):828–34.

24. Prez,Carlos. Parkinson Dataset with replicated acoustic features . UCI Machine Learning Repository. 2019.

25. Ramani, G. and Sivagami, G. (2011) Parkinson Disease Classification Using Data Mining Algorithms. International Journal of Computer Application, 32. - References - Scientific Research Publishing [Internet]. [citado 27 de outubro de 2023]. Disponível em: https://www.scirp.org/(S(lz5mqp453edsnp55rrgjct55.))/reference/referencespapers.aspx?referenceid=1912175

26. Armañanzas R, Bielza C, Chaudhuri KR, Martinez-Martin P, Larrañaga P. Unveiling relevant non-motor Parkinson's disease severity symptoms using a machine learning approach. Artif Intell Med. 1º de julho de 2013;58(3):195–202.

27. Caglar MF, Cetisli B, Toprak IB. Automatic Recognition of Parkinson's Disease from Sustained Phonation Tests Using ANN and Adaptive Neuro-Fuzzy Classifier. Mühendis Bilim Ve Tasar Derg. 2010;1(2).

28. Cho CW, Chao WH, Lin SH, Chen YY. A vision-based analysis system for gait recognition in patients with Parkinson's disease. Expert Syst Appl. 1º de abril de 2009;36(3, Part 2):7033–9.

29. Hashim SM. PARKINSON'S DISEASE DETECTION USING DEEP LEARNING BASED ON VOICE RECORDING.

30. Ahire N, Awale RN, Wagh A. Learning disability identification with EEG signal analysis using machine learning approach. Em Annapolis, USA; 2023 [citado 17 de outubro de 2023]. p. 020002. Disponível em: http://aip.scitation.org/doi/abs/10.1063/5.0175631

Figure 1:

Our artificial neural network (ANN) architecture comprises an input layer, two hidden layers of 64 units, and an output layer using ReLu and Sigmoid activation functions. ANN was applied to 3 different linear and spectral voice parameter datasets containing 248 Parkinsons' disease patients and 124 healthy subjects.