



PARKINSON'S DISEASE IDENTIFICATION USING MACHINE LEARNING BASED ON VOICE DISORDER

Dr.SUJA G P^{id*},

Assistant Professor, Department of Computer Science & Research Centre,

Muslim Arts College (Autonomous),

Thiruvithancode, Kanniyakumari-629 174.

*Corresponding Author Email: sujamaran89@gmail.com

ORCID: <https://orcid.org/0000-0002-9303-4589>

DOI: <https://doi.org/10.63300/arjst506092026.02>

Date of Submission: 21-08-2026

Date of Acceptance: 01-09-2026

Abstract

Parkinson's disease is the second most prevalent late-life neurological illness after Alzheimer's (PD). It is common around the globe and mostly affects individuals over 60. Tremors, stiffness, and sluggish motion are symptoms of Parkinson's disease, and persons with PD have more severe deterioration. In recent years, neural networks have become more popular in prediction issues. This paper described a unique method for detecting Parkinson's disease using ANN (Artificial Neural Networks) and KNN (K-Nearest Neighbor), emphasizing speech problems. It includes many settings for predicting Parkinson's disease based on extracted attributes from 26 separate speech samples per individual. The LOSO (leave-one-subject-out) technique will be used to verify the results. Based on Pearson's coefficient of correlation, Mathews' coefficient of correlation, principal component analysis, and self-organizing charts, a few feature selection strategies were applied to boost the algorithms' efficiency and minimize data. Matthews' correlation coefficient-based function collection yielded the best test accuracy results, and the most important voice samples were identified. Multiple ANNs are the most effective classification approach for identifying Parkinson's disease without needing the function selection method (on raw data). Finally, a neural network with a test precision of 96.47% is completed.

Keywords: PD, ANN, Voice Disorders, Matthews's correlation coefficient, KNN, LOSSO

I INTRODUCTION

Parkinson's disease (PD) is a neurological disorder characterized by tremors, stiffness, bradykinesia, cognitive failure, sleep disturbance, and depression [1, 2]. Based on the clinician's expertise, the unified PD Scale (UPDRS) is utilized as a standard practice for measuring quantitative PD. Patients' presence in the clinic is often required, and evaluations take time for both patients and professionals. Alternative screening approaches that can be performed remotely are desperately required. Hypokinetic dysarthria is a speech impediment associated with Parkinson's disease. The voice of a Parkinson's disease patient is less understandable, breathable, and soft [3]. Discomfort is one of the early indications of Parkinson's disease and has been used to help diagnose the illness. Because it is non-intrusive and ideal for online applications, researchers have investigated speech features for detecting Parkinson's disease [3-6]. It also provides a platform for objectively tracking the progression of the illness. Many studies have employed time-frequency features extracted from speech signals to differentiate between PD and control participants [7-9].

Parkinson's Disease Symptoms

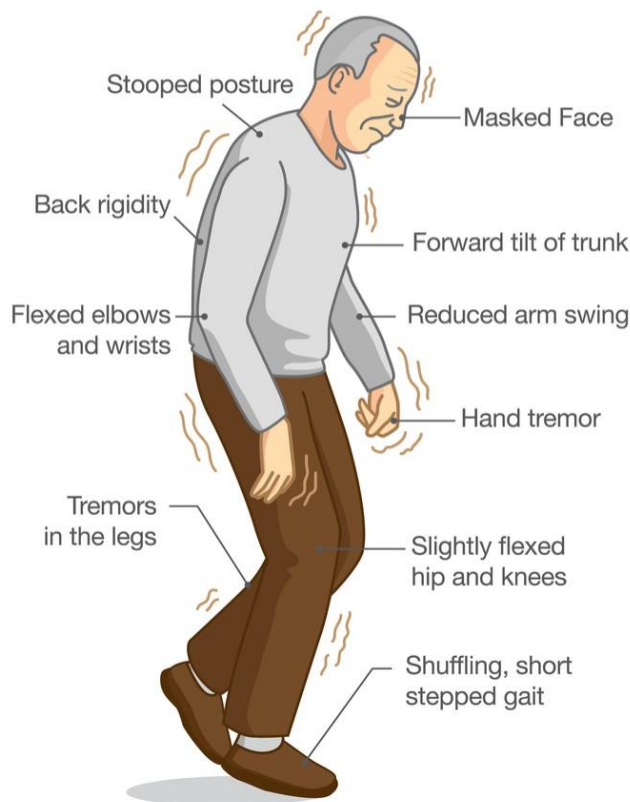


Figure 1: Parkinson's disease Symptoms

Jitter, Shimmer, Pitch, Harmonics to Noise Ratio, Autocorrelation, and unvoiced and voiced frames [10] are all details, as are speech breathability and pulse. Jitter and glow functionality, on the other hand, detects short-term variability in phonation and has proven inadequate for measuring variations in more seriously damaged voices [8]. To overcome this limitation, research [5, 7, 11] employed a mix of time-frequency-based non-linear dynamics characteristics such as detrended fluctuation analysis, correlation dimension, and recurrence period entropy to categorize the two groups and found varying classification accuracies.

Deep learning in speech synthesis has shown significant achievements in recent years, such as speech emotion identification [12] and voice pathology diagnosis [13]. Deep learning may extract learning skills automatically from vast data arrays and high-level models. It encourages unsupervised raw-data learning and separates essential properties crucial to the study aims, in contrast to typical machine learning methodologies [14]. Deep learning was the primary motivation for this study in identifying between the natural and aberrant voices of Parkinson's disease patients. ANN is recommended for voice-based PD diagnosis because it can establish the relevant data features for automated signal categorization. This research describes an ANN-based approach for distinguishing the spectral features of PD and healthy volunteer voice data. It also tracks factors such as audio speed, frame size, the number of coevolutionary layers, maps, and the topology of entirely linked layers on the ANN's output.

This paper is organized as follows. Section 1 presents an overview of the speech impairments associated with Parkinson's disease. The method utilized to perform this literature review is described in Section 2. Section 3 of this article summarises the findings of the official assessment. Section 4 outlines the results and debates. Section 5 contains the overall conclusion of this work.



II BACKGROUND STUDY

Dahmani, M., & Guerti, M. [3] The reference voice of PD, Spasmodic Dysphonia, and natural voice was established as neurological speech disorders. Glottal Signal Parameters generated from voice output were utilized to classify the voice disorder using K-Nearest Neighbors (KNN). The results showed that the KNN became more effective when the input vector Glottal signal parameters were changed. According to the final results, the KNN classification has a median accuracy of 93.33 percent for neurological voice problems. Because it impacts voice quality, the articulator information of the vocal fold in the frequency and time domain offered may be relevant for determining different kinds of vocal fold illnesses and neurological voicing problems.

Fayyazifar, N., & Samadiani, N. [5] Parkinson's syndrome is a chronic illness that worsens the patient's health over time. As a result, there has been a lot of interest in the early detection of Parkinson's disease. Because the reliance on data is often overlooked in previously offered methodologies, replications of voice recordings have not been thoroughly explained to identify PD. The authors of this paper proposed a way to bridge the gap between function collecting and data categorization. Our suggested technique will use fewer grouping characteristics and achieve a higher detection rate than competing systems.

Jovanov, E. et al. [6], A unique approach for diagnosing and unfreezing gait in Parkinson's patients has been developed. The preliminary estimation indicates that the suggested approach can unfreeze gas in real-time.

Lee, S.-A. et al. [8] Systematic biological research on biomarkers and molecular grids aid in demonstrating the complexity of progressive brain disease and casting the present age of potential PD routes and therapy approaches. Schizophrenia, Parkinson's disease, and Alzheimer's may share genetic networks and pathways leading to major mental diseases.

Moharkan, Z. A. et al. [9] show that the suggested technique works well as a comprehensive Parkinson's detection system. The user may add Parkinson-related information, develop models using appropriate algorithms, and then report on forecasts. Although this study generates K-NN-based models, it may be utilized to apply additional classification algorithms to identify Parkinson's illness. The results show that the authors can virtually properly predict whether a person has Parkinson's disease by applying the right classifiers on appropriate data sets. The suggested strategy simplifies and streamlines the whole procedure. This system may also be utilized as a research tool for comparing various datasets and methods.

Pun, U. K. et al. [11] A thorough investigation of the data of Hausdorff's PD patients was conducted. The authors used a variety of simulation measurements to develop a Parkinson's intensity formula with 90% of the correct diagnostic scale based on Hausdorff's training collection. This diagnosis needs simply a brief examination. After the right test environment was constructed, the specialist's participation was not necessarily required for the whole test.

III SYSTEM MODEL

The uncertainty matrix is frequently used to evaluate classifiers. We then use the evaluation parameters produced from this matrix to determine the output of a classifier. Some researchers focused their study on overall accuracy, a measure of overall success since it indicates the exact mapping of the percentage among all areas and calculates performance regardless of class size. The overall precision is commonly expressed as a percentage and represents a full classification at 96.47 percent in magnitude, with all reference sites correctly classified.

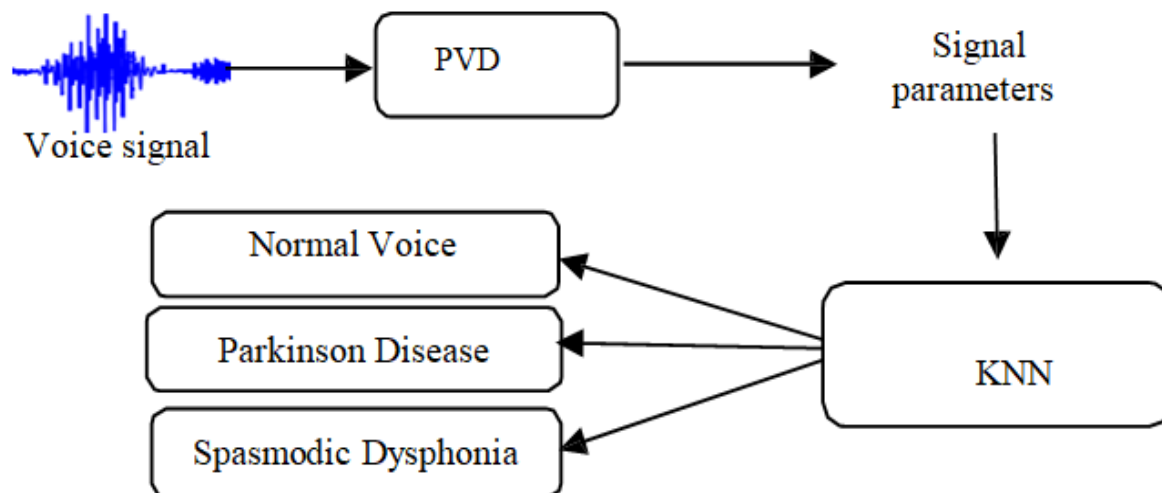


Figure 2: Method of Voice disorder diagnosis

3.1 Neurodegenerative disease:

Individual, societal, and economical consequences of neurodegenerative illnesses exist on personal, technical, and social levels. It is a progressive illness that affects the brain and neurological system, eventually leading to nerve cell death. Alzheimer's and Parkinson's diseases are the most well-known and prevalent. Losing the basic ganglia of dopamine-producing neurons is particularly connected with Parkinson's disease. PD medicine costs a lot of money. At this moment, no solution has been identified. Medicines are restricted to early-stage therapies that enhance the patient's quality of life. Various approaches have been developed to diagnose Parkinson's disease symptoms, but most of them need engine behaviors that only look advanced.

3.2 Generalization to Unseen Data: Leave-One-Subject-Out

We may not have separate validation samples; therefore, we must create predictors that utilize subsets of data samples for training and validate the remainder of the data for neural network model validation. The standard leave-one-out or bootstrapping technique will result in estimated bias. The validation strategy for a leave-one-subject-out (LOSO) is utilized due to the data collection structure (consisting of many sound recordings per participant). The key advantage of LOSO is that it is substantially less biased and offers almost unbiased forecasts. The LOSO validation technique is constructed in our neural network algorithm utilizing the cell array architecture, such that every recording of a single individual is recorded in distinct cells. Because the data set comprises 40 people, the LOSO validation technique uses k-fold validation of 40 folds.

3.3 Matthews's correlation coefficient:

The detection of Parkinson's syndrome is dependent on the use of multiple classifiers. They are differentiated by measurement parameters such as classification accuracy, the Matthews correlation coefficient (MCC), the Spearman coefficient of correlation, specificity, sensitivity, and F-score (F-measure). There are formulae for calculating these factors and determining the most qualitatively appropriate categorization for the sample. Before identifying specific conditions, we must focus on the uncertainty matrix. It is a tool for measuring the performance of a learning model and verifying the extent of its predictions compared to reality in classification challenges.

3.4 K-Nearest Neighbors Algorithm:

The K-Nearest Neighbor (KNN) method is the most fundamental of all machine learning algorithms. All potential data points are recorded, and instances are categorized based on similarities (Euclidian distance). This approach is expanded by the kNN Classifier, which takes the k points closest to the majority class. However, the near-ideal behavior of the closest neighbor

rule is guaranteed only at the maximum since the number of training samples might go on indefinitely. [3].

To make things easier, the number (usually 1, 3, or 5) is usually selected such that no ties occur. Larger k values reduce the impact of noisy points in the data set; cross-validation is often used to determine k . The supplied k will change the assigned red star class. Where $k=3$ (purple circle), the star belongs to the blue polygons class since the three nearest neighbors are two blue polygons and one green rectangle. At the same time, when $k=5$ (black circle), the star is allocated to the green class since the following five neighbors have more green rectangles than blue polygons (three green rectangles vs. two blue polygons).

- K is a positive integer.
- Calculate the distance $d(x, x_i)$ for all $i=1,2,3,\dots,n$ where 'd' denotes the Euclidean distance, it is given by :
- $d(x, x_i) = \sqrt{\frac{(x - x_i)^2}{n}}$ -----(1)
- Arrange the 'n' distance in non-decreasing order.
- Take the first k distances.
- Find those k points corresponding to this k - distances.
- Let K_i denote the number of points belonging to the i^{th} class among the k points; $i=1, 2, \dots, C$ (k_i for some classes can be zero, and the sum of all K_i is equal to k)
- Put x in class i if $K_i > K_j$ for all $j \neq i$.

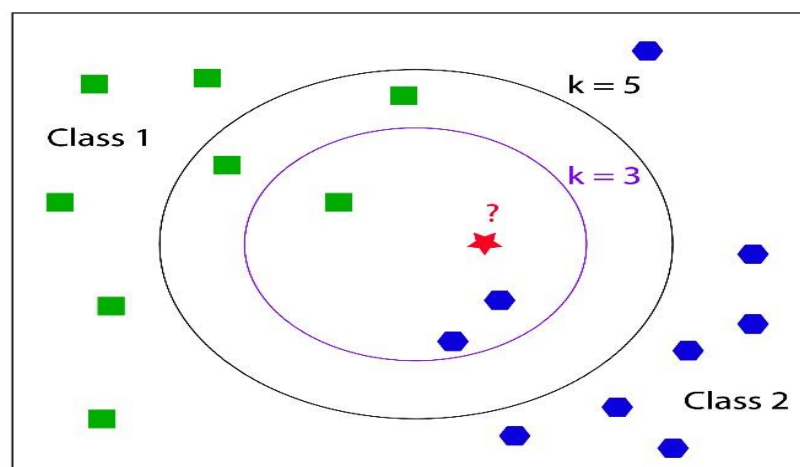


Figure 3: K-Nearest Neighbor (KNN) algorithm principle



3.5 Calculation of traditional measures:

MATLAB software was used to do this measurement. Traditional measures are based on applying short autocorrelation to successive signal sections, with peak peaks determining the vibration frequency of the vocal cords (F0 or pitch time) and the location at the beginning of each vibration cycle of the vocal cords (pitch marks). By calculating the consecutive absolute deviations between the frequencies in each cycle and estimating the average for the varying number of periods, which progressively normalizes by the overall average, the frequency series for each vocal cycle may be used to measure the jitter and time disruption. The shimmer and amplitude disturbance steps are formed from each vocal cycle's greatest amplitude sequence.

3.6 Calculation of Nonstandard measures:

The time lag combining the signal to rebuild the phase space of the non-linear dynamic system to generate the speech signal determines the connection dimension measure (D2). A geometrically self-similar (fractal) object illustrated the fluid dynamics involved in dysphonia in this replication space. Time Series Analysis is used in our implementation (TISEAN). The RPDE estimates the extent to which dynamics may be regarded solely recurrent and repeated following time-related embedding in the reconstructed process. T is a repeating signal that returns to the same place in phase space after a specific time. The deviation of these recurrence intervals from the periodicity of the entropy H distribution is P(T), which is a useful predictor of general voice disorders and leads general voice pathology to preserve proper vocal fold vibration.

IV DISCUSSIONS

One of the most typical challenges in decision-making is classification. The classification process is characterized in machine learning and statistics as an identification challenge based on a training set of data comprising observations (or instances) whose category membership is identified as a collection of categories (subpopulations) to which a new observation belongs. Several procedures have been taken to evaluate the effectiveness of our categorization. Precision, attention, detail, MCC, and uncertainty matrix are examples of these acts. An uncertainty matrix contains information about a classification system's real and predicted classifications. Confusion matrix components may indicate classification accuracy, sensitivity, specificity, and Matthews' coefficient of correlation (MCC).

Accuracy is the ratio of correctly classified instances to the whole instances:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}, \quad (1)$$

Where TP is the number of true positives, TN true negatives, FP false positives, and FN false negatives. Sensitivity and specificity are statistical measures of correctly classified positive and negative instances, respectively:

$$\text{Sensitivity} = \frac{TP}{TP + FN}, \quad (2)$$

$$\text{Specificity} = \frac{TN}{FP + TN}. \quad (3)$$

MCC is used to assess binary rating consistency. It considers both true and false positive and negative aspects and is commonly regarded as a neutral computation; however, the groups vary somewhat. The MCC metric is defined as follows:

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}. \quad (4)$$

MCC values range from -1 to +1. The MCC factor is +1 when a classifier predicts perfectly, 0 when predictions and actual values entirely differ, and -1 when the classification is no better than random guesses. All speech signals must be chosen using conventional and non-standard measurement techniques to determine the characteristics. Each approach creates a different quantity for each



signal. The ANN algorithm produced the best results. Depending on the data set and the number of acoustic features employed, the results obtained 96.47% classification accuracy for ANN.

Voice Signals

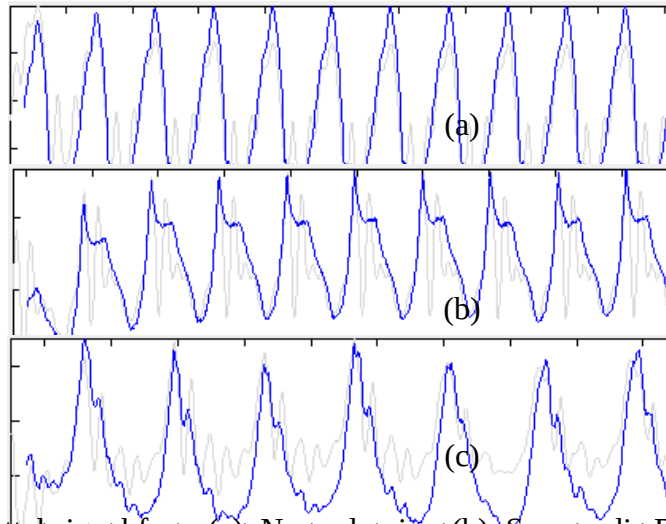


Figure 4: Glottal signal form (a): Normal voice, (b): Spasmodic Dysphonia, (c): Parkinson's Disease

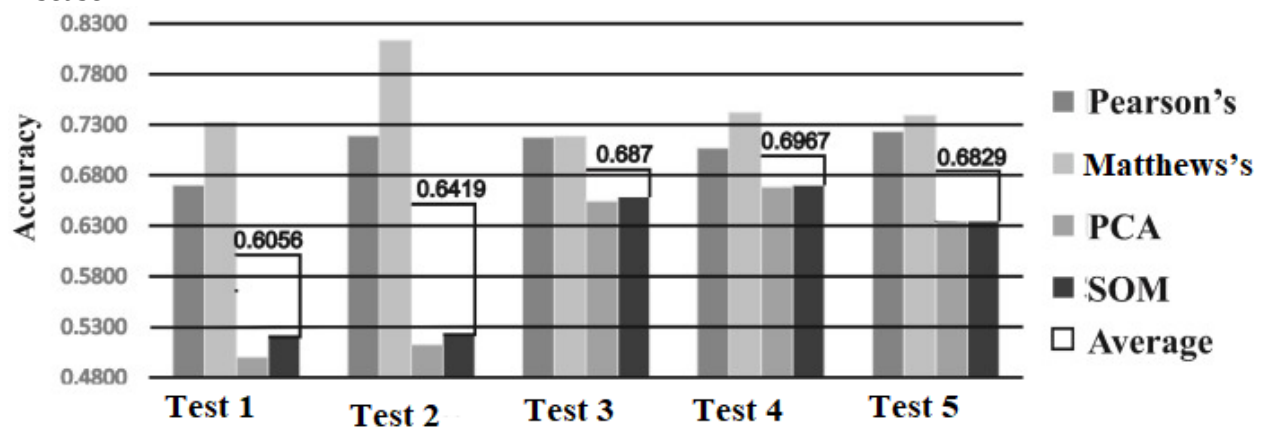




Figure 5: Accuracy comparison for Various Methods

It was found that multiple ANNs attain the highest precision among 67.25% of classifiers by LOSO cross-validation without the selection of functions. The accuracy was discussed with a one-dimensional ANN 10 design, although 100% accuracy was achieved.

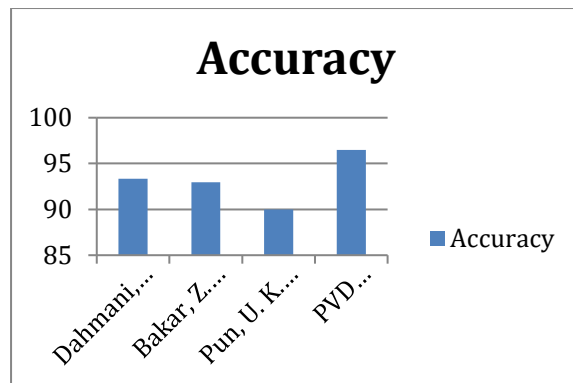


Figure 6: Accuracy Comparison for Existing authors

The second highest accuracy between classifiers of 96.47% was achieved by multiple ANNs through LOSO cross-validation, using an A-MCC filter-based selection system, and finishing the process. During this process, various implementations of different training algorithms, learning speeds, amount of learning eras, and designs were used for each ANN classifier. With one-dimensional ANN 10 topology and Matthews's correlation coefficient dependent function collection, the maximum ANN test accuracy of 81.33 percent was achieved.

V CONCLUSIONS

Parkinson's syndrome, Spasmodium dysphonia, and natural voice are reference voices in Neurological Speech Disorders. Glottal Signal Parameters generated from voice output were utilized to select the voice disorder using the KNN classifier. The results showed that KNN is more successful when input vector Glottal Signal Parameters are used. According to the final results, the KNN classification has a median accuracy of 93.33 percent for neurological voice problems. As articulation features of vocal folds in the frequency and temporal domain impact voice production, the conclusion might be that Glottal Signal Parameters are beneficial in diagnosing various forms of vocal fold disease and neurological voice issues. In this research, we presented the material and machine interface for the numerical treatment of the patient's speech signal using neural networks. The categorization provided by the ANN classifier is correct. The categorization rate varies between 80% and 96.47%. We proved in this study that an MCC-based function vector may be used to categorize normal and abnormal speech outcomes. In the preliminary step, the voice details are divided into two groups: natural and aberrant. The ANN with KNN has shown to be more efficient and accurate as a classifier than the time-frequency analysis technique. The ANN classifier is a low-cost, precise, automated pathological speech categorization technique that uses wavelet coefficients with uniform energy. It is a diagnostic tool that assists doctors and clinicians in analyzing speech disorders. Future research will concentrate on identifying the exact kind of disease-causing speech disorder. To strengthen the dependability of the findings, these study needs to be confirmed on a bigger database for speech pathology.

VI REFERENCES

- [1]. Asmae, O., Abdelhadi, R., Bouchaib, C., Sara, S., & Tajeddine, K. (2020). Parkinson's Disease Identification using KNN and ANN Algorithms based on Voice Disorder. 2020 1st International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET). doi:10.1109/iraset48871.2020.9092228



- [2]. Bakar, Z. A., Tahir, N. M., & Yassin, I. M. (2010). Classification of Parkinson's disease based on Multilayer Perceptrons Neural Network. 2010 6th International Colloquium on Signal Processing & Its Applications. doi:10.1109/cspa.2010.5545301
- [3]. Dahmani, M., & Guerti, M. (2018). Glottal signal parameters as features set for neurological voice disorders diagnosis using K-Nearest Neighbors (KNN). 2018 2nd International Conference on Natural Language and Speech
- [4]. Pun, U. K., Gu, H., Dong, Z., & Artan, N. S. (2016). Classification and visualization tool for gait analysis of Parkinson's disease. 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). Processing (ICNLSP). doi:10.1109/icnlsp.2018.8374384.
- [4]. Dasgupta, M., Konar, A., & Nagar, A. K. (2018). Online Prediction of Dopamine Concentration Using EEG-Induced Type-2 Fuzzy Abduction. 2018 IEEE Symposium Series on Computational Intelligence (SSCI).
- [5]. Fayyazifar, N., & Samadiani, N. (2017). Parkinson's disease detection using ensemble techniques and genetic algorithm. 2017 Artificial Intelligence and Signal Processing Conference (AISP). doi:10.1109/aisp.2017.8324074
- [6]. Jovanov, E., Wang, E., Verhagen, L., Fredrickson, M., & Fratangelo, R. (2009). deFOG — A real time system for detection and unfreezing of gait of Parkinson's patients. 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society.
- [7]. Kumar, K. K., Vijay Babu, P., Gopi, S. C., & Arfa, Z. (2020). Advanced And Effective Classification of Parkinson's Disease Using Enhanced Neural Networks. 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS). doi:10.1109/iciccs48265.2020.9120970
- [8]. Lee, S.-A., & Huang, K.-C. (2016). Differential Expression Profile of Genetic Network for Parkinson's Disease. 2016 5th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI).
- [9]. Moharkan, Z. A., Garg, H., Chodhury, T., & Kumar, P. (2017). A classification based Parkinson detection system. 2017 International Conference On Smart Technologies For Smart Nation (SmartTechCon).
- [10]. Muniz, A., Liu, W., Liu, H., Lyons, K. E., Pahwa, R., Nobre, F. F., & Nadal, J. (2009). Assessment of the effects of subthalamic stimulation in Parkinson disease patients by artificial neural network. 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society. doi:10.1109/iembs.2009.5333545
- [11]. Pun, U. K., Gu, H., Dong, Z., & Artan, N. S. (2016). Classification and visualization tool for gait analysis of Parkinson's disease. 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).
- [12]. Rahmani, F., Ansari, M., Pooyan, A., Mirbagheri, M. M., & Aarabi, M. H. (2016). Differences in white matter microstructure between Parkinson's disease patients with and without REM sleep behavior disorder. 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). doi:10.1109/embc.2016.7590901
- [13]. Wroge, T. J., Ozkanca, Y., Demiroglu, C., Si, D., Atkins, D. C., & Ghomi, R. H. (2018). Parkinson's Disease Diagnosis Using Machine Learning and Voice. 2018 IEEE Signal Processing in Medicine and Biology Symposium (SPMB). doi:10.1109/spmb.2018.8615607
- [14]. R. Saha, A. Mukherjee, A. Bal and D. Malakar, "An Explainable Hybrid Deep Ensemble Model Integrating Xception CNN and XGBoost for Parkinson's Disease Classification from Digital Drawing Biomarkers," *2026 International Conference on Computing, Intelligence, and Applications (CIACON)*, Durgapur, India, 2026, pp. 1-8, doi: 10.1109/CIACON70148.2026.11688802.