Prediction of Parkinson's Disease using Handwriting Analysis and Voice Dataset- A Review

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Abstract

Parkinson's disease is a common neurological movement illness that impairs motor coordination. Parkinson's disease (PD) symptoms and severity, however, differ from person to person. By extracting insights, trends, and possibilities from the data, data research can be utilized to uncover solutions to problems in medical research by utilizing data, machine learning algorithms, and cutting-edge technology. Among the less evident early signs of Parkinson's disease are tremors, muscle stiffness, imbalance problems, and difficulty walking. There is currently no test to detect the illness early on, when symptoms might not be evident. However, handwriting and hand- drawn subjects in humans have been linked to PD. In addition to being a useful tool for PD prediction, speech smearing functions as an early warning system. In order to control symptoms and maybe halt the disease's progression, early detection makes it possible to organize treatments and intervene promptly. For those with Parkinson's disease, early application of certain therapies and medications can extend survival and enhance quality of life.

Keywords: PD, Hand Writing, Voice Dataset, Machine Learning Methods, Early Diagnosis

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1. Introduction

The slow and frequently undetectable onset of PD, which is typified by a progressive loss of dopamine-producing neurons, poses a significant diagnostic challenge. Medical professionals need to diagnose PD’s early in order to create individualized treatment programs that will effectively control both motor and non-motor symptoms. There is presently no reliably good diagnosis to distinguish PD from other conditions that show clinical similarity [1]. This is a progressive neurological disorder that first appears in adults and becomes more prevalent with aging. People over sixty are typically affected by PD [16]. Therefore, a practical and conclusive detection strategy is required to assist patients in improving the quality of their lives [17]. Tremors, stiffness (or stiffness in the muscles), a slowdown in the reflex response to daily activities, changes in facial expression, and postural instability that increases the risk of falling are the main signs of PD [6]. The symptoms can be categorized into five phases based on how gradually they worsen. There aren't many symptoms in the early stages. The seriousness of it is impossible to assess because they are so light. Stage 2 symptoms differ greatly from those of stage 1 symptoms and are indicative of the common type of PD. More pronounced changes could include shaking, trembling, and rigidity. The third stage of the sickness is thought to be a turning point. The symptoms of Stage 1 Parkinson's disease are comparable to those experienced by the majority of patients. On the other hand, balance and reflexes would be impaired in those suffering from PD. Generally, movement happens more slowly. One thing that seems to separate PD stages three and four is independence. The patient can stand by themselves at stage four stages. Nevertheless, additional help, like a walker, could be needed for the patient. There are several stages of PD, all of which are better than the fifth. Leg stiffness progresses to the point that standing or walking become difficult [17]. All things considered, a proactive, all- encompassing strategy that promotes better treatment outcomes, scientific discoveries, and a longer-term healthcare environment is early detection of PD. Apart from the direct benefits to patients, there are other reasons why it is required.

2. Literature Survey

The existing approaches utilized for PD detection include the following:

Data Preparation Methods

- **Spiral Dataset:** Histogram equalization, image scaling, and contrast enhancement andcorrection
- **Voice Dataset:** Specifically, Pairwise Correlation and Exploratory Data Analysis.

Methods

- **Spiral Dataset:** VGG16-CNN, k-Nearest Neighbors classifier, and logistic regressionclassifier.
- **Voice Dataset:** techniques for pattern identification and fuzzy c-means (FCM) clustering.

Datasets

- The UCI machine learning repositories contain the following datasets: Parkinson's Disease Voice and Speech, PPMI, and the Parkinson's Telemonitoring dataset.

Below is the detailed literature survey of the 20 papers related to Parkinson's disease prediction using ML algorithms.

Table.1 Literature Survey

Si.No	Year	Features/ parameters	Dataset	Methodology	Accuracy
[1]	2022	1)Signal error drop standardisation 2)Firming bacteria foraging Optimization (FBFO)	"UCI Machine Learning Repository's Parkinson's Telemonitoring Voice Data Set"	1)Deep learning 2) "Deep Brooke inception net classification Algorithm" 3)WCF clustering	96.8%
[2]	2017	13 features	"PPMI dataset (Parkinson's Progression	1) Deep Learning (DEEP) 2) Classification Trees (TREE)	96.45% accuracy

			Markers Initiative)"	3) Boosting 4) Random Forest(RF) 5)Logistic Regression(LOGIS) 6)Discriminant Analysis(DIS) K-nearest neighbor (KNN)Support Vector Machines(SVM)	
[3]	2018	22 attributes corresponding to different voice features	PD dataset	1) Logistic Regression 2) KNN 3) NB 4) SVM 5) DT 6) RF	Among the machine learning algorithms employed, KNN achieved the highest comparable accuracy rate of 95.52%
[4]	2021	Least Absolute Shrinkage and Feature Selection (LAFS)- for feature selection Features are (speech problem, shivering, Movements)	PD Data set	1) Logistic Decision Regression (LDR) 2) SVM 3) CNN	LDR offers 95% accuracy
[5]	2021	22 attributes corresponding to different voice features	"Dataset created by Max Little of the University of Oxford, which was in collaboration with the National Centre for Voice and	1) Decision tree 2) Logistic Regression 3) K-NN 4) SVM	Among the ML algorithms Decision Tree showed a high accuracy of 94.87%

			Speech, Denver, Colorado."		
[6]	2020	Audio features including: Six Amplitude parameters Eleven Frequency parameters Two harmonicityparameters -Two Complexity parameters -One Signal scaling parameters	Audio data from PPMI	1) Logistic reg 2) Naive bayes 3) Gradient Boost 4) Random forest 5) Hard voting 6) Soft voting 7) bagging 8) xgb and lgb	Out of these models Random Forest has higher accuracy of 94%
[7]	2020	753 speech signal attributes	PD Speech data-set	1) SVM 2) LR 3) k-NN 4) Random Forest (RF) 5) AdaBoost (AdB)	Among the ML algorithms SVM showed a high accuracy of 94.1%
[8]	2022	Three VGG16 CNNs were parallelly employed for feature extraction.	NewHand PD and ParkinsonH W	Deep Neural Network VGG16 - CNN	>93.53% accuracy.
[9]	2019	1) Movement Disorder Society - Unified Parkinson Disease Rating Scale (MDS-U PDRS) 2) Unified Parkinson Disease Rating Scale (UPDRS)	PPMI Dataset	Cortico Basal Degeneration – case of APD CNN Model Imaging for Parkinson's disease Swallow Tail segmentation.	93.5% accuracy
[10]	2020	10 different image augmentation parameters for wave	Kaggle's data repository that contains spiral	Multistage classification	93.3%

		and spiral sketches each.	and wave drawings	1) Convolutional Neural Networks (CNN) 2)Ensemble Voting Classifiers	
[11]	2023	1)Models are trained on only 22 attributes 2)Principal Component analysis(PCA) 3)Removal of imbalance attributes	MDVP audio data from PPMI and UCI databases	KNN Algorithm Logistic regression ROC-AUC curve and accuracy	91.835% accuracy
[12]	2023	1) ELU activation function 2) No. of strides 3) No. of filters 4) 4)Adam optimizer 5) Batch size 6) Kernel size 7) Target size	Dataset given by NIATS of the Federal University of Uberlandia	Convolutional Neural Networks	92.58%
[13]	2019	frequency- based features from spectrograms	PC-GITA database	long short-term memory (LSTM) layers other recurrent neural architectures.	91.7%
[14]	2019	Features of FOG(Freezing of gait) detection Min, Max, Median, HarmMean, GeoMean, Trim mean, Mode, Range features extracted from Accelerometer, gyroscope, etc.	1) Wearabl e sensor dataset 2)Daphnet dataset 3)Cupid dataset	1) Decision Trees 2) Support Vector Machines(SVM) 3) Neural networks 4) Sensor data processing 5) Unsupervised and Semi-Supervised Models.	>90% accuracy in FOG prediction.
[15]	2020	ANFIS model Fuzzification Implication Normalisation defuzzification Combining	Five datasets that obtained from the archive of UCI	1) Metaheuristic' s algorithms, 2) Fog computing, 3) Internet of Things (IoT) 4) Adaptive neuro-fuzzy inference	87.5% accuracy

				system (ANFIS).	
[16]	2020	Features extraction depends on Histogram of Oriented Gradient (HOG) algorithm	PD Image Dataset (Spiral and Wave)	1) SVM 2) Decision Tree 3) Gradient Boosting 4) K-NN 5) Logistic Regression 6) Random Forest	Gradient Boosting algorithm got 86.67%
[17]	2023	Function features are position in terms of coordinates, pressure, altitude, displacement and acceleration. Parameter Features	Dataset that has a total of 108 images (spiral and wave drawings)	1) AlexNet 2) GoogleNe t 3) VGG Net 4) ResNet	Accuracy of 86.67 % in the case of spiral drawing and 83.30% with wave drawing.
[18]	2022	1) Unsupervised-subtype Identification 2)Supervised early prediction 3)Biomarker based prediction(PDvec1 and PD vec3)	PPMI (Parkinson's Progression Marker Initiative) Dataset	1) Latent Vector Analysis and mapping. 2) Gaussian mixture model. 3) PDBP (Parkinson's Disease Biomarkers Program) study.	AUC-ROC curve of accuracy 84%
[19]	2020	1D-signals coming from foot sensors measuring the vertical ground reaction force (VGRF) Gait features from different input signals.	"Public database collected by Physionet"	1) 1D convolutional neural network 2) Unified Parkinson's Disease Rating Scale (UPDRS). 3) RF and MLP based feature vector classification	Global accuracy of 85.3% (equivalent to the average recall)

[20]	2020	1) First Layer - Formation of Gaussian-type fuzzy neurons 2) Weights and parameters used by the neural aggregation network (third layer) are calculated analytically, through the Moore Penrose pseudoinverse	Voice recording replications database (240 recordings consisting of people with PD and healthy people)	1) Fuzzy neural network (FNN) 2) Concepts of Extreme Learning Machine 3) LARS(Least Angle Regression)	Final accuracy of 80.88%

2.1 Gaps Identified

- Applying ensemble learning with additional classification methods, including kernel dictionary learning, SVM, and enhanced k-NN; the models were constructed using a small Vocal test and Spiral test data set.
- To increase the reliability and robustness of the models, more data from patients with PD in the early stages of the disease from around the world are required.
- Expanding the dataset to include more cases of each severity class and combining patient voice data with more patient attributes like handwriting and gait features.
- Making the system functional in reliable production environments and real-world situations.
- Parkinson's disease diagnosis is often dependent on the patient's history, assessments, and observations from the clinical examinations and questionnaires about particular symptoms because currently there are no approved, definite biomarkers or specific neuroimaging findings.
- Using ensemble learning with additional classification methods, like enhanced k-nearest neighbors and SVMs.

2.2 Dataset

Voice Dataset: The dataset contains various measurements of speech collected from 31 individuals, 23 of whom have been diagnosed with Parkinson's disease. Each row in the table corresponds to one of the 195 voice recordings made by these individuals, with each column representing a specific speech measurement. The "status" column indicates whether the individual is healthy (0) or has Parkinson's disease (1). The data is stored in CSV ASCII format, where each row represents a single voice recording. Each patient has approximately six recordings, with the patient's name listed in the first column.

Table 2. Maximum and Minimum Values for Voice Data Attributes

Attribute	Description	Target 0		Target 1	
		Maximum	Minimum	Maximum	Minimum
MDVP:Fo(Hz)	Average vocal fundamental frequency	260.105	110.739	223.361	88.333
MDVP:Fhi(Hz)	Maximum vocal fundamental frequency	592.03	113.597	588.518	102.145
MDVP:Flo(Hz)	Minimum vocal fundamental frequency	239.17	74.287	199.02	65.476
MDVP:Jitter(%)	Several measures of variation in fundamental frequency	0.0136	0.00178	0.03316	0.00168
MDVP:Jitter(Abs)		0.00008	0.000007	0.00026	0.00001
MDVP:RAP		0.00624	0.00092	0.02144	0.00068
MDVP:PPQ		0.00564	0.00106	0.01958	0.00092
Jitter:DDP		0.01873	0.00276	0.06433	0.00204
MDVP:Shimmer	Several measures of variation in amplitude	0.04087	0.00954	0.11908	0.01022
MDVP:Shimmer(dB)		0.405	0.085	1.302	0.09
Shimmer:APQ3		0.02336	0.00468	0.05647	0.00455
Shimmer:APQ5		0.02498	0.00606	0.0794	0.0057
MDVP:APQ		0.02745	0.00719	0.13778	0.00811
Shimmer:DDA		0.07008	0.01403	0.16942	0.01364
NHR	Two measures of the ratio of noise to tonal components in the voice	0.10715	0.00065	0.31482	0.00231
HNR		33.047	17.883	29.928	8.441
RPDE	Two nonlinear dynamical complexity measures	0.663842	0.25657	0.685151	0.263654
D2		0.785714	0.62671	0.825288	0.574282
spread1	Three nonlinear measures of fundamental frequency variation	-5.198864	-7.964984	-2.434031	-7.120925
spread2		0.291954	0.006274	0.450493	0.063412
PPE		2.88245	1.423287	3.671155	1.765957
DFA	Signal fractal scaling exponent	0.252404	0.044539	0.527367	0.093193

Table 2 describes the all the Maximum and Minimum values for Voice data attributes for both target 0(Healthy) and target 1(parkinsons)

Spiral Dataset: It comprises images of spiral drawing drawn by a group of individuals: those diagnosed with PD and healthy controls. This dataset consists of 100 images of training set and 50 images of testing set. These images are analyzed to discern the differences in motor control and aid in the development of diagnostic tools of ML models for Parkinson’s disease.

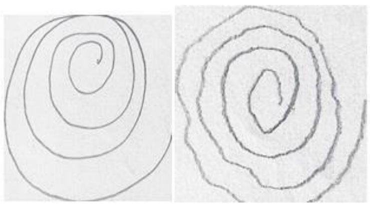

Figure 1. Healthy Spiral Drawing and Parkinson’s Disease Affected Person Spiral Drawing

Wave Dataset: It comprises of drawings of people diagnosed by Parkinson’s disease and healthy control. Similar to spiral dataset this also consists of 100 images in training set and 50 images in testing set. They help in assessing motor control and identify disease related characteristics and enhancing the reliability of findings regarding the Parkinson’s disease detection.

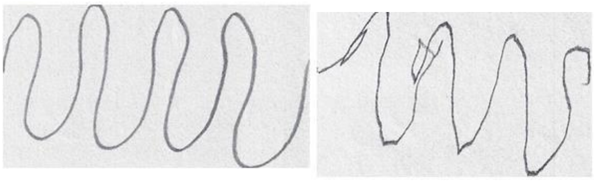

Figure 2. Healthy Spiral Drawing and Parkinson’s Disease Affected Person Wave Drawing

3. Existing Methodologies

Various machine learning algorithms have been used to forecast Parkinson's disease; the selection of an algorithm is frequently influenced by the dataset's unique properties, the features that are retrieved, and the objectives of the prediction assignment.

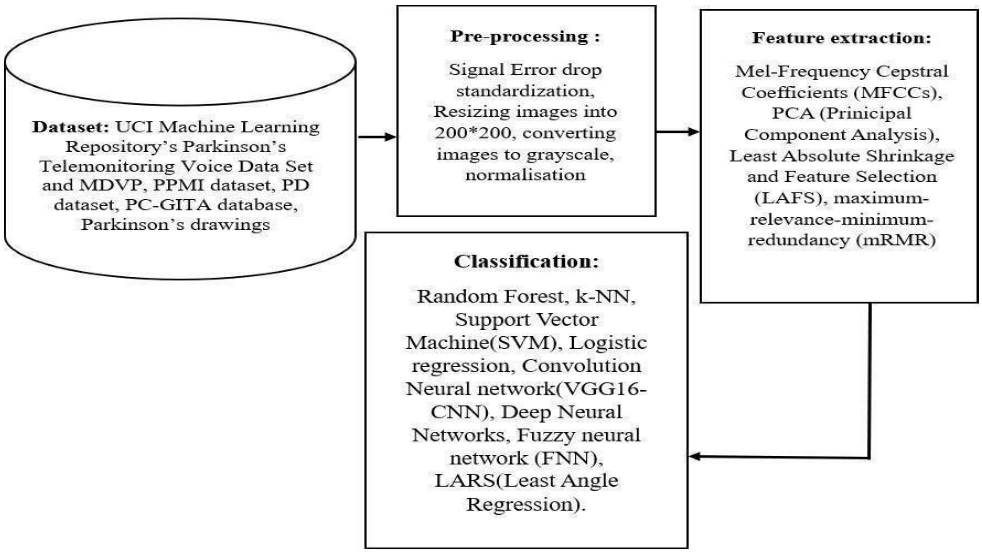

Figure 3. Existing Methodologies

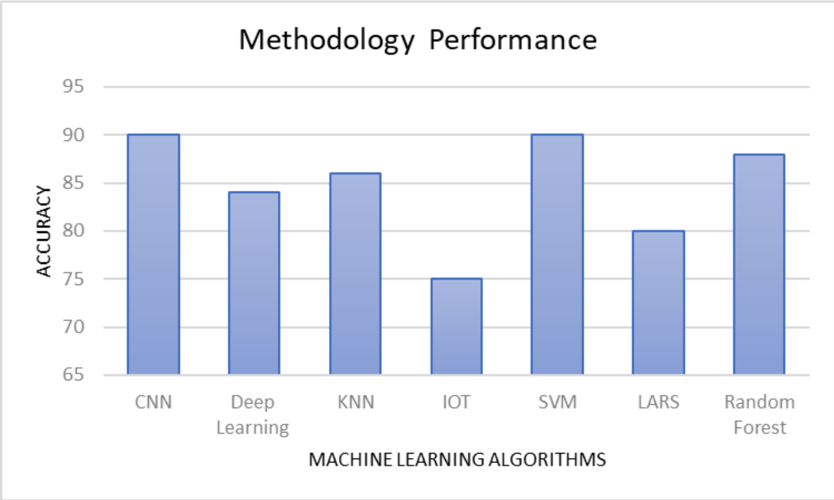

Figure 4. Performance of ML Algorithms

The bar graph provides a comparative analysis of the accuracy of six different machine learning algorithms. The vertical axis, labeled 'ACCURACY,' measures the percentage accuracy of each algorithm, ranging from 65% to 95%. The horizontal axis lists the algorithms: CNN (Convolutional Neural Network) [9], Deep Learning [8], KNN (K-Nearest Neighbors)[2], IOT (Internet of Things)[15], SVM (Support Vector Machine)[4], Random Forest(RF)[7], LARS[20].

Each algorithm is represented by a blue bar indicating its accuracy level. The graph shows that while all the algorithms perform with a high degree of accuracy, there are slight variations among them, which could be significant depending on the application. This visual representation is crucial for understanding the effectiveness of each algorithm in specific scenarios and can guide the selection process for machine learning tasks.

4. Discussion

Through a thorough examination of numerous studies, this in-depth review highlights a multitude of creative methods for using machine learning to diagnose Parkinson's disease in its early stages. These systems try to identify possible warning indicators before traditional symptoms appear by looking at speech patterns and handwriting, which presents a viable avenue for early intervention.

The variety of machine learning algorithms used by the diagnostic methods covered in this overview, such as Random Forests and Support Vector Machines, demonstrates the adaptability needed for such a significant healthcare project. A fundamental tenet of these programs is their dedication to non- invasiveness and accessibility, which is in line with healthcare ethics and meets the increasing demand for fair medical care on a global scale.

The aim of these many endeavors is to provide a flexible structure that will enable the early identification and treatment of Parkinson's disease to be considered standard procedures in healthcare. The combined effect of these studies points to a future in which cutting-edge technology will be essential to enhancing patient outcomes and lessening the strain on healthcare infrastructures.

Through the adoption of novel machine learning techniques, scientists are establishing the foundation for a future in medicine where early detection is feasible, useful, and easily available. This dedication to providing fair and moral healthcare could revolutionize the diagnosis and treatment of Parkinson's disease, with far-reaching benefits that could enhance countless lives around the globe.

The outcomes of these joint efforts highlight how crucial collaborative research is to advancing healthcare technologies and resulting in medical breakthroughs.

5. Conclusion

The combination of cutting-edge data sources and machine learning presents a novel prospect for Parkinson's disease early diagnosis. This study explored the field of predictive modelling and found a wealth of untapped potential in speech and handwriting datasets. These minute patterns, which range from the complex subtleties of strokes to the rhythmic cadence of speech, provided are evolutionary pathway for early intervention. The project's accessibility focus, which makes use of non-invasive analysis, improves diagnostic capabilities and creates opportunities for a more diverse healthcare environment. As we consider the variety of ML algorithms, from Random Forests' collective intelligence to Support Vector Machines' resilience. The journey signifies a call to propel healthcare into a future where predictive analytics is synonymous with proactive management, emphasizing the collective efforts needed to shape this future reality.

References

[1] Sarankumar, R., D. Vinod, K. Anitha, Gunaselvi Manohar, Karunanithi Senthamilselvi Vijayanand, Bhaskar Pant, and Venkatesa Prabhu Sundramurthy. "Severity prediction over Parkinson's disease prediction by using the deep brooke inception net classifier." Computational Intelligence and Neuroscience 2022 (2022).

[2] Wang, Wu, Junho Lee, Fouzi Harrou, and Ying Sun. "Early detection of Parkinson's disease using deep learning and machine learning." IEEE Access 8 (2020): 147635-147646.

[3] Anand, Anuj, Md Amaan Haque, John Sahaya Rani Alex, and Nithya Venkatesan. "Evaluation of Machine learning and Deep learning algorithms combined with dimentionality reduction techniques for classification of Parkinson's Disease." In 2018 IEEE international symposium on signal processing and information technology (ISSPIT), pp. 342-347. IEEE, 2018.

[4] Krishna, P. Gopala, and D. StalinDavid. "An Effective Parkinson's Disease Prediction Using Logistic Decision Regression and Machine Learning with Big Data." Turkish Journal of Physiotherapy and Rehabilitation 32, no. 3 (2021): 778-786.

[5] Roobini, M. S., Yaragundla Rajesh Kumar Reddy, Udayagiri Sushmanth Girish Royal, Amandeep K. Singh, and K. Babu. "Parkinson's Disease Detection Using Machine Learning." In 2022 International Conference on Communication, Computing and Internet of Things (IC3IoT), pp. 1-6. IEEE, 2022.

[6] T. Kumar, P. Sharma and N. Prakash, "Comparison of Machine learning models for Parkinson's Disease prediction," 2020 11th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), New York, NY, USA, 2020, pp. 0195-0199,

[7] Pramanik, Anik, and Amlan Sarker. "Parkinson's disease detection from voice and speech data using machine learning." In Proceedings of International Joint Conference on Advances in Computational Intelligence: IJCACI 2020, pp. 445-456. Springer Singapore, 2021.

[8] Alissa, Mohamad, Michael A. Lones, Jeremy Cosgrove, Jane E. Alty, Stuart Jamieson, Stephen L. Smith, and Marta Vallejo. "Parkinson's disease diagnosis using

convolutional neural networks and figure-copying tasks." Neural Computing and Applications 34, no. 2 (2022): 1433-1453.

[9] Gottapu, Ram Deepak, and Cihan H. Dagli. "Analysis of Parkinson's disease data." Procedia computer science 140 (2018): 334-341.

[10] Chakraborty, Sabyasachi, Satyabrata Aich, Eunyoung Han, Jinse Park, and Hee-Cheol Kim. "Parkinson's disease detection from spiral and wave drawings using convolutional neural networks: A multistage classifier approach." In 2020 22nd International Conference on Advanced Communication Technology (ICACT), pp. 298-303. IEEE, 2020.

[11] Aditi Govindu, Sushila Palwe,Early detection of Parkinson's disease using machine learning,Procedia ComputerScience, Volume 218,2023,Pages 249-261,

[12] Alniemi, Omar & Mahmood, Hanaa. (2023). Convolutional neural network for thedetection of Parkinson disease based on hand-draw spiral images. Indonesian Journal of Electrical Engineering and Computer Science. 30. 267. 10.11591/ijeecs.v30.i1.pp267-275.

[13] M. Wodzinski, A. Skalski, D. Hemmerling, J. R. Orozco-Arroyave and E. Nöth, "Deep Learning Approach to Parkinson's Disease Detection Using Voice Recordings and Convolutional Neural Network Dedicated to Image Classification," 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, 2019, pp. 717-720, doi: 10.1109/EMBC.2019.8856972.

[14] Pardoel, Scott, Jonathan Kofman, Julie Nantel, and Edward D. Lemaire. "Wearable-sensor-based detection and prediction of freezing of gait in Parkinson's disease: a review." Sensors 19, no. 23 (2019): 5141.

[15] M. El-Hasnony, S. I. Barakat and R. R. Mostafa, "Optimized ANFIS Model Using Hybrid Metaheuristic Algorithms for Parkinson's Disease Prediction in IoT Environment," in IEEE Access, vol. 8, pp. 119252-119270, 2020, doi: 10.1109/ACCESS.2020.3005614.

[16] Ferdib-Al-Islam and L. Akter, "Early Identification of Parkinson's Disease from Hand-drawn Images using Histogram of Oriented Gradients and Machine Learning Techniques," 2020 Emerging Technology in Computing, Communication and Electronics (ETCCE), Bangladesh, 2020, pp. 1-6, doi: 10.1109/ETCCE51779.2020.9350870.

[17] Ranjan, Nihar & Mate, Gitanjali & Bembde, Maya. (2023). Detection of Parkinson'sDisease using Machine Learning Algorithms and Handwriting Analysis. Journal of Data Mining and Management. 8. 21-29.10.46610/JoDMM. 2023.v08i01.004.

[18] Dadu, Anant, Vipul Satone, Rachneet Kaur, Sayed Hadi Hashemi, Hampton Leonard, Hirotaka Iwaki, Mary B. Makarious et al. "Identification and prediction of Parkinson’s disease subtypes and progression using machine learning in two cohorts." npj Parkinson's Disease 8, no. 1 (2022): 172.

[19] Imanne El Maachi, Guillaume-Alexandre Bilodeau, Wassim Bouachir, Deep 1D-Convnet for accurate Parkinson disease detection and severity prediction from gait, Expert Systems with Applications, Volume 143, 2020, 113075, ISSN 0957-4174 https://doi.org/10.1016/j.eswa.2019.113075.

[20] Guimarães, Augusto Junio, Paulo Vitor de Campos Souza, and Edwin Lughofer. "Hybrid model for Parkinson’s disease prediction." In International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems, pp. 621-634. Cham: Springer International Publishing, 2020.