Early Detection of Parkinson's Disease using Handwriting and Voice Analysis: A Machine Learning Approach

Himaja G
Department of AI and ML
BNM Institute of Technology and Management
Bangalore, India
himu.492002@gmail.com

Kundan K M
Department of AI and ML
BNM Institute of Technology and Management
Bangalore, India
kundankm602@gmail.com

Dr. Nagarathna C R
Department of AI and ML
BNM Institute of Technology and Management
Bangalore, India
nagarathna.binu@gmail.com

Jayasri A
Department of AI and ML
BNM Institute of Technology and Management
Bangalore, India
jayasria45@gmail.com

Abstract

Parkinson's Disease (PD) has motor deficits that affect movement, such as tremors and muscle stiffness. PD can easily go unnoticed as its symptoms vary with individual patients. As such, current diagnostic methods are not sensitive to the early stages of PD when symptoms are minimal. However, new evidence affirms the possibility of utilizing speech and handwriting abnormality roots to detect PD early. Early diagnosis of PD is critical as it ensures that the first instance of the disease is diagnosed and treated at the earliest possible stage. Furthermore, physicians have improved abilities to manage the development of the disease this way. Patients ultimately get to spend more years with their families and friends. Nevertheless, data-driven identification models enable the early diagnosis of PD and mandatory early intervention. Optimizing diagnostic accuracy using data analytics and technology allows researchers to expedite treatment while also improving patient quality of life. The model is the integration of 3 models which gives the accuracy level of Voice, Spiral and Wave model of 97%, 86.67% and 76.65% with respect to Support Vector Machine and Random Forest algorithms.

Keywords—Machine Learning Algorithms, Spiral and Wave Drawing, Voice dataset, Random Forest, Support Vector Machine

I. INTRODUCTION

Parkinson's disease (PD) is a major global health concern that affects millions of people worldwide. Even though Parkinson's disease (PD) is common, early detection of the condition remains challenging due to limitations in the diagnostic procedures now in use, such as MRIs, PET scans, and mini-mental state examinations. These techniques are often invasive, time-consuming, and may not correctly detect symptoms in their first stages, which can postpone diagnosis and lessen the efficacy of treatments in later stages. To solve these challenges, the aim of this study is to develop a novel prediction model for PD identification. Using machine learning techniques, the model will integrate data from spiral and wave drawings, voice recordings, and other sources to create a more user-friendly and efficient diagnostic tool. The main objective is to improve diagnostic accuracy so that medical practitioners can more accurately and precisely diagnose Parkinson's disease (PD) in its early stages. Among neurodegenerative conditions, Parkinson's disease (PD) presents a significant difficulty because of its gradual development, which sometimes results in delayed diagnosis and reduced effectiveness of interventions in later stages.

The revolutionary potential of early identification and intervention in transforming the way PD is managed is what drives our effort. Our goals as we work through the complexities of this complicated disease include creating a predictive model, looking

into biomarkers, looking into cutting-edge therapeutic strategies, and maximizing prompt treatment. This extensive project includes assessing the financial effects, encouraging clinical trial participation, increasing scientific knowledge, and developing a proactive paradigm for the treatment of Parkinson's disease.

Parkinson's disease (PD) poses significant challenges due to delayed diagnosis until later stages, hindering therapy effectiveness. Early detection is pivotal for transforming PD care and improving outcomes. Addressing this requires a multidisciplinary approach to overcome diagnostic delays and manage complexities. Early detection initiatives are crucial to counteract PD's gradual onset and enable timely interventions, revolutionizing treatment efficacy. Leveraging diverse datasets and advanced technology offers unprecedented opportunities for early PD detection, facilitating the development of novel diagnostic tools. Prompt detection allows for tailored interventions, enhancing patient outcomes and quality of life. Proactive early detection programs also aim to mitigate social and financial burdens associated with advanced PD stages, emphasizing the broader societal impact of prioritizing early intervention strategies.

This research is driven by the revolutionary potential of early identification and intervention as well as the pressing need to address the complex problems presented by Parkinson's disease (PD). Recognizing the disease's gradual start and consequent diagnostic delays, our all-encompassing strategy includes a variety of goals. Our goals are to investigate possible biomarkers, create a complex predictive model with advanced machine learning techniques, and improve the model's sensitivity for early-stage PD detection. Furthermore, we endeavour to explore innovative therapeutic modalities and enhance prompt, focused interventions. We also include evaluating the financial effects, encouraging clinical trial participation, increasing scientific knowledge, and developing a proactive paradigm change in the treatment of Parkinson's disease. In addition to improving patient outcomes, our multifarious goals also aim to advance medical research, societal well-being, and scientific understanding of the complexity of Parkinson's disease.

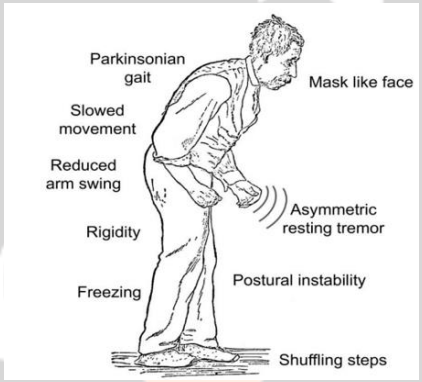

Fig 1: Parkinson’s Disease Symptoms

II. LITERATURE SURVEY

The purpose of the survey is to conduct a thorough synthesis of academic literature, including studies on biomarker identification, predictive modelling breakthroughs, early detection techniques for Parkinson’s disease(PD).

The preprocessing approaches used in the current prediction system includes Histogram equalization, image scaling, contrast enhancement for spiral drawings and Specifically Pairwise Correlation, Exploratory Data Analysis for Voice dataset. The methods included in the present study are VGG16-CNN, k-Nearest Neighbours classifier, Logistic Regression classifier for Spiral dataset and Pattern recognition fuzzy c-means(FCM) clustering for voice dataset. The datasets used were from UCI Machine Learning repositories which includes Parkinson’s disease Voice and Speech, PPMI and the Parkinson’s Telemonitoring dataset.

In Voice and Speech detection Wu Wang, Junho Lee and team [2] introduces an innovative deep learning technique to early uncover whether an individual is affected with PD or not based on the study of Rapid Eye Movement and olfactory loss, Cerebrospinal fluid, and dopaminergic imaging markers. A comparison between the proposed deep learning model and 12 Machine Learning and ensemble learning methods based on relatively small data including 183 individuals and 401 early patients shows the superior detection performance of the designed model, which achieved the accuracy of 96.45% on average and also feature importance on PD detection process was based on Boosting method. Anik Pramanik and Amlan Sarkar [7] proposed a model that introduced different data pre-processing methods, such as data standardization, multicollinearity diagnosis, dimensionality reduction technique to improve the quality of data. Different Machine Learning (ML) classifiers (k-Nearest Neighbour, Support Vector Machines, Random Forest, AdaBoost, Logistic Regression) were used for classification of PD. Hyper-parameter tuning, cross fold validation and grid search were employed in this experiment to maximize the performance of the classifiers and preserve the class distribution of the imbalanced dataset. Among all the ML algorithms SVM achieved the highest accuracy of 94.10%. A Deep Learning approach was proposed for Voice Recordings by Marek Wodzinski and team[13]

were they approached to the detection using vowels with sustained phonation and a ResNet architecture dedicated originally to image classification.

In Spiral and Wave drawings detection Sabyasachi Chakraborty, Satyabrata Aich, and their team[10] proposed a thorough system design in order to analyse Spiral and Wave drawing patterns in both healthy and Parkinson's disease patients. The methodology they used involved two distinct convolutional neural networks (CNNs), each devoted to the analysis of drawing patterns-specifically spiral and wave sketches. Moreover, ensemble voting methods where used to train the prediction probabilities on a meta classifier and hence the prediction power increased. This strategy made it easier to make a weighted prediction based on evaluations of spiral and wave sketches where the model was trained on a dataset comprising 55 patients and achieved an astounding accuracy of 93.3% after undergoing intensive training. This resulted model helped a created system's ability to distinguish between healthy and Parkinson's patient based on the drawing patterns. Yash Khare and Pratima Singh [12] trained a CNN model on 500 spiral drawings from Parkinson's disease patients using NIATS dataset of Federal University of Uberlandia which consisted of 500 images of spiral drawings made by healthy and Parkinson's patients each. Marek Wodnizki, Andrzej Skalski and team [13] prepared a deep learning approach for detecting Parkinson's disease using voice recordings and used a ResNet architecture for image classification. They used a data of 100 patients , with each recorded 3 times and achieved an comparable accuracy of 90%.

III. METHODOLOGY

In methodology employed in this paper integrates the module that collaborates data analysis, feature extraction, classification of patients based on their health status- whether healthy or diagnosed with Parkison's disease.

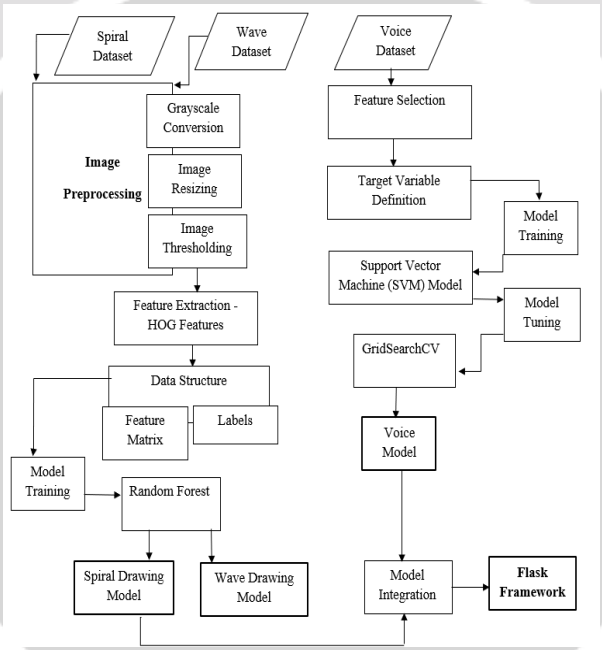

Fig 2: The proposed data flow diagram

A. Data Acquisition

1)Voice dataset: It consists of a diverse range of biological speech measurements that is collected from 31 individuals, with 23 of them diagnosed with Parkinson's disease. Each row in the table corresponds to one of the 195 voice recordings made by these people ("name" column), with each column representing a specific voice measure. The "status" column, which is set to 0 for healthy and 1 for PD, serves as the primary means of differentiating between individuals without Parkinson's disease (PD) and those with it. The information is in CSV ASCII format. Each row in the CSV file represents a single voice recording occurrence. Each patient has about six recordings; the patient's name appears in the first column.

Matrix column entries (attributes):

- **name** - ASCII subject name and recording number
- **MDVP:Fo(Hz)** - Average vocal fundamental frequency
- **MDVP:Fhi(Hz)** - Maximum vocal fundamental frequency
- **MDVP:Flo(Hz)** - Minimum vocal fundamental frequency
- **MDVP**:Jitter(%), MDVP:Jitter(Abs), MDVP:RAP, MDVP:PPQ, Jitter:DDP - Several measures of variation in fundamental frequency
- **MDVP**:Shimmer,MDVP:Shimmer(dB),Shimmer:APQ3,Shimmer:APQ5,MDVP:APQ,Shimmer:DDA - Several measures of variation in amplitude
- **NHR, HNR** - Two measures of the ratio of noise to tonal components in the voice
- **status** - The health status of the subject (one) - Parkinson's, (zero) - healthy
- **RPDE, D2** - Two nonlinear dynamical complexity measures
- **DFA** - Signal fractal scaling exponent
- **spread1, spread2, PPE** - Three nonlinear measures of fundamental frequency variation

Fig 3: 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

Fig 4: Minimum and Maximum values for Voice data attributes

2)Spiral dataset: It comprises images of spiral drawing drawn by a group of individuals: those diagnosed with Parkinson's disease 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.

Fig 5: Healthy spiral drawing and Parkinson's disease affected person spiral drawing

3)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.

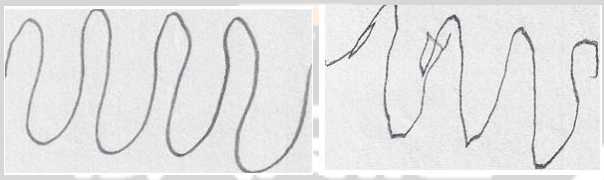

Fig 6: Healthy spiral drawing and Parkinson's disease affected person wave drawing

B. Data preprocessing

1) Voice Data Preprocessing: The voice feature values are either entered manually or automatically into the system as a process of preprocessing process. This process involves in deciding which features are most relevant and have a high influence on the correctness and that significantly impact the accuracy of the model. The use of Machine Learning preprocessing techniques and the patterns indicating the presence of illness identification of key voice features or characteristics like pitch variation or loudness is effectively achieved that help with the precise diagnosis and therapy planning.

2)Image preprocessing: Before feature extraction the images need to go through necessary preprocessing stages in order to undergo essential transformations to standardize and enhance their quality. Firstly, the images are transformed from colour to grayscale tomes, while preserving the structural elements. Subsequently, the images are resized to a standard size of 200x200 pixels in dimensions throughout the dataset, hence helping in promoting the analysis consistency. Finally, thresholding is applied to segment the images into foreground and background noise sections according to the pixel intensity levels. In the end, the preprocessing techniques are crucial for improving computational efficiency, by enhancing the image quality and preparing the dataset for accurate feature extraction.

C. Feature Extraction of images

Extraction of critical shape and texture information from pre-processed images, the Histogram of Oriented Gradients (HOG) feature extraction approach is crucial in identifying Parkinson's disease. The HOG features are adept at highlighting significant

patterns in images, making them effective for the extraction purpose. The retrieved HOG characteristics are then used to train a Machine Learning model, a Random Forest Algorithm model, after preprocessing. The model gains ability to characterize between the healthy patients and Parkinson's disease patients during training. By analysing the patterns and characteristics found in HOD features, it creates decision boundaries, that helps in the identification of fresh data instances. The model then can be trained on the extracted features to recognize Parkinson's disease with accuracy based on the visual traits that the HOG feature descriptors capture. This approach makes it possible to accurately and automatically identify Parkinson's disease from the image data, that helps in early diagnosis and successful treatment of disorder.

D. Data Structuring for Spiral and Wave model

The feature matrix is essential for structuring extracted featured from images into a format that can be used to train a model. The machine learning algorithm uses this matrix as its basis to find patterns and relationships in the data. Each data point has a label which indicates whether a person is healthy or has been diagnosed with Parkinson's disease. With the help of these labels, which provide vital information for supervised learning, the algorithm is then able to forecast using the input data. This kind of architecture helps the model in distinguishing between several classes, aiding in accurate disease diagnosis. By streamlining this process, the structured approach improves the model's capacity to generalize the new data and raise the accuracy of Parkinson's disease diagnosis.

E. Machine Learning Models

1) Voice models: In voice data classification, various machine learning models are employed to differentiate between healthy individuals and those affected by Pakinson's disease.

Metric	DT	RF	LR	SVM	NB
Accuracy	0.8474	0.9491	0.8305	0.9661	0.7627
F1-Score	0.8421	0.9411	0.7826	0.9600	0.6500
Recall	0.9230	0.9230	0.6923	0.9230	0.5000
Precision	0.7741	0.9600	0.9000	1.0000	0.9285
R2-Score	0.3811	0.7937	0.3123	0.8624	0.0372

(DT-Decision Tree, RF-Random Forest, LR-Logistic Regression, SVM-Support Vector Machine, NB- Naive Bayes)

Table 1: Comparison table for different Machine Learning models for Voice data classification

Decision Tree model, with a moderate accuracy of 84.75% shows some success in the classification. Random Forest model, boasting a notable accuracy of 94.92%, emerges as a strong candidate for ensemble learning in disease categorization. Logistic Regression performs respectably at 83.05% accuracy but falls short compared to more complex models. Support Vector Machine(SVM) stands out as the best performer, achieving an accuracy of 96.61%, showcasing its robustness in Parkinson's disease classification. Naive Bayes, however lags behind with an accuracy of 76.27%, suggesting limitations in capturing intricate illness patterns. SVM seems to be the best option overall because of its higher classification accuracy for Parkinson's illness.

The voice data model uses GridSearchCV to adjust its hyperparameters by fine tuning. Through cross-validation, it methodically investigates a predetermined grid of parameter values, refining model parameters to improve performance and generalization capability. This exhaustive search aids in identifying the set of parameters that produce the greatest model performance, enhancing the precision and dependability of the machine learning models used to classify Parkinson's disease and healthy using voice data.

*1) Spiral and Wave models:*The accuracy rates of the Random Forest and XGBoost algorithms in idenitfying the Wave and Spiral models are shown in the table below. Random Forest performs better in both tasks.

Algorithms	Spiral model	Wave model
Random Forest	86.86%	76.65%
XGBoost	73.33%	73.33%

Table 2: Accuracy table for Spiral and Wave classification

The primary reason for preference of Random Forest Classifier over XGBoost and Neural Netwroks is because of its superior accuracy in disease classification tasks. To reduce overfitting and improve predicton accuuracy, Random Forest employs a collection of decsion trees which is appropriate. By combining the predictions from several trees, it mitigates the chance of lowering the bias and variance related to individual trees, which produces predictions that are more dependable and consistent. As Random Forest is interpretable, silent when it comes to overfitting, very accurate and simple to use, it is a desirable choice for this application in identifying illness.

F. Prediction of the models

After training, the model is tested on a distinct set of images and speech attributes to see how well it can identify Parkinson's disease. At this stage, the model's ability to distinguish between the people having Parkinson's disease and healthy individuals is been evaluated. This step involves visualizing the test outcomes, like displaying predictions in a user friendly format or exporting results for medical review. Medical experts and Researchers can evaluate the model's efficiency and feasibility for practical use in Parkinson's disease detection by looking at the results.

The final output categorizes the input data as either '0– Healthy' or '1- Parkinson's', indicating the presence or lack of symptoms associated with Parkinson's disease.

IV. RESULTS

The proposed approach successfully detected whether the person has Parkinson's disease or not. Based on the model's testing and detection by the combined approach towards Spiral, Wave and Voice data.

The Fig 7 shows the prediction of Wave drawing picture of an healthy person using wave model which gave an accuracy of 87%.

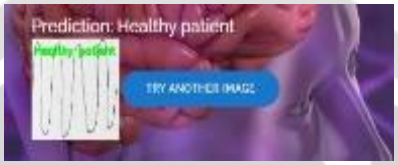

Fig 7: Results from Wave drawing

Fig 8: Results from Spiral drawing

The above Fig 8 shows us the prediction of spiral drawing picture of a Parkinson's patient using the spiral model which gave an accuracy of 86.67%.

The below Fig 9 shows us the prediction of voice data based on the attribute values entered using Voice model which gave an accuracy of 97%.

Fig 9: Results from Voice data

Fig 10 shows the AUC-ROC curve for the SVM algorithm used in the Voice model for detecting Parkinson's disease.

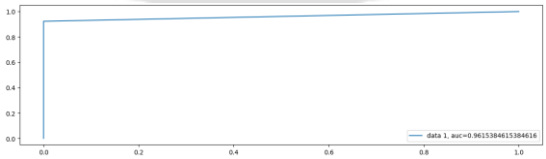

Fig 10: AUC- ROC curve for Voice model

V. CONCLUSION

Through a comprehensive approach to early identification and intervention, the entire initiative seeks to improve our understanding of and ability to treat Parkinson's disease. The new understandings of the complex nature of Parkinson's disease have been made possible by the combination of a wide range of datasets, advanced Machine Learning models and research into biomarkers and treatment approaches. Future development or enhancements concentrate on improving the machine learning model by adding more data sources, using cutting edge technology like wearables, encouraging partnerships with medical

experts. Longitudinal studies in conjunction with ongoing research into novel biomarkers and therapies provide opportunities for future progress.

VI. FUTURE ENHANCEMENTS

Future advancements in Parkinson's disease (PD) detection aim to harness cutting-edge technologies and methodologies to enhance diagnostic accuracy and patient outcomes. By incorporating diverse data sources like wearable sensors and neuroimaging scans alongside voice and handwriting data, a comprehensive understanding of PD progression can be achieved. Furthermore, the exploration of advanced machine learning techniques, including deep learning algorithms, holds promise in identifying subtle patterns indicative of PD onset and progression, thereby improving diagnostic precision. Longitudinal data analysis presents opportunities for personalized medicine by tracking disease evolution over time and customizing treatment approaches to individual requirements. Real-time monitoring tools such as wearable devices and mobile applications have the potential to facilitate proactive symptom management and timely intervention. Collaboration with healthcare professionals is vital to ensure the seamless integration of these innovations into clinical practice, ensuring that novel diagnostic tools meet rigorous standards and ultimately enhance the quality of life for PD patients.

REFERENCES

[1] R. Sarankumar, D. Vinod, K. Anitha, Gunaselvi Manohar, Karunanithi Senthamilselvi Vijayanand, Bhaskar Pant, Venkatesa Prabhu Sundramurthy, "Severity Prediction over Parkinson's Disease Prediction by Using the Deep Brooke Inception Net Classifier", Computational Intelligence and Neuroscience, vol. 2022, Article ID 7223197, 9 pages, 2022. https://doi.org/10.1155/2022/7223197

[2] M. S. Roobini, Y. R. K. Reddy, U. S. G. Royal, A. K. Singh and K. Babu, "Parkinson's Disease Detection Using Machine Learning," 2022 International Conference on Communication, Computing and Internet of Things (IC3IoT), Chennai, India, 2022, pp. 1-6, doi: 10.1109/IC3IOT53935.2022.9768002.

[3] 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, doi: 10.1109/UEMCON51285.2020.9298033.

[4] Ram Deepak Gottapu, Cihan H Dagli,Analysis of Parkinson's Disease Data,Procedia. Computer Science,Volume 140,Pages 334-341,ISSN 1877-0509,https://doi.org/10.1016/j.procs.2018.10.306.

[5] Chakraborty, Sabyasachi & Aich, Satyabrata & Jong-Seong-Sim, & Han, Eunyoung & Park, Jinse & Kim, Hee-Cheol. (2020). Parkinson's Disease Detection from Spiral and Wave Drawings using Convolutional Neural Networks: A Multistage Classifier Approach. 298-303. 10.23919/ICACT48636.2020.9061497.

[6] Aditi Govindu, Sushila Palwe,Early detection of Parkinson's disease using machine learning,Procedia ComputerScience, Volume 218,2023,Pages 249-261,ISSN 1877 0509,https://doi.org/10.1016/j.procs.2023.01.007.

[7] Alniemi, Omar & Mahmood, Hanaa. (2023). Convolutional neural network for the detection 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.

[8] 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.

[9] Pardoel S, Kofman J, Nantel J, Lemaire ED. Wearable-Sensor-based Detection and Prediction of Freezing of Gait in Parkinson's Disease: A Review. Sensors (Basel). 2019 Nov 24;19(23):5141. doi: 10.3390/s19235141. PMID: 31771246; PMCID: PMC6928783.

[10] I. 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.

[11] Ferdib-Al-Islam and L. Akter, "Early Identification of Parkinson's Disease from Handdrawn 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.

[12] Ranjan, Nihar & Mate, Gitanjali & Bembde, Maya. (2023). Detection of Parkinson's Disease using Machine Learning Algorithms and Handwriting Analysis. Journal of Data Mining and Management. 8. 21-29. 10.46610/JoDMM.2023.v08i01.004.

[13] Dadu, A., Satone, V., Kaur, R. et al. Identification and prediction of Parkinson's disease subtypes and progression using machine learning in two cohorts. npj Parkinsons Dis. 8, 172 (2022). https://doi.org/10.1038/s41531-022-00439-z

[14] Imanne El Maachi, Guillaume-Alexandre Bilodeau, Wassim Bouachir, Deep 1DConvnet 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.

[15] Information Processing and Management of Uncertainty in Knowledge-Based Systems.2020; 1238: 621–634. Published online 2020 May 15. doi: 10.1007/978-3-030-50143-3_49.