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Early Parkinson's Disease Detection Using by Machine Learning Approach

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Parkinson's disease (PD) is a progressive neurodegenerative disorder that affects movement and motor skills. Early diagnosis and treatment of Parkinson's disease are crucial for improving patient outcomes; however, traditional diagnostic methods are time-consuming and subject to observer bias. This study aims to use a machine learning model for the detection of Parkinson's disease. The model will be trained on a public repository dataset of biomedical voice measurements from individuals with and without Parkinson's disease and its performance will be evaluated in terms of accuracy and precision. The results of this study have the potential to revolutionize the diagnosis of Parkinson's disease by providing a fast, non-invasive, and reliable diagnostic tool. The study's results could also have implications for the development of similar diagnostic tools for other neurodegenerative disorders.

Keywords: Machine learning; Parkinson's disease; diagnosis.

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1. INTRODUCTION

"Parkinson's disease (PD) is a progressive neurodegenerative disorder that affects millions of people worldwide" [1]. "It is characterized by the loss of dopamine-producing neurons in the substantia nigra, which leads to a reduction in dopamine levels in the basal ganglia" [2]. "This reduction in dopamine levels results in a range of motor symptoms, including tremors, rigidity, bradykinesia (slowness of movement), and postural instability, as well as non-motor symptoms, such as depression, anxiety, cognitive impairment, and sleep disturbances" [2]. "There is currently no cure for PD, but various treatments, such as medications and surgical treatments, can help manage symptoms and improve quality of life" [3]. The introduction of PD highlights the importance of continued research into this disorder, which affects millions of people worldwide. Understanding the underlying mechanisms of PD and the development of new treatments is critical for improving the quality of life of people with the disorder. The study of Parkinson's disease (PD) has been an active area of research in recent years, and there have been several significant advancements. The study of Parkinson's disease (PD) has been an active area of research in recent years, and there have been several significant advancements. The following are some notable developments:

i. Genetic Risk Factors: A study published in Nature Genetics in 2021 identified 25 genetic variants associated with an increased risk of PD. This study analyzed data from over 42,000 individuals with PD and over 1.4 million control individuals. The authors suggest that these genetic variants may help identify new targets for therapeutic interventions [4].
ii. "Brain Stimulation: Deep brain stimulation (DBS) has been shown to be an effective treatment for PD. A recent study published in Lancet Neurology in 2021 compared the effectiveness of DBS to the best medical therapy (BMT) in patients with early-stage PD. The study found that DBS was more effective than BMT in improving motor symptoms and quality of life" [5].
iii. Blood Biomarkers: Researchers are exploring the use of blood biomarkers to aid in the diagnosis and monitoring of PD. A study published in Movement Disorders in 2020 identified a set of plasma biomarkers that could potentially distinguish individuals with PD from healthy controls. The authors suggest that these biomarkers could be used as a screening tool to identify individuals at risk of developing PD [6].
iv. "Gut Microbiome: There is increasing evidence to suggest that the gut microbiome may play a role in the development and progression of PD. A study published in Nature Communications in 2021 found that the gut microbiome of individuals with PD was different from healthy controls. The authors suggest that these findings may lead to new treatments for PD that target the gut microbiome" [7].

The rapid pace of discovery in this area highlights the importance of continued investment in PD research, which has the potential to lead to new treatments that can help improve the lives of people with PD. Machine learning (ML) has become a valuable tool for the study and treatment of Parkinson's disease (PD). ML can be used to predict Parkinson's disease by analyzing various medical data sources such as clinical data, imaging data, and genetics data.

Machine learning has shown great potential in the diagnosis, monitoring, and treatment of Parkinson's disease (PD). Some notable developments in recent years are:

i. Predicting Motor Symptoms: Machine learning models have been developed to predict motor symptoms in individuals with PD. A study published in Nature Scientific Reports in 2019 used machine learning to predict the severity of bradykinesia in individuals with PD using data from wearable sensors. The authors suggest that these models could be used to personalize treatment plans for individuals with PD [8].
ii. Detecting Fluctuations: Machine learning models have also been used to detect fluctuations in motor symptoms in individuals with PD. A study published in the Journal of Parkinson's Disease in 2020 used machine learning to detect fluctuations in motor symptoms using data from wearable sensors. The authors suggest that these models could be used to improve the accuracy of medication dosing and reduce the burden of in-person assessments [9].
iii. Optimizing Deep Brain Stimulation: Deep brain stimulation (DBS) is a common

treatment for PD, but the optimal stimulation parameters are often difficult to determine. Machine learning models have been developed to optimize DBS parameters in individuals with PD. A study published in Movement Disorders in 2018 used machine learning to identify the optimal DBS parameters for individuals with PD. The authors suggest that these models could improve the effectiveness of DBS and reduce the need for multiple surgeries [10].

iv. Personalized Treatment Plans: Machine learning can be used to develop personalized treatment plans for individuals with PD. A study published in the Journal of Parkinson's Disease in 2020 used machine learning to develop personalized treatment plans for individuals with PD based on their clinical characteristics. The authors suggest that these personalized treatment plans could improve outcomes for individuals with PD [11].

2. RELATED WORKS

There has been a growing interest in using machine learning techniques for the prediction of Parkinson's disease (PD). The goal of these study is to use an ML algorithm that can accurately predict the onset of PD and/or monitor its progression.

Parkinson's disease affects the nervous system. It causes trembling in the hands, trouble walking, and balance and coordination issues. The research in [12] was to identify the illness in early prediction utilizing clinical imaging and machine learning approaches, with the goal of detecting Parkinson's disease. A comparison of many machine learning classifier methods, including XGBoost, Random Forest, KNN, and SVM, was conducted, and the best model was suggested. This model was utilized to create predictions and determine accuracy. With an accuracy rate of 90%, Random Forest appears to perform better. The adoption of suitable and prompt remedies was made possible by automatic detection with increased precision, which will make Parkinson's disease screening a cost-effective and efficient process.

In [13], they proposed "a strategy for the prediction of Parkinson's disease severity using deep neural networks using Parkinson's Telemonitoring Voice Data Set of patients from UCI. In order to diagnose the condition, they developed a machine learning model and a neural network to predict the severity of the disease. Random Forest Classifier and neural networks were used to categorize Parkinson's disease".

Parkinson's motor symptoms are caused by a lack of dopamine processing when these cells are damaged. The steps in the suggested technique in [14] included data gathering, feature selection, model training, and model prediction. This study investigated the use of multiple classifiers for machine learning (ML)-based diagnosis of Parkinson's disease (PD) and their diagnostic accuracy when predicting outcomes. According to the experimental findings, the Gradient Boost algorithm provided the greatest test accuracy, 91.53%.

The researchers suggested an effective method for effectively predicting Parkinson's illness via voice samples in the study in [15]. They used Extreme Learning Machine. A trustworthy dataset from the UCI repository had been used to evaluate the method's performance. The suggested technique correctly differentiated between those with Parkinson's disease and healthy people in the training dataset with an accuracy of 90.76% and 0.81 MCC. The suggested technique demonstrated 81.55% accuracy when evaluated on a separate dataset of individuals with Parkinson's disease. Our approach's performance is contrasted with that of other methods, including neural networks and support vector machines. The outcomes showed that the procedure suggested is accurate for diagnosing Parkinson's disease.

A Fully Complex-Valued Radial Basis Function network (FC-RBF), a Meta-Cognitive Fully Complex-Valued Radial Basis Function network (Mc-FCRBF), and an Extreme Learning Machine (ELM) were suggested for use in the study in [16] to detect Parkinson's disease. The severity of Parkinson's disease was anticipated with the use of the Unified Parkinson's Disease Rating Scale (UPDRS), and for untreated individuals, the UPDRS scale spans the range (0-176).

"Using the UCI dataset, which consists of biomedical voice recording samples of healthy and Parkinson's Disease-affected individuals, a comparative evaluation of various prediction models was conducted in" [17]. For accuracy and effectiveness, these prediction models were developed and evaluated. For precise early

Parkinson's Disease prediction, the performance analysis of the top five models was reported in the publication. In order to determine if these models were appropriate for lightweight mobile apps in the context of ubiquitous computing, their processing speed was also examined.

The researchers used five distinct classifiers in the suggested technique in [18]. The objective of the study was to improve the dataset's feature correctness. The wrapper and filter techniques were merged to create the hybrid feature selection approach, which was employed for optimization. It was called Recursive Feature Elimination. Using nine characteristics out of a possible 22, the classifier XGBoost achieved the greatest accuracy, 97.43%.

The work in [19] shows "how the Synthetic Minority Oversampling Method (SMOTE), which enhances minority class detection, addresses the issue of class imbalance in PD stage-wise classification. By measuring the differences between the samples that were created and demonstrating the lack of replication or overlapping, the procedure was verified. Spatial and temporal gait factors, as well as their regularity and symmetry characteristics, were taken into account. Classifiers' prediction accuracy attributes were examined after they were trained on balanced and unbalanced datasets. The model's generalizability improved as a result of the results, which demonstrated an improvement in identifying the minority class by the model trained with the balanced dataset".

3. METHODOLOGY

The section describes a detailed description of how the dataset was gathered, pre-processed, and visualized. It also discussed the implementation of Support Vector Machine Classifier machine learning technique.

3.1 System Architecture

System architecture refers to the structural design of a complex system, which includes its components, its relationships, and the principles and guidelines governing its arrangement [20]. It is important for ensuring the effective and efficient functioning of a system, as it provides a clear and comprehensive view of the system and its components, and enables the identification of potential issues and areas for improvement [21]. Fig. 1 shows the system architecture for the proposed system. The dataset will be gathered from the Oxford Parkinson's Disease Detection Dataset, a public repository. The dataset is then pre-processed by preparing the raw data and making it suitable for a machine learning model. It is then divided into training and test data for evaluation and classification. New data can then be fed into the system to predict whether a patient has Parkinson's disease or not.

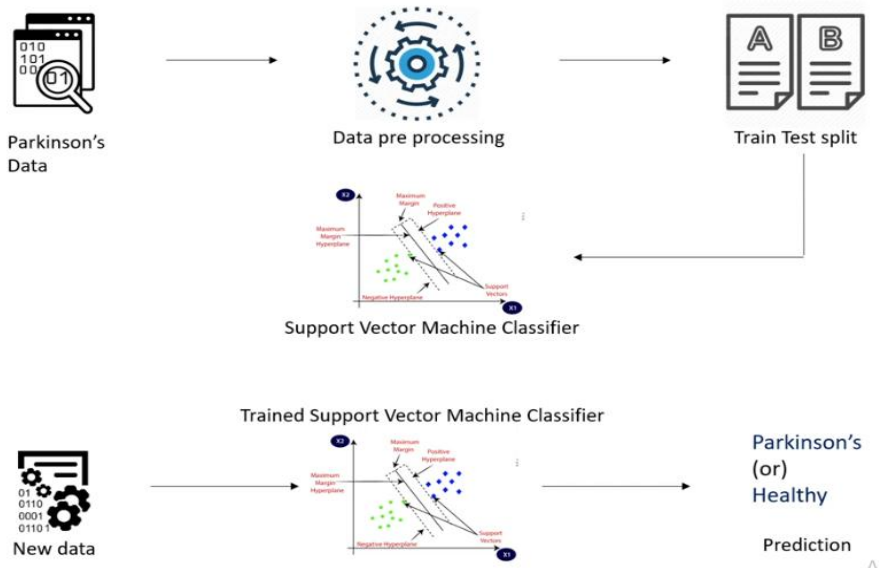

Fig. 1. System architecture

3.2 Data Preprocessing

Data preprocessing is an essential step in machine learning, as it helps to transform raw data into a format that can be easily understood by machine learning algorithms. Techniques used in data pre-processing for the study are data cleaning [22], data transformation [23], feature engineering [24], data integration [25], and data reduction [26].

3.3 Dataset Description

The Oxford Parkinson's Disease Detection Dataset was harvested from a public repository and contains 195 rows and 24 columns. This dataset is composed of a range of biomedical voice measurements from 31 people, 23 with Parkinson's disease (PD). Each column in the table is a particular voice measure, and each row corresponds to one of 195 voices recording from these individuals ("name" column). The main aim of the data is to discriminate healthy people from those with PD, according to the "status" column which is set to 0 for healthy and 1 for PD. The data is in ASCII CSV format. Table 1 shows the attribute information and meaning of each attribute.

3.4 Support Vector Machines

Support Vector Machines (SVMs) are a popular type of machine learning algorithm that can be used for both classification and regression tasks. The idea behind SVMs is to find the best hyperplane that separates data points of different classes in a high-dimensional space [27]. The hyperplane is chosen so that the margin between the two closest data points from different classes is maximized. SVMs have been widely used in a variety of applications such as text classification, image classification, and bioinformatics. In conclusion, SVMs are a powerful and versatile machine learning algorithm that has been widely used for classification and regression tasks. Their ability to handle non-linear and high-dimensional datasets, along with their simplicity and interpretability, make them a popular choice for many applications [28].

“Support Vector Machine (SVM) is a supervised machine learning algorithm used for both classification and regression. Though it is regarded that regression problems as well its best suited for classification” [29]. “The objective of the SVM algorithm is to find a hyperplane in an N-dimensional space that distinctly classifies the data points. The dimension of the hyperplane depends upon the number of features” [29]. “If the number of input features is two, then the hyperplane is just a line. If the number of input features is three, then the hyperplane becomes a 2-D plane. It becomes difficult to imagine when the number of features exceeds three” [29].

Let’s consider two independent variables x1, x2, and one dependent variable which is either a blue circle or a red circle as shown in Fig. 2.

Table 1. Attribute information

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	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

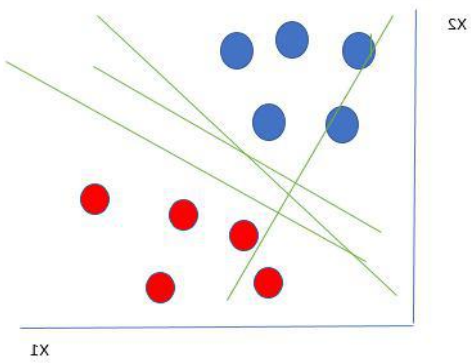

Fig. 2. SVM Hyperplane

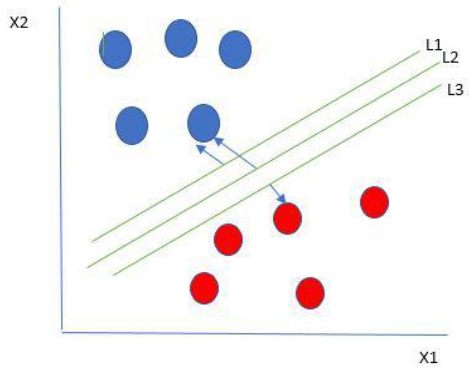

Fig. 3. Selection of best-fit hyperplane

From Fig. 2, it's very clear that there are multiple lines (our hyperplane here is a line because we are considering only two input features x1, x2) that segregates our data points or does a classification between red and blue circles. So, choosing the best line or in general the best hyperplane that segregates our data points is the best option. Selecting the best hyper-plane is one of the most important steps in SVM. One reasonable choice as the best hyperplane is the one that represents the largest separation or margin between the two classes as seen in Fig. 3.

So, choosing the hyperplane whose distance from it to the nearest data point on each side is maximized. If such a hyperplane exists it is known as the maximum-margin hyperplane/hard margin. So, from the above figure, L2 is chosen as the maximum-margin hyperplane/hard margin.

4. RESULTS AND DISCUSSION

This section reviews the outcomes and results of the research. The step-by-step procedure, tools, and methods used in implementing Parkinson's disease classification using the Support Vector Machine Classifier model.

4.1 Distribution of Target Variable

The first step in implementing the Support Vector Machine Classifier model is to check the distribution of the target variables in the dataset. "1" means Parkinson's positive and "0" means Healthy. For the target distribution in the dataset, there are 147 Parkinson's positive cases and 48 Healthy cases as shown in Table 2.

Table 2. Status Table for the dataset

Name	Status
1	147
0	48

4.2 Training and Test Data

In machine learning, the goal is to develop models that can generalize to new, unseen data. To accomplish this, the model typically split our available data into two sets: a training set and a test set. The training set is used to train the model. The model learns from the training data, adjusting its parameters to minimize the error on this set [30]. The model should not have access to the test set during training, as this would allow it to overfit the test set, which would result in poor performance on new, unseen data [30].

The test set is used to evaluate the performance of the trained model. Once the model has been trained, it is evaluated on the test set to measure its performance on new, unseen data. This is important because the goal is not just to fit the training data well, but also to generalize well to new data [31]. Fig. 4 shows the screenshot of the trained dataset after splitting and X was used to represent.

4.3 Accuracy of Training and Test Data

Implementing the model on both train and test data after importing the SVM library as shown in Fig. 5. The accuracy of the model for both training and test data is evaluated to determine if the model can be used or not. It was observed from Fig. 5 that the accuracy on training data was "0. 8846153846153846" while the accuracy

on training data was “0. 8717948717948718”. The model showed enough accuracy to use for the prediction of Parkinson’s disease whether an individual is healthy or not.

4.4 Confusion Matrix

A confusion matrix is a table that is used to describe the performance of a classification algorithm, such as a supervised machine learning algorithm [32]. Each row of the matrix represents the instances in a predicted class, while each column represents the instances in an actual class (or vice versa) [32-34]. For the research, a confusion matrix for both the test and training data sets was generated to represent instances of the predicted and actual classes. For the test data set, the confusion matrix was generated as seen in Table 3, and trained data in Table 4.

```
print(X_train)
```

```
[[ 0.63239631 -0.02731081 -0.87985049 ... -0.97586547 -0.55160318
   0.07769494]
 [-1.05512719 -0.83337041 -0.9284778  ...  0.3981808  -0.61014073
   0.39291782]
 [ 0.02996187 -0.29531068 -1.12211107 ... -0.43937044 -0.62849605
  -0.50948408]
 ...
 [-0.9096785  -0.6637302  -0.160638   ...  1.22001022 -0.47404629
  -0.2159482 ]
 [-0.35977689  0.19731822 -0.79063679 ... -0.17896029 -0.47272835
   0.28181221]
 [ 1.01957066  0.19922317 -0.61914972 ... -0.716232    1.23632066
  -0.05829386]]
```

Fig. 4. Screenshot of trained data

```
# Model Training

# Support Vector Machine Model
model = svm.SVC(kernel='linear')
```

```
# training the SVM model with training data
model.fit(X_train, Y_train)
```

```
SVC(kernel='linear')
```

```
# accuracy score on training data
X_train_prediction = model.predict(X_train)
training_data_accuracy = accuracy_score(Y_train, X_train_prediction)
```

```
print('Accuracy score of training data : ', training_data_accuracy)
```

```
Accuracy score of training data :  0.8846153846153846
```

```
print('Accuracy score of test data : ', test_data_accuracy)
```

```
Accuracy score of test data :  0.8717948717948718
```

Fig. 5. Implementation of SVM algorithm and Accuracy of Training data

Table 3. Confusion matrix for test data

	Actual True	Actual False
Predicted True	5	3
Predicted False	2	29

Table 4. Confusion matrix for training data

	Actual True	Actual False
Predicted True	27	13
Predicted False	5	111

```
input_data = (197.07600,206.89600,192.05500,0.00289,0.00001,0.00166,0.00168,0.00498,0.01098,0.09700,0.00563,0.00680,0.0

# changing input data to a numpy array
input_data_as_numpy_array = np.asarray(input_data)

# reshape the numpy array
input_data_reshaped = input_data_as_numpy_array.reshape(1,-1)

# standardize the data
std_data = scaler.transform(input_data_reshaped)

prediction = model.predict(std_data)
print(prediction)


if (prediction[0] == 0):
  print("The Person does not have Parkinsons Disease")

else:
  print("The Person has Parkinsons")
```

```
[0]
The Person does not have Parkinsons Disease
```


Fig. 6. Parkinson Predictive System

4.5 Building the Breast Cancer Predictive System

The aim of the study was to build a system that could easily predict if a person had Parkinson disease or not based on input values. Fig. 6 shows the Parkinson's disease predictive system. A sample value was inputted into the system to determine if a patient was healthy or not. The input data shows that the output as "The person does not have Parkinson's Disease".

5. CONCLUSIONS

In conclusion, the research paper highlighted the effectiveness of the SVM machine learning technique in the early detection of Parkinson's disease. The study focused on the use the SVM machine learning algorithms to classify Parkinson's disease patients and healthy individuals using various features extracted from voice recordings. The results demonstrate that the Support Vector Machine algorithm performed with an accuracy of 88.46%.

The study has significant implications for the early diagnosis of Parkinson's disease, which can help in the timely treatment and management of the disease. The use of machine learning algorithms in the diagnosis of Parkinson's disease has the potential to reduce the number of false negatives and false positives, thus providing more accurate diagnoses and better patient care. Furthermore, the study demonstrates the potential for using voice recordings as a non-invasive and cost-effective tool for the early detection of Parkinson's disease.

However, further research is needed to validate the results of this study using a larger and more diverse dataset. Additionally, future research should focus on the development of more sophisticated machine learning models that can leverage various types of data to enhance the accuracy of Parkinson's disease detection.

In summary, the study provides strong evidence for the effectiveness of machine learning in the early detection of Parkinson's disease, which has significant implications for the development of better diagnostic tools and improved patient care.

REFERENCES

1. Obeso JA, Martinez-Lage JM, Luquin MR, Bolio N. Intravenous lisuride infusion for Parkinson's disease. Annals of Neurology. 14:252.
PMID 6625541
DOI: 10.1002/ANA.410140213
2. Parkinson's Foundation. Parkinson's Disease; 2021.
Available:https://www.parkinson.org/Understanding-Parkinsons/What-is-Parkinsons
3. Obeso JA, Grandas F, Vaamonde J, Rosario Luguin M, Martínez-Lage JM. Apomorphine infusion for motor fluctuations in Parkinson's disease. Lancet (London, England). 1:1376-7.
PMID 2884483
DOI: 10.1016/S0140-6736(87)90679-9

4. Liu G, Yao L, Liu J, Jiang Y, Ma Y, Ma X, Zheng X. Identification of 25 new susceptibility loci for Parkinson's disease. Nature Genetics. 2021;53(7):826-837.
5. Schuepbach WMM, Tonder L, Schnitzler A, Krack P, Rau J, Hartmann A, Volkmann J. Long-term effects of early subthalamic nucleus deep brain stimulation in Parkinson's disease. The Lancet Neurology. 2021;20(2):107-118.
6. Mollenhauer B, Batrla R, El-Agnaf OM, Galasko DR, Lashuel HA, Merchant KM, Shaw LM. A user's guide for α-synuclein biomarker studies in biological fluids: Perianalytical considerations. Movement Disorders. 2020;35(9):1621-1633.
7. Romano S, Savva GM, Bedarf JR, Charles IG, Hildebrand F, Narbad A. Meta-analysis of the Parkinson's disease gut microbiome suggests alterations linked to intestinal inflammation. NPJ Parkinson's Disease. 2021;7(1):27.
8. Gómez-Verdejo V, Fernandez-Garcia C, Sanchez-Ferro A, Alvarez I. Using machine learning to predict bradykinesia severity in Parkinson's disease patients. Scientific Reports. 2019;9(1):1-10.
9. Warmerdam E, Hausdorff JM, Atrsaei A, Zhou Y, Mirelman A, Rochester L. Long-term monitoring of Parkinson's disease using wearable sensors: A comparison of monitoring completeness and accuracy between clinic-based and unsupervised at home settings. Journal of Parkinson's Disease. 2020;10(4):1511-1519.
10. Little S, Beudel M, Zrinzo L, Foltynie T, Limousin P, Hariz M, Neal S. (Bilateral adaptive deep brain stimulation is effective in Parkinson's disease. Journal of Neurology, Neurosurgery, and Psychiatry. 2018;89(7):710-714.
11. Espay AJ, Hausdorff JM, Sanchez-Ferro A, Klucken J, Merola A, Bonato P, Maetzler W. A roadmap for implementation of patient-centered digital outcome measures in Parkinson's disease obtained using mobile health technologies. Movement Disorders. 2020;35(1):48-54.
12. Kanakaprabha S, Arulprakash P, Srikanth R. Parkinson Disease Detection Using Various Machine Learning Algorithms, 2022 - International Conference on Advanced Computing Technologies and Applications (ICACTA), Coimbatore, India. 2022;1-6. DOI:10.1109/ICACTA54488.2022.9752925
13. Raundale P, Thosar C. and Rane, S. Prediction of Parkinson's disease and severity of the disease using Machine Learning and Deep Learning algorithm, 2021 2nd International Conference for Emerging Technology (INCET), Belagavi, India. 2021;1-5, DOI: 10.1109/INCET51464.2021.9456292
14. Vigneswari DA, Aravinth J. Parkinson's disease Diagnosis using Voice Signals by Machine Learning Approach, 2021 - International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT), Bangalore, India. 2021;869-872. DOI:10.1109/RTEICT52294.2021.9573689
15. Agarwal A, Chandrayan S, Sahu SS. Prediction of Parkinson's disease using speech signal with Extreme Learning Machine, 2016 - International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT), Chennai, India. 2016;3776-3779. DOI: 10.1109/ICEEOT.2016.7755419
16. Gokul S, Sivachitra M, Vijayachitra S. Parkinson's disease prediction using machine learning approaches, 2013 Fifth International Conference on Advanced Computing (ICoAC), Chennai, India. 2013;246-252, DOI: 10.1109/ICoAC.2013.6921958.
17. Kumar T, Sharma P, Prakash N. 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;0195-0199. DOI:10.1109/UEMCON51285.2020.9298033
18. Wasif T, Hossain MIU, Mahmud A. Parkinson disease prediction using feature selection technique in machine learning, 2021 - 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India. 2021;1-5. DOI:10.1109/ICCCNT51525.2021.9580151
19. Balakrishnan A, Medikonda J, Namboothiri PK, Natarajan M. Parkinson's Disease Stage Classification with Gait Analysis using Machine Learning Techniques and SMOTE-based Approach for Class Imbalance Problem, 2022 - International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics

(DISCOVER), Shivamogga, India. 2022; 277-281. DOI:10.1109/DISCOVER55800.2022.9974754.
20. Shaw M, Garlan D. Software architecture: perspectives on an emerging discipline. Prentice-Hall, Inc; 1996.
21. Kruchten P. The rational unified process: an introduction (3rd ed.). Addison-Wesley Professional; 2004.
22. Little RJA, Rubin DB. Statistical Analysis with Missing Data (3rd ed.). John Wiley & Sons; 2019.
23. Alpaydin E. Introduction to Machine Learning (3rd ed.). The MIT Press; 2020.
24. Kelleher JD, Tierney B, Tierney B. Data Science An Introduction. CRC Press; 2015.
25. Doan A, Halevy A, Ives ZG. Principles of Data Integration. Elsevier; 2012.
26. Kohavi R, John GH. Wrappers for feature subset selection. Artificial Intelligence. 1997;97(1-2):273-324.
27. Boser BE, Guyon IM, Vapnik VN. A training algorithm for optimal margin classifiers. Proceedings of the Fifth Annual Workshop on Computational Learning Theory. 1992;144-152.
28. Schölkopf B, Smola AJ. Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond. MIT Press; 2002.
29. Geeks; 2023. Available:https://www.geeksforgeeks.org/support-vector-machine-algorithm/
30. Hastie T, Tibshirani R, Friedman J. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer; 2009.
31. Goodfellow I, Bengio Y, Courville A. Deep Learning. MIT Press; 2016.
32. Johnson RA, Wichern DW. Applied Multivariate Statistical Analysis, Prentice-Hall; 2002.
33. Oh SL, Hagiwara Y, Raghavendra U, Yuvaraj R, Arunkumar N, Murugappan M, Acharya UR. A deep learning approach for Parkinson's disease diagnosis from EEG signals. Neural Computing and Applications. 2020;32:10927-33.
34. Pantaleo E, Monaco A, Amoroso N, Lombardi A, Bellantuono L, Urso D, Lo Giudice C, Picardi E, Tafuri B, Nigro S, Pesole G. A machine learning approach to Parkinson's disease blood transcriptomics. Genes. 2022;13(5):727.

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