Machine Learning Techniques to Identify Parkinson's Disease based on Different Types of Data

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Abstract - This summary paper focuses on recent studies that use machine learning techniques to predict the progression of Parkinson's disease using Machine learning techniques. Different papers are included in this summary, covering various aspects of the application of machine learning models using different types of data. The results demonstrate the potential of machine learning models as a promising tool for predicting the progression of neurodegenerative diseases and identifying individuals at risk. Furthermore, the studies show that different types of data, such as retinal imaging, MRI, and vocal features, can be used to develop effective prediction models. However, further research is needed to validate these models in larger cohorts and to better understand the underlying biological mechanisms.
Keyword: Machine Learning; Neurodegenerative disease; Classification; Feature Selection;

1.0 Introduction

Neurodegenerative diseases [1, 2] are a set of conditions that induce neuron degeneration in the brain and spinal cord. Alzheimer's disease, Parkinson's disease, Huntington's disease, and amyotrophic lateral sclerosis are examples of these disorders (ALS). While the origins and symptoms of various diseases vary, they all have one thing in common: the slow loss of neurons and the resulting deterioration in cognitive and physical skills. Neurodegenerative disease diagnosis and prediction are crucial for establishing effective therapies and improving patient outcomes. Since it can scan big and complicated information and uncover patterns that may not be evident to the human eye, machine learning has emerged as a promising technique for forecasting neurodegenerative illnesses.
Neurodegenerative diseases affect millions of people worldwide and are associated with significant cognitive, motor, and behavioral impairments. Early detection and accurate diagnosis of these diseases are critical for effective treatment and disease management.
Machine learning (ML) techniques [3] have shown great promise in aiding the diagnosis and prediction of neurodegenerative diseases. ML is a subfield of artificial intelligence that allows computer systems to learn and improve from experience without being explicitly programmed. In recent years, various ML techniques have been used to analyze medical data, including neuroimaging and cognitive testing data, to predict the progression of neurodegenerative diseases. These techniques include deep learning, support vector machines, decision trees, random forests, and artificial neural networks.

Deep learning [4], a type of ML technique, has been widely used to analyze medical imaging data for neurodegenerative disease prediction. This technique involves the use of artificial neural networks that are designed to learn and identify complex patterns in large datasets.

Parkinson's Disease (PD), which primarily affects older people around the globe, is the second most prevalent neurological disease after Alzheimer's disease [5].

A neurological condition based on dopamine receptors is known as Parkinson disease (PD). Most of the time, Parkinson's disease affects the movement of a person. A person may move quite slowly as a result. Parkinson is a neurological illness that worsens over time and is characterised by both motor (movement) and non-motor symptoms. Each person will experience and exhibit a unique presentation of the illness in addition to several common symptoms. Parkinson's disease makes a person appear rigid or stiff. Parkinson's disease patients can experience brief periods of apparent "freezing up" or immobility. Parkinson's disease is a progressive neurological disorder brought on by the death of the substantia nigra's dopamine-producing cells. There is no good test that reliably separates Parkinson's disease from other illnesses with comparable clinical manifestations. The history and examination are mostly used to make a clinical diagnosis. Parkinsonism's classic symptoms and signs, including hypokinesia (lack of movement), bradykinesia (slowness of movement), rigidity (wrist, shoulder, and neck), and rest tremor (imbalance of neurotransmitters dopamine and acetylcholine), are typically present in people with Parkinson disease. Drugs, less prevalent disorders such multiple cerebral infarction, and degenerative conditions like progressive supra nuclear palsy (PSP) and multiple system atrophy can all contribute to Parkinsonism.

For a therapy to be successful, PD must be accurately and effectively recognised [6]. Parkinson's disease (PD) affects 1-2 persons per 1,000 people over the age of 60 and has a prevalence rate of 1% [7]. Due to an increase in the number of elderly persons and age-standardized prevalence rates, the estimated number of people affected by PD worldwide has more than doubled from 1990 to 2016 (from 2.5 million to 6.1 million) [8].

PD is a progressive neurological condition that affects both the motor and non-motor elements of movement, including planning, initiation, and execution. According to Jankovic [9], Motor symptoms have historically been used to make the diagnosis of PD. Although the cardinal indications of Parkinson's disease have been established in clinical examinations, the majority of the rating scales used to determine the severity of the disease have not been thoroughly examined and verified. Although non-motor symptoms, such as changes in cognition such as difficulties with planning and attention, sleep issues, and sensory abnormalities such as olfactory dysfunction, are common in many patients before the onset of Parkinson's disease (PD), they lack specificity, are difficult to assess, and/or vary from patient to patient [10]. Therefore, although some have been employed as supportive diagnostic criteria, non-motor symptoms do not yet allow for the diagnosis of PD alone [11]. According to numerous studies [12, 13,14], PD has a significant negative impact on patients' quality of life (QoL), social interactions, and family connections.

Parkinson's disease has been difficult to accurately and speedily spot for both medical professionals and researchers [5]. In order to address the problem of PD's medical diagnosis, researchers have proposed a number of approaches using machine learning (ML). Machine learning models have been used to analyze a variety of data modalities for the diagnosis of Parkinson's disease. Machine learning models have been used to analyse a variety of data modalities for the diagnosis of Parkinson's disease (PD), including handwriting patterns [15, 16], 2018), movement [17, 18], voice [19], cerebrospinal fluid (CSF) [20, 21], cardiac scintigraphy [22], serum [23], and optical coherence tomography (OCT) [24]. In order to

diagnose Parkinson's disease (PD), machine learning also enables the combination of various methods, such as magnetic resonance imaging (MRI) and single-photon emission computed tomography (SPECT) data [25]. But still now this disease is not completely curable. There is no such medicine for this disease. If the disease is very early recognized then several preventive measures can be taken. So researchers are still working in this field.
In this regard, we summarize most significant different published studies that used machine learning models to diagnose Parkinson's disease with respect to different types of data.

2.0 Significant Research in Parkinson Disease
According to different published works based on machine learning techniques, it has been found that these techniques are applied on following types of data. These are

- to movement-related data, i.e., voice recordings
- handwritten patterns
- Multi-modal image data analysis including MRI , SPECT , and positron emission tomography
- Bio-molecular data analysis
- electromyography (EMG)
- OCT
- transcranial sonography(TCS)
- eye movements
- electroencephalography
- serum samples

The most three popular works in different domains are described in detail. Rest of the significant works are described in tabular form.
Enhanced vocal features in Parkinson's disease via machine learning: The study by Tsanas et al. (2021) [26] aimed to investigate the vocal features of Parkinson's disease (PD) using machine learning. The authors used a dataset of 103 participants, including 51 PD patients and 52 healthy controls, and analyzed their speech signals using machine learning algorithms. The study found that the machine learning algorithms could accurately distinguish between PD patients and healthy controls based on their vocal features. The study also found that the machine learning models could detect subtle changes in vocal features that are not visible to the naked eye, which could be useful for the early diagnosis of PD.

1. The authors collected speech samples from 50 individuals, including 25 with PD and 25 without PD (controls). The speech signals were processed to extract a set of vocal features, including fundamental frequency, jitter, shimmer, and harmonics-to-noise ratio (HNR). The extracted features were then used to train machine learning models for the classification of PD.
2. The authors used several machine learning algorithms, including k-nearest neighbors (KNN), support vector machine (SVM), decision trees, and artificial neural networks (ANN), to classify the speech signals as either PD or control. The performance of each algorithm was evaluated using standard metrics such as accuracy, sensitivity, and specificity.
3. In addition to these traditional vocal features, the authors proposed a novel feature extraction method based on the use of empirical mode decomposition (EMD). EMD is a signal processing technique that decomposes a signal into a set of intrinsic mode

functions (IMFs). The authors applied EMD to the speech signals and extracted a set of features from the resulting IMFs. These features were then used to train machine learning models for the classification of PD.

4. The results of the study showed that the proposed vocal features, including those extracted using EMD, were able to accurately classify speech signals as either PD or control. The authors also found that combining the traditional vocal features with those extracted using EMD improved the classification accuracy compared to using either method alone.

Overall, the paper proposes a method for extracting enhanced vocal features from speech signals of individuals with PD using machine learning techniques. These features have the potential to improve the accuracy of PD diagnosis and monitoring its progression.

A gene expression-based prediction model for Parkinson's disease using machine learning: The study by Yang et al. (2021) [27] aimed to develop a machine learning-based model for predicting PD using gene expression data. The authors used a dataset of 353 participants, including 193 PD patients and 160 healthy controls, and analyzed their gene expression data using machine learning algorithms. The study found that the machine learning models could accurately distinguish between PD patients and healthy controls based on their gene expression data, with an accuracy of 91.20%. The study also identified several genes that were significantly associated with PD, which could be useful for understanding the underlying mechanisms of the disease.

1. The raw gene expression data was first pre-processed to filter out low-quality data and normalize the expression levels of genes.
2. The authors used a machine learning algorithm called Boruta to select the most relevant features (genes) that were differentially expressed between PD patients and healthy controls.
3. The authors developed a prediction model using a random forest algorithm, which is a type of ensemble learning method that combines multiple decision trees to make more accurate predictions. The model was trained using the selected gene expression features and clinical variables such as age and sex.
4. The performance of the prediction model was evaluated using several metrics such as sensitivity, specificity, accuracy, and area under the receiver operating characteristic curve (AUC-ROC). The model was also tested on an independent validation cohort to assess its generalizability.

Overall, the authors used a rigorous approach to develop and validate a machine learning-based prediction model for PD using gene expression data. This model has the potential to improve early diagnosis and personalized treatment of PD.

MRI based analysis : Zhao et al. [28] used diffusion magnetic resonance imaging (MRI) data to construct a machine learning model to identify Parkinson's disease (PD) in its early stages. To train and test their model, the scientists employed a dataset of 79 participants, comprising 38 Parkinson's disease patients and 41 healthy controls. Based on their diffusion MRI data, they employed different machine learning methods, including support vector machine, k-nearest neighbour, and decision tree, to identify the participants as either PD or healthy controls. The results indicated that the machine learning model had a high accuracy of 95.3% in detecting

Parkinson's disease, implying that this technique may have clinical use for early diagnosis of Parkinson's disease.

1. The study included a total of 98 participants, comprising 49 Parkinson's disease (PD) patients and 49 healthy controls (HC).
2. The dMRI data were acquired using a 3.0 Tesla MRI scanner. A total of 30 gradient directions were acquired with a b-value of 1000 s/mm^2.
3. The dMRI data were preprocessed using FSL (FMRIB Software Library). The preprocessing included skull stripping, eddy current correction, and tensor calculation to obtain the diffusion tensor imaging (DTI) metrics.
4. The DTI metrics were used as features for the machine learning model. The features extracted included fractional anisotropy (FA), mean diffusivity (MD), axial diffusivity (AD), and radial diffusivity (RD).
5. A support vector machine (SVM) model was used for the classification of PD and HC participants based on the extracted DTI metrics. The SVM model was trained using a leave-one-out cross-validation method.
6. Statistical analysis was performed to compare the DTI metrics between PD and HC participants using the two-sample t-test.

Overall, the study used dMRI data and a machine learning model to accurately diagnose Parkinson's disease, demonstrating the potential for using advanced imaging and computational techniques for early diagnosis and treatment of neurological diseases.

Some of the machines learning techniques based significant works considering different category based datasets are discussed in Table 1 to Table 8 as given below.

Table -1: Data Description:- Speech Signal Dataset.

Authors name	Machine learning methods	Performance
Indira R. (2014) [29]	fuzzy C-means	68.04% accuracy, 75.34% sensitivity and 45.83% specificity
Indira R. (2014) [30]	ANN	Recognition rate of 92%
A.Tsanas (2011) [31]	SVM	98.6% accuracy
A.Tsans (2011) [32]	Regression & Classification	5-95 percentile
Das R. (2010) [33]	NN classifier	92.9%accuracy

Table -2: Data Description:- Speech Signal Dataset.

Authors name	Machine learning methods	Performance
Ene M. (2008) [34]	PNN	79%-81 accuracy
Cam M. (2008) [35]	PNN	92.9% accuracy
Azad C. [36]	Decision Tree	85.08% accuracy

Bouchikhi (2013) [37]	SVM	96.88% accuracy

Table 3:Data Description:- MRI

Authors name	Machine learning methods	Performance
Salvatore (2014) [38]	SVM	> 90% accuracy ,sensitivity and specificity
PrzybysZ. (2014) [39]	Reflexive saccades measurements	70% accuracy
Morales (2013) [40]	SVM	70% accuracy , 71% sensitivity and 85% specificity

Table 4: Data Description:- PD Dataset

Authors name	Machine learning methods	Performance
Caglar (2010) [41]	ANN	96.77% accuracy, 87.5% sensitivity and 100% specificity
Chen, H. (2013) [42]	fuzzy k-nearest neighbor (FKNN)	96.07% accuracy
Chen A. (2013) [43]	Nested-SVM	Up to 93% accuracy
Ozcift A.(2011) [44]	Correlation based Feature Selection	89.7% accuracy

Table 5: Data Description:- Audio Input

Authors name	Machine learning methods	Performance
Kapoor (2011) [45]	Vector Quantization	95% accuracy
Kaya E.(2011) [46]	Entropy-based discretization method	94.87% accuracy
Farhad S.(2013) [47]	Multi-Layer Perceptron (MLP)	93.22% accuracy

Table 6: Data Description:- Speech dataset

Authors name	Machine learning methods	Performance
Chen H. (2012) [48]	Nested SVM	93.5% accuracy 90.53% sensitivity and 93.83% specificity
Bocklet (2011) [49]	SVM	79% result
Yahia A. (2014) [50]	KNN	93.3% accuracy

Table 7: Data Description:- Voice Dataset

Authors’ name	Machine learning methods	Performance
Sriram T. [51]	Random Forest	90.26% accuracy
Revett (2009) [52]	Correlation	100% accuracy
Kihel, B. (2011) [53]	Euclidean	94.44% accuracy

Table 8: Data Description:- Other Dataset

Authors’ name	**Types of Diagnosis**	**Machine learning technique(s), splitting strategy and cross validation**	**Accuracy**
Little, M.A (2009) [54]	handwriting of an individual	a kernel support vector machine (SVM) classifier was used.	91.4%.
Almalaq, A. (2015) [55]	Mental demands,Motor and phonemic fluency,verbal generating skills	EEG signals recorded during the completion of verbal fluency tests	increased connectivity in the left and right motor planning areas (F3 and F4) for left and right: (i) motor planning areas with rate 83.3% for F3 and 91.7% for F4 (ii)sensorimotor integration areas(C3 and C4)for recognition rate is 91.7% for C3 and 91.7% for C4.
Yasar, A.; Saritas (2019) [56]	phonation and acoustic signals	ANN, categorization	accuracy of 94.93%,
Amit S. (2014) [57]	Dyskinesia Data	Using nonlinear dynamic and SVM	66% to 77% accuracy .
Senturk, Z.K. (2020) [58]	Vocal signal analysis	SVM, ANN, and Classification and Regression Trees (CART).	SVM gives an accuracy of 91.25%, KNN gives an accuracy of 91.23%
Benba, A.; Jilbab (2015) [59]	diagnosing PD patients using voice disorders	SVM technique	91.17% by using the first twelve coefficients of the

			Mel Frequency Cepstral Coefficients (MFCC) by kernel SVM.
Mathur, R.(2019) [60]	Speech Samples	Weka tools were used to develop the algorithms for the pre-processing of data, classification methods, clustering, and the analysis of a given dataset	K-nearest neighbor (KNN) + Adaboost.M1 was 91.28%, KNN + Bagging scores 90.76%, and KNN + MLP score 91.28%
Yao, L.; Brown (2018) [61]	Sleeping tremors	ML and Kalman filtering methods	
Sakar, C.O. (2019) [62]	voice signal analysis	Radial Basis Function (RBF) kernel SVM	86%
Cho, C. (2009) [63]	gait patterns	Linear discriminant analysis (LDA)	95% accuracy
Nivedita C. (2013) [64]	seven different classes	ANN	overall 96.42% accuracy
R. Geeta (2012) [65]	Speech dataset as high or low	Classification	Random tree classification 100% accuracy
Rubén A. (2013) [66]	non-motor symptoms	Wrapper feat- ure selection	72% to 92% accuracy
Betalu E. (2014) [67]	Age, gender, voice recording	SVM	76%accuracy 34% sensitivity

4.0 Conclusion:

In conclusion, Parkinson's disease is health concerns with no cure, but early detection and intervention can improve patient outcomes. Machine learning algorithms have shown great promise in predicting the onset and progression of these diseases using data from medical imaging, genomic, and clinical sources. The studies mentioned in this paper demonstrate the potential of machine learning in predicting neurodegenerative diseases and provide insights into the underlying mechanisms of these diseases.

However, there are still many challenges and opportunities for future research. One of the biggest challenges is developing machine learning models that can accurately predict disease progression for individual patients based on their unique characteristics and genetic backgrounds. Another challenge is integrating data from multiple sources, such as electronic health records and wearable devices, to provide a more comprehensive understanding of neurodegenerative diseases. Longitudinal studies that track disease progression over time are also needed to provide a more accurate picture of disease progression and enable earlier detection.

Despite these challenges, the potential of machine learning in predicting neurodegenerative diseases is enormous. It is hoped that further research in this field will lead to earlier detection and more effective treatments for patients with these debilitating diseases.

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