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A COMPREHENSIVE REVIEW ON PARKINSON'S DISEASE DETECTION TECHNIQUES

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ABSTRACT

Millions of people worldwide suffer from Parkinson's disease (PD), a progressive neurodegenerative illness that manifests both motor and non-motor symptoms. Effective intervention depends on early and precise detection. Recent developments in PD detection using a variety of modalities, including neuroimaging, speech, handwriting, gait, and wearable sensor data, are reviewed in this survey. It highlights how crucial feature extraction, classification, and preprocessing methods are to improving diagnostic performance. The advantages, drawbacks, and clinical applicability of machine learning, deep learning, and transfer learning methodologies are examined in this paper. New developments indicate that multimodal systems hold increasing promise for increased accuracy. The need for explainable AI, high computational costs, and data imbalance are major obstacles. All things considered, the review emphasizes integrative techniques as a viable path toward scalable and trustworthy PD detection.

Keywords: Parkinson's Disease (PD), Machine Learning (ML), Deep Learning (DL), Artificial Intelligence (AI), Quantum Machine Learning (QML), Neurodegenerative illness.

1. INTRODUCTION

Parkinson's disease (PD) is a progressive neurodegenerative disorder first described by James Parkinson in 1817, and today it stands as the second most prevalent neurodegenerative condition after Alzheimer's Disease. It primarily affects middle aged and old aged individuals. James Parkinson described in his essay named "An Essay on the Shaking Palsy" about its conditions and symptoms.PD is defined by the degeneration of dopamine-producing neurons in the brain, present in substantia nigra. Dopamine is the neurotransmitter involved in controlling movement. When these dopamine-producing neurons begin to deteriorate,the symptoms of Parkinson's like tremors, stiffness, and slowness of movements, start to show.

Today, there are many different competing theories on how Parkinson's develops. While dopamine deficiency clearly contributes to the disease's symptoms, Parkinson's is now largely considered a synucleinopathy, a condition linked to the abnormal behavior of a protein called alpha-synuclein in the brain. Yet, despite its strong association with the disease, scientists still don't fully understand the exact role alpha-synuclein plays in how Parkinson's begins or progresses. Clinical symptoms of PD can be divided into motor symptoms and non-motor symptoms, motor symptoms result from a decrease in dopamine, including resting tremor, bradykinesia, muscle rigidity, postural instability and difficulty in balancing. Overtime these symptoms increase and it can be challenging to perform daily tasks like eating, walking and dressing etc. Non-motor symptoms include mental symptoms, mood disorders, sleep problems, cognitive function change, language barrier and autonomic nervous dysfunction. Well known symptoms of PD are as depicted in figure 1. Although most PD cases are sporadic and of unknown cause, research points to a complex interplay of genetic and environmental influences. Familial clustering is observed in 5–15% of cases, while environmental exposures such as to pesticides are implicated in many sporadic cases. At the cellular level, processes such as mitochondrial dysfunction, oxidative stress, neuroinflammation, impaired autophagy, and α-synuclein aggregation are believed to drive neurodegeneration. Clinically, diagnosing PD relies on the presence of cardinal motor signs, as there is no definitive laboratory or imaging test. Current treatments focus on symptom relief, primarily aiming to restore dopamine function through medications like levodopa, dopamine agonists, or enzyme inhibitors. While these therapies improve quality of life, they do not halt disease progression making the search for disease-modifying treatments an urgent priority

It has been reported that 50 years aged people or older have been suffering from Parkinson's Disease (PD). It appears more often in men than women. As the global increase in life expectancy and population the prevalence of Parkinson's disease is becoming a significant public health concern. Reports suggest that the number of people living with PD might double as of now in the next two decades. This growing prevalence highlights the urgent need to better understand the causes of disease, reasons behind its rising incidence and the importance of early diagnosis. Early detection of PD is crucial for effective management, but traditional diagnostic methods can be subjective and limited.

The diagnosis of PD is usually made through a combination of clinical examination and neurological tests or by observing a person's symptoms, especially movement-related ones such as tremors, slow movement (bradykinesia), muscle stiffness, and balance problems. Doctors use clinical guidelines like those from the UK Parkinson's Disease Society or the Movement Disorder Society to support their diagnosis. Though Brain imaging techniques like MRI, CT, PET, EEG cannot be used to detect Parkinson's disease, they are useful in ruling out the possibility of other conditions like ET(Essential Tremor) which possess similar conditions. EEG (electroencephalography), which records brain activity, is not usually helpful in early stages of Parkinson's because it often appears normal. However, recent research is exploring advanced methods like quantitative EEG (qEEG)[11] to detect subtle brain wave changes, especially in patients with memory or thinking problems. In some cases a DaTscan, a special imaging test that shows dopamine levels in the brain can help clarify the diagnosis. Despite these developments, there is still no single test to confirm Parkinson's disease, so clinical observation and medical history remain the main tools for diagnosis.

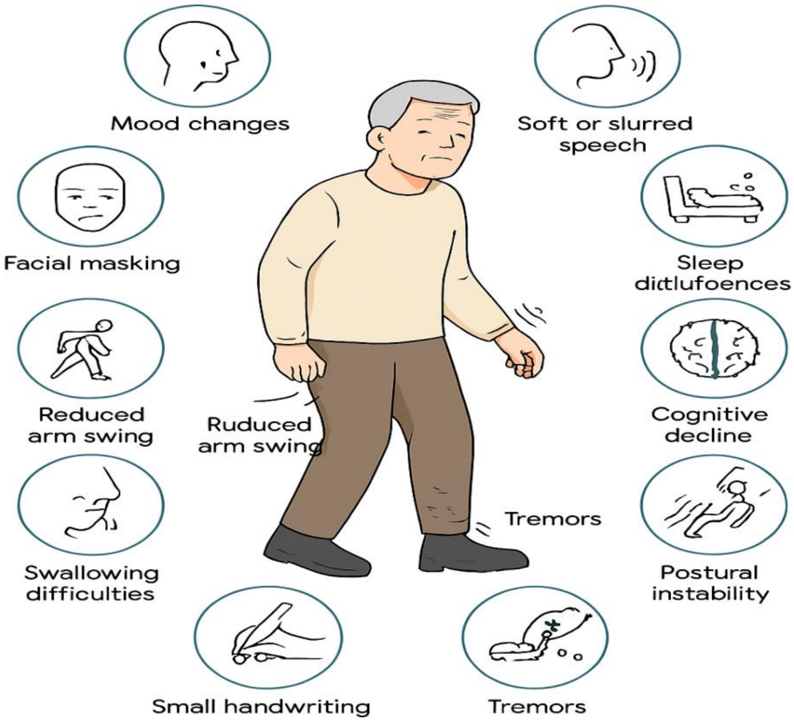

Figure 1: Symptoms of PD

According to recent research, analyzing biomedical audio data can be a viable method for the early detection and diagnosis of Parkinson's disease. In the early stages, it is remarkable that most patients suffer from voice impairment. Thus, recent studies are based on vocal analysis to detect PD patients. Speech signals and other sounds produced by the human body are referred to as biomedical audio data, the use of speech signals in the telediagnosis system is easy and economical. These sounds can reveal important details about the patient's motor symptoms and voice traits. By analyzing the biological audio data, machine learning methods can be used to categorize the patient as having PD or not having PD. The detection of PD is done in three phases mainly, i.e., data preprocessing, feature extraction, and at last the classification process which indicates that a person is having PD or not.

ML and deep learning techniques have been applied widely in the medical field. Deep Learning techniques like CNN(Convolutional neural network) and ANN(Artificial Neural Network) were applied for the voice datasets from the UCI machine learning repository. The results demonstrated that CNN outperformed ANN in classifying PD and healthy individuals, achieving maximum accuracy of 86.9%.[4] Also the study evaluates various classification algorithms or models including Logistic Regression, K-Nearest Neighbours(KNN), Decision Tree, Random Forest, and AdaBoost, based on their accuracy, sensitivity and specificity. .

2. DATASETS FOR PARKINSON'S DISEASE

Method and analysis which is performed in your research work should be written in this section. A simple strategy to follow is to use keywords from your title in first few sentences.

2.1 Voice pattern analysis

The dataset for the PD analysis consists of audio data pertaining to voice modulations of PD patients. There are 31 individuals, out of which 23 individuals were suffering from this disease [9]. There are totally 195 samples which contain columns, where each column refers to voice measure. The dataset was labelled, which gives the difference between the records of healthy individuals (status = 0) and those with Parkinson disease (status=1). These datasets include voice recordings from both the affected individuals and the healthy controls, along with the features like jitter, shimmer, harmonic-to-voice-ratio [17]. It also has a Multidimensional Voice Program (MDVP) that focuses on vocal folds. After preprocessing, analysis and visualization of the data, this data was separated into two parts – part1 (80%) for training machine learning models and part2 (20%) for testing purposes. The initial way is that the dataset is first imported from a pre-defined folder.This data includes voice samples from individuals [18]. Some samples may have noise, while others are clear. Some of the acoustic dataset created by Max Little was recorded at the National Centre for Voice and Speech in Denver. It contains 195 voice recordings from 31 people (23 with PD and 8 healthy patients) and 23 attributes (22 biomedical measures and a status column which takes the value of "1" for PD and "0" for healthy. Voice based Deep learning medical diagnosis system contains the dataset which includes 240 recordings of the sustained for 80 subjects. 40 of them were PD patients (13 women and 27 men) and 40 were healthy people (18 women and 22 men), people of older age than 50 years.

2.2 Handwriting datasets analysis

Researchers found that there are hundreds and lakhs of datasets and databases which are available for the evaluation of handwriting patterns.Some of the datasets consist of handwriting dataset which is available at the Neurology Department. This includes 40 individuals diagnosed with PD. Only 30 of these PD patients were able to participate actively but the remaining 10 individuals were unable to complete the required task. However, the Online Arabic Handwriting dataset for the PD detection contains 30 individuals who are diagnosed with PD (16 women and 14 men) with an average age of 58 years and 30 healthy controls (10 women and 20 men) with an average age of 60 years [5]. The healthy individuals were selected based on the criteria of which no one had essential tremor and no history of intracranial diseases or neurological symptoms. None of the participants had a history of alcohol or drug abuse and none of the healthy controls had a family history of PD. It contains the Movement Disorders Society Unified Parkinson's Disease Rating Scale (MDS-UPDRS) during off and on periods. The neurologists identified the specific phenotypes of PD patients, also differentiated them as either tremor-dominant (TD) or postural instability/gait difficulty (PIGD) subtypes.The severity of Parkinson's disease patients was assessed using the Hoehn and Yahr (H-Y) stage. In this stage, Parkinson's disease patients underwent some examinations during both "Off" and "On" periods. This dataset was created by employing a Wacom digitizing tablet. It mainly consists of 5 tasks. Participants were made to sit in a comfortable chair with a seat height fixed at 45cm.They were instructed to maintain contact between their elbows and a table at a height of 80cm. Participants were instructed to replicate 5 different handwriting tasks which were displayed on the right side of the digitizing tablet.The first task was to trace an ellipse repeatedly for almost thirty seconds.The second task involved drawing a spiral. The third task was to write the digit 8 eight times. The fourth task involved writing Arabic words two times. The last one was tracing the Latin character "1" continuously eight times.

2.3 Finger testing and video processing

This examines concerned video recordings from 90 members which incorporates 66 individuals diagnosed with Parkinson's sickness (PD) and 24 wholesome adults of similar age. The PD individuals had been inside 5 years of prognosis, confirmed by means of a motion disorder professional consistent with the UK PD mind bank criteria. All recordings took place at UF health. participants had been excluded in the event that they had a record of stroke, brain tumors, implanted electrical devices (inclusive of pacemakers or neurostimulators), aneurysm clips, or if they have been pregnant or breastfeeding. Those assembly all requirements completed two recording sessions: a baseline consultation and some other three hundred and 65 days later. For consistency, each consultation changed into carried out in an OFF-medication state, which means individuals refrained from taking Parkinson's medicines overnight earlier than checking out. Those sessions blanketed both motor and cognitive tests, including the MDS-UPDRS III assessment. The PD organization changed into a part of a scientific trial investigating the consequences of rasagiline. However, for the reason that no vast variations were determined among baseline and observe-up rankings for any measured outcomes (along with MDS-UPDRS III), treatment undertaking changed into now not considered as a have a look at variable. Also manipulated members were recruited from the network and finished an unmarried baseline session with comparable motor and cognitive testing [2]. During trying out, all MDS-UPDRS III checks were recorded on video. The setup was made for seating the participant in a chair at the same time as a widespread RGB video camera, hooked up on a tripod, captured their performance at 30 frames in keeping with a second and 1920×1080 resolution. The videos were stored in a local server for later analysis. The duties were guided by a skilled clinician, who additionally supplied overall performance rankings based on predefined criteria—ranging from zero (ordinary motion) to 4 (severe impairment). Some PD participants had simple one video recording (baseline or observe-up), whilst others had recordings at each visit. To ensure fairness in fact illustration, best one recording consistent with player turned into used—baseline motion pictures for those with two recordings, and the unmarried to be had video for others. All healthful controls had one recording. informed consent turned into obtained from all participants, and they have a look at was approved by way of the University of Florida Institutional assessment forums, following the assertion of Helsinki pointers. For evaluation, the MDS-UPDRS III movies have been reviewed to mark the start and give up factors of the Finger Tapping test for both the left and right arms. These segments had been processed using a custom-constructed pipeline. As part of the manner, Google's Media Pipe markerless hand pose estimation and monitoring machine became used to come across and track 21 particular landmarks at the palms like masking the hand's base, joints, and fingertips. This algorithm's accuracy in PD sufferers has been proven in advanced studies. With the help of those landmarks, the angular separation between the thumb and index finger was calculated. This was completed with the help of measuring the perspective shaped among vectors connecting the recommendations of the palms to the base of the hand. This fact was then used for similarity motion and overall performance analysis

2.4 Gesture data analysis

The study gathered gesture data using a custom-built, wrist-worn system equipped with 24 thin, flexible electrodes connected to capacitance sensors [11]. This lightweight and comfortable device measured changes in skin capacitance caused by muscle contractions in the wrist and forearm during different hand movements.Nine healthy participants took part in the experiments [15]. Each person wore the device and was asked to perform six distinct hand and wrist gestures such as finger flexion, wrist flexion/extension, ulnar deviation, radial deviation, and forearm rotation (supination/pronation) [22]. To clearly mark the start and end of movements, each gesture was split into two classes: movement from a relaxed posture to the target position (RM) and return to relaxed posture (MR), resulting in 12 gesture classes in total. Every gesture was repeated 20 times per subject, producing 120 recordings per participant. To ensure consistent timing, a flickering light cue was used—gestures toward the target position were made when the light was on, and return movements were made when it was off. The setup allowed for controlled, repeatable data collection while keeping subjects comfortable and ensuring the dataset captured both motion and rest phases for accurate classification [30]

2.5 MRI images data analysis

The study used MRI scans from the Parkinson's Progression Markers Initiative (PPMI) database. A total of 7,240 images were collected. The images were evenly split into individuals who are affected by Parkinson's disease (PD) and healthy controls, with 3,620 images in each group. All scans were T1-weighted. This method allows for the detection of early changes in the brain's shape, which are promising for diagnosing Parkinson's disease [25]. The scans were saved in JPEG format. These also involve the three main anatomical planes such as axial, coronal, and sagittal. The MRI scanner collects data to create the images [26]. Participants in the PD group had a confirmed diagnosis, while the control group consisted of healthy individuals with no neurological or systemic illnesses. Images with motion blur, incomplete data, or signs of secondary Parkinsonism, such as changes caused by small vessel disease, were excluded to maintain data quality. The study focused on whole-brain scans, allowing the deep learning model to identify important disease-related patterns across the brain instead of just specific areas.The analysis used a DenseNet201 deep learning architecture to extract detailed imaging features from the MRI scans. Instead of a typical softmax classifier, the network's output is connected to a pattern recognition neural network with three dense layers for final classification [27]. The workflow included image resizing, pixel value normalization, feature extraction, pooling, and classification [29].The dataset was divided in the ratio 80:20 where 80% used for training and remaining 20% for testing datasets. Model training moved quickly, with the best accuracy reached by the 15th epoch. On the validation set, the model achieved 99.4% accuracy, 99.5% precision, 99.3% recall, and an F1 score of 99.4%. On the test set, it achieved 99.2% accuracy, 99.3% precision, 99.1% recall, and a 99.2% F1 score. Confusion matrices and ROC curves showed the model's strong ability to differentiate PD cases from controls, reflecting high sensitivity and specificity.

Table 1: Parkinson's Disease Datasets

Published Year	Author	Dataset Used	Total Samples	Type of Dataset	Description
2020	Julian D. Loazia Duque. [10]	Disorders Unit of the Hospital Clinic of Barcelona	19 PD patients, 20 ET patients, and 12 HS	Angular Velocity	Collected with built in gyroscope of iPhone 5S
2022	Audil Hussain. [9	National Centre for Voice and Speech	195 recordings from 31 people	Voice	Voice Dataset by Max Little with 23 PD and 8

	]				Healthy cases.
2023	Raziya Begum [6]	Parkinson's Progression Markers Initiative (PPMI) MRI dataset	700+ Patients	MRI	MRI and clinical data from the PPMI dataset includes PD,Healthy and SWEDD cases.
2023	Hongli Chang [11]	Odd Ball Data	24 individuals	EEG	EEG signals were recorded.
2018	Donato Impedovo [5]	Patients at First Department of Neurology, Masaryk University and at the St. Anne's University Hospital, in Brno, Czech Republic	75 individuals	Handwriting tasks	The individuals were asked to do writing..
2024	Diego L. Guarín [2]	Diagnosis confirmed by movement disorders specialist using the UK PD Brain Bank diagnostic criteria.	66 PD and 24 Healthy individuals	Finger Tapping Test	All study-related data acquisition sessions occurred at UF Health.

3. PARKINSON'S DISEASE CLASSIFICATION FRAMEWORK

As shown in figure 2, a usual Parkinson's Disease classification process starts by collecting data from different sources. The data is then cleaned to remove noise. Next, important features are extracted and separated to find useful patterns. These features are selected and given to ML algorithms. The algorithms learn to tell the difference between healthy people and those with Parkinson's Disease. Finally, the model is tested and its performance is checked using measures like accuracy, precision, specificity and sensitivity.

3.1 Dataset Collection

Dataset collection is the process of gathering organized data from various sources to form a structured and accessible set of information for analysis, processing, and machine learning. This collection can involve collecting structured data, such as numbers in a table, or unstructured data, like images, audio, and text[3]. Various methods are used, including web scraping, conducting surveys and interviews, observing phenomena, and analyzing existing content.Data collection for Parkinson's disease research is typically carried out using a variety of modalities such as medical imaging (MRI, PET, SPECT) or medical image analysis, voice patterns and speech recordings, handwriting datasets analysis, finger testing and video processing, gesture and posture data analysis. Large-scale open-source datasets like PPMI (Parkinson's Progression Markers Initiative) or clinical hospital records are often used.

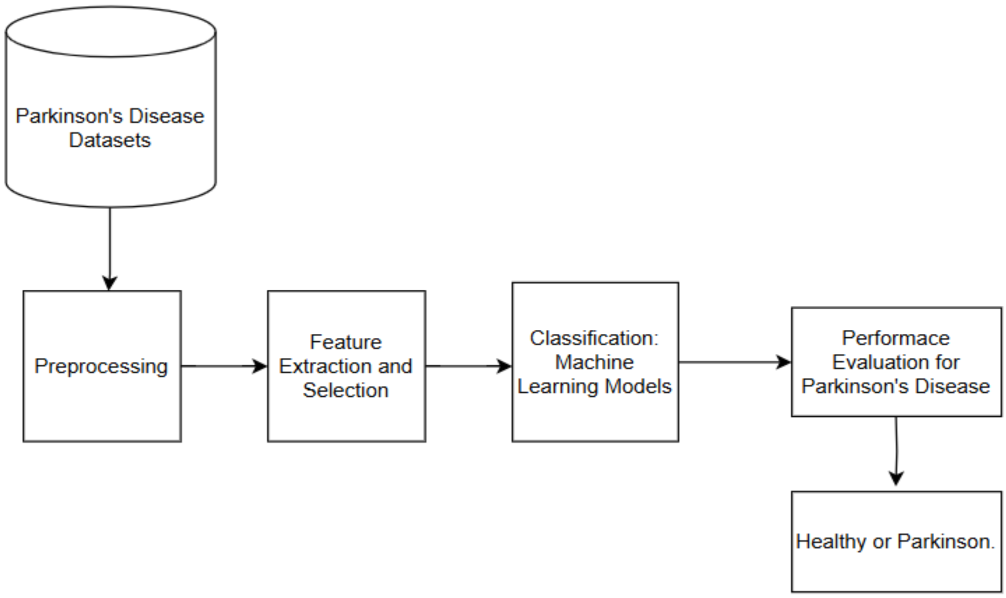

Figure 2: Parkinson's Disease Classification Framework

3.2 Data Preprocessing

Preprocessing is a building step for Parkinson's disease classification frameworks, since raw data usually contains noise, artifacts, and inconsistent formats, so preprocessing plays a crucial role before applying machine learning. For various datasets preprocessing is done at different levels. For imaging data, preprocessing includes gray-level normalization, histogram equalization, denoising (wavelet filtering, Gaussian smoothing), and contrast enhancement to improve visibility of features. For speech data, preprocessing involves noise removal, silence trimming, and normalization of pitch or intensity. In handwriting and gait data, preprocessing may include segmentation, smoothing, and temporal alignment[12]. Overall, preprocessing ensures that the input data is standardized, noise-free, and highlights subtle variations that are essential for reliable Parkinson's detection. This process also includes normalization to maintain consistency in the input data, improving the model's ability to accurately distinguish between normal and Parkinson's Disease cases. Effective or proper preprocessing boosts the accuracy and reliability of the machine learning models that follow. Also techniques like image resizing, noise reduction, data normalization, etc. contributes to improving the model accuracy and performance.

3.3. Feature Extraction and Selection

Feature extraction turns unstructured data into interpretable representations that can distinguish between subjects with Parkinson's Disease and those in good health. Jitter, shimmer, fundamental frequency, formants, and Mel-frequency cepstral coefficients(MFCCs) are typical characteristics in speech-based research[10]. Kinematic and dynamic characteristics like pen pressure, tremor frequency, stride length, and velocity are extracted in handwriting and gait analysis. While deep learning techniques automatically learn features through convolutional layers, texture-based features, intensity distributions, and brain connectivity measures are used for medical imaging. Following extraction, dimensionality is decreased and only the most informative features are kept by using feature selection techniques like Principal Component Analysis(PCA), Linear Discriminant Analysis(LDA), or recursive feature analysis.

3.4. Machine Learning Models

Machine Learning is a subset of Artificial Intelligence that allows computers to learn and improve from experience, without being explicitly programming. ML models are used for predictions and improve the accuracy. Before applying models or algorithms to preprocessed dataset. It is splitted into train and testing data where 80 percent of data is set to training and 20 percent is set to testing data[8]. The selection of appropriate machine learning algorithms will depend on the specific analysis goals and the nature of the data. The algorithms used for classification problems include SVMs, k-NN, and Decision Trees, Random Forest, Logistic Regression, AdaBoost Classifier, XG Boost algorithm, SVM vector,etc. These algorithm's performance can be measured using several measures such as accuracy, precision, and recall. Thus, selecting the right machine learning model is a critical step for achieving reliable and meaningful outcomes in any classification task.

3.5. Performance Evaluation for Parkinson's Disease

After performing various ML algorithms, the one demonstrating with maximum performance is selected. Performance Evaluation plays a crucial role in assessing the effectiveness of computational models and clinical methods used for the early detection and monitoring of Parkinson's Disease because PD is a progressive neurodegenerative disease with complex motor and non-motor symptoms. Standard metrics like accuracy, precision, recall, F1-score, sensitivity, specificity, and the area under the ROC curve (AUC) are typically used to assess performance in machine learning and medical research. These metrics aid in assessing a model's ability to categorize disease severity levels or distinguish between Parkinson's patients and healthy people. Furthermore, statistical significance tests and cross-validation are employed to confirm the models' generalizability and robustness[6]. In addition to pointing out the advantages and disadvantages of various strategies, a thorough performance evaluation helps researchers refine algorithms, enhance feature selection, and guarantee that the created techniques are reliable in actual clinical settings. This comparison can be represented through various visualizations like heat map, bar chart, table format for better understanding.

The final step is to classify or predict whether a patient is a healthy person or a person with Parkinson's Disease using a trained model with extracted features. Also this step involves validating the model using test data. This prediction provides clinically meaningful results that support early diagnosis and treatment.

4. MACHINE LEARNING TECHNIQUES

Machine Learning (ML) methods are now widely used to detect and study Parkinson's Disease (PD). These techniques help in finding small changes in data such as voice, handwriting, walking style, EEG signals, and brain images which are not easily noticed by doctors. Different ML models work well for different kinds of data. Some are useful for small datasets, while others perform better when there is a large amount of data.

4.1 Support Vector Machines (SVM)

SVM is one of the first algorithms used for PD detection. It works by drawing a line or boundary that separates patients from healthy people. SVM gives good results when the dataset is small but has many features. For example, when it was tested on the UCI voice dataset, it showed accuracy above 85%. However, when the dataset is very large and complicated, SVM is not always the best choice unless advanced kernels are used.

4.2 Decision Trees and Random Forests

Decision Trees are simple models that split data into groups using “if–then” type rules. Random Forest is an improved version that combines many trees together, giving more accurate results. These methods are often used in handwriting data where doctors study writing speed, pressure, and tremor. Random Forest has shown accuracy close to 90% for classifying PD patients from healthy people. These models are easy to understand but may not work well with very complex data.

4.3 k-Nearest Neighbors (k-NN)

The k-NN algorithm classifies a new patient by comparing them to the most similar patients in the dataset. It works well for small and clean datasets. In one study using voice recordings, k-NN gave the highest accuracy of about 96.6%, even better than SVM or Decision Tree. But k-NN is slow when there is too much data and its performance drops when the data is noisy.

4.4 Logistic Regression (LR)

Logistic Regression is one of the simplest models used for PD. It works well when the data is easy to separate and gives probability scores for prediction. It is fast and easy to understand, but it cannot deal with complicated patterns in the data. Because of this, it is often used as a baseline model but not for final predictions.

4.5 Artificial Neural Networks (ANN)

ANNs are inspired by the human brain and can learn complicated patterns in data. They have been used in handwriting, voice, and movement datasets. They usually perform better than traditional models if enough training data is available. But they need more computing power and careful tuning to work properly.

4.6. Deep Learning Models (CNN, RNN, LSTM)

Deep learning methods are now very popular in PD research. Convolutional Neural Networks (CNN) are used for images such as MRI and PET brain scans, where they can automatically learn features. CNN models trained on the PPMI MRI dataset reached very high accuracy, sometimes more than 99%. Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models are used for speech or walking data since they can handle time-based changes. CNN and RNN can also be combined to analyze videos of patient movements, giving better results than traditional ML models.

4.6. Ensemble Learning Methods

Ensemble learning means combining many models to get stronger predictions. Methods like AdaBoost, Gradient Boosting, and XGBoost have been used in PD detection. They are especially good when the dataset is unbalanced, meaning there are more PD cases than healthy ones. These methods usually perform better than single models and provide good sensitivity and specificity, which are very important for medical diagnosis.

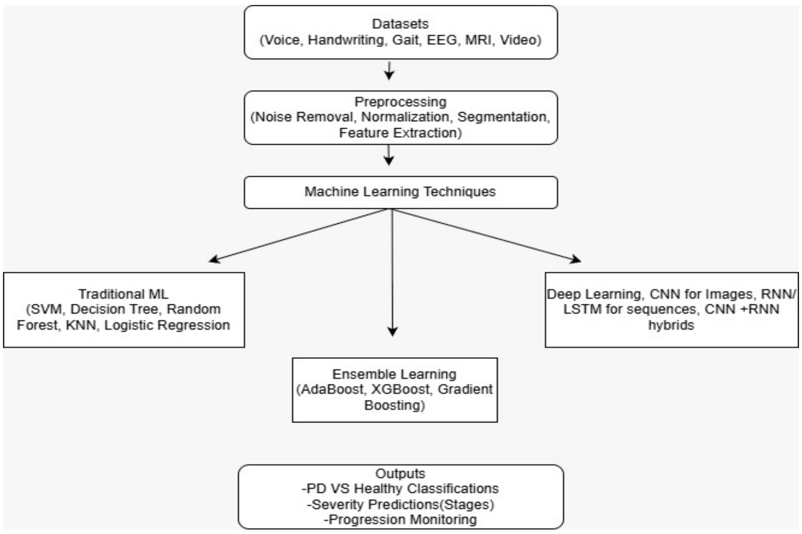

Figure 3: Machine Learning Techniques Framework for Parkinson’s Disease

The figure 3 shows the general process of applying machine learning for Parkinson's Disease. Data is collected from different sources such as voice, handwriting, gait, EEG, MRI, and video. This is followed by preprocessing to clean and normalize the signals. Features are then extracted and given to different ML models. Traditional models like SVM, Decision Trees, Random Forest, k-NN, and Logistic Regression are used for smaller datasets. Deep learning models such as CNN, RNN, and LSTM are applied for images and sequential data. Ensemble methods like AdaBoost and XGBoost combine models to improve classification. Finally, the models give outputs such as PD vs healthy classification, severity prediction, and progression monitoring.

Table 2: Parkinson's Disease Detection Techniques

Year	Author	Technique	Dataset	Accuracy
2020	Loazia Duque et al. [10]	Random Forest, SVM	Smartphone Gyroscope	97%
2021	R. Begum et al.[6]	CNN(DenseNet201)	PPMI MRI Dataset	99.2%
2022	Audil Hussain[9]	SVM, KNN, Decision Tree	UCI Voice Dataset	KNN-96.6%
2023	Hongli Chang[11]	CNN-RNN Hybrid	EEG Dataset	94%
2024	Diego L.Guarin et al.[2]	Pose Estimation Classifier	Finger Tapping Videos	>80%

5. CONCLUSION

This literature survey shows that machine learning has become a strong tool for predicting Parkinson's disease by analyzing various patient data. Voice pattern analysis, improved by classification and deep learning models, has identified early vocal problems that often go unnoticed during routine clinical exams. Handwriting datasets and finger-tapping tests, processed with feature extraction and supervised learning algorithms, have captured fine motor issues that indicate disease progression. Gesture recognition and video processing, using computer vision and neural networks, provide non-invasive ways to track motor symptoms in everyday settings. At the same time, MRI image analysis with machine learning and deep learning techniques has uncovered subtle structural and functional brain changes. Together, these studies suggest that a multimodal, machine learning-driven approach can significantly improve the accuracy and reliability of Parkinson's disease detection.Early and accurate predictions made possible by machine learning can give patients access to treatment when it's most effective, reduce uncertainty for families, and help healthcare providers make timely decisions. The future lies in bringing these techniques together across voice, motor, gesture, and imaging data into strong, understandable, and patient-friendly systems. This could turn technological advances into practical healthcare solutions that provide hope, dignity, and a better quality of life for people impacted by Parkinson's disease.

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