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A Review on Detecting Parkinson’s Disease Early with Machine Learning Techniques

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Abstract: Parkinson's disease (PD) is a progressive neurological disorder that affects motor functions and is often difficult to detect at an early stage. Traditional diagnosis mainly relies on clinical observation, which may delay timely treatment. In recent years, machine learning techniques have been widely explored to assist in the early diagnosis of Parkinson's disease by analyzing measurable physiological and behavioral signals. This paper presents a literature review of recent studies on machine learning-based approaches for Parkinson's disease diagnosis using multiple data modalities. The reviewed studies utilize different types of data, including speech and voice recordings, handwriting patterns, gait signals, and sensor-based measurements collected from real-world environments. A number of machine learning techniques like Support Vector Machine, Random Forest, and deep learning algorithm are examined and compared. The review highlights the strengths and limitations of existing approaches and emphasizes that multimodal systems, which combine multiple sources of data, can improve diagnostic reliability and accuracy. Results of this study provide an overview of current developments and indicate the potential of multimodal Machine learning methods to aid more effective Parkinson's disease diagnosis

Index Terms **-** Parkinson's Disease, Machine Learning, Multimodal Data, Deep Learning, Speech Analysis, Gait Analysis, Handwriting Recognition, Data Fusion, Predictive Modeling, Neurodegenerative Disorders.

I. INTRODUCTION

Millions of people are affected by Parkinson’s disease (PD), the second most common neurodegenerative condition in the world [40], and the impact of it on their quality of life is significant. Movement disorders like tremors, bradykinesia, and rigidity are the hallmarks of the disease, which is caused by a gradual decline in neurons that produce dopamine. These traits are also associated with the loss of these neurons. [39]. Without a definitive cure, there is no hope of finding effective therapeutic interventions that can slow the disease and manage symptoms, so early and precise diagnosis is essential. In spite of this, conventional diagnosis relies on a clinician’s subjective observation of these symptoms, which frequently manifest years after the disease’d beginning, making early identification difficult [43], [46]. The use of ML, a computational method that can analyse complex datasets and identify subtle, quantifiable patterns that occur before an official diagnosis, has become widespread. The capability is particularly crucial in a disease such as PD, where symptoms can be diverse and manifest from different sources. Multimodal approaches, which involve combining information from multiple data types rather than focusing on just one type, offer an increasingly robust and comprehensive perspective of the patient’s condition. This review paper summarizes ten key research articles in detail that analyse the diverse range of ML applications in PD detection and progression prediction.

A. Speech and Voice Recordings

The use of vocal impairments as early non-motor symptoms or potential biomarkers for the detection of Parkinson's disease (PD) has attracted increasing research attention [16], [20]. Speech-based analysis offers a non-invasive approach that may help identify early signs of the disease before more visible motor symptoms appear. This review examines a range of machine learning approaches used for voice-based PD detection, from traditional classifiers that rely on carefully engineered features to more recent methods based on advanced foundation models.

B. Gait and Movement Data

Gait and movement analysis have become important areas of research for the early detection and monitoring of Parkinson's disease. Changes in gait patterns, tremors, and other motor movements can serve as measurable biomarkers for diagnosis and symptom monitoring [1]. These movement patterns can be captured using wearable devices and inertial sensors, which allow researchers to collect real-world data during a patient's daily activities

C. Online Handwriting Data

Changes in handwriting, particularly the reduction in writing size known as micrographia, provide a valuable time-series data source for analyzing motor function in Parkinson's disease [19]. More advanced techniques such as the Beta-elliptical approach are used for feature extraction, along with Bidirectional Long Short-Term Memory (BLSTM) models for classification. The BLSTM-based classification method shows high accuracy in distinguishing individuals with Parkinson's disease from healthy controls and often outperforms existing approaches on publicly available datasets.

D. Multimodal and Advanced Data Integration

The diagnosis of Parkinson's disease is increasingly moving toward the use of multimodal data and advanced data integration techniques. PD is a complex disorder with many related symptoms, and relying on only one type of data is often not enough to fully represent the condition. Previous studies show that combining multiple data sources can provide a more reliable way to analyze the disease [31]

II. METHODOLOGIES

The literature review discusses various types of ML models from basic models including logistic regression, support vector machine (SVM), random forest, and k-nearest neighbors (k-NN) to more sophisticated models using deep learning techniques. Basic models may be less complicated to understand but are more effective when analyzing massive amounts of information; conversely, deep learning models have proven their superiority in analyzing high-dimensional data [44].

A. Machine Learning Models and Classification

A review on machine learning methods is present in the articles. In general these methods are applied in classification and prediction problems on different data sources types. Parkinson's disease is a multifactorial disease; thus the algorithm selection is linked with the data properties.

Traditional Classifiers

Several studies have employed traditional and interpretable classifiers, which are often preferred in medical research because their decision-making process is easier to understand. Common examples include Logistic Regression, Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbors (KNN). These models are widely used in clinical studies because their predictions can be traced back to specific input features, which increases the trust of medical professionals in the system.

Random Forest (RF)

Random Forest is an ensemble learning method that constructs a collection of decision trees during the training phase. For classification tasks, the final prediction is determined by combining the outputs of multiple trees through majority voting:

$$H(x) = mode\{h_1(x), h_2(x), \ldots, hK(x)\} \quad (1)$$

Where K is the total number of trees in forest. It is known that Random Forest classifier can perform well in the task of Parkinson's detection, and one experiment demonstrated 91.83% accuracy using a subject-dependent voice data set [27].

Support Vector Machines (SVM)

Support Vector Machines are powerful classification algorithms used to identify an optimal decision boundary that separates data points belonging to different classes. The main objective of SVM is to determine a data-driven Hyperplane, which maximizes the margin between the classes:

$$w \cdot x - b = 0 \quad (2)$$

SVMs have been used in Parkinson's disease detection. Their effectiveness is often increased when combined with preprocessing and dimensionality reduction techniques such as Principal Component Analysis (PCA). In several studies, applying PCA before this classification has performed quite well, with a reported accuracy of 91.83% in one of the papers [28].

K-Nearest Neighbors (K-NN)

K-Nearest Neighbors is a straightforward yet powerful non-parametric, instance-based algorithm. It classifies new samples based on their similarity to previously observed data using a distance function, most commonly Euclidean distance. The choice of K is crucial; when K is small, the algorithm can become sensitive to noise, and when K is large, it can blur class boundaries. In Parkinson's disease detection, KNN performed best when applied to a balanced dataset, underscoring the importance of preprocessing techniques like resampling and normalization.

Logistic Regression

Logistic Regression This method is popular in the area of binary classification problems. The output variable's probability is calculated using the logistic (sigmoid) function:

$$P(y = 1 \mid x) = \sigma(w \cdot x + b), \ \text{where} \ \sigma(z) = 1 / (1 + e^{-z}) \quad (5, 6)$$

Logistic Regression is particularly useful in medical prediction problems where estimating the likelihood of a condition is important. In one notable study, it was used as part of an interpretable prediction framework for Parkinson's disease detection [34].

B. Data Preprocessing and Feature Engineering

Medical datasets often present several challenges, such as high dimensionality and class imbalance. For this reason, preprocessing and feature engineering play an important role in building reliable predictive models. A common preprocessing step used in many studies is normalization, where each feature x is scaled using z-score standardization:

$$z = (x - \mu) / \sigma \quad (7)$$

Dimensionality reduction techniques such as Principal Component Analysis (PCA) are also widely used. PCA identifies directions of maximum variance through the covariance matrix:

$$C = (1/(n-1)) \, \Sigma \, (x_i - \bar{x})(x_i - \bar{x})^T \quad (8)$$

Methods such as Recursive Feature Elimination with Cross-Validation (RFECV) and optimization techniques like the Zebra Optimization Algorithm (ZOA) have been explored. For example, one study used PCA to reduce 22 features to 5 key components, which improved the performance of SVM classifiers [26]. Another important issue in medical datasets is class imbalance, Where techniques like KMeans-SMOTE can be applied to generate synthesized samples of minority classes [37].

C. Model Evaluation and Validation

Models for Parkinson's disease were developed as predictive tools they applied a set of guidelines to scrutinize the detection and management processes. An extensive range of metrics and evidence for effectiveness was employed, reliability and generalizability were also ensured through various methods.

A number of different performance measurements were taken on the prediction outcomes, in order to provide an interesting range of information, and to give an in depth analysis of its predicting ability. The percentage of the predictions which were accurate are known as accuracy, this can be represented as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \qquad (10)$$

where *TP* and *TN* are the true positives and true negatives,
and *FP* and *FN* are the false positives and false negatives.

Insufficient datasets can lead to inaccurate medical diagnostics. Precision assesses the correctness of positive predictions, particularly in confirming that a predicted positive case is indeed true, this ensures that the model is more likely to correctly predict the presence of a disease, resulting in fewer false alarms.

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (11)$$

Recall, sometimes referred to as sensitivity, measures the correct identification of a true positive. It is particularly useful in minimizing false negatives in screening tools:

$$\text{Recall} = \frac{TP}{TP + FN} (12)$$

performance indicators in the ROC curve, TPR and FPR are denoted by their relative values. As the complexity of a decision increases, the FPR becomes more significant and provides supplementary information on the trade-off between sensitivity and specificity.

D. Datasets Used

The quality, size, and type of data used to train a machine learning model have a big effect on how well it works. Because there are so many different symptoms of Parkinson's disease, researchers have been looking at a lot of different types of data sources.

Speech and Voice Datasets

Speech and voice recordings are highly valuable sources of data for Parkinson's disease research. Several studies rely on publicly available datasets such as those provided by the UCI Machine Learning Repository, which contains speech recordings from 252 subjects with approximately 7,576 recordings and more than 750 features including MFCCs, wavelet-based coefficients, jitter, shimmer, and frequency-related measurements [22].

Gait and Movement Datasets

Data on physical movement, including gait measurements, is of utmost importance for analyzing the fundamental motor indications of PD. In one study focused on fall risk prediction, foot-worn sensors were used for a two-week period to capture real-world gait data, accessed via the FallRiskPD public platform (https://osf.io/h6apq/wiki/home). Non-contact gait analysis systems were also used to measure differences in gait parameters between PD patients and healthy controls, with concurrent validity established through the Zeno instrumented walkway, regarded as the clinical the best way to do a quantitative gait analysis [4].

Handwriting Datasets

Changes in fine motor control are a common symptom in patients with Parkinson's disease. One study introduced an online Arabic handwriting dataset consisting of samples from 30 PD patients and 30 healthy controls. The widely used Parkinson's

Handwriting dataset (PaHaW), available at https://zenodo.org/record/5795845, contains online handwriting recordings from 37 participants [48]. Unlike traditional static datasets, PaHaW records dynamic information such as pen pressure, velocity, and acceleration. These temporal features enable models such as BLSTM and CNNs to capture complex movement patterns associated with Parkinson's disease.

Multimodal and Clinical Datasets

Multimodal datasets play an important part in Parkinson's disease research because they combine multiple types of data to give a better picture of the patient's health. The Parkinson's Progression Markers Initiative (PPMI) dataset, accessible at https://www.ppmi-info.org/access-data-specimens/download-data, contains demographic, clinical, and imaging data including diffusion MRI scans. In addition, some studies combine neurological signals such as EEG with data on motion from inertial measurement units (IMUs) to investigate complex symptoms such as freezing of gait (FoG) [8].

III. RESULT COMPARISON AND DISCUSSION

A. Comparative Analysis of Diagnostic and Predictive Modalities

Voice and Speech-Based Diagnostics

Speech analysis has emerged as an effective modality for identifying Parkinson's disease. One traditional approach involves the XRFILR model, which achieved a testing accuracy of 96.46% according to ablation analysis [34]. Feature selection using Recursive Feature Elimination (RFE) outperformed PCA, which achieved a lower accuracy of 87.17%.

Gait and Mobility Assessment

Gait and mobility analysis represents another important domain for Parkinson's disease detection and monitoring. One study reported a maximum balanced accuracy of 74.0% for fall risk prediction using a Random Forest classifier applied to real-world gait data [7], compared to 68.0% from standardized gait assessments. Non-contact gait monitoring systems achieved an accuracy of 91.43% for early-stage PD classification [32], with a strong correlation ($R^2 = 0.897$) with the clinical MDS-UPDRS III score.

Online Handwriting and Multimodal Kinematic Analysis

The latest tool for discovering PD through online handwriting demonstrated high efficacy, achieving classification accuracies ranging from 90.00% to 96.25%. The PaHaW database consistently performed better than existing methods. According to a study on the prediction of Freezing of Gait (FoG), combining EEG and IMU data through a multimodal model-fusion technique outperformed models relying on a single data modality, achieving 92.1% accuracy [8]. A multitask deep learning model predicting multiple outcomes, including depression and the development of PD, reached a testing accuracy of 95.81% with a six-time-step configuration [29].

B. Performance Summary Tables

TABLE I — COMPARATIVE MODEL PERFORMANCE BY MODALITY

Modality	**Best-Performing Model/Methodology**	**Key Performance Metric**	**Value**
Voice/Speech	XRFILR model	Testing Accuracy	96.46%
Voice/Speech	Ensemble of fine-tuned foundation models	AUC	91.35%
Gait	Random Forest (real-world gait)	Balanced Accuracy	74.0%
Gait	Non-contact video-based system	Classification Accuracy	91.43%
Handwriting	BLSTM with Beta-elliptical features	Classification Accuracy	90.00–96.25%
Multimodal (FoG)	EEG + IMU ensemble neural network	Accuracy (1s PH)	92.1%
Multimodal (PD+Dep)	Multitask Deep Learning (VAE+BiLSTM)	Testing Accuracy	95.81%

TABLE II — GAIT-BASED COMPARISON PREDICTION

Aggregation Level	Data Source	Balanced Accuracy (%)	Sensitivity (%)	Specificity (%)
Participant-wise	Real-world gait	74.0	60.0	88.0
Daily	Real-world gait	64.0	60.0	68.0
Bout-wise	Real-world gait	62.0	62.0	62.0
Participant-wise	Standardized gait assessment	68.0	68.0	68.0
Daily	Standardized gait assessment	55.0	56.0	54.0
Bout-wise	Standardized gait assessment	55.0	55.0	55.0

C. Discussion of Challenges, Trade-offs, and Future Directions

The research underpins the importance of raw performance measures, such as accuracy, not being the sole measure of the true value of a model in clinical utility. To be deemed clinically effective, an acceptable solution must pass through a complex, multidimensional trade-off space of accuracy, interpretability, and practicality. A critical example is the negative correlation between the success of the FoG model in being accurate and its prediction horizon (PH). While the model had a remarkable accuracy of 92.1% at a 1-second PH, accuracy dropped to 86.2% when the PH was increased to 5 seconds, which would be more practical for intervention.

Another important trade-off is finding the right balance between sensitivity and specificity. Although the fall risk prediction model exhibited high specificity of 88.0%, the sensitivity was still pretty low at 60.0% [7]. Addressing demographic biases is also a key challenge; one study on speech found that foundation models differed in performance based on gender, with the male population demonstrating better classification abilities than female subjects. This finding highlights the need for a wider range of data and gender-based approaches in research.

IV. CONCLUSION

The analysis shows that machine learning is being applied increasingly more in the diagnosis and evaluation of Parkinson's Disease (PD). Traditional diagnosis is frequently made using the identification of symptoms, which usually occurs much later than the appearance of the disease [43], [46]. In contrast, systems based on ML enable far earlier detection of more subtle changes in a person's speech, handwriting, walking style, and mood. These small indications, not usually noticed during routine medical check-ups, can be used by algorithms to identify and interpret PD.

Some of the best positive work involves combining different types of data — speech, handwriting, clinical documentation, and imaging techniques to get a full picture of the patient's health. Conventional algorithms such as Random Forest and SVM are still being used, while deep learning models are proving to be extremely popular with larger and more diverse datasets.

Overall, the evidence is strong that machine learning can transform the detection of PD from a late, symptom-based approach to a proactive, data-driven process. By leveraging different cues and machine learning methods, these systems can help with the diagnosis of the disease as it progresses, monitor its progression, and formulate personalized treatment strategies. Research is extremely beneficial, proposing improvements in the lives of persons who have PD and reducing the cost to healthcare systems.

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