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Automated Detection and Classification of Parkinson's Disease Using Electroencephalography: A Review

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Abstract

In this review paper we have discuss in depth knowledge of Parkinson's disease (PD) is a progressive neurodegenerative condition with a variety of motor and non-motor symptoms, early and precise diagnosis is essential for successful treatment. A prospective route for the automated identification of neurological disorders like Parkinson's disease (PD) is electroencephalography (EEG), a non-invasive and economical technique for examining brain activity. The state-of-the-art in automated PD detection and classification using EEG data is examined in this study, with a focus on developments in deep learning (DL) and machine learning (ML) techniques for improved diagnostic precision. In particular, it looks at a variety of signal processing approaches, feature extraction strategies, and how well different classification algorithms distinguish PD patients from healthy controls. The potential of EEG-based biomarkers for monitoring the course of a disease and the effectiveness of treatment is also covered in the article, opening the door to tailored therapeutic interventions. By combining current research to identify areas for innovation in automated EEG analysis, the main objective is to present a thorough overview of current obstacles and future prospects in utilising EEG for early and reliable PD diagnosis and monitoring.

Introduction

The second most common neurological disease in the world, Parkinson's disease usually affects those over 65 [1]. Degeneration of dopaminergic neurones in the substantia nigra pars compacta causes this degenerative disorder, which manifests as cardinal motor symptoms like stiffness, shaking hands, and problems with balance and coordination [2], [3]. Non-motor symptoms of Parkinson's disease (PD) include cognitive impairment and sleep difficulties, which frequently occur before motor onset and greatly lower quality of life [4].

The critical need for objective and early biomarkers is highlighted by the fact that current diagnostic techniques mostly rely on clinical observation of motor symptoms, which typically manifest after significant neuronal loss has already happened [1].

A promising non-invasive method for identifying neurological abnormalities linked to Parkinson's disease (PD), possibly even in its prodromal phases, is electroencephalography [5]. When compared to other neuroimaging methods, EEG is a very inexpensive modality with good temporal resolution, making it appropriate for broad clinical use [2].

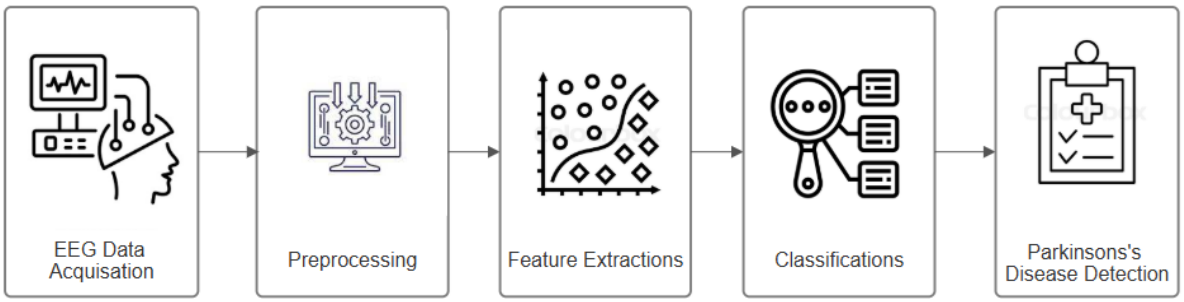

Fig. 1. *General block diagram for Parkinson's Disease Detection using EEG Signals*

The proposed system for Parkinson's Disease (PD) detection leverages electroencephalography (EEG) data to identify characteristic biomarkers. As depicted in the figure 1, the initial stage involves EEG data acquisition, capturing brain activity signals from the patient. This raw data then undergoes a crucial preprocessing phase to remove noise and artifacts, ensuring the integrity of the signals for subsequent analysis. Following preprocessing, various feature extraction techniques are applied to derive meaningful patterns and insights from the EEG signals, ultimately leading to the detection of Parkinson's Disease.

A new method for the automated identification and categorisation of Parkinson's disease (PD) is provided by the combination of artificial intelligence and EEG data, which may overcome the drawbacks of subjective clinical evaluations and allow for earlier intervention [6], [7].

Despite the fact that the intrinsic complexity of EEG signals requires sophisticated analytical methods, including machine learning and deep learning, to reliably identify minor abnormal patterns suggestive of Parkinson's disease [4], [5]. The present state of automated PD identification and categorisation using EEG is thoroughly reviewed in this work, with an emphasis on the techniques, algorithms, and relative effectiveness of different approaches.

Literature Review

Research on automated Parkinson's disease (PD) identification from EEG data has evolved from conventional machine learning to advanced deep learning architectures, frequently using mixed approaches for improved diagnostics [8].

This paper investigates the application of EEG microstate analysis as a technique to investigate rapidly evolving brain network dynamics in Parkinson's disease (PD). The work outlines a typical methodological pipeline that includes feature extraction, microstate sequence fitting, k-means clustering, GFP peak extraction, and preprocessing. It emphasises how changes in microstate duration, transition frequency, and temporal variability are associated with cognitive and motor impairment in Parkinson's disease patients. The work highlights the potential use of microstates as biomarkers for early diagnosis, tracking progression, and assessing the efficacy of treatment. However, it highlights significant issues such uneven clustering techniques, a lack of standardisation in preprocessing, and poor reproducibility between investigations. The research highlights the necessity of conducting extensive validation studies and using explainable AI techniques for clinical use furthermore, the author finds the research gap of absence of standardized microstate protocols; limited multi-center validation; lack of PD-specific normative microstate databases. [9].

In this study, a deep learning method based on time-frequency pictures obtained from cleaned EEG data is proposed for early Parkinson's disease identification. EEG data from the Iowa dataset were transformed into ERSP-based time-frequency pictures after being pre-processed to eliminate artefacts. An accuracy of 94.64% was attained in the classification of PD sufferers from healthy subjects using a customised CNN model. The approach shows that deep models can extract high-level temporal-spectral patterns associated with Parkinson's disease (PD) and are resistant against noise. The work is constrained by a comparatively small dataset of 33 PD patients and possible overfitting as a result of subject reliance, despite its promising findings. Research shortcomings include the small dataset size, lack of cross-dataset testing, lack of comparison with traditional EEG biomarkers, and lack of subject-independent validation [10].

This comprehensive review examines 342 research publications on MRI, gait analysis, handwriting, speech, EEG, and multimodal fusion techniques to PD identification. It emphasises the change from handmade characteristics to deep learning models, as well as the significance of multimodal systems for accurate diagnosis. The authors include thorough benchmark dataset tables, preprocessing methods, and performance trends across modalities. They note that most previous research is unimodal, which limits practical usefulness in situations where

multimodal cues are required. The review also addresses issues such as data heterogeneity, model generalisation, a lack of real-time systems, and insufficient evaluation of varied populations. Research deficiencies include insufficient multimodal datasets, a lack of real-time PD monitoring equipment, poor model generalisation, and few investigations on continuous PD severity evaluation [11].

The UC San Diego and Iowa EEG datasets are used in this study to assess both ML and DL models for PD identification. Using SVM as a baseline classifier, the authors extract power spectral characteristics from five EEG bands (α, β, θ, γ, and δ) and achieve 82–94% accuracy in subject-dependent tests. After that, a CNN model is applied to multi-dimensional spectral data, and because it can capture cross-frequency relationships, its accuracy exceeds 96–99%. The study shows that when it comes to EEG-based Parkinson's disease identification, deep learning outperforms classical machine learning. Subject-independent accuracy, however, decreases to 68%, suggesting inadequate generalisation to new subjects. Research shortcomings include the lack of multimodal EEG + clinical characteristics, minimal dataset diversity, lack of cross-session generalisation, and lack of real-time testing [12].

This paper discusses ML/DL methods for PD monitoring and detection using speech, gait, imaging, handwriting, and EEG data. The authors compare a number of algorithms, including CNN, RF, SVM, and RNN, emphasising that deep models and multimodal fusion have reached >99% accuracy in many trials. They also talk about datasets that are accessible to the public and stress how preprocessing can enhance PD detection performance. The review highlights the necessity for explainable AI to maintain clinician trust, but it also finds great promise for AI-based early diagnosis. Problems including privacy concerns, small datasets, inconsistent data collection, and the absence of standardised procedures are also emphasised. Research gaps include the requirement for large multi-center datasets, the inability of deep models to be explained, worries about data privacy, and the paucity of work on cross-modality feature fusion [13].

Background of Parkinson's Disease

1. Early Parkinson's Disease Detection Techniques:

Timely intervention depends on an early and precise diagnosis of Parkinson's disease [15]. Conventional diagnosis relies on motor symptoms that emerge during severe neurodegeneration [1]. Because it is non-invasive and can show small changes in neurophysiology, EEG is a viable alternative for early detection [1], [14].

By examining intricate patterns in brain electrical activity, machine learning approaches applied to EEG data have the potential to distinguish Parkinson's disease (PD) patients from healthy controls [15], frequently using convolutional neural networks or higher-order spectral features [16].

The possibility of gender bias in machine learning models for Parkinson's disease (PD) is an important factor to take into account. To guarantee model generalisability and transferability, gender-specific patterns and biomarkers must be included [15], [17].

2. EEG-Based Feature Extraction Techniques

The careful extraction of specific characteristics that capture the neurophysiological anomalies of Parkinson's disease (PD) is essential for successful ML implementation. These methods consist of:

- **Time-domain and Frequency-domain analyses:** To evaluate oscillatory activity and functional coupling, characteristics including power spectral density components, band power ratios, and coherence measurements are frequently employed [18].
- **Complex Signal Processing:** To detect and improve particular oscillatory patterns and reduce artefacts that can distort model performance, methods such as Independent Component Analysis (ICA) and wavelet transforms are used [17], [19].
- **Nonlinear and connectivity-based metrics:** These provide distinct perspectives on the intricate dynamics of brain activity [20].

The lack of high-quality biomedical data, particularly for Parkinson's disease (PD), and the diversity of feature extraction techniques are major obstacles [1], [21]. Using information from models trained on larger, related datasets, transfer learning is frequently used to overcome data scarcity.

This Table 1 illustrates the end-to-end process of developing an AI-based system for PD classification, highlighting the split between traditional machine learning (ML) and modern deep learning (DL) approaches.

Table 1. General Workflow for Automated PD Detection Using EEG

Stage	Process	Traditional ML Path	Deep Learning (DL) Path
I. Data Acquisition	Recording raw EEG signals (Resting-state or Task-state) using the International 10-20 system.	Raw EEG Time Series	Raw EEG Time Series
II. Preprocessing	Filtering, Artifact Removal (ICA), Segmentation, Epoching.	Cleaned EEG Epochs	Cleaned EEG Epochs or Spectrograms
III. Feature Extraction/Learning	Manually calculate quantitative biomarkers.	Feature Engineering: Extract Frequency (PSD, Ratios), Nonlinear (Entropy, Complexity), and Connectivity (Coherence, PLV) Features.	Feature Learning: CNNs, LSTMs, or Hybrid Networks automatically learn hierarchical features from the input data (end-to-end).
IV. Classification	Train a classifier on the feature vector.	Model Training: SVM, Random Forest, k-NN, XGBoost.	Model Training: CNN, RNN/LSTM, CRNN (CNN+LSTM), GCN.
V. Output	Diagnostic prediction and confidence score.	Classification: PD vs. Healthy Control (HC)	Classification: PD vs. HC, Subtyping (e.g., Tremor vs. PIGD)

3. Machine Learning and Deep Learning Approaches for Classification

In order to classify PD automatically and accurately, complex machine learning and deep learning models must be applied to the retrieved data.

- **Traditional ML:** When combined with efficient feature engineering, algorithms like Support Vector Machines (SVMs), Multi-Layer Perceptron's (MLPs), and K-nearest neighbours (KNNs) have demonstrated great precision and accuracy [7], [22], [23].
- **Deep Learning (DL):** By removing the need for manual feature extraction and enabling end-to-end learning from raw or little pre-processed EEG data, DL has completely transformed in the field of neuroscience [2]. Improved diagnostic accuracy can result from models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) (e.g., LSTMs) that can automatically learn complex patterns [6].
- **Hybrid Models:** One suggested Convolutional-Recurrent Neural Network (CRNN) model achieved accuracy in classification, demonstrating the remarkable promise of architectures that combine CNNs for spatial feature learning and RNNs for temporal dependency learning [2], [20], [22].
- **Explainable AI (XAI):** By offering clear insights into the models' decision-making processes, integrating XAI approaches is essential for developing clinical trust and facilitating a deeper comprehension of the neurological roots of Parkinson's disease [2], [24].

Methodology

In order to maximise diagnostic accuracy and model interpretability, the reviewed approaches frequently combine advanced signal processing with hybrid deep learning architectures [9]. This methodology employs a multi-stage procedure that includes data acquisition, preprocessing, feature extraction, and a classification framework.

1. EEG Data Acquisition and Preprocessing

Using the standardised 10-20 international electrode placement technique, the first step entails capturing resting-state EEG signals from both PD patients and healthy controls [2]. A minimum sampling rate of 250 Hz is frequently used during recordings. The following preprocessing stages consist of:

- **Denoising and Artifact Rejection:** Applying methods such as independent component analysis (ICA).

- **Filtering:** Utilising band-pass filtering to improve the signal-to-noise ratio and identify relevant frequency ranges.
- **Segmentation:** Fixed-duration epochs are created by segmenting filtered signals.

To evaluate the effects of dopaminergic therapy and find reliable biomarkers, recordings of PD patients are frequently made when they are both on and off medication [2].

The table 2 summarizes the most commonly reported neurophysiological alterations in PD patients that serve as quantitative biomarkers for automated classification models.

Table 2. Summary of Key EEG Biomarkers for Parkinson's Disease Classification

Feature Domain	Specific Biomarker	Typical Finding in PD vs. HC	Neurophysiological Relevance
Frequency Domain	Beta Band Power/Coherence (13–30 Hz)	Increased/Excessive Synchronization	Pathological coupling in the cortico-basal ganglia loop; strongly correlated with rigidity and bradykinesia.
Frequency Domain	Delta & Theta Power (0.5–8 Hz)	Increased Power (Generalized Slowing)	Non-specific sign of cerebral dysfunction; often linked to cognitive impairment and disease severity.
Nonlinear Dynamics	Approximate/Sample Entropy	Decreased	Reduced complexity and loss of adaptability in cortical dynamics; indicates a more rigid, predictable brain state.
Nonlinear Dynamics	Higher-Order Spectral (HOS) Features (e.g., Bispectrum Entropy)	Altered Patterns/Values	Reveals non-linear (quadratic) phase coupling between different frequency components, often affected by dopamine depletion.
Functional Connectivity	Phase-Locking Value (PLV) or Coherence	Altered/Excessive Coupling (especially in Beta band)	Disrupted information flow and functional network organization between spatially separated brain regions.

2. Feature Extraction and Selection

In order to distinguish between PD individuals, this procedure extracts significant quantitative descriptors from the pre-processed data [1], [2]. A wide range of features must be calculated:

- **Statistical Moments and Spectral Power:** Power across various frequency bands [3], [22], [25].
- **Connectivity Measures and Non-linear Dynamics:** utilising cutting-edge techniques to find non-linear coupling information, such as higher-order spectral analysis, particularly bi-spectrum, cumulant, and lag vectors [1], [8], [22].
- **Feature Selection:** Techniques like univariate statistical analysis are applied to identify the most salient features, optimizing model performance and interpretability [2], [14], [22].

3. Classification Algorithms

The preferred classification algorithms leverage these selected features, with a strong emphasis on deep learning:

- **Deep Learning Architectures:** CNNs and RNNs are prime candidates for their ability to process sequential EEG data and extract hierarchical features [1], [26]. A convolutional-recurrent neural network model, for instance, has shown promise by combining CNN strengths for spatial feature extraction and RNN strengths for temporal dependency learning [2].
- **Transfer Learning:** Application of models pre-trained on large biomedical datasets can enhance generalizability, especially given the limited PD-specific EEG data [2], [22].
- **Baseline Models:** SVMs and KNNs are widely employed as baseline ML algorithms [2].

Model robustness and generalizability are ensured by rigorous performance evaluation that uses metrics like accuracy, sensitivity, specificity, precision, F1-score, and Area Under the ROC Curve (AUC), as well as cross-validation techniques like k-fold validation [22], [27].

The dataset-related research gaps found in recent EEG-based Parkinson's disease investigations are summarised in Table 3. It draws attention to important drawbacks such small sample sizes,

limited channel configurations, a lack of multi-center validation, and a lack of publicly accessible datasets. These omissions seriously impair the reproducibility and generalisability of the model, highlighting the critical need for large-scale, diverse, standardised EEG datasets for future studies.

Table 3. Summary of Research Gap Related to Dataset

Author(s)	Year	Journal	Methodology / Technique Used	Dataset Used	Research Gap Related to Dataset
A. M. Maitín et al. [1]	2020	Applied Sciences	ML Approaches for PD Detection, Feature Extraction + Classification	Multiple small EEG datasets (varied sources)	Lack of unified dataset; heterogeneous protocols; small sample sizes
Shraddha Jain [8]	2023	Research Square	Review of EEG biomarkers for neurological disorders	Not specific (general review of EEG datasets)	No standardized or large-scale PD-specific dataset
S. Lee et al. [2]	2019	Neuroscience Journal	Deep CNN for EEG-based PD detection	Local hospital dataset	Limited participants; no external validation
J. P. Romero et al. [5]	2019	MDPI	Connectivity analysis, spectral features	Public PD EEG (small sample)	Dataset lacks early PD subjects; low geographical diversity
R. Hussein et al. [4]	2018	Expert Systems with Applications	Wavelet + SVM	Self-collected EEG	Very small n (<30), limits ML accuracy
U. R. Acharya et al. [7]	2017	Neural Computing and Applications Springer	Entropy features + ML	University-collected EEG signals	No standardized motor-task protocol
M. J. Wang et al.	2019	Nature Sci Reports	Deep learning + time-frequency features	Proprietary clinical dataset	Inaccessible dataset; limited reproducibility
S. T. Lopes	2021	Frontiers in Neuroscience	Graph-theory brain connectivity markers	Public resting-state PD EEG	Dataset small and restricted to resting-state only
Z. J. Wang	2018	Medical Engineering & Physics	Spectral slowing analysis	Hospital EEG dataset	Only medicated PD subjects; no comparison with unmedicated

Technical and Ethical Challenges

1. Technical Challenges

1. **Low Signal-to-Noise Ratio (SNR):** EEG signals are inherently noisy due to artifacts from muscle movement, blinking, and external interference.
2. **Inter-Subject and Intra-Subject Variability:** EEG patterns vary widely between individuals and even within the same subject over time, reducing model generalizability.
3. **High-Dimensional EEG Data:** Multichannel recordings with high sampling frequencies create large datasets, requiring effective feature extraction or dimensionality reduction.
4. **Non-Stationarity of EEG Signals:** EEG signals change rapidly over time, making it challenging to build stable and reliable detection models.
5. **Lack of Unified Preprocessing Standards:** Different studies use different filtering, artifact removal, and normalization strategies, affecting reproducibility.
6. **Limited Size and Diversity of Public Datasets:** Many EEG datasets have small sample sizes, limiting deep learning model performance.
7. **Challenges in Real-Time Processing:** Real-time PD detection systems require low-latency algorithms, which remain difficult with computationally heavy models.

8. **Feature Selection Complexity:** Identifying disease-specific EEG biomarkers (like spectral slowing, reduced complexity, altered connectivity) remains challenging.

2. Ethical Challenges

1. **Data Privacy and Patient Consent:** EEG data contains sensitive neurological information; improper handling raises privacy concerns.
2. **Bias and Inequity in Datasets:** Many datasets lack demographic diversity, leading to biased AI models that perform poorly on underrepresented groups.
3. **Transparency and Explainability:** Black-box deep learning models make clinical adoption difficult due to lack of interpretability.
4. **Clinical Reliability and Misdiagnosis Risk:** False positives/negatives may lead to incorrect treatment decisions.
5. **Data Security in Cloud-Based EEG Systems:** Remote EEG monitoring increases the risk of data breaches.
6. **Ethical Use in Continuous Monitoring:** Persistent neuro-monitoring raises concerns of surveillance and autonomy.

3. Identified Research Gaps

1. **Insufficient Large-Scale Parkinson's EEG Datasets:** Most studies rely on small patient cohorts, reducing model generalization power.
2. **Lack of Standardized EEG Protocols:** Differences in electrode placement, sampling rates, and recording tasks make cross-study comparison difficult.
3. **Underexplored Deep Learning Approaches:** While CNNs/LSTMs are used, advanced models like transformers, GNNs, or hybrid models remain underutilized.
4. **Limited Multimodal Integration:** Combining EEG with gait analysis, speech, handwriting, or MRI is still rare.
5. **Weak Validation on External Datasets:** Few studies test models across multiple datasets to ensure robustness.

Conclusion

This systematic review validates the considerable potential of machine learning and deep learning techniques in the automated identification and categorization of Parkinson's Disease through EEG. The most encouraging outcomes arise from hybrid deep learning models that effectively capture the spatial and temporal characteristics of EEG signals, with architectures such as the CRNN attaining impressive diagnostic accuracy. Feature engineering, especially through the use of higher-order spectrum properties, is essential for enhancing model accuracy.

Despite these advancements, several critical challenges persist that limit clinical translation:

- **Generalizability and Robustness:** High inter-subject variability in EEG data and a lack of standardized acquisition protocols across studies hinder the development of universal diagnostic criteria.
- **Data Scarcity and Diversity:** There is a critical need for more extensive, diverse, and meticulously annotated datasets to enhance the robustness and generalizability of diagnostic models.
- **Model Interpretability:** The "black-box" nature of complex AI models is a barrier to clinical acceptance, underscoring the necessity for Explainable AI (XAI) techniques to foster clinician trust and provide insights into neural mechanisms.

Future research must prioritize developing standardized, large-scale, multi-center datasets and explore multimodal data fusion (combining EEG with genetic, imaging, and clinical data) to yield a more comprehensive understanding and improve diagnostic and prognostic capabilities. Ultimately, integrating these advanced, explainable AI models with real-time monitoring holds the promise for a more proactive and comprehensive approach to PD diagnosis and personalized treatment strategies.

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