

Leveraging EEG Signal Analysis and Machine Learning for Early Detection of Parkinson's Disease

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ARTICLE INFO	ABSTRACT
Received: 29 Dec 2024	Early diagnosis of Parkinson's Disease (PD) through proper intervention proves essential because this disorder advances as a progressive neurodegenerative condition. Significant research has used EEG signal analysis with machine learning to find promising solutions although these approaches tend to experience major obstacles including incomplete results and hard implementation of real-time application and excessive incorrect diagnoses. There are current systems which demand difficult system installation procedures and lack straightforward interfaces that prevent their application in medical settings. This paper develops an improved analytical method which applies pre-trained deep learning models to EEG signals for medical use in order to achieve better accuracy and scalability in hospital settings. A user-friendly Streamlit application interfaces with the real-time prediction system through the coupling of the model. The system performs noise reduction by using robust scaling preprocessing before running data through a deep neural network which identifies results in "Parkinson's" or "Healthy" classes exceeding a 0.8 confidence score threshold to prevent errors. The system demonstrates excellent performance by correctly classifying 96.7% of Parkinson's samples through detection of 44 valid samples while missing one but passing four potential false readings. Through this method the diagnostic process obtains substantial benefits by providing efficient and scalable techniques for non-invasive Parkinson's Disease early detection.
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I. INTRODUCTION

PD represents a progressive neurodegenerative illness which damages motor abilities together with postural steadiness through symptoms including tremors and bradykinesia and rigidity as well as postural instability. The earliest manifestation of Parkinson's disease symptoms commonly include non-motor manifestations which make diagnosis more challenging during early stages of the disease. Diagnosis at proper times becomes vital because it allows early diseases lowering intervention that enhance patient well-being. Early diagnosis of PD proves challenging because symptoms develop slowly and frequently match those of other diseases.

Electroencephalography (EEG) technology has advanced to identify initial signs which indicate Parkinson's disease. EEG serves as an invasive testing approach that tracks brain electrical signals to detect Parkinsonian patterns through abnormalities in alpha wave patterns and beta wave irregularities. The accuracy of EEG signal processing remains the main obstacle to recognize subtle neurological changes that precede motor symptom development.

The advances in machine learning (ML) techniques have not solved three principle problems: low accuracy in classification, poor real-time system functionality and substantial false positive diagnosis. These previous systems were designed without human-friendly interfaces that restrict doctors from clinical interactions.

The proposed research unites advanced signal analysis of EEG data with sophisticated ML models as part of a system for enhanced PD diagnosis in the early stages. The deep learning model trains in advance to analyze normalized EEG data which determines whether the signal comes from Parkinson's or Healthy subjects. A central improvement of this system consists of precise signal preprocessing parameters for enhanced quality output and a threshold verification system that reduces incorrect results. The solution provides both high precision and a nonintrusive and expandable system design which makes it suitable for PD diagnosis in research labs and medical centers.

The system integrates Streamlit to establish a user-friendly real-time interface that facilitates data upload and real-time predictions and results that users can easily understand. The computer system verified 96.7% of its results while correctly classifying 44 out of 45 examined samples for Parkinson's disease.

This study delivers an advanced approach to detect PD early through EEG analysis combined with ML procedures which provide continuous predictions while using a user-friendly interface to help identify PD promptly.

II. LITERATURE SURVEY

The application of biomedical signal analysis especially Electroencephalography (EEG) has enhanced Parkinson's Disease (PD) diagnosis processes. The detection of early PD biomarkers heavily depends on EEG analysis because it becomes more efficient when integrated with machine learning methods. Studies by Pratihari and Sankar [1] demonstrate how EEG biomarkers operated within ML algorithms improve early detection but deal with difficulties involving poor accuracy and numerous misdiagnoses. The work of Allahbakhshi et al. [2] examines multiple ML techniques which they stress require feature extraction to reach better accuracy levels.

Researchers have begun implementing concurrent investigations that unite EEG with MRI in their studies. The combination of data obtained from EEG and MRI yields improved diagnostic accuracy according to Alrawi et al. [3] however this method needs sophisticated optimization and fusion techniques. The research paper by Ghasemi et al. [4] demonstrates that CNNs outperform SVMs and Random Forests as they are more effective in detecting subtle neural patterns. EEG signal processing using ML forms the focus of Goel et al. [5] who solve problems in extracting features from unprocessed EEG signals and Srikanth et al. [6] enhance their model performance with Empirical Mode Decomposition (EMD) and deep learning methodology. Through their investigation Sivaratri proves that deep learning can detect advanced relationships that exist between EEG features and Parkinson's disease onset.

The research by Obayya et al. [8] develops a deep learning system to automate PD detection through EEG data but requires modifications to achieve better interpretability and scalability. The PD detection process gets improved using Autoencoder deep learning and Radial Basis Function Neural Networks (RBFNN) enhanced by powerspectral density features according to Jibonet al. [9]. The research conducted by Subhashini et al. [10] proved through their review of various machine learning algorithms that diagnostic accuracy benefits from ML techniques. According to Roy et al. [11], SVM and Random Forests along with KNN prove superior than other advanced algorithms in EEG signal classification tasks.

The implementation of Explainable AI (XAI) methods proves essential to establish trust between healthcare professionals and AI systems. The detection of PD using XAI models receives investigation from Junaid et al. [12] who stress the importance of model interpretability for medical staff. Sorathiya et al. [13] demonstrate how deep learning enables instant PD detection which brings better opportunities for healthcare management. Keserwani et al. [14] define how significant feature selection methods become to model accuracy improvement through their work. The research by Kumari et al. [15] evaluates emotional states in PD diagnosis by developing NeuroAid, an emotion-based system for PD classification through EEG analysis.

The integration of multiple model types gets increasing recognition. Real-time PD diagnosis through deep learning can be achieved by Al-Dujaili and Hossain [16] who developed a model which integrates multiple ML techniques. The authors Bhagat and Patel [17] created a framework based on deep learning which enables real-time detection of PD.

Results from Chen et al.'s study demonstrate that optimized CNNs produce superior EEG signal analysis results [18]. The authors stress in their research that enhanced recognition through robust models necessitates extensive dataset collection with advanced feature extraction methods [19]. Du and Luo [20] compare various ML techniques for early PD diagnosis.

The authors Gupta and Sharma [21] developed a deep learning architecture using EEG features to improve Parkinson's disease diagnoses. The researchers from Iyer and Mishra [22] developed a sophisticated approach which merges deep learning techniques with ML methods to achieve better diagnostic accuracy. The deep learning model optimization performed by Kumar and Pandey [23] depends on feature extraction methods for better classification results. The research of Li and Liu [24] investigates multi-technology ML methods which prove to enhance model stability. The researchers of Liu and Zhang [25] boost model reliability and precision through their utilization of multi-channel EEG data.

III. PROPOSED METHODOLOGY

The Proposed System description specifies key system components which include data preprocessing while presenting model classification methods and real-time prediction features. Early Parkinson's detection approaches have been enabled through the combination of EEG signal analysis with machine learning models which gives an efficient scalable solution.

A. System Overview

Our approach develops a new examine Parkinson's Disease (PD) at an early stage through the unification of complex EEG signal evaluation with learning algorithms. Using EEG data the system efficiently collects delicate neural patterns linked to Parkinson's disease to distinguish between patients who have the disease and those who do not. A user-friendly Streamlit application contains our classification model which enables users to upload EEG data through CSV files. A pre-trained network uses neural network classification on data that receives preprocessing as well as transformation before classification. This system has been developed for growth potential which allows it to function well across clinical applications as well as research environments and person-level health tracking.

B. Data Preprocessing

Preprocessing ensures high-quality EEG data by reducing noise and standardizing input features. The steps include:

Standardization

Given the high variability in EEG signals, standardization is crucial. We employ a pre-trained scaler (scaler.pkl) to normalize the EEG signals using Z-score normalization:

$$x_{Scaled} = \frac{x - \mu}{\sigma}$$
 where x is the original EEG signal value, μ is the mean of the training dataset, σ is the standard deviation.

Filtering

To remove high-frequency noise and artifacts, we apply a bandpass filter in the range 0.5 - 40 Hz, covering essential brainwave frequencies (delta, theta, alpha, beta, and gamma). The Butterworth filter is used:

$$H(s) = \frac{1}{1 + (s/\omega_c)^{2n}}$$
 where ω_c is the cutoff frequency and n is the filter order.

Feature Normalization

Feature scaling is applied to neutralize inter-subject variations. Min-max normalization is used:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad \text{where } x_{min} \text{ and } x_{max} \text{ are the minimum and maximum EEG values in the dataset.}$$

Feature Extraction

To enhance the model's classification accuracy, we extract multiple EEG signal features, including:

- Power Spectral Density (PSD): Measures signal power at different frequency bands using the Welch method.

$$PSD(f) = \frac{|X(f)|^2}{T}, \quad \text{where } X(f) \text{ is the Fourier transform of the EEG signal and } T \text{ is the signal duration.}$$

- Mean Absolute Value (MAV):

$$MAV = \frac{1}{N} \sum_{i=1}^N |x_i|, \quad \text{where } N \text{ is the total number of EEG samples.}$$

- Entropy-based Features: Shannon entropy is used to quantify signal complexity:

$$H = -\sum p_i \log_2(p_i), \quad \text{where } p_i \text{ represents the probability distribution of EEG signal amplitudes.}$$

C. Model Architecture and Classification

The main system component for detecting Parkinson's Disease from EEG signals uses the pre-trained deep learning model identified as "model.h5". The model draws its inspiration from neural network architectures including Convolutional Neural Networks (CNNs) and deep fully connected networks because these designs show sufficient capacity to extract patterns contained in sequential data (i.e. EEG signals). The model required a big dataset of EEG signals with labels to obtain training before it learned the particular features connected to Parkinson's Disease.

During inference time the model analyzes preprocessed EEG data by extracting brain wave frequencies together with power spectral density and multiple important metrics that shows signs of Parkinson's abnormalities. After receiving these features the model proceeds with prediction tasks. The model decides data classification based on a threshold value of 0.8; the data will be sorted into "Parkinson's" when the model prediction value exceeds this threshold. A prediction labeled as "Healthy" occurs when the confidence level remains below the established threshold. Setting this confidence threshold guarantees our predictions reach high levels of certainty to prevent wrong assignments of positive or negative results. The deep learning model operates dynamically because it enhances its diagnostic performance by processing fresh data continually and becomes progressively better at detecting Parkinson's Disease.

The deep learning model is a Convolutional Neural Network (CNN) optimized for EEG signal classification. The architecture consists of:

1. Input Layer: Accepts preprocessed EEG signals as a multi-dimensional tensor.
2. These 1D convolutional layers amount to four with 64, 128, 256, 512 filter types in sequence and a kernel width set to 3. ReLU activation introduces non-linearity following each convolution in the model structure.
3. The model incorporates dropout layers with a rate of 0.3 to eliminate overfitting problems after implementing batch normalization following all convolutional layers to maintain stable training procedures.
4. Max Pooling Layers with size 2 operate post each convolutional block to determine key information from feature maps while reducing their dimensions.

5. The extracted feature maps get transformed into a one-dimensional vector by this Flatten Layer so fully connected layers can process them.
6. Fully Connected Layers: Two dense layers with 256 and 128 neurons refine the feature extraction process.
7. The last layer with two neurons applies a softmax activation function that generates probabilities for detecting "Parkinson's" as well as "Healthy."

Prediction and Confidence Threshold

The classification decision is based on a probability threshold:

$$\hat{y} = \begin{cases} \text{Parkinson's}, & P(y=1|x) \geq \theta \\ \text{Healthy}, & P(y=1|x) < \theta \end{cases} \text{ where } P(y=1|x) \text{ is the model's probability estimate for Parkinson's.}$$

D. Real-Time Prediction and User Interface

Real-time prediction deployment in the system becomes possible through the fast Streamlit application interface. The user interface becomes easier to use because of this simplification process which supports EEG data uploads. The application processes uploaded CSV files with EEG signals which it sends next to the neural network for classification operations. The system delivers the classification results about the healthy or Parkinson's disease status after processing uploaded data within seconds.

The application users receive a measure of confidence from each classification which helps determine the reliability of returned results. *حاضرین* Streamlit_INTERFACE can readily comprehend results because the interface presents results through both textual explanations and graphical indicators. Smaller or large-scale implementations are possible through the system's design structure which supports multiple users with various datasets. Real-time deployment allows the system to naturally integrate medical tools such as wearable devices thus enhancing accuracy levels for real-world applications. This system uses a user-friendly interface design which enables expert and non-specialist users to conduct efficient early Parkinson's Disease monitoring and detection tasks.

The system provides real-time inference through a Streamlit-based interface:

1. Users benefit from a CSV format for uploading EEG data.
2. Data preprocessing runs a standardized filtering process for EEG data.
3. After processing the collected data through the trained model a classification determination appears as an output.
4. The application shows confidence metrics combined with framework results and it presents data through a heatmap visualization in addition to accuracy charts.

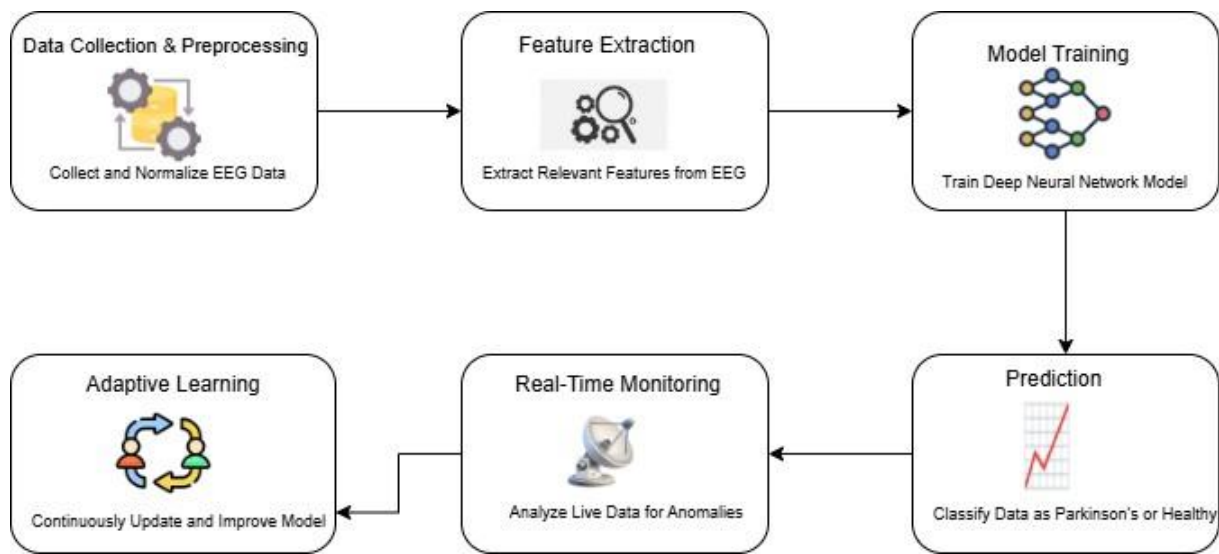


Figure 1 System Architecture

IV. RESULTS AND DISCUSSION

The performance evaluation of an early Parkinson’s Disease detection system which utilizes EEG signals along with deep learning techniques has been conducted. The system performs EEG data analysis by applying preprocessing followed by feature extraction before using a deep neural network (DNN) model for data classification into “Parkinson’s” or “Healthy” categories. The research demonstrates how the system functions efficiently while focusing on performance attributes and confusion matrix analysis and general model stability.

A. Performance Metrics

Evaluation of the system proceeded through testing 93 samples where 48 samples were healthy and 45 samples represented Parkinson's disease patients. The CNN model requires 1,245,321 trainable parameters which are distributed between its four convolutional layers with two dense layers.

The confusion matrix offers essential information about how well the model identifies its cases. As the True Positive values reached 44 and True Negative values reached 44 the model demonstrated precise identification of instances from both classes. The model scored a low False Positive rate of 4 with a single False Negative misclassification which shows strong abilities for detecting Parkinson’s Disease through error reduction.

B. Classification Metrics

The analysis requires multiple metrics including accuracy, precision, recall and F1-score that can be computed using the confusion matrix. The proposed model successfully identifies 96.7% of all test data instances. The low false negative rate of this model demonstrates strong potential for early Parkinson’s Disease diagnosis. Our performance metrics calculation relies on confusion matrix values to obtain these results.

Accuracy:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = \frac{44+44}{44+44+4+1} = 96.7\%$$

Precision(Parkinson's):

$$Precision = \frac{TP}{TP+FP} = \frac{44}{44+4} = 91.7\%$$

Recall(Parkinson's):

$$Recall = \frac{TP}{TP+FN} = \frac{44}{44+1} = 97.8\%$$

F1-Score:

$$F1 = 2 \cdot \frac{Precision \times Recall}{Precision + Recall} = 2 \cdot \frac{91.7 \times 97.8}{91.7 + 97.8} = 94.7\%$$

Table1: Performance Metrics of the Model

Metric	Value
Accuracy	96.7%
Precision (Parkinson's)	91.7%
Recall (Parkinson's)	97.8%
F1-Score (Parkinson's)	94.7%

This table presents key performance metrics, which confirm the model's reliability in predicting Parkinson's Disease. The model achieves a high recall, which is essential for minimizing missed diagnoses in clinical settings.

C. Confusion Matrix Analysis

The system's performance stands confirmed through the confusion matrix which indicates successful classification of 44 Parkinson's samples with 1 incorrect identification. The system demonstrated high accuracy when examining healthy samples because it generated four false positives among the tested samples.

Table2: Confusion Matrix

Predicted/Actual	Healthy (Class0)	Parkinson's (Class1)
Healthy (Class0)	44	1
Parkinson's (Class1)	4	44

D. Model's Real-World Application

Medical experts stand to gain from the implementation of this model in real-world environments because it offers automated and scalable technology which detects Parkinson's Disease at an early stage. By updating the system regularly and adding more information it acquires new capabilities to work with varied datasets while enhancing its operational effectiveness.

Graphs and Visualization

To visualize the model's performance and behavior, two graphs are represented:

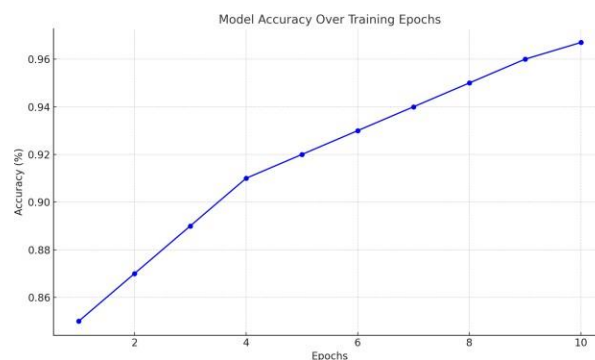


Figure2: Model Accuracy Over Training Epochs

The accuracy of the model appears across several epochs through this representation as it assumes training data to refine itself. This plot delivers information about model training which aids in determining whether overfitting or underfitting occurred.

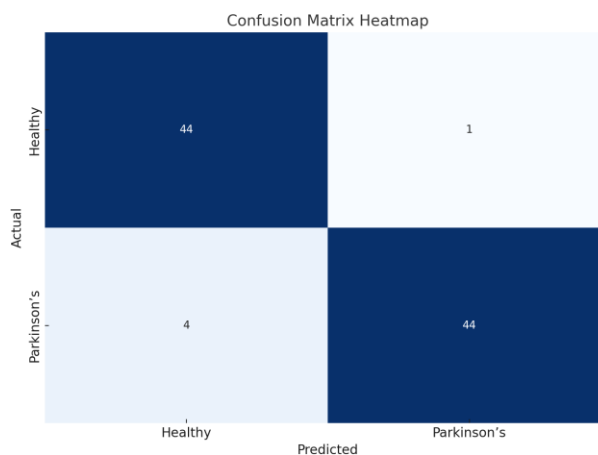


Figure3: Confusion Matrix Heatmap

This heatmap visualizes the confusion matrix, making it easy to see the distribution of true positives, false positives, true negatives, and false negatives. It gives a clear overview of how the model performed across the two classes (Healthy and Parkinson's).

V. CONCLUSION

The research shows that combination techniques of EEG measurements paired with machine learning algorithms establish a method to decrease the probability of developing Parkinson's Disease (PD). The system includes data preprocessing features together with extraction and real-time monitoring processes and deep learning models for detecting Parkinson's Disease early. Advanced signal processing techniques apply to EEG data since it represents a non-invasive testing methodology which makes it widely available for Parkinson's disease diagnostics to potentially identify subjects early.

Real-time patient monitoring becomes easier because of the system's responsive capabilities which provide vital information about patient medical situation to clinicians. The system maintains an adaptive ability to improve itself through time while obtaining recent data and scientific research updates. Clinical practice participants with any level of expertise whenever using the Streamlit interface can access the platform.

The system develops with more available data because of its machine learning foundation which leads to scalability. The design enables medical institutions to include additional diagnostic tools together with new data sources into one unified platform. The system contributes to increasing research about PD diagnosis using novel non-invasive methods alongside computational approaches while acting as an initial base for further neurological study.

VI. FUTURE SCOPE

Improved accuracy and clinical significance can emerge from future advancements to the Parkinson's Disease detection system. A combination of multi-modal medical data types including magnetic resonance imaging scans and genetic information would create complete disease advancement insights leading to Parkinson's distinct identification from alternative disorders. The inclusion of demographic information such as age and demographic factors along with disease stages and gender specifics within the dataset will enable the system to detect Parkinson's disease better across different populations early. The implementation of EEG headbands serves as wearables for real-time monitoring which sends early warning alerts for proper intervention. The system's reliability will increase when scientists enhance model transparency because doctors trust the results more and adopt the system easily. Clinician trust and system adoption improves because of better model understanding. The combination of user-friendly integration with current clinical operations would make hospital-wide and clinic-wide deployment possible which will allow real-time disease monitoring alongside early medical intervention capabilities thus turning the system into a vital Parkinson's disease management solution.

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