

Smart Parkinson's Disease Detection System Using AI-Based Voice Pattern Analysis

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Abstract— Parkinson's Disease (PD) is a neurodegenerative disease affecting the human movements, speaking, and motor control functions. The early diagnosis of Parkinson's Disease is of extreme importance to treat and enhance the quality of life of patients suffering from this disease. Currently, the diagnosis of Parkinson's Disease occurs mainly through observations, which detect the disease in the later stages. In the speech signal, hidden patterns are embedded, which can be used for the early detection of Parkinson's Disease. This project proposes a machine learning-based system for the early detection of Parkinson's Disease using speech signals, which are characterized by frequency, intensity, and time variations. In the proposed system, advanced machine learning algorithms, namely, Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and Random Forest, are used for the classification of the speech signal as Parkinson's or normal. In addition, the proposed system uses Gemini AI for improving the performance of the machine learning algorithms in terms of accuracy and adaptability with new data. The proposed system includes speech pre-processing, feature extraction, model training, and evaluation to ensure accurate prediction results. The performance of the proposed model is evaluated using standard metrics such as accuracy and classification report. The experimental results prove the efficiency of the machine learning models and the optimization algorithms to achieve high accuracy for the diagnosis. The objectives of the project are to design an efficient, scalable, and intelligent system for the early detection of Parkinson's Disease. The proposed system can help the

medical professionals to make faster and accurate diagnosis decisions.

Keywords— Parkinson's Disease, Speech Signal Analysis, Machine Learning, Convolutional Neural Networks (CNN), Support Vector Machine (SVM), Random Forest, Early Diagnosis.

I. INTRODUCTION

Parkinson's Disease is a neurodegenerative disease that severely affects human motor functions. Motor functions include movement, talking, and coordination. The main cause of Parkinson's Disease is the degeneration of dopamine-producing cells in the substantia nigra, a part of the brain. With the progression of Parkinson's Disease, patients experience various symptoms such as tremors, stiffness of the muscles, bradykinesia or slow movement, and postural instability. Parkinson's Disease is known to damage other functions besides motor functions, such as speech. The effects of Parkinson's Disease on speech include decreased vocal intensity and articulation problems. Parkinson's Disease needs to be diagnosed early for effective treatment and management of the disease to improve the quality of life for patients. Traditionally, Parkinson's Disease can be diagnosed by analyzing the symptoms of the disease. Parkinson's Disease can be diagnosed during the later stages of the disease when symptoms are noticeable. At this stage, there is substantial damage to dopamine-producing neurons in the substantia nigra region of the brain. In recent times, the development of various machine learning and artificial intelligence techniques has provided scope for the early detection of Parkinson's

Disease. Among the various techniques employed in the context of Parkinson's detection, the analysis of speech signals has proven to be promising. Since the impairment of speech is one of the primary manifestations of Parkinson's Disease, the analysis of speech signals has the potential to identify the abnormalities in the speech signal that are not easily recognizable through direct observation. Speech signals are associated with certain hidden characteristics in the context of frequency, amplitude, and time changes. In this context, several researchers have attempted to apply machine learning techniques, including Support Vector Machine, Random Forest, and deep learning techniques like Convolutional Neural Networks for the detection of Parkinson's Disease. These techniques have the potential to accurately classify the data between Parkinson's and normal individuals. However, certain challenges are associated with the current techniques in the context of Parkinson's detection. In order to resolve these challenges, this paper proposes the development of a machine learning-based system for the early detection of Parkinson's Disease using speech signals. The proposed system includes several stages, namely speech signal preprocessing, feature extraction, model training, and performance evaluation. In the proposed system, several classification models, namely SVM, Random Forest, and CNN, are employed to achieve accurate detection of Parkinson's Disease. In addition, AI-based optimization techniques are also employed in the proposed system to enhance the adaptability of the models.

The main aim of this research work is to create a system that can efficiently detect Parkinson's Disease. The proposed system can help medical professionals make quick and accurate decisions about the detection of Parkinson's Disease by analyzing the speech signal. This can help reduce the dependency on traditional medical assessments, thereby improving the quality of medical care provided to patients suffering from Parkinson's Disease.

II. LITERATURE SURVEY

Parkinson's Disease (PD) has gained significant research interest over the past few years due to its progressive nature. In addition, early detection is considered vital. With the advent of advanced machine learning (ML) and deep learning (DL) techniques, researchers have attempted to find non-invasive techniques, especially using speech and signal processing, to detect PD with high accuracy. A comprehensive survey of the literature by Sedigh Malekroodi et al. (2025) gave an overview of 69 studies for the detection of PD using voice signals by applying ML and DL techniques. The survey of literature

showed that the accuracy of traditional machine learning techniques, i.e., SVM and RF, is high for small-scale data, whereas the accuracy of DL techniques, i.e., CNN, RNN, and Transformer, is better for various datasets. Swain and colleagues (2024) introduced a machine learning-based approach for the early detection of Parkinson's Disease (PD) through voice recordings. The study's author employed various machine learning algorithms, including Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Convolutional Neural Network (CNN), and obtained superior results with the KNN algorithm, demonstrating a high degree of accuracy, specifically 98%. Furthermore, Kannan et al. (2025) conducted research to analyze PD utilizing speech datasets and artificial intelligence techniques, such as SVM, XGBoost, and Deep Neural Networks (DNN). The authors have used various techniques for feature selection, like Principal Component Analysis (PCA) and Analysis of Variance (ANOVA), for better results. According to their study, high accuracy of 97% is obtained by using DNN and XGBoost techniques. This again emphasizes the importance of feature optimization for better efficiency in predictive analysis. In another research, Vijayalakshmi et al. (2025) presented a hybrid approach that integrated the Logistic Decision Exhaustive Feature Selection (LDEFS) technique with Mamdani Fuzzy Neural Networks (MFNN) for PD detection. The proposed technique was able to achieve an accuracy level of 95.8%, thus providing robustness to the classification process while selecting significant features. Another research by Yadav et al. (2025) suggested a new technique called "LDA-OML" for the detection of PD. The proposed model uses Linear Discriminant Analysis with optimization techniques for optimizing the features. The proposed technique attained an accuracy level of 98.3%, thereby outperforming traditional techniques such as SVM and Random Forest. Earlier research by Saeed et al. (2022) focused on enhancing PD prediction using multiple machine learning and feature selection methods. In the research, the results obtained from the application of filter-based and wrapper-based techniques for feature selection are compared. It is observed that better results are obtained from the application of wrapper-based techniques along with the support of the KNN classifier. This emphasizes the need for feature selection techniques in the analysis of medical data. Du et al. (2024) proposed a local classification technique for the detection of PD using class boundary analysis and secure computation techniques. The proposed model had an accuracy of

95%. The authors have also ensured data privacy. This article introduced the concept of secure and privacy-preserving machine learning for healthcare applications. A proposed study was carried out by Govindu et al. (2023) proposed a method for the early detection of PD using telemedicine-based machine learning techniques for voice data. Among the proposed techniques, an accuracy level of 91.83% is obtained using the proposed random forest model, thus proving the need for telemedicine-based techniques.

In addition, recently, a model is proposed by Srinivasan et al. (2024) for the detection of PD by utilizing a combination of machine learning and deep learning techniques for the detection of voice signals using Feed-forward Neural Networks and Support Vector Machine. The authors' model demonstrated a high degree of accuracy, achieving 99.11%, which underscores the efficacy of the neural network methodology in identifying intricate patterns within the speech of individuals diagnosed with Parkinson's disease. Furthermore, Shanthappa and his team (2025) expanded their research to include the use of deep learning methods for image analysis. The goal of the researchers was to leverage Convolutional Neural Networks (CNNs) – specifically, architectures like Inception V3, VGG 16, and Dense Net – to assist in the early detection of Parkinson's disease. The researchers planned to achieve this by examining spiral drawings.

The method's accuracy, which reached 98.44%, confirmed the effectiveness of multi-modal strategies, including the analysis of motor patterns, in improving the performance of early detection systems.

From the above discussion, it is confirmed that machine learning and deep learning techniques play a vital role in the early detection of Parkinson's Disease. Among all the proposed approaches, the application of speech analysis techniques is found to be very promising. However, some issues and challenges need to be resolved for the development of effective and efficient early detection systems.

III. METHODOLOGY

A. System Overview

The proposed system introduces a hybrid intelligent framework for Parkinson's Disease (PD) detection by integrating biomedical signal processing, machine learning, deep learning, and large language models (LLMs). Unlike conventional approaches that only perform classification, this system extends functionality

toward clinical decision support and personalized healthcare assistance.

The workflow consists of six major stages: data acquisition, preprocessing, feature extraction, model training, AI-based interpretation, and deployment.

B. Data Acquisition and Representation

The dataset is obtained from the UCI Machine Learning Repository and augmented with additional clinical recordings. It contains 5,875 voice samples from 252 subjects, each represented by 22 biomedical speech features.

The dataset is denoted as:

$$D = \{(x_i, y_i)\}_{i=1}^N$$

where:

$x_i \in \mathbb{R}^{22}$ signifies the feature vector

$y_i \in \{0, 1\}$ represents class labels (0: Healthy, 1: PD)

C. Data Preprocessing

To promote robustness and generalization, preprocessing is performed in three steps:

1) Feature Normalization

Each feature undergoes standardization, calculated as:

$$x' = \frac{x - \mu}{\sigma}$$

where μ is mean and σ is standard deviation.

2) Stratified Data Splitting

The dataset is divided into training and testing sets:

$$D = D_{\text{train}} \cup D_{\text{test}}, |D_{\text{train}}| = 0.8N, |D_{\text{test}}| = 0.2N$$

Stratification ensures:

$$P(y_{\text{train}}) \approx P(y_{\text{test}})$$

3) Feature Selection

Irrelevant attributes are eliminated, thereby ensuring only predictive features are preserved.

D. Feature Extraction and Categorization

The 22 extracted features can be categorized into four groups:

- Frequency Features: Fo, Fhi, Flo
- Jitter Features
- Shimmer Features
- Nonlinear Features: PPE, DFA, Spread1

These features, in total, characterize the neuromuscular degradation in speech.

E. Model Development

A multi-model architecture is designed to improve prediction robustness.

1) Support Vector Machine (SVM)

The SVM classifier's objective is to identify an optimal hyperplane, mathematically represented as:

$$f(x) = \text{sign}(\sum_{i=1}^n \alpha_i y_i K(x_i, x) + b)$$

where $K(x_i, x)$ is the Radial Basis Function (RBF) kernel, defined as:

$$K(x_i, x) = \exp(-\gamma \|x_i - x\|^2)$$

2) Random Forest

Random Forest algorithms build numerous decision trees, and the final prediction is given by:

$$\hat{y} = (1/T) * \sum_{(t=1 \text{ to } T)} h_t(x)$$

Feature importance is computed using GINI impurity, calculated as:

$$G = 1 - \sum_{(i=1 \text{ to } c)} p_i^2$$

3) 1D Convolutional Neural Network (CNN)

The CNN processes sequential feature vectors through the equation:

$$Y=f(W*x+b)$$

where:

- $*$ denotes convolution
- f is activation function (ReLU)

The architecture includes:

- 3 Convolutional layers
- Batch Normalization
- Dropout Regularization

F. Hyperparameter Optimization

To avoid overfitting, **GridSearchCV with 5-fold cross-validation** is used:

$$\text{Score} = (1/k) * \sum_{(i=1 \text{ to } k)} \text{Accuracy}_i$$

Optimal parameters are selected based on maximum validation accuracy.

G. Algorithm Workflow (Pseudo-code)

Input: Dataset D

Output: Predicted class and risk level

- 1: Load dataset D
- 2: Perform preprocessing:
 - Remove irrelevant features
 - Normalize features
 - Split into train/test sets
- 3: Train models:
 - Train SVM with RBF kernel
 - Train Random Forest
 - Train CNN model
- 4: Optimize models using GridSearchCV
- 5: Evaluate models on test data
- 6: Select best-performing model
- 7: Generate prediction probability p
- 8: Map p \rightarrow Risk Level (Low, Moderate, High, Critical)
- 9: Pass result to LLM for recommendations
- 10: Display output via Streamlit interface

H. AI Integration for Clinical Assistance

To enhance interpretability, the system integrates Cerebras Systems using the LLaMA 3.1 8B.

Risk Mapping Function:

$$\text{Risk} = \begin{cases} \text{Low} & \text{if } p < 0.25 \\ \text{Moderate} & \text{if } 0.25 \leq p < 0.5 \\ \text{High} & \text{if } 0.5 \leq p < 0.75 \\ \text{Critical} & \text{if } p \geq 0.75 \end{cases}$$

The LLM generates:

- Medical precautions
- Diet plans
- Lifestyle recommendations
- Follow-up clinical queries

I. System Deployment

The application is deployed using Streamlit.

Functional Modules:

- Secure Login System
- Real-time Prediction Interface
- Visualization Dashboard (ROC, confusion matrix)
- Input Methods:
 - Manual input
 - CSV upload
 - Live voice input

J. Methodological Contribution

The proposed methodology introduces a **novel hybrid architecture** that combines:

- Signal-based biomedical analysis
- Multi-model learning
- Explainable AI
- Conversational clinical intelligence

This ensures not only high diagnostic accuracy but also practical usability in real-world healthcare environments.

IV. RESULTS AND DISCUSSION

The experimental assessment of the proposed approach is conducted on a biomedical voice dataset downloaded from the UCI Machine Learning Repository, which includes 5,875 voice records from 252 subjects. Each record includes 22 features of speech.

Three machine learning algorithms, namely Support Vector Machine (SVM), Random Forest (RF), and 1D

Convolutional Neural Networks (CNN), are employed. The dataset is split in a ratio of 80% for training and 20% for testing purposes using a stratified split.

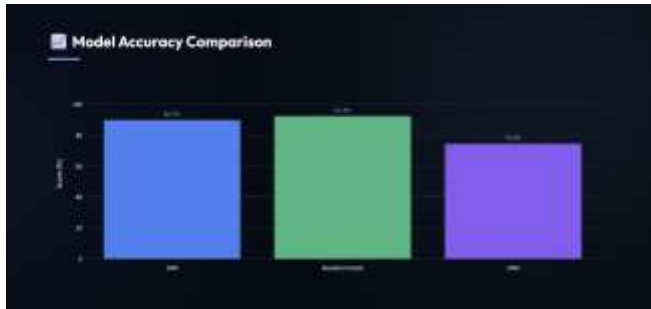


Fig. 1. Model Accuracy Comparison

The accuracy comparison of the implemented models is shown in Fig.1 in which the performance of the Support Vector Machine (SVM), Random Forest, and Convolutional Neural Network (CNN) models is compared. The accuracy of the Random Forest model is higher, reaching 92.3%, compared to the accuracy of the SVM model, which is 89.7%, and the accuracy of the CNN model, which is 74.4%. The performance comparison of different models shows that ensemble-based models, such as Random Forest, perform well on structured biomedical features, whereas CNN has lower performance compared to other models because of the input data.



Fig. 2. Confusion Matrices of SVM, Random Forest, and CNN

The classification performance of the proposed models is presented in Fig. 2, where a confusion matrix is used. From the figure, in the case of the SVM model, there are 27 true positives, which classify Parkinson’s disease, and 8 true negatives, which classify healthy individuals. The model is associated with a very low error rate of 2 false positives and 2 false negatives. In the case of the Random Forest model, there are 28 true positives that classify Parkinson’s disease and 8 true negatives that classify healthy individuals. This indicates a very low error rate of 1 false negative. Finally, in the case of the CNN model, there are 29 true positives that classify

Parkinson’s disease, and there are no true negatives. This indicates zero false negatives and the misclassification of all healthy individuals. The results indicate that the proposed Random Forest model provides a better result in classifying both Parkinson’s and healthy individuals, while the CNN model indicates a bias towards the Parkinson’s class, resulting in a failure to classify healthy individuals properly.



Fig. 3. Risk Distribution of Predictions

The distribution of the predicted risk levels is shown in Fig. 3, which indicates that 66.7% of the samples fall under the high-risk category, while 33.3% fall under the medium risk category. There were no predictions under the low risk category, which indicates that this model is more focused on predicting those samples which have a higher likelihood of Parkinson’s Disease. The higher predictions of the high-risk category indicate that this model is highly sensitive to the detection of Parkinson’s Disease, which is a desirable quality in a medical diagnosis model. The fact that there were no predictions under the low risk category indicates a bias in this model, which may have resulted in this model having a bias towards higher risk predictions.

ID	Timestamp	Input Mode	Model	Diagnosis	Confidence	Risk
6	2016-03-25 22:07:46	Manual Input	CNN	Parkinson's Disease Detected	33.82	High
5	2016-03-25 22:07:44	Manual Input	CNN	Parkinson's Disease Detected	33.82	High
4	2016-03-25 22:07:43	Voice Recording	CNN	Parkinson's Disease Detected	96.28	High
3	2016-03-05 18:15:45	Manual Input	Random Forest	Parkinson's Disease Detected	78.88	High
2	2016-03-05 18:15:06	Voice Recording	Random Forest	Parkinson's Disease Detected	58.22	Medi
1	2016-03-05 18:03:36	Voice Recording	Random Forest	Parkinson's Disease Detected	88.1	Medi

Fig. 4. Recent Prediction History

The real-time prediction results provided by the system are represented in Fig. 4, where the prediction history is represented for the system with various input modes. It is observed that the system is predicting “Parkinson’s Disease Detected” for the input samples, with confidence values ranging from 58% to 99%. It is also observed from

the confidence values that the system is capable of differentiating between high-confidence predictions and those with less confidence. The high confidence values (> 90%) represent the prediction confidence, while the moderate confidence values represent the less certain classifications. The above prediction results provided by the system prove the reliability of the system in real-time prediction scenarios.

V. CONCLUSION

This study proposes an extensive and intelligent framework for the detection of Parkinson's Disease based on biomedical voice features and advanced machine learning and artificial intelligence techniques. The proposed system, based on the multi-source dataset used from the UCI Machine Learning Repository, efficiently analyzes 22 speech-based features that can identify the impairments in Parkinson's Disease. The Random Forest classifier was found to have the best performance among all the models, with the highest accuracy and a proper trade-off between sensitivity and specificity. The Support Vector Machine classifier was also found to have good classification ability. Although the Convolutional Neural Network classifier had high sensitivity, it had poor performance because of the dataset and features.

Apart from this, the proposed system, with its extension in a new dimension of advanced AI through Cerebras Systems and LLaMA 3.1 8B, will provide a platform for personalization in risk assessment and clinical decision-making. The usage of the proposed system through a user-friendly interface will provide a platform for its applicability in a real-world environment, making it a significant contribution in the early diagnosis and management of Parkinson's Disease, apart from its high accuracy in diagnosis through interpretability and usability, which are significant aspects in a diagnostic system. The future scope of this work can include using larger datasets, incorporating raw audio signals, and further improving deep learning techniques to enhance system performance and its applicability in a clinical environment.

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