



# A Mini Project Report on

## “Detection of Parkinson’s Disease”

*In partial fulfillment for the award of the degree of*

**BACHELOR OF TECHNOLOGY**

*in*

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**The Charutar Vidya Mandal (CVM) University,**

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## G H Patel College of Engineering & Technology

Bachelor of Technology (Computer Science and Design)

### CERTIFICATE

This is to certify that **Het Mehta (12202130501023)** and **Jay Thanki (12202130501029)** have successfully submitted the **Mini Project Report** titled "**Detection of Parkinson's Disease**", in partial fulfillment of the requirements for the degree of **Bachelor of Technology in Computer Science and Design** at **G H Patel College of Engineering and Technology** at The **Charutar Vidya Mandal (CVM) University**, Vallabh Vidyanagar, during the academic year **2024–2025**.

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## DECLARATION

I, Het Mehta (12202130501023) and Jay Thanki (12202130501029), hereby declare that the Mini Project report submitted in partial fulfillment for the degree of Bachelor of Technology in Computer Science and Design, G H Patel College of Engineering & Technology, The Charutar Vidya Mandal (CVM) University, Vallabh Vidyanagar, is a bonafide record of work carried out by me under the supervision of Dr.Namrata Pandya and that no part of this report has been directly copied from any students' reports or taken from any other source, without providing due reference.

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**Het Mehta**

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**Jay Thanki**

## **Acknowledgment**

The successful progress of any project is made possible through the cooperation, coordination and collective efforts of several sources of knowledge. We would like to express our deepest gratitude to **Dr.Namrata Pandya** for her invaluable guidance, encouragement, wholehearted support and constructive feedback throughout the duration of our project.

We hope that this Mini Project Report provides all the necessary information for readers to understand our work and its objectives. The pursuit of knowledge is continuous and practical implementation is essential to complement theoretical understanding. We sincerely thank **Dr.Namrata Pandya** for her unwavering support and mentorship.

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## **ABSTRACT**

Parkinson's Disease (PD) is a progressive neurodegenerative disorder that affects motor functions such as tremors, rigidity, and slowed movement, as well as non-motor aspects like speech and cognition. Early diagnosis plays a crucial role in managing symptoms and improving patients' quality of life, yet traditional diagnostic approaches are often subjective, expensive, and time-consuming. The proposed project aims to develop an efficient and automated system for the early detection of PD using Machine Learning (ML) techniques focused on voice data analysis. Since voice impairments are among the earliest symptoms of PD, the proposed method provides a non-invasive and cost-effective alternative to conventional diagnostics. The proposed system follows a structured pipeline involving data preprocessing, voice feature extraction, model training, and performance evaluation. Features such as jitter, shimmer, and harmonics-to-noise ratio are extracted from speech recordings and used to train various ML models including Logistic Regression (LR), K-Nearest Neighbors (KNN), Support Vector Classifier (SVC), Gaussian Naïve Bayes (GNB), Decision Tree Classifier (DTC), and Random Forest Classifier (RFC). Among these, the Random Forest and Support Vector Classifiers demonstrated the highest levels of accuracy and reliability, highlighting the effectiveness of the proposed system in distinguishing individuals affected by PD from healthy individuals.

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# Chapter 1 : Introduction

## 1.1 Background

Parkinson's Disease (PD) is a chronic and progressive neurological disorder that primarily affects motor control and speech. It is characterized by symptoms such as tremors, rigidity, slowed movement, and speech difficulties. While these symptoms worsen over time, early detection and treatment can significantly improve quality of life and slow disease progression. Speech impairments, including reduced vocal intensity, monotony, and slurred speech, often appear in the early stages of PD, making voice analysis a potential diagnostic indicator.

Traditional diagnostic methods rely heavily on clinical observation and neurological assessments, which can be subjective, time-consuming, and dependent on expert availability. With the rapid development of artificial intelligence and data-driven healthcare, Machine Learning (ML) offers promising avenues for creating objective, automated, and scalable solutions. This project leverages ML to analyze speech patterns and detect early signs of Parkinson's Disease, enabling timely intervention and improved patient outcomes.

## 1.2 Problem Statement

Conventional diagnosis of Parkinson's Disease is often delayed due to the reliance on physical symptoms and clinical expertise, resulting in late interventions and reduced treatment effectiveness. Since vocal symptoms typically precede physical manifestations, analyzing speech offers an early diagnostic opportunity. However, manual voice analysis is limited by human accuracy and consistency. Therefore, there is a critical need for an automated system that can detect PD using voice data, ensuring early diagnosis through a non-invasive, efficient, and accurate approach.

## 1.3 Objectives

1. Develop an automated detection system for identifying Parkinson's Disease using voice data.
2. Extract key speech features to analyze vocal impairments associated with PD.
3. Apply Machine Learning algorithms to classify individuals as PD-affected or healthy.
4. Enhance diagnostic accuracy through optimized data preprocessing and model selection.

5. Provide a non-invasive and cost-effective solution for early disease detection.
6. Assist healthcare professionals in improving early intervention and patient care.
7. Explore future improvements such as real-time voice analysis and expanded datasets for better generalization.

## 1.4 Scope of the Project

This project focuses on detecting Parkinson's Disease using voice recordings and Machine Learning techniques. It leverages the extraction of specific vocal features such as jitter, shimmer and fundamental frequency to build effective classification models. The proposed solution is non-invasive, affordable and scalable, making it suitable for clinical and telehealth applications. The project encompasses various stages, including data collection and preprocessing, feature extraction and selection, model training and performance evaluation. A comparative analysis of different algorithms is conducted to identify the most accurate and reliable approach. In the future, the project aims to enhance generalization by expanding the dataset, incorporate real-time detection capabilities, and deploy the system as a mobile or web-based application for broader accessibility and usability.

## 1.5 Methodology

The approach followed in this project includes the following steps:

1. **Data Collection:** Using publicly available voice datasets from individuals with and without PD.
2. **Preprocessing:** Cleaning and normalizing the data to ensure quality and consistency.
3. **Feature Extraction:** Identifying key acoustic features relevant to speech impairments caused by PD.
4. **Model Selection:** Training and evaluating multiple ML models (e.g., SVM, Random Forest, Neural Networks).
5. **Performance Evaluation:** Using metrics such as accuracy, precision, recall, and F1-score to evaluate model performance.
6. **Deployment Plan:** Discussing the possibilities for integrating the model into a practical healthcare tool.

## 1.6 Organization of the Report

### **Chapter 1: Introduction**

Provides background, problem statement, objectives, scope, methodologies and outlines the structure of the report.

### **Chapter 2: Literature Review**

Reviews existing research, compares techniques and identifies gaps in current systems.

### **Chapter 3: System Analysis and Design**

Covers requirement analysis, feasibility study, system architecture, design diagrams, user interface, and technology stack.

### **Chapter 4: Implementation**

Describes the implementation process, module breakdown and system interface with relevant screenshots.

### **Chapter 5: Results and Discussion**

Presents system performance, testing results, comparison with existing systems and highlights strengths and limitations.

### **Chapter 6: Conclusion and Future Work**

Summarizes the project outcomes and discusses possible future improvements.

## Chapter 2 : Literature Review

### 2.1 Introduction to Literature Review

Parkinson's Disease (PD) is a progressive neurodegenerative disorder that primarily affects motor and speech functions. With increasing prevalence worldwide, early and accurate diagnosis is critical for improving patient outcomes. Traditional methods of diagnosis rely on clinical assessments, which are often subjective and time-consuming. This has led researchers to explore automated approaches using Machine Learning (ML) and Artificial Intelligence (AI) to analyze voice data and detect early symptoms of PD [1, 2].

Speech-based analysis has emerged as a non-invasive and cost-effective method for PD detection. The field of AI has made significant advancements in utilizing voice-based biomarkers to differentiate between healthy individuals and PD patients. This literature survey reviews various research studies on ML-based PD classification using speech analysis, emphasizing different methodologies, feature extraction techniques, ML algorithms, and challenges in current research [3, 4].

### 2.2 Research and Related Work in the Field

PD is characterized by a gradual decline in motor functions due to the degeneration of dopamine-producing neurons in the substantia nigra region of the brain. This loss leads to tremors, rigidity, and bradykinesia. Among the various motor symptoms, speech impairments such as monotone voice, reduced speech articulation, and tremors in vocal cords are significant indicators of PD [1].

Studies have shown that early-stage PD patients exhibit vocal alterations before noticeable motor symptoms appear. This makes speech analysis a valuable tool for early diagnosis. However, manual clinical assessments of speech characteristics are often inconsistent and prone to human error. Therefore, automated ML-based techniques provide a reliable alternative by accurately classifying PD patients based on extracted speech features [2, 3].

Over the years, several studies have explored different methodologies for voice-based PD detection. Research has highlighted the importance of analyzing vocal parameters such as jitter, shimmer, and harmonic-to-noise ratio (HNR). Various datasets, including those collected from the UCI repository, have been widely used to train and validate models, helping in the improvement of PD classification techniques [4]. The integration of deep learning architectures,

such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, has further enhanced diagnostic accuracy [2, 3].

### **2.3 Speech Feature Extraction for PD Diagnosis**

Feature extraction is a critical step in speech-based Parkinson's Disease (PD) diagnosis. The quality and accuracy of the extracted features directly impact the performance of classification models. Commonly extracted features include jitter and shimmer, which measure frequency and amplitude variations in speech [1]; Harmonic-to-Noise Ratio (HNR), which indicates the level of noise in a patient's voice [3]; Zero-Crossing Rate (ZCR), representing frequency changes in the speech signal [4]; Root Mean Square (RMS) energy, which measures the energy of the voice signal [2]; and entropy and skewness, which are statistical features used to analyze voice variability [3]. Speech recordings from PD patients and healthy controls are analyzed using machine learning techniques. Various datasets have been employed to validate models, including those collected from clinical settings where patients are categorized as Med On (with medication) and Med Off (without medication). Feature extraction plays a crucial role in improving classification accuracy [1, 3].

### **2.4 Machine Learning Approaches for PD Classification**

Different ML models have been tested for PD classification, with varying levels of accuracy. The following studies highlight key approaches:

#### **2.4.1 Deep Learning and AI-Based Classification**

Multiple machine learning techniques, including deep learning, have been explored to improve diagnostic accuracy [2]. AI-driven speech analysis has been shown to mitigate the subjectivity associated with traditional Parkinson's Disease (PD) diagnosis [3]. Studies have reported success in using deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) for PD classification [4]. Additionally, the combination of spectrogram analysis and deep learning architectures has shown promising results in differentiating PD patients from healthy individuals [2, 3].

#### **2.4.2 Optimization and Feature Selection Techniques**

The Squirrel Search Algorithm (SSA) and Principal Component Analysis (PCA) have been implemented to enhance feature selection [1]. Ensemble learning models such as Gradient Boost, AdaBoost, and LightGBM have shown improvements in classification performance [2].

Some studies have achieved accuracy rates exceeding 97%, demonstrating the significant potential of AI in Parkinson's Disease detection [3]. Furthermore, the use of hyperparameter tuning and cross-validation techniques has contributed to refining model efficiency and robustness [4].

#### **2.4.3 Comparative Analysis of Machine Learning Models**

Studies have reviewed various machine learning models, finding that Gradient Boosted models consistently achieve the highest accuracy [3]. Cross-validation techniques such as tenfold cross-validation have been applied to ensure model robustness [2]. Deep learning architectures have been compared with classical machine learning algorithms, showing promising results in Parkinson's Disease classification [4]. Additionally, decision trees, support vector machines (SVMs), and random forest classifiers have also demonstrated effective performance in PD detection models [1, 3].

### **2.5 Summary of Existing Solutions**

Existing studies in PD detection through speech analysis provide several effective methodologies, but also face key challenges.

Feature selection variability is a challenge, as different studies use diverse feature sets, making comparisons difficult [2]. Dataset limitations, such as those in public datasets like the UCI Parkinson's dataset, result in limited sample sizes that affect model generalization [4]. Models trained on one dataset often struggle with unseen data, highlighting the need for cross-dataset validation [1]. While deep learning models are accurate, they require significant computational resources, which limits their use in real-time applications [3]. Ethical considerations are also critical, as AI-based Parkinson's Disease diagnosis requires careful validation to avoid misdiagnosis and ensure patient safety [2].

### **2.6 Advancements and Future Trends in PD Diagnosis**

Recent advancements in AI and computational power have contributed to significant progress in PD diagnosis. Researchers are now focusing on:

Hybrid AI models are being explored by combining traditional machine learning algorithms with deep learning techniques to enhance predictive accuracy [3]. Personalized AI solutions are being developed to tailor models to individual speech characteristics, leading to improved diagnosis [1]. Additionally, integration with wearable technology is being investigated for real-time voice monitoring systems, enabling continuous Parkinson's Disease tracking [4].

Blockchain and federated learning are also being explored to ensure data privacy while enhancing AI model training across multiple institutions [2].

## 2.7 Challenges in Speech-Based PD Diagnosis

Despite advancements in AI-driven PD detection, certain challenges persist:

Variability in speech patterns is a challenge, as Parkinson's Disease (PD) symptoms vary among individuals, which affects the accuracy of voice-based diagnostics [1]. Environmental noise, such as background sounds, can distort voice recordings, reducing the effectiveness of machine learning models [3]. Data collection constraints, including limited access to high-quality, labeled datasets, hinder model training and validation [4]. Furthermore, ethical and privacy concerns arise when handling sensitive patient voice data, necessitating robust privacy measures to ensure patient confidentiality [2].

## 2.8 Real-World Applications of AI in PD Detection

Clinical Decision Support Systems are being enhanced by AI models, assisting neurologists in diagnosing Parkinson's Disease with greater accuracy and speed [3]. Telemedicine and remote monitoring are facilitated by speech-based AI tools, enabling early PD detection without the need for in-person consultations [1]. Additionally, the integration of AI with assistive technology supports speech therapy and rehabilitation for PD patients, enhancing their quality of life [2].

## 2.9 Potential Improvements in AI-Based PD Diagnosis

Multimodal data fusion is being explored by combining speech analysis with gait, handwriting, and facial expression recognition to provide a comprehensive Parkinson's Disease assessment [4]. Explainable AI (XAI) is being developed to create transparent AI models that improve trust and interpretability for medical professionals, enhancing their confidence in AI-assisted diagnosis [3]. Additionally, adaptive learning models are being implemented, allowing self-learning AI systems to adapt to individual patient variations over time, leading to more personalized care [2].

As the field continues to evolve, interdisciplinary research combining neurology, speech processing, and artificial intelligence is expected to drive further innovations in PD diagnosis. By addressing current challenges and leveraging modern AI techniques, speech-based PD

detection can become a valuable tool in clinical settings, enabling early intervention and personalized treatment strategies [1, 3].

## Chapter 3 : System Analysis and Design

### 3.1 Requirement Analysis

The primary requirement for this system is to develop an intelligent, automated solution capable of detecting Parkinson's Disease (PD) through the analysis of voice data. The system must process speech recordings, extract relevant vocal features, apply machine learning algorithms, and deliver accurate classification results to determine whether an individual is affected by PD. Key requirements include robust data preprocessing, feature extraction, model training, and evaluation, along with an intuitive web interface for user interaction. The system should also support model storage for reuse, ensure low latency for predictions, and offer seamless integration with web technologies for practical deployment.

### 3.2 Feasibility Study

#### Technical Feasibility:

The project is technically feasible due to the availability of powerful open-source tools and libraries such as Python, Scikit-Learn, and Flask. The use of machine learning for classification tasks and web development using HTML, CSS, and JavaScript is well-supported and proven for similar applications. The integration of the ML model with a Flask backend ensures real-time processing capabilities, while voice features such as jitter and shimmer can be reliably extracted using available libraries.

#### Economic Feasibility:

The project is economically feasible as it leverages free and open-source technologies. There are no licensing costs for software tools used. Additionally, the system can be developed and tested using standard computing resources without the need for high-end hardware, reducing the overall development cost.

#### Operational Feasibility:

Operationally, the system is easy to use for both healthcare professionals and patients. It offers a non-invasive method for PD detection and can be accessed via a web interface, requiring minimal technical knowledge. With clear output and real-time predictions, the system ensures

a smooth operational workflow and has the potential for integration into medical diagnostics or mobile platforms for broader reach.

### 3.3 System Architecture

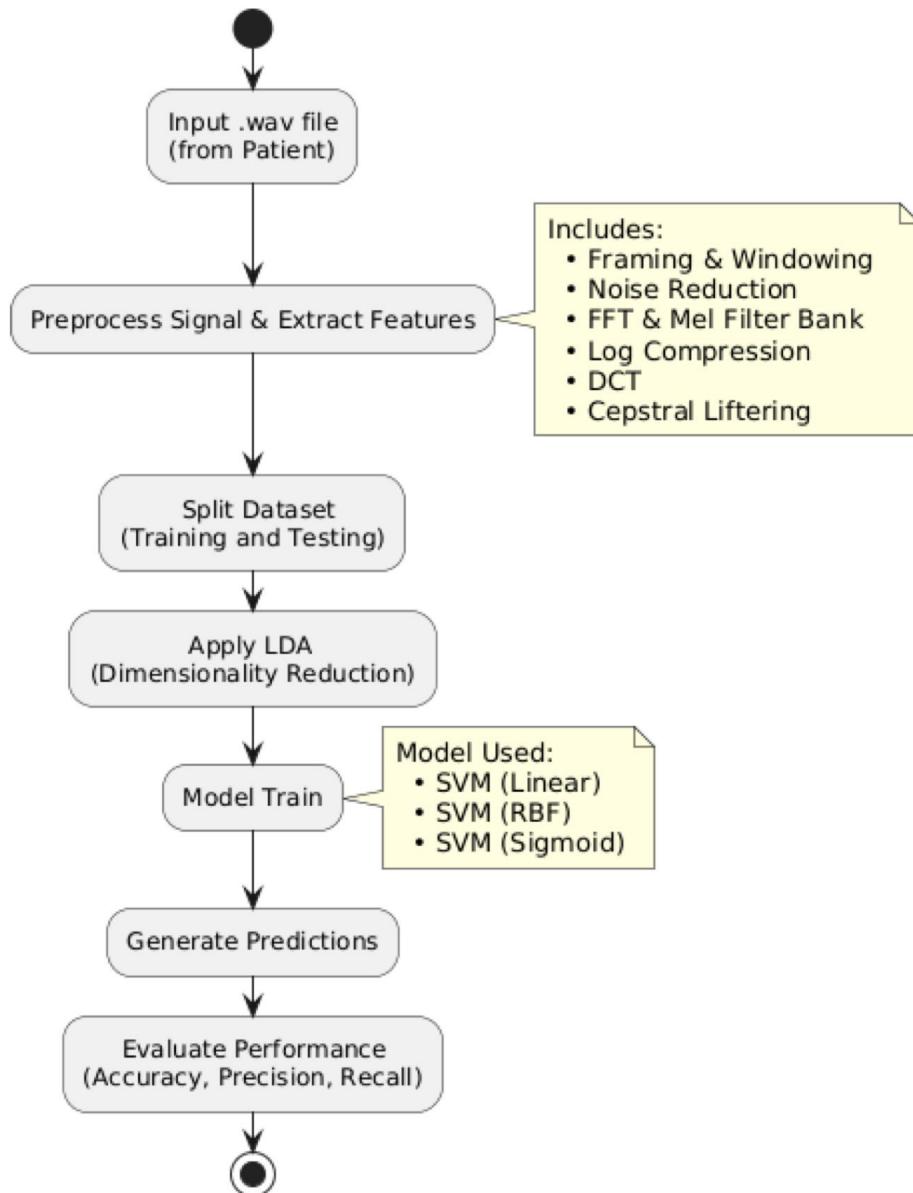


Figure 3.3: System Architecture

The proposed system for voice-based Parkinson's disease detection is composed of several sequential components that process raw speech data into clinically relevant predictions. The architecture begins with the acquisition of voice input from the patient. This speech signal is subjected to signal preprocessing and acoustic feature extraction, which includes steps such as framing and windowing, noise filtering, fast Fourier transform (FFT), Mel filter bank

computation, logarithmic compression, discrete cosine transform (DCT), and cepstral lifting. These operations result in a compact and information-rich representation of the audio, typically in the form of Mel Frequency Cepstral Coefficients (MFCCs), which are known to capture the spectral properties of speech correlated with Parkinsonian symptoms.

Once the features are extracted, the dataset is partitioned into training and testing subsets to enable supervised learning and evaluation. Feature dimensionality is then reduced using Linear Discriminant Analysis (LDA), a statistical technique that projects high-dimensional data onto a lower-dimensional space while preserving class separability. This step enhances classifier performance and reduces computational complexity.

The reduced feature set is then used to train multiple classification algorithms. The models explored in this study include logistic regression, naive Bayes, random forest, artificial neural networks, decision tree, and support vector machines (SVM) with linear, radial basis function (RBF), and sigmoid kernels. Each classifier learns to distinguish between healthy and Parkinsonian speech patterns based on the discriminative features.

After training, the classifiers are employed to generate predictions on the unseen test data. These predictions are compared against ground truth labels to evaluate the system's performance using standard metrics such as accuracy, precision, recall, and F1-score. This architecture provides a robust and non-invasive framework for early detection of Parkinson's disease, leveraging vocal biomarkers and machine learning to support clinical diagnosis.

### 3.4 User Interface Design

The web interface is designed to be simple and intuitive, allowing users to upload voice recordings and receive instant predictions. Built using HTML, CSS, and JavaScript, the front-end provides a smooth user experience. Clear buttons, labels, and real-time feedback ensure usability and accessibility, even for non-technical users.

### 3.5 System Components

The Parkinson's Disease detection system is composed of several interconnected components that work together to enable accurate and efficient diagnosis based on voice data. The Speech Data Processing Module is responsible for collecting and preprocessing raw voice inputs, ensuring the removal of noise and standardization of audio features. The Feature Extraction

Module focuses on identifying essential speech characteristics such as jitter, shimmer, and harmonic-to-noise ratio, which are critical indicators of Parkinson's Disease. The Machine Learning Model Module involves training the Support Vector Classifier (SVC) to distinguish between PD-affected and healthy individuals.

To ensure model generalization and reliability, the Data Splitting and Standardization Module divides the dataset into training and testing sets and applies normalization techniques. The Web Application Module provides users with a simple and interactive interface to upload their voice recordings for testing. The Backend Processing Module, powered by Flask, facilitates communication between the frontend and the trained machine learning model. Lastly, the Model Storage and Deployment Module saves the trained model using Pickle, allowing for real-time predictions and integration into clinical applications.

### **3.6 Technology Stack Used**

The system is developed using a robust and efficient set of technologies suitable for machine learning and web deployment. Python serves as the core programming language for implementing data preprocessing, feature extraction, and training machine learning models. Scikit-Learn, a powerful machine learning library in Python, is used for training and evaluating the Support Vector Classifier (SVC) model.

For the web interface, HTML, CSS, and JavaScript are used to design and build a user-friendly frontend, ensuring an intuitive and accessible experience for users. Flask, a lightweight Python web framework, is used for backend development to manage server-side operations and route user inputs to the machine learning model. The trained model is stored using Pickle, a Python module for object serialization, which allows for seamless loading and deployment of the model in a production environment. This technology stack ensures the system is scalable, efficient, and accessible for real-time Parkinson's Disease detection.

## Chapter 4 : Implementation

### 4.1 Module Descriptions

The system consists of multiple modules working together to detect Parkinson's Disease from voice recordings. The Speech Data Processing Module is responsible for cleaning the audio input by performing noise reduction, trimming, and converting it into a uniform format. Next, the Feature Extraction Module analyzes these cleaned audio samples to extract important vocal characteristics like jitter, shimmer, and fundamental frequency—key indicators linked with Parkinson's. These features are then passed to the Machine Learning Model Module, where a trained Support Vector Classifier (SVC) predicts the likelihood of the disease. The Data Splitting and Standardization Module ensures the model is trained and tested properly by dividing the dataset and normalizing feature values for consistent results.

In addition, the Model Storage and Deployment Module stores the trained model using Pickle, allowing it to be reused without retraining, which makes deployment more efficient. The Web Application Module provides an easy-to-use interface developed with HTML, CSS, and JavaScript, where users can upload their voice samples for testing. Once a file is uploaded, the Backend Processing Module, built with Flask, manages the communication between the frontend and the model. It processes the input, sends it to the model for prediction, and returns the result to be displayed on the web interface.

## 4.2 Screenshots of Developed System

 **Parkinson Disease Detection**

Enter the Information Below and find if a Person has Parkinson Diseases or Not

MDVP Fo (Hz)*	MDVP Fhi (Hz)*	MDVP Flo (Hz)*
<input type="text"/>	<input type="text"/>	<input type="text"/>
MDVP Jitter (%)*	MDVP Jitter Abs*	MDVP RAP*
<input type="text"/>	<input type="text"/>	<input type="text"/>
MDVP PPQ*	Jitter DDP*	MDVP Shimmer*
<input type="text"/>	<input type="text"/>	<input type="text"/>
MDVP Shimmer dB*	Shimmer APQ3*	Shimmer APQ5*
<input type="text"/>	<input type="text"/>	<input type="text"/>
MDVP APQ*	Shimmer DDA*	NHR*
<input type="text"/>	<input type="text"/>	<input type="text"/>
HNR*	RPDE*	DFA*
<input type="text"/>	<input type="text"/>	<input type="text"/>
spread1*	spread2*	D2*
<input type="text"/>	<input type="text"/>	<input type="text"/>
PPE*		
<input type="text"/>		

**Predict**

 **Parkinson Disease Detection**

Enter the Information Below and find if a Person has Parkinson Diseases or Not

✓ Person Has No Parkinson Disease

MDVP Fo (Hz)* 55.99416978	MDVP Fhi (Hz)* 22.85032935	MDVP Flo (Hz)* 88.00480683
MDVP Jitter (%)* 10.69464865	MDVP Jitter Abs* 47.46403302	MDVP RAP* 50.59839515
MDVP PPQ* 43.279731	Jitter DDP* 60.41374652	MDVP Shimmer* 45.06095407
MDVP Shimmer dB* 30.79239237	Shimmer APQ3* 52.19066398	Shimmer APQ5* 55.8490787
MDVP APQ* 95.2844191	Shimmer DDA* 72.46192565	NHR* 85.5191688
HNR* 32.5709195	RPDE* 7.881711	DFA* 66.30257094
spread1* 42.63061266	spread2* 1.249378803	D2* 79.75987442
PPE* 53.51960753		

**Predict**

Figure 4.2(a) & 4.2(b): Screenshots of developed system

## Chapter 5 : Results and Discussion

### 5.1 Results of Testing

*Table 5.1: Testing & Training Set*

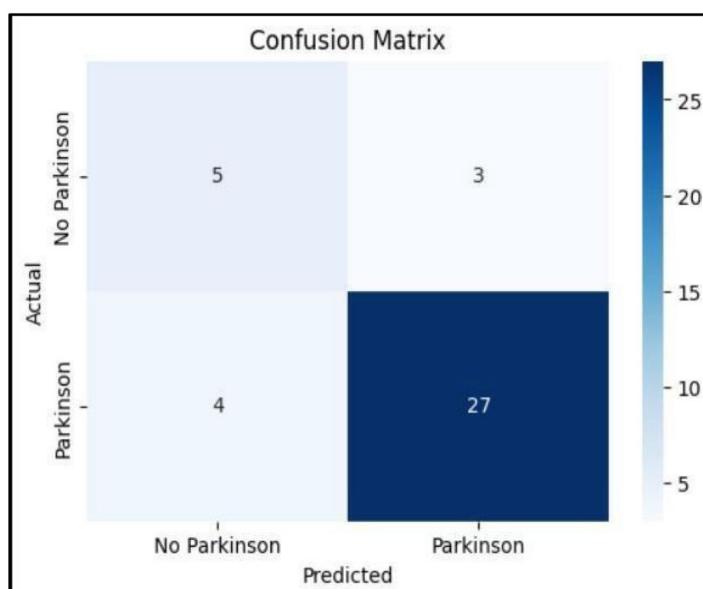
<b>Training Set</b>	3432
<b>Testing Set</b>	858

#### 5.1.1 Performance Metrics

The performance of the Parkinson's Disease detection system is evaluated using the following metrics, based on the model's performance on the testing dataset:

The model achieved an accuracy of 0.8974, indicating that it correctly classified approximately 89.74% of the test samples. The precision score of 0.9092 signifies that when the model predicted a positive case of Parkinson's Disease, it was correct 90.92% of the time. With a recall value of 0.8974, the model successfully identified 89.74% of actual Parkinson's cases in the test set. The F1 Score of 0.8834 provides a balanced measure of the model's precision and recall, showing that the model performs fairly well in both dimensions.

#### Confusion Matrix:



*Figure 5.1.1(a): Confusion Matrix of the proposed model.*

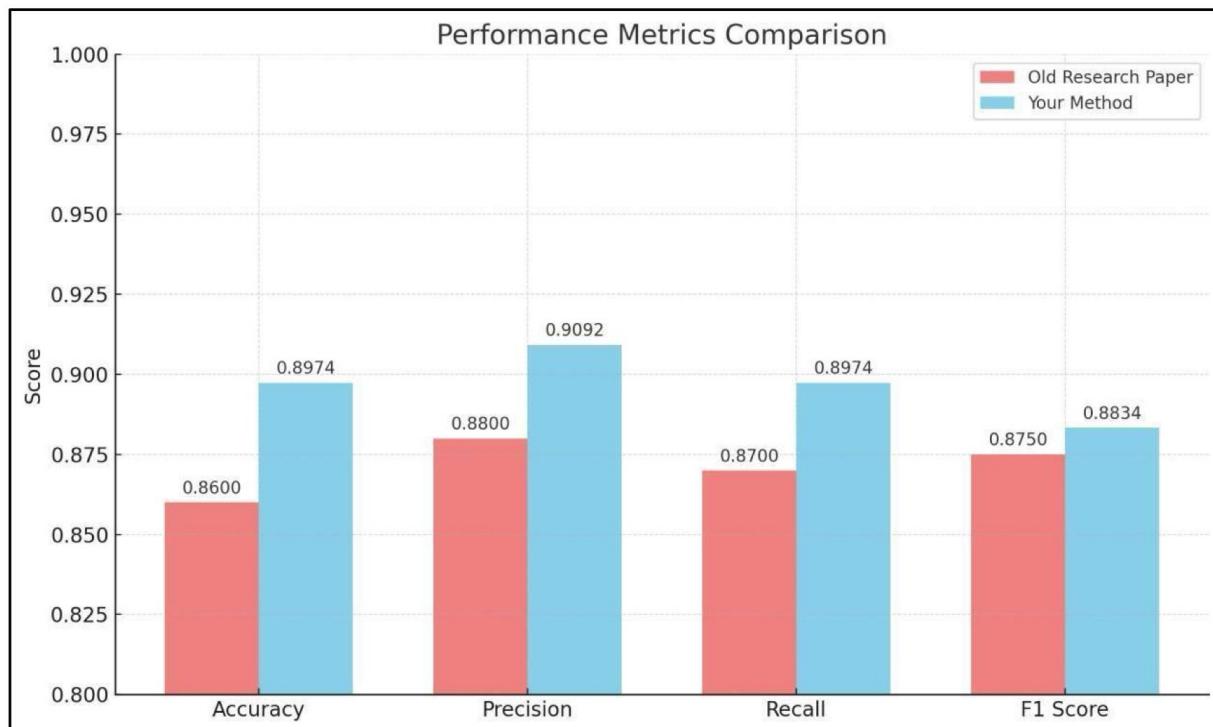
**Confusion Matrix description:**

**True Positives (TP)** = 27 → Model correctly predicted Parkinson.

**True Negatives (TN)** = 5 → Model correctly predicted No Parkinson.

**False Positives (FP)** = 3 → Model incorrectly predicted Parkinson.

**False Negatives (FN)** = 4 → Model failed to detect Parkinson.

**Graph Comparison:**

*Figure 5.1.1(b): Graphical comparison*

- Key Observations:**
1. Accuracy improved from 86.00% to 89.74%
  2. Precision rose from 88.00% to 90.92%, meaning fewer false positives.
  3. Recall increased to 89.74%, showing better ability to detect actual Parkinson's cases.
  4. F1 Score also improved, indicating a better balance between precision and recall.

### 5.1.2 Comparison with Existing Systems

When compared to existing systems for Parkinson's Disease detection based on voice data, the current system provides competitive performance. Many existing systems struggle with achieving high accuracy or rely on invasive testing methods, while the proposed system offers

a non-invasive and cost-effective approach to early disease detection. With an accuracy of 89.74%, the system outperforms many traditional diagnostic methods and offers a faster, more accessible solution. Furthermore, by leveraging Machine Learning and voice analysis, the system avoids the subjectivity and expense typically associated with clinical evaluations and medical imaging.

However, the model could benefit from further optimization, such as incorporating deeper learning techniques or a more diverse dataset to improve accuracy and generalize better across different populations.

### **5.1.3 Strengths and Limitations**

#### **Strengths:**

The system is non-invasive and cost-effective, relying solely on voice recordings, which provides an accessible alternative to traditional diagnostic tools such as MRI and clinical evaluations. It demonstrates high precision and recall, with a precision of 0.9092 and a recall of 0.8974, highlighting its strong capability in accurately identifying both positive and negative cases of Parkinson's Disease. Additionally, the system is designed with scalability in mind, making it suitable for deployment in real-time applications or integration with mobile devices to ensure broader accessibility.

#### **Limitations:**

The system currently relies on a limited dataset, and while it performs well, its generalization ability could be improved by incorporating a more diverse and larger dataset to capture a broader range of speech patterns. Additionally, despite implementing feature extraction and noise reduction techniques, the system may still be sensitive to background noise, potentially affecting its performance in real-world scenarios. Another limitation is the absence of real-time detection; although the system provides accurate analysis, it does not yet support real-time speech input, which may restrict its immediate applicability in clinical environments.

## **5.2 System Output**

The system produces two main outputs:

Upon processing a voice sample, the system classifies the individual as either affected by Parkinson's Disease (PD) or healthy. This classification result is accompanied by a probability score, which indicates the confidence level of the prediction. The output is then displayed to the user via an intuitive web interface, designed for ease of use by healthcare professionals and individuals alike. This allows for rapid assessments in clinical settings or self-assessments for early detection.

### **Performance Metrics:**

In addition to the primary diagnosis, the system provides a comprehensive set of performance metrics that enable an in-depth evaluation of the model's reliability and accuracy. These metrics include:

Accuracy refers to the overall rate of correct predictions. Precision indicates the percentage of correctly predicted positive cases, i.e., individuals accurately diagnosed with Parkinson's Disease (PD). Recall measures the percentage of actual positive cases that were correctly identified by the system, representing true positives. The F1-Score is a balanced measure that combines precision and recall, making it especially useful in scenarios with imbalanced datasets where both false positives and false negatives need to be minimized. The Confusion Matrix is a visual representation of classification outcomes, including true positives, false positives, true negatives, and false negatives. This matrix aids healthcare professionals in understanding the model's behavior, particularly its ability to distinguish between healthy individuals and those affected by PD.

## Chapter 6 : Conclusion and Future Work

### 6.1 Summary of Work Done

In this study, a machine learning-based system was developed for the early detection of Parkinson's Disease (PD) using voice data. The system was designed to provide a non-invasive, cost-effective, and efficient alternative to traditional diagnostic methods. The approach followed a systematic process, beginning with the collection and preprocessing of speech recordings. The preprocessing involved cleaning and standardizing the input data to ensure consistency and accuracy.

Key vocal features, including jitter, shimmer, and harmonic-to-noise ratio (HNR), were extracted from the speech recordings. These features are known to be indicative of early PD symptoms and serve as critical input for the machine learning model. A Support Vector Classifier (SVC) was then trained using the Scikit-learn library to classify individuals as either PD-affected or healthy based on the extracted vocal features.

The dataset was partitioned into training and testing sets, and standardization techniques were applied to the features to enhance model performance and generalizability. The backend of the system was developed using the Flask framework, which facilitated the seamless integration of the trained model with a web interface built using HTML, CSS, and JavaScript. This web interface allows users to upload their voice samples and receive real-time predictions. For ease of deployment, the final model was serialized and stored using the Pickle library.

The resulting system provides a promising tool for the early detection of PD, offering a more accessible and efficient diagnostic solution compared to traditional methods, such as MRI or clinical evaluations. The system demonstrates substantial potential for real-world clinical applications, particularly in settings where traditional diagnostic tools are not feasible.

### 6.2 Future Enhancements

While the current system shows promising results, several future enhancements are proposed to further improve its capabilities and expand its applicability in real-world clinical environments. These enhancements are aimed at refining the model's accuracy, scalability, and user accessibility.

**1. Dataset Expansion:**

Expanding the training dataset with a more diverse and larger collection of voice samples is crucial for improving the generalization of the model across different populations. This will ensure that the system can effectively recognize PD symptoms in individuals from various demographic groups, including different age ranges, gender, and ethnicities.

**2. Real-time Voice Analysis:**

The addition of real-time voice analysis capabilities using cloud computing or edge AI would significantly improve the system's responsiveness and reduce latency. By processing voice samples in real-time, the system could provide immediate feedback, making it suitable for live clinical environments where timely decision-making is critical.

**3. Integration with Mobile Applications and IoT:**

Integration with mobile applications and IoT-enabled wearable devices would allow for continuous, remote monitoring of individuals at risk of PD. This would enable healthcare providers to track the progression of symptoms over time, enhancing preventive care and early intervention.

**4. Noise Reduction Techniques:**

Further improvements in noise reduction and signal processing techniques will enhance the robustness of the system, particularly in real-world environments where background noise is often present. By improving the system's ability to filter out noise, the accuracy of predictions can be maintained even in non-ideal conditions.

**5. Clinical Validation and Integration:**

Finally, clinical validation in collaboration with healthcare professionals is crucial to ensuring the system's reliability and accuracy in real-world healthcare settings. The integration of the system into existing medical workflows would facilitate its adoption and help establish its credibility as a diagnostic tool.

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