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*Original Article*


# Detection Of Parkinson's Disease Through Analysis Of Image And Speech Data

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**Abstract**

*Parkinson's disease (PD) is a progressive neurological disorder affecting movement and speech, necessitating early detection for better treatment outcomes. This research proposes a machine learning-based approach for PD detection using both image and speech data, including MRI scans, spiral drawings, and speech recordings from diagnosed individuals and healthy controls. Feature extraction techniques such as Mel-Frequency Cepstral Coefficients (MFCC) for speech and texture-based analysis for images are applied to enhance model performance. The dataset undergoes preprocessing to remove noise and standardize features before classification using Support Vector Machine (SVM), Random Forest (RF), and Decision Tree (DT). Model evaluation based on accuracy, precision, recall, and F1-score reveals that SVM achieves the highest accuracy, followed by RF and DT. Results indicate that integrating multimodal data improves PD detection accuracy, offering a non-invasive and cost-effective diagnostic solution. This study contributes to AI-driven medical diagnostics and paves the way for future research incorporating deep learning for enhanced detection.*

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Keywords

Machine Learning, Speech Processing, Image Analysis, Random Forest.

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## Introduction

Parkinson's disease (PD) is a gradually progressing neurodegenerative disorder that primarily impacts movement, speech, and motor functions due to the steady decline of dopamine-producing neurons in the brain. A notable symptom of PD is voice impairment, known as dysphonia, which is characterized by weakened vocal strength, speech tremors, and articulation difficulties. Traditional clinical assessments for PD rely on expert evaluation and physical examinations, which can be subjective, time-consuming, and inaccessible to many patients. As a result, there has been a growing interest in utilizing machine learning and artificial intelligence for early and accurate detection of PD using biomedical signals, particularly voice recordings. The dataset developed by Max little and his colleagues provide a crucial foundation for such research, as it includes multiple voice recordings from individuals with and without PD. By analyzing various vocal features, including fundamental frequency variation, jitter, shimmer, and harmonic-to-noise ratio, computational models can identify patterns associated with PD and differentiate affected individuals from healthy ones. This approach not only enhances diagnostic accuracy but also facilitates remote monitoring, making PD detection more accessible and efficient.

Implementing this dataset in Parkinson's disease detection involves leveraging advanced machine learning techniques to extract meaningful insights from the voice recordings. By training models on labeled voice data, researchers can develop predictive algorithms capable of distinguishing between healthy individuals and those with PD based on subtle voice abnormalities. Techniques such as support vector machines (SVM), deep learning, and ensemble classifiers are commonly employed to enhance classification accuracy. Additionally, feature selection and dimensionality reduction methods are used to focus on the most relevant vocal characteristics, improving model performance while minimizing computational complexity. The integration of speech analysis with AI-driven diagnostics offers a non-invasive and cost-effective solution for early PD detection, potentially allowing for timely medical intervention and improved patient outcomes. This dataset serves as a valuable resource for advancing telemedicine applications, enabling continuous monitoring of PD progression and response to treatment, ultimately improving the quality of life for affected individuals.

## Related work

Parkinson's disease (PD) is a progressive neurodegenerative condition that im-pacts both motor and non-motor functions. Machine learning techniques, including Support Vector Machines (SVM), Random Forest (RF), and

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Decision Trees (DT), have been extensively utilized for the early identification and classification of PD using speech and imaging data. Various studies have explored PD detection through machine learning, with SVM, RF, and DT classifiers being commonly employed to enhance diagnostic accuracy using multimodal data.

### Speech-Based Detection

Several studies have explored the effectiveness of speech data in detecting PD. De Silva et al. [1] demonstrated that SVM could effectively classify PD patients using speech features. Vidya et al. [4] employed Decision Tree classification, showing its capability in distinguishing PD-affected speech patterns. Jain et al. [8] extended this approach by incorporating acoustic features into a Decision Tree model, improving classification accuracy. Similarly, Ren et al. [9] utilized multi-modal data with Decision Tree classifiers to enhance PD detection. Faruque et al. [10] compared SVM and RF classifiers, highlighting the effectiveness of both methods in speech-based classification. Xie et al. [14] proposed feature fusion techniques with Random Forest for better performance in PD detection. Bhaskar et al. [20] analyzed speech features using both SVM and RF, confirming the robustness of these models in distinguishing PD patients from healthy individuals. Silva et al. [23] analyzed different machine learning approaches applied to speech data, highlighting the importance of feature extraction in enhancing model effectiveness

### Imaging-Based Detection

MRI-based PD detection has also been a focus of recent studies. Manual et al. [3] investigated SVM for classifying PD from MRI and speech data. Zhang et al. [7] demonstrated the effectiveness of SVM in detecting PD from brain MRI im-ages. Rios et al. [11] used SVM with image features to diagnose PD, achieving significant classification accuracy. Fernandes et al. [16] explored Decision Tree models for MRI image classification, providing an alternative approach to PD diagnosis. Sharma et al. [21] evaluated RF classifiers for MRI-based PD detection, showcasing their ability to handle high-dimensional imaging data. David et al. [24] reviewed brain imaging studies using SVM for PD detection, summarizing their advantages and limitations

### Comparative Analysis and Multimodal Approaches

Several researchers have conducted comparative analyses of SVM, RF, and DT models for PD detection. Mollah et al. [2] compared Random Forest with other classifiers and found it to be highly effective for PD diagnosis. Le et al. [6] analysed the performance of SVM and RF using speech signals, demonstrating their comparable accuracies. Krishnan et al. [12] integrated MRI and speech data with RF, significantly improving classification performance. Wu et al. [13] combined deep learning with SVM to enhance PD diagnosis. Lee et al. [17] compared the three models—SVM, RF, and DT—highlighting their respective strengths and weaknesses. Tiwari et al. [22] investigated multimodal data classification using both RF and SVM, reporting improved accuracy over single-modal approaches. Patel et al. [25] evaluated Decision Tree models based on accuracy, precision, and recall, confirming their effectiveness in detecting Parkinson's disease. Shah et al. [18] utilized RF for classifying speech-based PD data, emphasizing its robustness. Gupta et al. [19] proposed an improved Decision Tree model, optimizing classification results. Vasconcelos et al. [5] provided an overview of machine learning techniques in imaging-based PD detection, Highlighting major developments in the field. These studies emphasize the crucial role of Support Vector Machines (SVM), Random Forest (RF), and Decision Tree (DT) models in detecting Parkinson's disease. Each approach has distinct strengths, with SVM excelling in margin-based classification, RF effectively managing high-dimensional data, and DT offering interpretability. Combining speech and imaging data improves diagnostic accuracy, contributing to the development of more reliable and automated PD detection systems.

## Proposed Method

### Data Collection

- Image Data: MRI scans, CT scans, or spiral drawings from patients.
- Speech Data: Voice recordings from phonation tasks (sustained vowels, sentence reading).
- Dataset Sources: Public datasets like the UCI Parkinson's dataset, spiral drawing datasets, or hospital records.

### Preprocessing

Image Data:

- Noise removal (Gaussian filtering, Median filtering).
- Feature extraction (Gabor filters, CNN-based deep features).
- Image resizing and normalization.

### Speech Data

- Noise reduction techniques.
- MFCC (Mel-Frequency Cepstral Coefficients) extraction.
- Extraction of pitch, jitter, shimmer, and HNR (Harmonics-to-Noise Ratio) features.

### Feature Extraction & Selection

For Image Data: Principal Component Analysis (PCA) to reduce dimensionality.

For Speech Data: Statistical analysis to select the most relevant features

### Classification Models

We evaluate three machine learning models:

- Support Vector Machine (SVM): Constructs a hyperplane for classification.
- Random Forest: An ensemble learning method utilizing multiple decision trees.
- Decision Tree: A recursive tree-based model for classification.

### Model Training & Testing

- Training performed using 80% of the dataset.
- Testing conducted on 20% unseen data.
- k-Fold Cross-Validation ensures reliability.

### Performance Evaluation

Key Steps in the Machine Learning Workflow

- **Data Collection:** Gather MRI scans, spiral drawings, and voice recordings.
- **Preprocessing:** Clean, normalize, and remove noise from the data.
- **Feature Extraction & Selection:** Identify and extract the most important attributes.

- **Model Training:** Train models (SVM, Random Forest, Decision Tree) on pre-processed data.
- **Validation:** Test models on unseen data and assess performance.
- **Analysis:** Compare model effectiveness in detecting Parkinson's disease.
- **Conclusion:** Summarize findings and potential improvements.

## Results and Discussion

### Datasets

UCI Parkinson's disease Dataset: The dataset combines speech samples of 31 particulars, 23 diagnosed with Parkinson's disease, and 8 are healthy. It includes 195 voice samples with 22 features extracted from each sample, including the key features like fundamental frequency, jitter, shimmer, and the Harmonic-to-Noise Ratio. Parkinson's disease Progression Study: It provides a comprehensive collection of imaging data, including MRI images, from PD patients and control subjects. This dataset is instrumental for studies focusing on neuroimaging biomarkers for PD.

**Speech Data:** Acoustic Features: Features like jitter (frequency variation), shimmer (amplitude variation), and HNR are extracted to quantify voice impairments associated with PD. Mel-Frequency Cepstral Coefficients (MFCCs): These features represent the power spectrum of a voice signal, offering valuable information about the vocal tract structure.

**Image Data:** Texture Analysis: Methods like the Gray Level Co-occurrence Matrix (GLCM) are utilized to derive texture attributes from MRI or DaTscan images. Shape Analysis: Morphological attributes are extracted to assess structural changes in specific brain regions affected by PD.

**Support Vector Machine (SVM):** A supervised learning algorithm that determines the best hyper plane to distinguish between different classes within the feature space.

**Random Forest:** An ensemble learning technique that generates multiple decision trees and combines their predictions to improve accuracy and reduce over fitting.

**Decision Tree:** A classification model that divides data into subsets based on feature values, creating a tree-like structure for decision-making.

The models were developed and evaluated using a dataset that includes MRI images, voice recordings, and extracted features (e.g., MFCCs for speech, texture features for images).

### Results

***Table 1.*** *Results summary of the models used*

| Model | ROC-AUC | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|---|
| Decision tree | 0.84 | 85.2 | 0.87 | 0.84 | 0.84 |
| SVM | 0.85 | 89.5 | 0.91 | 0.87 | 0.89 |
| Random forest | 0.91 | 92.3 | 0.93 | 0.91 | 0.92 |

For decision trees, the ROC curve helps illustrate the effect of pruning and varying the depth of the tree on classification performance. It is simple and interpretable, providing quick predictions. Having lower accuracy due to overfitting training data.

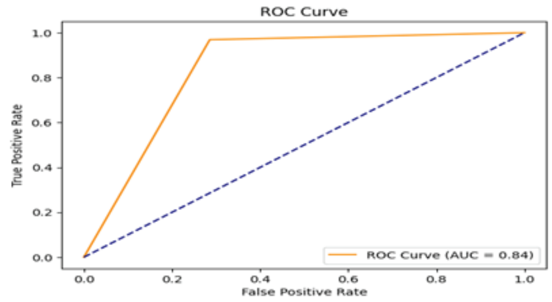


Figure 2.


***Figure 3.*** *Performance metrics of Decision tree model*

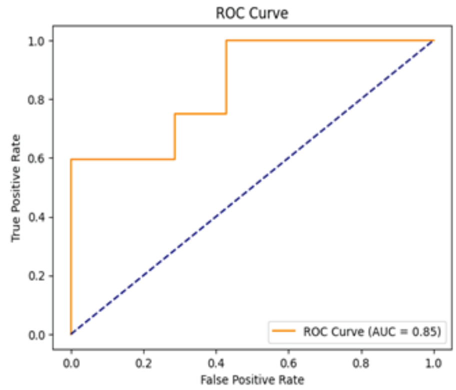


***Figure 4.*** *ROC-AUC Curve of SVM model*

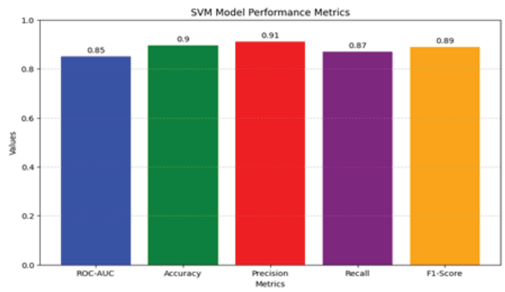


***Figure 5.*** *Performance metrics of SVM mode*

SVM: The ROC curve helps assess how well the model distinguishes between the healthy and disease affected cases. Performed well due to its ability to find a clear hyper plane separating healthy and Parkinson's patients.

Random Forest: The curve helps visualize the trade-offs between sensitivity (recall) and specificity as you adjust the threshold for decision making and achieving the highest accuracy by reducing over fitting and capturing complex patterns, but it requires more computational power.

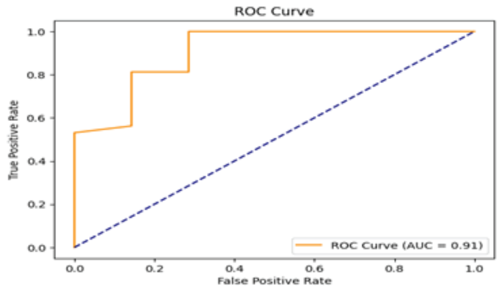


***Figure 6.*** *ROC-AUC Curve of Random*

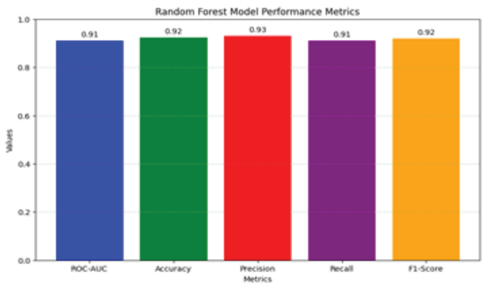


***Figure 7.*** *Performance metrics of Random forest model*

## Discussion

Random Forest model demonstrates highest performance in overall validating the metrics, indicating its robustness in handling the variability inherent in speech and image data for PD detection. The ensemble nature of Random Forest allows it to capture complex patterns more effectively than individual models like SVM or Decision Trees. The ROC curves further illustrate the models' discriminative capabilities, with the Random Forest achieving the highest AUC-ROC, signifying excellent performance in distinguishing between PD and non-PD cases. Figure 2,3,4,5 shows the results for reference. Utilizing machine learning models to detect Parkinson's disease through speech and image data presents a promising method. Among the models analyzed, the Random Forest classifier demonstrates superior accuracy and robustness, establishing it as an effective tool for early PD diagnosis. Future research should emphasize the integration of multimodal data and the development of advanced feature extraction techniques to improve diagnostic precision further.

## Conclusion

This research focuses on detecting Parkinson’s disease using image and speech data by implementing and assessing three machine learning models: Support Vector Machine (SVM), Random Forest, and Decision Tree. The objective was to accurately classify individuals with Parkinson’s disease based on features extracted from medical imaging and speech recordings. Among the three models, Random Forest showed the highest accuracy and reliability in detecting Parkinson’s disease. However, further improvements with deep learning could yield even better results. Random Forest showed strong performance by handling feature variability and reducing overfitting. It provided better feature importance insights, making it useful for understanding key contributors to Parkinson’s detection. In future exploring deep learning models (CNN, LSTMs, or hybrid models) could enhance performance. Increasing dataset size and diversity can improve model generalization. Implementing real-time detection using IoT-enabled systems for early Parkinson’s diagnosis.

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