Digitized spiral drawing classification for Parkinson’s disease diagnosis

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Introduction

- Parkinson's disease (PD) is a progressive neurodegenerative disorder characterized by motor symptoms such as tremor, rigidity, and bradykinesia, as well as non-motor symptoms including cognitive impairment and mood disorders.
- The early and accurate diagnosis of Parkinson's disease is crucial for managing the disease effectively and improving the quality of life for patients.
- Traditional diagnostic methods primarily rely on clinical assessments and neuroimaging techniques, which can be subjective, time-consuming, and expensive. Therefore, there is a pressing need for more accessible, objective, and efficient diagnostic tools.
- Digitized spiral drawings, captured using tablets or smartphones, can be analyzed to extract features indicative of Parkinson's disease.

Existing system

- In existing system, naive Bayes is a probabilistic classifier based on Bayes' theorem, assuming strong (naive) independence between the features.
- Despite its simplicity, it has been effectively applied in various domains, including medical diagnosis.

Disadvantage:

- Naive Bayes assumes that features are conditionally independent given the class label.
- While Naive Bayes is computationally efficient for small to moderately sized datasets, it may not scale well for very large datasets or high-dimensional feature spaces, especially when feature interdependencies are complex

Motivation

- Early diagnosis and effective management can lead to better treatment strategies, potentially slowing the progression of the disease and minimizing the impact on daily life.
- Our work could potentially contribute valuable data to ongoing research studies. Improving Patient Outcomes
- Remote monitoring of spiral images could be implemented, allowing individuals to perform regular assessments from the comfort of their homes. So we could contribute to this alarming cause.
- Early diagnosis and effective management can lead to better treatment strategies.

Objectives

The main objective of our project is,

- To detect or to predict the input is either dynamic or static spiral to predict parkinson’s .
- To implement the deep and machine learning algorithm such as CNN-2D, Logistic regression, random forest and KNN.
- To enhance the overall performance for classification algorithms.
- To compare the various classification algorithms.

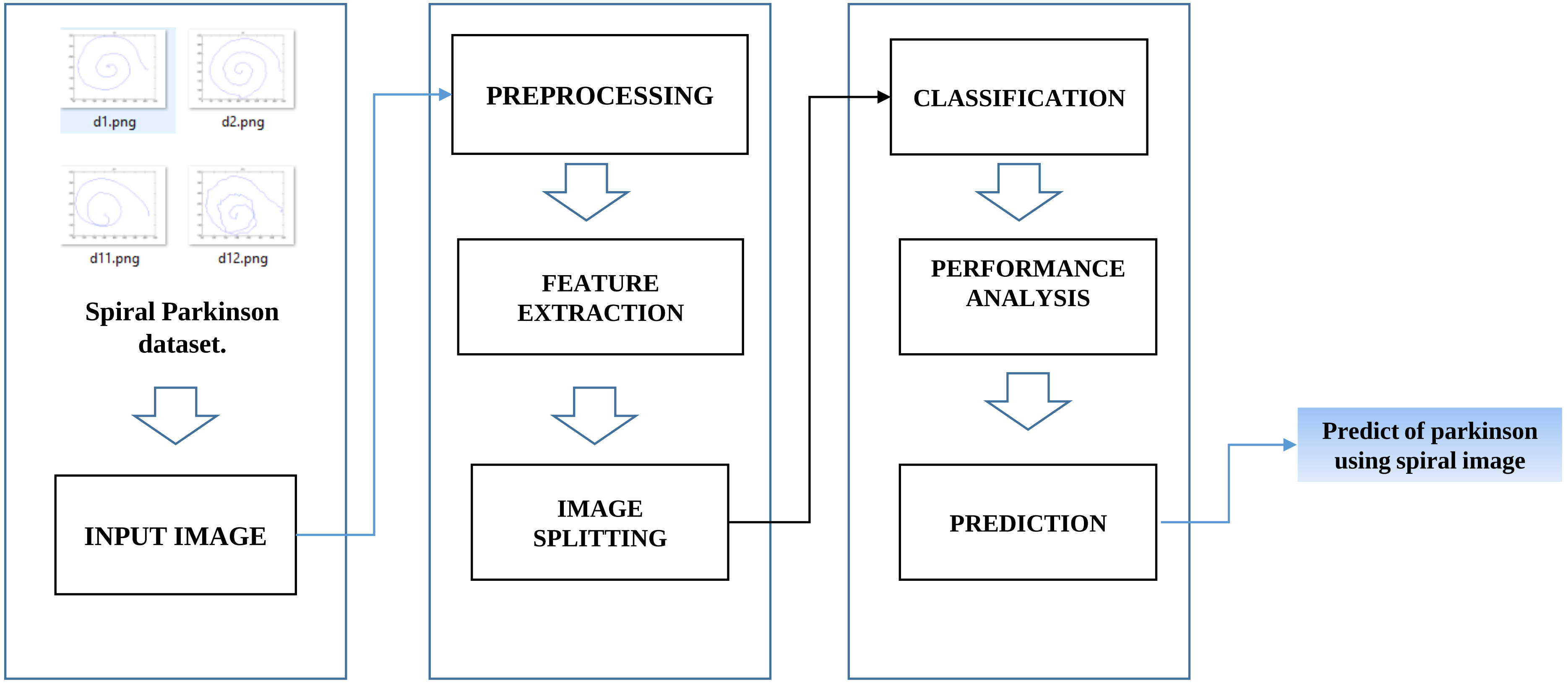
Proposed system

- The proposed system aims to diagnose Parkinson's disease by classifying digitized spiral drawings collected from Kaggle. These images are resized and converted to grayscale to standardize the input for feature extraction.
- Features are extracted using Grey Level Co-occurrence Matrix (GLCM) to capture texture properties, and statistical measures like mean, median, and variance to describe the overall distribution and variability of the pixel intensities. The dataset is then split into training and testing subsets to evaluate the models' performance. For classification, a Convolutional Neural Network (CNN) , KNN, RF and LR.
- The system's performance is assessed using various metrics: accuracy, precision, recall, F1-score, error rate, execution time, mean iteration time, average precision score, and the Area under the Precision-Recall Curve (AUC-PR).

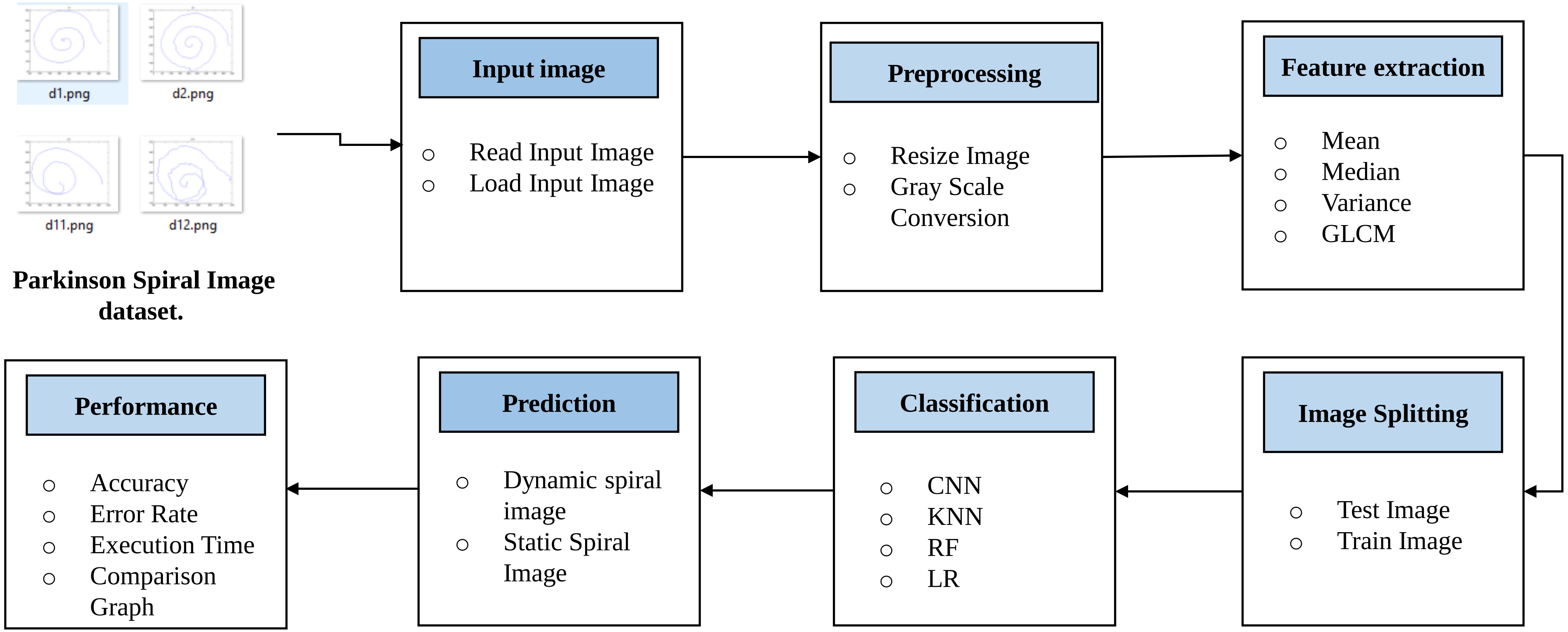
Advantages

- It is efficient for large number of datasets.
- Time consumption is low.
- By leveraging both deep learning (CNN) and traditional machine learning algorithms (Random Forest, Logistic Regression, and KNN), the system benefits from diverse approaches to pattern recognition, which can improve the overall accuracy of Parkinson's disease diagnosis.

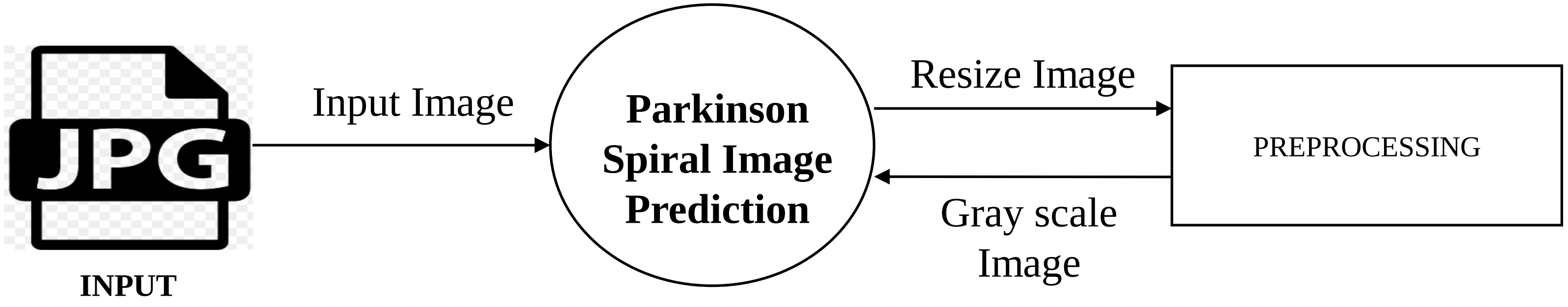
Architecture diagram



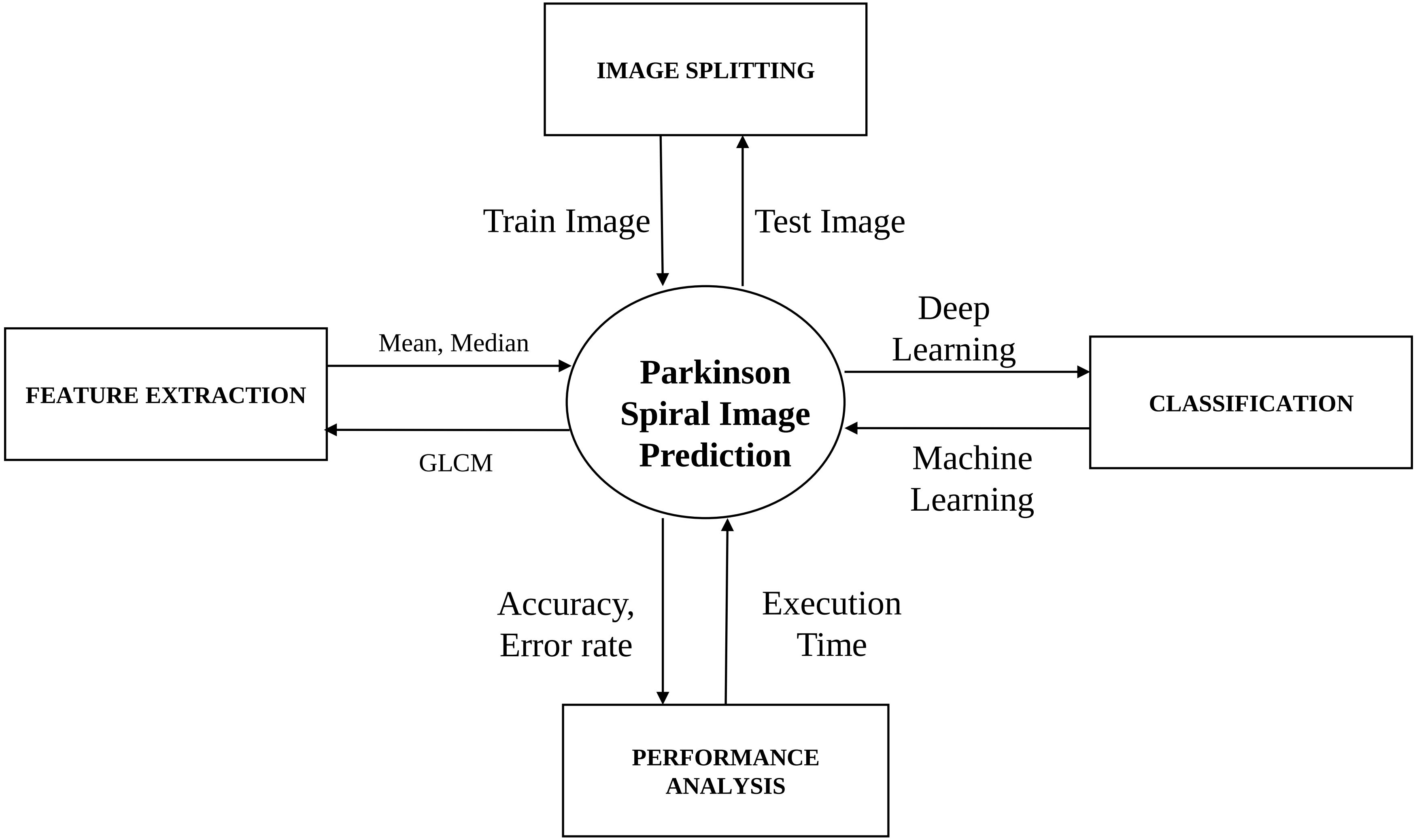
Flow diagram



DFD diagram – Level 0



DFD diagram – Level 1



Modules

- Image selection
- Image preprocessing
- Feature Extraction
- Classification
- Prediction
- Result Generation

Image selection

- The dataset, **Parkinson spiral image** dataset is implemented as input. The dataset is taken from dataset repository. The input dataset is in the format ‘.png, ‘.jpg.
- In this step, we have to read or load the input image by using the imread () function.
- The input image is used to detect or classify the input image.
- In our process, we are used the tkinter file dialogue box for selecting the input image.

Image Preprocessing

- In our process, we have to resize the image and convert the image into gray-scale.
- To resize an image, you call the resize () method on it, passing in a two-integer tuple argument representing the width and height of the resized image.
- The function doesn't modify the used image; it instead returns another Image with the new dimensions.
- Convert an Image to Grayscale in Python Using the Conversion Formula and the matplotlib Library.
- We can also convert an image to grayscale using the standard RGB to grayscale conversion formula that is imgGray = 0.2989 * R + 0.5870 * G + 0.1140 * B.

Feature Extraction

- Mean, median, and variance are also commonly used in image processing to characterize the statistical properties of pixel values within an image. Here's how they are applied:
- **Mean**: In image processing, the mean can be calculated across pixel values within a region of interest (ROI) or the entire image.
- **Median**: The median is particularly useful for noise reduction in images. Median filtering replaces each pixel value with the median value of its neighborhood.
- **Variance**: Variance measures the variability or contrast in pixel values within an image. High variance indicates a wide range of pixel intensities, while low variance suggests a more uniform distribution of intensities.

Feature Extraction Contd..

- GLCM stands for Gray-Level Co-occurrence Matrix, a texture analysis method widely used in image processing and computer vision.
- It is particularly useful for quantifying texture properties within an image by capturing the spatial relationships between pixel intensity values.
- A GLCM is a two-dimensional matrix where each element represents the frequency of occurrence of a pair of pixel intensity values at a given spatial relationship within an image.

Image Splitting

- During the machine learning process, data are needed so that learning can take place.
- In addition to the data required for training, test data are needed to evaluate the performance of the algorithm in order to see how well it works.
- In our process, we considered 80% of the input dataset to be the training data and the remaining 20% to be the testing data.
- Data splitting is the act of partitioning available data into two portions, usually for cross-validator purposes.
- One Portion of the data is used to develop a predictive model and the other to evaluate the model's performance.
- Separating data into training and testing sets is an important part of evaluating data mining models.
- Typically, when you separate a data set into a training set and testing set, most of the data is used for training, and a smaller portion of the data is used for testing.

Classification

- A **convolutional neural network (CNN or ConvNet)** is a network architecture for deep learning that learns directly from data. CNNs are particularly useful for finding patterns in images to recognize objects, classes, and categories. They can also be quite effective for classifying audio, time-series, and signal data.
- **K-Nearest Neighbours (KNN):** KNN is a simple yet powerful instance-based learning algorithm. It classifies data points based on the majority class of their nearest neighbours in the feature space.
- **Random Forest**: Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes (classification) or mean prediction (regression) of the individual trees
- **Logistic Regression** is a widely used statistical method for binary classification problems. It models the probability that a given input belongs to a particular class, making it suitable for diagnosing Parkinson's disease.

Result generation

- The Final Result will get generated based on the overall classification and prediction. The performance of this proposed approach is evaluated using some measures like,
- **Accuracy**
- Accuracy of classifier refers to the ability of classifier. It predicts the class label correctly and the accuracy of the predictor refers to how well a given predictor can guess the value of predicted attribute for a new data.

$$AC= (TP+TN)/ (TP+TN+FP+FN)$$

- **Error Rate**: Error rate, also known as classification error or misclassification rate, measures the frequency of incorrect predictions made by an algorithm compared to the ground truth.

Result generation

- **Precision**: The ability of the model to identify only relevant instances, calculated as the ratio of true positives to the sum of true positives and false positives.
- **Recall**: The model's ability to capture all relevant instances, defined as the ratio of true positives to the sum of true positives and false negatives.
- **F1-score:** The harmonic mean of precision and recall, providing a single metric that balances both concerns.
- **Mean Iteration Time**: The average time taken per iteration during the training phase, reflecting the computational efficiency of the algorithm.
- **Average Precision Score**: A measure that summarizes the precision-recall curve, giving an overall indication of the model's performance across different thresholds.

Result generation

Model Applied	Precision	Recall	F1 Score	Accuracy%
Logistic regression	100	52.5	68.85	92.5
Random Forest Classifier	100	53.5	133.33	97.5
CNN-2D	90.90	100	95.2	99.321
KNN	96	52.5	68.85	87.5

Model Applied	Time of Execution	Mean Iteration Time	Average Precision	AUC PR Curve
Logistic Regression	122.67ms	0.122µs	132.37	100
Random Forest Classifier	188.228ms	0.268µs	136.33	96
CNN-2D	44.39ms	4.4393µs	133.33	100
KNN	21.64ms	0.021µs	131.37	98

Conclusion

- In conclusion, the proposed system holds promise as a valuable tool for early detection and monitoring of Parkinson's disease.
- By integrating advanced machine learning techniques with rigorous evaluation methods, it aims to contribute to improved patient outcomes and clinical decision-making in the field of neurology.
- Further refinement and validation of the system through clinical studies and real-world applications can enhance its utility and reliability in diagnosing Parkinson's disease.

Future Work

- In future, Integration of additional data sources such as voice recordings, gait analysis, or smartphone sensor data can provide complementary information for more robust diagnosis and monitoring of Parkinson's disease.
- Exploration of advanced feature extraction techniques, such as deep learning-based feature learning or hierarchical feature representations, may uncover more discriminative features from spiral drawings, potentially enhancing the diagnostic accuracy of the system.
- Investigating methods for fusing information from multiple modalities, such as combining spiral drawings with clinical assessments or genetic markers, can lead to a more comprehensive and holistic diagnostic approach.

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