

Quantitative Spiral Pattern Analysis for Parkinson's Disease Diagnosis Using ML Techniques

Aishwarya B R*, Vidyashree Y C*, Nishanth S**

*Students, VII Sem, Dept. of AIML, Jawaharlal Nehru New College of Engineering, Shivamogga

**Assistant Professor, Dept. of AIML, Jawaharlal Nehru New College of Engineering, Shivamogga

Abstract—Parkinson's Disease (PD) is a progressive neurodegenerative disorder that primarily affects motor function, often remaining undiagnosed in its early stages due to subtle and gradual symptom onset. Early detection is critical for timely clinical intervention and effective disease management. This paper presents an automated machine learning-based approach for early Parkinson's Disease detection using spiral drawing analysis, a clinically established assessment for evaluating fine motor control. Spiral drawings collected from both healthy individuals and Parkinson's patients are subjected to comprehensive preprocessing steps, including resizing, grayscale conversion, noise reduction, normalization, and data augmentation to enhance robustness and reduce variability. A compact and regularized Convolutional Neural Network (CNN) is designed to learn discriminative patterns associated with Parkinsonian motor impairments, such as tremor-induced oscillations, irregular stroke dynamics, and structural deviations in spiral geometry. Experimental evaluation demonstrates that the proposed model effectively differentiates between normal and Parkinson-affected spiral drawings, achieving reliable classification performance and strong generalization across augmented datasets. The proposed framework offers a non-invasive, cost-effective, and easily deployable screening solution that can support clinicians in early Parkinson's Disease identification and has strong potential for integration into telemedicine and remote health monitoring systems.

Keywords—Parkinson's Disease Detection; Spiral Drawing Analysis; Machine Learning; Convolutional Neural Networks; Motor Impairment Assessment; Medical Image Analysis; Early Diagnosis

I. INTRODUCTION

Parkinson's Disease (PD) affects the central nervous system and predominantly impairs motor function. Early detection is crucial for clinical management and can significantly improve patient quality of life. Traditional diagnosis relies on clinical scales and neurologist assessment; however, objective, low-cost, and scalable diagnostic aids are desirable. Handwriting and drawing tasks (e.g., drawing spirals

or writing sentences) have long been used as non-invasive probes of motor function. Spiral drawing captures tremor amplitude, frequency, and fine motor control and is therefore a rich source for PD detection research.

A low-cost, automated screening tool using spiral drawings could enable earlier detection, continuous monitoring, and remote assessments. The project repurposes digital spiral drawings and image processing pipelines with machine learning classification to distinguish PD patients from healthy controls.

Given a dataset of spiral drawings captured digitally or scanned from paper, design an end-to-end pipeline to preprocess the images, extract discriminative features (shape-based, tremor-based, dynamic if available), and train classifiers to detect Parkinson's disease presence. Existing diagnostic approaches predominantly depend on clinical expertise, physical examinations, and subjective assessment scales like the Unified Parkinson's Disease Rating Scale (UPDRS) and Hoehn & Yahr staging, which are time-consuming and often identify the disease only after substantial neuronal degeneration has occurred. This reliance on observational evaluation limits the possibility of early intervention. Consequently, there is a pressing need for objective, automated, and data-driven diagnostic methods capable of detecting subtle motor impairments at an early stage. Among various motor assessment tasks, spiral drawing analysis has emerged as a sensitive indicator of Parkinsonian symptoms, as tremor and rigidity introduce measurable distortions in stroke smoothness, curvature, and drawing dynamics. Leveraging computational and machine learning techniques to analyze these variations presents a promising solution for developing an accurate, non-invasive, and early screening system to support clinical diagnosis of Parkinson's Disease.

II. RELATED WORK

Handwritten drawing tests, particularly spiral and wave sketches, have long been recognized as reliable non-invasive indicators of motor dysfunction in PD patients. Consequently, significant research efforts have focused on leveraging machine learning and deep learning techniques to automatically analyze these drawing patterns for early PD detection.

Recent studies have demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in extracting discriminative visual features from spiral and wave drawings. Multistage classification approaches that train separate CNN models for different drawing types and combine their outputs using ensemble learning techniques such as Logistic Regression and Random Forest have reported strong performance. These systems benefit from data augmentation strategies to overcome small dataset limitations and have achieved accuracies exceeding 90%, confirming the feasibility of using simple sketch-based biomarkers for PD screening. However, these approaches remain constrained by limited sample sizes, restricted drawing patterns, and demographic bias, which affect robustness and generalization.

Hybrid deep learning models have also been explored to balance performance and computational efficiency. Lightweight architectures such as SqueezeNet combined with traditional classifiers like Support Vector Machines (SVMs) have shown promising results, particularly in mobile and tablet-based diagnostic applications. By extracting deep features from spiral images and applying classical classifiers, these systems achieve competitive accuracy while remaining suitable for deployment on resource-constrained devices. Despite their efficiency, most hybrid approaches focus on binary classification (PD vs. healthy) and lack temporal or longitudinal analysis, limiting their diagnostic depth. Several studies have emphasized detailed feature-based spiral analysis by transforming drawing trajectories into polar coordinates and extracting motor-related parameters such as radial error, crossing rate, pressure variation, and drawing time. These approaches provide strong interpretability and capture clinically meaningful motor characteristics. Nonetheless, many such systems remain exploratory, with limited datasets and without fully integrated prediction models, reducing their immediate clinical applicability.

Beyond handwriting-based imaging, machine learning methods using acoustic features and traditional feature selection techniques have also been applied to PD detection. Wrapper-based feature selection combined with classifiers such as K-NN, SVM, and Random Forest has improved prediction accuracy on benchmark datasets. While these methods offer valuable insights, they rely solely on voice-based features and do not exploit complementary motor biomarkers such as handwriting or drawing patterns.

Transfer learning with deep CNN architectures, including InceptionV3, DenseNet, ResNet, and VGG variants, has further advanced spiral-based PD detection. These models benefit from pretrained representations, enabling effective learning even with limited datasets. High recall rates and near-zero false negatives reported in such studies indicate strong potential for early screening. However, these systems often lack clinical validation, longitudinal evaluation, and differentiation between PD and other movement disorders such as essential tremor.

Overall, existing literature confirms that spiral and wave drawings are effective, low-cost, and non-invasive biomarkers for Parkinson's Disease detection. Deep learning, particularly CNN-based and hybrid ensemble approaches, has significantly improved classification accuracy and robustness. Nevertheless, challenges persist in terms of dataset size, demographic diversity, model generalization, multimodal integration, and real-world clinical validation. These gaps motivate the development of robust multistage classification frameworks that combine multiple sketch types, advanced deep learning, and ensemble strategies to enhance early PD detection reliability and practical applicability.

III. SYSTEM ARCHITECTURE

The Parkinson's Disease Detection System allows users to upload a spiral drawing, which is displayed in the Streamlit web interface. The image then undergoes preprocessing steps such as resizing, converting to grayscale, and normalization to prepare it for analysis. This processed image is passed to a trained CNN model built using TensorFlow/Keras. The model predicts whether the drawing indicates a healthy individual or Parkinson's condition. Finally, the system displays the predicted class along with a confidence score and a bar chart for easy

interpretation. The system begins with the user uploading a spiral drawing image in standard formats such as JPG or PNG. This upload operation is handled through the Streamlit-based web application. Once the image is uploaded, it is immediately rendered on the interface, allowing the user to visually verify the selected input. This confirmation step improves usability and ensures that the correct spiral drawing has been provided for analysis. Streamlit serves as the front-end interface that connects user input with backend processing and model inference. The application is divided into two main sections. The main content area is responsible for image upload, displaying the input and processed images, and presenting the final prediction along with the confidence score. The sidebar section provides supplementary information such as project details, model descriptions, usage instructions, and system guidance, helping users understand the workflow and purpose of the application. After the spiral image is uploaded, it is passed to the image processing module, which prepares the image for model inference. The first stage involves general preprocessing using image processing techniques such as resizing the image to the required dimensions, converting it to grayscale, normalizing pixel intensity values, and reshaping the image to match the model's input format. In the second stage, model-specific preprocessing is applied to ensure compatibility with the trained CNN. This includes adding the required channel and batch dimensions. Together, these preprocessing steps standardize the input and enhance the model's ability to detect subtle motor irregularities.

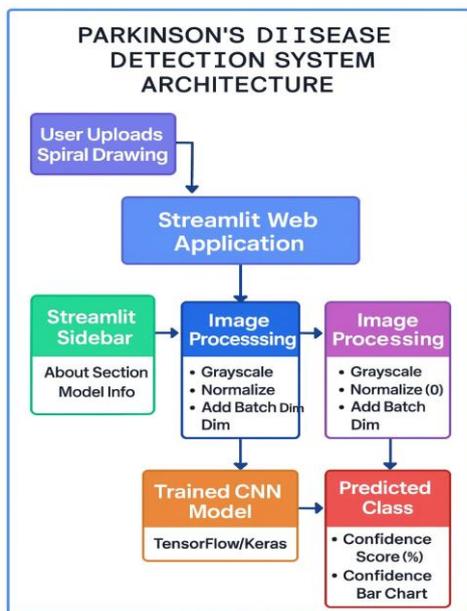


Figure 1: Proposed system architecture

The preprocessed image is then fed into a trained Convolutional Neural Network implemented using TensorFlow and Keras. The model has been trained on spiral drawings from both healthy individuals and Parkinson's Disease patients. During inference, the CNN analyzes visual patterns such as tremor-induced shakiness, inconsistent curvature, and irregular stroke boundaries. These learned features enable the model to distinguish between normal spiral drawings and those affected by Parkinsonian motor impairments.

Once the image passes through the trained model, the system generates the prediction output. The result indicates whether the input spiral drawing is classified as Healthy or Parkinson's Disease. Along with the predicted class, a confidence score is displayed to represent the model's certainty. To enhance interpretability, the system also visualizes prediction probabilities using a bar chart, allowing users to compare confidence levels across both classes. This visual feedback helps users better understand the model's decision-making process.

IV. IMPLEMENTATION

Algorithm: Parkinson's Disease Detection Using CNN (TensorFlow)

Input: Spiral drawing image

Output: Classification result (Healthy / Parkinson's Disease) with confidence score

1. Start
2. Load the trained CNN model using TensorFlow/Keras.
3. Launch the Streamlit web application interface.
4. Accept spiral drawing image upload from the user.
5. Display the uploaded image for user verification.
6. Preprocess the input image:
 - Resize image to required dimensions.
 - Convert image to grayscale (if applicable).
 - Normalize pixel values.
 - Add channel and batch dimensions.
7. Pass the preprocessed image to the CNN model.
8. Perform model inference to obtain prediction probabilities.
9. Determine the predicted class based on maximum probability.
10. Display the prediction result and confidence score.

11. Visualize prediction probabilities using a bar chart.
12. End.

To adapt the pre-trained feature extractors for binary classification, a custom classification head is appended to each base model. This head consists of a Global Average Pooling layer to reduce spatial dimensions, followed by a fully connected dense layer with rectified linear unit activation to learn high-level abstractions. A dropout layer is introduced to reduce overfitting by randomly deactivating neurons during training. The final output layer uses a sigmoid activation function to generate a probability score for binary classification between Healthy and Parkinson's Disease classes. For training and evaluation, the spiral drawing dataset is divided into training and testing subsets. The training set is used to optimize the model parameters, while the testing

set is reserved for performance evaluation. This separation ensures that the model's generalization capability is assessed on previously unseen data. The training process is carried out using the TensorFlow and Keras frameworks, enabling efficient optimization and experimentation with multiple architectures.

V. RESULTS AND DISCUSSIONS

The home screen shows a user interface for a Parkinson disease prediction interface. The interface includes a title, "Parkinson Disease Prediction", and a section for users to upload an image. It features a file input field with a "Choose File" button and a submission button labeled "Upload and Predict" the design is clean and straightforward, providing a simple way for users to interact with the application.

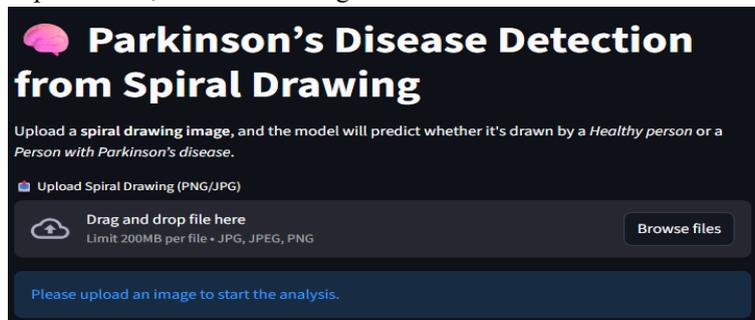


Figure 2: Home Screen

The upload image gives the user interface for a Parkinson disease prediction application. The interface includes a title, "Parkinson Disease Prediction", and a file upload section labeled "Select an Image". A file is displayed in the input field. Below it, there is a button labeled "Upload and Predict" to proceed with the prediction.

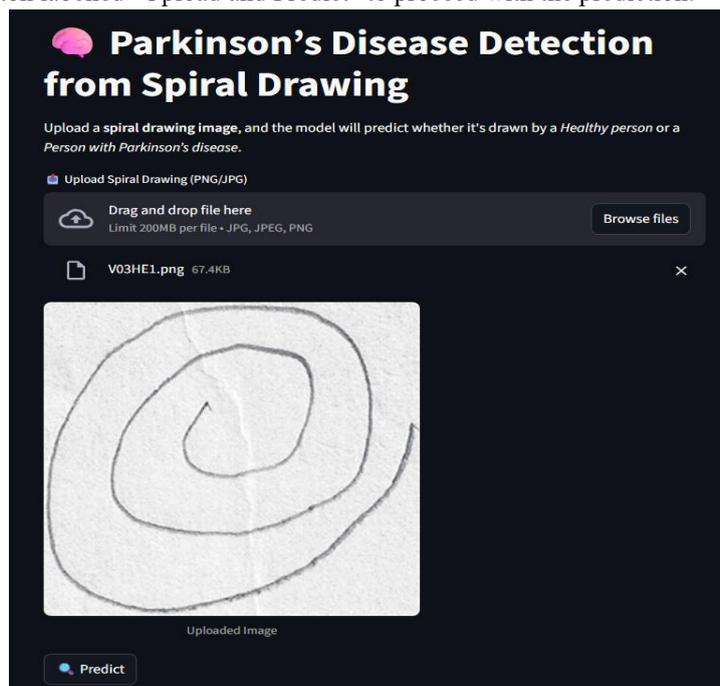


Figure 3: Upload Image

In this page the user gets the user gets to see what kind of a Parkinson disease they are facing and how it is triggered and what are the precautionary measures the user can take to so he/her can be safe and don't get affected by it. It is help full when they are in their early stages and understand learn how to deal with it.

The experimental results demonstrate that the proposed system effectively identifies Parkinsonian motor impairments from spiral drawing images. The

use of transfer learning with multiple pre-trained CNN architectures enables robust feature extraction, capturing subtle tremor patterns, stroke irregularities, and curvature deviations. Comparative analysis across models highlights differences in learning behavior, convergence speed, and generalization capability. The visualization of predictions and confidence scores further improves interpretability, making the system suitable as a clinical decision-support tool rather than a standalone diagnostic solution.

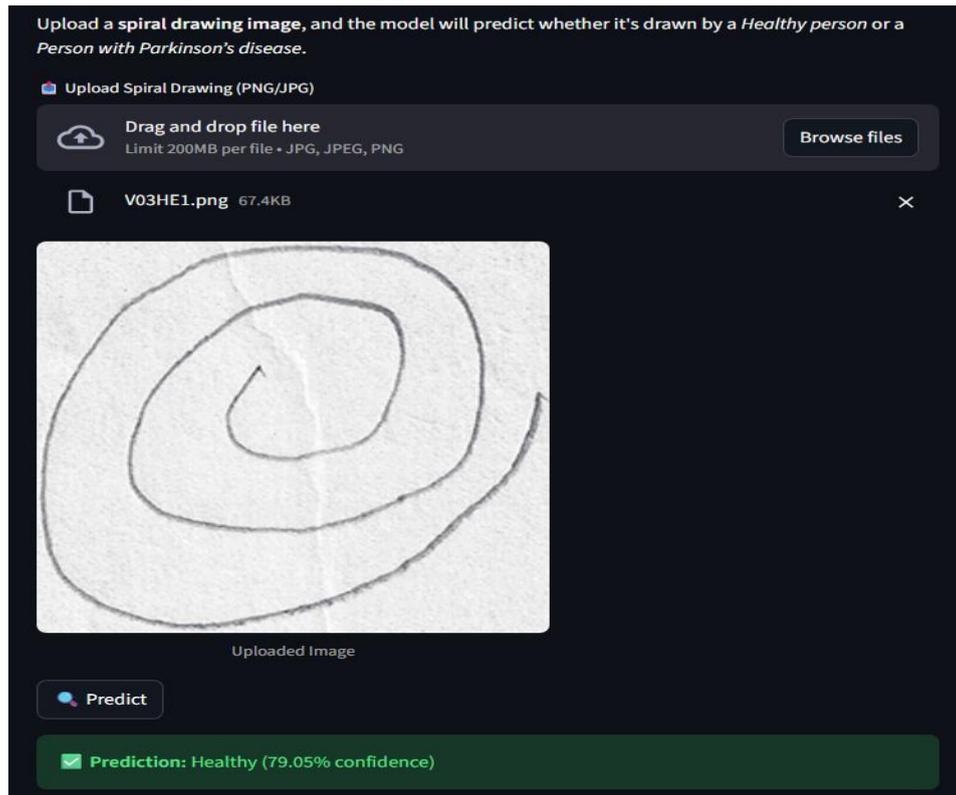


Figure 4: Predicted Outcome

The comparative analysis of the pre-trained models highlights distinct strengths and trade-offs in their performance for Parkinson's Disease detection using spiral drawings. VGG19 demonstrates stable learning behavior and effectively captures fine-grained stroke details, though it requires higher computational resources. InceptionV3 excels in identifying both local and global spiral patterns through multi-scale feature extraction but demands careful preprocessing to maintain consistency. ResNet50V2 benefits from

residual connections that enable deep representation learning and strong performance, albeit with slightly longer training times. DenseNet169 offers efficient feature reuse and improved gradient flow, making it well-suited for capturing subtle structural variations, though at the cost of increased memory usage. Overall, the comparison emphasizes the importance of selecting an appropriate model based on performance requirements and available computational resources.

Table 1: Comparison of models for Parkinson disease detection

Model	Strengths Observed	Limitations Observed
VGG19	Stable learning and effective extraction of fine-grained stroke details	Higher computational complexity
InceptionV3	Captures multi-scale features and global spiral	Requires careful preprocessing

	structure effectively	
ResNet50V2	Strong performance due to residual connections and deep representation	Slightly higher training time
DenseNet169	Efficient feature reuse and strong gradient flow	Increased memory usage

VI. CONCLUSION AND FUTURE SCOPE

This project effectively demonstrates the application of deep learning techniques for the automated analysis of spiral drawings to support the early detection of Parkinson’s Disease. By employing transfer learning with pre-trained convolutional neural network architectures such as VGG19, InceptionV3, ResNet50V2, and DenseNet169, the system is able to extract meaningful visual features that reflect motor impairments commonly associated with Parkinson’s Disease. The use of multiple models enabled a comparative study of different architectural strengths, highlighting the ability of CNNs to capture fine-grained stroke variations, tremor-induced oscillations, and structural irregularities in spiral patterns. The integration of image preprocessing, model inference, and result visualization within a Streamlit-based application demonstrates a complete end-to-end implementation, from user input to prediction output. Overall, the project showcases how artificial intelligence and deep learning can be effectively applied to develop a practical, non-invasive screening support system for Parkinson’s Disease using handwriting-based motor assessments.

The proposed Parkinson’s Disease detection system can be further enhanced by incorporating a larger and more diverse dataset to improve robustness and generalization. The application can be extended to mobile or web platforms to enable real-time and remote screening. Adoption of advanced deep learning models and integration of multimodal inputs such as handwriting dynamics, gait, and voice signals can improve diagnostic capability.

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