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A BiLSTM-ENHANCED CNN ARCHITECTURE FOR EARLY DETECTION OF PARKINSON'S DISEASE

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ABSTRACT

A novel method for the detection of Parkinson's Disease (PD) through the analysis of spiral and wave drawings, utilizing a hybrid Convolutional Neural Network (CNN) and Bidirectional Long Short Term Memory (BiLSTM) architecture. PD diagnosis often involves motor function assessments, and drawing tasks present discernible patterns reflective of PD-related motor impairments. Our proposed approach integrates a CNN for spatial feature extraction from the drawings and an BiLSTM for sequential stroke analysis, enabling a comprehensive examination of motor patterns indicative of PD. This non-invasive and objective method holds promise for early-stage PD detection, offering quantifiable and accessible diagnostic insights that could potentially facilitate timely interventions and improve patient outcomes. Automated analysis of drawing-based tasks through deep learning techniques represents an innovative avenue for PD screening, presenting opportunities for enhanced diagnostic accuracy and expanded accessibility in healthcare assessments.

Keywords: CNN, BiLSTM, Parkinson's Disease (PD)

1. INTRODUCTION

A degenerative neurological ailment that affects the nervous system and the body's nerve- controlled areas is PD. The symptoms appear gradually at first. The first symptom could be a barely noticeable tremor in one hand. While tremors are common, the illness can also cause stiffness or reduced movement. In its early stages, a person with PD may show little or no facial expression. Arms may not swing freely while walking. Speech could get softer or slurred. PD symptoms get worse with time. PD does not currently have a recognized cure. However, medications can significantly reduce symptoms. In rare cases, a physician may recommend surgery to relieve symptoms and control particular brain regions. For prompt intervention and management of PD, an early and precise diagnosis is essential. Medical imaging has transformed the understanding and diagnosis of PD, even if clinical assessment and neurological exams remain the main diagnostic techniques. Image-based methods have demonstrated promise in improving diagnostic accuracy and tracking the course of disease in recent years. This is especially true when employing sophisticated imaging techniques and image drawings. Changes in PD-related brain structures, including the substantia nigra, basal ganglia, and cortical regions, can be seen in structural MRI, which offers comprehensive anatomical information about the brain. Diffusion tensor imaging (DTI) makes it possible to evaluate white matter integrity and shows changes in brain connections linked to Parkinson's disease (PD). DAT availability and presynaptic dopaminergic function can be measured by PET imaging and radiotracers that target dopaminergic pathways, such as [18F] fluorodopa and [11C] dihydrotetrabenazine. Amyloid and tau tracers are used in PET investigations to help evaluate concomitant neurodegenerative diseases in PD, including Alzheimer's disease. Measures of presynaptic dopamine transporter binding are obtained by SPECT imaging using radiotracers like [123I] FP-CIT (DaTscan), which helps in the differential diagnosis of PD. Patients are asked to draw a clock face with predetermined time settings as part of the clock-drawing exam, which evaluates visuospatial and executive function. Deviations from a typical clock face could be a sign of PD- related cognitive impairment.

S. Chakraborty, et al [1] proposed a system design for analyzing spiral drawing patterns and wave drawing patterns in patients suffering from PD and healthy subjects. The system developed in the study leverages two different CNNs (AlexNet and GoogLeNet), for analyzing the drawing patterns of both spiral and wave sketches respectively. M. E. Mital, et al [2] employed standardized tests such as static and dynamic spiral tests (SST and DST). On top of these, machine learning, specifically, transfer learning is implemented. 14 pre-trained models are considered; 3 solvers are evaluated for each machine - these processes are repeated in 4 different scenarios. Based on the results, the pre- trained model with the highest accuracy is MobileNetV2 (93.94 %), while the model with the sub-optimal performance is VGG -19 (27.27%). Ferdib-Al-Islam, et al [3] investigated an approach to predict PD from hand-drawn wave and spiral images using computer vision and machine learning techniques. Decision Tree, Gradient

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Boosting, K-Nearest Neighbor, Random Forest, and some other classification algorithms with the HOG feature descriptor algorithm were applied. G. V. Dhruva Kumar, et al [4] proposed a model of CNN alone that is used to diagnose PD which takes into account the data collected by patients and spiral drawings to come up with a diagnosis. It can then classify the person as either a healthy or a Parkinson's patient. S. Kalash, et al [5] considered a diagnostic tool for the early detection and diagnosis of PD by analyzing hand-drawn spiral and wave patterns. This innovation opens up a realm of possibilities, particularly in enabling remote monitoring and timely intervention. In this paper, two deep learning models, Inception V3 and Xception, to predict the risk of PD based on the pattern of the drawings were used. The models were trained on augmented data consisting of more than 4500 images. Diagnostic tool achieves an accuracy rate of 91% which ultimately improves the lives of countless individuals battling this challenging condition. B. Karthikeyan, et al [6] proposed a new approach to detect and classify PD phases using drawing models and the universal You Only Look Once (YOLO) object recognition framework. Data used in the study were collected from 70 patients with mild PD, 70 patients with moderate PD, 70 patients with severe PD, and 70 healthy controls, who were asked to draw certain shapes with pen and paper. M. V. D. N. S. Madhavi, et al [7] used the unique learning model (ULM) for hand drawings to detect PD; a dataset was collected containing drawings from both people with PD and healthy individuals. The dataset was large enough to ensure that the machine learning algorithm could accurately distinguish between the two groups. S. Kamoji, et al
[8] analyzed various datasets and ran through certain algorithms to detect several symptoms. The Freezing of Gait dataset was used to predict if there were symptoms related to the legs and trunk by analyzing the patient's gait. Also, the Parkinson Clinical speech dataset to detect a deviation in audio frequency and the PD wave and spiral drawing dataset to find out impairment in writing due to a tremor in hand were used. K. M. M. Rao, et al [9] proposed a predictive model that uses the combination of the voice data set and spiral drawing dataset and gives the intensity of the PD for affected persons. D. Impedovo, et al [10] addressed the most relevant results obtained in the field of online (dynamic) analysis of handwritten trials by AD and PD patients. The survey was made from a pattern recognition point of view so that different phases are described. Data acquisition deals not only with these devices but also with handwriting tasks. This paper also highlights the most profitable research directions.

2. DATASET

The spiral and wave drawings of PD patients and healthy individuals are collected from the Kaggle. Both of these images were used in the system to train the model. The handwriting database includes 72 PWP (People with Parkinson) and 16 healthy persons. This image dataset statistics were attained in 2009.

SPIRAL IMAGE DATASET

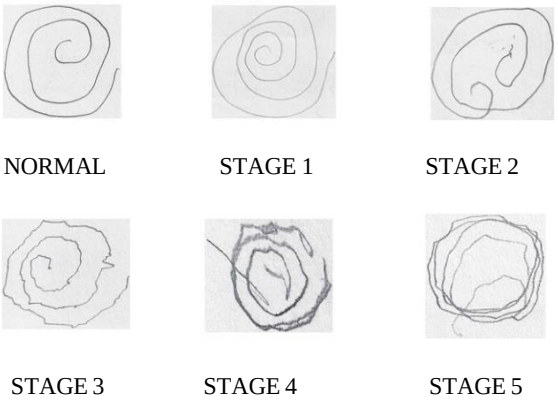

Fig 1. Spiral drawings by normal and various stages of PD

WAVE IMAGE DATASET

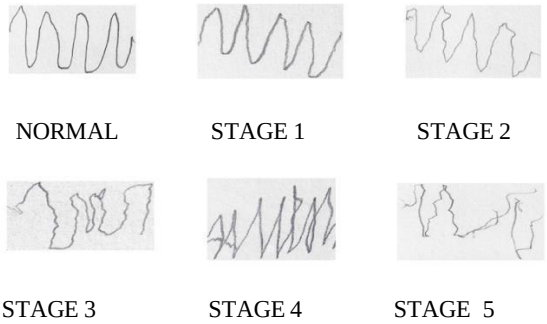

Fig 2. Wave drawings by normal and various stages of PD

3. DATA DISTRIBUTION

The following graphs show the distribution of data for the train and test set. If the data set is divided into such a training set and then a test set, 75% of the data should be used for training and 25% for testing.

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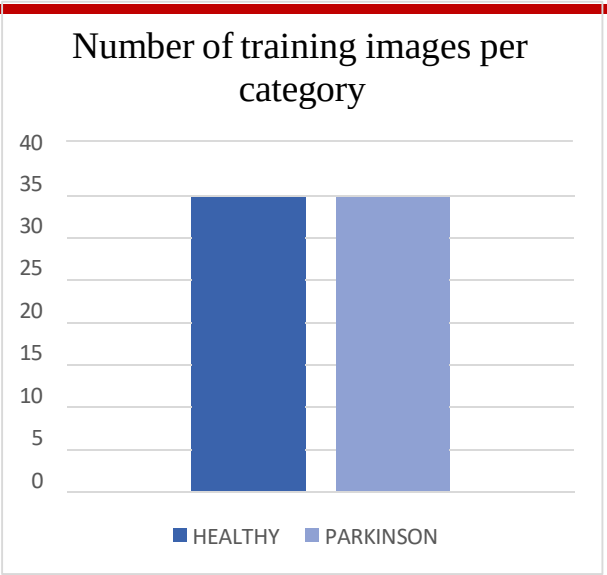

Fig 3. No. of training images per category

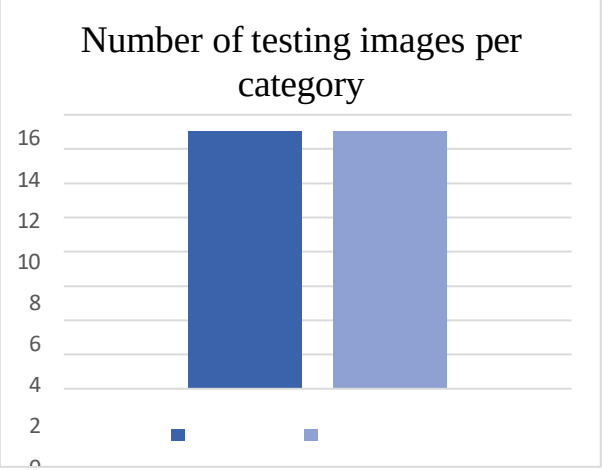

Fig 4. No. of testing images per category

4. DATA AUGMENTATION

Data augmentation is a technique in data analysis that involves adding a slightly modified copy of current data or newly created synthetic data to enrich existing data. It is frequently used to avoid overfitting. Data enrichment improves the performance and outcomes of machine learning models by integrating new examples into training datasets. A large and diverse dataset will considerably increase the model's performance. Data augmentation technology can help firms save operating costs by transforming datasets.

Data augmentation acts as a form of regularization by adding noise or variability to the training data. This helps prevent the model from memorizing the training set and encourages it to learn more generalizable features. Generating augmented data is often more cost-effective than collecting and labeling new data from scratch. This is particularly advantageous in situations where obtaining large quantities of labeled data is time- consuming or expensive.

4.1 DATA DISTRIBUTION AFTER AUGMENTATION

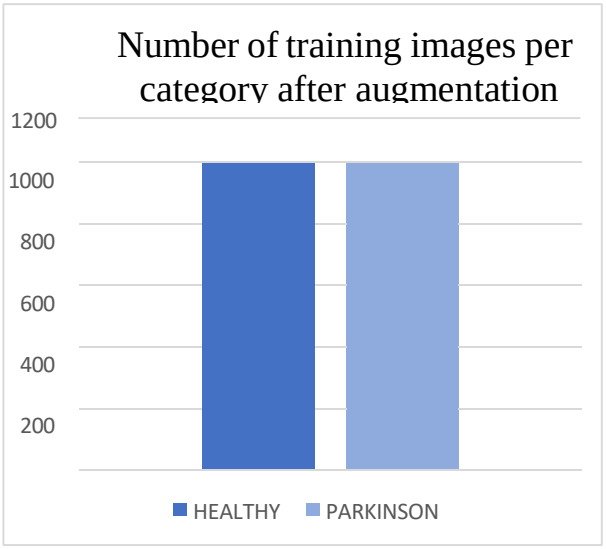

Fig 5. No. of training images after augmentation

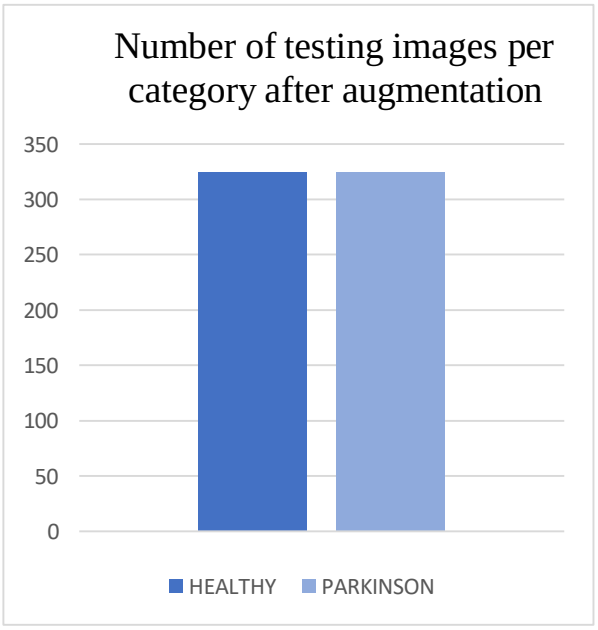

Fig 6. No of testing images after augmentation

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5. CONVOLUTIONAL NEURAL NETWORK(CNN)

Convolution Neural Network (CNN) model architecture that includes: Three convolution layers with filters of 32, 64, and 128. A MaxPool 2D layer with filters of various filter sizes comes after each convoluted layer. The process known as "maximum pooling" shows the maximum score for each patch in each feature map. Two completely linked layers, which have been discovered to perform better than the standard pooling of machine learning applications like picture identification, come after the convolution block. A flattening layer, commonly used before fully connected layers, takes a multi-dimensional tensor (like the output from convolutional layers) and converts it into a 1D vector. This allows fully connected layers to process the data efficiently. All neurons are connected by a fully connected layer using flattened inputs. If it exists, the FC layer is often located at the end of the CNN design and can be used to maximize objectives such as class evaluation.

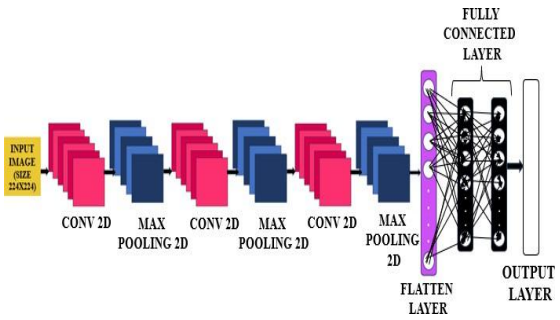

Fig 7. CNN-3 layered architecture

6. BIDIRECTIONAL LONG SHORT TERM (BiLSTM)

A BI-LSTM layer is a type of Recurrent Neural Network (RNN) layer specifically designed for sequence processing tasks. Unlike a standard LSTM layer that processes data only in the forward direction, a BiLSTM leverages two LSTMs. This LSTM processes the sequence element by element, capturing dependencies between earlier and current elements. It learns how the beginning of the sequence influences the later parts. The input sequence is reversed and fed into another LSTM. This LSTM processes the sequence backward, capturing dependencies between later and earlier elements. It learns how the latter parts of the sequence influence the meaning of earlier elements.

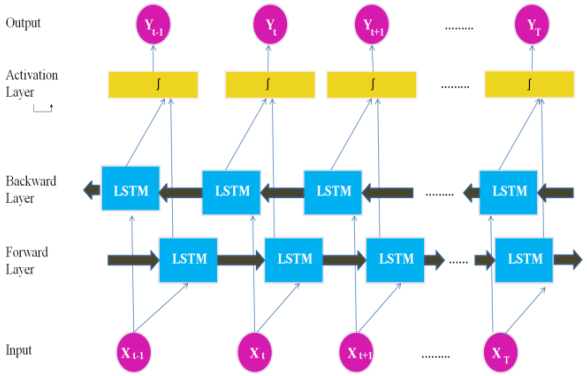

Fig 8. BILSTM architecture

7. HYBRID MODEL

The system aims to revolutionize PD detection by leveraging cutting-edge deep learning techniques, specifically a hybrid CNN and BiLSTM architecture, to analyze spiral and wave drawings.

In the initial phase, the system acquires standardized spiral and wave drawings from individuals, ensuring consistency in data collection protocols. Subsequently, the acquired drawings undergo preprocessing to normalize dimensions and convert them into suitable data representations. This preprocessing step sets the stage for effective feature extraction.

The CNN component of the architecture is responsible for extracting spatial features from the drawings. By analyzing patterns and structures within the images, the CNN identifies spatial characteristics associated with PD. Concurrently, the BiLSTM component analyzes the sequential strokes and temporal patterns present in the drawings, capturing the dynamic evolution of drawing trajectories over time.

Integration of the CNN and BiLSTM outputs creates a comprehensive feature representation, capturing both spatial and temporal aspects of the drawings. This integrated approach enables the model to leverage both local spatial features and global sequential patterns for more accurate PD detection. Once trained on a labeled dataset containing PD and healthy control samples, the hybrid CNN-BiLSTM architecture performs classification using appropriate algorithms. Evaluation metrics such as accuracy, sensitivity, specificity, and F1-score are employed to validate the system's performance across diverse datasets through cross-validation and independent testing. The clinical application of this system holds immense promise as a non-invasive screening tool for early-stage PD detection in clinical settings.

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In the proposed model, the initial layer is the input layer followed by three Convolutional 2D layers and three MaxPooling2D layers. The convolution 2D layer consists of 32, 64, and 128 filters respectively with a size of 3x3. The MaxPooling2D layer consists of a pooling window of size 2x2 that reduces the spatial dimensions and controls overfitting. The CNN layers have a ReLU activation function that prevents the exponential growth in computation. The third MaxPooling layer is followed by a flatte2n layer that flattens the output from the previous layers into a 1D array preparing for fully connected layers. The reshaping layer used here reshapes the output into a 3D tensor with the shape of (-1, -1), where -1 refers to the flattened size. The architecture adds eight BiLSTM layers with 400 units each that process the input sequence in both forward and backward directions. A fully connected layer with 512 units and ReLU activation is added before the output layer. The output layer with 12 units and a softmax activation is often used in multi-class classification problems. Adam optimizer, which is an iterative optimizer algorithm used to minimize the loss function during the training of neural networks is used.

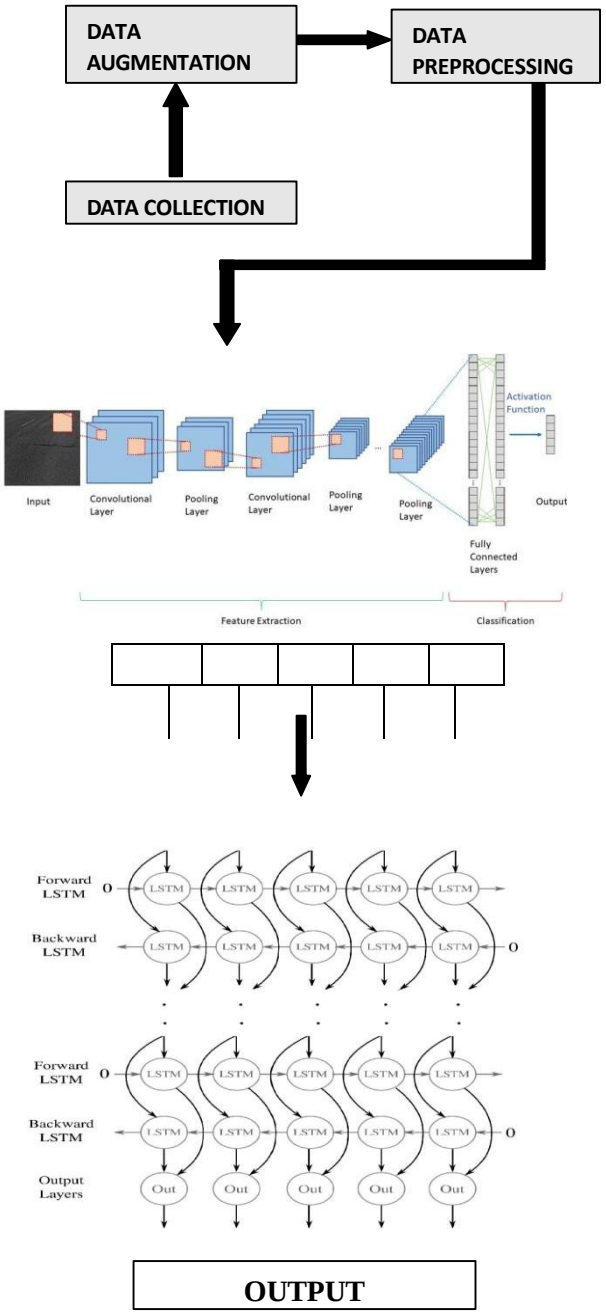

Fig 9. HYBRID MODEL ARCHITECTURE

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8. RESULT AND DISCUSSION

8.1 MODEL OVERVIEW

Layer [type]	Output Shape	Parameters
conv_1 (Conv2D)	(None, 222,222,32)	896
mp_1(MaxPooling2D)	(None, 111,111,32)	0
conv_2 (Conv2D)	(None, 109, 109, 64)	18496
mp_2(MaxPooling2D)	(None, 54, 54, 64)	0
conv_3 (Conv2D)	(None, 52, 52, 128)	73856
mp_3(MaxPooling2D)	(None, 26, 26, 128)	0
flatten (Flatten)	(None, 86528)	0
reshape (Reshape)	(None, 1, 86528)	0
bidirectional (Bidirectional)	(None, 800)	278172800
dense (Dense)	(None, 512)	41012
dense_1 (Dense)	(None, 12)	6156

Total params: 278, 682, 316
Trainable params: 278,682,316
Non-trainable params: 0

8.2 TRAINING AND VALIDATION

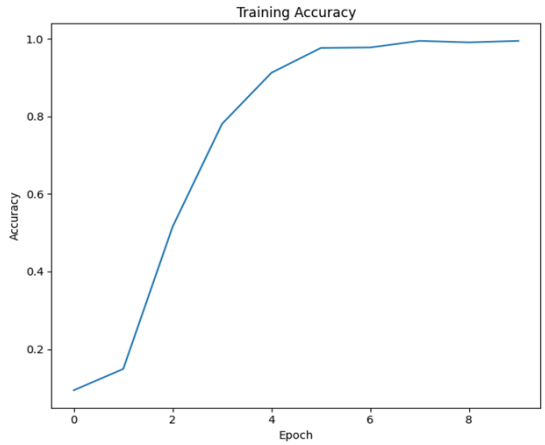

Fig 10. Training Accuracy Graph

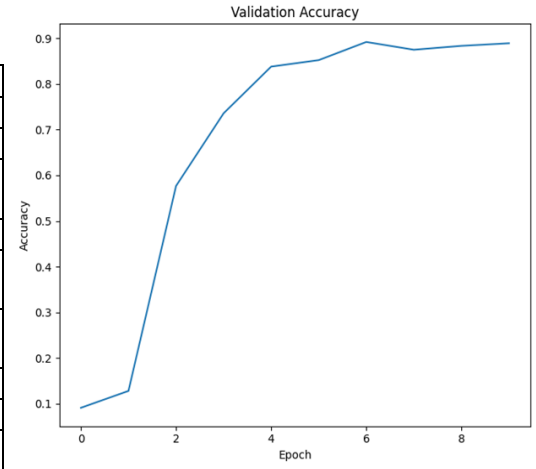

Fig 11. Validation Accuracy Graph

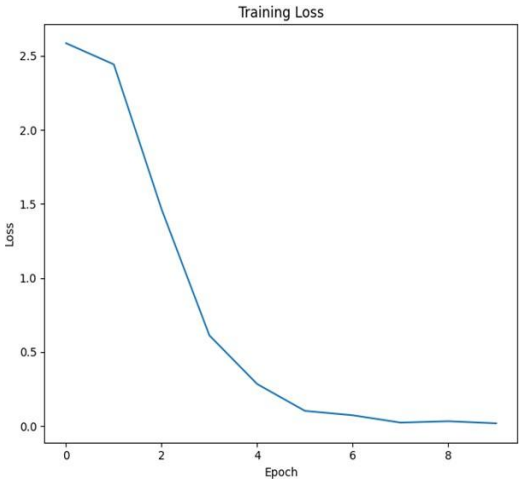

Fig 12. Training Loss Graph

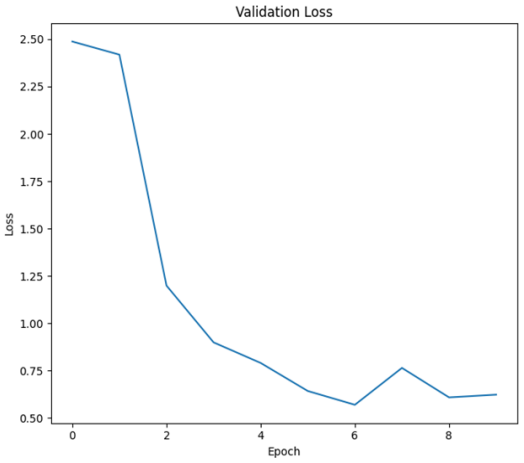

Fig 13. Validation Loss Graph

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8.3 GUI OUTPUT

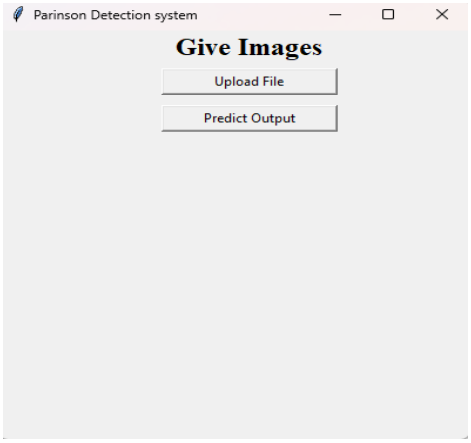

Fig 12. Parkinson Detection System (GUI)

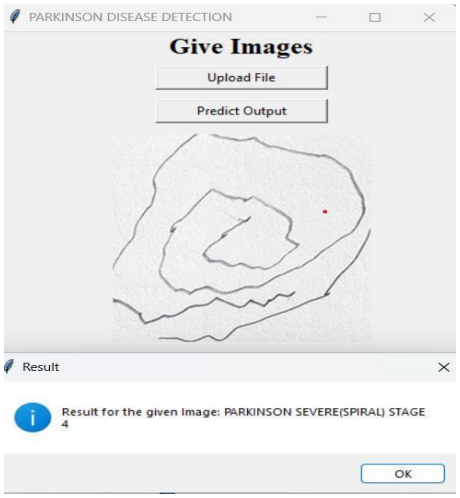

Fig 13.GUI output- Stage 4

8.4 WEBPAGE OUTPUT

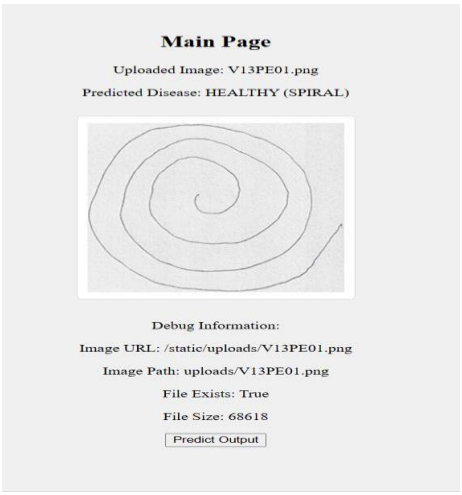

Fig 14. Webpage output- Spiral (Healthy)

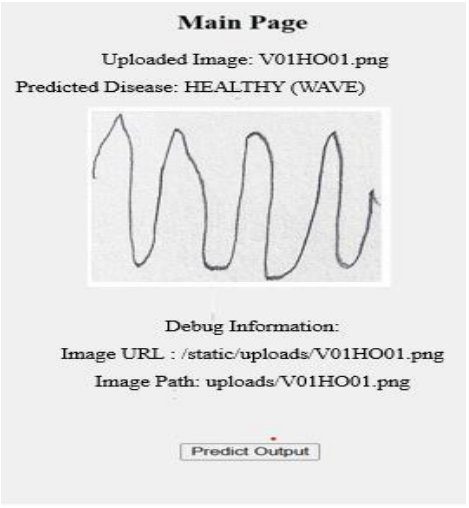

Fig 15. Webpage output- Healthy (Wave)

9. CONCLUSION

The study achieved a very promising result with an accuracy of 96% in detecting Parkinson's disease using a hybrid architecture. This suggests that the model can effectively discriminate between healthy individuals and those with Parkinson's disease. The high accuracy (96%) indicates the model's strong potential for aiding in Parkinson's disease detection. It is important to note that further research is likely needed to validate these findings on a wider range of data and to assess the model's generalizability. Additionally, while accuracy is a crucial metric, other factors such as precision, recall, and robustness to noise might also be considered for a more comprehensive evaluation.

Future work can be completed by integrating a touchpad with a computer. By drawing graphics on the touchpad, an illness can be anticipated in real-time within a few seconds.

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