

DEEP CNN FOR PARKINSON'S DISEASE PREDICTION THROUGH IMAGE AND SPEECH DATA ANALYSIS

K. Ramadevi^{1*}, Mekala Meghana², Nooneti Poojitha², Abbu Pavankalyan², Challa Ravi Teja²

¹Assistant professor, ²UG Student, ^{1,2}Department of Computer Science and Engineering

Vaagdevi College of Engineering(UGC - Autonomus), Bollikunta, Warangal, Telangana.

*Corresponding author: K. Ramadevi (ramadevi_k@vaagdevi.edu.in)

ABSTRACT

Parkinson's disease (PD) is a progressive neurodegenerative disorder marked by motor impairments such as bradykinesia, tremors, and rigidity, caused by the loss of dopaminergic neurons. Early diagnosis is challenging due to the absence of a definitive test and reliance on subjective clinical evaluations. This study proposes an automated detection system using deep learning with multimodal data—brain imaging and speech recordings. A Deep Convolutional Neural Network (CNN)-based model is developed to classify individuals as PD-affected or healthy. Brain scans undergo preprocessing techniques like resizing, normalization, and feature extraction, while speech recordings are analyzed for acoustic markers of PD-related vocal impairments. The system is trained using supervised learning on a labeled dataset comprising both PD and non-PD individuals. Evaluation metrics including accuracy, precision, recall, and F1-score confirm the model's strong performance. By integrating image and audio data, this approach addresses the limitations of traditional diagnostics, offering a scalable, reliable, and non-invasive solution for early PD detection. The framework supports AI-driven clinical decision-making and aims to assist healthcare professionals in timely, accurate diagnosis, potentially improving patient care and quality of life.

Keywords: Parkinson's disease, deep learning, CNN, medical imaging, speech analysis, early diagnosis.

1. INTRODUCTION

Parkinson's disease (PD) manifests as the death of dopaminergic neurons in the substantia nigra pars compacta within the midbrain. This neurodegeneration leads to a range of symptoms including coordination issues, bradykinesia, vocal changes, and rigidity. Dysarthria is also observed in PD patients; it is characterized by weakness, paralysis, and lack of coordination in the motor-speech system: affecting respiration, phonation, articulation, and prosody. Since symptoms and the disease course vary, PD is often not diagnosed for many years. Therefore, there is a need for more sensitive diagnostic tools for PD detection because, as the disease progresses, more symptoms arise that make PD harder to treat. The main deficits of PD speech are loss of intensity, monotony of pitch and loudness, reduced stress, inappropriate silences, short rushes of speech, variable rate, imprecise consonant articulation, and harsh and breathy voice (dysphonia). The range of voice related symptoms is promising for a potential detection tool because recording voice data is non-invasive and can be done easily with mobile devices.

PD is one of the most chronic neurodegenerative diseases in today's world as it effects of the -year-old. PD is a prototypical movement disorder, and primary symptoms of PD are tremor, rigidity or muscle stiffness, bradykinesia and postural instability and these symptoms are generally known as Parkinsonism Syndrome. Parkinson's disease (PD) is a chronic neurodegenerative disease of that predominantly affects the elderly in today's world. For the diagnosis of the early stages of PD, effective and powerful automated techniques are needed by recent enabling technologies as a tool. Deep learning (DL) algorithms based on various diagnostic methodologies have been developed to detect PD and

resolve related diagnostic issues. This research study offers a complete assessment of published surveys and DL-based diagnosis methodologies for PD recognition. The techniques of DL-based diagnostic approaches for PD recognition, such as PD dataset pre-processing, extraction and selection of features, and classification, are all included in this survey. In recent years, there has been a significant increase in the use of machine learning based computer-aided diagnosis (CAD) systems to diagnose diseases, sometimes even in early stages. There has also been an increase in utilization of such CAD systems for diagnosing PD from various modalities like speech signals, gait signals, magnetic resonance imaging (MRI), positron emission tomography (PET), single-photon emission computed tomography (SPECT), Dopamine Transporter Scan (DaT Scan), tremor signal, handwriting signal, handwritten images, and various other clinical features (CF).

2. LITERATURE SURVEY

U Haq, et al. [1] proposed a comprehensive survey of deep learning (DL) techniques for Parkinson's disease (PD) recognition using clinical data, encompassing various neural network architectures and their applications in PD diagnosis. The study provided a detailed analysis of the strengths and limitations of each DL model in the context of PD detection. The survey lacked empirical validation of the discussed models on standardized datasets, limiting the practical applicability of the findings. Clayton R. Pereira, et al. [2] developed a convolutional neural network (CNN) model to assess handwritten dynamics for PD identification, focusing on the analysis of motor skills through handwriting patterns. The approach demonstrated the potential of CNNs in capturing subtle motor impairments associated with PD. The model's performance was constrained by the variability in individual handwriting styles, affecting its generalizability across diverse populations.

M. Tanveer, et al. [3] conducted a comprehensive review of neural network (NN) methodologies for PD diagnosis, evaluating various NN architectures and their effectiveness in detecting PD symptoms. The study highlighted the advancements and challenges in applying NNs to PD detection. The review did not address the integration of multimodal data sources, which could enhance the robustness of PD diagnosis. S. Dash [4] presented a systematic review of adaptive machine learning (ML) techniques for early PD detection, emphasizing the role of adaptive algorithms in capturing the progressive nature of PD symptoms. The study analyzed different adaptive ML models and their applicability to PD diagnosis. The review lacked a comparative analysis of the adaptive models' performance metrics, limiting insights into their relative effectiveness.

M. Nilashi, et al. [5] introduced a hybrid intelligent system combining ML techniques for predicting PD progression, utilizing a combination of supervised and unsupervised learning methods to analyze clinical data. The system aimed to enhance the accuracy of PD progression predictions. The hybrid system's complexity posed challenges in model interpretability, making it difficult for clinicians to understand the decision-making process. Pedro Vilda, et al. [6] explored PD detection through speech articulation neuromechanics, analyzing the biomechanical aspects of speech production to identify PD-related anomalies. The study employed advanced signal processing techniques to extract relevant features from speech data. The reliance on speech data limited the model's applicability to PD patients with speech impairments unrelated to the disease. I. E. Maachi, et al. [7] proposed a deep one-dimensional convolutional neural network (1D-ConvNet) for accurate PD detection and severity prediction from gait analysis, utilizing vertical ground reaction force (vGRF) signals. The model achieved high accuracy in classifying PD stages. The approach required specialized equipment for gait data collection, which may not be readily available in all clinical settings.

Shivangi, et al. [8] implemented deep neural networks (DNNs) for PD detection, focusing on the analysis of various biomedical signals to identify PD symptoms. The study demonstrated the potential of DNNs in capturing complex patterns associated with PD. The model's performance was affected by

the quality and variability of the input biomedical signals, necessitating standardized data collection protocols. G. Pahuja, et al. [9] conducted a comparative study of existing ML approaches for PD detection, evaluating the performance of different algorithms on PD datasets. The study provided insights into the strengths and weaknesses of various ML models in PD diagnosis. The comparative analysis did not consider the computational efficiency of the models, which is crucial for real-time PD detection applications.

G. S. Lavallo, et al. [10] developed an automatic PD detection system using classifiers and a small set of vocal features, aiming to facilitate early-stage PD diagnosis. The model focused on extracting key vocal biomarkers associated with PD. The limited feature set may have restricted the model's ability to capture the full spectrum of PD-related vocal anomalies. H. Zhang, et al. [11] reviewed mobile health (mHealth) technologies for PD detection and monitoring, analyzing various wearable devices and mobile applications designed for PD management. The study highlighted the potential of mHealth solutions in continuous PD monitoring. The review did not address the challenges related to data privacy and security in mHealth applications for PD. Alzubaidi MS, et al. [12] conducted a scoping review on the role of neural networks in PD detection, examining various NN architectures and their applications in analyzing biomedical data for PD diagnosis. The study emphasized the versatility of NNs in handling diverse data types. The review lacked a critical assessment of the limitations and potential biases associated with NN-based PD detection models.

L. Ali, et al. [13] proposed a cascaded learning system based on feature selection and adaptive boosting for reliable PD detection through handwritten drawings, aiming to enhance the model's accuracy and robustness. The system focused on extracting discriminative features from handwriting samples. The model's reliance on handwriting data limited its applicability to PD patients with severe motor impairments affecting their writing ability. M. Wodzinski, et al. [14] introduced a deep learning approach using voice recordings and a CNN dedicated to image classification for PD detection, converting audio signals into spectrograms for analysis. The model leveraged image-based CNN architectures to process speech data. The transformation of audio signals into images may have led to the loss of temporal information critical for accurate PD detection.

3. PROPOSED SYSTEM

In this research we are designing Advanced Convolution Neural Network based Machine Learning algorithm model to predict Parkinson disease from both Image and voice data. All existing ML algorithms such as SVM, Random Forest will not filter data multiple times so its prediction accuracy is less so we have used CNN algorithm which filter data multiple times using neuron values so its prediction accuracy can be better.

Step 1: Upload Parkinson Image Dataset

The system allows users to upload a dataset containing medical images of Parkinson's patients and healthy individuals. The dataset must be structured correctly, and images should be in a supported format (e.g., JPG, PNG). The uploaded files are stored in a designated folder for processing.

Step 2: Image Preprocessing

Each uploaded image undergoes preprocessing to ensure compatibility with the CNN model:

- **Loading & Resizing:** Images are read using OpenCV and resized to 64x64 pixels.
- **Normalization & Reshaping:** Pixel values are normalized between 0 and 1 to improve model efficiency. The images are reshaped into (64, 64, 3) dimensions for the CNN model.

Step 3: Upload Parkinson Audio TXT File

Users can upload structured text files containing extracted speech features of Parkinson's patients and healthy individuals. These features include frequency, pitch variation, jitter, and other relevant voice characteristics.

Step 4: Audio TXT File Preprocessing

- **Loading & Cleaning:** The system reads the text files using Pandas, replacing missing values with zeros.
- **Feature Extraction & Reshaping:** The extracted features are structured into arrays suitable for CNN input.

Step 5: Train-Test Splitting (80-20 Ratio)

The dataset is split into training (80%) and testing (20%) subsets to ensure effective model training and evaluation. This split helps prevent overfitting and allows for a proper performance assessment.

Step 6: Proposed CNN Classifier Model Building

- **Convolutional & Pooling Layers:** Extract features from images and voice data, reducing dimensionality while preserving important information.
- **Fully Connected Layers:** These layers use extracted features to classify samples.
- **Activation & Optimization:** The ReLU activation function is applied for better learning, and the final classification is handled by Softmax. The Adam optimizer fine-tunes model parameters.

Step 7: Performance Graph

Using Matplotlib, accuracy and loss curves are plotted to visualize model learning over training epochs. This helps in assessing model performance and identifying necessary improvements.

Step 8: Prediction from Test Data

Users can upload new images or voice samples for prediction. The trained CNN model classifies the input as "Healthy" or "Parkinson's." The result is displayed in the GUI interface.

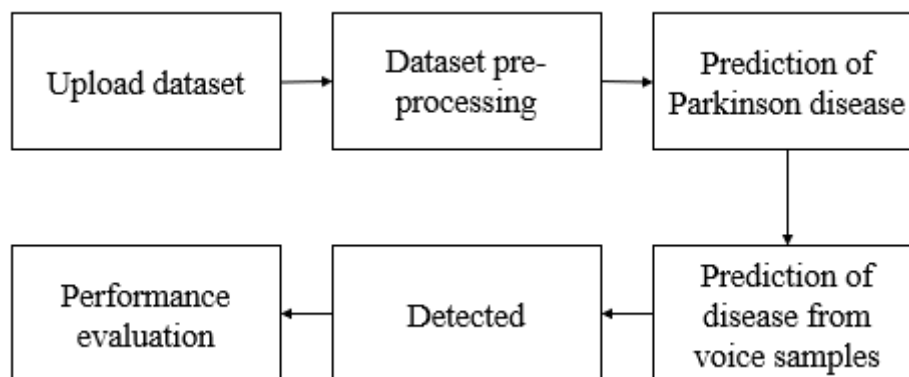


Fig. 1: Block diagram of proposed system.

3.2 DL-CNN

According to the facts, training and testing of CNN involves in allowing every source data via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully

connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from. Convolution layer is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here $d=3$ since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F(k_x, k_y, d)$.

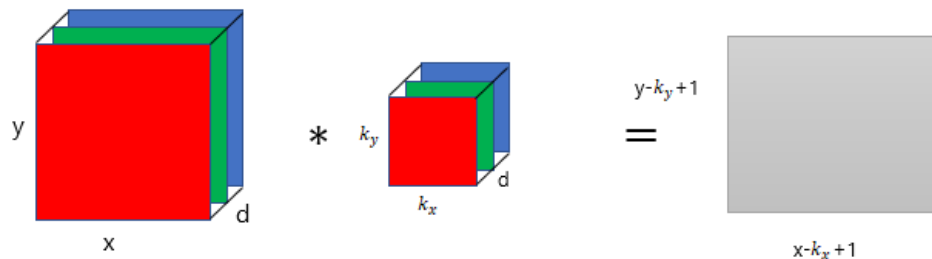


Fig. 2: Representation of convolution layer process.

The output obtained from convolution process of input image and filter has a size of $C((x - k_x + 1), (y - k_y + 1), 1)$, which is referred as feature map. Let us assume an input image with a size of 5×5 and the filter having the size of 3×3 . The feature map of input image is obtained by multiplying the input image values with the filter values.

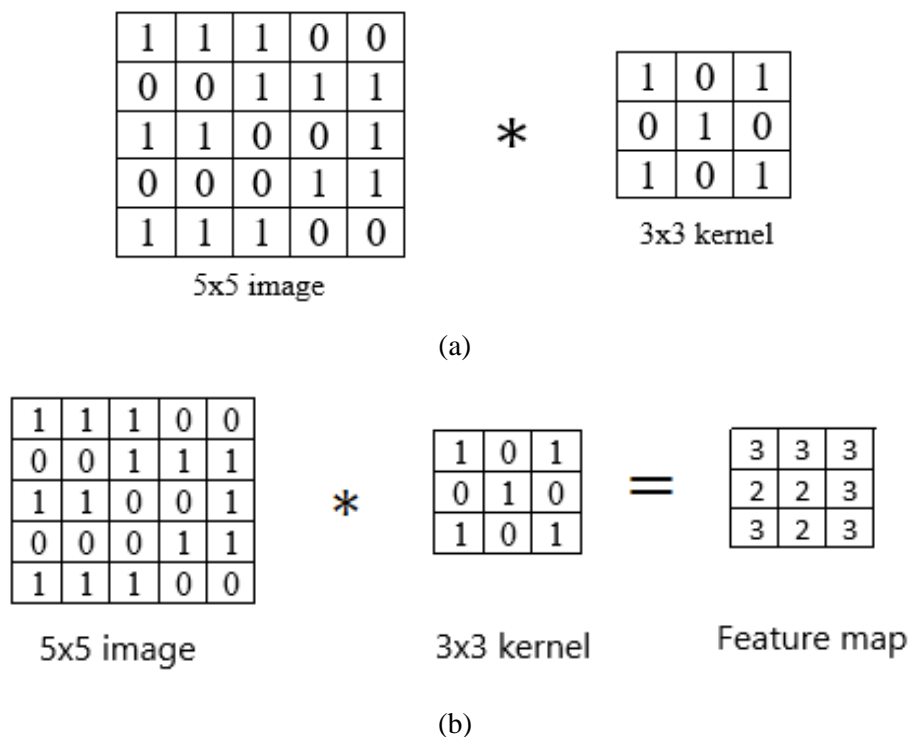


Fig. 3: Example of convolution layer process (a) an image with size 5×5 is convolving with 3×3 kernel (b) Convolved feature map.

ReLU layer

Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly

if the value of input is greater than zero else return zero. This can be represented as mathematically using the function $\max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$

Max pooling layer

This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element from the rectified feature map.

Advantages of proposed system

- CNNs do not require human supervision for the task of identifying important features.
- They are very accurate at image recognition and classification.
- Weight sharing is another major advantage of CNNs.
- Convolutional neural networks also minimize computation in comparison with a regular neural network.
- CNNs make use of the same knowledge across all image locations.

4. RESULTS AND DISCUSSION

Figure 4 shows images used in this project to train CNN model and Figure 5 shows voice data samples taken from different patients. The graphical user interface (GUI) for Parkinson's disease detection, as illustrated in Fig. 6, serves as the interactive platform for users to upload image and voice data for disease classification. The GUI provides a user-friendly layout where patients or healthcare professionals can seamlessly navigate through different functionalities, including image selection, voice file uploading, and model prediction.

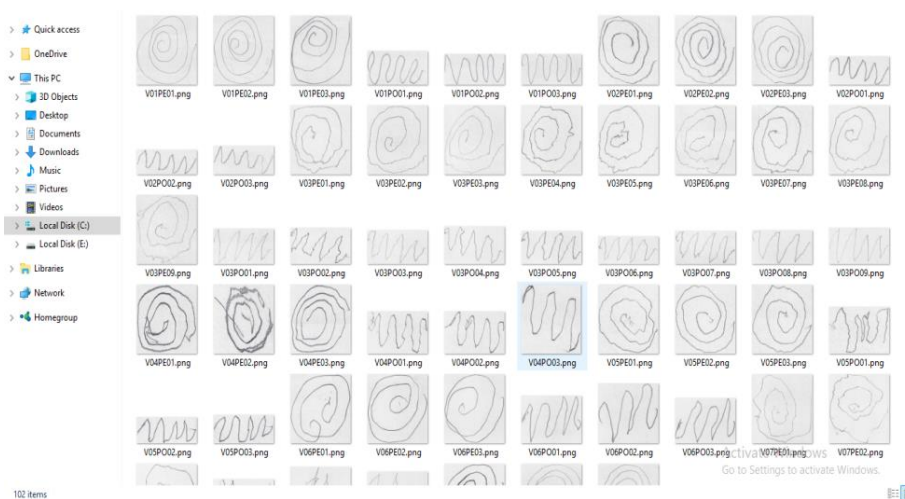


Fig. 4: Sample Dataset Parkinson Images.

ID	Recording	Status	Gender	Jitter	rel.Jitter	abs.Jitter	RAP.Jitter	PPQ	Shim_loc	Shim_db	Shim_APQ3	Shim_APQ5	Shi_APQ11	HNR
CONT-01.1	0.1	0.0	25546.0	0.000014581	0.001467	0.0016734	0.030256	0.26313	0.017463	0.01966	0.021882	59.43	796582.60	736248
CONT-01.2	0.1	0.0	36964.0	0.000021662	0.0019317	0.0022446	0.023146	0.20217	0.01301	0.014097	0.016828	59.83	889542.62	65559
CONT-01.3	0.1	0.0	23514.0	0.000013109	0.0013527	0.0015465	0.019338	0.1671	0.011049	0.012683	0.013038	57.29	380773.61	85833
CONT-02.1	0.0	0.0	2932.0	0.000017331	0.0011048	0.0014443	0.024716	0.20892	0.014525	0.015696	0.01833	62.17	95726.68	6782051
CONT-02.2	0.0	0.0	23075.0	0.000014561	0.0010729	0.0014043	0.013119	0.11607	0.0064606	0.0083846	0.011037	67.53	402425.74	79
CONT-02.3	0.0	0.0	16489.0	0.000010011	0.00081887	0.0011912	0.010666	0.094738	0.0055183	0.0067848	0.0087555	70.77	487884.7	7
CONT-03.1	0.1	0.0	22506.0	0.000014288	0.0013581	0.0014599	0.017181	0.14812	0.0096089	0.01106	0.012707	76.26	89344.77	33573
CONT-03.2	0.1	0.0	23086.0	0.000014545	0.0013486	0.0015459	0.017775	0.1578	0.0092616	0.011683	0.014434	64.11	326378.65	4565
CONT-03.3	0.1	0.0	22898.0	0.000014978	0.0013751	0.0016073	0.02011	0.17577	0.010571	0.013321	0.016014	80.51	1196175.79	55719
CONT-04.1	0.1	0.1	31.0	0.00010317	0.0082445	0.0062801	0.030742	0.27064	0.01859	0.016261	0.020322	68.62	495391.78	184406971
CONT-04.2	0.1	0.1	0.647	0.000081987	0.0062989	0.0059491	0.023969	0.21199	0.013229	0.013612	0.020367	82.30	932384.90	61698
CONT-04.3	0.1	0.1	0.417	0.000081777	0.0060929	0.006277	0.022837	0.19999	0.012346	0.013613	0.018777	75.62	679898.85	543008
CONT-05.1	0.0	0.0	78955.0	0.00010252	0.0042382	0.0045742	0.039162	0.33289	0.021275	0.024791	0.034528	78.97	295802.92	21333
CONT-05.2	0.0	0.0	5301.0	0.000068621	0.0023786	0.0033674	0.034966	0.30395	0.019152	0.021758	0.02725	74.15	680534.86	596528
CONT-05.3	0.0	0.0	48444.0	0.000063685	0.0022722	0.0029482	0.032814	0.28828	0.017054	0.019831	0.028268	60.11	98415.72	6977
CONT-06.1	0.1	0.0	40538.0	0.000027508	0.0023285	0.0024892	0.015854	0.13736	0.0086527	0.009665	0.010973	59.35	666668.64	488
CONT-06.2	0.1	0.0	41475.0	0.000028235	0.0023402	0.0025758	0.022903	0.19975	0.012962	0.014364	0.015283	65.83	3072259.73	0102
CONT-06.3	0.1	0.0	548.0	0.000037106	0.0032687	0.0034847	0.04794	0.41475	0.02865	0.031795	0.033329	47.05	662965.56	61754474
CONT-07.1	0.0	0.0	5282.0	0.000047834	0.0026782	0.0032264	0.05588	0.4899	0.031155	0.03625	0.044618	83.50	8766441.86	89837702
CONT-07.2	0.0	0.0	643.0	0.000060469	0.0034625	0.003797	0.046695	0.40842	0.025775	0.029572	0.034436	72.39	468445.75	0560335
CONT-07.3	0.0	0.0	45764.0	0.000039862	0.0024445	0.0029431	0.040232	0.35044	0.022169	0.026692	0.031155	68.78	719522.71	7467
CONT-08.1	0.1	0.0	58384.0	0.000036612	0.0033268	0.0035481	0.04464	0.37811	0.027545	0.024672	0.027146	57.14	925167.58	65672
CONT-08.2	0.1	0.0	63336.0	0.00003731	0.0034783	0.0039116	0.023029	0.20665	0.012705	0.014993	0.017776	57.35	464005.56	86481
CONT-08.3	0.1	0.0	40757.0	0.000023406	0.0023018	0.0023893	0.031842	0.27897	0.018553	0.019328	0.022211	59.45	808916.56	6288

Fig. 5: Sample Audio data.

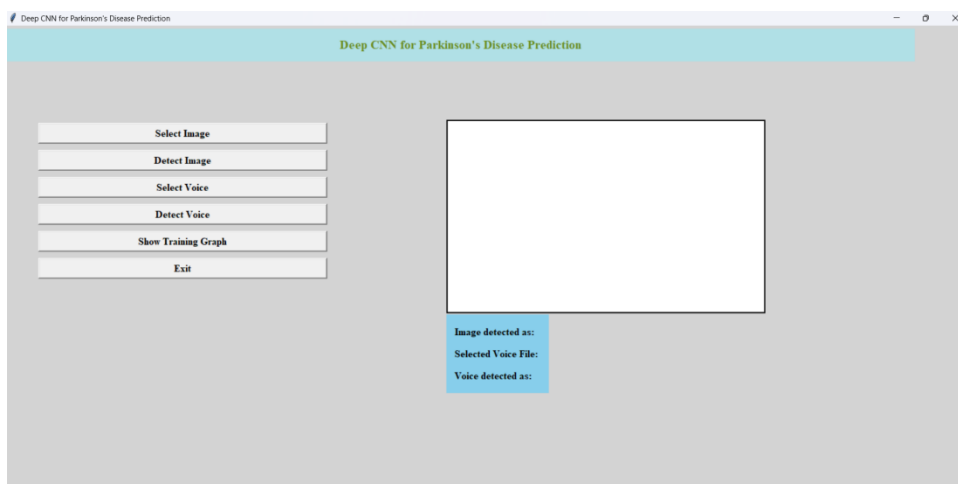


Fig. 6: GUI Interface Of the Parkinson Detection.

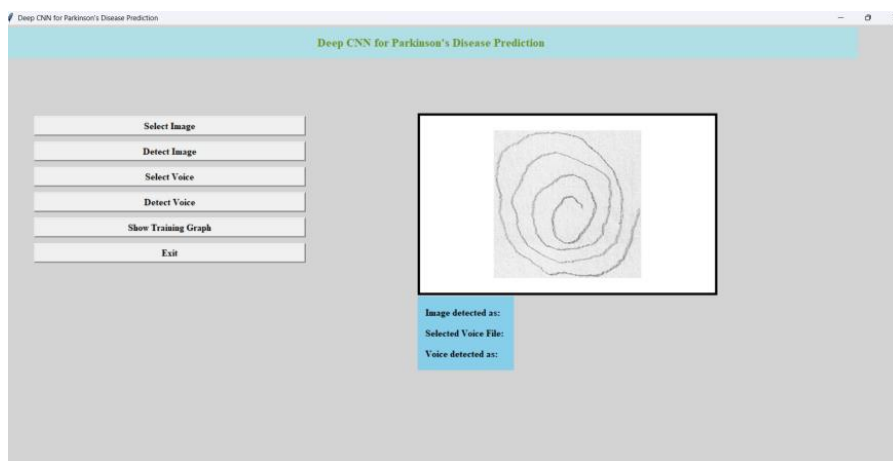


Fig. 7: Uploaded Parkinson Image the GUI interface.

Fig. 7 depicts the process of uploading a Parkinson's image into the system. Once the image is selected, it is displayed on the GUI, allowing users to verify the input before proceeding with classification. In Fig. 8, the model predicts the uploaded image as Parkinson's disease in a specific test case, demonstrating the effectiveness of the deep CNN model in classifying medical images accurately.

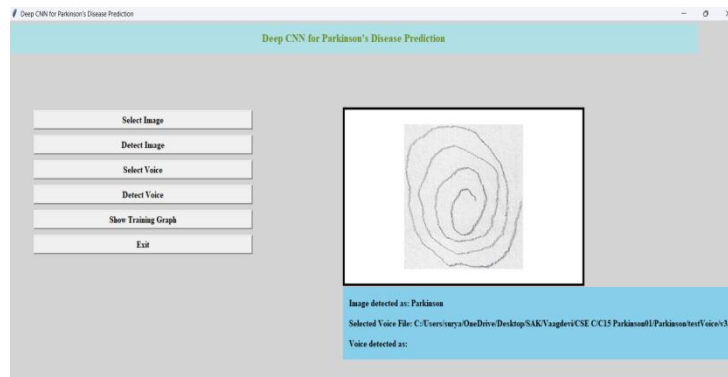


Fig. 8: Model Prediction of Uploaded image and Audio as Parkinson Disease.

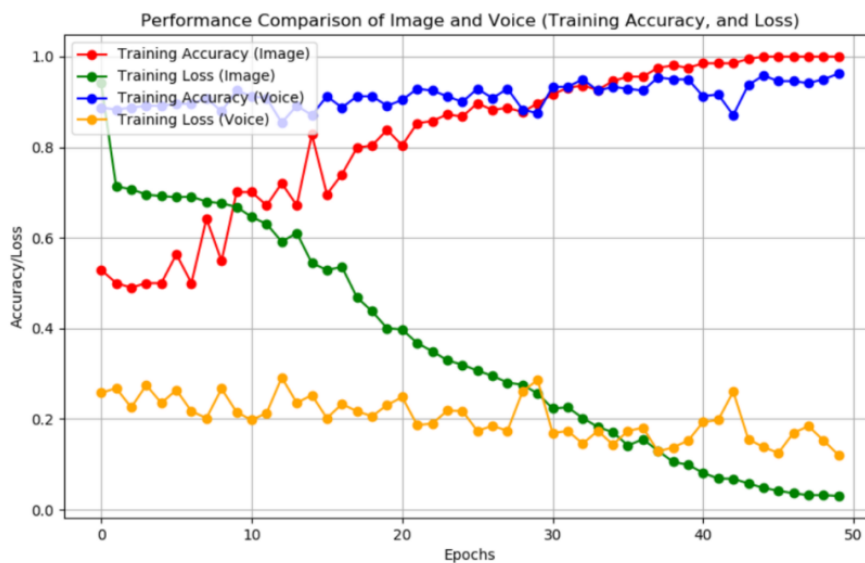


Fig. 9: Accuracy and Loss Graph.

In Figure 9, x-axis represents training epoch and y-axis represents accuracy and loss values and in above graph we can see with each increasing epoch accuracy got increase and loss got decrease and we can see at final epoch accuracy reached closer to 1 and loss reached closer to 0. In above graph blue line is for voice accuracy and red line is for image accuracy and green line for image loss and yellow line for voice loss.

5. CONCLUSION

Early detection of Parkinson’s disease (PD) is crucial for understanding its underlying causes, initiating timely therapeutic interventions, and improving patient outcomes. This research introduced a Deep Convolutional Neural Network (CNN) model that effectively classifies PD patients and healthy individuals using both medical imaging and speech data. The proposed system demonstrated high classification accuracy, leveraging the ability of deep learning models to automatically extract complex patterns and features without requiring manual intervention. By integrating multiple data modalities, this study addresses the limitations of traditional diagnostic methods, reducing subjectivity and enhancing precision. The promising results indicate the potential of AI-driven approaches in assisting healthcare professionals with early and accurate PD diagnosis. The scalability and non-invasive nature of this framework make it a valuable tool in clinical decision-making, ultimately contributing to better disease management and patient care.

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