TuijinJishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 1 (2024)

Parkinson's Disease Progression using the Deep Structured Algorithm

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Abstract:-Parkinson's disease is a degenerative brain illness that results in movements that are uncontrollable, coordination, balance problems, and stiffness. Early identification and treatment are critical since the illness proceeds in three phases. The aim of the project is to develop an application that uses a Convolutional Neural Network, a Deep Learning method, to analyse and predict if a patient has Parkinson's disease and at what stage of the illness they are infected. Using publicly accessible DaTScan datasets, we report a successful CNN Inception V3 model for properly recognizing and forecasting Parkinson's disease and its development.

Keywords: *Parkinson's disease (PD), neurodegenerative disease, graphical user interface (GUI), DaTScan, Convolutional Neural Networks (CNNs), functional magnetic resonance imaging (fMRI), support vector machines (SVM), artificial neural network (ANN).*

1. Introduction

Parkinson's disease (PD) is a central nervous system neurodegenerative disease that mostly affects the elderly. This disease is thought to be caused mostly by dopaminergic neuron loss. Early-stage Parkinson's disease refers to the time before the emergence of significant motor symptoms such as resting tremors, stiffness, balance impairment and slowness of muscular movement. Anosmia, weariness, sleep problems and weight swings are examples of non-motor symptoms. A medical examination thoroughly checks gait and movement patterns and those with Parkinson's disease are more likely to have autonomic nervous system issues. Machine learning models have been utilized in the healthcare sector to identify Parkinson's disease utilizing a range of data modalities, including handwriting trends, gait patterns, and neuro-imaging approaches. Nevertheless, with the use of Computer-Aided Diagnostic models especially Deep Learning, the main motivation of this paper is the early identification and treatment of Parkinson's disease thereby decreasing the risk of future illness development.

In this paper, the CNN Inception V3 deep learning approach is discussed to detect and predict Parkinson's disease, as well as the stage at which the patient was detected, that included mild, moderate, severe and no PD detections. A software was also with a graphical user interface (GUI) to present the analysis findings depending on the user's input picture. The Confusion Matrix was also used to summarize performance evaluations for our suggested model. For training and graded pre- processed DaTScan pictures, the Confusion Matrix assesses performance aspects such as Accuracy, Precision, Recall, and F Score. As a result, our suggested paradigm improves early detection and awareness of Parkinson's disease, enabling patients to recover more quickly. Furthermore a combination of Convolutional and Recurrent Neural Networks can be used to create a composite deep learning approach for processing huge datasets and making predictions as the future enhancement.

2. Literature Survey

In the paper titled "Early Diagnosis of Parkinson's Disease in Brain MRI Using Deep Learning Algorithm" by A. Bhan, S. Kapoor, M. Gulati, and A. Goyal [5], it is identified that the purpose of this study is to highlight the importance of early Parkinson's disease diagnosis since it may help with prompt treatment administration, enhance patient outcomes and lower the risk of disease progression. The purpose of this research is to use a deep learning approach based on Convolutional Neural Networks (CNNs), specifically the LeNet-5 architecture, to diagnose and forecast Parkinson's disease.An MRI dataset of patients with and without Parkinson's disease was used to train the algorithm. The attributes collected are then used to identify whether or not fresh MRI images show Parkinson's disease. Nevertheless, there are significant flaws in this study. One of the major disadvantages is the issue of over fitting images in specific analytical situations, which has a severe impact on the model's accuracy and performance. This emphasizes the need to further modify and test the proposed technique in clinical practice to ensure its robustness and reliability.

The paper titled "Prediction of Parkinson's Disease by Studying fMRI Data and Using Supervised Learning" by A. H. Neehal, M. N. Azam, M. S. Islam, M. I. Hossain, and M. Z. Parvez [8], discusses the prediction and diagnosis of Parkinson's disease in patients. Data from functional magnetic resonance imaging (fMRI) and supervised learning algorithms are used to do this. This research highlights the potential value of fMRI data as a tool for identifying Parkinson's disease since it gives insights into the functional changes in the brain that occur in a Parkinson's disease patient. The proposed method analyses fMRI data and discovers patterns indicative of Parkinson's disease using supervised learning methods such as support vector machines (SVM) and decision trees. To generate time series data, pictures from functional magnetic resonance imaging are first converted (fMRI). The time series data is then analysed to extract characteristics using the short-time Fourier transform (STFT) technique. Lastly, depending on the data acquired, an SVM classifier is used to define the prodromal stage. The paper's main fault is its limited sample size of just eight patients employed for data analysis. Small sample numbers may introduce bias and unpredictability into data processing, leading to incorrect conclusions. In this situation, the limited sample size may restrict the results' generalizability to a wider group of Parkinson's disease patients. As a consequence, in order to prove the validity and reliability of the findings, the research must be repeated with a bigger sample size.

The paper "Parkinson's Disease Detection Using SPECT Imaging and Interpretable AI: A Tutorial" by TheerasarnPianpanit, SermkiatLolak, PhattarapongSawangjai, ThapanunSudhawiyangkul, and TheerawitWilaiprasitporn [6], describes a simple artificial intelligence-based method for identifying Parkinson's disease using single-photon emission computed tomography (SPECT) images (AI). The article started by outlining the signs and diagnosis of Parkinson's disease, emphasizing the need for early detection. It then describes the SPECT imaging technique, which analyses blood flow in the brain and may aid in the diagnosis of Parkinson's disease. The concepts of interpretable AI, as well as a variety of interpretable AI solutions, such as decision trees, rule-based systems and local interpretable model-agnostic explanations, were also examined (LIME). The research outlined a step- by-step method for identifying Parkinson's disease using interpretable AI techniques. SPECT images of Parkinson's disease patients and healthy controls were used to train and evaluate the model. Lastly, the model's flaws were explored, such as its limited sample size and the need for further validation on bigger datasets. The use of interpretable AI algorithms for the detection of various neurodegenerative illnesses was also studied. Overall, this paper provides a thorough examination of using interpretable AI algorithms to detect Parkinson's disease in SPECT scans.

The paper "Prediction of Parkinson's Disease in Unsupervised Way Using Hybrid Approach Utilizing MRI Images," by Kamalesh Kumar Dubey and Anjali Goswami [7], explored a hybrid approach for predicting Parkinson's disease using unsupervised machine learning algorithms on MRI images, as well as the challenges associated with diagnosing using MRI images, such as data complexity and high dimensionality. The clusters were identified as Parkinson's disease or healthy controls using Support Vector Machine (SVM) classification. Several machine learning algorithms performed better than their method, such as k-means clustering and SVM classification. According to the study, the proposed hybrid technique outperformed the other options in predicting Parkinson's disease. The method's capacity to detect other neurodegenerative disorders has also been investigated. The study has some limitations, including the need for further validation on larger and more diverse datasets. The study concluded by emphasizing the importance of unsupervised machine learning methodologies in Parkinson's disease and other neurodegenerative illnesses diagnosis.

3. Proposed Methodology

We began by obtaining and analysingDaTScan photos from a public database. The pre-processing method entails deleting extraneous features and improving image quality by utilizing a median filter for noise reduction and adaptive histogram equalization for image enhancement. The images were then trained using the InceptionV3 model and categorized with the learned model, which assisted in theprediction of Parkinson's disease. To assess the performance of the InceptionV3 deep learning model, its accuracy, precision, sensitivity, and F1 score were examined.

Image Pre-processing

Picture pre-processing is an important phase in deep learning where the model attempts to convert raw photographs into a format that the model can easily analyze and comprehend. Raw photos are often separated by variances in picture size, colour, lighting and other properties, making it difficult for a model to accurately recognize and categorize them. As a consequence, image pre- processing is necessary to standardize the pictures and eliminate any inconsistencies.

In this context, the DaTScan images from a public database was obtained which records changes in brain chemistry, such as dopamine deficiency, which is characteristic of Parkinson's disease (PD) and other Parkinsonian disorders. These images were gathered in order to train and test a deep learning model for detecting and categorizing Parkinson's disease (PD) severity, which included mild, moderate, severe, and no PD detections.

To prepare these photos for deep learning analysis, we used a range of pre-processing approaches, including noise removal, contrast enhancement, and image scaling. A median filter was used to reduce noise and adaptive histogram equalization to boost contrast, both of which are common image processing techniques. The same pre-processing techniques were used for each of the image's three- color channels (red, green, and blue) separately before merging them using the 'cat' function to generate a single RGB image with increased contrast and lower noise as in Figure 1, 2 & 3. Finally, to standardize the picture sizes for the deep learning network, the pre-processed photos were downsized to 299 by 299 pixels.

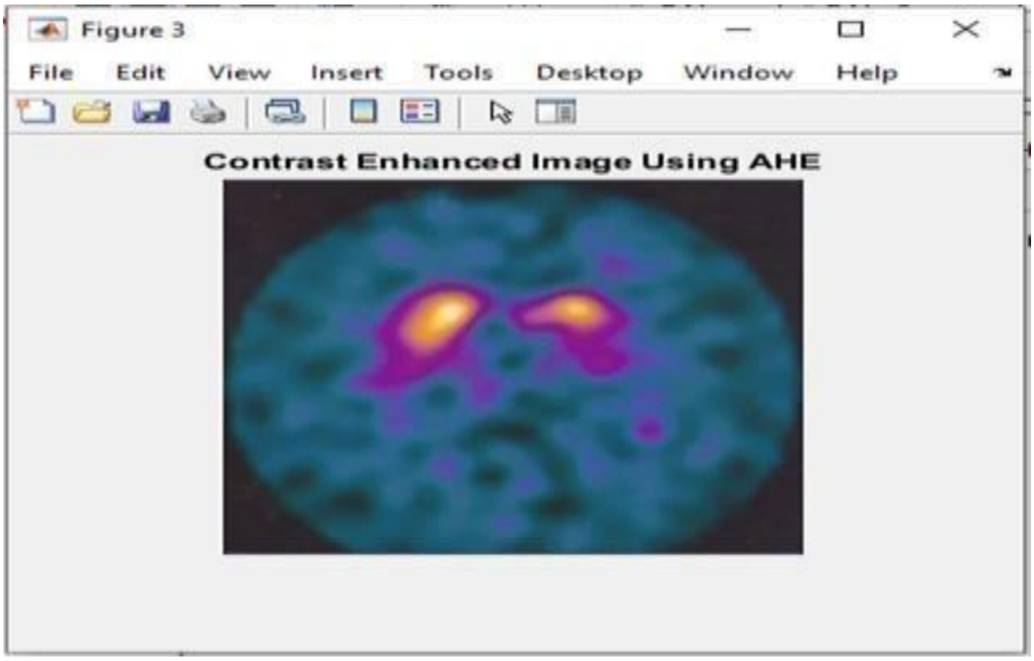

Figure. 1 Image Pre-processing-contrast enhancement

Figure. 2 Image Pre-processing-Noise Removal using median filter

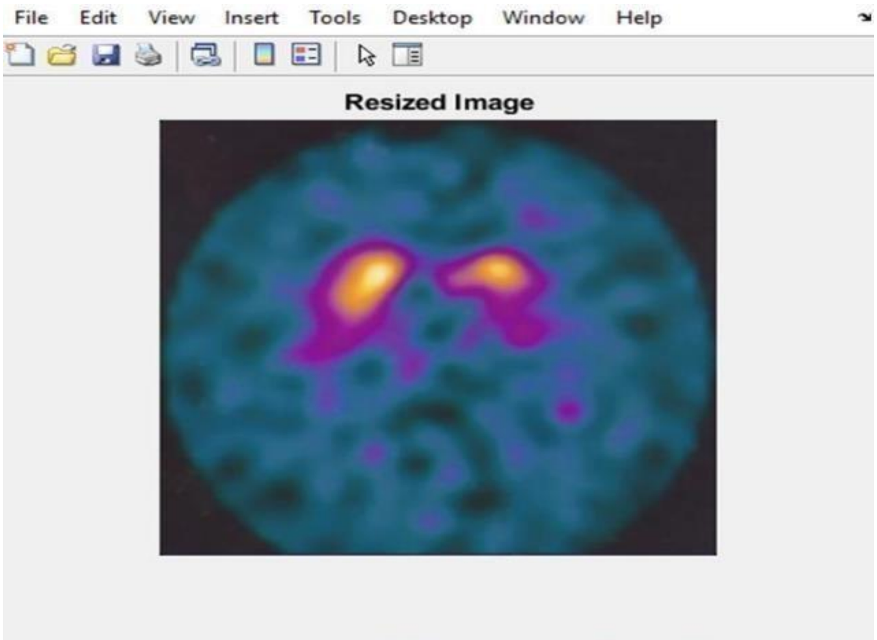

Figure.3 Image Pre-processing-Resized Image

Model Development

Model development involves the CNN algorithm and Inception V3 as its architecture model for analysis and prediction

Convolutional Neural Network

Convolutional Neural Network (CNN) is the most desired Deep Learning Method for recognizing patterns in images. They are built up of neurons with programmed biases and weights that receive a variety of inputs, much like the human brain. These inputs are weighted and processed by an activation function to produce an output. CNNs are designed to handle grid-like inputs like photos. A CNN is often made up of numerous layers, each of which analyses the input data in a different way, resulting in a hierarchical representation of the input by feeding the output from one layer into the next.

The 3 layers of CNN are: convolutional layers, pooling layers and fully-connected layers.

Convolutional Layer: The convolutional layer, which is made up of several convolutional kernels, is the brain of a convolutional neural network. Several convolutional kernels may be used to achieve varying quality. In contrast to a traditional neural network, which requires each neuron in the preceding layer to be attached to every other neuron, a convolution neural network just gathers information from the preceding layer's local perception, reducing the number of parameters. Multi- core convolution may learn a wide range of features due to the relationship between the number of convolution kernels and the number of output feature maps. Convolution kernel density may be raisedto help collect more features and, to a lesser degree, enhance the expressiveness of the model. The "convolution" process is carried out by the convolutional layer.

Pooling Layer: Pooling layers are often employed between convolutional layers in convolutional neural networks to minimize network complexity and processing. This is accomplished using a sub sampling method that reduces the spatial size of the input while retaining the depth dimension. Pooling reduces over fitting during network training by lowering input size. Average and maximum pooling arethe two most prevalent kinds of pooling.

$$W_n = \frac{W_o - K}{L} + 1$$

$$H_n = \frac{H_o - K}{L} + 1$$

$$D_n = D_o$$

The above specified equations take into consideration the pooling layer's output size in width and height dimensions. In contrast, the input size is represented by Wn, Hn, and Dn for width, height, and depth, respectively. The kernel and stride sizes, denoted by K and L, represent the degree of kernel shifting on the input picture.

Fully Connected Layer: The top layer of convolutional neural network (CNN) architecture is often a completely connected layer, similar to a typical artificial neural network (ANN). After training, each neuron in this layer is connected to every neuron in the layer below it, and the total dataset score for each class is shown. To improve the CNN, the rectified linear unit (ReLU) is utilized as an element- wise activation function to the output of the previous layer's activation instead of a sigmoid. The ReLU function is represented by the following equation:

Relu(v)=max(0,v)

Because of its modest compute footprint and low training time, the SoftMax classifier is often employed at the output layer to solve multi-classification challenges. During learning, CNNs go through two stages: feature extraction and classification. Convolution is applied to the input data used by the filter or kernel to produce a feature map during feature extraction. At the classification step, CNN assesses the chance that the picture belongs to a certain class or label. CNNs are very beneficial for picture classification and identification because they can automatically learn features rather than needing human feature extraction. When used to retrain a CNN for usage in a new domain, transfer learning has also been demonstrated to increase classification performance.

Inception V3 Model

The Inception V3 model is an upgraded version of the 2014 Inception V1 model. The Inception V3 model is an improved version of the Inception V1 model that includes a number of network optimization strategies to boost model flexibility. The deep learning model Inception V3 beats its predecessors, Inception V1 and V2. To begin with, it is more efficient, which means it can process more data in less time. Despite its more advanced network structure, the Inception V3 model maintains its efficiency, making it an extraordinarily efficient image classification model. Second, Inception V3 is less computationally demanding than prior versions, needing fewer resources to do the same task. Lastly, auxiliary classifiers are used as regularized in the Inception V3 model, which reduces over fitting during training and results in a more robust model.

Overall, these advantages make the Inception V3 model suitable for a broad variety of deep- learning applications. The Inception V3 model has undergone significant alterations, including factorization into smaller convolutions and spatial factoring into asymmetric convolutions. Moreover, the model employs auxiliary classifiers and efficient grid size reduction. These upgrades have resulted in a more efficient network that is faster without compromising depth. The use of auxiliary classifiers also functions as a regularizer, lowering the model's computing cost.

Working Model

The photos that had been pre-processed were employed in the training procedure, which was split 70:30 between training and validation. MATLAB and the Inception V3 pre- trained model were used to train the pictures. After the import of the Inception V3 model, network analysis was carried out, with the layers shown in the Figure 4 and graphical structure formats. Since we wanted to predict four types of Parkinson's disease (no PD detection, mild, moderate, and severe PD detection), the model's of the last two layers (Fully Connected and Classification layer) were fine-tuned into four classes by dividing the 1000 classes into four classes. The imageDataAugmenter() method was then used to do data augmentation or image augmentation, which is a key approach in deep learning that increases the number of photographs learned, resulting in improved accuracy.

To expand the size and variety of the training set, this approach comprises enlarging, flipping, resizing, and rotating the photos, as well as removing noise. Because of the use of Picture Augmentation, the model's learning process becomes more in-depth. The training model includes hyper parameters such as 150 MaxEpoch, SGDM Optimizer, Shuffle, InitalLearnRate and Plots to regulate the learning process and influence the model's performance and generalization potential. The trained Network (pictures, layers, options) function was used to train a neural network for image classification and regression tasks, with the layers given in the images argument and the training parameters defined in the options parameter. The images parameter included improved images, the layers parameter contained retrained layers from the Inception V3 model and the options parameter contained model hyper parameters. The completed network was saved as a mat file and utilized throughout testing. The trained model network is then used to verify the tested pictures. The model is built using the trained model, test image findings and user images from the GUI application as shown in Figure 5, which are forecasted according to the stages of Parkinson's disease.

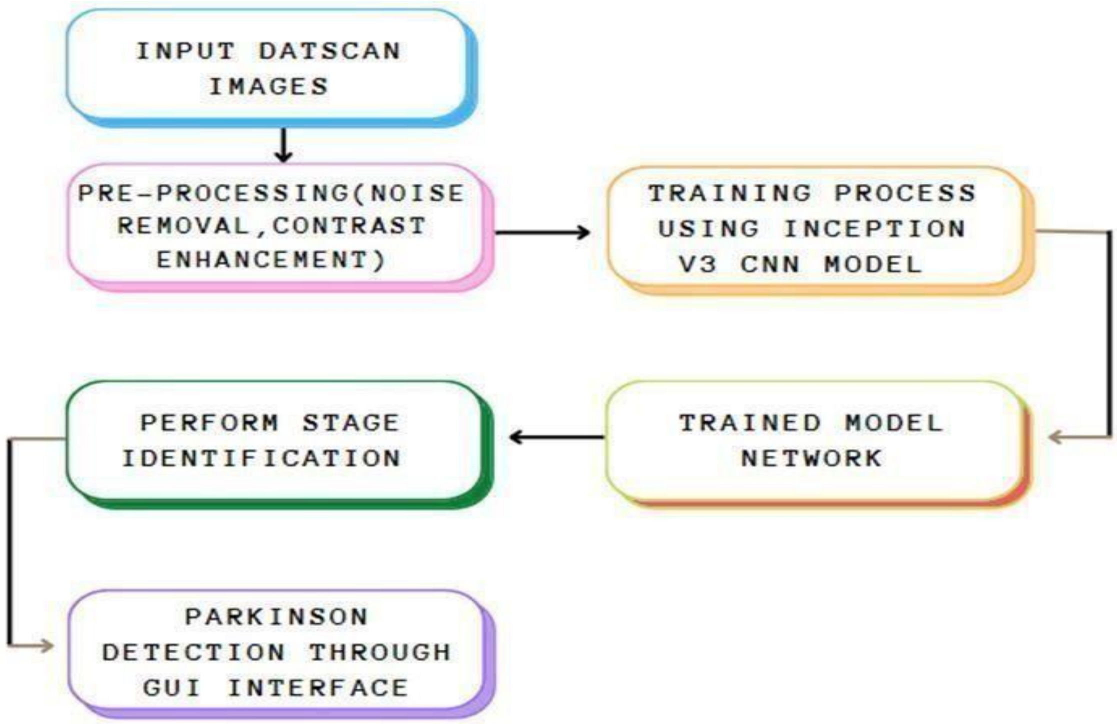

Figure. 4 System Architecture

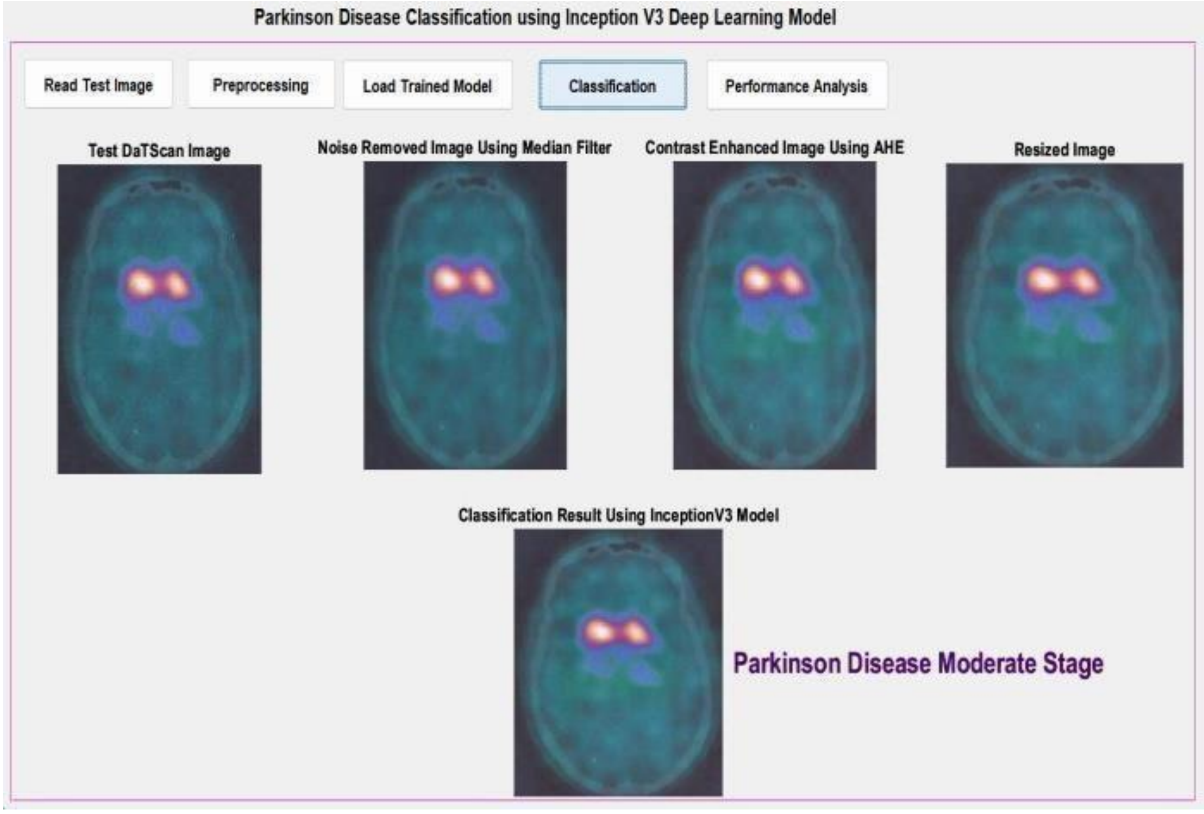

Figure. 5 GUI displaying the result of the input image

Performance Measure

After that, the performance analysis of the suggested model was done. The study makes use of pre-processed trained and tested picture files, which are imported and used to predict labels using the Inception V3 method. A Confusion Matrix is constructed to assess the model's performance. The Confusion Matrix as shown in Figure 6, is a table that displays the model's accurate and wrong predictions for each class. The matrix assists in determining how well the model is doing and where it may need to be improved. The model's performance measures are assessed using the Confusion Matrix. Accuracy, Precision, Recall and F Score are among these measurements. Precision evaluates how many of the anticipated positives are really positive, while accuracy measures how well the model properly predicts the classes.

Recall, on the other hand, assesses how many true positives the model properly identifies. F Score is a composite of Precision and Recall that offers an overall assessment of the model's performance. Lastly, a bar graph displays the classification findings, which comprise mild, moderate, severe, and no PD detections. The graph depicts the model's performance at each level, making it easy to spot areas where the model may need to be improved. Overall, the performance analysis as shown in Figure 7 & 8 gives useful insights into the success of the proposed model and aids in the identification of areas for future modification. Consequently, by analyzing the DaTScan image dataset and training the model, we were able to correctly categorize and forecast the phases of Parkinson's disease, lowering the risk of disease progression.

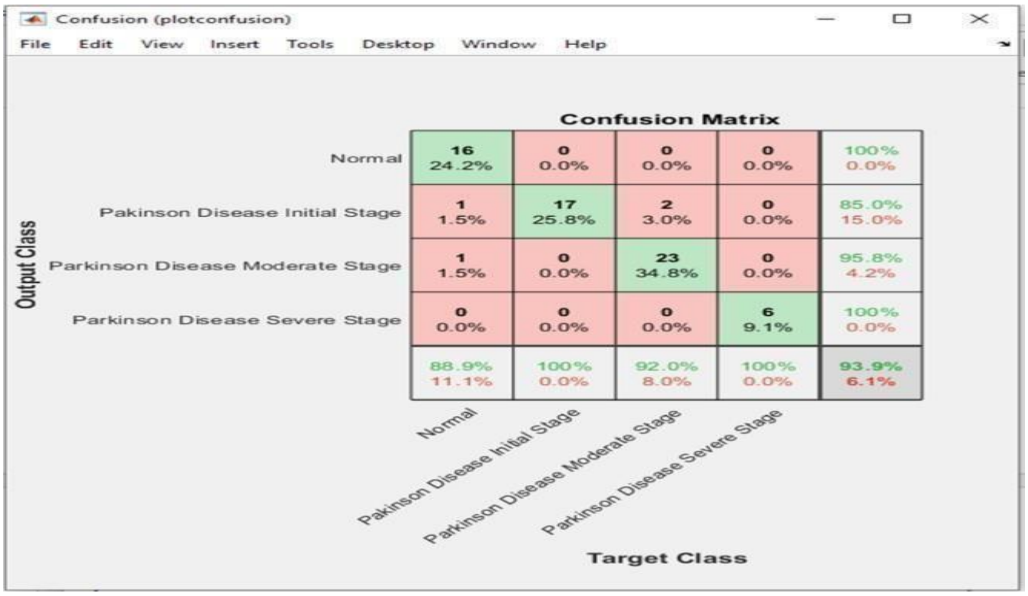

Figure. 6 Confusion Matrix of the model

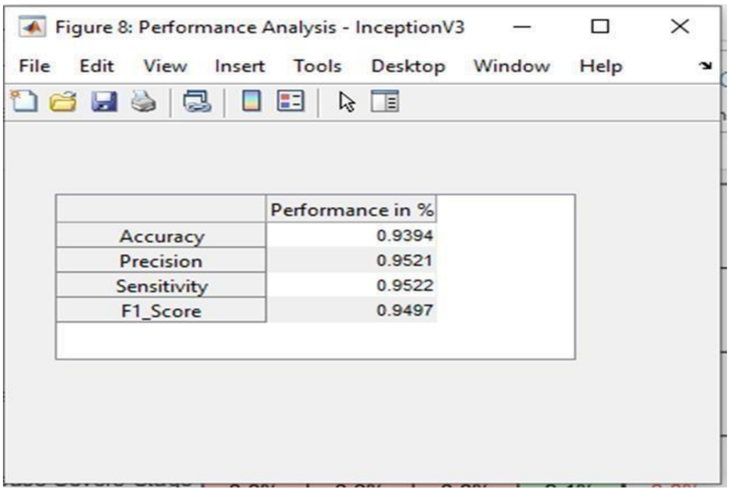

Figure. 7 Performance Analysis

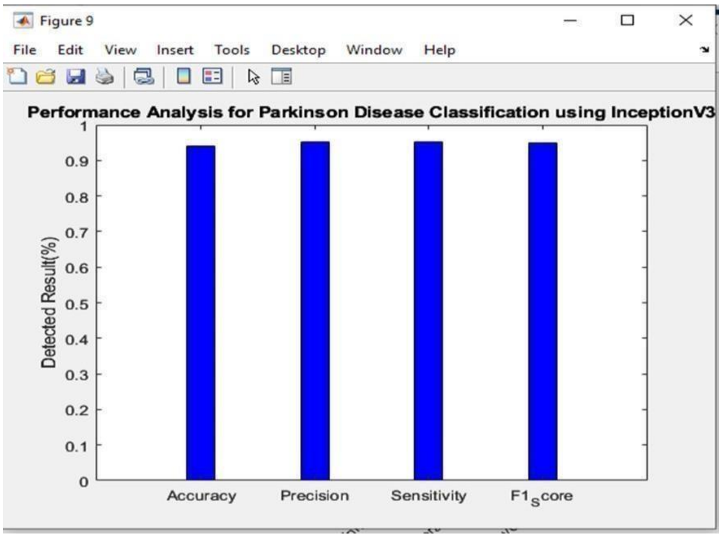

Figure. 8 Performance Analysis represented by bar graph

4. Result

Deep Learning's capacity to produce considerable clinical performance for DaTScan image interpretation and analysis is shown in this work. DaTScan imaging is often utilized in Parkinson's disease to uncover pathophysiological alterations. By providing a CNN Inception V3 model for prediction and stage identification, we contribute to the categorization of Parkinson's disease and its many phases, which include mild, moderate, severe and no PD detections. Moreover, an easy-to-use GUI program was developed that generated the output depending on the user's input picture. When applied to the DaTScanPD dataset, the suggested CNN model obtained a classification accuracy of 93.94%. Overall, this work adds to the expanding corpus of research on the use of deep learning in medical imaging and provides a realistic method for improving Parkinson's disease diagnosis and therapy.

5. Conclusion& Future Work

In recent years, Deep learning algorithms have considerably enhanced our capacity to make accurate forecasts of medical problems. We were able to determine if a person had Parkinson's disease and what stage they were in by using the collection of DaTScan images in conjunction with the Convolutional Neural Network Inception V3 model. These categorization and prediction systems have the potential to accelerate illness recovery while also opening new opportunities in the healthcare and medical industries. As a future work, a combination of Convolutional and Recurrent Neural Networks will be used to create a composite deep learning approach for processing huge datasets and making predictions.

References

[1] Pardo-Moreno, Anabel Himan& Ramos Rodriguez Victoria & Suleiman-Martos, Sami & Rivas-Domínguez, Teresa &García-Morales, Antonio & Mohamed-Mohamed, Juan Jose &Melguizo-Rodríguez, Lucía& González-Acedo,. (2023) “Current Treatments and New, Tentative Therapies for Parkinson’s disease”, Pharmaceutics. 15. 770. 10.3390/pharmaceutics15030770

[2] Chitra&Darji, Dr& Yadav, Vyas, Rutvi& Desai, Shivani&Tanwar, Sudeep, Raj & Solanki, (2022), “Deep Learning-based Scheme to Diagnose Parkinson's Disease”, Expert Systems, 39.10.1111/exsy.12739.

[3] Oh, Shu Lih, Yuki Hagiwara, U. Raghavendra, RajamanickamYuvaraj, N. Arunkumar, M. Murugappan, and U. Rajendra Acharya. "A deep learning approach for Parkinson’s disease diagnosis from EEG signals." *Neural Computing and Applications* 32 (2020): 10927-10933

[4] T. N. Nagabhushan , GunjanPahuja (2021), “A Comparative Study of Existing Machine Learning Approaches for Parkinson's Disease Detection”, IETE Journal of Research, 67:1, 4- 14, DOI: 10.1080/03772063.2018.1531730,

[5] Bhan, Anupama& Kapoor, Sona& Gulati, Manan &Goyal, Ayush. (2021)., “Early Diagnosis of Parkinson’s Disease in brain MRI using Deep Learning Algorithm”, 1467-1470. 10.1109/ICICV50876.2021.9388571.

[6] Pianpanit, Theerasarn&Lolak, Sermkiat&Sawangjai, Phattarapong&Sudhawiyangkul, Thapanun&Wilaiprasitporn, Theerawit. (2021)., “Parkinson's Disease Recognition Using SPECT Image and Interpretable AI: A Tutorial”, IEEE Sensors Journal. PP. 10.1109/JSEN.2021.3077949.

[7] K. K. Dubey and A. Goswami, "Prediction of Parkinson Disease in Unsupervised Way using Hybrid Approach through MRI Images," *2021 2nd International Conference on Computational Methods in Science & Technology (ICCMST)*, Mohali, India, 2021, pp. 229- 232, doi: 10.1109/ICCMST54943.2021.00055.

[8] Neehal, Ahmed Hasin&Azam, Md& Islam, MdSazzadul& Hossain, Md&Parvez, Mohammad Zavid. (2020), “Prediction of Parkinson's Disease by Analyzing fMRI Data and using Supervised Learning”, 362-365. 10.1109/TENSYMP50017.2020.9230918.

[9] Silke A.T. Danilo R. Pereira, João P. Papa, Weber, Christian Hook, Clayton R. Pereira,Victor Hugo C. de Albuquerque, A survey on computer-assisted Parkinson's Disease diagnosis, Artificial Intelligence in Medicine,Volume 95,2019,Pages 48-63,ISSN 0933-3657,

[10] E. Celik and S. I. Omurca, "Improving Parkinson's Disease Diagnosis with Machine Learning Methods," *2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT)*, Istanbul, Turkey, 2019, pp. 1-4, doi: 10.1109/EBBT.2019.8742057.

[11] Davie, Charles. (2008), "A review of Parkinson's disease", British medical bulletin.,86. 109- 27. 10.1093/bmb/ldn013.

[12] Marle M. van Hienen, Maria FiorellaContarino, Huub A.M. Middelkoop, Jacobus J. van Hilten, Victor J. Geraedts, "Effect of deep brain stimulation on caregivers of patients with Parkinson's disease: A systematic review,Parkinsonism& Related Disorders,Volume 81, 2020, Pages 20-27, ISSN 1353-8020.