Parkinsons Disease Classification Using Neural Network

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Abstract- *Parkinson's disease (PD) is a progressive brain ailment that deteriorates with time and affects the neurological system of the body which results in uncontrollable and involuntary movements such as trembling, rigidity and problems with coordination and balance. This illness has three stages and must be recognized early in order to be treated. The idea of this work is to design software that examines and forecasts if a user has been diagnosed with Parkinson's disease and the stage of the disease at which they are affected using convolution neural network (CNN) a deep learning approach. This work proposed an efficient deep CNN inception-v3 model to classify PD on publicly available datasets and their results demonstrated that the proposed CNN model is more effective in classifying various stages of PD than existing models.*

I. INTRODUCTION

Parkinson's disease (PD) is considered a neurodegenerative disease because it involves the degeneration and death of neurons. It is most frequently seen in adults over the age 50. The most recognizable symptoms of PD initially are movement related and generally involve a tremor that is worse when a person is at rest, bradykinesia, which is slowness of movement, rigidity and postural impairment. PD patients also often experience non-motor symptoms like cognitive impairment or psychiatric symptoms. The causes of PD are not fully understood, but a combination of genetic and environmental factors is likely involved. PD patients have low levels ofthe neurotransmitter dopamine present in the basal ganglia, a group of structures involved with movement (among other functions).The region of the basal ganglia known as the substantia nigra has a large number of dopamine neurons, but by the latter stages of PD individuals have lost more than half of the dopamine neurons in this region, which is the reason of these low dopamine levels.The region of the basal ganglia known as the substantia nigra has a large number of dopamine neurons, but by the latter stages of PD individuals have lost more than half of the dopamine neurons in this region, which is the reason of these low dopamine levels.It is crucial to detect PD and its stage of affection as soon as possible in order to prevent further illness complications. This paper focuses on its main aim of early prediction of PD. It is done using DaT Scans that are explored for predicting PD or not and its current stage, whether it is mild, moderate or severe using convolutional neural network (CNN) a deep learning approach. This paper focuses on its main aim of early prediction of PD. It is done using DaT Scans that are explored for predicting PD or not and its current stage, whether it is mild, moderate or severe using convolutional neural network (CNN) a deep learning approach. Since deep Learning has been a key technique for issues with self-perception, such as comprehending visual cues, human speech, and robots voyaging around the environment. Instead of having a layer of neurons that are fully linked, the convolutional neural network examines the mapping of visual pixels with the neighbourhood space.It has been shown to be a very effective image processing tool.

Even in areas like segmentation, classification, and handwriting identification of natural objects, CNN has outperformed all other approaches previously employed in the computer vision sector.DaT scan dataset images are employed in this study because they can detect Parkinson's disease (PD) far earlier than other methods, at a level of 30% loss of dopamine-producing brain cells as opposed to 80–90%. The amount and location of dopamine transporters in the synapses of striatal dopaminergic neurons can be seen using a molecular imaging technique called DaT Scan. Adults with likely parkinsonian syndrome can be distinguished from those with other movement disorders, such as essential tremor, using DaT imaging.Section II discusses many similar studies in which the major focus is on detecting PD rather than on its various stages (mild, moderate, severe), for which the patient has been given a diagnosis. The fundamental flow diagram and the different processes it contains are discussed in Section III. It contains a thorough discussion of CNN, the Inception-v3 pretrained model, and deep learning models. Section IV provides information on the experimental analysis.This section explains image acquisition, preprocessing, categorization, and performance measures. The results of the model are discussed in Section V. Results from training and testing, performance indicators, a confusion matrix, and the final outcomes are all included.

II. RELATED WORK

To create automated detection models, several researchers have been studying the field of disease detection.Based on computer-assisted diagnosis technologies, deep learning has previously been effectively applied to increase productivity, particularly in the sectors of medical imaging, image categorization, and picture restoration. Another approach includes the pre-processing of images, feature extraction, and classification phases. The authors used a variety of feature sets, such as statistical features, textural features, and shape-based features, during the feature extraction stage to capture various facets of the DaT scan pictures. The support vector machine (SVM) classifier was subsequently trained. It includes numerous phases, including as feature extraction, categorization, and picture pre-processing. The authors used a variety of feature sets, such as texture features, shape features, and gray level co-occurrence matrix (GLCM) features, in the feature extraction stage to capture various facets of the DaT scan pictures.They subsequently used a mixture of these feature sets to train a k-nearest neighbor (KNN) classifier to differentiate between PD patients and healthy controls. The authors of the study utilized a total of 372 radiomics characteristics to capture various facets of the brain imaging. They then used these variables to construct a random forest classifier to identify between patients with PD, MSA, and PSP.Pre-processing, feature extraction, feature selection, and classification using a support vector machine algorithm are the four modules that make up the authors' web-based solution. They stated in their examination that their total accuracy was 91.3%.In order to increase classification accuracy, the authorscombined features retrieved from the SPECT pictures, such as shape, texture, and intensity features. To differentiate between PD patients and healthy controls, they applied a support vector machine (SVM) classifier. They employed reliable features, such as those connected to regional uptake and asymmetry indices, that were retrieved from the SPECT pictures. For the categorization job, they also utilized an SVM classifier.

All of the aforementioned studies are focused on identifying Parkinson disease; however, none of them classify the disease's stages, which is seen as their primary flaw. Our suggested effort will therefore address this issue by improving detection accuracy.

III. PROPOSED METHODOLOGIES

The dataset description, preprocessing, and deep learning models are briefly covered in this section. The workflow diagram for the study's approach is shown in Fig. 1.

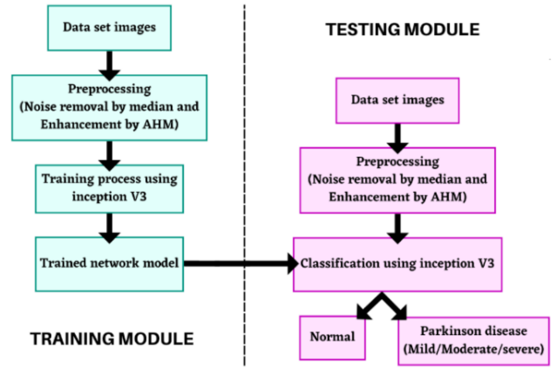


Fig 1 Basic flow diagram.

Imagesof the Dopamine Transporter scan, or DaT scan, are gathered from a public database. A critical step in the picture analysis process is preprocessing. The goal of preprocessing is to improve the quality of photographs by removing extraneous features. We can decide more wisely if we do this. We suggest a median filter for noise removal in order to achieve this. Start the training phase after the preprocessing is finished.During the training phase, the inception-v3 model is used to train images as feature maps. After the model has been trained, the input image will be provided, preprocessed, and passed to the inceptionv3 classifier to categorize the image into various phases of Parkinson's disease based on the training model. The outcome of the inception-v3 deep learning model is finally evaluated in terms of accuracy, precision, sensitivity, and F1_score.

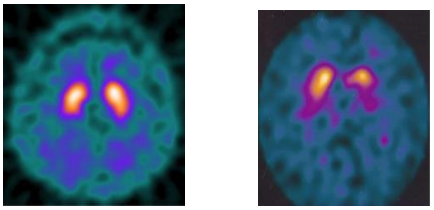
A. DATASETDESCRIPTION

The Parkinson dataset repository is where the dataset was gathered. This dataset includes the DaT scans of 78 individuals, 55 of whom have Parkinson's disease, and 23 healthy control individuals.

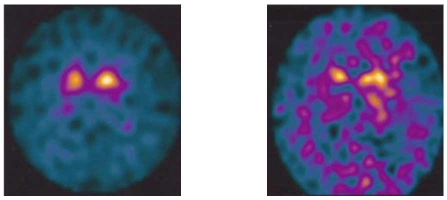
IMAGE TYPE	PD	NPD	TOTAL
DATSCAN	590	330	920

Table 1NTUA Parkinson Dataset

The available datasets are classified with respect to the American Journal of Neuroradiology [11].



(a) Person with no PD (normal) (b) Person with PD (mild)



(c) Person with PD (moderate) (d) Person with PD (severe)

Fig 2 Sample DaT scan images.

B. PRE-TRAINED DEEP LEARNING MODELS

Constructing a deep network from scratch is challenging in reality. In a large deep neural network, weights are continually adjusted based on the datasets and the loss function after being randomly assigned prior to training. A lack of training data may eventually cause the deep network to become overfit because it takes time to modify the weight in this manner. Transfer learning can be used to address the aforementioned deep learning problems.It utilizes a convolutional deep neural network that has already been trained and was created using a separate dataset. As mentioned earlier, a CNN may be trained to detect hierarchical representations in images, and the data stored in the pretrained model's weights can be used for a variety of tasks.The lower-level convolutional layer is where lower-level properties like edges and vertices are gathered. As a result, only representations at a higher level can be trained using an existing dataset; representations at a lower level can be transferred. The effectiveness of the fine-tuning procedure, which modifies the weights of higher hidden layers, depends on the separation of the source and target datasets. Trained models are trained using suitable datasets, and a wide variety of tasks have been successfully used to train a deep CNN utilising pre-trained weights. The most important deep learning model i.eCNN,it substitutes convolution for conventional matrix multiplication. CNN is frequently utilised to categorise objects using image data. In a CNN, there are three layers. The input layer builds an artificial input neuron that gets the initial data ready for the system's later processing. The input and output layers are connected by the hidden layers, with the output layers producing results for the input layer. The layer-wise architecture of the CNN model employed in this investigation is depicted in Figure 3. These models' fundamental building pieces are layers of CNN. An activation happens when a filter is applied to an input. This is the fundamental process of convolution. After several iterations of the same filter to the same input, a feature map is constructed, which displays the locations and intensities of a detected pattern in the input, as well as an image of the pattern. A pooling layer is yet another component of a CNN architecture. As a result, both the amount of network processing and the number of parameters to learn are decreased. In a particular area, the pooling layer adds the features to a feature map created by the convolution layer. The initial layer of the CNN model consists of a 2DConv layer with 256 filters and a 3 × 3 kernel. This 2DConv layer is followed by the activation layer with the ReLU activation function.

C. INCEPTION-V3 MODEL

An improved version of the inception-v1 model is the inception-v3 model. The inception-v3 model optimises the network in a variety of ways for improved model adaptability [17]. In comparison to the Inception-v1 and v2 models, it features a larger network. The inception-v3 model is a deep CNN that was trained on a PC with minimal settings. Training can be time-consuming and challenging, sometimes up to several days. Transfer learning [18], which retains the final layer of the model for new categories, is used to tackle this problem.The inception-v3 model is deconstructed as the final layer is eliminated using the transfer learning technique, while the parameters of the preceding layers are preserved.

IV. EXPERIMENTAL EVALUATION

The parkinson classification is done by the following modules:

A. IMAGE ACQUISITION

A general definition of image acquisition in the context of image processing is the action of retrieving an image from a source, typically one that makes use of hardware. so it can be passed through whatever processes need to occur afterward. DaT scan images are collected from public database.

B. PREPROCESSING

The second stage is preprocessing, which includes noise removal, contrast enhancement and image resizing. In that case, a median filter is used to remove the noise in the DaT scan image. Noise destroys the most part of the digital image information, so noise removal becomes essential. The most common noises that would present in the digital image include salt and pepper noise and Gaussian noise.

C. CLASSIFICATION

Following preprocessing, an inception-v3 model is used to extract features from the DaTScan image and classify it into various stages of normal and PD. Based on the hyper parameters such as epochs, learning rate, batch size, and optimizer (SGDM), the proposed model was trained to build aclassification that classifies the image into different types such as normal, Parkinson disease mild stage, Parkinson disease moderate stage, and Parkinson disease severe stage.

D. PERFORMANCE MEASURE

Finally, our proposed model's performance was measured in terms of accuracy, precision, recall, and f1_score performance metrics.

Accuracy: It measures the analysis of TP and TN to the total no. of test images. It is given in (1).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad (1)$$

Precision: It is the estimation analysis of true positive to the aggregate value of true positive and false positive rate. It is given in (2).

$$\text{Precision} = \frac{(TP)}{(TP+FP)} \qquad (2)$$

Recall: It is the estimation analysis of true positive rate to the aggregate value of the true positive and false negative rate. It is given in (3).

$$\text{Recall} = \frac{(TP)}{(TP+FN)} \qquad (3)$$

F-Score: The harmonic mean of recall and precision is known as F-Measure. The conventional F-measure (F1) balances precision and recall equally. It appears in (4).

$$F_{\varepsilon} = (1+\varepsilon^2)\frac{\text{Recall} \times \text{Precision}}{\varepsilon^2 .\ \text{Precision} + \text{Recall}} \qquad (4)$$

RESULTS

A. TRAINING AND TESTING RESULTS

The loss and accuracy curves as well as thetraining and testing precision of the inception-v3 with CNN model are shown. With more training data, the inception-v3's CNN testing accuracy improves. We trained the ensemble deep learning models using a total of 100 epochs, and the results were significantly better.

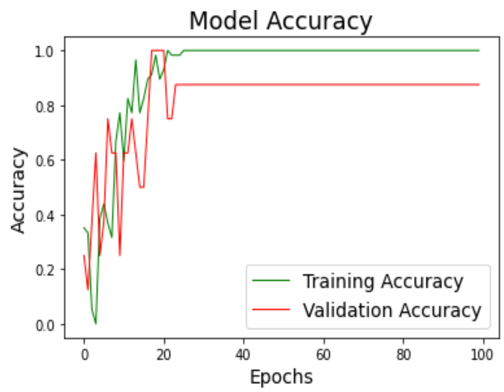


Fig 3 Training and validation accuracy.

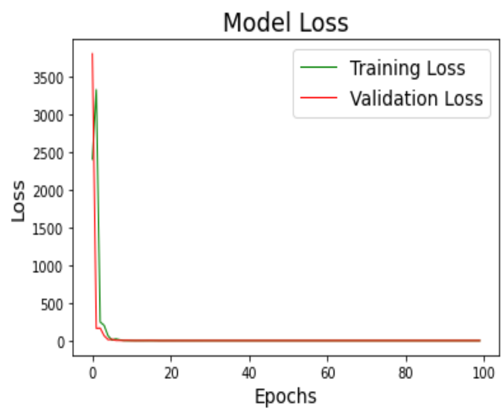


Fig 4 Training and validation loss.

Fig. 3 shows the training and validation accuracy of the model and Fig. 4 shows the training and validation loss of the model.

B. PERFORMANCE METRICS

With the help of performance measure it is found that accuracy is achieved about 96 %.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	21
1	0.89	0.94	0.92	18
2	0.95	0.91	0.93	23
3	1.00	1.00	1.00	6
accuracy			0.96	68
macro avg	0.96	0.96	0.96	68
weighted avg	0.96	0.96	0.96	68

Fig 5 Performance metrics

Fig. 5 shows the performance metrics in which the precision, recall and f1_score is evaluated as 0.96.

C. CONFUSION MATRIX

A table called a confusion matrix is used to describe how well a classification system performs. The output of a classification algorithm is visualised and summarised in a confusion matrix.

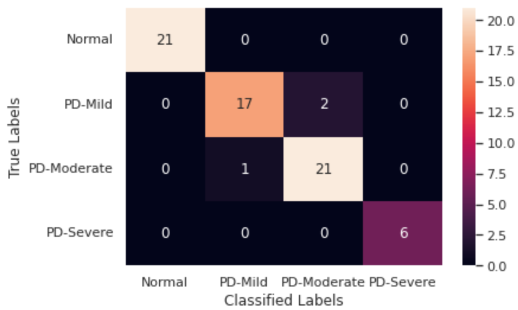
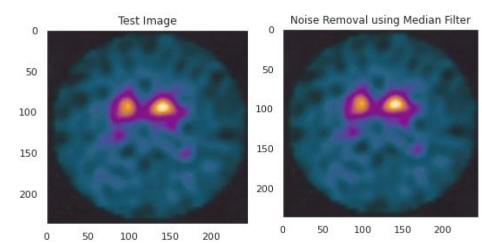


Fig 6 Confusion matrix.

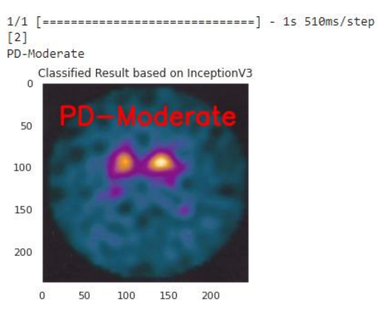
In Fig. 6 the input of 68 test images is given.Out of 68 images 65 images are classified correctly based on the severity rate. Only 3 images are mismatched to its class. It efficiently shows that accuracy of 96% is achieved.

D. OUTPUT

With the help of inception-v3 the outputs obtained are:



(a) Selection of image.(b) Preprocessed image.



(c) Classified image.

Fig 7 Results obtained.

In Fig. 7 first the test image is randomly selected by the user by giving the input in numerical basis, the randomly selected may be either normal. mild, moderate or severe and then the selected image is preprocessed that is noise removal and resizing is done to the corresponding image. Finally the test image is classified by the inception-v3, a pre-trained model whether the patient has PD and its corresponding stage is shown (mild/moderate/severe). In the above case the patient has PD and suffering from moderate stage.

V. CONCLUSION AND FUTURE SCOPE

This work shows that deep learning for SPECT scan interpretation and analysis can be used to achieve significant clinical examination performance. It may be necessary to use DaTScan imaging to assess pathophysiological changes in order to correctly diagnose PD. In this work, we propose an inception-v3 model for different stages of Parkinson disease classification. Based on hyper parameters, the proposed network model was fine-tuned for better classification. The results of the experiments demonstrate that our suggested CNN model, which has a sound architecture, is capable of accurately classifying various Parkinson disease stages.

The classification accuracy of 96.00% is attained in the proposed CNN model for the PD dataset. In subsequent research, we can utilise an effective algorithm enhancing the classification precision of Parkinson's illness, expand the dataset, and train our system more effectively than the current system.

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