Parkinson's Disease Detection Using R-CNN

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Abstract

Pattern recognition in the biological sciences is significantly aided by machine learning techniques and algorithms. These methods have helped academics categorise medical pictures and forecast models to have a thorough grasp of challenging medical issues. In this study, region-based CNN (R-CNN) has been used to separate or distinguish brains afflicted by Parkinson's disease (PD) from brains that are healthy and normal. Complex clinical data must be categorised in order to identify disorders like Parkinson's disease or determine the disease's stage. A machine learning system called R-CNN uses rich data sources including MRI, spiral and wave drawings as datasets for the detection of Parkinson disease (PD) and prediction models for precise picture categorization. This study's objective was to assess how well deep learning Information based on a quicker R-CNN model is available to identify imaging features suggestive of idiopathic Parkinson's (PD). Parkinson's disease (PD) affects neurological, behavioural, and physiological functions. Early Parkinson's disease changes are small, making diagnosis challenging. Pathologists and neurologists assess PD patients' speech, writing, walking, tremor, facial expressions, and drawing. Traditional machine learning techniques call for a number of human processes, including decomposition, feature extraction, and classification. High accuracy was demonstrated by faster R-CNN when separating PD from non-PD patterns. We effectively distinguished Spiral and Wave of PD patients from healthy controls in MRI data using R-CNN, and we achieved accuracy of 100% during training and 96-.99% during testing using batch normalisation. Our created prototype outperformed all currently used state-of-the-art methods, and it is now prepared to be verified with more varied datasets in the future.

Keywords: Parkinson’s Disease, CNN, RCNN.

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1 Introduction

More than 6 million individuals worldwide suffer with Parkinson's disease, a neurological illness. It is frequently diagnosed using clinical assessments and a progression scale, which typically depend on the skill of the medical professional. Accuracy varies widely across different examiners, and it also takes a long time to diagnose correctly. In order to diagnose PD patients, this paper suggests creating a computer-aided diagnostic method that uses brain MRI images, individual spiral and wave drawings of PD patients, and other techniques to reduce cross-examiner variability and the time needed to accurately distinguish between PD and Control subjects.

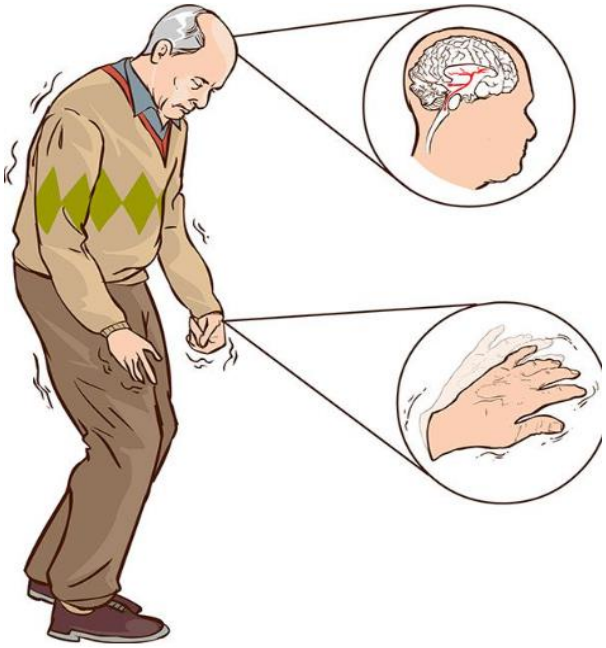

Fig 1. View of PD effected

Parkinson's, a central nervous system illness, causes movement problems. Low dopamine levels in the brain cause the symptoms to appear gradually. Chemical neurotransmitter dopamine is in charge of carrying impulses from the body to the brain. Dopamine levels fall as a result of shrinking the neurons that produce it, which reduces the brain's ability to coordinate with the body. Since there is currently no treatment for this illness, it is imperative to develop a rapid and practical method to anticipate the sickness as technology develops.

PD goes through 5 phases. The illustration below shows the symptoms for each stage.

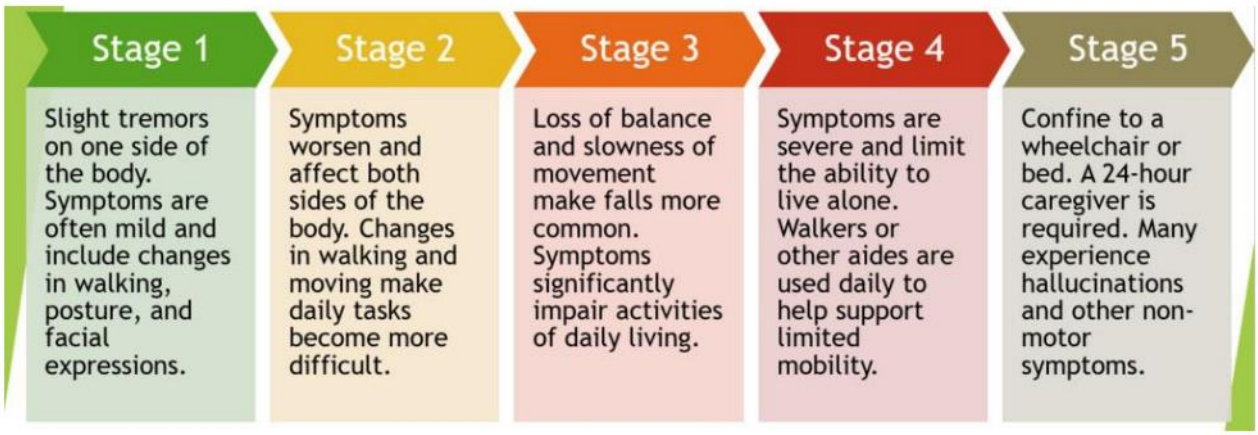

Fig 2 Symptoms associated with PD depending on stage

Medical imaging is essential nowadays. CT, MRI, and other imaging modalities aid diagnostic and treatment planning. As an illustration, consider esophageal cancer, which is a primary malignant tumour of the oesophagus. Radiotherapy is one of the major therapies for esophageal cancer in China, where it affects at least 200,000 individuals annually. However, reliable descriptions of the organs at risk and the planned target volume (PTV) are crucial for radiation treatment planning. The success or failure of radiation as well as the likelihood of problems are influenced by the precision of organ counter segmentation, which defines the quality of dose planning optimisation in radiotherapy. Cholinergic, serotoninergic, and noradrenergic systems may generate nonmotor (cognitive or neuropsychiatric) symptoms. Idiopathic PD and other mobility disorders can coexist. The visualisation of neuroanatomical and functional processes in PD is made possible recently by a number of sophisticated imaging markers (11). The nigral structure is now being shown by MRI to have the neuropathologic signs of PD neurodegenerative alterations. In particular, it can be used to track disease progression (12), detect distinctive PD symptoms, and distinguish PD from other parkinsonian disorders. Currently, one can quantify biochemical alterations in the brain using techniques such local neuromelanin (NM) decrease, iron deposition, and microstructural integrity. Preventing significant PD side effects requires early PD identification. Handwriting and drawing impairments are among the first signs of PD. Non-invasive methods like sketching spirals, waves, or other handwritten messages can distinguish Parkinson's patients from others. Researchers and clinicians have connected spiral designs and handwriting to early Parkinson's disease. The main problem with these diagnoses is that handwriting and sketches need to be properly interpreted. In the past, sketches or handwritings were done on papers and painstakingly read by interpreters who were experts in respective subjects.

2 Literature Survey

To aid our study, several researchers have used machine learning techniques to create an automated system using Parkinson's disease datasets. The ageing of the population has grown widespread throughout the world, in both industrialised and developing nations. Classifying clinical medical data may lead to the creation of a prediction model that can classify PD patients from healthy controls or determine the disease's stage.

Neurons and brain cell connections shrink with ageing. Nerve cells cannot repair like muscle, skin, or bone cells. Age destroys neurons [1]. The generation of the neurotransmitter dopamine is controlled by these neurons. Less dopamine is produced as a result of damaged or dead neurons, which causes PD. A recent research from the Parkinson's Foundation estimates that PD affects more than 10 million individuals worldwide [2].

The diagnosis of PD has been approached in a number of ways utilising various approaches [3]. Expert interviews, neuroimaging techniques, speech signals, and physiological tests are some of these techniques. It is subjective, time-consuming, and prone to mistake for professional neurologists to ask patients to do various tasks, such as walking, reading, writing, and drawing, in order to evaluate their health. [4], [5].

In comparison to neuroimaging approaches, signal processing techniques need fewer recordings, are computationally quick, economical, and non-radioactive. Electromyogram (EMG) [12] and Electrocardiogram (ECG) [11] signals did not effectively identify PD [13]–[17].

Early Parkinson's disease signs include rhythmic entropy and power. SVM and knn classifiers calculated the absolute and relative strength of the 1, 2, 1, and 2 rhythms [20]. Wavelet-based rhythmic analysis detects PD [21]. A linear discriminant analysis (LDA) classifier classified the relative wavelet energy (RWE) and wavelet coherence (WC) of the deconstructed bands of the,,,, and rhythms [22].

For the categorization of PD, DWT-based decomposition, sample entropy computation, and then a three-way decision model based on OCCA have all been applied. Filtering, source localisation, and power spectral density (PSD) have all been employed to detect PD [23]. By using source localization and independent

component analysis, the brain sources were chosen. Welch periodogram function was used to determine the PSD of detected sources, and SVM and k-nn classifiers were used to categorise them. Highly rated characteristics have been computed and chosen using t-test and higher-order spectra (HOS). Several machine learning algorithms used these attributes to create a PD diagnosis index (PDDI) [24].

A thirteen-layered convolutional neural network identifies and extracts PD characteristics [28].

Thus, empirical and practical signal processing and classifier settings may restrict performance. Thus, PD detection requires an accurate, automated procedure. For the automated recognition of emotions and schizophrenia, SPWVD and CNN have recently been utilised [30].

We are the first group, to the best of our knowledge, to describe an R-CNN-based technique for the automated identification of PD and HC. The paper's structure continues: Section II describes related work. Section V covers technique, whereas Section VI presents results. Section VII finishes.

3 Problem Statement

Most generally it is true that Parkinson's disease is more commonly diagnosed in individuals over the age of 60, and it has been observed to be prevalent among war veterans. Developing a Parkinson's disease detector based on voice features has the potential to be a useful tool for early detection of the disease. To identify that we are using Machine learning algorithms can be trained on a dataset of voice recordings from individuals with and without Parkinson's disease, allowing them to identify patterns and features that differentiate the two groups. Once trained, these algorithms can predict whether a new voice recording is likely to be from someone with Parkinson's disease or not.

However, it is essential to recognize that no diagnostic tool is 100% accurate, and a positive prediction from the Parkinson's disease detector should always be followed up with a visit to a medical professional for confirmation. Additionally, the use of such a tool should not replace regular medical check-ups and screenings, as it is crucial to consult healthcare providers for comprehensive evaluations and assessments.

In conclusion, developing a Parkinson's disease detector based on voice features could be a valuable addition to the existing diagnostic tools, especially for individuals who may face challenges in accessing medical professionals or costly diagnostic tests.

4 Methodology

Object Detection Using R-CNN Algorithms

The following three procedures form the basis of object detection models for areas using CNNs:

- Here the Objects were searched and are recommended for region identification.
- Use regional CNN for Classification and.
- extracted features are sorted.

Fast R-CNN

Like the R-CNN detector, the Fast R-CNN [3] provides region suggestions using Edge Boxes. Instead of shrinking and resizing region suggestions, the Fast R-CNN detector assesses the whole image. Fast R-CNN pools CNN characteristics for each area proposal, while R-CNN detectors classify each region. Fast R-CNN outperforms R-CNN because it shares calculations for overlapping regions. R-CNN has these stages.

1.A pretrained network serves as the foundation of the R-CNN model. The last three categorization layers are swapped out for fresh ones that are tailored to the kinds of objects you wish to find.

2. Fast R-CNN builds on R-CNN. A box regression layer improves item placement. This layer learns box offsets. ROI pooling layers pool CNN characteristics for each area proposal.

3. The Faster R-CNN model adds features. An area proposal network generates region proposals instead of using external methods.

To put it simply, R- CNN takes an image's features and reduces its dimensions without losing any of the original image's qualities.

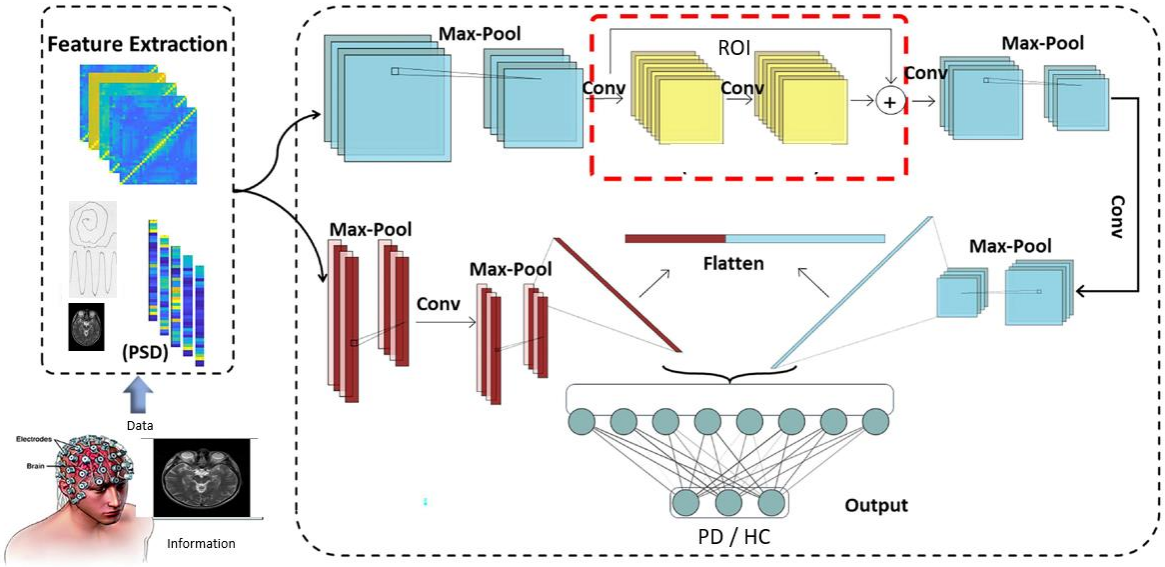

Fig 3 Architecture of Proposed methodology

Deep ensemble learning is a powerful technique that can be employed to develop an early detection method for Parkinson's disease (PD) using MRI datasets. PD is a neurological disorder characterized by motor system abnormalities, which manifest as involuntary or uncontrolled movements of the body. While the precise cause of PD remains unknown, some cases are believed to have a genetic basis, while others are thought to be influenced by a combination of genetic and environmental factors. In PD, the area of the brain responsible for producing the neurotransmitter dopamine undergoes damage or degeneration, resulting in a deficiency of dopamine and impairments in fluid and deliberate movement.

One challenge in using MRI datasets for detecting PD lies in the variability of brightness, colour, and noise levels across the images. To mitigate the impact of these undesirable factors on the training and testing process, image filtering techniques and histogram equalization can be employed. These procedures aim to enhance the contrast of the images, making the relevant features more distinguishable and facilitating accurate detection of PD-related abnormalities.

By utilizing deep ensemble learning, which involves training and combining multiple neural network models, we can harness the collective knowledge and predictive capabilities of these models. Each individual model within the ensemble learns different aspects of the data and contributes to the final decision-making process. This approach helps to improve the robustness and generalization of the detection model, enhancing its ability to identify early signs of PD.

From this we conclude that by applying deep ensemble learning techniques to MRI datasets, we can develop an effective early detection method for Parkinson's disease. By addressing the challenges posed by image variability through filtering and contrast enhancement, we can ensure that the models capture the relevant features for accurate detection. This research holds promise for improving the diagnosis and management of PD, potentially enabling earlier interventions and better patient outcomes.

5 Formulas and Parameters

S.no	Parameter	Formula
1	Error	Loss (mdl, X, Y) calculates the mean squared error (err) for the model, predictor values, and responder values.
2	Time	T=time t(f)
3	Accuracy	$Accuracy = \frac{Correct\ prediction}{Total\ Cases} * 100\%$

4	Mean Square Error	$MSE = \frac{1}{N}\sum_{i=1}^{N}(y - y\hat{})2$

RESULTS ANALAYSIS

An in-house multistage classifier employing convolutional neural networks and machine learning techniques predicted Parkinson's disease using Spiral and Wave Sketches. This study's model has 97.3 accuracy. To evaluate the model's generalizability, the full dataset was cross validated 10-fold. The model generalised well across the two classes and had a constant accuracy and recall across the random data folds of training, validation, and testing.

discovered that those individuals' sketches were distorted and resembled Parkinson's patients'. Since all the healthy patients were matched by age, a healthy Parkinson's patient may advance.

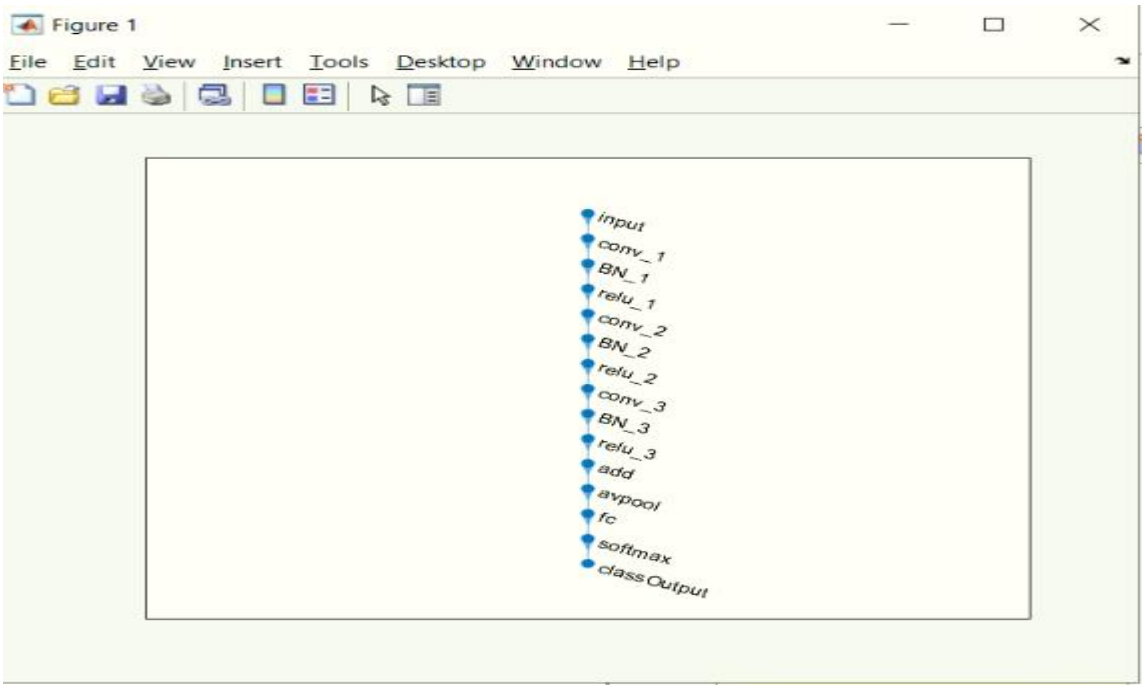

Fig 4 Initial Neural Network Layers

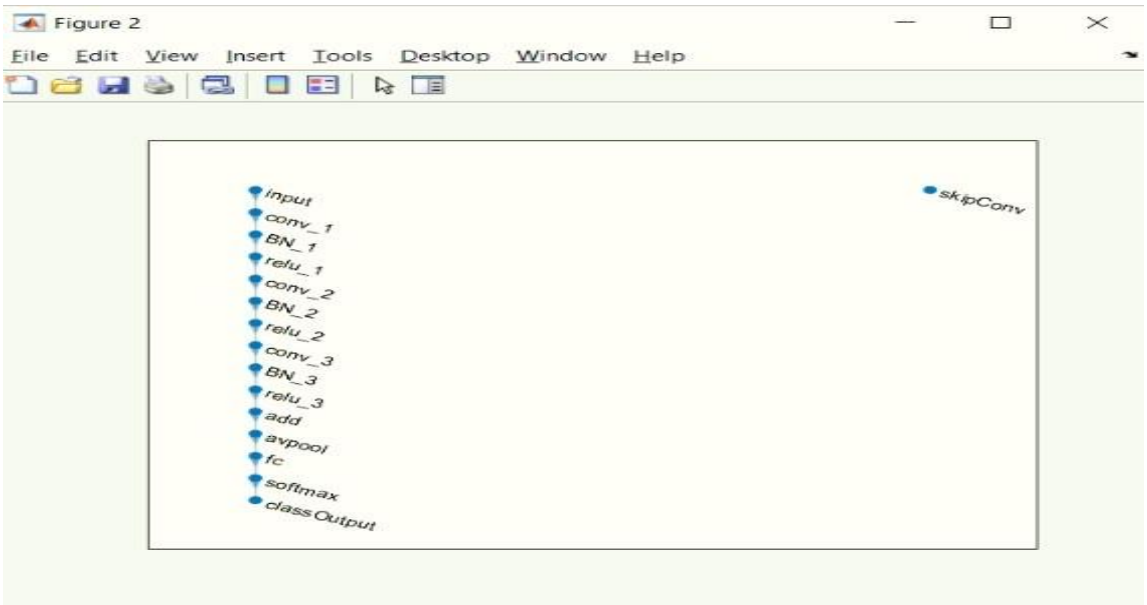

Fig 5 Split channel Graph

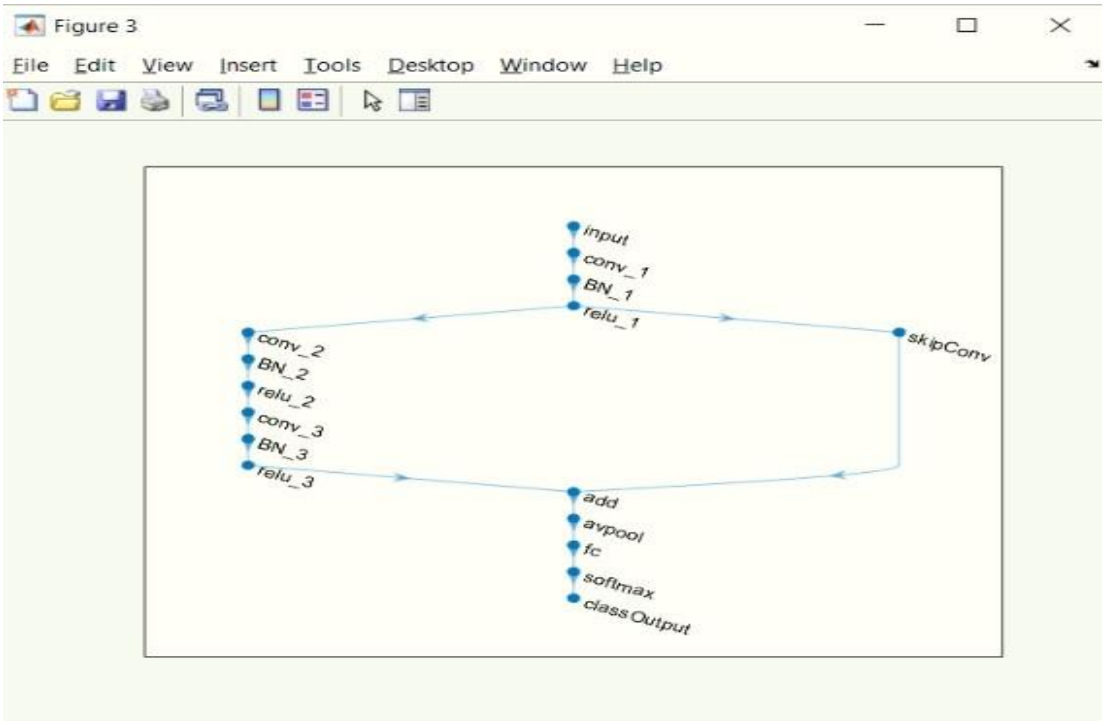

Fig 6 Final layer graph

Here we consider 30 images for each of a spiral and wave drawing and a spiral sketch were included in the testing dataset of size 30 images. Utilising a programme that can segment the data sample picture for improved visualisation and image quality is essential for early detection of PD. In the present day, with the rise of several applications, MRI Classify PD from MRI Samples plays a significant role as it may help with image segmentation for a clear comprehension of the target afflicted side, leading to the detection of PD in every stage.

Now that the odds of those two are incorrectly categorised among samples and had been thoroughly examined, using our proposed R-CNN method. While in training we used an Baseline model with an sample of 15 images (trained data) for validation of data and different losses that we had seen. The graphs of the two top-chosen models' confusion matrices and loss and accuracy functions are shown below.

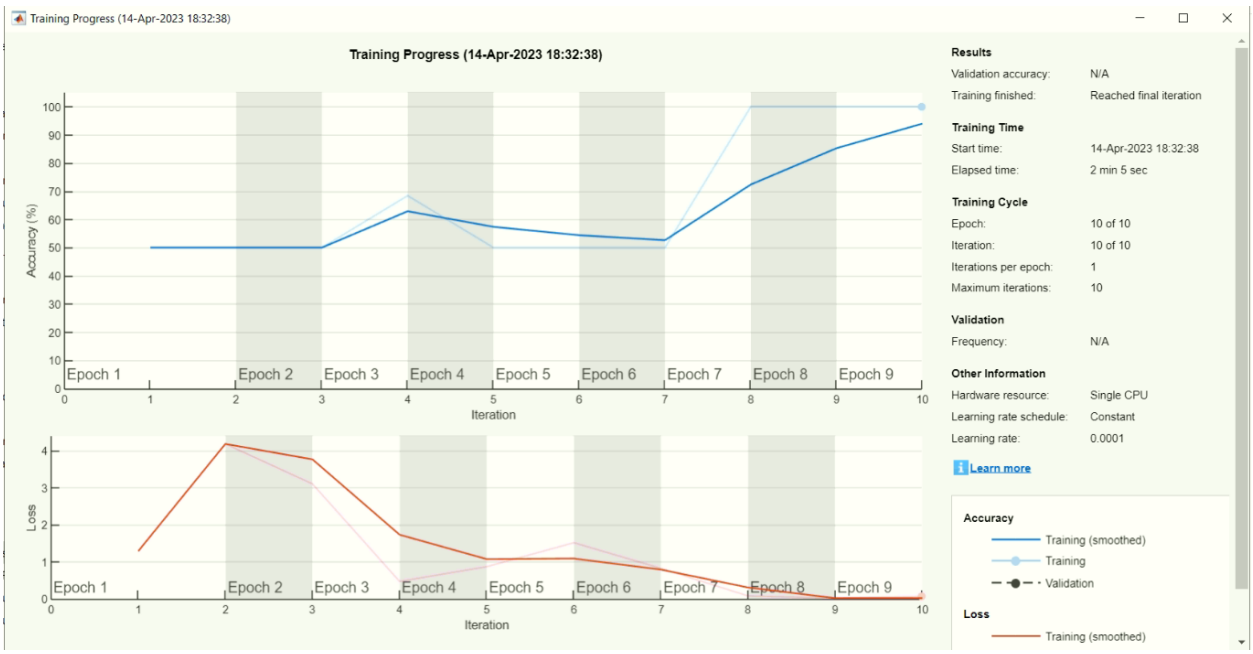

Fig 7 Accuracy and loss plot for training

From the above figure we can clearly identify that when number of epochs increases the accuracy will also increases whereas the loss will be reduces. We were able to evaluate how the models had previously been overfitting from the above two model performances because for most patients' MRI scans, part of the image slices were used as the training dataset and some as the test dataset, but both sets belonged to the same patient.

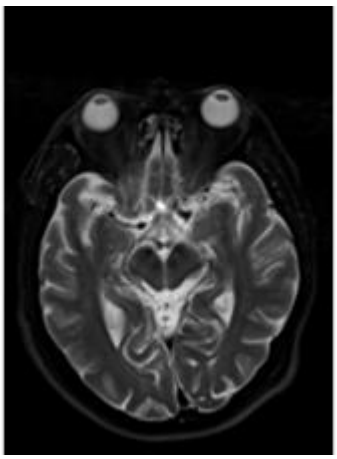

Fig 8 Pd MRI image

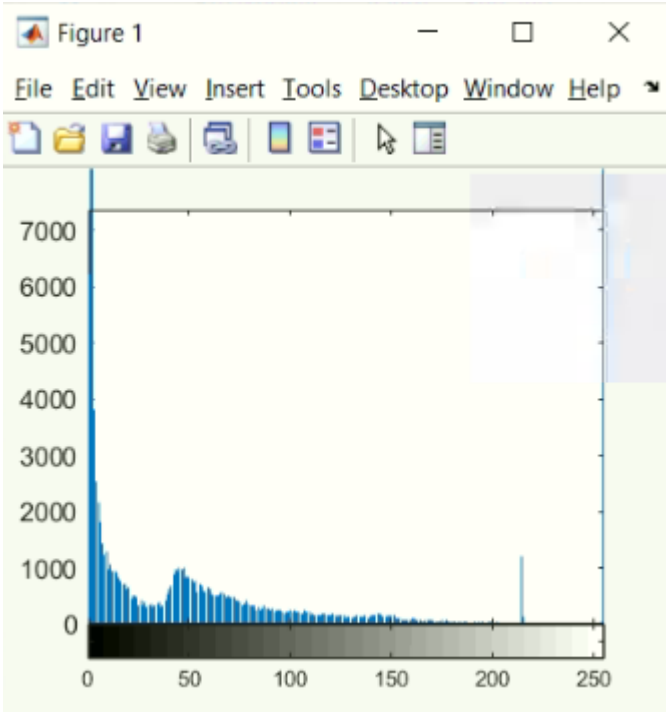

Fig 9 Histogram of MRI PD image

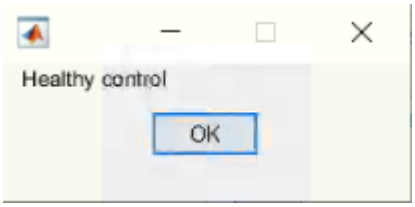

Fig 10 Final classified output

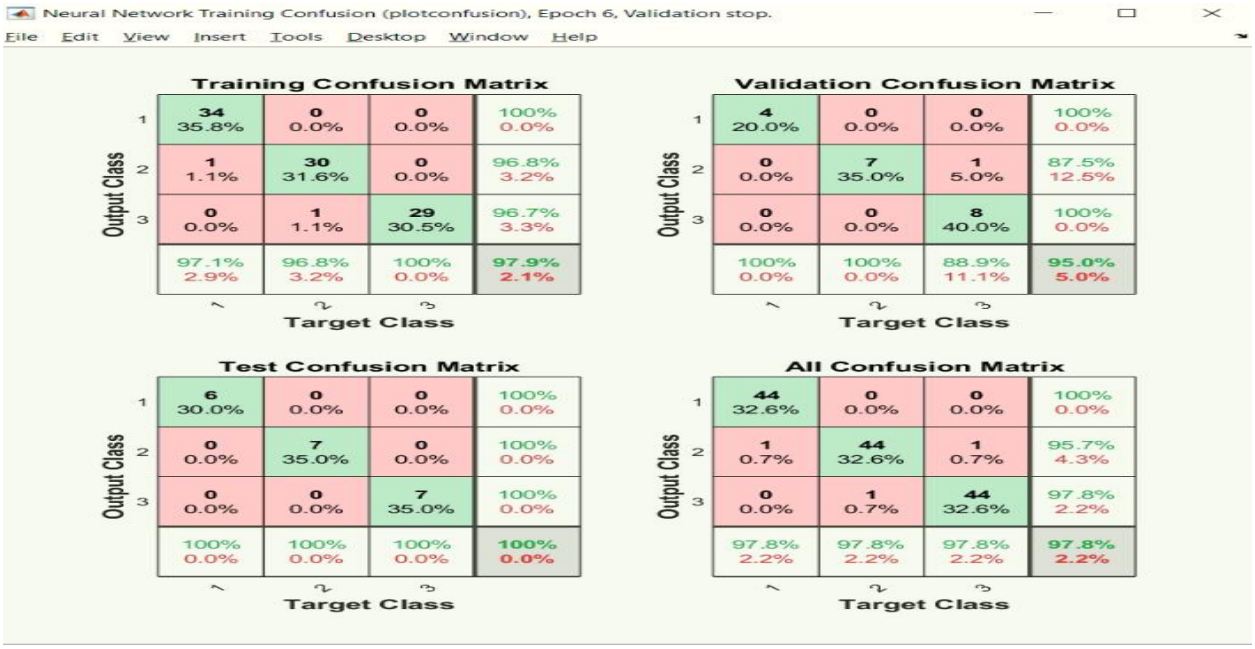

Fig 11 Confusion Matrix

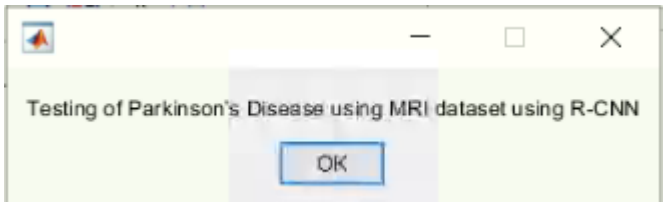

Fig 12 Single-CPU training.

In this we had consider a lose of 2.11% for 30 images while training in testing the accuracy of 100% is achieved at most cases where as the overall confusion matrix shows 97.8% accuracy.

Initializing input data normalization.

```
|=========================================================================================|
| Epoch | Iteration | Time Elapsed | Mini-batch | Mini-batch | Base Learning |
|       |           | (hh:mm:ss)   | Accuracy   |    Loss    |     R ate     |
|=========================================================================================|
|     1 |         1 |     00:00:57 |     50.00% |     1.2826 |    1.0000e-04 |
|    10 |        10 |     00:02:05 |    100.00% |     0.0677 |    1.0000e-04 |
|=========================================================================================|
Enter input :'tt.jpg'

 Classification Accuracy (R-CNN): 97.3333 %
 Processing Time (s): 30.090872
Elapsed time is 30.892851 seconds.
```

Model Performance Without Batch Normalisation

After the tenth epoch, this model's training accuracy was 100%, while its test accuracy was 98.63%. The actual loss was.07%. The graphs for the model loss and accuracy are shown below.

Conclusion

This study uses ensemble voting classifiers and convolutional neural networks to diagnose

Parkinson's disease in spiral and wave paintings using multistage classification. Parkinson's patients and healthy people's spiral and wave doodles were utilised to categorise. The article's approach appears to distinguish Parkinson's sketches from healthy ones. The model tested white 98.3% accurately. Even if the findings of the classifier appear to be rather good right now, the paper's technique and the classifier's performance both have room for improvement. The current methodology can be improved by significantly increasing the number of data samples, using different types of drawings besides spiral and wave, and choosing cutting-edge architecture for the second section after going through several iterations. However, the current system gave us great confidence that this type of technology could be used in solid production environments and real-world circumstances. We may draw the conclusion that R-CNN outperforms the previous techniques, with higher accuracy and lower mean square error, of the three dataset models. This indicates that the model is unable to accurately forecast the minority classes, which will lead to inaccurate case prediction.

FUTURE WORK:

This deep learning-based medical image analysis method lets scientists and doctors identify and choose traits to predict fresh data. The suggested PD stage classification approach will be tested for multi-label classification. We will also consider more complicated DL network topologies like deep hybrid models with additional layers or deep reinforcement learning models to improve performance.

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