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Novel Siamese Neural Network Model for Early Detection of Parkinson's Disease using MRI Imaging

Aryan Ganesh [1 *]

[1]Christopher High School, Gilroy, CA, USA

*Corresponding Author: gvanamu@gmail.com

Advisor: Gyan Krishna Sreekar, gyankrishna06@gmail.com

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Abstract

Since there is no cure for Parkinson's it's essential detecting the disease early and accurately. However, it's extremely challenging because brain MRIs in the early stages looks normal to a human eye. Deep learning convolution neural network models using custom and transfer learning approaches were used to detect and classify Parkinson's disease. MRI images were collected from Alzheimer's Disease Neuroimaging Initiative datasets for both Parkinson's and control-normal classes. VGG16, ResNet-50 and DenseNet-169 base models were used for the transfer learning convolution neural network study. Transfer learning models VGG16, ResNet-50 and DenseNet-169 achieved score for accuracy and precision of (68, 77), (63, 64) and (81, 87) respectively but their performance was impacted by fewer number of datasets and class imbalances. Siamese neural networks which work well with fewer number of datasets was used in this study. For Siamese neural network, transfer learning approach was used via ResNet-50 for Parkinson's disease classification. Siamese neural network model achieved on outstanding score for accuracy and precision of (99,99). Siamese neural network approach also detected and extracted the region of interest as the corpus callosum region.

Keywords: Parkinson's, SNN, MRI

1. Introduction

One of the most common neurodegenerative diseases after Alzheimer's disease is Parkinson's disease (PD). Around 7-10 million people are suffering from this disease in the world and therefore research in this field is warranted (Mhyre et al., 2012 & Jose et al., 2010). As individuals age, the occurrence of Parkinson's disease rises, and it impacts approximately 1% of the population aged 60 and above. This neurodegenerative disorder is caused by insufficient production of specific neurotransmitters, such as dopaminergic neurons, in the brain (Chinta and Andersen, 2005). The resulting dopamine imbalance leads to motor dysfunction and tremors. Tremors, which initiate in a limb and eventually spread throughout the entire body, are a primary manifestation of Parkinson's Disease (Bhatia et al., 2018).

It is crucial to differentiate PD progression from other conditions such as frontotemporal dementia (FTD), psychiatric disorders, vascular dementia, or Alzheimer's disease since their symptoms can be easily misdiagnosed in PD patients (Finger et al., 2016). Despite being a noninvasive imaging technology, Magnetic Resonance Imaging (MRI) has been rarely used in PD detection. However, recent advancements in MRI have made detection comparatively easier. Although experts have been utilizing MRI imaging to detect PD, it has become increasingly challenging for physicians as an MRI scan of the brain in the early stages may appear normal to the human eye. Misdiagnosing PD as healthy could lead to disease progression and difficulty in controlling it in patients. In recent years, researchers have been exploring new MRI techniques that may improve the accuracy of PD diagnosis. For example, diffusion tensor imaging (DTI) is a type of MRI that can detect changes in the white matter of the brain that may be associated with PD. Other techniques, such as functional MRI (fMRI), may help identify changes in brain activity patterns that are specific to PD. Despite these advances, however, MRI remains a challenging diagnostic tool for PD, particularly in its early stages (Pahuja et al., 2016). The corpus callosum is a thick bundle of nerve fibers that connects the two hemispheres of the brain, allowing them to communicate and send signals to each other. Notable volume loss occurs in the corpus callosum in PD, with specific neuroanatomic distributions in PDD and relationships of regional atrophy to different cognitive domains. Callosal volume loss may contribute to clinical manifestations of PD cognitive impairment (Goldman et al. (2017).

Deep learning is a branch of machine learning that involves training artificial neural networks on vast data sets to tackle intricate problems. Various studies have employed convolutional neural network (CNN) models in deep learning to identify and categorize Parkinson's disease (PD) automatically using different network architectures (Alissa et al., 2022, Liu et al., 2018 & Jahan et al., 2021). The findings suggest that CNNs can enhance the learning process and deliver more accurate classification outcomes for diagnosing PD (Jindal and Tripathi, 2020). The study used MRI brain scans from PD patients and healthy controls to train the CNN and achieved an accuracy rate of over 90% in detecting PD. The use of machine learning in detecting Parkinson's disease (PD) is limited by several challenges. Firstly, the scarcity of available MRI data for PD patients makes it challenging to apply machine learning accurately. Secondly, few studies have focused on identifying the region of interest (ROI), which is a critical factor in medical diagnosis (Mehmood et al., 2020). Accurately identifying the ROI can provide insight into the disease and improve model performance. Finally, the class imbalance is a significant issue in many studies. This occurs when one class has significantly more instances than other classes, leading to a misinterpretation of the model (Kanghan et al., 2019).

In this work, custom CNN model and a transfer learning approach were used with pre-trained VGG-16, ResNet-50 and DenseNet-169 architectures for feature extraction to classify PD MRI images (Ganesh and Vanamu, 2022). The most popular publicly available database for MRI images is Open Access Series of Imaging Studies (OASIS) (Marcus et al., 2007), also called Kaggle databases. Siamese neural network (SNN) is a novel artificial neural network which compares two images and then separates all the images into sub-groups, which then separate into your actual classification groups eventually. In this study a transfer learning SNN model using ResNet-50 was also developed to efficiently classify MRI datasets with a smaller number of images.

Research objectives in the study are to , to obtain a custom model with outstanding accuracy and precision for detecting PD using MRI images, compare various deep learning models against the custom model and identify ROI. Hypothesize is to develop a novel SNN model for accurately detecting PD using smaller MRI datasets compared to other custom and transfer learning CNN models. Additionally, prediction was that transfer learning CNN approach using DenseNet-169 would have better performance compared to VGG-16 and ResNet-50 because of its more layers.

2. Materials and Methods

2.1 Data acquisition and preprocessing

Data from the Kaggle databases were fed into the model after data preprocessing. In the preprocessing step, all the images were resized to be consistent at 224 x 224 pixels to match the academic standard. The axial T1 star images of the axial brain MRI scans were used for Kaggle to classify the stage of the AD and to find the region of interest. The OASIS database, also called Kaggle, is freely available to the scientific community. Kaggle compiles a multi-modal dataset generated by the Knight Alzheimer Disease Research Center (Knight ADRC) and its affiliated studies.

The data augmentation was very crucial in this project as the dataset was much smaller than the Kaggle dataset, and only less than 170 PD images were available for training, consisting of five classes. Therefore, some augmentation techniques i.e., rotation, flipping etc. were used which helped the model to be more generalizable and reduce over-fitting of the dataset.

2.2 ML and neural networks terms

The pre-trained models used in this study are VGG-16, ResNet-50 and DenseNet-169. The programming

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language used in this study is Python with opensource library used to develop ML model and the computing platform used was NVIDIA GPU for high data processing. Accuracy shows how often a classification ML model is correct overall. Precision shows how often an ML model is correct when predicting the target class. Accuracy is a helpful metric when you deal with balanced classes and care about the overall model "correctness" and not the ability to predict a specific class, whereas precision is useful when you have "unbalanced" classes as in this study.

An epoch indicates the number of passes of the training dataset the ML algorithm completes. Initially, a random kernel was used and the performance was low. The number of epochs is the number of times that the algorithm will work through the entire training dataset. One epoch means that each sample in the training dataset has had an opportunity to update the internal model parameters. The performance of the model stops improving because the model detection rate is not getting better.

SNN consists of two identical sub-networks that are joined together at their output. The initialization for both the sub-networks involves the same weights and parameters. Parameter updating happens while training also gets shared across these networks.

2.3 Reference transfer learning models

Transfer learning is all about gaining insights by addressing a problem and leveraging the knowledge gained and its application on a problem that is similar in nature. For example, parts of knowledge gained in recognizing one kind of automobile can be applied for recognizing all kinds of similar vehicles. This kind of transfer of knowledge and repurposing saves us from reinventing the wheel and has the potential to significantly improve the efficiency of the target output. Several problems related to computations, data availability, and analytics have taken advantage of this transfer learning method. Particularly for image processing and identification, the transfer learning model can gain potential knowledge by analyzing an image, which can easily be applied to a wide range of datasets and classes.

3. Results

3.1 Architecture for the model

A custom CNN model was developed for feature extraction and to classify PD MRI images. Transfer learning using well established existing pre-trained VGG-16, ResNet-50 and DenseNet-169 base models were also implemented in the image classification to extract the features and created a custom dense layer for classification of the stage of the PD. Model was tested using both Kaggle databases.

Two classes of PD images were obtained using the Kaggle database, namely: control normal (healthy) and Parkinson's disease images (Figure 1). A total of 177 images for PD and 487 images for normal (healthy) with a total of 654 images were obtained. The data was split into three sets: a training set consisting of 60% of the dataset (398 images), a validation set consisting of 15% of the dataset (100 images), and a testing set consisting of 25% of the dataset (166 images). 106 images, 292 images for training, 26 images, 74 images for validation and 44 images, 122 images were used for testing for each of the classes PD and normal respectively for standard CNN models. Since the SNN uses a twin CNN model where pairs of images are compared all the images are used for training validation and testing.

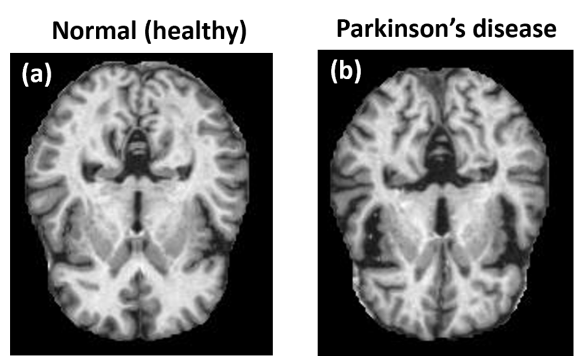

Figure 1: Example of Kaggle MRI images for (a) Control normal (healthy) (b) Parkinson's disease.

3.2 Test results for Custom CNN model

A custom model was developed with 12 layers (6 layers of convolutions and 6 layers of max pooling) to train all the model. An epoch is a process of training the neural network with the training data for one-cycle. The number of

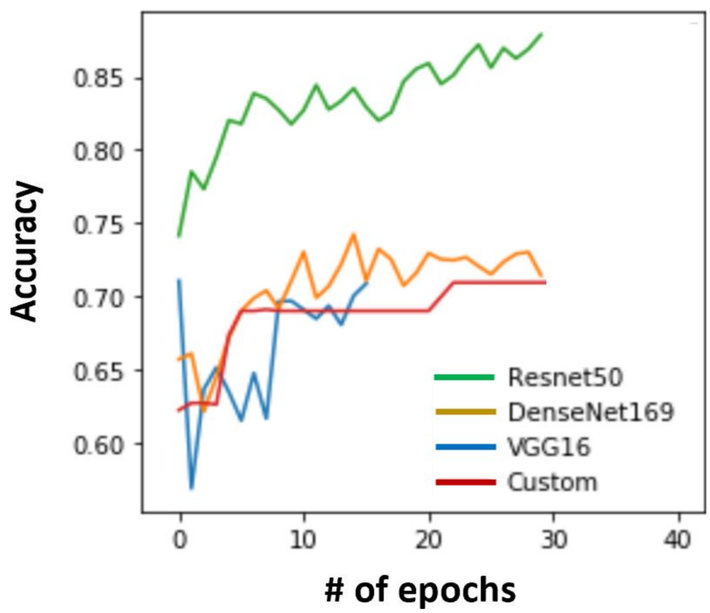

Figure 2: Validation performance of the custom model and other transferring learning models (VGG-16, ResNet-50 and DenseNet-169) across epochs. The validation accuracy for each of the model's custom-CNN, VGG-16, ResNet-50 and DenseNet-169 were 0.705, 0.7, 0.86, and 0.71 after 30 epochs, respectively.

epochs is the number of times that the algorithm will work through the entire training dataset. The performance of the custom model was calculated across epochs as shown by the red line in the plot below (Figure 2). The validation accuracy for the custom model was 0.705, after 30 epochs. The model showed an increasing trend in performance until it reached their final values. The testing accuracy for the custom model was 0.71 based on 166 MRI test images calculated using the confusion matrix (Figure 3). The testing precision for the custom model came out low with 0.79.

3.3 Test results for CNN transfer learning models

A transfer learning approach was used to train all the reference models (VGG-16, ResNet-50 and DenseNet-169). The performance of the models was calculated across epochs using the custom dense layer developed (Figure 2). The validation accuracy for each of the models VGG-16, ResNet-50 and DenseNet-169 were 0.7, 0.86, and 0.71 after 30 epochs, respectively. Both DenseNet-169 and VGG-16 showed an increasing trend in the accuracy until 10 epochs and then saturated. ResNet-50 showed increasing trend until 30 epochs and saturated after that. The testing accuracy for each of the models VGG-16, ResNet-50 and DenseNet-169 were 0.68, 0.83, and 0.70, respectively, based on 166 MRI test images calculated using the confusion matrix (Figure 3). The testing precision for each of the models VGG-16, ResNet-50 and DenseNet-169 were 0.77, 0.85, and 0.78, respectively.

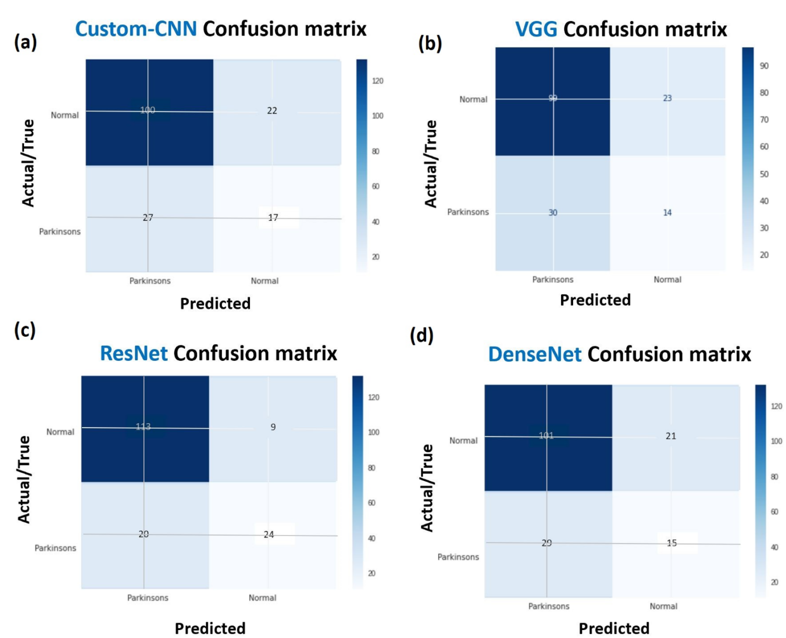

Figure 3 (a-d): Confusion matrix showing testing accuracy and precision performance of the custom model (a) and other transferring learning models, VGG-16 (b), ResNet-50 (c) and DenseNet-169 (d). The testing accuracy for each of the model's custom-CNN model, VGG-16, ResNet-50 and DenseNet-169 were 0.71, 0.68, 0.83, and 0.70, respectively, based on 166 MRI test images. The testing precision for each of the model's custom-CNN model, VGG-16, ResNet-50 and DenseNet-169 were 0.79, 0.77, 0.85, and 0.78, respectively.

3.4 Test results for SNN model

A SNN model was developed using transfer learning (ResNet-50 as a base model). The performance of the SNN model was calculated across epochs (Figure 4). The training accuracy for the SNN model 0.975

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after 15 epochs. SNN model showed an increasing trend in the accuracy until it reached its final values. The validation accuracy for the SNN model was 0.96, after 15 epochs. Similarly, the model showed an increasing trend in performance until it reached their final values. The testing accuracy for the SNN model was 0.991, based on 654 MRI test images calculated using the confusion matrix (Figure 5). The testing precision for the SNN model came out outstanding with 0.988. SNN model also determined the ROI to be the Corpus Callosum region on the brain axial MRI images (Figure 6).

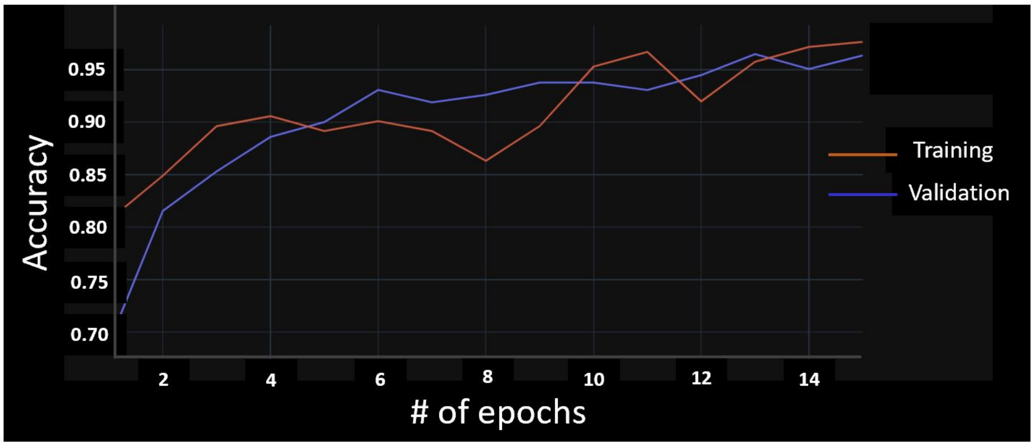

Figure 4: Validation performance of the SNN model across epochs. The training and validation accuracy for SNN model 0.975 and 0.96 respectively.

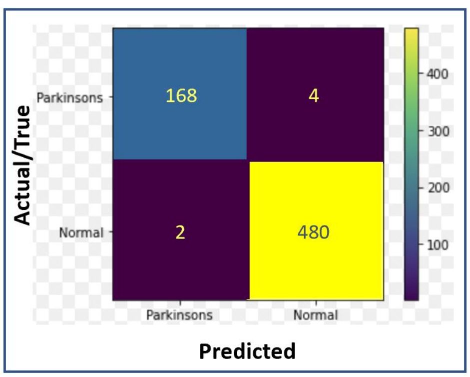

Figure 5: Confusion matrix showing testing accuracy and precision performance of the SNN model. The testing accuracy and precision for the SNN model shows 0.991 and 0.988, respectively.

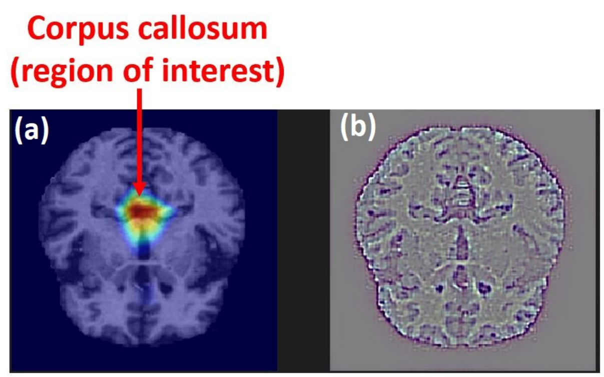

Figure 6 (a): Region of interest (ROI) using Kaggle data showing the Corpus Callosum on the brain axial MRI images of the VGG-16 data. Red color shows the accurate location of the ROI. Figure 6 (b) on the right shows the image without the ROI and left shows with the ROI.

4. Discussion

In this work, custom CNN model was compared with the transfer learning CNN models for detection of PD using MRI images. Based on the testing dataset model performances, it can be concluded that the ResNet-50 model outperformed all the other models (custom, VGG-16 and DenseNet-169). The reason ResNet-50 model showed better training performance compared to the custom and VGG-16 model, may be because ResNet has more layers (50 layers) compared to VGG model. However, ResNet-50 also showed better performance compared to DenseNet-169 which has 169 layers. ResNet-50 has been previously shown to have better performance on the ImageNet dataset (Liu et al., 2021), a large dataset of annotated photographs intended for use in development of visual object recognition software, relative to other models. This is probably because ResNet-50 has a skip connection architecture unlike the other two models (VGG and DenseNet) which have straight forward architecture (Sun et al., 2014). ResNet-50 did not show any

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improvement with an increasing number of epochs past 30 suggesting the model saturated.

Hypothesis was partly correct and SNN was able to get detect PD using smaller MRI datasets with better precision compared to other custom and transfer learning CNN models. Additionally, it was predicted that transfer learning CNN approach using DenseNet-169 would have better performance compared to VGG-16 and ResNet-50 because of its more layers. It is also possible that DenseNet-169 may have too many layers and images may not have enough features to extract, leading to overfitting of the dataset.

To the best of our knowledge, SNN model performance (testing precision = 0.988) is the highest compared to other studies using CNN transfer learning (Sabyasachi et al., 2020 & Shah et al., 2018). SNN is a novel artificial neural network allowing efficient learning with small amounts of data (Xing et al., 2021 & Figueroa-Mata et al., 2020) and doesn't get affected by the class imbalance (Bedi et al., 2020). SNN is a twin neural network which compares every two images and then separates all the images into sub-groups, which then separate into your actual classification groups eventually. Because these networks consider the similarity/dissimilarity using both positive and negative samples, they form the neighborhood relationship, keeping similar samples closer and the dissimilar ones far apart. Because of the same reason, these networks have proven to be vigorous against class imbalance.

In this study and unlike previously published work, automatic detection was employed and extraction of ROI. Deep learning model determined that the ROI was the corpus callosum region brain axial MRI images. Previous studies have shown corpus callosum volumes were smaller in the Parkinson's patient groups with PD (Goldman et al., 2017). Corpus callosum abnormalities may contribute to PD cognitive impairment by disrupting information transfer across interhemispheric and callosal–cortical projections (Bledsoe et al., 2018 & Gu et al., 2022).

5. Conclusion

In summary different models were compared and found out that ResNet-50 performed better compared to all other CNN models including the custom model. SNN model showed outstanding accuracy and precision for detecting PD using MRI images better than the ResNet-50 model. This study also identified the ROI, which identifies the location of the region which could be the root cause of the disease and hence provides good understanding of the disease as well as increases the performance of the models. Additionally, the issue with the class imbalance and fewer amount of labelled data was overcome using a novel SNN model.

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