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Deep-learning Residual Network Based Image Analysis for An Efficient Two-Stage Recognition of Neurological Disorders

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***Abstract*—An increase in research and awareness of neurological disorders has caused several medical practitioners to consider taking the assistance of AI/ML and reduce the recovery time for patients. MRI-based detection of neurological disorders has become popular in the field of bio-medical analytics. In this paper, a novel two-stage approach was proposed, which split the task of disease identification and severity identification from MRI data. The proposed two-stage approach benefits from improved efficiency due to automated simultaneous testing of multiple diseases. This reduces the time to diagnosis or diagnostic delay. The proposed two-stage approach was able to yield an accuracy of up to 94.29%, which was significantly better than the simpler one-stage approach while also being flexible to future upgrades.**

Keywords— Classification, Deep Convolutional Neural networks, ResNet Brain MRI, Alzheimer's disease, Parkinson's Disease, Autism spectrum Disorder

I. INTRODUCTION

Alzheimer's Disease (AD), Parkinson's Disease (PD), and autism spectrum disorder (ASD) are neurological disorders. "AD is a most common type of dementia with mild memory loss, the decline in cognitive abilities, and losing the ability to continue conversations" [1]. The cause of AD is due to the combination of age-related changes in brain tissues, the environment of living, and genetics. AD causes brain cells to shrink and destroy. Medications may temporarily slow the progression of AD. Often AD is observed in the age group above 65 [2]. The disease process is mostly associated with amyloid plaques, neurofibrillary tangles, and loss of neuron connections in the brain [3].

Researchers trying to understand the cause of AD are focused on the role of two proteins, Plaques which potentially get between the neuron-to-neuron signalling [4]. If the brain can't signal and delay information, then the functioning of the brain will be impaired. These plaques may block response and cause inflammation which might lead to damage to neurons. This amyloid plaque can also be around blood vessels in the brain called amyloid angiopathy. This Amyloid angiopathy weakens the walls of the blood vessels and increases the risk of brain hemorrhage or blood loss [4].

Another feature of AD is tangled, and these are located inside the cell as opposed to the beta-amyloid plaques [4]. Like other cells neurons are held together by their cytoskeleton these are track-like structures, that act as sharing nutrients as a railway. A unique protein called tau drives the way the cytoskeleton of cells does not smash. Beta-amyloid plaque constructs a way inside the neuron that can guide activating kinase an enzyme to transmit phosphate groups to tau protein [4]. Tau protein is then conveyed and removed from the cell and gets together with an additional tau protein called neurofibrillary tangles. Neurons with tangles in the cell membrane can't let the cell function and choke the signal and periodically experience cell death.

PD is another type of brain disorder that causes inadvertent movements of motors, such as stiffness, shaking, and difficulty to handle or balancing things. The PD-affected person may face mental and behavioural changes, sleep problems, and fatigue. The dopamine-producing neurons in the substantia nigra of the brain undergo degeneration. Some research studies suggest this disease affects more men than women [5]. There are likewise multiple usually weakening non-motor symptoms some of them are depression and stress, mental shortages, sleep disorder, and loss of smell. Parkinson's affects many areas of the nervous system and different types of neurons. However, much focus has been placed on neurons in brain regions associated with the symptoms.

The symptoms of PD occur when nerve cells in the basal ganglia, a region in the brain which controls movement, get impaired and result in nerve cell death. These nerve cells produce an important chemical called dopamine. When neurons get impaired there is less production of dopamine, which causes a loss of control of movement. The first symptom may be a slightly noticeable tremor in just one hand. Tremors are typical, but the disorder may also cause immobility or slowing activity. In the early stages of Parkinson's disease, your face may exhibit little or no expression.

ASD is a neurological and developmental disorder that affects how people interact with each other and communicate. ASD can be a lifetime disorder but using some medications and services can improve a person's symptoms and daily activities. Studies suggest that a person's genes along with their environment affect development that leads to ASD [6]. Autism is mainly seen in children where the Development of the brain impacts and how they are isolated. As a result, isolation (removed from social interaction and communication) causes ASD. Autism is described in several pervasive developmental disorders which include Asperger syndrome, and childhood disintegrative disorder. Often some children show autism symptoms within a year or between 18-24 months of age.

Plenty of research work has been conducted to find a cure for AD, PD, and ASD, but they have not been identified yet. However, there are many methods and suggestions to slow down the development of AD, PD, and ASD. Many Machine Learning algorithms and Deep Learning Algorithms are developed to increase the assistance of neurologists to gain a second opinion.

MRI is more accessible and less expensive compared to other tests while providing sufficient details for diagnosis. Hence, it can be recommended to a wide range of people. A General Neurologist who is specific to a field might not be able to identify different diseases quickly. Our proposed ML model can perform these operations and give solutions. The current solutions only allow individuals a repetitive process for verifying the disorder. But the proposed two-stage model can classify the diseases based on a single MRI scan to avoid numerous tests. Our proposed two-stage model is a combined model where it can classify different disorders simultaneously.

II. Literature Survey

Alzheimer's and Parkinson's are neurodegenerative diseases and Autism is a neurodevelopment disorder. These neurological diseases cannot be acknowledged in a single lab diagnosis. Although Parkinson's disease can't be cured, medicines might extremely improve your symptoms. To improve the accuracy of prediction between AD, PD, ASD, and Control. A qualified neurologist can get a second opinion and improve the efficiency of the work. Classification of AD, PD, ASD, and Control can better specify the disease with its severity level.

There have been several strategies developed to classify different levels of AD, PD, and ASD. J. Liu, M. Li, W. Lan, F. Wu, Y. Pan, and J. Wang worked on the classification of AD using Whole Brain Hierarchical Network [7], classifying between AD/HC (health controls), AD/MCI (mild cognitive impairment) to extract the important features for MRI-based classification with spatial-correlations for better accuracy and the features are selected according to F-scores. And the final classification is done using a multiple kernel classifier.

A. Rao, Y. Lee, A. Gass, and A. Monsch worked on the classification of AD from structural MRI using Sparse Logistic Regression with Optional Spatial Regularization [8]. Both methods were able to perform better than Penalized Logistic Regression (PLR) and Maximum uncertainty Linear Discriminant Analysis (MLDA) [8]. Spatially Regularized Sparse Logistic Regression (SRSLR) gave smoother consistent weighted images than SLR. Freddie Åström, Rasit Koker worked on a parallel neural network approach to the prediction of PD [9]. Parallel systems increase the reliability in the same way it is represented that the performance of the prediction has been increased compared to other unique networks.

Shi, Yinghuan; Suk, Heung-Il; Liu, Mingxia worked on the early diagnosis of Autism Disease by Multi-channel CNNs [10] using Multi-Channel Convolutional Neural Networks with multiple CNN and combining the results with Fully Connected Networks and performing predictions with the proposal of patch extraction from MRI. Heinsfeld, Anibal Sólon; Franco, Alexandre Rosa; Craddock, R. Cameron; Buchweitz, Augusto; Meneguzzi, Felipe worked on the identification of ASD using Deep Learning and the ABIDE dataset [11] using Deep Neural Network achieved good accuracy when compared to Support Vector Machine and Random Forest suggesting that deep learning methods may classify large datasets.

H. R. Kambhampaty, B. N. D. Saikiran et.al, worked on a five-way classification of the degree of affectedness of AD using a 15-layer custom Sequential Deep Convolutional Neural Network (CNN) on MRI data [12]. The classification accuracy obtained was 93.57%. Chen, Rong, Yun Jiao, and Edward H. Herskovits. [13] Summarized findings from studies to based on voxel morphometry in ASD and discussed diagnostic models related to ASD.

III. Methodology

In this section, the datasets and procedures used to perform and validate the experiments are explained. Results and Analysis present the results and analysis of the results of the experiments performed. The datasets used in this paper have all been obtained from the Laboratory of Neuro Imaging {R+1}, maintained by the Mark and Mary Stevens Neuroimaging and Informatics Institute at the University of Southern California. The datasets include Parkinson's Progression Markers (PPMI) [15] for PD-related data, Autism Brain Imaging Data Exchange (ABIDE) [16] for ASD-related data, Alzheimer's Disease Neuroimaging Initiative (ADNI) database [17] for AD-related data. And dataset also contains Control dataset which contains healthy brains [18] which is taken from Kaggle dataset having CC0 1.0 Universal (CC0 1.0) Public Domain Dedication. The data downloaded strictly comprises 3D, T1-weighted data. All the MRI data from different neurological disorder and healthy brain are combined and formed into different classes. The training dataset is distinct from the testing dataset.

The data is also oversampled using Synthetic Minority Over-sampling Technique (SMOTE) [19] to account for the imbalance in the number of images among the classes. In the dataset there are significantly lower number of images for ASD and Control Classes these are increased using SMOTE which takes feature space samples and its nearest neighbours then it generates examples which gives more general samples.

Table I shows the number of images selected from each neuro diseases dataset with their respective severities. Four categories include AD, PD, ASD, and Control. The Control class consists of healthy test subjects that are used as a

reference for contrasting with the affected patients. The AD group consists of four severities, i.e., Early Mild Cognitive Impairment (EMCI), Mild Cognitive Impairment (MCI), Late Mild Cognitive Impairment (LMCI), and Significant Memory Concern (SMC), the PD group consists of two severities (Prodomal, and PD), and the ASD group consists of only one severity (Autism).

TABLE I. AGGREGATED DATASET SIZE

Disease	Severity	No. of Images for Training	No. of Images for Testing
AD	EMCI	3690	790
	MCI	2330	449
	LMCI	3575	775
	SMC	2508	478
PD	Prodomal	2023	422
	PD	3531	760
ASD	Autism	1565	336
Control	Control	1071	198

The complete data is divided into 80% training and 20% testing using the "train_test_split" method in the TensorFlow library. The training data is used for the model and evaluation data set is used to keep incremental training. The data is fed to the model through dataloader with batch size of 1024 and each image of size 224x224.

A. One-Stage Approach

In the One-Stage Approach, all the severities (mentioned in Table I) for all diseases are taken as individual classes for classification. In this approach, only a single 8-way classifier trained using the ResNet50_V2 [14] Deep CNN architecture is used. ResNet50_V2 contains 50-layer convolutional neural network which have 48 convolutional layers, one MaxPool and one average pool layer. ResNet50_V2 is the modified version of ResNet50 which is performers better. It contains some modifications on connections between the blocks and skip connections. This approach has some advantages as only a single training session is required for the classification. The final accuracy of predication is the same as the classification accuracy of the entire 8-way classifier.

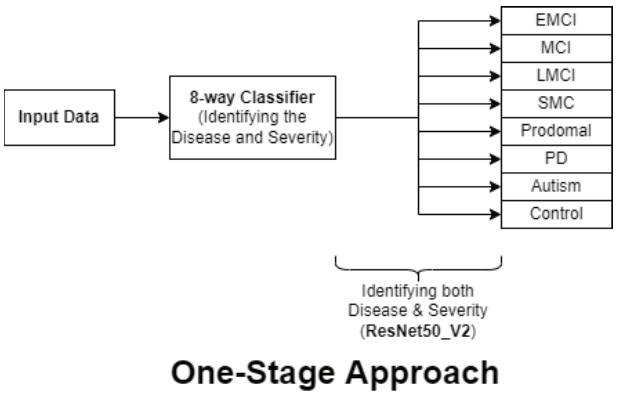

Fig. 1. System Architecture for One-Stage Approach

Fig. 1, illustrates the System Architecture for One-Stage Approach, where test data is directly given as input to the 8-way classifier, which produces a disease class label as output. The produced disease class label is used to identify the disease and its severity in one step. This approach directly gives the severity without first classifying into AD, PD, and ASD disease, it also have less overhead because all the classes of data (AD, PD, ASD and Control) is given to the model during training but training time is significantly increased because of more number of MRI images. The model is trained to give output of 8 types of disease severity directly.

B. Two-Stage Approach

In the Two-Stage Approach, the first stage involves the identification the disease, which is performed by one 4-way classifier trained using the AlexNet CNN architecture. The second stage involves the identification of the severity of the disease using ResNet50 V2 [14], which is done by multiple different classifiers based on the levels of severity for each disease. The two-stage approach benefits from the flexibility to choose the most optimal ML/DL algorithm and progressively improve the classification accuracy.

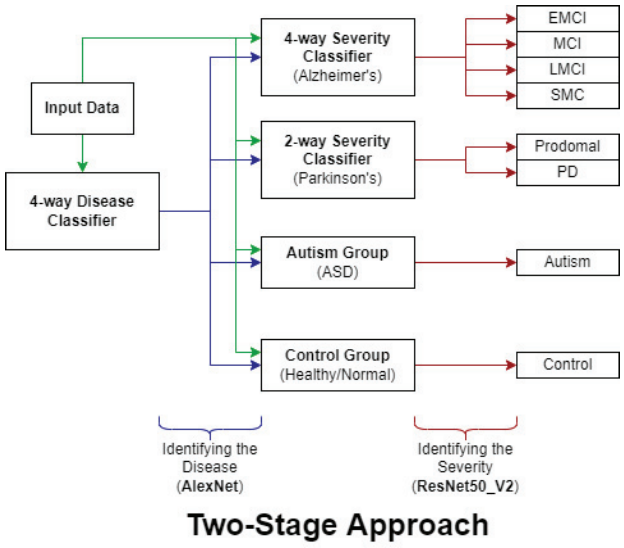

Fig. 2. System Architecture for Two-Stage Approach

In this approach, one 4-way classifier trained using ResNet50_V2 Deep CNN architecture is used for identification severity of AD, and one 2-way classifier for identification of severity of PD. Since ASD has only one severity, a second-stage classifier is not used. Similarly, Control group consists of healthy individuals and does not have a second-stage classifier as well. The final accuracy of prediction is the product of the classification accuracy of the first-stage classifier and the respective second-stage classifier. Fig. 2 illustrates the System Architecture for Two-Stage Approach, where test data is given as input to the firs-stage classifier, which produces a single class label to indicate the disease.

The test data is again given as input to the respective second-stage classifier, which produces a severity class label as the output. In the first stage AlexNet is used over ResNet50,

GoogleNet because it gave better accuracy and its less complex CNN architecture with only 8 layers deep. Various Deep CNN models are compared in both first and second stage and AlexNet for first stage and ResNet50_V2 for the second stage gave better results than other combination of models. A Sample of Images used in Two-stage Approach from AD, PD, ASD, and Control is shown in Fig. 3.

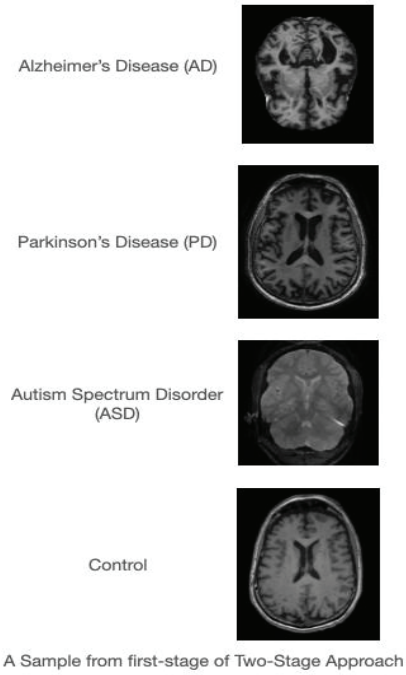

Fig. 3. A Sample image from each class from a Two-Stage Approach

IV. RESULTS AND ANALYSIS

A. One-Stage Approach

Fig. 4 illustrates the Confusion Matrix of the One-Stage Approach using ResNet50_V2 Deep CNN architecture. And trained the data with the batch size of 1024 and used SMOTE to equalize the number of images in each class to avoid imbalanced data. "SoftMax" is used to give the maximum probability class. "Categorical Crossentropy" is used in the loss function. It can be observed that there is significant correlation between Autism and Control class where Control class is predicted as Autism. Consequently, there is slight correlation between LMCI and SMC where some of SMC data is being classified as LMCI. The final accuracy obtained is 91.02%.

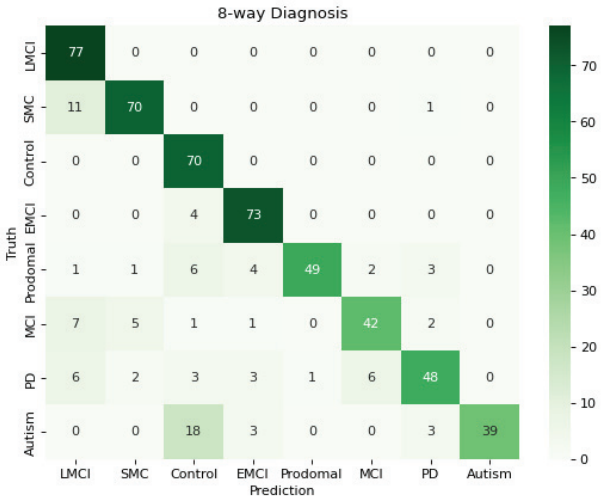

Fig. 4. Confusion Matrix of One-Stage Approach using ResNet50_V2

By Analysing the Accuracy curve (Fig. 5) of the model over the training data, the model is performing well and the fluctuations in validation data are due to the high correlation between Autism and Control which decreased the accuracy.

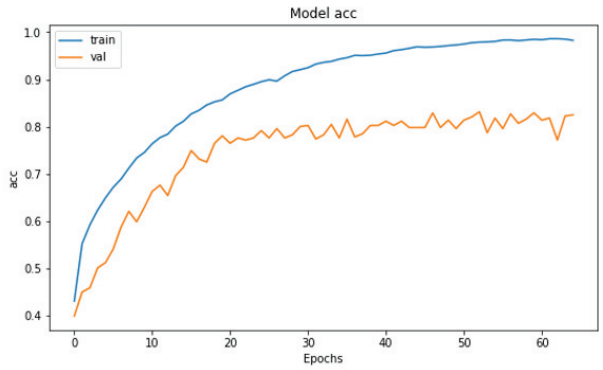

Fig. 5. Accuracy Curve of One-Stage Approach using ResNet50_v2

B. Two-Stage Approach

Fig. 6 illustrates the Confusion Matrix of the first-stage of Two-Stage Approach for disease classification using Resnet. It can be noted that the model (AlexNet) is able to classify between different class of diseases with good precision. The first-stage accuracy obtained is 94.29%. The number of wrongly predicted classes are very less and model performed well classifying between AD, ASD, PD and Control.

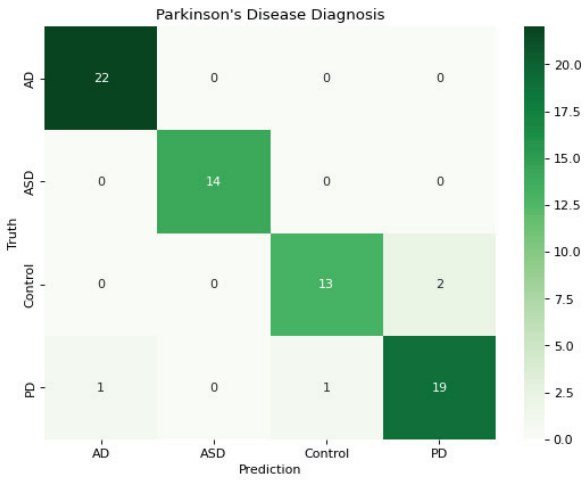

Fig. 6. Confusion Matrix of the first-stage of Two-Stage Approach using AlexNet

From Fig. 7 the model is trained using the modified dataset which contains PD, AD, ASD, and Control MRI scans and the accuracy of the model increased in the first 30 to 40 epochs, and then the validation score is increasing gradually.

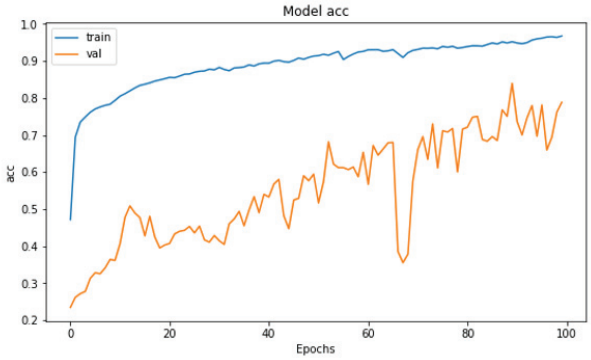

Fig. 7. Accuracy curve of first stage of Two-stage approach using AlexNet

Fig. 8 illustrates the Confusion Matrix of the second-stage of Two-Stage Approach for severity classification of AD using ResNet50_V2. In Confusion Matrix the correlation between LMCI and SMC is high and with EMCI and SMC, this behaviour is also observed in 8-way classification where LMCI is begin predicted for SMC. Because of the correlation between EMCI, LMCI with SMC accuracy of the model is decreased for the AD class. The second-stage accuracy obtained is 82.74%. Here, the classification accuracy of the second-stage AD severity-classifier can be improved by using a better classification algorithm or network architecture.

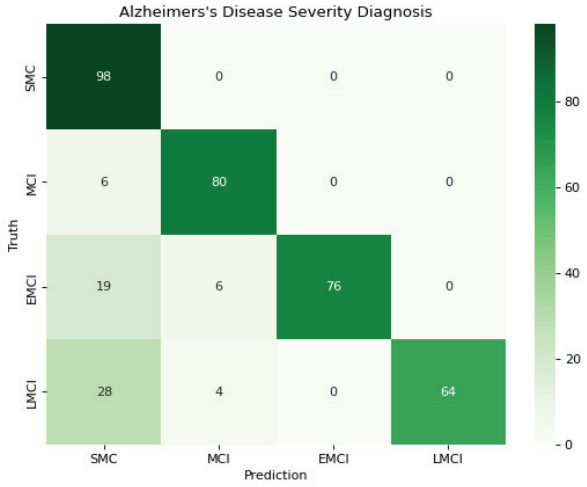

Fig. 8. Confusion Matrix of the second-stage of Two-Stage Approach for severity classification of AD using ResNet50_V2

From Fig. 9 the fluctuations in the validation curve are due to the high correlation between LMCI and SMC, and EMCI and SMC which decreased the testing accuracy. These fluctuations can be avoided using more data points.

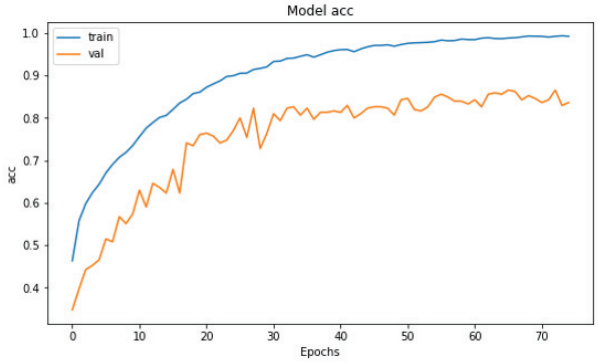

Fig. 9. Accuracy curve of second stage of Two-Stage Approach for severity classification of AD using ResNet50_V2

Fig. 10 illustrates the Confusion Matrix of the second-stage of Two-Stage Approach for severity classification of PD using ResNet50_V2. In the Confusion Matrix Maximum of the predictions made are true and there is very less correlation exists. The ResNet50_V2 performed better for the classification of PD because of skip connections in the architecture which deactivate some neurons. The second-stage accuracy obtained is 99.8%.

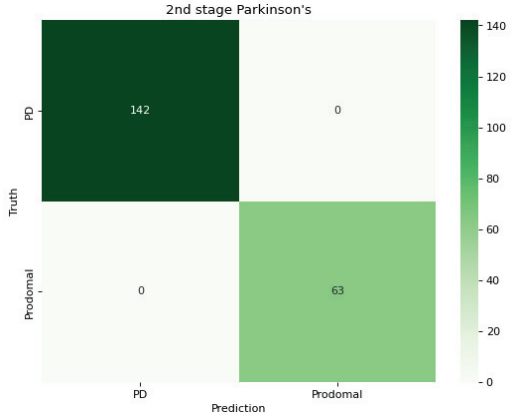

Fig. 10. Confusion Matrix of the second-stage of Two-Stage Approach for severity classification of PD using ResNet50_V2

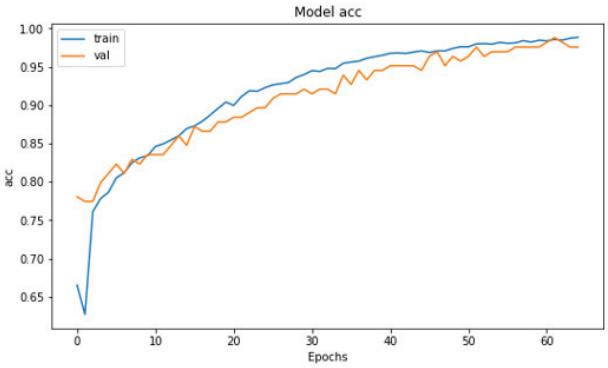

Fig. 11. Accuracy curve of second stage of Two-Stage Approach for severity classification of PD using ResNet50_V2

From Fig. 11 the ResNet50_V2 is performing well by observing the training and validation curves merging. This is because of less number of classes and the correlation between them.

TABLE II. ACCURACY OF CLASSIFICATION USING THE TWO STAGE APPROACH

Disease	Severity	Classification Accuracy
AD	EMCI	78.10%
	MCI	
	LMCI	
	SMC	
PD	Prodomal	94.29%
	PD	
ASD	Autism	94.29%
Control	Control	94.29%

Table II shows the final classification accuracies obtained using the Two-Stage Classifier, which ranges between 78.10% and 94.29%. Because ASD and Control don't have any classification to be performed they are directly using AlexNet. By combining the accuracies of first and second stage can give an accuracy around 94%. Improvement of accuracy can be performed by using a more sophisticated network architecture or using more comprehensive dataset. Two-Stage approach can better represent the disease in first-stage and then identify the severity after the classification of disease this decreases the number of calculations between different classes.

V. CONCLUSIONS

In this paper, a one-stage and the proposed two-stage approach were implemented and compared on MRI data [15][16][17]. The one-stage approach benefitted from simpler design and easier model training, while the two-stage approach allowed for a higher degree of flexibility in use of DL algorithms. The one-stage approach was able to yield a classification accuracy of 91.02%, while the two-stage approach was able to achieve up to 94.29% in the same.

This study can be further extended in two aspects. Firstly, other ML and DL algorithms with better severity-specific accuracy can be investigated and augmented to the second-stage of the proposed two-stage approach. Secondly, other neurological disorders can also be investigated and augmented to the first-stage.

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