DEEP LEARNING BASED ANATOMICAL BRAIN SEGMENTATION AND CLASSIFICATION OF ALZHEIMER'S STAGES USING MULTI-FACET FEATURES

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Abstract

Alzheimer's Disease (AD) has emerged as one of the serious causes of death worldwide effecting the elderly population. As the development of this disease is related to neuronal loss in brain sub regions, the focus of this paper is on segmenting the brain into sub regions like GM (Grey Matter), WM (White Matter) and CSF (Cerebrospinal Fluid) followed by AD classification. This paper presents a complete framework for AD classification using feature maps of segmented tissue of brain. Two novel approaches have been proposed for classification task, where in first approach Self-Augmenting CNN and in the second approach Modified ResNet model has been used. Segmentation model achieves the highest similarity score of 99.53% for DS (Dice Similarity) and 99.09% for IOU (Intersection of Union) on GM segment. For Multi-class classification, accuracy of 97.92% is achieved with Self-augmenting CNN, while Modified-ResNet model achieves 98.75% accuracy on segmented feature maps.

Keywords*:* Alzheimer's Disease, Transfer Learning, Structural MRI, Convolutional Neural Network.

1. Introduction

Alzheimer's disease (AD) is a neurological brain disorder that causes deterioration of the brain cells, eventually leading to the loss of ability to do everyday tasks [1,2]. The exact cause of AD is not fully understood and no effective treatment exists to combat the progression of the disease. But early diagnosis of AD may assist in reducing the rate of progression and may also enhance the quality of life of patient [3,4]. AD is a type of dementia in which the tissues of the brain get gradually destroyed, leading to a breakdown of neuronal functions and atrophy [5]. The transitional stage between cognitive healthy person and AD patient is MCI which is hard to detect. For individuals over the age of 60, it is estimated that 15-20% suffer from MCI, and roughly 30-35% of those with MCI progresses to Alzheimer's Disease within four years [6].

Deterioration in neurons is observed initially in GM and later spreads to other sub regions of brain like WM, and CSF. The idea is to study the factors and brain sub-regions which are highly contributing to the symptoms of AD and its different stages. This analysis requires segmenting the brain-sub-regions and a novel proposal in its classification which is a research element of this article. This work includes novel framework for classifying stages of AD using segmented feature maps obtained from Unet based hybrid model and further classification using self-Augmenting CNN model and Modified ResNet model on both segmented as well as complete MRI images.

The remainder of this paper is organized in following sections. In section 2 related work has been summarized, and in section 3 problem statement with solution plan has been discussed in brief. Proposed methodology has been explained in detail in section 4. Section 5 contains the experimental results for segmentation and classification. Finally, we conclude our paper in section 6 with challenges and future scope.

2. Related Work

MRI has emerged as the main diagnostic tool of AD for clinicians. The MRI scans of AD patients are generally used to determine the progression of this disease by assessing the atrophy in brain tissues. In [3], MRI volume is sliced into voxels and pre-processed using Gaussian filter followed by skull stripping. The model obtained good accuracy for binary classification but for multi-class classification only 86.70% is achieved. In [4] the authors employed multiple parallel 3D convolutional networks where each model is applied to individual tissue region like GM, WM, and CSF. Although the model gave robust results on randomly partitioned dataset but it lacked in focusing on MCI stage of the disease. In [7], the authors proposed an ensemble learning technique using 2D CNN to classify AD, MCI and CN stages of disease. The model gave good result in classifying AD/CN stages but for AD/MCI and MCI/CN classification, less accuracy of just 77.2% and 72.40% was obtained. The article [10] mainly focuses on Hippocampus segmentation using two architectures based on U-Net. In first architecture simple hyperparameter tuning is performed whereas in second ReNet blocks are under U-net architecture. Among the proposed models ResuNet achieved dice similarity score of 94% and classification accuracy of 93%.

In [13], auto-encoders are ensembled to obtain features from an 3D input image. Number of subjects used for classifying AD, MCI and CN stages were 200, 400 and 200 respectively. GM is extracted using segmentation technique. Our work introduces a framework where features are extracted from segmented tissue regions instead of directly extracting from whole MRI images, thus enhacing the efficiency of classification.

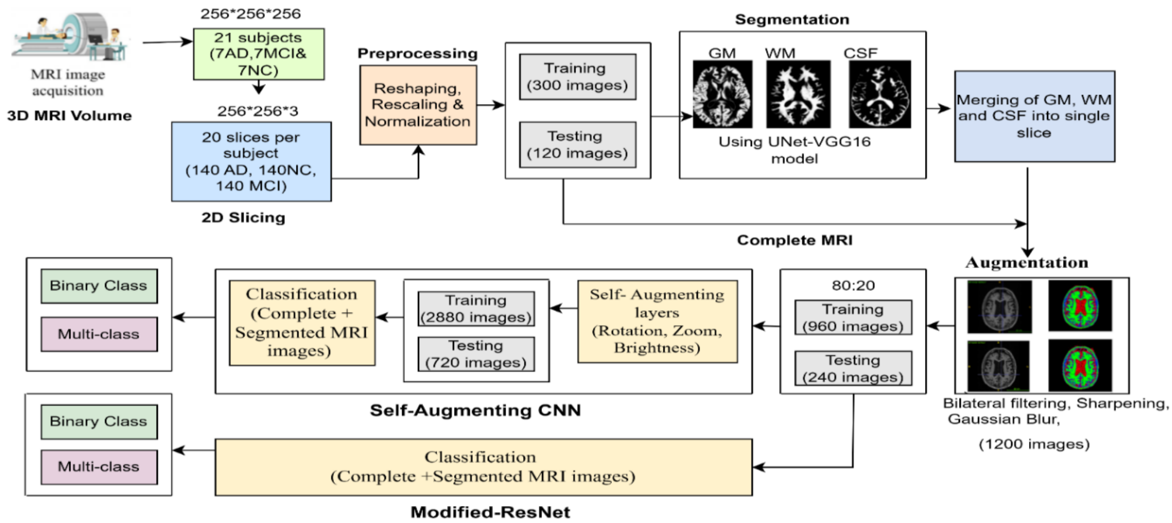


FIGURE 1. The detailed pipelined architecture of the proposed framework

TABLE 1 Demographic features of ADNI dataset

Data source	Research Group	Number of Subjects	Image Slices per subject	Total images	Male / Female	Age (In years)	Imaging Protocols
ADNI	NC	7	20	140	5M/2F	55-80	Axial, 3D, T1W & T2 W,1.5 & 3T field strength
	MCI	7	20	140	6M/1F	70-90	
	AD	7	20	140	4M/3F	60-85	

3. Problem Statement and Solution Plan

Segmentation and classification of medical MRI images using deep learning has gained sufficient popularity due to its global adaptability. we propose a novel deep learning scheme to detect various stages of Alzheimer's disease using binary as well as multi-class classification approaches on small dataset. The main contributions of this paper are listed as follows:

- U-Net based hybrid model has been proposed for segmenting the MRI images into GM, WM and CSF subregions separately.
- Feature maps obtained through segmented tissue regions are passed through different channels of RGB image to obtain a Composite Feature Map, which later is used for classification.
- For classification, two novel approaches have been proposed. In first approach, a Self-Augmenting CNN model with all customized attributes has been built and in second approach Modified-ResNet model has been proposed. These classification models are developed with novel feature engineering through brain MRI segmentation.
- The proposed methodology explores effect of using the complete MRI as well as segmented MRI images for generating complimentary features for AD classification. Here, it produces best performance outcomes in terms of accuracy, sensitivity, and specificity.

4. Methods and Materials

The complete workflow of the framework has been shown in Fig. 1.

4.1 Data handling and Preprocessing

Data used in our work are obtained from ADNI (ADNI | Alzheimer's Disease Neuroimaging Initiative (usc.edu)) dataset which is publicly available online. 3D MRI

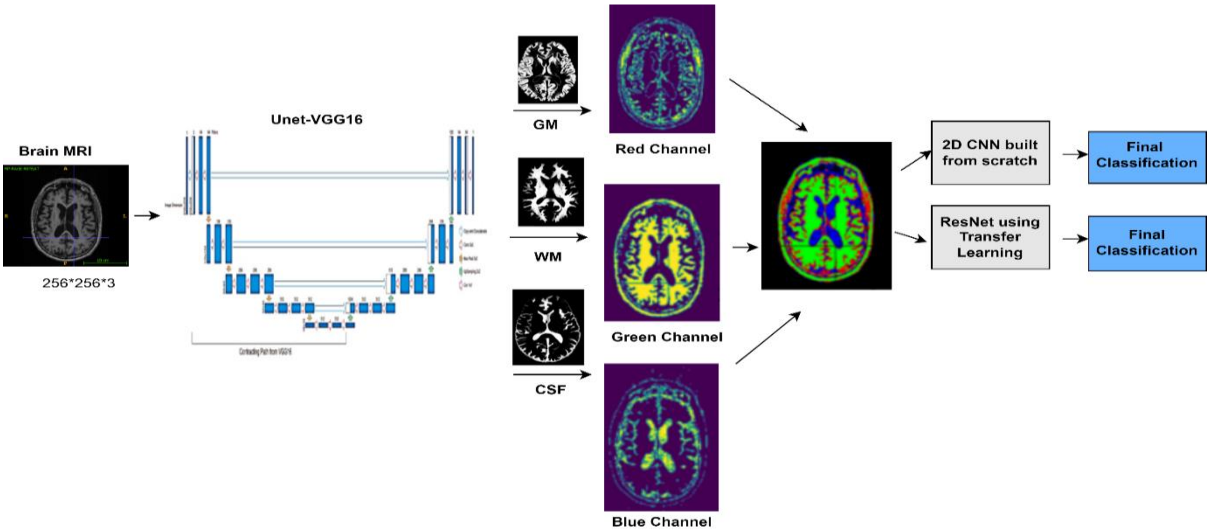


FIGURE 2. Segmented sub-regions sent through different channels of RGB image for classification

volume has been downloaded for the experiment in the NIfTI (Neuroimaging Informatics Technology Initiative) format [8,9]. **Table 1** depicts the demographic data of the subjects from the ADNI dataset.

4.2 Preprocessing

The data available in form of 3D volume (NIfTI format) is converted into 2D slices in DICOM (Digital imaging and communication in medicine) format and thereafter reshaped to size of 256×256. Reshaping is done to change the number of pixels and aspect ratio of an image to match the desired input size for the model. Further rescaling operation is performed to adjust the intensity value of the pixel between 0 to 255. Finally, normalization is performed which ensures that all pixel values lie within a certain range thus reducing the variations like contrast, brightness etc in images.

4.3 Proposed Segmentation Method

Performing segmentation of brain MRI before classification is important in analysis and diagnosis of medical images. Segmented data can be analysed more accurately as it isolates and clearly identifies various structures in brain. For segmentation of 2D MRI slices UNet-VGG16 architecture has been used where GM, WM and CSF brain sub-regions were separately fed into the segmentation model separately. U-Net architecture has been preferred due to its excellent performance in biomedical image segmentation tasks and its capability of learning from very small training sets. The choice of VGG16 was made due to its similarity with U-Net's contracted layer.

In the proposed method VGG16 architecture is used in encoder and decoder sections of the U-Net model. The skip connection between layers of encoder and decoder sections are used to combine the corresponding feature maps through concatenation operation [9,11]. The proposed method does not freeze the contraction layer in UNet-VGG16, so the weighted layers get updated while executing training data. The number of trainable parameters is 23,748,241 and that of non-trainable parameter is 4,032. A novel approach has been applied in which segmented GM, WM and CSF are sent through three different channels of RGB image, where GM was sent through red channel of RGB image, WM through green channel and CSF through blue channel. These are later merged before the classification is performed. The main benefit of using this approach is that the regions and edges of all three sub-regions are clearly visible and easily distinguishable which proved helpful during classification. Fig 2 represents the Segmented sub-regions sent through different channels of RGB image for classification.

For classification of AD, two novel approaches have been proposed. In the first approach Self-Augmenting CNN has been proposed. In this approach model performs data augmentation within the training loop, allowing the model to generate

4.4 Proposed Classification Model

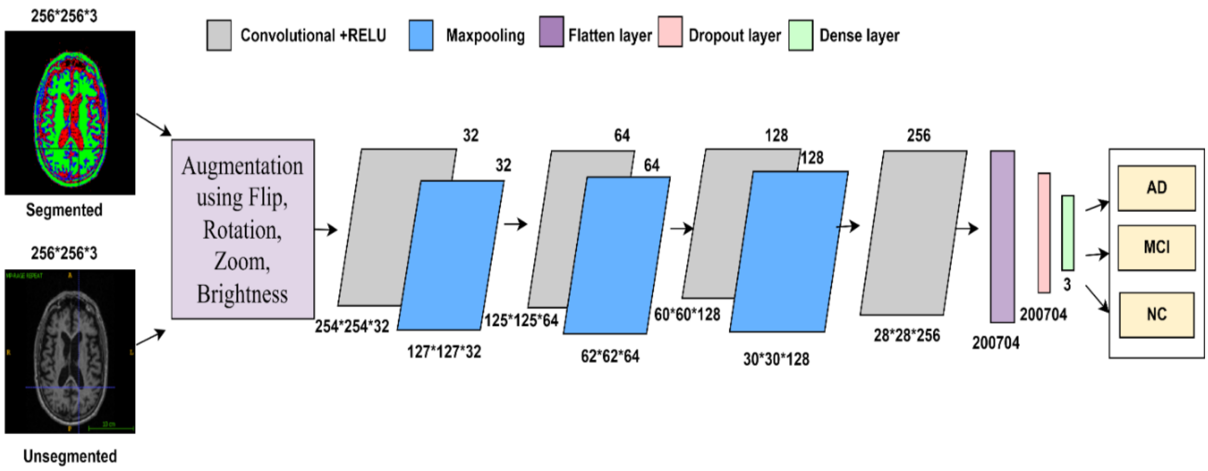


FIGURE 3. Block diagram of proposed Self-augmenting CNN model

augmented versions of its own training data during training. To achieve this, data augmentation layers have been incorporated within the model architecture, as shown in Fig 3.

In the second approach Modified ResNet model has been proposed. MRI images of size 256×256 are given as input to the ResNet model and after the second convolution block the subsequent block layers are replaced with new layers. After the second convolution four convolutional layers, three max-pooling layers were added followed by flatten, dropout and dense layer. Replacing layers, helped in customizing the architecture that better suited the task we are working on. ResNet's skip connections facilitate the flow of gradients during backpropagation, making it easier to train deeper networks [11,12]. The reuse of early layers of ResNet and replacing the later layers leverage the pre-trained feature extraction capabilities while training task-specific layers. It is also helpful in reducing the computational complexity of model making it efficient for resource constrained devices. The number of trainable parameters is 545,379 and that of non-trainable parameter is 86,400.

5. Experimentation and Results

In this work, to validate the performance of the proposed models we have performed several experiments for segmentation part and the classification part of the problem. The models proposed for segmentation and classification have been implemented using Python version 3 run on Google Colab with GPU Tesla T4, NVIDIA CUDA version 12.0 on 2.20 GHz Intel Xeon processor and 24 GB RAM.

5.1 Segmentation

In the proposed work MRI slices are segmented into three brain sub-regions GM, WM, and CSF. During the training process the model was trained using Adam optimizer with 20, 14 and 50 epochs for GM, WM, and CSF respectively. The size of convolution kernel is 3×3 and the max pooling of 2×2 is done with stride 1. Relu is used as activation function for hidden layers and Sigmoid function in dense layer. Batch size is set to 32 with learning rate 0.001. Number of images used for segmentation was 300 where each stage consisted 100 images. These training samples were split in the ratio 80:20 making 240 images for training and 60 images for testing purpose. We analysed similarity measures such as DS (Dice similarity) and IOU (Intersection of union) to detect the overlapping regions between ground truth and segmented regions. The model achieves the highest similarity score of 99.53% for DS and 99.09% for IOU on GM segment. Whereas overall score obtained for DS and IOU is 98.86% and 96.79% respectively.

5.2 Classification

Binary as well as multi-class classification was performed on three stages of Alzheimer's disease AD, MCI, and CN on both segmented as well as unsegmented MRI images. During training process, the model was trained using Adam optimizer with 20 epochs for binary and multi-class. The size of convolution kernel is 3×3 and that of max pooling is 2×2 with stride 1. Relu is used as activation function for hidden layers and Softmax function in dense layer. Batch size is set to 32 with learning rate 0.001 and dropout as 0.5. Categorical cross entropy has been used as loss function. In the first approach self-augmenting CNN model is proposed. It increased the training set size to 2880 and test set size to 720 for multi-class and for binary class training and test set size increased to 1920 and 480 images respectively. The Figure 4 presents the accuracy obtained by Self-Augmenting CNN for each class where we can observe accuracy obtained on segmented images is more than that of complete MRI images. For binary class AD/CN and MCI/CN achieves the highest accuracy of 99.80% on segmented as well as on unsegmented images. Whereas accuracy of 97.92% and 96.25% is achieved for multi-class on both segmented and unsegmented images respectively.

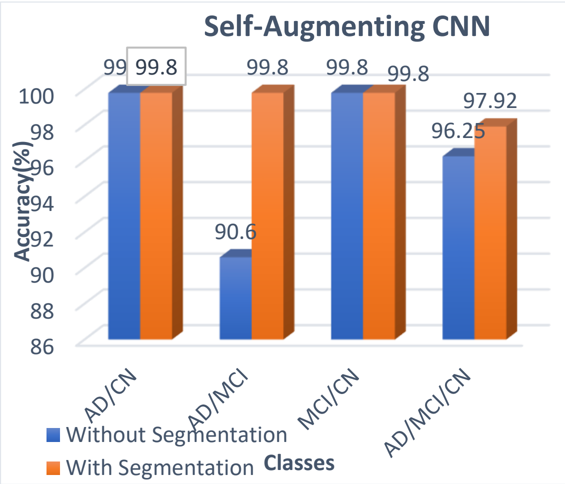


FIGURE 4. Accuracy graph for all the four stages using Self-Augmenting CNN

In the second approach for Modified-ResNet model the training set size is 960 images and test set size 240 images for multi-class and for binary class training and test set size is 640 images and 160 images respectively. The Figure 5 represents the accuracy obtained by Modified-ResNet model.

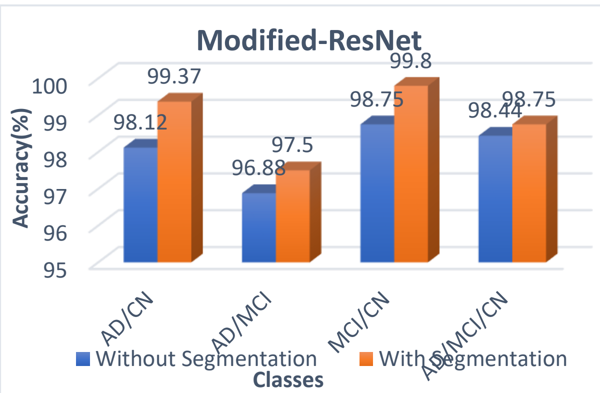
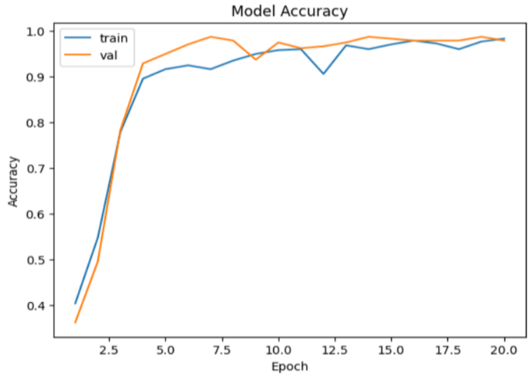
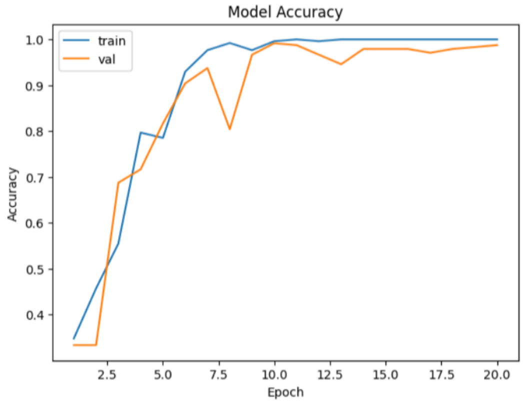


FIGURE 5. Accuracy graph for all the four stages using Modified ResNet

From the result obtained we can observe that accuracy over segmented images is more compared to the case with complete MRI image for each class. For binary class MCI/CN achieves the highest accuracy of 99.80% on segmented images and 98.75% on unsegmented images. Whereas accuracy of 98.74% and 98.44% is achieved for multi-class on both segmented and unsegmented images respectively. Fig 6(a) presents the accuracy curves for segmented image when Self-Augmenting CNN is used, and Fig 6(b) presents accuracy graphs obtained when Modified-ResNet is used.



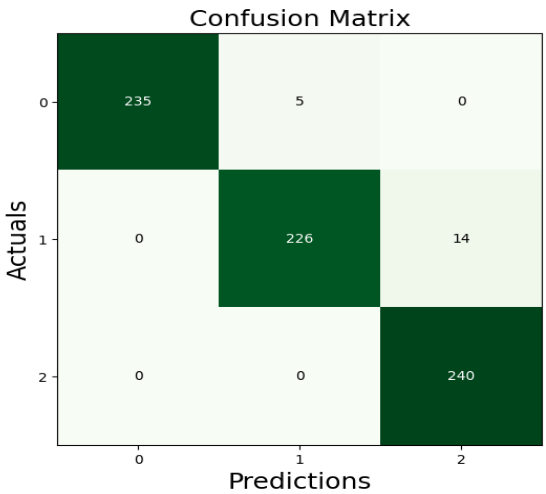
(a)



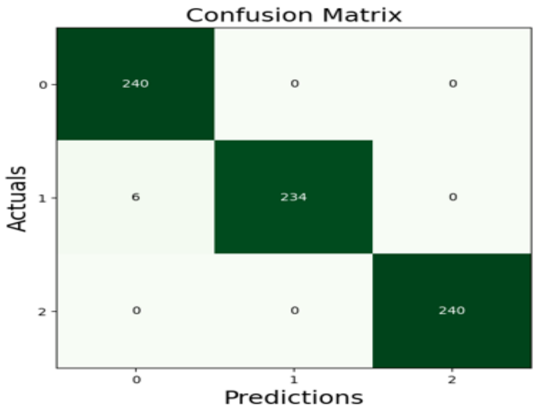
(b)

FIGURE 6. Learning curve for training and Validation accuracy for multi-class classification on Segmented images when a) Self-Augmenting CNN b) Modified-ResNet is used

From the above figures we can observe that the accuracy curves for both training and validation is continuously increasing in both cases.



(a)



(b)

Fig.7 Confusion matrix for multi-class classification on Segmented images when a) Self-augmenting CNN b) Modified-ResNet is used

Moreover, the gap between both the curves in very less, thus we can say that our proposed model acquires a good fit on segmented MRI images. Figure 7(a) and 7(b) presents the confusion matrix from the results obtained from both the model.

6. Conclusion and Future Scope

In this paper, a complete framework for medical image segmentation and classification for the detection of AD is proposed based on deep learning models. Brain MRI is segmented into various sub-regions like GM, WM, and CSF using U-net based hybrid model. Classification is performed on both segmented as well as complete MRI images. Two novel approaches are used for classification purpose. In first approach Self-Augmenting CNN whereas in second approach Modified-ResNet model is proposed. The efficiency of models is evaluated using five performance metrics and results are compared with the existing state-of-the-art approaches. From the above empirical findings, we can say that the proposed models comprise of simple structures that helps in reducing the amount of computation, and memory requirements. It also provided a goodfit in manageable time and with small dataset. Our model not only gave better result for binary classification but also outperformed for the multi-class classification. For the future research we have planned to work on other imaging modalities like PET, DTI, fMRI etc and explore other deep models.

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