Differentiation of Alzheimer Conditions in MR Brain Images Using a Single Inception Module Network

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Abstract. In this study, an attempt has been made to differentiate Alzheimer's Disease (AD) stages in structural Magnetic Resonance (MR) images using single inception module network. For this, T1-weighted MR brain images of AD, mild cognitive impairment and Normal Controls (NC) are obtained from a public database. From the images, significant features are extracted and classified using an inception module network. The performance of the model is computed and analyzed for different input image sizes. Results show that the single inception module is able to classify AD stages using MR images. The end-to-end network differentiates AD from NC with 85% precision. The model is found to be effective for varied sizes of input images. Since the proposed approach is able to categorize AD stages, single inception module networks could be used for the automated AD diagnosis with minimum medical expertise.

Keywords. Alzheimer's Disease, Mild cognitive impairment, Magnetic Resonance Imaging, Inception module

1. Introduction

Alzheimer's Disease (AD) is the most dominant type of dementia, leading to progressive and irreversible loss in cognitive abilities. It is estimated that by 2050, 152 million populations worldwide will suffer from AD [1]. Due to the increasing prevalence, accurate diagnosis of the prodromal stage of AD, Mild Cognitive Impairment (MCI), is crucial for delaying the progression of the disease [2].

The brain atrophy associated with AD is considered to be a significant biomarker in characterizing the disease progression [3]. Structural Magnetic Resonance Imaging (sMRI) is a widely preferred non-invasive neuroimaging technique for analyzing the tissue losses in the brain regions. Based on sMRI estimates, several Computer-Aided Decision support (CAD) systems have been developed for the early prediction of AD [2][3]. Some of the CAD approaches include k-nearest neighbor [3] and support vector

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machine [2]. These methods employ handcrafted features which may not be suitable with subsequent classifiers, thus leading to reduction in the performance of the system.

Recently, Convolutional Neural Networks (CNNs) achieve competitive performance in classifying medical images. Due to the ability to perform task-specific feature extraction for constructing classifiers, CNNs have been widely utilized in developing CAD systems for AD diagnosis [10]. A deep CNN model has been used to differentiate AD stages from axial view MR brain images [8]. Hippocampal regions have been extracted from sMRI to train 2D CNN for AD prediction [4].

In this work, an analysis on the effect of a single inception module network in the automated differentiation of AD, MCI and NC subjects using sMRI brain images has been carried out [5]. A single layer end-to-end inception network is developed for characterizing the AD stages with a limited training dataset. The performance of the model is computed and analyzed by tuning the size of input images.

2. Methods

2.1. Image Database

The T1-weighted brain MR images of 29 AD, 63 MCI and 92 NC subjects are acquired from the Open Access Series of Imaging Studies (OASIS) cross-sectional database [6]. The subjects are divided into AD, MCI and NC based on Clinical Dementia Rating. Out of 176 slices, 90th slice in the sagittal and trans-axial view are considered in the study [2][3]. In this study, all the images are converted into grayscale format and are resized to 256 x 256, 128 x 128 and 64 x 64 to study the effect of size of the input image on the performance of the inception network.

2.2. Network Architecture

To extract features and differentiate AD, MCI and NC MR brain images, an inception network is employed, the pipeline of which is shown in Figure 1. The network comprises Convolutional (Conv) layers of different sizes, Maximum (Max) and average pooling layers, a Fully Connected Layer (FCL) and a softmax layer. In order to align the patches, inception architecture employs convolution filters of sizes 1 x 1 (Conv 1), 3 x 3 (Conv 3) and 5 x 5 (Conv 5) [5]. Rectified linear unit is used as the non-linear activation function in the proposed network. An FCL that connects all the neurons from the preceding layer is employed [5]. The outputs of the non-linear softmax activation are used as probability scores for classification.
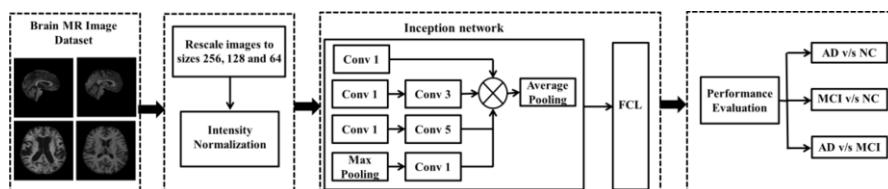

Figure 1. Block diagram of study

In this study, the inception network consists of three Conv layers and a Max pooling layer. Each Conv layer has varying number of filters such as 4, 8, 16, 24 and 32 and is all zero-padded. The Max pooling layer has a pool size and stride of 2 and 1

respectively. These layers are concatenated which are further fed into an average pooling layer of size 3. The number of epochs and batch size are fixed empirically to 50 and 10 respectively. An Adam optimizer with a learning rate of 0.01 is used.

The input images are split into training and testing set at a ratio of 80–20. The network is trained and tested for three binary classification problems (AD v/s NC; AD v/s MCI and MCI v/s NC). The performance of the model is evaluated using performance matrices such as accuracy, recall, precision and F-measure [2][3].

3. Results and Discussion

The representative brain MR images of AD (a, d), MCI (b, e) and NC (c, f) subjects are shown in Figure 2. It is observed that the white matter structures such as corpus callosum, brainstem and cerebellum are clearly visible in the sagittal view images. An enlargement in the lateral ventricles is observed in the trans-axial view images from NC to AD subjects. It is seen that the brain structures have different sizes and shapes as the diseases progresses.
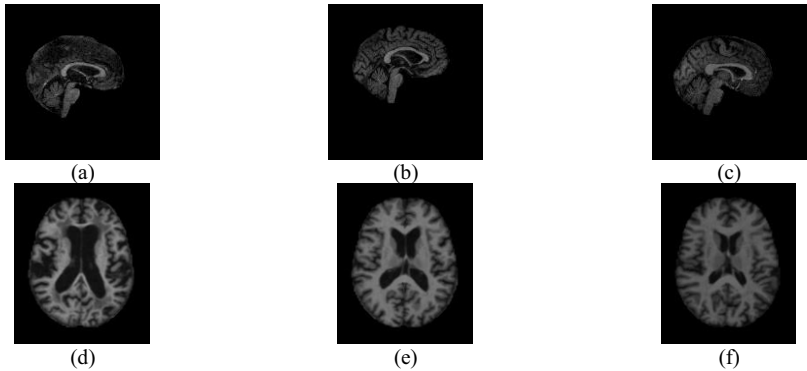

| (a) | (b) | (c) |
| (d) | (e) | (f) |

Figure 2. Representative MR brain images in sagittal (a-c) and trans-axial (d-f) view of AD (a,d), MCI (b,e) and NC (c, f) subjects

The training accuracy and loss of the inception network for varying number of epochs using different input image sizes is shown in Figure 3 (a-c) and Figure 3 (d-f) respectively. It is seen from Figure 3 that for all the binary classifications, AD v/s NC (a, d), MCI v/s NC (b, e) and AD v/s MCI (c, f), the variations in the accuracy and training loss with number of epochs are maximum when image size is 256 and minimum for an image size of 64. It is found that the accuracy decreases with the decrease in image size and remains almost constant throughout the training process.

The diagnostic performance of the inception network in differentiating AD v/s NC, MCI v/s NC and AD v/s MCI for different input image sizes is tabulated in Table 1. It is seen that the accuracy and recall of the model in differentiating AD and NC remains similar when image sizes are 256 and 128. For AD v/s MCI, the maximum accuracy is observed for an image size of 256. The approach exhibits maximum performance in differentiating AD and NC. A maximum performance of 70% is observed in differentiating MCI and NC when the image size is 128. The least performance of model is obtained in categorizing AD and MCI. This could be due to subtle changes in the brain structures with disease progression.
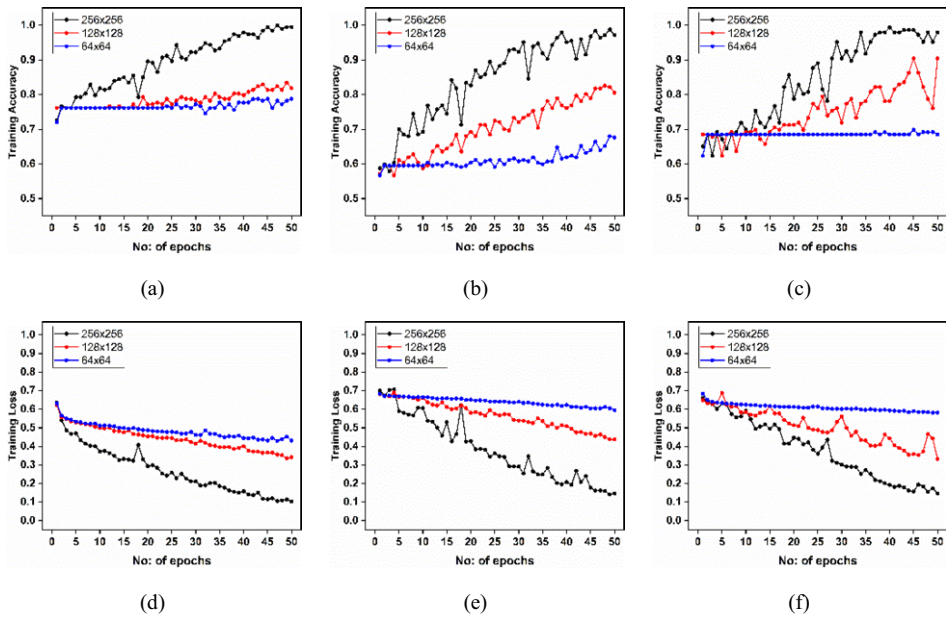
(a)   (b)   (c)

(d)   (e)   (f)

Figure 3. Variations in training accuracy and loss for varied number of epochs using different input image sizes AD v/s NC (a, d), MCI v/s NC (b, e) and AD v/s MCI (c, f)

Table 1. Performance (%) of the proposed method in classifying AD v/s NC, MCI v/s NC and AD v/s MCI

Image size	Class	Accuracy	Precision	Recall	F-measure
256x256	AD v/s NC	78	78	78	**78**
	MCI v/s NC	59	57	59	57
	AD v/s MCI	**68**	**67**	**68**	**68**
128x128	AD v/s NC	78	75	78	72
	MCI v/s NC	**70**	**70**	**70**	**70**
	AD v/s MCI	58	54	58	55
64x64	AD v/s NC	**82**	**85**	**82**	77
	MCI v/s NC	60	59	60	53
	AD v/s MCI	61	45	61	52

Table 2. Performance (%) comparison of the proposed approach with the state-of-the-art methods

Author	Class	Model	Learning	Accuracy	F-measure
Islam and Zhang [7]	Multiclass	Deep CNN	FS	73.75	-
Hon and Khan [8]	AD v/s NC	VGG16	FS	74.12	-
Puente-Castro et al. [9]	AD v/s NC	ResNet	TL	86.47	32.07
Proposed method	AD v/s NC	Single Layer Inception Network	FS	82	77
	MCI v/s NC			70	70
	AD v/s MCI			68	68

FS – From Scratch; TL – Transfer Learning

F-measure is a widely used evaluation metric to assess the performance of binary classification problems. It is the harmonic mean of recall and precision and is a reasonable measure for the evaluation of imbalanced classes [10]. In this study, the proposed model achieves an F-measure of 78%, 70% and 68% in differentiating AD

v/s NC, MCI v/s NC and AD v/s MCI respectively, validating the reliability of the model.

The performance of the proposed approach has been compared with the state-of-the-art methods using OASIS database (see Table 2). Hon and Khan [8] have proposed a VGG16 trained model to classify AD from NC and obtained an accuracy of 74.12%. Recently, transfer learning has been used to differentiate AD and NC [9].

A limitation of this study is that the parameters used for fine-tuning the network is based on random search method [11]. In future, optimization can be used to determine the tuning parameters. Also, the confidence of the model can be improved by using large number of clinical images with adaptive learning and cross-database training.

4. Conclusion

CNNs are widely used in AD prediction due to their ability to perform task-oriented feature extraction and classification. In this study, an end-to-end single layer inception module network has been developed for predicting AD stages. The key contribution of the study is to analyze the discriminative ability of the inception network in classifying AD stages using different sizes of MR images. The results indicate that the performance of the model varies with the image size. The model achieves highest performance in differentiating AD from NC. Thus single inception module networks could be used for the automated AD diagnosis with minimum medical expertise.

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