Different Stages Of Alzheimer's Disease Classification Using Deep Convolutional Neural Network

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Abstract

Alzheimer's disease is a progressive disorder that causes the brain cells to waste away and die that is the most common typical explanation for insanity. It causes the continues decline in thinking and also behaviour, and disrupts a person's to perform function independently. The early stage of Alzheimer's disease is MCI. There are two types of MCI is available. That is Early Mild Cognitive Impairment (EMCI) and Late Mild Cognitive Impairment (LMCI). T1 weighted MRI image is employed as a dataset that has been downloaded from Alzheimer's Disease Neuroimaging Initiative (ADNI). This work build and validate the deep learning algorithm for predicting the individual diagnosis of Alzheimer's disease (AD), Mild Cognitive Impairment (MCI) and Cognitive Normal (CN) based on T1 w Magnetic Resonance Imaging (MRI) input images. Using Convolutional Neural Network (CNN) architecture, we successfully classified different stages of AD with highest accuracy.

Keywords: *Convolutional Neural Network, Alzheimer's disease, Mild cognitive impairment, Cognitive Normal, ADNI, MRI image.*

1. Introduction

Alzheimer's disease (AD) is one in all the foremost growing disease that have an effects on human's behaviour and additionally affect the daily activities of human. Nerve cell harm and death will cause the brain's inability to transmit and store data. The signs and symptoms of Alzheimer's disease will vary from person to person. Behavioural symptoms are communication impairments, needing facilitate to hold out tasks, obtaining lost in places that were once acquainted, etc. Physical symptoms are tremors, weakness of muscles, and lack of balance and loss of weight. The initial stage of AD is memory loss which is the one constituent of Mild Cognitive Impairment (MCI). MCI is the early stage of AD. If MCI gets severe it will be reborn into AD that cannot be curable.

In recent years numerous methods are introduced to exploits MRI data for distinguishing AD and its dementia stages that are LMCI, EMCI, and CN. With the recent developments of deep learning approach, Convolutional Neural Network (CNN) algorithm is used for medical imaging applications. Solely many deep learning strategies are used for classification of neuro-images into different diagnosis groups. In this paper, we tend to build a 2D Convolutional Neural Network(CNN) and supply a straightforward technique to interpret totally different regions of the brain. Our method uses MRI data and utilizes a simple data augmentation strategy of downsampled MRI images for training purposes. Experiments on the ADNI dataset show superior results of our model that is CNN architecture.

2. Literature Survey

Imaging used for diagnosing different stages of Alzheimer's disease is explained in [4]. Classification of AD, CN, EMCI and LMCI patients has been established in several machine learning algorithm[3] using MRI input images particularly in Support Vector Machine(SVM) [1] which extract the high dimensional informative features from MRI. However, feature definition and extractions are typically difficult.SVM is the complex to image processing , time consuming and computational demanding[7]. Author proposed Random forest prediction for diagnosing Alzheimer's disease using pairwise

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selection from time series data [2]. [5] MRI scan can be used for image processing to estimate the possibility of AD and their stages. Image processing technique used in MRI are clustering, k-Means and Region growing algorithm to extract the white and grey matter. [6] Random forest prediction of alzheimer's disease using pairwise selection from time series data. The TADPOLE grand challenge is current used as a datasets for classification of AD stages. The operation of ImageNet Convolutional Neural network is explain in [9]. In [10], author described how video can be classified in large scale using deep convolutional neural networks.

3. Datasets and Methods

In this section, we will present datasets used in this work and methods to define the classification of disease.2D MRI is a powerful imaging modularity for the classification of diseases. We proposed a deep learning framework based on CNN architecture.

3.1. Datasets

In these studies, all datasets were obtained from Alzheimer's Disease Neuroimaging Initiative(ADNI) which are available publically on the website **http://adni.loni.usc.edu/data-samples/access-data/.** ADNI database was launched in 2003 by the National Institute on Aging(NIA). ADNI dataset is to used to test the serial magnetic resonance imaging(MRI), positron emission tomography(PET) and other biological markers of EMCI, LMCI, AD, and CN. Specific goals of ADNI included the development of optimized and standardized methods for use across multiple centers.

3.2. Subjects

In this paper, we used MRI imaging data from the baseline visit of database of ADNI for evaluation. These imaging data were acquired from 577 ADNI participants this includes 165 AD,66 CN, 198 EMCI and 148 LMCI subjects whcich includes both testing and validation data. Table 1. represents the details of the studied subjects in this paper that are CN,EMCI,LMCI and AD.

Table 1. Demographic details of subjects

Diagnosis	Number	Age	Gender (M/F)
AD	165	30 to 90	93/72
CN	66	35 to 96	22/44
LMCI	198	32 to 89	117/81
EMCI	142	36 to 92	59/83

Table 2. Dataset splitup for training and validation

CLASSIFICATION	TRAINING		VALIDATION	
AD-CN:	AD	CN	AD	CN
	115	50	50	16
AD-EMCI:	AD	EMCI	AD	EMCI
	115	153	50	45
AD-LMCI:	AD	LMCI	AD	LMCI
	115	100	50	42

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CN-EMCI:	CN	EMCI	CN	EMCI
	50	153	16	45
CN-LMCI:	CN	LMCI	CN	LMCI
	50	100	16	42
EMCI-LMCI:	EMCI	LMCI	EMCI	LMCI
	153	100	45	42

4. CNN based Prediction model

CNN is a type of feed-forward artificial neural network which has been specifically used for image classification which has four layers that are convolutional layer, Dropout layer, Pooling layer, and Fully connected layer[8]. In the convolutional layer, the system reads an image as pixels and it is expressed as a matrix. Input for the system is 512x512 RGB image which has 3 channels. This layer uses the learnable filters which detect the presence of specific features present in the original image and that can be used for image classification. Different filters which detects different features that are convolved on the input file and a set of activation maps is generated as output which is passed to the next layer in the CNN. The activation function is used to decide if the neuron would fire or not. Rectified Linear Unit (ReLU) activation function is used as an activation function in all the layers except the output layer. The main advantage of ReLU is that it does not activate all the neurons at the same time. If the input of ReLU is positive value then output is same as input, if the input is negative value it is converted into 0. In practice, ReLU converges six times faster than the other activation functions. The Pooling layer is considered as one of the convolution layer. This layer basically reduces the number of parameters in the network, it reducing the spatial size of the network to controlling the over fitting. The operation involved in this layer is Average pooling or Maximum pooling.

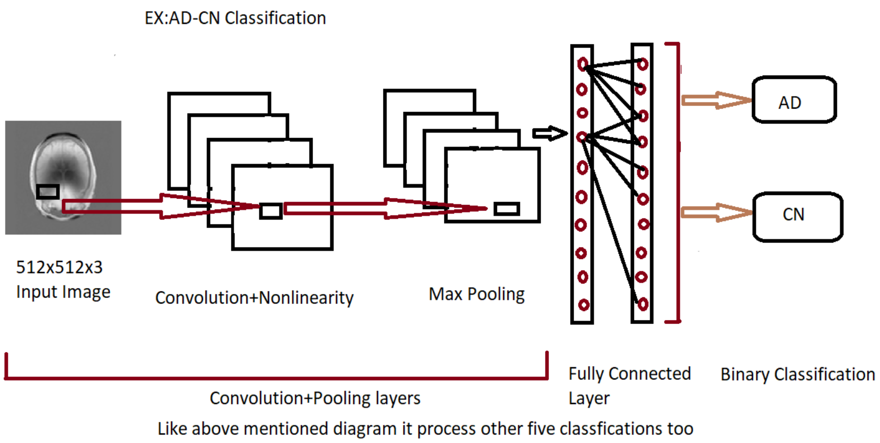

Figure 1. CNN Architecture for Diagnosing Alzhemer's Disease

Max pooling is mostly used operation. It will take out only the maximum value from the pool which is done with the use of filters and for every stride maximum parameter is taken out and rest of the parameters are dropped. This can be down-samples the neural input. At last, Fully connected layer which have a complete connection to all the activations from the previous layers. The number of nodes in this layer is same as number of classes to be predicted. This is the last phase of the CNN

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architecture. Figure.1 represents how MRI images are processed through the CNN layers. The layers and parameter of the CNN model is given below in Figure 2.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 511, 511, 16)	208
activation_1 (Activation)	(None, 511, 511, 16)	0
dropout_1 (Dropout)	(None, 511, 511, 16)	0
max_pooling2d_1 (MaxPooling2	(None, 255, 255, 16)	0
conv2d_2 (Conv2D)	(None, 254, 254, 32)	2080
activation_2 (Activation)	(None, 254, 254, 32)	0
dropout_2 (Dropout)	(None, 254, 254, 32)	0
max_pooling2d_2 (MaxPooling2	(None, 127, 127, 32)	0
conv2d_3 (Conv2D)	(None, 126, 126, 64)	8256
activation_3 (Activation)	(None, 126, 126, 64)	0
dropout_3 (Dropout)	(None, 126, 126, 64)	0
max_pooling2d_3 (MaxPooling2	(None, 63, 63, 64)	0
conv2d_4 (Conv2D)	(None, 62, 62, 128)	32896
activation_4 (Activation)	(None, 62, 62, 128)	0
dropout_4 (Dropout)	(None, 62, 62, 128)	0
max_pooling2d_4 (MaxPooling2	(None, 31, 31, 128)	0
flatten_1 (Flatten)	(None, 123008)	0
dense_1 (Dense)	(None, 64)	7872576
activation_5 (Activation)	(None, 64)	0
dropout_5 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 1)	65
activation_6 (Activation)	(None, 1)	0

Total params: 7,916,081
Trainable params: 7,916,081
Non-trainable params: 0

Figure 2. Layers and Parameters in CNN Model

4.1. Flow of process involved in CNN model

The sequence of steps involved in the CNN based prediction model is described in Figure 3. This model consists of different modules for performing each step is given below:

- Load the dataset to the algorithm.
- Preprocess the dataset involves reshaping the image size and image augmentation which involves shear range and zoom range.
- Divide the dataset into training dataset and validation dataset.
- Design the CNN model for predicting alzheimer's disease with appropriate activation function and loss function.
- Train the network model with samples in training dataset.
- Validate the network with samples in validation dataset.
- Repeat training and validation until to achieve desired accuracy with lesser amount of loss.
- Using the trained model, we can predict the disease in real time image data

For classification AD stages cover some of the modules and algorithm for processing. MRI input images are taken from the image reader. Afterwards we can choose the best suitable algorithm for the classification. In this work CNN is used as a deep learning algorithm for classification. When performing deep learning feature extraction, Pre trained network is used as a feature extractor which allows the input image to propagate forward to the layers and taking the output of the particular layer as a feature. In this work, activation functions ReLU and Sigmoid are used. ReLU is used in all the hidden layers and Sigmoid is used in output layer. Sigmoid function gives binary values 0 or 1 as an

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output. ReLU always gives the positive value. If the input is positive then output is same as input, otherwise the output is 0.

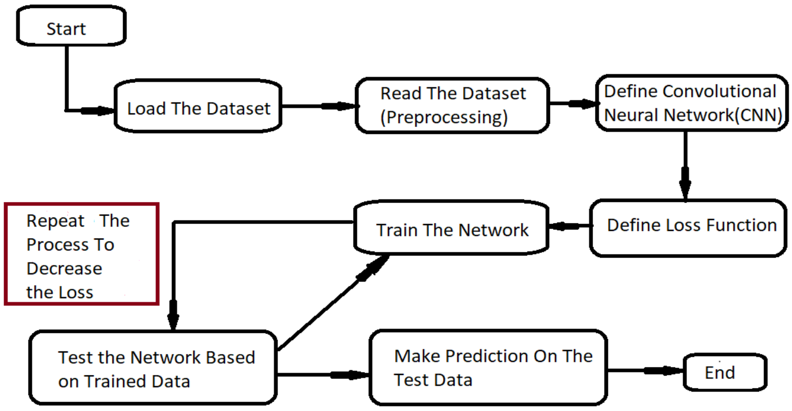

Figure 3. Flow of Process involved in CNN Model

The Sigmoid activation function is used in the last layer of CNN model. It is defined as

$$s(t)=1/(1+e^{-t})$$

Where

$$t = \sum_{i=1}^{n} w_i x_i + b$$

$w_1, w_2, w_3, \ldots w_n$ are weights used for the 'n' input features $x_1, x_2, x_3 \ldots x_n$ respectively. The value b is a bias used in the output layer. Initially these weights are choosen randomly and then its is updated based on the loss function it is updated. Loss function updated in this model is Mean Square Error(MSE).

4.2. Performance Metrics

This work considers accuracy and loss as the metrics for analyzing the performance of the proposed system. Accuracy is referred as how close the computed classified value to the correct value and which also ensures that the model success. Loss value represents how well or poorly the algorithm works. The loss must be below 25% then only the system gives moderate or good performance. If not we need to optimize the model or train with more data.

4.3. Result Analysis

In this work, CNN is trained by applying ADNI dataset for the purpose of classification of different AD stages. We run all the classifications and take accuracy with four convolution layer for 5 epochs, 10 epochs and 15 epochs. When increasing number of epochs accuracy is increased and loss gets reduced. Accuracy achieved in 6 different binary classification models are mentioned in the Table.3,4,5,6,7 and 8 for the classification between the stages AD vs CN, AD vs EMCI, AD vs LMCI, CN vs EMCI, CN vs LMCI and EMCI vs LMCI respectively.

Table 3. Performance Analysis of AD-CN

PARAMETERS	5 EPOCH	10 EPOCH	15 EPOCH
Training Loss	10.59	8.85	7.82

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Training Accuracy	84.81	87.52	89.21
Validation Loss	14.36	13.8	12.16
Validation Accuracy	82.7	84.74	87.52

Table 4. Performance Analysis of AD-EMCI

PARAMETERS	5 EPOCH	10 EPOCH	15 EPOCH
Training Loss	12.67	8.29	7.27
Training Accuracy	81.37	88.6	89.61
Validation Loss	22.13	15.73	18.46
Validation Accuracy	74.67	85.24	88.3

Table 5. Performance Analysis of AD-LMCI

PARAMETERS	5 EPOCH	10 EPOCH	15 EPOCH
Training Loss	6.41	3.74	2.75
Training Accuracy	91.16	95.1	96.27
Validation Loss	16.83	15.65	13.76
Validation Accuracy	90.16	91.15	91.34

Table 6. Performance Analysis of CN-EMCI

PARAMETERS	5 EPOCH	10 EPOCH	15 EPOCH
Training Loss	12.67	7.14	4.76
Training Accuracy	81.37	90.97	94.23
Validation Loss	17.13	16.18	13.04
Validation Accuracy	79.67	89.41	91.41

Table 7. Performance Analysis of CN-LMCI

PARAMETERS	5 EPOCH	10 EPOCH	15 EPOCH
Training Loss	3.58	6.27	3.58
Training Accuracy	95.6	92.34	95.6
Validation Loss	18.02	20.22	18.02
Validation Accuracy	89.64	90.41	92.64

Table 8. Performance Analysis of EMCI-LMCI

PARAMETERS	5 EPOCH	10 EPOCH	15 EPOCH
Training Loss	12.17	8.47	6.78
Training Accuracy	82.75	88.55	91.37
Validation Loss	16.57	19.26	17.56
Validation Accuracy	80.95	83.36	88.87

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Figure 4. describes the comparison between training accuracy and validation accuracy for various stages of alzheimer's disease classification. This figures shows training accuracy is somewhat higher than the validation accuracy. Accuracy can be increased by increasing number of input samples taken in each stage, appropriate number of filters to be selected, proper optimization function, appropriate number of layers to be used in the model. If the model takes too many parameters then size of the model is increased. We should reduce the size of model by using dropout layer in the appropriate convolution layers.

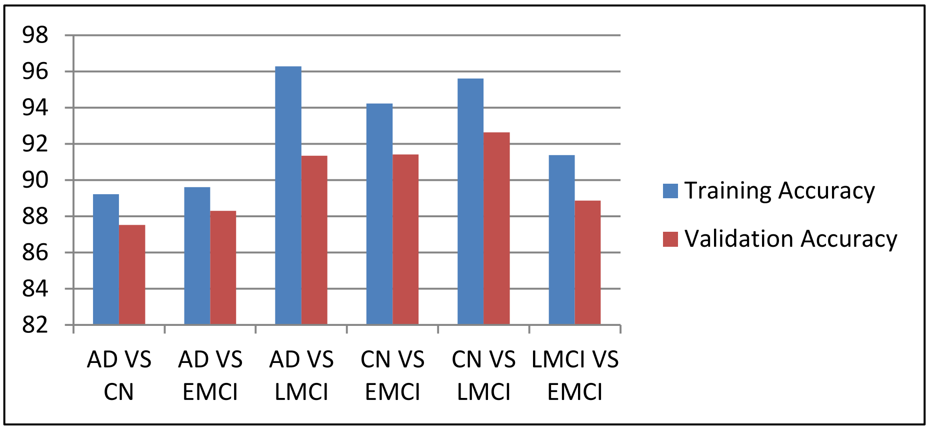

Figure 4. Performance Comparison of Different Stages of AD Classification

5. Conclusion

In this paper, we have proposed a classification framework based on deep Convolutional Neural Network architecture to capture the rich feature using the 2D T1 weighted MRI input images. There is no need for performing segmentation before extracting the features. The experimental result on the ADNI dataset have been shown that the proposed method has achieved higher performance for classification of AD and their stages.

6. Future Work

Future work will focus on performance improvement of the CNN model. The high accuracy can be achieved in a CNN model by increasing the number of images used for training and validation and also CNN model can be further improved by fine tuning. This studies mainly focused on the sagittal view of the T1 weighted MRI images. As a future enhancement, other views that is coronal and axial view which can be used as a identification of the landmark of the disease using both CNN and VGG16 architecture.

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