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A 2D-CNN Based System for the Classification of Alzheimer's Disease Using Brain MRI Scans

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Abstract.

Alzheimer's disease (AD) is a commonly spread brain illness. A computer-assisted method becomes vital for accurate and timely AD categorization. Deep learning algorithms offer substantial advantages over machine learning techniques. The execution of deep learning is extremely efficient in the area of AD diagnosis from MR brain scans. The principal aim of the projected model is to discover the outcome using a Convolutional Neural Network (CNN) applied to the MR scans for AD classification. A variety of CNN architectures are available. The projected model is an implementation of basic construction with a change as per the convolutional layer's kernel size and its strides. The study proposes a sequential CNN system for AD categorization. The proposed system reached 98.78% classification accuracy on the 'Alzheimer's Disease Neuroimaging Initiative (ADNI)' dataset for the multiclass categorization of AD. The outcomes were promising for the detection of AD.

Keywords: Alzheimer's disease, Convolutional Neural Network, MRI scans.

1 Introduction

Alzheimer's Disease (AD) is an advanced neurological disorder. It is a neural illness in which the demise of nerve cells is responsible for cognitive impairment and amnesia. Also, it is a form of dementia and has a terrible influence on the patient and the social interactions of the family members [11]. A primary AD analysis is truly helpful, as no proper treatment is available to cure the disease [1]. The most substantial risk components for AD are patient histories and the existence of associated genes in an individual's genome. The most important objective of AD diagnosis is to determine whether the person has MCI or not [24]. Thus, it is crucial for appropriate treatment to design policies for the discovery of MCI at the initial phase to avoid its progression to AD [7]. Previously, a lot of research work was concentrated on the AD vs. NC problem. Such studies were used only to understand the early signs of AD [10].

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According to recent statistics, the number of dementia patients will be more than 131.5 million in 2050. Mild cognitive impairment (MCI) is a transitional state from cognitively normal (CN) to Alzheimer's. The transformation rate of MCI to AD is close to 10% [1]. Apart from blood or cerebrospinal fluid, MR scans are other biomarkers that imply early diagnosis of AD [12]. MRI is often used in AD detection and forecasting. MRI measures are superior to other techniques in several ways. It is not expensive and is used in many medical situations [5].

In computational intelligence, deep learning (DL) is a machine learning subclass that imitates the way the human brain analyses the data and identifies designs to address intricate decision-making challenges. DL methods have given nearly accurate performance in several areas including classification [14]. In the sphere of medical imaging, DL is very successful especially, in the classification of 2D images.

DL is of excessive attention to numerous technical disciplines, particularly medical image analysis. DL is currently an extremely successful machine learning technique for numerous medical applications. The study of deep learning methods in AD has drawn attention over the past many years [6]. DL procedures have prominent advantages over regular machine learning algorithms. Such methods can retrieve data representations automatically from images without much preprocessing. This feature makes methods fast and focused on objectives. These algorithms are most suitable for the analysis of high-dimensional medical images obtained from different modalities. The increase in processing capability has permitted the creation of innovative DL algorithms [25].

In the realm of preventive imaging, DL algorithms such as CNNs—have demonstrated encouraging outcomes in illness identification. Deep learning models can recognize patterns linked to the disease and reveal representations using neuroimaging data, connecting seemingly unrelated areas of images [6]. DL algorithms have been effectively useful in investigating medical images such as MRI, X-ray, and USG. Such algorithms have been widely used by researchers for the identification of AD from Medical images. Deep learning is attracting neuroscientists due to its capabilities to address the complexities involved in neuroimaging [3].

CNNs are multilayer backpropagation networks. CNNs can learn high-dimensional non-linear mappings from a rich pool of images to manufacture them for use in image identification, subdivision, and diagnosis [2]. CNNs are an effective explanation for most visual imaginary problems and demonstrated remarkable efficacy in diagnosing AD. The efficacy of CNN is apparent in its comprehensive implementation areas, both as an autonomous prototype and as a network mechanism [17]. A CNN network involves various convolutional layers and then non-linear activations. The non-linearity offers learning through backpropagation. A CNN consists of many convolutional blocks. A convolutional block has a convolution layer, activation function, batch normalization, and pooling layer. Pooling's objective is to downsample the feature map and batch normalization is implemented after convolution to standardize the batch of data. It normalizes the preceding activation to improve the performance and steadiness of CNN. A basic CNN structure is shown in Fig. 1. Both 2-D and 3-D CNNs can be applied in AD classification.

ADNI is an open library accessible for neuroimaging data that is used for research work on AD. It is the library that enables simpler access for researchers to existing information on AD or linked disorders. The rest of the document is prearranged as follows: the related work is described in sect. 2. Sect. 3 presents the materials and methods; outcomes are discussed in sect. 4. Finally, sect. 5 finishes the paper.

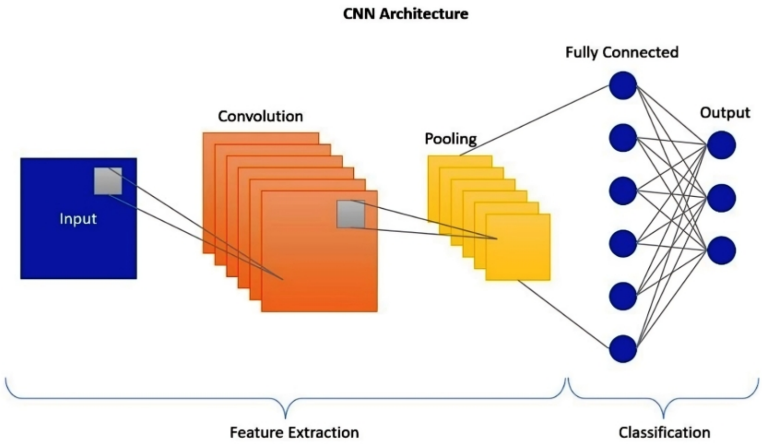

Fig. 1. The basic structure of Convolutional Neural Network.

2 Related Work

There are two common approaches to AD-categorization. Many studies have performed two-class categorization or binary-classification in which the images are identified in two classes: CN against AD or MCI. In the second approach, multi-classification is performed, which categorizes the illness into many categories such as CN, AD, MCI, etc. Table 1 displays the AD-classification studies based on CNN.

Authors in [15] proposed research to recognize several AD classes, making use of a DNN pipeline on MR scans and using ROC examination to confirm the robustness of the framework.

Authors in [20] employed a hybrid approach based on CNN-SVM, attained an accuracy of 94.57% and concluded that computational intelligence resolves the challenges in diagnostic imaging.

Authors in [8] suggested a U-Net architecture system for AD detection which automatically divides the left and right hippocampus and the achieved accuracies were 93.61% & 95.17% for 2D &3D multiclass phase categorization.

Authors in [21] extracted substantial features from imaging data efficiently and observed the association between brain parts and the progressive decline of AD.

Authors in [1] projected a sequential CNN framework for two-class and multiclass categorization and achieved great outcomes. The attained accuracy was 99.8 % for binary classification and 97.5% for multiclass classification.

Authors in [23] designed a framework demonstrating that the patients in the normal control group with MCI are less able to distinguish between healthy people who have AD and those who do not. The study's conclusions were 83% correct for CNN.

Authors in [22] assessed the translation risk from MCI to AD. The Region of Interest is preferred over the regular region because it can enhance the discriminative ability in ML.

Authors in [4] suggested a hybrid system based on CNN-RNN to improve the illness categorization. Spatial and longitudinal characteristics were extracted using CNN & RNN. The obtained accuracy is 91.33%.

Authors in [13] performed brain image analysis on multimodal data to obtain improved outcomes and exhibit improved accuracy [13]. Authors in [19] suggested a decision-making system to predict the probability of moving from MCI to AD. A high-volume dataset needs to be employed for training of CNN framework.

Authors in [9] presented a transfer learning- approach for AD identification. It was observed that on a low volume of training datasets, the model gives an improved performance. It was presented that hyperparameters tunning is required using grid search to attain better results.

Authors in [18] executed a system on the dataset to classify AD using LeNet CNN architecture and reached an accuracy of 96.85%. The paper proposed that for higher accuracy more layers are required to be added to the CNN model.

Authors in [16] discovered that the 3D approach achieved better accuracy for 3-way classification and attaining accuracies for 2D and 3D are 85.53% & 89.47% respectively. Summary of CNN approaches for AD prediction is given in Table 1.

Table 1. Summary of CNN approaches for AD prediction.

Model used	Data description	Data archive	Performance
DNN [15]	MR T1-weighted scans	ADNI & OASIS	Accuracy=99.68%, sensitivity=100%, specificity=100%
CNN-SVM [20]	MR T1-weighted scans	ADNI	Accuracy=95.47%
U-Net [8]	MR T1-weighted scans	ADNI	Accuracy(2D)= 93.61% Accuracy(2D)= 95.17%
CNN-SVM [21]	MR T1-weighted scans	NA-ADNI	Accuracy= 0.88 AUC= 0.95
CNN [1]	MR scans	ADNI	Accuracy=97.5% for multiclass, 99.8% for two class
CNN [23]	MR scans	OASIS	Accuracy =83%

CNN [22]	MR Images	ADNI	Accuracy =97.58%, 67.33%, and 84.71% for GoogleNet Accuracy = 98.71%, 72.04%, and 92.35% for CaffeNet
CNN-RNN [4]	T1-weighted structural MR scans	ADNI	Accuracy = 91.33% (AD vs. NC)
CNN [13]	T1-weighted MR scans	ADNI	Accuracy = 89.5%
CNN-SVM [19]	MR Brain scans	ADNI	Accuracy =91% for Linear Kernel, Accuracy =90.0% for Polynomial kernel RBF kernel= 92.33%
VGG16 [9]	Structural MR scans	OASIS	Accuracy using VGG16 = 92.3%
LeNet CNN [18]	MRI 3D MP-RAGE Sequence	ADNI	Accuracy =96.85%
CNN [16]	MR scans	ADNI	Accuracy(2D)= 85.53% Accuracy(3D)= 89.47%

3 Materials and methods

This paper offers a sequential CNN system for AD categorization. The model includes data acquisition, preprocessing, augmentation, model preparation, AD-classification and validation as the main steps. The pipeline diagram in Fig. 2 shows the flow regarding the suggested model.

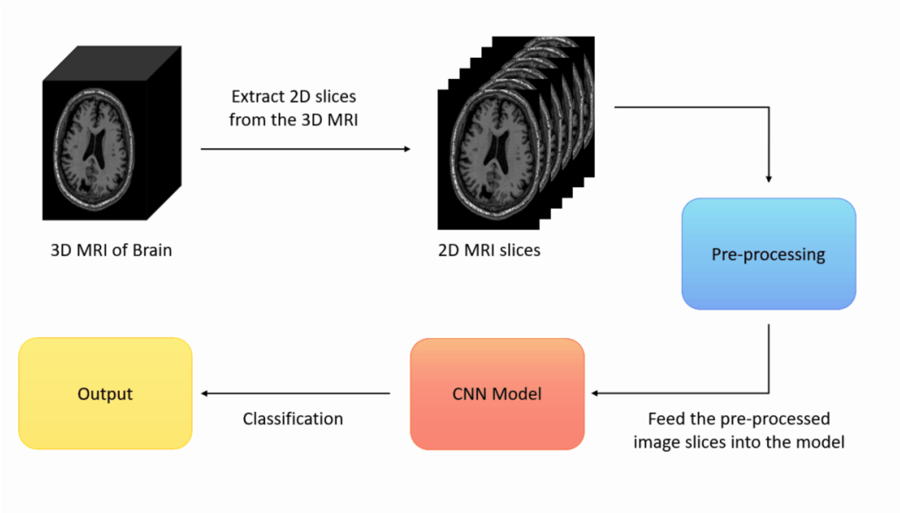

Fig. 2. The pipeline diagram of the proposed model.

3.1 Data Acquisition and Data Augmentation

The data archive for the analysis is a publicly accessible dataset of brain MRI scans from the ADNI. It has a total of 5164 3-D MRI images. The extraction of 2-D slices from the images has been performed. The total number of images after augmentation reaches 19292 of three different classes AD, MCI, and CN. Fig. 3 shows the brain MRI scans of all three classes. Data augmentation factors include rotation with 10 degrees, horizontal and vertical flips, brightness shifting with a range of 0.3 to 1.7, shearing with a range of 0.8, and zooming with a range of 0.2. Although, shearing and zooming the images has increased the dataset size but it led to distorted MRIs and loss of information, so these two factors were removed finally. Preprocessing was performed to prepare the images for statistical analysis.

3.2 Proposed Method

Convolutional Neural Networks (CNNs) excel at handling extensive datasets of visual information, including images and video content. Their structure, which features multiple layers built around convolutional operations, draws inspiration from the biological organization of the visual cortex in the brain. CNNs are particularly effective on datasets with numerous nodes and parameters.

The study has proposed 27 layers in the complete CNN's architecture. The description of different layers is mentioned in Table 2. The data records were divided into training and testing datasets, 80 % of scans were used for training the model, and 20% of scans were designated for testing. In the training dataset, 20% of scans were used for validation. A validation set is utilized to fine-tune the hyperparameters and considered as part of the model training. The model has used an Adam (Adaptive momentum estimation) optimizer to perform backpropagation in case of loss. The learning rate has been set to 10^{-4}. Detailed information on layers is provided in consecutive sections.

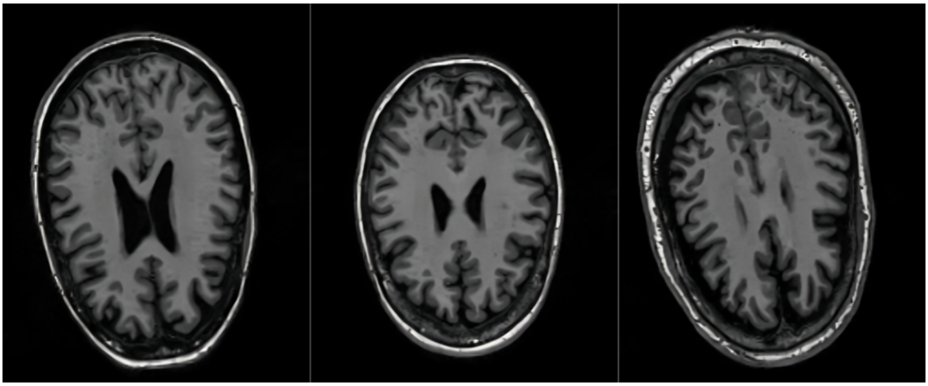

Fig. 3. Sample MRI Brain scans of CN, MCI, and AD.

3.2.1 Convolutional Layer

This is the crucial part of a CNN that extracts all related patterns and features present in the inputs. This layer performs a 2D convolution on the input data, by maintaining the height and width and increasing the channels up to the same number of kernels used as shown in (1), i.e. 32 output channels using 32 kernels of size 3x3 and a stride of 1 shown in (2).

Sample convolution operation:

$$(width, height, channel) = [\left(\frac{w+2p-f}{s}+1\right), \left(\frac{h+2p-f}{s}+1\right), c'] \tag{1}$$

w = width, h = height, c=channel, c'=number of kernels,
p=padding, s=stride, f=size of kernels

$$(160, 160, 32) = [\left(\frac{160+2(1)-3}{1}+1\right), \left(\frac{256+2(1)-3}{1}+1\right), 32] \tag{2}$$

3.2.2 Activation Layer

The activation function provides non-linearity. The non-linearity helps in backpropagation learning. This layer's key work is to nonlinearly transform the input signal into an output signal so that the subsequent layer can use it as an input. There are a variety of activations such as Sigmoid, tanh, ReLU, ELU, etc are not linear [2].

3.2.3 Batch Normalization

Batch normalization is employed to normalize the inputs of the preceding layer helping with the training speed and stability of the neural network. It is used to standardize the batch of data after the convolution operation. It performs the normalization of images in batches [2]. In the proposed model, 16 images were taken in a batch. It helps in improving training speed and gives stability to the network.

3.2.4 Max Pooling Layer

Pooling is employed to downsample the feature map. It is a contraction layer. It contracts the convolutional block. It is imperative to reduce the number of parameters and equations in the model to limit the volume of spatial depiction. It is applied in each convolution block after batch normalization. It is used to compact images and reduces overfitting [2].

3.2.5 Flatten Layer

The Flatten layer flattens the input into a 1D array from a 3D array, making the data ready for the fully connected layers. The flatten layer transforms the output of the preceding layer into a one-dimensional vector so that it can be supplied into subsequent fully connected layers.

3.2.6 Dense Layer

In a densely connected layer of neurons, each neuron is fully connected to every neuron present in the next layer, for non-linearity, the ReLU activation function is used. All neurons have contributed to the output image. Fully Connected layer is a deep neural network used for classification.

3.2.7 Dropout Layer

The dropout layer helps in the prevention of overfitting. This layer randomly sets a fraction of input units from the previous layer to 0 at each update during training. In this proposed architecture approximately 20% of neurons were dropped using the dropout layer to avoid overfitting. This layer enhances the generalizability of the model.

3.2.8 Output Layer

The last tier of the system is the output layer. The final layer has 3 neurons representing the classes or categories in the categorization task. The softmax activation function is used in the last layer to get the probability for each class, with the classified class having the highest likelihood. It is used in the case of multiclass categorization.

Table 2. Description of Layers.

Layer Name	Type	No. of layers	Description
Conv2D	Convolutional Layer	5	This layer performs a convolution operation on the input image to create an output of the same height and width with ‘n’ channels by using ‘n’ kernels of size m x m.
ReLU	Activation Function Layer	5	Applies a non-linearity to the previous layer's output by setting negative values to zero.
BatchNorm	Batch Normalization Layer	5	Normalizes the batch output from the previous layer, helping with the training speed and stability of the neural network.
MaxPool2D	Max Pooling Layer	5	Performs 2D max pooling, reducing the spatial dimensions of the input by taking the maximum value in a pool size of 2x2, thereby downsampling the data.
Flatten	Flatten layer	1	Flattens the input into a 1D array, preparing the data for the fully connected layers.
Dense	Fully Connected layer	3	A densely connected layer with a series of neurons each connected to every neuron in the previous layer.
Dropout	Dropout Layer	2	Randomly drops the information when passing from one layer to another in each iteration during the training process, which helps prevent overfitting.
Output	Output Layer	1	The final output layer with 3 neurons representing the classes or categories in the classification task.

4 Results and discussion

The experiments were achieved with the following hardware specifications: 15GB Tesla T4 GPU; 13GB RAM; Intel Xeon CPU with 2 vCPUs and software specifications: Python programming language (3.10.12), and TensorFlow (2.15.0).

In the CNN architecture, filter sizes are (3,3) and (2,2) for the convolutional and max-pooling layers respectively. A Filter is a small matrix used for modifying the frequency of contents of input. It slides along the input matrix and generates a feature map. The total parameters in the model are 12,288,963- 12,287,491 trainable parameters and 1472 non-trainable parameters. Trainable parameters are modified throughout the training procedure, while non-trainable parameters are remained constant. A loss function is employed to determine the loss between ground truth labels and the anticipated labels. Fig. 4 shows the loss graph to demonstrate the decrease in loss value as the number of epochs increased.

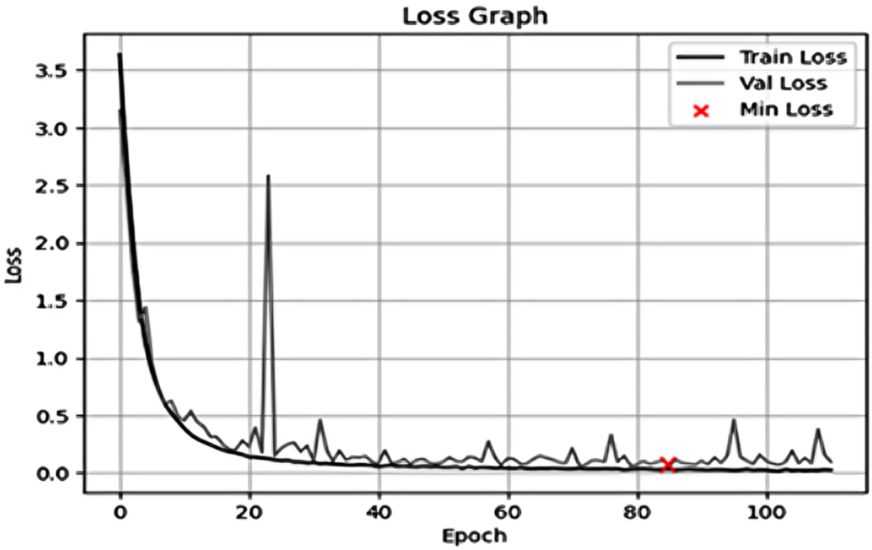

Fig. 4. The loss graph for the suggested CNN architecture.

The experiment findings demonstrate that our proposed CNN model achieves leading edge performance in AD confirmation. The model has achieved excellent accuracy. It indicates its ability for the use of AD diagnosis in the clinical environment.

The identical quantity of illustrations was constantly processed from every group. In each epoch, it's arbitrarily experimented with individual class. The model worked with an overall batch size of sixteen illustrations. It is detected that most models start getting underfit or overfit at some point after getting trained for some number of epochs. Early stopping is applied to avoid unnecessarily model training for full epochs even when the model is not learning anymore, i.e. validation loss is not decreasing. For the proposed model the training was triggered with 150 epochs set initially, and got early stopped when there was no more enhancement noticed in validation loss after the 86th epoch.

The efficacy of the processing pipeline is assessed. Fig. 5 shows the accuracy value for the presented architecture. The classification report indicates that the model has reached an accuracy of 98.78%, which shows it appropriately forecasts the class labels for approximately 99% of the scans in the dataset. This suggests that the model is doing exceptionally well in classifying the data.

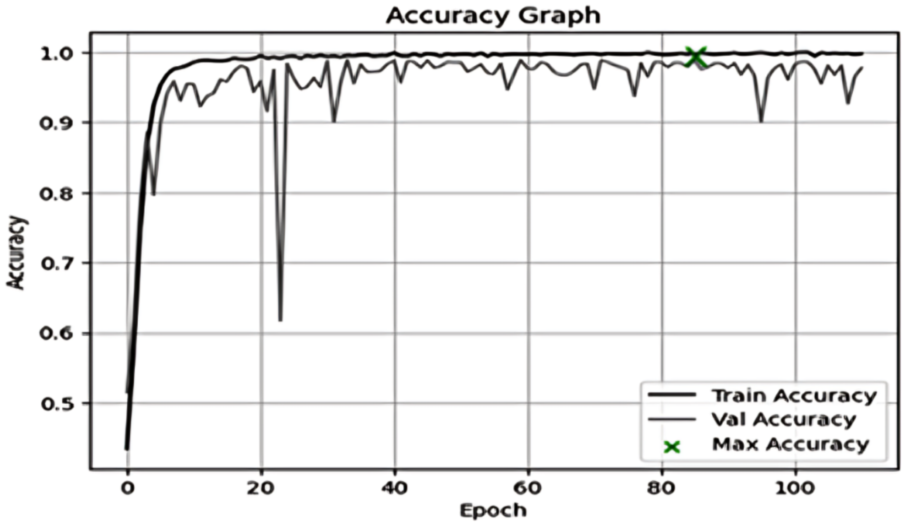

Fig. 5. The accuracy value for the suggested CNN architecture.

5 Conclusion

The initial discovery of AD is critical to enhance the lives of the people affected by this neurological disease. A huge population is suffering from irreparable disorder. This paper projected a sequential layered framework for AD categorization based on convolutional neural networks. Deep learning approaches such as CNN are used to diagnose AD on MRI brain scans. In the first step, the ADNI dataset with 3D brain images was acquired, and 2D slices were extracted. Then the 2D slices of the MRI were pre-processed to make it feedable to the CNN model. Finally, the model is trained to perform the categorization of AD. The achieved classification efficacy is 98.78%, which shows the model is doing exceptionally well in the classification task. The model can help caregivers to make decisions about patient's medical care policies, and it can offer assistance in the progress and assessment of novel remedies for AD by categorizing people at high risk for the illness.

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