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Improved Classification Model using CNN for Detection of Alzheimer's Disease

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Abstract: Alzheimer's Disease (AD) is commonly called a neurodegenerative disorder and it is a common form of dementia. There is no permanent cure for this brain disease hence the early diagnosis of such disease using medical imaging system is highly significant. Machine learning models play a vital role in the detection of AD. Since most of the conventional machine learning models find it difficult to detect the essential features to classify the disease, an advanced deep learning framework called Convolutional Neural Network (CNN) is used in this study to detect essential features automatically and classify the disease. The building components of the proposed CNN-based classification method include convolution layer, batch normalization process, ReLU, and Max-pooling operation. The main objective of this CNN-based classification method is to predict whether the patient is suffering from Alzheimer's disease through the analysis of brain MRI. The proposed methodology implemented is identical to a classification-based system that undergoes training, evaluation, and testing process. Finally, the softmax layer is applied for classification, and the Adam optimization technique is applied for reducing the loss, and by applying Adam quicker convergence can be achieved. The proposed improved CNN classification method achieves an accuracy of 97.8%.

Keywords: Alzheimer's Disease Detection, Magnetic Resonance Imaging, Convolution Neural Network, Deep Learning

Introduction

Alzheimer's disease is a neuropsychiatric ailment that causes memory loss in persons over the age of 65. Alzheimer's disease affects 50 million people worldwide, with the number expected to nearly quadruple by 2050.The aberrant build-up of proteins in and around brain cells is assumed to be the origin of AD. The brain tissues get damaged due to Alzheimer's disease and it may lead to nerve cell death if it was not diagnosed in its earlier stages. AD leads to memory loss and also disrupts the human body's functions like speaking, writing, and reading. Alzheimer's disease patients usually suffer from lung dysfunction, malnutrition, cognitive impairment (Soysal *et al*., 2014), and functional dependence. Precise and accurate detection of AD is quietly not possible since improper medications are required. Detection of AD in its earlier stages (also called a pre-clinical stage) can save the patient's life and also helps in the retreatment process (Dubois *et al*., 2016). The symptoms of AD will develop slowly but the defection effects are severe when it starts in the human brain (Picón *et al*., 2019). Several medical tests are required to detect Alzheimer's and it leads to the generation of multivariate heterogeneous data (Davuluri and Rengaswamy, 2020). A standard medical workup for Alzheimer's disease often includes structural imaging with Magnetic Resonance Imaging (MRI) or Computed Tomography (CT) (Davuluri and Rengaswamy, 2022a).

To resolve various kind of problems that is related to brain image data analysis can be done by using Machine Learning (ML) and deep CNN based approaches (Mehmood *et al*., 2020). For diagnosing the disease, MRI is used (Davuluri and Rengaswamy, 2022b). Deep Learning (DL) algorithms are mostly applied for object recognition tasks and competitions like Imagenet Large Scale Visual Recognition Challenge (ILSVRC) (Russakovsky *et al*., 2015) that intersect with time and increased use of medical records and image detection process. DL algorithms are mostly used to analyze large datasets and it is very useful for the diagnosis of AD. CNN is an effective technique to detect and classify Alzheimer's and its stages using brain MRI images (Salehi *et al*., 2020).

The convolutional network effect and its accuracy are investigated in the large-scale image detection setting (Simonyan and Zisserman, 2014). By using the increasing depth architecture, the network evaluation is carried out and very small convolution filters of size (3 x 3) are used.

Related Works

Several research works have been carried out for the classification of images using CNN technique. The basic and most significant task of visual recognition is image classification. The architecture of CNN is applied to the other recognition tasks such as object detection and localization, semantic segmentation, etc. These recognition tasks are generally obtained from the network architecture in the process of image classification (Wang *et al*., 2019). For the classification of MRI images, a learning algorithm is built by using CNN. In specific the 3-Dimensional (3D) CNN (3D-CNN) and fully stacked bidirectional long short-term memory (FSBi-LSTM) are exploited in this learning algorithm. The 3D-CNN is initially designed for deriving the representation of deep features from both MRI and positron emission tomography. Later FSBi-LSTM has applied deep featured maps of concealed spatial information that helps in improve the performance further. The average accuracies obtained during differentiating the AD class from the Normal Control (NC) Class, Mild Cognitive Impairment (MCI) class from NC class MCI class from AD class are 94.82, 86.36, and 65.35% respectively (Feng *et al*., 2019). A DL technique is applied to classify the AD subjects (Sarraf and Tofighi, 2016). Here high to low-level features are extracted using the scale and shift-invariant method from the whole brain data by using CNN architecture. DL approach based on CNN model was proposed to identify the AD classes with good accuracy and here to design the convolutional neural network the leaky Rectified Linear Unit (ReLU) and max-pooling layers are applied. In addition, the activation functions such as Sigmoid, ReLU, and leaky ReLU were also applied. The 3 pooling functions used here were also tested with 3 factors such as max-pooling, average pooling, and stochastic pooling (Wang *et al*., 2018).

For the classification process, a framework using a combination of fuzzy C-means and weighted probabilistic NN was presented. The research began with the extraction of RoI from brain MRI images that were associated to the Hippocampus and Posterior Cingulate Cortex (Duraisamy *et al*., 2019). Apprehensive data samples are deleted from the training data to improve classification performance. When compared to previous machine learning algorithms, DL approaches offer significant and notable benefits (Esteva *et al*., 2019). For instance, pre-processing is not required using DL approaches and an optimum data representation can be generated automatically from the gathered raw images. Furthermore, there is no need to select features beforehand. As a result, DL algorithms produce processing that is more objective, takes less time, and is less biased (Vieira *et al*., 2017). Large-scale data processing and high-dimensional medical imaging analysis are particularly suited for DL approaches (Zhou *et al*., 2021). The convolutional layer, pooling layer, and fully connected layer are the three basic layers that make up the unique convolutional neural network design (Yamashita *et al*., 2018).

CNN model works with the concept called parameter sharing i.e., multiple neurons share the same weights among them in the particular feature map. Each neural that is connected to the particular region of the image comes under the concept of local connectivity but in the concept of Artificial Neural Networks (ANNs) all neurons are fully connected types (Jain *et al*., 2019). Functioning over volumes, and distinct regular NN where the vector is taken as input (multi-channeled image e.g., RGB image is taken as the input) are some of the advantages of CNN over ANN.

A methodology was proposed to investigate the classes of Alzheimer's and its detection accuracy. By utilizing the pre-prepared DL network, the deep features are analyzed and this characterization model was fully dependent on deep features. The performance of this method was analyzed by taking the activation layers such as Soft-Max, ReLU, and Support Vector Machines (SVM) (Raghavaiah and Varadarajan, 2021). On the basis of deep features and a pre-trained AlexNet model, a system for detecting Alzheimer's disease stages was suggested (Nawaz *et al*., 2021). The initial layers are transferred from this pre-trained AlexNet model and deep features are extracted from the CNN. The classification of retrieved deep features is done using machine learning techniques like a k-nearest neighbor, SVM, and Random Forest (RF). The deep feature-based model outperformed the handcrafted with the best accuracy (Nawaz *et al*., 2021).

Proposed Method: Improved CNN Classification Model

A Neural Improved classification model using CNN is proposed here since deep learning techniques have prominent advantages when compared with the ML technique. In deep learning, the algorithm collections are motivated by the human brain anatomy structure that intimates human brain functions, and this process is termed a Neural Network (NN). The input image is passed over a non-linear transformations series before getting the actual output and hence these algorithms are called as deep. One of the best DL algorithms is a convolutional neural network in which the non-linear transformations series are carried out for the input image using the operation called convolution.

The sample input images that consist of all three stages of Alzheimer's such as normal controls, mild cognitive impairment, and AD are taken for the CNN classification as given in Fig. 1. Convolutional NNs are the specialized class of NN for processing the data or image that has a known grid-like topology.

In the place of general matrix multiplication, the convolution operation is used in at least one of the layers. The building components of the proposed CNN-based improved classification method include non-linearity transformation layers such as convolution operation, batch normalization process, ReLu, and Max-pooling operation. Once the convolution process is completed then the fully connected layer combines all the processed features. Finally, the softmax activation (classification layer) is applied to classify the predicted output classes of NC, MCI, and AD.

System Methods

The proposed convolutional neural network model performs the following operations in each convolution process. Each convolution process is carried out with four layers of operation such as follows convolution steps $\rightarrow$ {convolutional$\rightarrow$batch_normalization $\rightarrow$ ReLU $\rightarrow$ Max_Pooling}

Convolutional Layer

The convolutional layer is the primary layer during the image convolution process and this layer is used to execute heavy computations that make the further process easier. This convolution layer works with an input layer of size 256 × 256 × 1 (i.e., 256 pixels in length and breadth; and 1 is referred to as the depth of the image, the color channels). 3 × 3 filter matrices will slide over all the spatial locations. The input image is taken from the dataset and convolution operations are performed with the image (l × b × 1), of kernel size k, padding p, and size of stride s which produces the output of size $\frac{l-k+2p}{s+1} \times \frac{b-k+2p}{s+1}$. Here the kernels act as feature detectors that are convolved with the image and therefore a convolved feature set is produced. In NN, the kernel size is referred to as the receptive field of the neuron, which enforces the neuron's local connectivity to the previous volume.

Batch Normalization

This batch normalization layer allows every layer of the network to perform the learning more independently. The main motive of using the batch normalization layer is to normalize the outputs of the previously convoluted layers. During the normalization process, the activations scale the input image layer. Learning becomes more efficient while using batch normalization also it can be used as regularization for avoiding the model over fitting. This batch normalization layer is summed up to the sequential model for standardizing the inputs or the outputs. This process can be carried out multiple times in between the layers of the convolution process. Once the sequential model is designed then the convolution process is often performed once after performing the convolution and pooling layers.

Max-Pooling Layer

The max-pooling operation performs the process of aggregation which extracts the maximum region size of l × b on image size l × b, following this kernel size which is specified ask, and the size of the stride sizes. Therefore, the max-pooling operation generates the output of size $\frac{l-k}{s+1} \times \frac{b-k}{s+1}$. Insertion of Max-pooling layer operation is significant among successive layers of convolution since it gradually minimizes the spatial representation size i.e., values of l and b and hence the parameters that are to be trained will become less and therefore the overall computation of the network system gets reduced. Max-pooling operation owns the advantages of controlling over fitting. The flow chart of the proposed method is given in Fig. 2. The common value of k and s is 2 which down samples l and b using a factor of 2. The highest weighted feature is extracted in the Max-pooling layer and it is achieved by converting the above 3 × 3 matrices into 2 × 2 matrices. This process of matrix conversion involves only the highest weighted feature that is presented in 3 × 3 matrices. The pooling layer function is used to down-convert the volume makes the computation faster and minimizes the need for memory.

ReLU Layer

Rectified Linear Unit layer is applied for activation. ReLU layer executes the threshold operation for each input element and here any value that is lesser than zero is set the same as zero. In the output of the convolutional layer, the element-wise activation is applied. The ReLU function with its variants (simple ReLU and noisy ReLU) can be expressed mathematically using Eq. 1:

$$f(x) = \max(0, x)$$
$$f(x) = \begin{cases} x, & x \geq 0 \\ 0.01x, & otherwise \end{cases} \quad (1)$$

Therefore, this ReLU function returns zero if negative input is received and if ReLU function receives a positive value then it returns the value of x, the same value that x holds.

Fully Connected (FC) Layers: The neurons of FC are connected to all other neurons that are presented in the previous layer. The fully connected layer is the last elemental layer used in a deep neural classifier. FC is fed by the features that are extracted by the successive convolutional layers.

CNN Layers Design and its Description

The input image size is 256 × 256 × 1 which is a gray scale image passed into the convolutional neural network layer. Filter size is defined as the local region size to which the neurons are connected in the input. The filter size taken here is [6, 6]. The block diagram of the proposed methodology of CNN classification is given in Fig. 3.

First Convolution

Convolution2dlayer: 1, 64 convolutional filters, filter size to be [66] and 64 is represented for the feature value.

Input → 256 × 256 × 64; output → 251 × 251 × 64; neurons → 4032064.

Second Convolution

Convolution2dlayer: 2, 64 convolutional filters, filter size to be [66] and 64 is represented for the feature value.

Input → 125 × 125 × 64; output → 120 × 120 × 64; neurons → 921600.

Third Convolution

Convolution2dlayer: 3, 64 convolutional filters, filter size to be [66] and 64 is represented for the feature value.

Input → 60 × 60 × 64; output → 55 × 55 × 64; neurons → 193600.

Fourth Convolution

Convolution2dlayer: 4, 64 convolutional filters, filter size to be [66] and 64 is represented for the feature value.

Input → 27 × 27 × 64; output → 22 × 22 × 64; neurons → 30976.

Fifth Convolution

Convolution2dlayer: 5, 64 convolutional filters, filter size to be [66] and 64 is represented for the feature value.

Input → 11 × 11 × 64; output → 6 × 6 × 64; neurons → 2304. Stride denotes the number of steps that move in each convolution process. Here the stride to be (Feng *et al*., 2019) and padding to be [0 0 0 0] which denotes zero padding. The spatial dimensions can be maintained without any reductions with zero padding.

Batch normalization is tightly coupled with activation. This process of batch normalization normalizes the prior activations to improve the stability and performance of CNN. The complex problems can be solved through ReLU activation function by performing a series of non-linear transformations to the input images. The flattening layer transforms the pooled feature map into a 1-dimensional matrix vector that is used as the input of an artificial neural network. To reshape the output and restore the structure of a sequence of feature vectors of the convolutional layers the flattened layer is inserted between the convolutional layers and the FC layer. The FC layer which is present before the last convolutional layer holds the feature information such as contrast, edges, shapes, and blobs. Therefore, the FC layer aggregates the information from the previously presented layers. Finally, SoftMax is used in the output to enhance the classification process.

Adam (adaptive moment estimation) (Suresha and Parthasarathy, 2020) optimizer is the optimization function used in this CNN-based classification model. Adam optimizer is mainly used to reduce the losses. Adam is defined as the optimization algorithm with two gradient descent methodologies which helps in the training process of DL models. In addition, it combines the Root Mean Square (RMS) property and Stochastic Gradient Descent with Momentum (SGDM).

For each weight, the Adam optimizer adjusts the learning rate of the NN by estimating the gradient's first moment and second moments. Therefore, applying the Adam optimizer; fastens the convergence process. Exponentially Decaying Average (EDA) of past squared gradients (g_t) is stored along with an EDA of past squared gradients (e_t) which are given in Eq. 2 and 3:

$$e_t = \beta_1 e_{t-1} + \left(1-\beta_1\right) \nabla j\left(\theta\right) \tag{2}$$

$$g_t = \beta_2 g_{t-1} + \left(1-\beta_2\right) \nabla j\left(\theta\right)^2 \tag{3}$$

β_1 and β_2 are represented here for exponential decay rates, e_t represents the estimation of first momentum (mean value) and g_t represents an estimation of second momentum (variance) respectively. The past squared gradients e_t and g_t are biased in the direction of zero and the bias-corrected approximation is computed through the Adam update rule as given in Eq. 4:

$$\overline{e_t} = \frac{e_t}{1-\beta_1^{\,t}} \overline{g_t} = \frac{g_t}{1-\beta_2^{\,t}} \theta_{t+1} = \theta_t - \left(\delta \Big/ \sqrt{\overline{g_t} + \in} \right) \overline{e_t} \tag{4}$$

Softmax Layer

The softmax layer is the very final layer of this proposed CNN model. It is the last function of the activation of NN which normalizes the network output to the distribution of probability over the predicted classes of output. The Softmax activation function is applied in this softmax layer; here generalization logistics function is mapped to multiple dimensions. This layer allows the decimal probabilities for each class. Therefore, the output layer classifies the inputted images into cognitive normal, mild cognitive impairment, and AD. FC layer takes the output of all the neurons from the former layer. The designed layers are used for the training and testing of images. Figure 4 shows the proposed CNN model layers designs and descriptions.

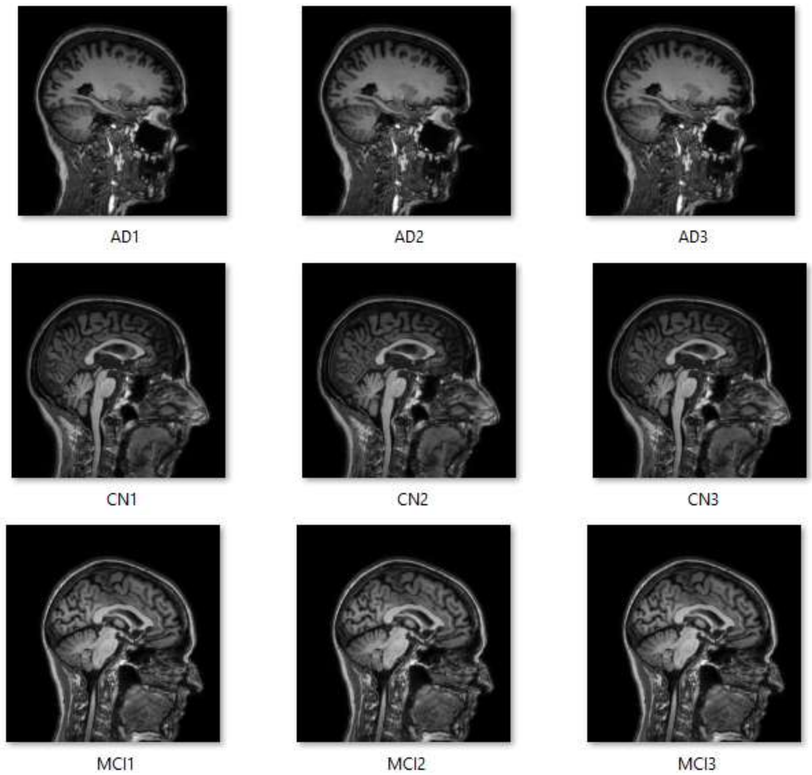

Fig. 1: Sample input images for CNN classification

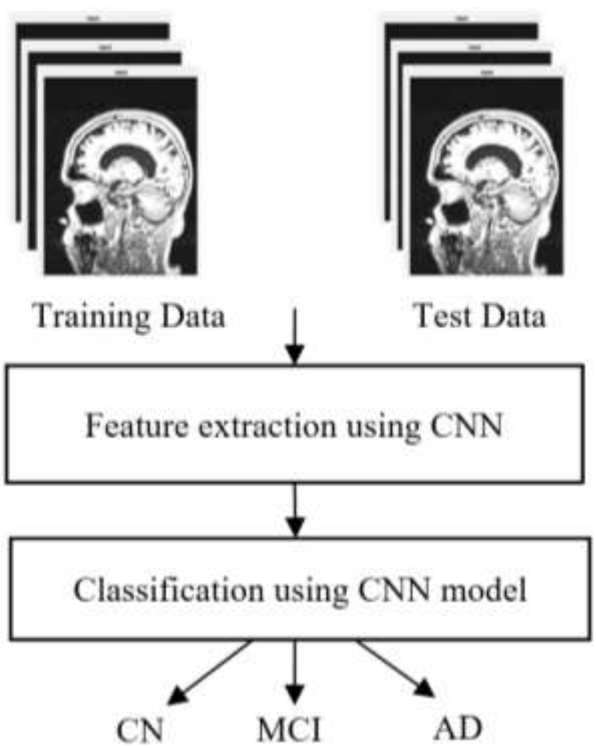

Fig. 2: Block diagram of the proposed methodology

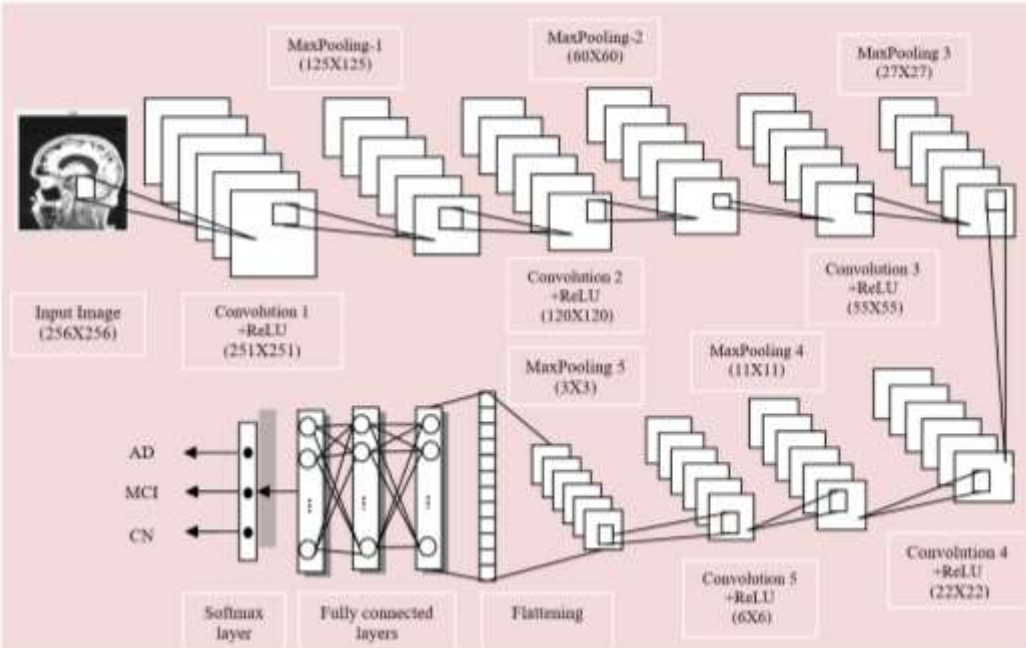

Fig. 3: Block diagram of proposed CNN classification

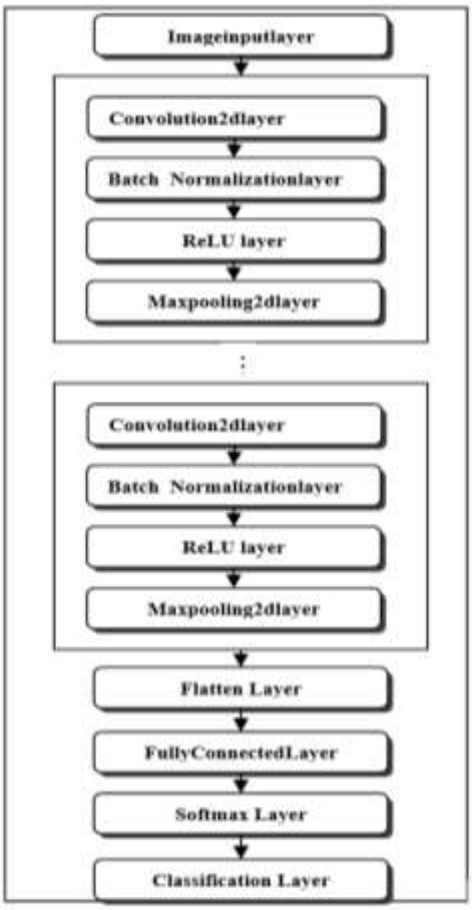

Fig. 4: Common building blocks of the proposed CNN architecture

Data Set

Magnetic Resonance Imaging (MRI) technology is a non-invasive imaging tool that can be used to diagnose and treat disease. Data used in the preparation of this article were obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu). In this study, a total of 3720 MRI images are obtained from the ADNI database. It has AD, MCI, and CN MRIs of individuals of different age groups, both male and female.

Results and Discussion

The implementation process is carried out with the help of MATLAB r2021. The ratio of images taken for the training process and testing process is 70:30. The ADNI neuroimaging dataset with the sagittal images is taken as input and the classified output of AD, Normal controls, mild cognitive impairment, and its intensity level are measured through accuracy.

The proposed CNN architecture design comprises five convolution processes. The classification process is done for the inputted images with three output classes NC, MCI, and AD. Figure 5 shows the Schematic of the first convolutional layer of CNN. This layer learns 64 filters of size 6 × 6. Figure 6 shows the 25 × 1 layer array for proposed CNN Layers that involves during the convolution process of classification.

To achieve faster convergence, the Adam optimization process is carried out. Also applying various sample size values and activation function improves the performance of accuracy. The confusion matrix shows the evaluation results in Fig. 7 for the classes such as NC, MCI, and AD. Accuracy measurement is defined as the number of precise predictions made and it is termed a different label classification. The predicted values such as True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) are calculated for accurate predictions. The accuracy is measured using the Eq. 5:

$$Accuracy(\%) = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{5}$$

$$Accuracy\ for\ AD = \frac{1221+2424}{1221+2424+46+21} = 0.98$$

$$Accuracy\ for\ CN = \frac{1090+2554}{1090+2554+33+35} = 0.98$$

$$Accuracy\ for\ MCI = \frac{1280+2325}{1280+2325+42+65} = 0.79$$

The recall is measured through the fraction of actual positive predictions which are classified correctly and it is often referred to as sensitivity or true positive rate which is given in Eq. 6:

$$Recall(\%) = \frac{TP}{(TP+FN)} \tag{6}$$

$$Recall\ for\ AD = \frac{1221}{1221+21} = 0.98$$

$$Recall\ for\ CN = \frac{1090}{1090+35} = 0.96$$

$$Recall\ for\ MCI = \frac{1280}{1280+65} = 0.95$$

Precision is measured through the fraction of positive predictions and it is given in Eq. 7:

$$Precision(\%) = \frac{TP}{(TP+FP)} \tag{7}$$

$$Precision\ for\ AD = \frac{1221}{1221+46} = 0.96$$

$$Precision\ for\ CN = \frac{1090}{1090+33} = 0.97$$

$$Precision\ for\ MCI = \frac{1280}{1280+42} = 0.96$$

F1 score is otherwise called as Dice Similarity Coefficient (DSC), which combines both the precision and recall into one metric and it is given in Eq. 8:

$$F1-score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{8}$$

$$F1-score\ for\ AD = \frac{2 \times 0.96 \times 0.98}{0.96+0.98} = 0.96$$

$$F1-score\ for\ CN = \frac{2 \times 0.97 \times 0.96}{0.97+0.96} = 0.96$$

$$F1-score\ for\ MCI = \frac{2 \times 0.96 \times 0.95}{0.96+0.95} = 0.95$$

We may conclude from the comparison of experimental findings in Table 1 that the proposed model outperforms traditional deep learning algorithms in Alzheimer's disease diagnosis. Figure 8 shows the performance measures across AD, MCI, and CN for the proposed method.

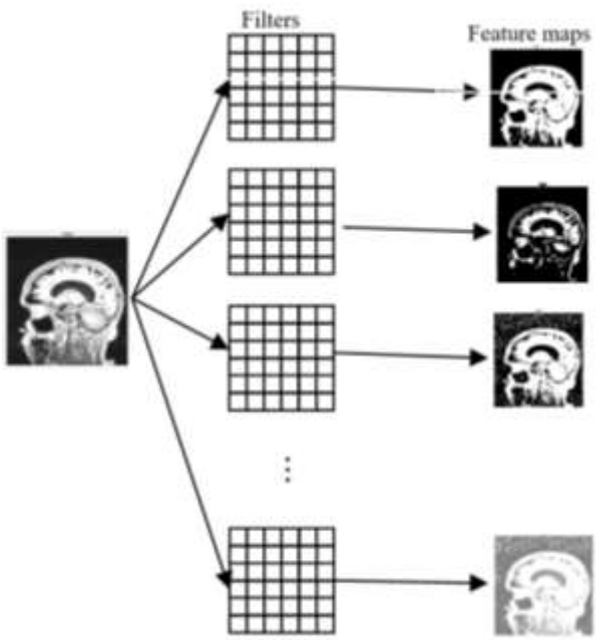

Fig. 5: Schematic of the first convolutional layer of a CNN

Table 1: Comparison of the proposed approach with previous frameworks

Author and year	Methodology	No of Images	Accuracy (%)
Liu *et al*. (2018)	Cascaded CNNs	397	93.26
Li *et al*. (2018)	Multiple cluster dense convolutional networks	831	89.50
Basheera and Ram (2019)	CNN	1820	90.47
Solano-Rojas and Villalón-Fonseca (2021)	Dense Net neural network	3512	86.00
Sarraf and Tofighi (2016)	LeNet-5	190	96.80
Oh *et al*. (2019)	convolutional auto encoder	694	86.60
Cheng and Liu (2017)	Multilevel CNN	193	89.64
Cheng *et al*. (2017)	Multiple CNN	427	87.15
Lu *et al*. (2018)	Multimodal and multi scale deep neural network	1242	82.40
Sarita *et al*. (2022)	Convolution neural networks	150	87.00
Proposed Model	Improved CNN	3720	97.80

```
layers =

  25x1 Layer array with layers:

     1   'input'                  Image Input             256x256x1 images with 'zerocenter' normalization
     2   'conv_1'                 Convolution             64 6x6 convolutions with stride [1  1] and padding [0  0  0  0]
     3   'batch_norm1'            Batch Normalization     Batch normalization
     4   'relu1'                  ReLU                    ReLU
     5   'max1'                   Max Pooling             2x2 max pooling with stride [2  2] and padding [0  0  0  0]
     6   'conv_2'                 Convolution             64 6x6 convolutions with stride [1  1] and padding [0  0  0  0]
     7   'batch_norm2'            Batch Normalization     Batch normalization
     8   'relu2'                  ReLU                    ReLU
     9   'max2'                   Max Pooling             2x2 max pooling with stride [2  2] and padding [0  0  0  0]
    10   'conv_3'                 Convolution             64 6x6 convolutions with stride [1  1] and padding [0  0  0  0]
    11   'batch_norm3'            Batch Normalization     Batch normalization
    12   'relu3'                  ReLU                    ReLU
    13   'max3'                   Max Pooling             2x2 max pooling with stride [2  2] and padding [0  0  0  0]
    14   'conv_4'                 Convolution             64 6x6 convolutions with stride [1  1] and padding [0  0  0  0]
    15   'batch_norm4'            Batch Normalization     Batch normalization
    16   'relu4'                  ReLU                    ReLU
    17   'max4'                   Max Pooling             2x2 max pooling with stride [2  2] and padding [0  0  0  0]
    18   'conv_5'                 Convolution             64 6x6 convolutions with stride [1  1] and padding [0  0  0  0]
    19   'batch_norm5'            Batch Normalization     Batch normalization
    20   'relu5'                  ReLU                    ReLU
    21   'max5'                   Max Pooling             2x2 max pooling with stride [2  2] and padding [0  0  0  0]
    22   'flatten'                Flatten                 Flatten
    23   'fc_layer'               Fully Connected         3 fully connected layer
    24   'sfmax_layer'            Softmax                 softmax
    25   'classification_layer'   Classification Output   crossentropyex
```

Fig. 6: 25 × 1 layer array for proposed CNN layers

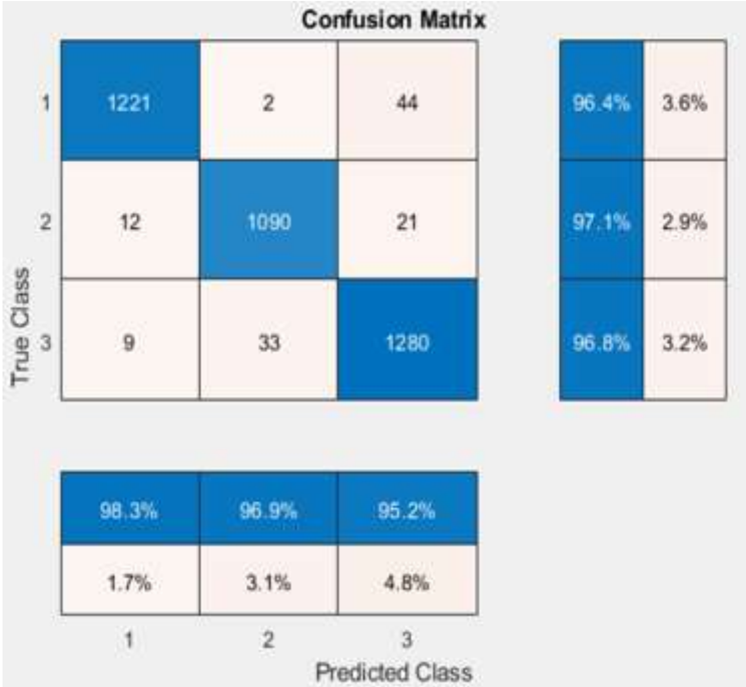

Fig. 7: Confusion matrix and accuracy detection

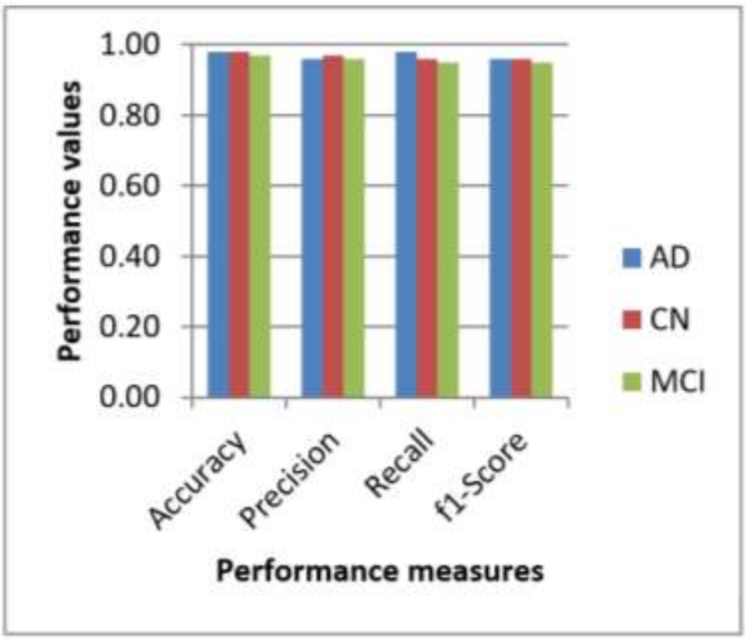

Fig. 8: Performance measures across AD, MCI, and CN

Conclusion

Earlier detection of Alzheimer's disease is necessary to save the patient's life. Therefore, it is necessary to diagnose the affected region with good accuracy is a mandate. Here, an improved classification model using CNN is proposed to detect the AD. The main objective of this improved classification model using CNN is to predict and classify the NC, MCI, and AD with better accuracy based on the patient's brain MRI images. CNN building components of the proposed method are designed with the layers such as convolution layer, batch normalization process, ReLU, and Max-pooling operation. Along with the softmax layer an Adam optimization technique is also used to reduce the loss and achieve quicker convergence. The proposed method of improved CNN classification of AD model achieves an accuracy of 97.8%. In the future, multi parametric MRI (such as diffusion-tensor imaging, task functional MRI, and resting-state MRI) can be considered to improve the accuracy of AD detection. Also, other modalities such as Positron Emission Tomography (PET) can be utilized as well.

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Author's Contributions

Ragavamsi Davuluri: Contributed to conception, design, acquisition of data and writing the Entire Manuscript.

Ragupathy Rengaswamy: Contributed to the analysis, interpretation of data and evaluation of the Manuscript.

Ethics

This article is unique and contains unpublished material. The comparing creator affirms that all of different writers have perused and endorsed the composition what's more no moral issues included.

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