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Alzheimer's Disease Detection in MRI images using Deep Convolutional Neural Network Model

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Abstract

Alzheimer's disease (AD) is a neurodegenerative disease that affects cognitive abilities (thinking and memory etc) primarily among the elderly, due to which collective cognitive skills deteriorate, ultimately leading to death. Early detection of Alzheimer's disease is crucial for determining appropriate therapeutic options. This research investigates the use of a Deep Convolutional Neural Network (CNN) for detecting Alzheimer's disease. Due to similar brain patterns and pixel intensities, CNN demonstrates promising results in diagnosing AD through automated feature extraction and characterization. Deep Learning algorithms are designed to perform automated feature extraction and categorization of input image datasets. In this study, a two-way classifier categorizes each image as either Healthy Control (HC) or Alzheimer's disease (AD). Experiments were carried out with the MIRIAD dataset, and the accuracy of disease classification into binary categories was evaluated. The recorded results of CNN with 4- and 5 -layer architectures confirms the effectiveness of the proposed method for AD detection.

Keywords: Alzheimer's disease detection, MIRIAD datasets, Confusion Matrix, CNN architecture, ReLu, Dropout, Normal and Abnormal MRI images

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1. Introduction

Alzheimer's disease (AD) is the most common type of dementia and the leading cause of cognitive disability in the elderly worldwide. The three most prevalent patterns of Alzheimer's disease patterns are mild, moderate and severe [1]. Early Alzheimer's disease detection is essential in order to provide patients with appropriate treatments at an early stage. Structural Magnetic Resonance Imaging (MRI) is a commonly used diagnostic tool which generates high-resolution images with excellent contrast between the brain's grey and white matter. The evolution of big data and artificial intelligence has increased the scope of the use of innovative deep learning techniques within problem solving. [2 - 4]. Researchers have explored deep learning-based algorithms for AD detection reported on their efficacy.

Structural magnetic resonance imaging (MRI) is a non-invasive medical imaging modality used to visualize the anatomy of human internal organs, serving as a reliable source for the identification of brain abnormalities. To visualize the structural details of the brain, physicians rely on the most sensitive and reliable imaging modalities. The brain's intrinsic architectural features and morphological analysis reveal its essential components, namely white matter (WM), grey matter (GM), and cerebrospinal fluid (CSF). An intelligent computer-aided diagnosis system can learn patterns of WM, GM, and CSF to perform AD detection and classification. Performance is evaluated using metrics such as Accuracy, Precision, Recall, and F1-Score. Related research work is discussed in the following section; the methodology of Deep Convolutional Neural Networks (DCNN) is then described in Section III, results and discussions presented in section IV and the conclusion provided in Section V.

2. Related Work

A novel mathematical model PFSECTL based on transfer learning and CNN architecture has been developed by Jin et al., [5]. This approach classifies AD into three categories using images selected from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, achieving an accuracy of 95.73%. Another innovative method for transfer learning was employed by Bo Cheng et al. [6] aimed to create multi-score domain data to improve classification performance for early AD analysis. Sajna et al. established a new two-stage CNN model for early AD diagnosis and prediction [7]. In this model, image patches are first accepted as input for landmark detection, utilizing a two-stage CNN model to learn the intrinsic correlations between local image patches and target landmarks. The entire image is then used as input for the second CNN, which identifies the AD case. A new technique for automatic recognition of AD using a deep learning model was created by Suhuai Luo et al. [8]: a CNN-based classification model for AD detection from 3D brain images. The results of the new method showed that the sensitivity and specificity of the enhanced AD detection accuracy were 100% and 93%, respectively, using T1-weighted MRI images taken from the MIRIAD dataset.

This paper's main objective is to use the most advantageous feature set to categorize the numerous brain images. A Deep Learning CNN model is designed to perform classification on the generated feature vector. Naganandhini et al. [22] developed a new method for Alzheimer’s Disease classification Using machine learning algorithms. Additionally, Naganandhini et al. [23] developed the optimized EMLR imputation classifier based on six different brain MRI features for classifying mild AD, moderate AD, non-demented and very mild AD.

3. Proposed Work

Convolution Neural Network is generally used with a deep learning framework [9, 10], with application ranging from object recognition and object tracking [11], pose estimation [12], text detection and recognition [13], visual saliency detection [14] and action recognition [15] to scene labelling [16] and many other contexts [17].

3.1. Neural Network

A machine learning approach known as a neural network (NN) is used to emulate the concept of how biological and logistical neural networks work. Neurons are grouped together to form a neural network with multiple layers. In this context, the deep learning neural network can be trained upon the MIRIAD dataset.

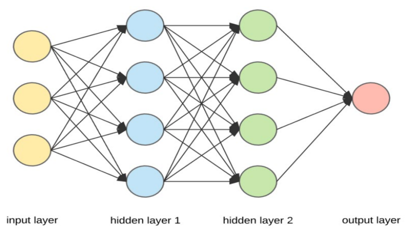


Fig 1: Basic Neural Network Architecture

3.2 Convolutional Neural Network (CNN) and Image Classification

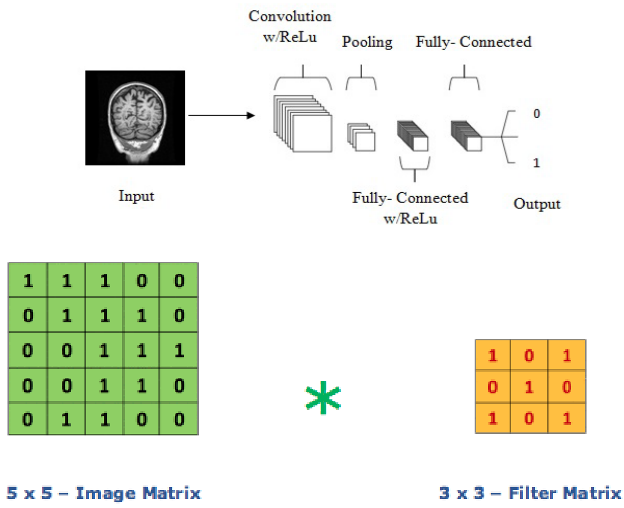


Fig 2: CNN architecture with 4 layers (Proposed)

A Convolutional Neural Network (CNN) architecture is a specialized variant of Artificial Neural Networks (ANN) that is extensively used for image categorization. The architecture consists of several key layers, including convolutional, nonlinear (ReLU), pooling, dropout, flatten, and fully connected layers. These layers work together to generate the output for AD detection.

Convolution layers: The core of the CNN architecture is the convolutional layer, which applies a convolution operation to the input image using filters to extract essential features. This involves applying a mathematical convolution operation on matrices of input sub-images and filters, which must be of the same size. Typically, filters are odd-sized matrices. Smaller filters can extract more detailed features from the image.

Fig 3: Convolution Operation of Image and Filter

Nonlinear Layer (ReLU): The Rectified Linear Unit (ReLU) is used for non-linear operations. The ReLU function is defined as:

$$f(x) = max(0, x) \qquad (1)$$

The primary purpose of ReLU is to is to introduce non-linearity into the ConvNet, ensuring that the model can learn from the non-linear aspects of the input data. The selection of an optimal filter size, combined with the application of ReLU, enhances the performance of feature extraction, leading to improved overall model performance.

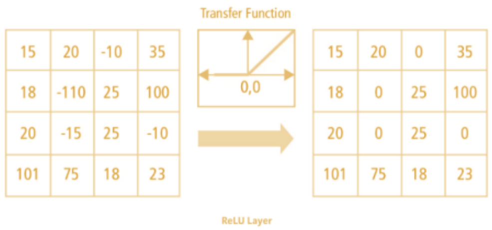


Fig 4: ReLU operation

Pooling Layer: When image size is too large, the pooling layer reduces the number of features by performing spatial pooling, also known as subsampling or downsampling. There are various types of spatial pooling, including:

a. Max pooling
b. Average pooling
c. Sum pooling
d.

In the proposed method, max pooling extracts the largest fragments from the corrected feature map, helping to reduce dimensionality while retaining the most significant features.

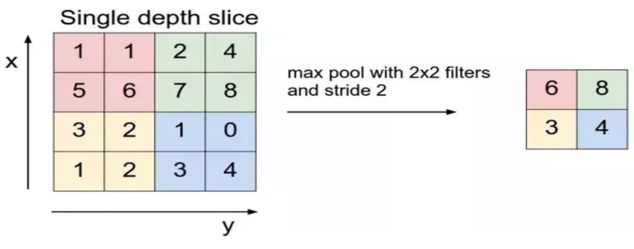


Fig 5: Max Pooling Layer

Dropout layer: To prevent overfitting, a dropout rate set to 0.8 in this research.

Fully Connected Layer (FC): Typically, the convolution layer, ReLU layer, and max pooling layer are repeated throughout the network in order to increase the depth of the neural network. The extracted features are fed into the FC layer for the purpose of classification.

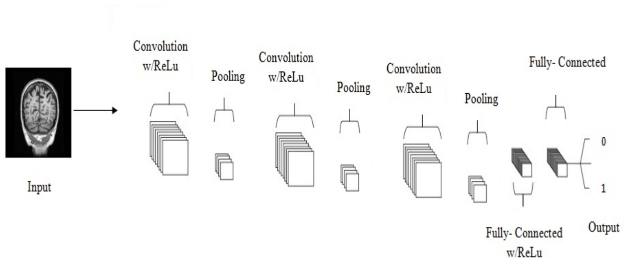


Fig 6: Architecture of DCNN (Proposed)

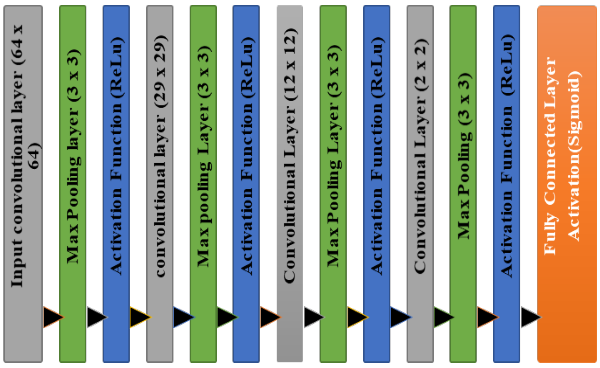


Fig 7: Architecture of DCNN System (Proposed)

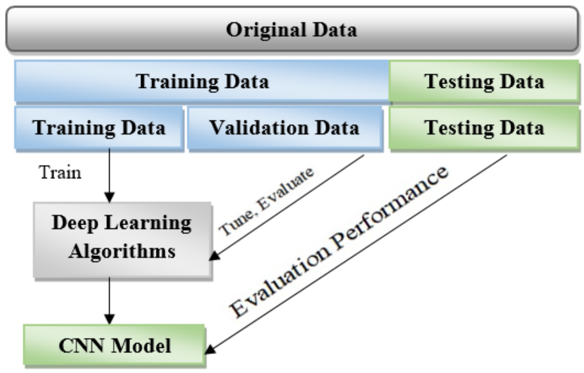
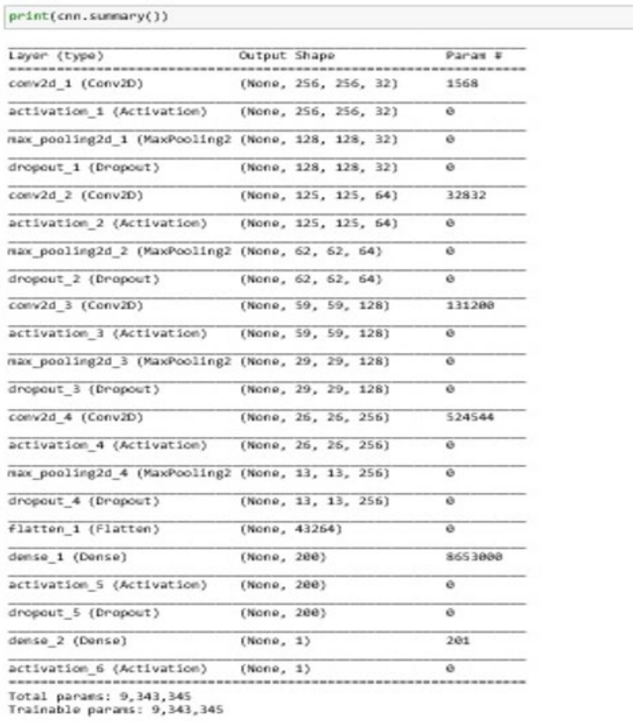


Fig 8: Dataset Distribution



```
print(cnn.summary())

Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 256, 256, 32)      1568
activation_1 (Activation)    (None, 256, 256, 32)      0
max_pooling2d_1 (MaxPooling2 (None, 128, 128, 32)      0
dropout_1 (Dropout)          (None, 128, 128, 32)      0
conv2d_2 (Conv2D)            (None, 125, 125, 64)      32832
activation_2 (Activation)    (None, 125, 125, 64)      0
max_pooling2d_2 (MaxPooling2 (None, 62, 62, 64)        0
dropout_2 (Dropout)          (None, 62, 62, 64)        0
conv2d_3 (Conv2D)            (None, 59, 59, 128)       131200
activation_3 (Activation)    (None, 59, 59, 128)       0
max_pooling2d_3 (MaxPooling2 (None, 29, 29, 128)       0
dropout_3 (Dropout)          (None, 29, 29, 128)       0
conv2d_4 (Conv2D)            (None, 26, 26, 256)       524544
activation_4 (Activation)    (None, 26, 26, 256)       0
max_pooling2d_4 (MaxPooling2 (None, 13, 13, 256)       0
dropout_4 (Dropout)          (None, 13, 13, 256)       0
flatten_1 (Flatten)          (None, 43264)             0
dense_1 (Dense)              (None, 200)               8653000
activation_5 (Activation)    (None, 200)               0
dropout_5 (Dropout)          (None, 200)               0
dense_2 (Dense)              (None, 1)                 201
activation_6 (Activation)    (None, 1)                 0
=================================================================
Total params: 9,343,345
Trainable params: 9,343,345
```

Fig 9: Summary of the DCNN Model (Proposed)

4. Dataset Description

The performance of the proposed DCNN model is assessed using 930 normal and abnormal 930 chosen from the **MIRIAD dataset:** (http://www.ucl.ac.uk/drc/research/methods/miriad-scan-database) [19].

5. Result and Discussion

Images taken from the MIRIAD dataset were used to train and test the DCNN model classifier. Classification metric including precision, accuracy, recall and F1-score were calculated. Experimental analysis was conducted on both 4- Layer and 5-Layer configurations, and obtained results were meticulously recorded.

Table 1: Performance Analysis of DCNN Model (4 Layers)

Group	Precision	Recall	F1-Score	Support
Normal (0)	1.00	0.21	0.34	102
AD (1)	0.56	1.00	0.72	102
Classification Model Report				
Micro Avg	0.60	0.60	0.60	204
Macro Avg	0.78	0.60	0.53	204
Weighted Avg	0.78	0.60	0.53	204
Accuracy: 0.602941176 (0.60%)				

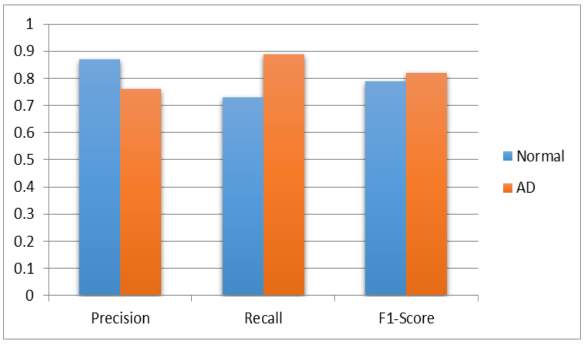


Fig 10: Performance Analysis of DCNN Model

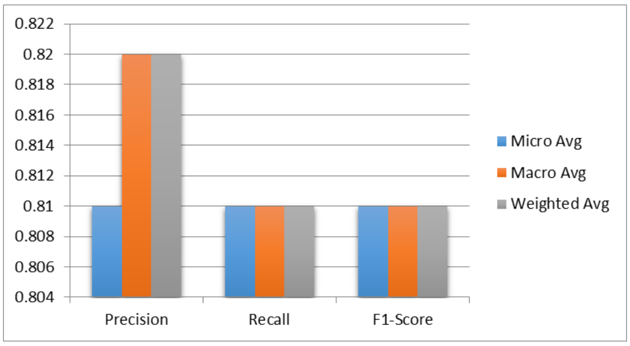


Fig 11: Performance analysis of classification report for DCNN model

Table 2: Performance analysis of DCNN model (5 Layers)

Group	Precision	Recall	F1-Score	Support
Normal (0)	0.87	0.73	0.79	102
AD (1)	0.76	0.89	0.82	102
Classification Model Report				
Micro Avg	0.81	0.81	0.81	204
Macro Avg	0.82	0.81	0.81	204
Weighted Avg	0.82	0.81	0.81	204
Accuracy: 0.8088235294117647 (0.81%)				

Table 2 shows the performance analysis of the DCNN model using a 5-Layer configuration, achieving an accuracy of 60%. The confusion matrix is depicted in Fig 12, while the classification report is shown in Fig 13.

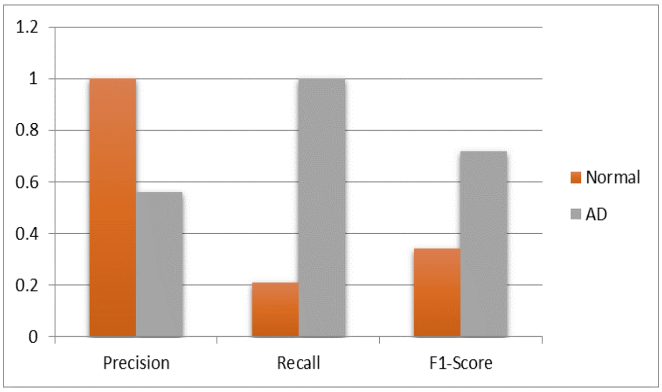


Fig 12: Performance analysis of DCNN model (5 Layers)

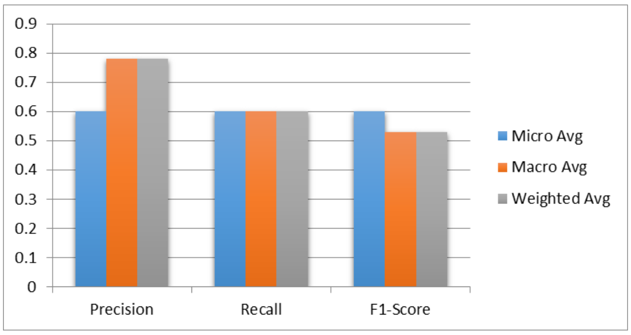


Fig 13: Performance Analysis of Classification Report for DCNN Model (5 Layers)

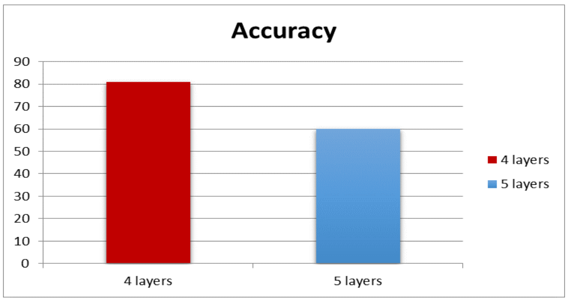


Figure 14: Performance analysis of DCNN model Accuracy

5. 1. Performance Evaluation Matrices

Evaluation metrics are a critical component in assessing classifier model performance [20-21]. The confusion matrices in Table 1 and Table 2 illustrate correctly and incorrectly identified instances for each class across the three problem classes. Accuracy, a widely used metric, effectively measures the correct classification rates for all groups. These metrics are defined as follows:

$$Precision = \frac{tp}{(tp+fp)} \quad (2)$$

$$Recall = \frac{tp}{(tp+fn)} \quad (3)$$

$$F - Measure = \frac{(1+\beta)^2 * Recall * Precision}{\beta^2 * Recall * Precision} \quad (4)$$

β is a co-efficient to adjust the importance of precision and recall (usually β =1)

$$FPrate = \frac{FP}{(FP+TN)} \quad (5)$$

$$TPrate = \frac{TP}{(TP+FN)} \quad (6)$$

The proposed DCNN model for AD classification achieves a maximum accuracy of 81% with 5-Layers, using ReLU and the dropout value as 0.8.

6. Conclusion

This article introduces an effective method for Alzheimer's Disease (AD) classification using MRI brain data. The DCNN model used in the study achieved an accuracy of 81%. This model can facilitate early diagnosis of AD through binary classification and activation function. In the future, it is intended to test the proposed model on various AD datasets encompassing other brain abnormalities, in order to extend the scope of the research and provide further data on its potential diagnostic capabilities, which ultimately helps in making the best healthcare decisions.

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