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# Alzheimer's Disease Classification Based on Transfer Learning of New-CNN Model

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**_Abstract_**

*The long-term, irreversible brain disorder "Alzheimer's disease (AD)" currently has no known cure. Nonetheless, current medications may impede their advancement. Globally, those over 65 are the primary population affected by Alzheimer's disease. Accurate detection of this condition requires early diagnosis. Because there are so many people who come with an ailment, manual diagnosis by health specialists is laborious and prone to error. Early detection of AD is a difficult undertaking in clinical practice and only very few diagnostic techniques are available. To prevent brain damage and arrest the disease's progression, patients may benefit from early detection of mild cases, which can help direct further medical care. "Deep learning (DL)" has attracted attention lately as an early AD identification method. Several scientists and academics are working to develop techniques for early identification utilizing MRI pictures to halt the progression of AD. In this paper, 6400 images are gathered from secondary sources for the current investigation. Preprocessing is done using the normalization procedure. CNN is fed these preprocessed, normalized images. CNN's training and testing accuracy are improved by the normalized images. CNN obtains 94.89% classification accuracy for AD in image testing. Furthermore, the outcome demonstrates that the pre-trained New-CNN model performs better during transfer learning.*

**Keywords:** Alzheimer disease (AD), classification, convolutional neural network (CNN), detection, deep learning (DL), brain disease

## INTRODUCTION

Millions of individuals all over the world suffer from the crippling effects of brain diseases, like Epilepsy, Meningitis, etc., as shown in Figure 1. One of these brain ailments that has a catastrophic impact on patients is "Alzheimer's disease (AD)" [1]. It is depressing for patients as well as their loved ones since it is an illness which progressively decreases cognitive abilities like memory, perception, and language. There is not a proven disease-modifying medication or precise diagnosis available now. Additionally, the expense of patient care is significant due to the abrupt and acute memory loss that characterizes AD symptoms [2]. There are three widely acknowledged stages of AD: "normal control (NC)", "moderate cognitive impairment (MCI)", and AD. Specifically, AD's early stage, or MCI, is the intermediate state between AD and normal control. The 4 different classes of AD are shown in Figure 2. Memory loss and poor memory are indicators of MCI. Some people with MCI progress to AD, while others stay in MCI. For treatment to be successful and to impede the cause of the disease, early diagnosis is essential. For several reasons, AD detection is still a difficult task in computer vision fields. When compared to other image classification datasets, such as ImageNet, the size of the picture collection is insufficient [3]. The obtained medical images are typically of low quality, with segmentation results that are comparatively coarse noise. Medical images are

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very complex when compared to those from other fields. Since images are obtained using a variety of devices with varying capabilities, pre-processing takes longer. It is difficult to distinguish between MCI, AD, and NC in computer vision.

There has been enormous growth the field of “Artificial Intelligence (AI)” in last decade, and engineers and researchers have studied many aspects of AI. These studies can be divided into two groups: DL and ML. “Support Vector Machines (SVM)”, “Random Forests (RF)”, “Linear Regression (LR)”, “Naïve Bayesian”, etc. are examples of conventional machine learning techniques [4]. Neural networks using convolution and recursive architecture are examples of deep learning methodologies. To identify AD, multitudes of biomarkers are required like MRI, genetics, and clinical and biological materials. Biomarkers are unprocessed data that are utilized to identify AD. As such there is not any solid proof of which biomarker is the best for detection, it is imperative to identify the right one. The diagnostic significance of spatial features, like brain surface area, volume, and cortical CT data, is increased since they can be identified after processing. These features can be automatically retrieved from biomarkers using both manual and deep learning processing approaches [5].

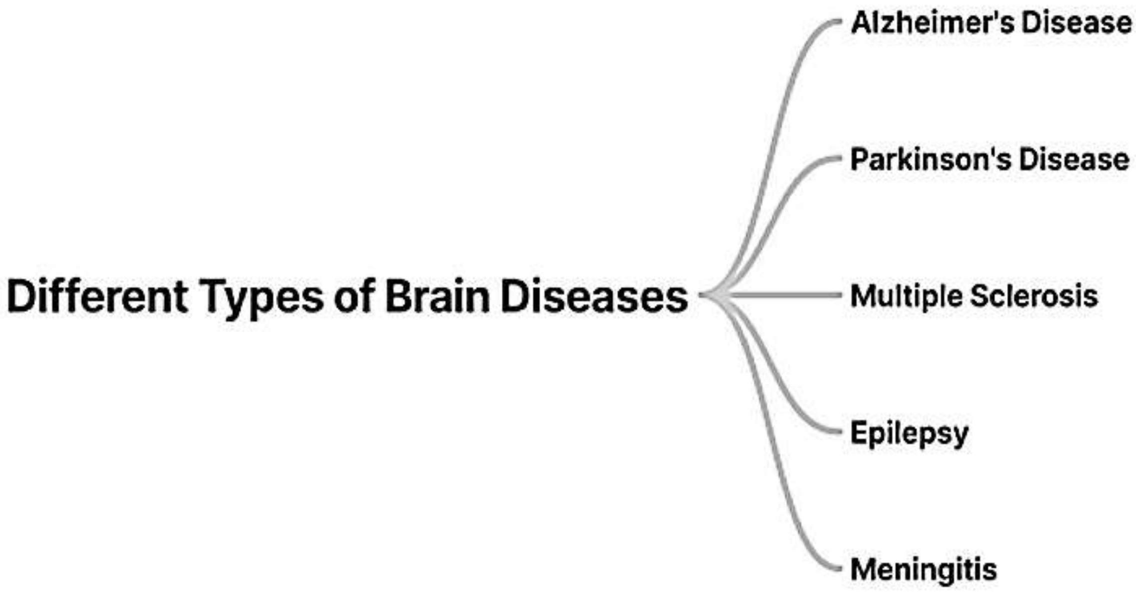


**Figure 1.** Different types of brain diseases.

Researchers continue to face numerous obstacles in their efforts to use DL to detect AD efficiently. The lack of high-quality medical pictures, imbalanced class distribution, and challenges in locating brain areas of interest (ROI) all contribute to the detection of AD. Convolutional neural networks are among the DL designs that have drawn the most attention because of their exceptional classification performance. Deep learning speeds up and improves the efficiency of the detection process by automating it. When early detection is critical for effective treatment, a precise diagnosis is vital. DL algorithms have extraordinary ability to understand patterns from large-scale, multidimensional data [6]. They can get beyond the drawbacks of conventional techniques by automatically extracting relevant information from the images.

The structure of this document is as follows: Section 2 of this document aims at examining the literature on AD using a variety of methods. Section 3 provides an explanation of the materials utilized to propose the model. Section 4 discusses the results based on various terms, and Section 5 compares the most sophisticated models. The conclusion portion with potential future scope is shown in the final Section 6.

 

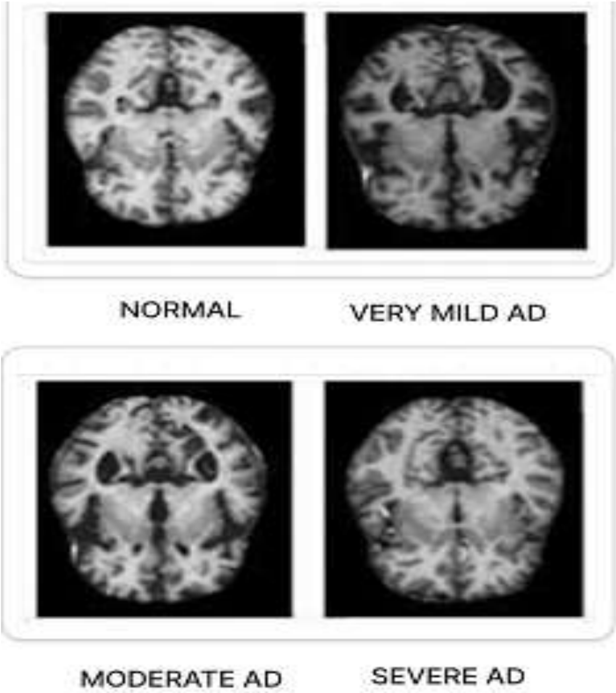


**Figure 2.** Four classes of AD.

## LITERATURE REVIEW

Ibrahim R. et al. [7] offer a novel hybrid model that improves detection and classification capabilities by fusing the model with Particle Swarm Optimization (PSO) method. The technique finds the best hyper-parameters by applying the PSO algorithm. The suggested model attains accuracy score of around 98.83% for Kaggle brain tumour dataset, and 97.12% for ADNI dataset. Mujahid M. et al. [6] offer a model by integrating VGG 16 and EfficientNet B2 to deliver a precise diagnosis of the disease. To create a model and subsequently add it to other layers for increased robustness, the input as well as the output of each of the two models were combined. For multiclass datasets, the approach attained 97.35% accuracy and AUC of 99.64. Thangavel P. et al. [8] discussed the EAD-DNN algorithm which has been applied to the MRI data. ResNet and CNN have been trained on the MRI dataset. With ResNet's assistance, this model can attain vital data from the network. The feature information from the MRI data has been chosen by the modified Adam optimization.

Singh A. and Kumar R. [9] detect the different stages of AD in older and younger patients. Different CNN models were used for diagnosis of AD at early stage. The result was evaluated based on different metrics and the Mobile Net model scored the highest accuracy, which is 98.74%. Balaji P. et al. [10] developed a hybrid DL model that includes the multimodal with LSTM and CNN combines with the MRI and basic tests scores. Marwa E. G. et al. [11] put forward a shallow CNN model which utilized more than 6400 AD images from a publicly available dataset. Here, the proposed model result was assessed with different models named VGG16. The accuracy of this model is 99.68%. Arafa D. A. et al. [12] suggested a VGG16 model based on transfer learning. Based on different evaluation metrics the VGG-16 (fine tunned) model got an overall accuracy of 97.44%.

Rajesh Khanna M. [13] proposed an ensemble learning model in combination with DL model for diagnosis. The classification and detection result was obtained based on six different evaluation metrics named as, computational time, F1-score, recall scores, precision scores, and "the area under the curve (AUC)". The result obtained shows a specificity of 95% with 94% sensitivity. Yellu R. R. et al. [14] discussed about the promising outcomes that have been observed in several medical imaging tasks, including AD diagnosis, thanks to recent developments in deep learning. DL models: CNN and "recurrent neural networks (RNNs)" in particular – may be able to diagnose AD more precisely and automatically. El-Latif A. A. et al. [15] put forward a model which uses MRI data. The strategy combines the concept of feature extraction as well as classification into one stage, removing the requirement for deeper layers and achieving great detection performance without them. The data was gathered from Kaggle repository and the model achieved 99.22% accuracy and 95.93% accuracy for binary and multiclass classification, respectively.

## MATERIALS AND METHODS

The suggested model for identification and classification of AD is shown in Figure 3.

### Dataset Gathering

To evaluate the proposed model, an open-source dataset was utilized. With the help of a radiologist, the dataset was manually labelled after being collected from various sources. Each image in the collection is meticulously classified into one of four classes: Non-Dementia (ND), Very Mild-Dementia (VMD), Mild Dementia (MD), or Moderate Dementia (MOD). These image categories are employed in testing and training. For the experiment, a total of 6400 images were gathered.

### Data Pre-Processing

During this transformation process, the images are resized from 176×208 to 100×100. Resizing the images is an essential step in the model training process. After the image scaling, begins the process of normalization begins. The picture is adjusted to normal. Here the process of normalization is used which converts pixels in an image from a specified range (0–255) to a (0–1). Finally, the updated images are saved in a pickle file.

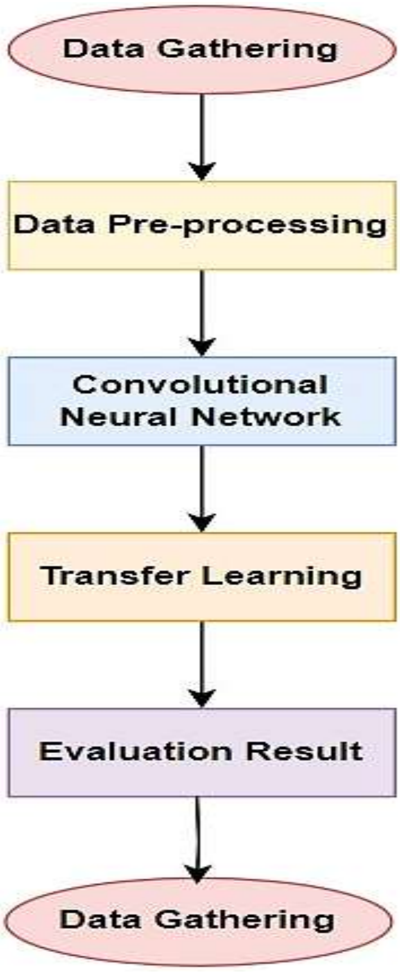


**Figure 3.** Proposed model for AD classification.

**Proposed New-CNN Model**

With the best performance, neural network techniques have recently gained popularity in speech recognition, computer vision, healthcare, and medical picture classification. A non-linear function determines the output of the neuron to send signals to other neurons. According to CNN, this neural architecture is the most widely used. CNN's capacity to handle large datasets and achieve strong classification performance is one of its most important aspects. In this network, there are 3 convolution layers. Each layer has (3, 3) kernel size, a ReLU activation function, and padding which is set to "same". Following each convolution layer, the suggested model uses a 2D max pooling layer with sizes of (3, 3) and (2, 2). The 2D dimension arrays in feature map are flattened and converted to a single vector. To demonstrate the efficiency of the dropout the 0.5 dropout is used. The batch size of the network is set to 32 and the epochs is set to 50. Figure 4 explains the diagrammatic flow of the data from one layer to another in proposed CNN model.

- CNN uses convolution layers to produce maps by discarding the kernel at a specific size.
- The activation function helps it learn complex data and decide which neurons to stimulate.
- There are many parameters left over after the convolution layer extracts features, necessitating additional processing power. Feature maps' dimensions are decreased using pooling layers, which decrease the requirement of computing power required to process the data.

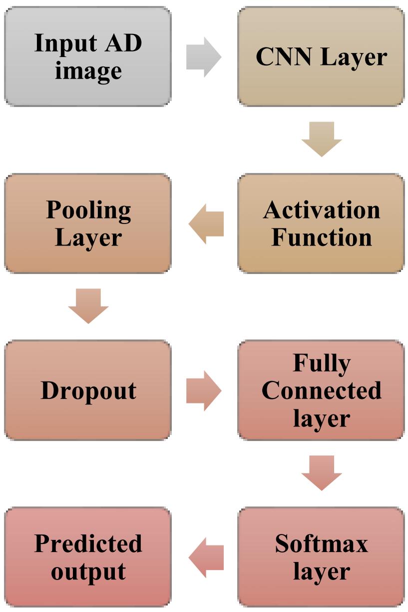


**Figure 4.** New-CNN workflow.

**EXPERIMENTAL RESULT**

A variety of assessment indicators are employed to assess the new-CNN model's performance. Firstly, the images are resized from 176×208 to 100×100. Image normalization can raise an image's intensity value. CNN is then used to receive these previously processed images. The normalization of images is calculated with below mentioned Equation (1).

$$range2 = max_{norm} - min_{norm} \tag{1}$$

$$Image_{Normalization} = (Image_{Normalization} \times range2) - min_{norm} \tag{2}$$

An image can have a minimum range of 0 pixel and a maximum range of 255 pixels. Equation (2) can be used to normalize the image. 100×100 pixel normalization is possible for the image. Figure 5 shows some sample image output of AD after resizing and normalization.

 

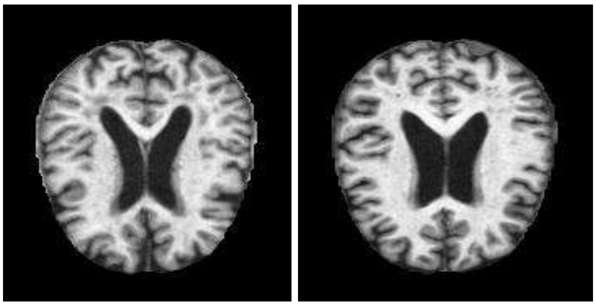

**Figure 5.** Sample normalized and resized images.

The AD images are classified using CNN. On a Jupyter notebook, CNN is implemented using the Python programming language. Sixty-four hundred images in all were gathered from secondary sources. 1280 of the 6400 photographs are chosen for testing, and 5120 of the images are used for training. A 100×100 image was used for CNN training, and a filter with a size of (16, 32) was applied. Lastly, a grid representation of the output from the filter with a size of 13*13*256 is displayed. SoftMax function is used for visualization following the output of an image with dimensions of 13*13*256. CNN uses the features of color, shape, and texture to classify images.

Transfer learning primarily uses New-CNN pre-trained model on a completely different dataset. The first three convolutional layers are frozen for classification. The primary concept of this approach is to figure out features that can be used in different types of pictures. The evaluation of the model is done using different scores, such as accuracy score, recall values, precision values, F1-scores, as shown in Figure 6.

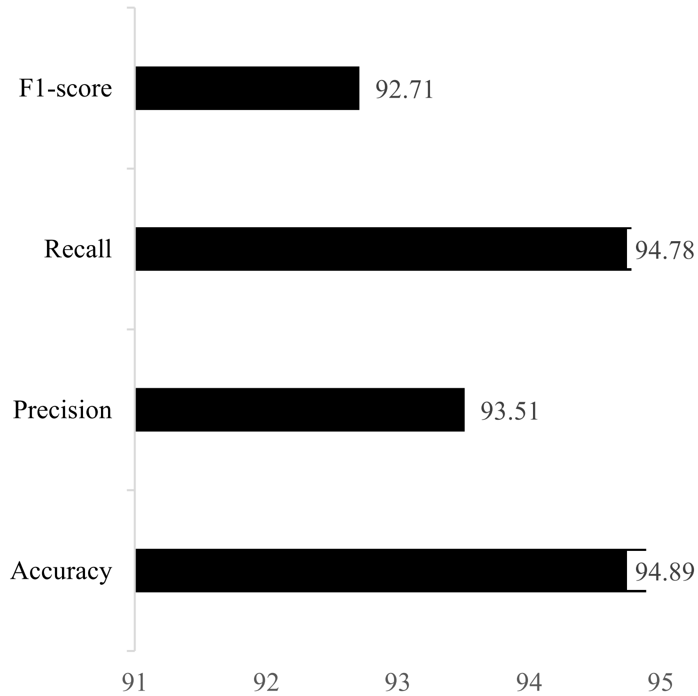


**Figure 6.** Evaluation result of AD.

**COMPARISON OF STATE-ART-MODELS WITH PROPOSED MODEL**

The result obtained with proposed New-CNN model shows an accuracy of 94.89% with recall score of 84.78%, precision score of 93.51% and F1 value of 92.71%. The differences in AD detection and classification performance between different models are shown in Table 1.

 

**Table 1.** Comparison of state-of-art-models with proposed model.

| Model Used | Accuracy |
|---|---|
| Proposed 3D CNN | 96% |
| Patch based SSA model | 95% |
| Eight-layer CNN | 97.65% |
| Deep Ensemble model | 92.5% |
| Ensemble of VGG16 and EfficientNet | 97% |
| New-CNN | 94.89% |

The suggested model's accuracy in identifying the illness is 94.89%. In this for CNN training, a 100×100 image was utilized, and a filter with a size of (16, 32) was applied. In conclusion, a 13*13*256 grid representation of the filter's output is shown. CNN uses the ReLu activation function in conjunction with max-pooling. The output of an image with dimensions of 13*13*256 is visualized using the SoftMax function. CNN classifies images based on color, shape, and texture attributes.

## CONCLUSIONS

Early detection of AD is difficult undertaking in clinical practice, and very few reliable techniques are available for the diagnosis process. To prevent brain damage and arrest the disease's progression, patients may benefit from early detection of mild cases, which can help direct further medical care. DL has attracted immense attention lately as a potential early AD identification method. Several scientists and academics are working to develop techniques for early identification utilizing MRI pictures to halt the progression of AD. An automatic classification approach for AD is presented in this research. The normalizing technique is applied to the secondary source picture dataset by the proposed system. CNN's training to testing ratio is enhanced with the use of the normalization technique. CNN receives the preprocessed, normalized picture input. The suggested approach performs well in terms of accuracy even with less training data. Also, by using many images for categorization, this model can be used to detect various diseases. In the future, the transfer learning approach will enable the New-CNN to be used with data-augmented images.

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