

# Comparable Study of Pre-trained Model on Alzheimer Disease Classification

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**Abstract.** The Alzheimer's disease (AD) is a type of dementia that affects millions of people worldwide every year and the occurrence will continue to be on the increase. The move to diagnose people suffering from AD at an earlier stage has been a daunting problem in mental health. In recent years, the advancement of deep learning in the likes of convolutional neural networks (CNN) has made a great effort towards an early detection of AD using magnetic resonance imaging (MRI) data. However, due to the need for highly discriminative features from MR images, it is still challenging to accurately use CNNs by training from scratch for early detection of AD. This paper aims to improve the early detection of Alzheimer's disease using deep learning for neuroimaging data. We have utilized the SqueezeNet, ResNet18, AlexNet, Vgg11, DenseNet, and InceptionV3 pre-trained models to automatically classify MR images. To validate our model, we experimented with the MR images obtained from the Open Access Series of Imaging Studies (OASIS) database. The average classification accuracy derived by SqueezeNet model for training and testing was 99.38% and 82.53% for binary class and multiclass, respectively.

**Keywords:** Alzheimer disease · CNN · Dementia · MR imaging · Transfer learning

## 1 Introduction

An irreversible progressive neurodegenerative disorder, called Alzheimer's Disease (AD), gradually destroys memory and induces complications in communication and carrying out daily activities such as speaking and walking [1]. Also, the progression of this disease slowly hips to an outspread loss of mental function such as memory defect, language impairment, disorientation, and personality change, eventually leading to death [2]. This disease is, currently, the paramount cause of neurodegenerative dementia in the world with an estimate of 131 million people projected to be living with dementia by 2050 [2]. The generic spread of AD represents a threat to healthcare and social systems

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[3], and even the drug to prevent or slow down cognitive decline in AD remains an unmet therapeutic need [4]. Thus, early, and accurate diagnosis of AD is of paramount need.

Therefore, accurate diagnosis of AD at the early stages based on the measurements of effective biomarkers can provide tangible information to assist researchers and clinicians develop a new treatment. A popular approach that is long-established in the diagnosis of AD is the neuroimaging techniques which are non-invasive and offer sufficient information for identifying abnormalities in the brain. Recently, several neuroimaging modalities, including structural Magnetic resonance imaging (sMRI) [5–7], functional magnetic resonance imaging (fMRI) [8–10], fluorodeoxyglucose positron emission tomography (FDG- PET) imaging [11, 12], amyloid positron emission tomography (PET), resting state- fMRI (rs-fMRI), and Diffusion tensor imaging (DTI) have been successfully utilized for AD diagnosis. However, some existing studies have successfully utilized a single modality to help to determine the onset of AD. For early diagnosis of AD, the most discriminating AD-related brain region based on MRI analysis includes the Cortical, Sub-cortical, and Hippocampus subfield [13–16]. For fMRI, some features such as Occipital_Mid_R, Precentral_L, Caudate_R, Postcentral_L, Temporal_Pole_Mid_L, Frontal_Inf_Oper_L, and Precuneus_L are highlighted in the discrimination of MCI and NCs [17–19]. As for FDG- PET, the average relative Cerebral glucose metabolic rate in the Precuneus, Superior Temporal gyrus in both hemispheres, Middle Frontal gyrus and superior frontal gyrus, middle cingulate cortex, and the angular gyrus in the left hemisphere [20, 21].

In recent years, several studies based on deep learning have focused on the analysis of MRI and showed that quantitative assessment of hippocampal atrophy via volumetric analysis can be utilized as a biomarker for AD [22–24]. In [25], a multi-task deep CNN model was proposed for hippocampus segmentation and hippocampus volumes based on the centroid of segmentation were computed for AD classification. An optimization technique was also proposed to measure hippocampus volume [26]. Hippocampal shape and intensity provide information that is independent of hippocampal volume [28]. In [29], the intensity and shape features on the decomposed image patches of the internal and external hippocampus are extracted for AD recognition.

Quite a few deep learning approaches have been successfully used to extract features from the hippocampus via different observations such as patched-based, voxel-based, and region-of-interest (ROI)-based. For instance, local patches, which are assembled into 2.5 dimensions, are extracted from MRI images [25]. Multi-task CNN learned features and extracted 3D patch covering the hippocampus based on the centroid of segmentation mask are passed as input to the 3D DenseNet model to learn more relevant features [26]. While most of the existing studies have focused on the use of CNN models by training from scratch [27–30]. However, training a model from scratch requires a large amount of dataset and consumes more time. The availability of pretrained models trained on large, labeled datasets such as ImageNet offer accurate learning models for deep feature representation. This approach that allows a pretrained network to be used as the starting point for a model on a second task is transfer learning. For example, authors in [31] utilized three pre-trained models to demonstrate the effectiveness of transfer learning to classify AD by updating all three model parameters. Here we present a comparative analysis of the effectiveness and sensitivity of different pre-trained models to classify

AD from MRI data. Open Access Series of Imaging Studies (OASIS) database of MRI scans of patients is used for the classification.

The contributions of this paper are summarized as follows:

- A new AD classification model based on deep transfer learning using whole-brain MR images for the classification of AD in the absence of preprocessing of the MR images with high accuracy is presented.
- The study focused on the detailed evaluation of binary (dementia or non-dementia) and multiclass (dementia or non-dementia or mild dementia) classification.
- The study compares the performance of different pretrained models such as AlexNet, Squuezenet, Inceptionv3, Resnet18, VGG16, DenseNet121 by applying a transfer learning method based on feature extraction.

The remaining paper is organized as follows: Sect. 2 includes a detailed literature survey of existing solutions. Section 3 describes the proposed method with an explicit explanation of transfer learning. The implementation details and the results obtained from our proposed method are presented in Sect. 4. Section 5 concludes the paper with future recommendations.

## 2 Related Works

The application of CNNs in classifying medical images has been a great success in the health care sector. However, training these models from scratch often needs a large amount of data. Therefore, the ImageNet dataset, consisting of millions of images has been used to train some CNN architectures, and this enables these models to utilize existing knowledge to know what to transfer, when to transfer, and how to transfer. The transfer learning performs some type of feature extraction scheme by training new layers after re-used layers to interpret their output. A good feature representation of the brain is identified at a reduced error rate and can allow a better prediction of AD patterns. The application of pre-trained CNN in different problems related to neuroimaging analysis has gained strength [32, 33]. For example, Authors in [34] utilized an end-to-end deep 3D CNN for the multiclass AD biomarker identification task, using the whole image volume from MRI. The study compared the performance of four pre-trained models and the best accuracy of 75.9% was obtained with the VGG network. The authors recommended the investigation of explainable techniques to understand brain regions involved in classification decisions. Authors in [35] presented a Siamese Vgg-16 model to classify dementia stages using a publicly available dataset open access series of imaging studies (OASIS) for evaluation. Authors in [36] presented a deep learning algorithm method using inception v3 CNN for detection of AD from ADNI data set. The proposed study considered the brain as a pixel-by-pixel volume in its classification. An efficient transfer learning architecture based on Pre-trained Alexnet was utilized to extract deep features in AD stage detection [38]. Authors in [39] proposed an efficient AD classification technique by fine-tuning a pre-trained AlexNet CNN model. The model was trained and tested for both binary and multiclass classification over the OASIS dataset. Authors in [38] investigated the use of transfer learning in the diagnosis of AD by exploring layer-wise transfer

learning on CNN architecture. The required information for AD diagnosis was extracted from MRI slices. Comparative performance analysis of three pre-trained models which include (AlexNet, GoogleNet, and ResNet50 were further performed using MR images from the OASIS database [40].

## 3 Experiments and Results

In this study, we have compared the performance of AlexNet, Vgg-16, Inceptionv3, Resnet50, DenseNet121, and SqueezeNet networks in classifying MRI brain images into No Dementia, Mild Dementia, and Dementia as using Open Access Series of Imaging Studies (OASIS) database. The workflow for this study is depicted in Fig. 1.

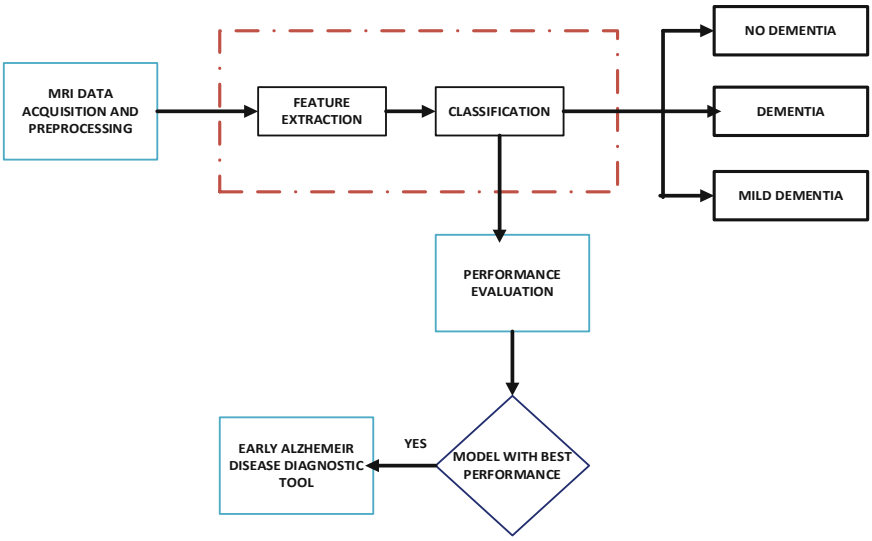


**Fig. 1.** Workflow used in this study

### 3.1 OASIS Dataset Description

The released data for the OASIS-3 dataset was utilized. The dataset consists of T1-weighted MRI of subjects with AD obtained from older adults between the age of 60 to 96 years. The subjects consist of 62 men and 88 women. Each image has a different number of slices, and a total of 1,566 slices for both non-dementia, mild dementia, and dementia were extracted. Figure 2 shows some examples of the slices that constitute the dataset used in this study. The first row corresponds to images with no dementia, the second row corresponds to images with dementia, and the third row corresponds to images with mild dementia.

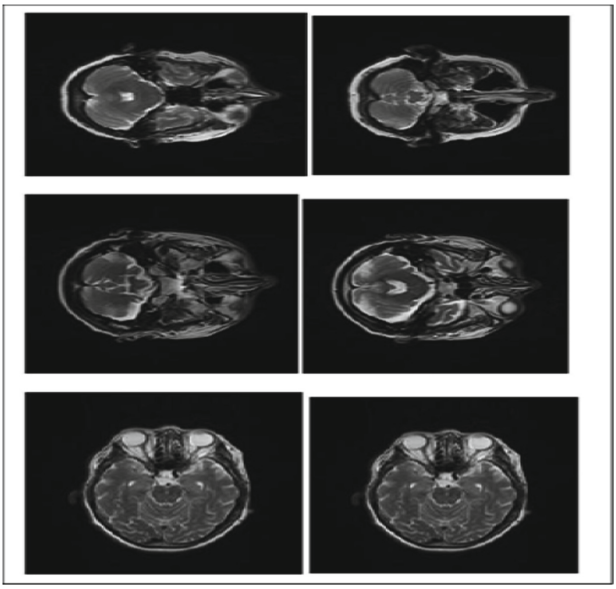

**Fig. 2.** Examples of slices of MR images from the OASIS database.

### 3.2 Experimental Setup

The base of CNN architectures are the convolutional and pooling layers, and the classifier consists of a couple of fully connected layers. We have reshaped the last fully connected layer of some of the pre-trained networks to have the same number of inputs as it was initialized and contains the same number of outputs as the number of classes in the dataset. For the training process, the stochastic gradient descent (SGD) optimization method was utilized to determine how to update the weights during training on the OASIS dataset for both binary and multiclass classification. Weight decay of 0.01 for L2 regularization was utilized through the optimizer. For each of the pretrained networks, various learning rates between 0.001 and 0.009 were tested, and a learning rate of 0.004 was utilized to train the pre-trained model. We have only trained the models for not more than 10 epochs and keeping the batch size at 8. This experiment was performed 5 times for each of the models to achieve the average classification accuracy of the model on different learning rates. The evaluation process for the OASIS dataset is conducted by using hold out. For the training (70%) and validation (20%) sets. The training dataset consists of 429 No Dementia, 390 Dementia, and 286 Mild Dementia. The validation data consist of 469. A data augmentation technique was implemented to increase the training samples. We have used PyTorch deep learning framework with anaconda for (Python 2.7; Python Software Foundation) to implement all pre-trained models because it easily offers transfer learning. All the models were trained on a single NVIDIA GPU. Table 1 shows the composition of the feature extraction layer of the pre-trained CNN models.

**Table 1.** Description of pretrained CNN models used in this study

| Pretrained CNN model | Reshape layer for feature extraction | Composition of the reshape layer |
|---|---|---|
| Resnet18 | Last layer (fully connected layer) | (fc): Linear (512 input layers, 1000 input layers, bias= **True**) |
| Alexnet | 6th layer | **(6):** Linear (4096 input / 1000 output features, bias = True) |
| Vgg 16 with batch normalization | 6th layer | (6): Linear (4096 input / 1000 output features, bias = True) |
| Squeeze net | 1st layer (1x1 convolutional layer) | (1): Conv2d (512, 1000, kernel_ size = (1, 1), stride = (1, 1)) |
| Densenet 121 | Classifier layer | (classifier): Linear (1024 input / 1000 output features, bias = True |
| Inception v3 | Two output Layers | (fc): Linear (768 input / 1000 output features, bias= **True**) (fc): Linear (2048 input / 1000 output features, bias= **True**) |

### 3.3 Performance Evaluation

Three metric measurements which include accuracy, sensitivity (recall), specificity, and precision were used to evaluate the classification performance of pre-trained CNN models depicted in Table 1. The binary and multiclass classification will pro-duce four outcomes which include True positive (TP), True negative (TN), False Negative (TN), and False Negative (FN), all terms are from the confusion matrix.

## 4 Results and Discussion

In this study, we evaluated the performance of different pre-trained models such as AlexNet, Vgg-16, Inceptionv3, Resnet50, DenseNet121, and squeezeNet using MRI imaging dataset from the OASIS database to identify the best classifier using 70% training samples and 30% for validation. Tables 2 and 3 show the performance obtained for each of the pre-trained CNN models during training and validation for binary classification and multiclass classification, respectively. These results show that squeeze net gave the best performance with 99.38% accuracy for binary classification and 82.53% accuracy for multiclass classification on the validation dataset. This could be explained because the first convolution layer of the classifier extracts deep image features that the final classification layer uses to classify the input image. Additionally, we noted that Inception v3 gave the least performance of 90.99% accuracy for binary class classification while ResNet 18 gave the least performance of 67.51% for multiclass classification. All these results obtained from the binary classification corroborates the results reported by [30] where the results of the pre-trained deep learning models show the effectiveness of pre-trained models in AD classification. Figure 3. shows a graph that outlines

**Table 2.** Binary classification performance comparison of different pre-trained CNN models based on accuracy for training and validation

| CNN pretrained model | Validation accuracy | Training accuracy |
|---|---|---|
| Resnet18 | 94.81% | 96.86% |
| Alexnet | 94.14% | 95.98% |
| Vgg 16 with batch normalization | 95.68% | 99.36% |
| Squeeze net | 99.38% | 99.41% |
| Densenet 121 | 95.02% | 98.28% |
| Inception v3 | 90.99% | 92.32% |

**Table 3.** Multiclass classification performance comparison of different pre-trained CNN Models based on accuracy for training and validation

| CNN pretrained model | Validation accuracy | Training accuracy |
|---|---|---|
| Resnet18 | 67.51% | 70.42% |
| Alexnet | 72.15% | 75.76% |
| Vgg 16 with batch normalization | 67.68% | 73.04% |
| Squeeze net | 82.53% | 86.40% |
| Densenet 121 | 67.72% | 67.31% |
| Inception v3 | 76.30% | 77.3% |

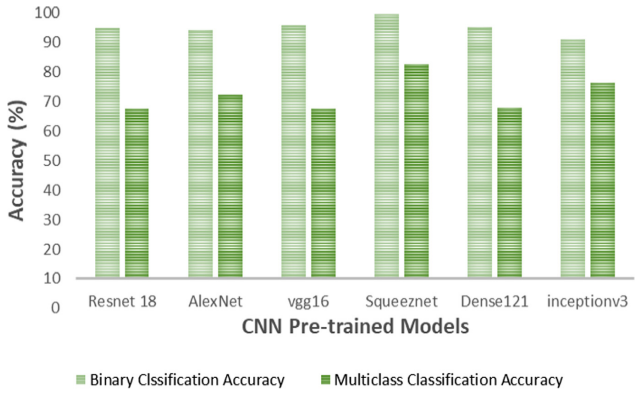


**Fig. 3.** Comparative results of various CNN models with binary and multiclass classification

the performance of the pre-trained networks against the number of classes utilized for classification.

The results from Tables 2 and 3 reveal that classification performance of the selected pre-trained models is affected by the number of predicted classes. The accuracy for

multiclass classification is lower than the accuracy for the binary class. This could be an account of certain reasons. First, the data set may contain not enough variation. Second, the performance of each model might also be related to the mild changes in the structures between patients with no dementia and mild dementia. Hence, it is difficult for the models to extract informative features that distinctly separate three classes. Tables 4 and 5 show classification performance from each of the pre-trained CNN models during validation for binary and multiclass classification.

**Table 4.** Binary class classification performance of pretrained model during validation

| CNN pretrained model | Specificity | Sensitivity | Precision |
|---|---|---|---|
| Resnet18 | 97.26% | 90.50% | 97.00% |
| Alexnet | 97.48% | 90.72% | 97.36% |
| Vgg16 with batch normalization | 97.92% | 93.40% | 97.80% |
| SqueezeNet | 99.89% | 98.88% | 99.88% |
| Densenet121 | 91.80% | 96.08% | 91.97% |
| Inceptionv3 | 92.24% | 89.72% | 91.94% |

**Table 5.** Multiclass class classification performance of pretrained model during validation

| CNN pretrained model | Specificity | Sensitivity | Precision |
|---|---|---|---|
| Resnet18 | 87.81 | 74.75 | 77.50 |
| Alexnet | 89.59 | 77.86 | 79.03 |
| Vgg16 with batch normalization | 87.85 | 74.59 | 75.62 |
| SqueezeNet | 90.07 | 80.33 | 83.42 |
| Densenet121 | 89.35 | 77.20 | 77.88 |
| Inception 3 | 86.99 | 72.97 | 80.97 |

From Tables 4 and 5, SqueezeNet is showing the best classification performance with 99.89% specificity and 98.88% sensitivity for binary classification likewise a specificity of 90.07% and 80.33 sensitivity for multiclass classification. High specificity and sensitivity can guarantee high true positive and true negative rates, respectively. And as regards neurodegenerative diseases it is of a high preferential to have a high sensitivity for all patients with AD to be effectively and accurately identified early. The current experimental results have shown a good view in terms of classification accuracy, and sensitivity when compared the results with existing classification experiments for binary and multiclass classification, especially squeeze net with 99.38% and 82.53 accuracies for binary and multiclass, respectively. To further show the performance of the pre-trained models on the OASIS data set. Figure 4. shows the per-class classification performance for sensitivity.

From Fig. 4, the performance comparison of per-class classification results of the pre-trained models has demonstrated outstanding performance for accurately positively classifying dementia in the case of squeeze net and inception with 96.74% and 91.86% respectively. The poor performance of the pre-trained models for positively classifying mild dementia could be due to the close brain changes between dementia and mild dementia as the two classes are both associated with reduced cortical thickness and surface area in the brain regions [41].

We can conclude from Tables 5 and Table 6 that SqueezeNet is a strong pre-trained model for MR image classification. SqueezeNet produced the best training and validation accuracy among other models. The second highest accuracies were obtained by VGG16 and Inceptionv3 for binary classification and multiclass classification, respectively.

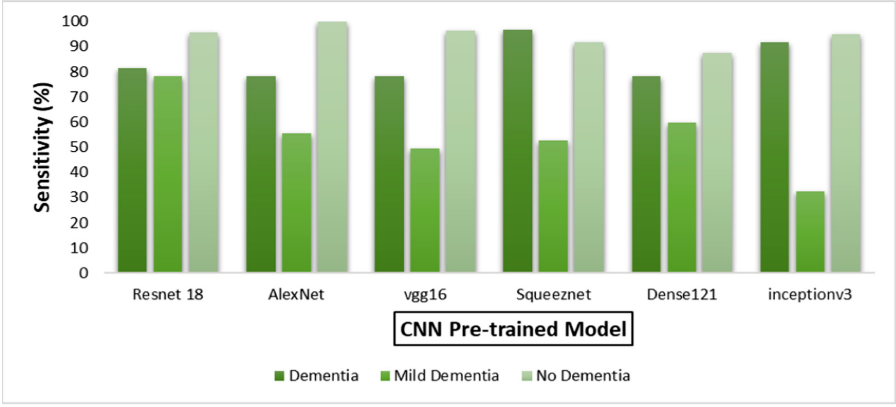


**Fig. 4.** Per class classification performance of the pre-trained models

## 5 Conclusion

Early detection of Alzheimer's disease remains a challenge, and deep learning classification has intrigued researchers due to its flexibility and ability to generate optimal findings. The availability of pre-trained models trained on big, labeled datasets like imageNet allows for reliable deep feature representation learning models.

Therefore, comparative analysis and evaluation of different pre-trained CNN architectures is presented in this study. We utilized transfer learning with a feature extraction approach using various CNN models which include DenseNet121, ResNet18, AlexNet, vgg16, SqueezeNet, and Inceptionv3 for accurate classification of MR images between three different classes, namely Dementia, No Dementia, and Mild Dementia. Analysis of the model was carried out by changing the learning rate and optimal performance was archived at 0.004 and 0.005 for binary and multiclass classification, respectively. The models had been well-trained for our OASIS dataset, and they were all effective at classification. SqueezeNet produced the highest validation accuracy of 99.38% and

82.53%. Hence, transfer learning as feature extraction using SqueezeNet is an effective technique to classify MR images into Dementia, Mild Dementia, and No Dementia.

In future, a visualization method could be added to the SqueezeNet to enhance the classification accuracy of multiclass classification.

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