

# An optimised deep learning approach for alzheimer's disease classification

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## ABSTRACT

Alzheimer's disease (AD) is a progressive and incurable brain disorder. It starts out subtly and gets worse with time. 60 to 70 percent of dementia cases are brought on by this illness. An Alzheimer's patient is diagnosed every two seconds, according to research. The complexity of the brain makes it often very challenging to identify in elderly people. In the area of medical imaging, deep learning is growing. Several deep learning techniques that attempted to identify and categorise the magnetic resonance imaging (MRI) brain images into four stages of AD will be compared in this work. 6400 MRI brain images were extracted from a dataset and divided into training, validation, and testing datasets. In our research on twelve deep learning architectures, inceptionV3 has given the best results with 99.56% and 97.75% accuracy on train and validation, respectively, and on test data, the model has achieved an accuracy of 95.81%. We trained the models using optimised ImageNet weights, which resulted in higher accuracy across all twelve models.

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## 1. INTRODUCTION

Alzheimer's disease (AD) is a degenerative brain disorder that gradually reduces one's capacity for thinking, remembering things, and performing even the most basic tasks. According to Aaparna and Rao [1], the first symptom of this disease is that it becomes hard to remember recent scenes. As the disease progresses, it will cause the person suffering from it to have mood swings, behavioural issues, self-neglect, and no motivation, and if the disease worsens even more, it may lead to depression and problems with speech. Although the life expectancy of AD-diseased people is around 3 to 9 years, gradually the person loses all of their body and momentary functions, which may lead to early death. Only a few people, less than 3% live more than fourteen years. One in ten people over the age of 65 has the potential to get infected with this disease. The signs start out moderate, but they steadily get worse. AD has three stages: stage 1, stage 2, and stage 3, which are non-sympathetic (generalised psychosis), mild (stage 1), severe (stage 2), and moderate dementia (stage 3) [2]. AD research focuses on reducing incidence and progression, but there is no evidence to support any approach because there are no illness modifying medications to cure AD. To find elements that can help prevent AD, further research is required. AD can be accurately classified and detected early using modern machine learning approaches like deep learning [3]–[8]. Early diagnosis of AD remains challenging, but machine

learning, especially deep learning, offers promising advances for more accurate and efficient diagnosis. While no cure exists, research is actively exploring new treatments targeting underlying disease mechanisms.

We conducted an in-depth analysis of the studies that have employed deep learning methods for the early identification of AD and the prognosis of AD progression [9]. The research studies were reviewed, categorised according to algorithm types and neuroimaging methods, and the results were gathered. We discussed two deep learning models that have given the best accuracy among the twelve deep learning models tested, as mentioned earlier, and the results obtained by performing them have been noted and visualised. According to Orouskhani *et al.* [10], the siamese deep neural network, an extension of the deep siamese network, uses brain scans from the open access series of imaging studies (OASIS) dataset. With 13 convolutional layers, the network improves performance by creating a triplet network with three different labels, reducing the euclidean norm and minimising loss. According to Chui *et al.* [11], the generative adversarial network (GAN), convolutional neural network (CNN), and transfer learning (TL) algorithm for AD detection uses three modules: GAN, CNN, and TL. CNN extracts feature from magnetic resonance imaging (MRI) images, while GAN generates additional data for minority classes. Three models are produced, refined using transfer learning, and hyperparameter tuned based on a trained GAN-CNN model.

Abed *et al.* [12] investigates using transfer learning to modify visual geometry group (VGG)-16, inception, and ResNet CNN architectures. VGG-19 uses tiny convolution filters, inception learns non-linear functions, and residual neural networks enhance network depth and quick convergence. The original architecture remains intact. According to Suresha and Parthasarathy [13], the system uses various feature extraction methods, with the sherlet transform (ST) include extraction strategy providing better results for AD discovery, with a 94.54% accuracy rate using the ST+K-nearest neighbour method. Research by Aparna and Rao [14], the technique accurately diagnoses Alzheimer's using weight-randomising deep features from the CycleGAN, MobilenetV2, and DenseNet121 networks. Four classes were created and trained using MRI slices, creating a balanced dataset of 6,400 pictures. Basaia *et al.* [15] developed a CNN-based deep learning model for predicting mild cognitive impairment (MCI) using a single brain MRI scan, with 95% accuracy on ADNI and 96.35% on non-ADNI datasets. Research by Hussain *et al.* [16], A 12-level CNN binary classification model is developed for recognising AD using brain MRI data. The model outperforms other CNN models using the OASIS dataset with a 96.75% score. According to Simon *et al.* [17], DICOM-formatted brain MRI images are used for training in deep neural networks, with the pre-trained networks Resnet, AlexNet, and GoogleNet analysed. Three networks are trained on 3000 photos, with common training settings. Performance comparisons are conducted based on accuracy and metrics. Pu *et al.* [18] proposes a four-stage approach to explore literature-based discovery for AD, including collecting an AD-specific corpus, constructing an AD knowledge graph, building 20 training and testing datasets, and inferring new knowledge using graph embedding-based link prediction methods, comparing different methods, and assessing their impact.

## 2. METHOD

This paper is an effort to use an Alzheimer's disease neuroimaging initiative (ADNI) dataset of various MRI images acquired from various sources. Building a deep learning model for the precise and early identification of AD is the main objective of this work. The dataset, neural network, and weight parameters that are learned during training make up the essential parts of any deep learning model. If the model takes advantage of these three factors to deliver the highest level of accuracy, it is said to be efficient. The suggested architecture is the inception V3 and VGG-19 models, which outperformed the other 12 architectures tested and trained on the same dataset [19], [20]. As shown in Figure 1 preprocessing is done on the repository dataset in accordance with the input size of the model. The ImageNet's weights are used to generate and initialise the suggested models, VGG19 and inception V3. The model is constructed with the metrics, optimizer, and loss function that are necessary and likely to provide good accuracy. The model will be tested on the test data after it has been created to determine its accuracy. After comparing accuracy, the diseased image is extracted from the data set. Thus, it is classified into four classes: non-demented, very mild demented, mild-demented, and moderate-demented.

### 2.1. Dataset description

The dataset contains 6,400 MRI images of AD, divided into mildly demented, very mildly demented, non-demented, and moderately demented categories. Every single image is a PNG file with a resolution of 224×224. The grayscale images were produced using three channels of RGB values that appeared repeatedly. The dataset is a massive amount of data needed for deep learning models. In Table 1 we representing the dataset is divided into training, testing, and validation sets, with 80% training data and 20% testing data.

### 2.2. Inception V3

The inception V1 is split into smaller convolutions, and these smaller convolutions are proportionally split into asymmetric convolutions to produce the inception V3. It will accept input with a dimension of 299×299×3 [21]. In order to regularise the classifier and evaluate the effect of label dropout during training, it

also has a feature called label smoothing regularisation. With this addition, the error rate is reduced by 0.2%. The batch normalization (BN) layer, which serves as a regularizer, is inserted by inception-v3 between the auxiliary classifier and the fully connected (FC) layer. The batch gradient descent approach may be used by the BN model to speed up deep neural network training and model convergence. The written BN formulae are as follows:

$$C = X_i \dots m, \beta, \alpha \tag{1}$$

$$y_i = BN\beta, \alpha(X_i) \tag{2}$$

$$\mu_C = \frac{1}{m} \sum_{i=1}^m X_i \tag{3}$$

$$\sigma_C^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (X_i - \mu_C)^2 \tag{4}$$

$$X_i \leftarrow \frac{X_i - \mu_C}{\sqrt{\sigma_C^2 + \epsilon}} \tag{5}$$

$$y_i \leftarrow \beta X_i + \alpha = BN\beta, \alpha(X_i) \tag{6}$$

Where X is the minimum activation value of batch C, m is the number of activations [22]. The values  $\beta$  and  $\alpha$ , are parameters which must be learned. For adapting the variance in the value distribution, the value  $\beta$  is responsible, and  $\alpha$  is responsible for modifying the position of the mean value,  $\mu_C$ , in one dimension. The feature map's standard deviation for each dimension is represented by the constant  $\sigma_C^2$  and  $\epsilon$  is a constant.

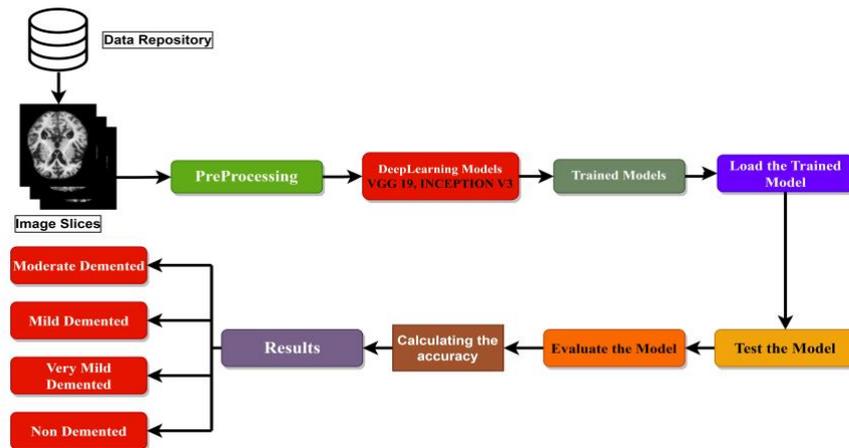


Figure 1. Flow chart for proposed methodology

Table 1. Split four classes of MRI image dataset for train, test, validation

Train/validation/test	Classification	No. of images	Total
For training	Mild demented	574	4096
	Moderate demented	41	
	Non-demented	2048	
	Very mild demented	1433	
For validation	Mild demented	143	1024
	Moderate demented	10	
	Non-demented	512	
	Very mild demented	359	
For testing	Mild demented	179	1280
	Moderate demented	13	
	Non-demented	640	
	Very mild demented	448	
	Total		6400

As shown in Figure 2 the inception v3 network uses convolutions and pooling techniques to extract low-level information from a 299×299×3 pixel image. The inception modules, consisting of multiple convolutional branches, are used to capture characteristics at different scales. Reduction modules are included to decrease spatial dimensions and increase feature map depth. The feature maps are downsampled using 1×1,

3×3 convolutions, and max pooling. The top layer produces predictions for various classes. Auxiliary classifiers are used at intermediary levels to solve the vanishing gradient issue and provide more supervision signals. The training of the model is done with the mentioned dataset. The images are reshaped to 299×299 by preprocessing. Utilising Imagenet weights, the inception V3 network has been set up. The inner layers and output layers have used rectified linear unit (ReLU) and softmax activations accordingly. The model is created using a categorical cross-entropy loss function and a stochastic gradient descent optimizer with a learning rate of 0.001. The model then went through 30 epochs of data training after that.

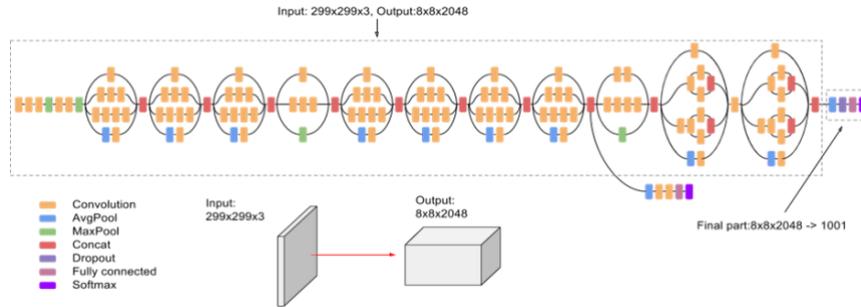


Figure 2. Inception V3 Architecture

2.3. VGG-19

The VGG at the University of Oxford has developed the CNN architecture known as VGG 19 [23]. In order to have deeper layers and offer greater performance in image classification tasks, it is an expansion of the original VGG 16 architecture. Convolutional, pooling, and FC layers are all included in the network’s total number of layers, which is represented by the “19” in VGG 19. The clear diagram of VGG 19 has been shown in Figure 3. Small 3×3 filters and 2×2 maximum pooling layers are used throughout the architecture, which has a straightforward and consistent topology. No further dense layers are added to the network to ensure clean and clear results for the actual VGG 19 model. We used the previously mentioned dataset for our experiment on VGG 19. The loaded dataset has been forwarded to preprocessing. Images of the size 224×224 are acquired and then sent to the model as input. There are 19 layers, 16 of which are convolutional ones using filters with a 3×3 size, 1×1 strides, and 1×1 padding. As was already said, the model has three FC layers and three layers with maximum pooling. In order to categorise the image, we have initialised ImageNet’s weights, utilised Relu activation for the inner layers, and Softmax with four classes for the final layer. Metrics are produced using the Adam optimizer with a learning rate of 0.001 and a categorical cross-entropy loss function, and metrics are calculated in terms of accuracy. The model is then compiled and run for 30 epochs on a GPU as a hardware accelerator. The output of each convolutional layer is represented by the subsequent (7).

$$C_n^h = \Phi \left( \sum_{m=1}^{M^{h-1}} C_m^{h-1} \times k_{mn}^h + b_n^{h-1} \right) \tag{7}$$

Here,  $x$  represents the convolutional function that connects the weights of the  $m$ th and  $n$ th features in the  $(h-1)$ th and  $h^{th}$  layers,  $b_j$  is the bias value, and  $\Phi$  is the activation function [24].

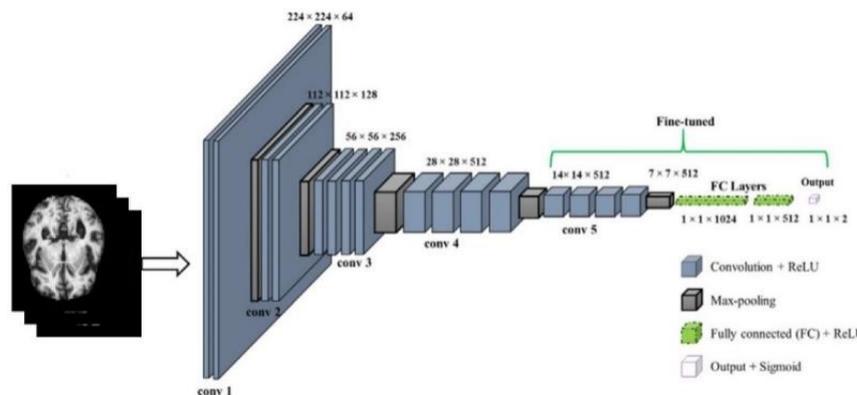


Figure 3. VGG-19 CNN architecture

## 2. RESULTS AND DISCUSSION

As previously mentioned, we used the weights from ImageNet to train the models, which allowed us to increase accuracy. Pradhan [25] classified the 6400 images from the same Alzheimer’s dataset using VGG 19 and Densenet 169. For DenseNet 169, they ran the model for 40 epochs without using Imagenet’s weights and obtained an accuracy of about 87% on the train data and about 80% on the test data; for VGG 19, they ran the model for 50 epochs and obtained an accuracy of about 88% and 82.6% on the train and test sets, respectively. We trained the identical models for 30 epochs using ImageNet’s weights, and the results were superior to those reported in the previous study. The accuracy of the training, validation, and test sets for the VGG 19 model was 98.51%, 95.02%, and 95.63%, respectively, while the accuracy of the same three sets for the DenseNet 169 model was 94.88%, 89.06%, and 88.43%. The best results in our research were produced by inception V3, but our models’ outcomes outperformed those of a few other studies. We achieved 99.56% accuracy on the train set, 97.75% accuracy on the validation set, and 95.81% accuracy on the test set for the inception V3 deep learning model. All twelve models are tested and run for 30 epochs, and Table 2 displays the training accuracy, validation accuracy, and testing accuracy for each model. When compared to other models that were run for the samenumber of epochs, it is evident that inception V3 and VGG 19 have produced better results. The accuracy data are graphically shown in Figure 4, respectively, as a line graph. Figure 4 shows the train, validation, and test accuracies as blue, red, and green lines, respectively.

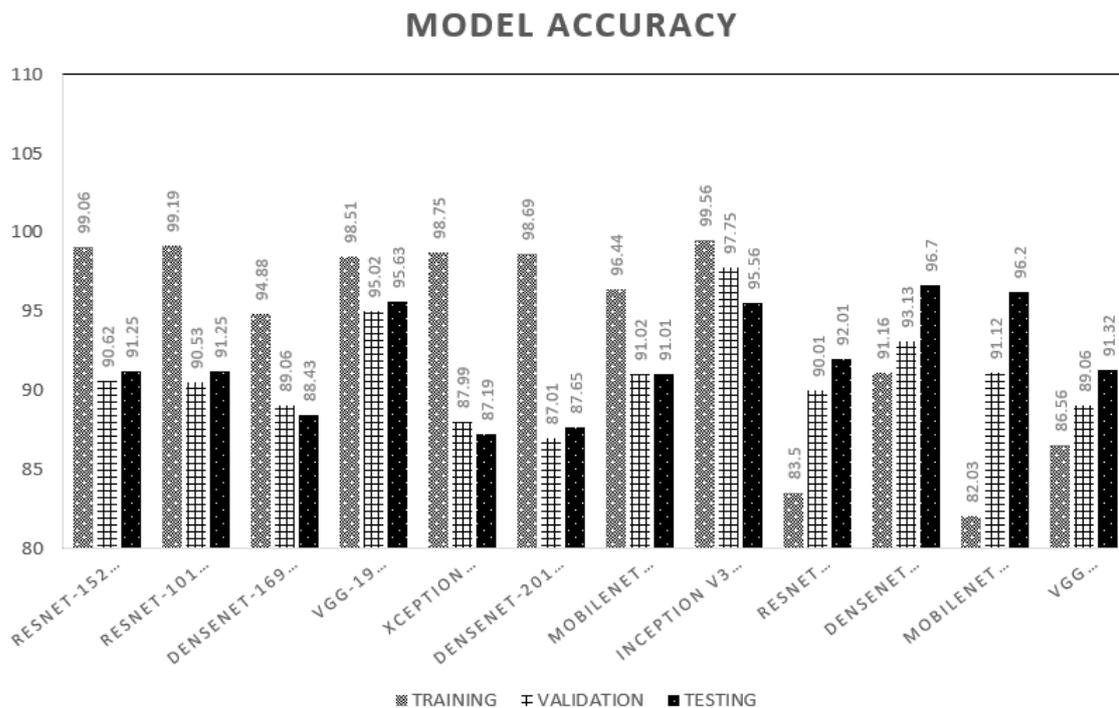


Figure 4. Train, test, and validation accuracies of 12 models are compared

Table 2. Train, test, and validation accuracies of 12 models run for 30 epochs

SNO	MODEL	Epochs	Train Acc	VAL Acc	Test Acc
1	XCEPTION	30	98.75	87.99	87.19
2	DENSENET-201	30	98.69	87.01	87.65
3	DENSENET-169	30	94.88	89.06	88.43
4	MOBILENET	30	96.44	91.02	91.01
5	RESNET-101	30	99.19	90.53	91.25
6	RESNET-152	30	99.06	90.62	91.25
7	VGG-16	30	86.56	89.06	91.32
8	RESNET 50	30	83.5	90.01	92.01
9	MOBILENETV2	30	82.03	91.12	96.2
10	DENSENET121	30	91.16	93.13	96.7
11	VGG-19	30	98.51	95.02	95.63
12	INCEPTION V3	30	99.56	97.75	95.81

### 3. CONCLUSION

In conclusion, this research paper has the motive of classifying the brain images into four classes of AD through deep learning. Twelve deep learning models were taken and trained on different numbers of epochs on a dataset consisting of 6400 MRI images that was taken from Kaggle. Through extensive analysis and experimentation, we have made several key observations and drawn significant conclusions. Additionally, we have identified a limitation in our research. For instance, the dataset that was taken is of a smaller size, i.e., the number of images is very low. We can apply GANs to increase the number of images, which can then be sent for training. Also, advancements in technology have brought changes to image capture. 3D brain images are also being produced and are being researched for better results in AD classification using deep learning. Our further work may include working on 3D images for the classification of AD and applying GANs if needed. Thus, our research paper sheds light on classifying the brain images as AD-infected or not based on 2D images.

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