How to Cite:
Rajendiran, M., Kumar, K. P. S., & Nair, S. A. H. (2022). Detection of Alzheimer's disease in MRI images using different transfer learning models and improving the classification accuracy. *International Journal of Health Sciences*, *6*(S3), 11851–11869. https://doi.org/10.53730/ijhs.v6nS3.8944

Detection of Alzheimer's disease in MRI images using different transfer learning models and improving the classification accuracy

M. Rajendiran
Research Scholar, Department of Computer and Information Sciences, Annamalai University, Chidambaram, India
Email: rajendiranmaha@gmail.com

Dr. K. P. Sanal Kumar
Assistant Professor, PG Department of Computer Science, R.V Government Arts College, Chengalpattu, India
Email: sanalprabha@yahoo.co.in

Dr. S. Anu H. Nair
Assistant Professor, Department of CSE, Annamalai University, Chidambaram, India [Deputed to WPT, Chennai]
Email: anu_jul@yahoo.co.in

***Abstract*---**Alzheimer's disease (AD) is a neurodegenerative illness that damages brain cells and impairs a patient's memory over time. If detected early so, the patient can avoid permanent memory loss and further damage to their brain cells. Various automated technologies and techniques have been developed in recent years for the detection of Alzheimer's disease (AD). Methods that focus on rapid, accurate, and early identification of the condition in order to reduce the negative impact on a patient's mental health are available. Medical imaging systems for Alzheimer's disease (AD) diagnostic performance have been greatly improved by machine learning models. There is a major difficulty with multi-class classification, however, which is the presence of brain structural characteristics that are extremely closely associated. It is possible to improve deep learning by increasing the number of layers and including features and classifiers at all levels of the classification hierarchy. Nevertheless, the vast majority of deep learning models (like traditional CNN model) fail to deliver acceptable results in real-world situations. The different transfer learning models (like AlexNet, VGG-16 Net, ResNet-50 and Google Net) classification model presented in this research aims to increase robustness. We have built and compare various transfer learning model. Based on OASIS dataset, we've gathered 8,980 MRI images to test our suggested

technique. According to our research, we have observed that a Google Net model outperforms than other transfer learning deep learning models.

***Keywords*---**deep learning, Alzheimer's disease, disease diagnosis, prediction, disease identification and medical image.

Introduction

AD was named by Emil Kraepelin in 1910 in honour of Alois Alzheimer, who first described the signs of the illness in 1906. Dementia of the Alzheimer kind is the most frequent type of dementia. People over the age of 65 are the primary victims of this degenerative and deadly neuro-disorder [1-3]. An estimated 26.6 million people throughout the world suffer from mental impairment as a result of this condition, according to a recent survey. Age-related anxieties or stress-related symptoms are thought to be the most common adverse effects of this illness. Memory loss is a hallmark of this condition. The beta-Amyloid protein is the most common cause of Alzheimer's disease. There is an increase in the creation or concentration of a beta-Amyloid protein in the brain, which damages or kills nerve cells [4-6]. Alzheimer's disease (AD) is characterised by slight memory loss at first, but as the illness progresses, people lose their capacity to communicate and respond to their surroundings. This neurodegenerative illness might be difficult to detect in its early stages. New criteria for effective diagnosis of brain-related disorders have been established thanks to neuroimaging [7,8].

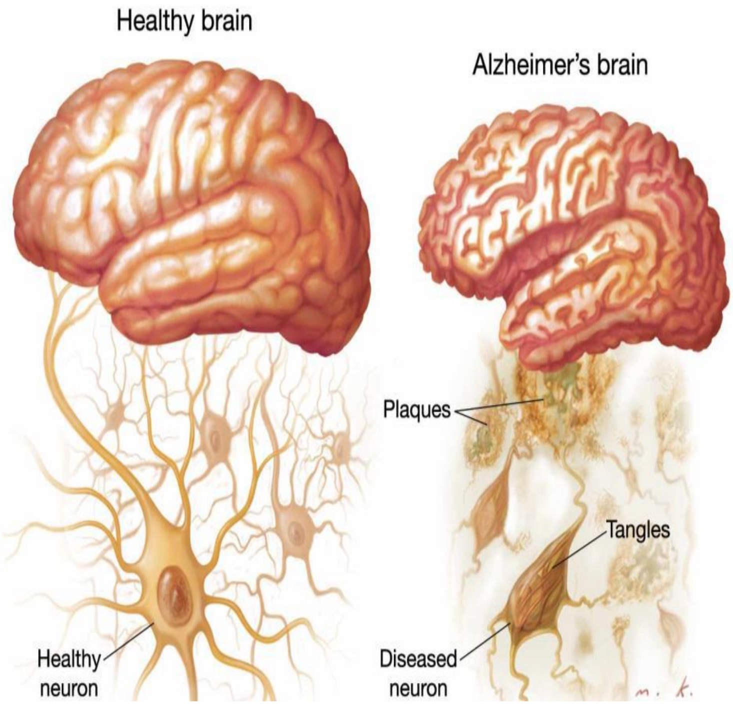

Fig 1. Normal Brain vs. AD Disease affected brain

The following are typical phases of degradation caused by Alzheimer's disease:

- Slight Memory Loss, Mood Swings, Low response for the actions and slow learning, anxiety of new situations, less energy level.
- Discomfort in speaking and comprehension, searching words during a conversation, inability to pay bills, and getting lost while traveling. Further, depression, irritability, and restlessness due to loss of control are also noticed.
- The other disorders are short-term memory loss, significant confusions in time, place, and possibly person, para-phasic speech.
- Incapability to dress correctly, being unaware about the circumstances around them, inability to recall simple details about themselves
- Loss of ability to recognize the faces of friends and relatives, inability in bladder and bowel control, significant behavior change.

The rest of this article will be organised as follows: In Section 2, we undertake a literature assessment of Alzheimer's disease classification approaches that have been used in the past. Section 3 explains the recommended processes for choosing and pre-processing MRI data, extracting the feature and classifying the illness using deep learning techniques. Section 4 compares the experimental outcomes of several classical classifiers. Section 5 concludes with a summary of the findings and recommendations for further research.

Literature Survey

In the recent several decades, many researchers have developed a variety of image processing approaches, such as artificial intelligence and machine learning, for the detection of Alzheimer's disease. There are a few stages to take in machine learning algorithms to effectively and efficiently classify Alzheimer's disease. In general, AD disease classification methods may be divided into three categories: traditional, machine learning-based and deep learning-based. In this section, we will explore the literature on the three methods we used to classify AD disease in earlier.

According to Chaplot et al. [9], a method exists that may translate MR brain images into wavelets, which can then be used as inputs for Self Organizing Maps (SOMs). These MR brain images are classed as either normal or pathological based on their appearance. This research improves the precision with which classifications are made. In 2010, El-Dahshan et al. [10] published a tri-phase AD classifier for MRIs that incorporates the retrieved features and dimensionality reduction for the classification of Alzheimer's disease. In order to identify the most relevant features for classification, the researchers utilised DWT, PCA, Feed-Forward Back-Propagation Artificial Neural Network (FP-ANN), and k-next-neighbor (k-NN). There was a 87 percent or higher accuracy rate for classification using these techniques. Joshi S et al. [11] produced a multi-layer perceptron, bagging, decision tree, Co-active Neuro-Fuzzy Inference System (CANFIS), and genetic algorithm that were created utilising different machine learning techniques for Alzheimer's disease categorization. The accuracy of the CANFIS method's classification was 88.55 percent.

Filipovych R et al. [12] employed an SVM model to categorise images using a supervised technique. MR brain images may now be classified into normal and AD-influenced images using a new approach developed by Herrera L J et al. [13]. In their method, MRI characteristics are extracted in the wavelet domain, reduced in dimension, then classified using SVM. The traditional machine learning based AD disease classification was not saturate because the feature extraction is made by hand-craft. So taking this issue into further, many researchers came to deep learning based AD disease classification. The deep learning based classification (Traditional CNN) is extracting the features automatically without hand-craft or man-made work. For the diagnosis of Alzheimer's disease (AD), Li et al. [14] offered a variation of the standard deep learning technique, and they explored the dropout impact as a solution for handling overfitting, caused by weighted co-adaptation. For this purpose, they proposed a new deep learning structure that incorporates the choice of stability, adaptive learning and multitask learning to classify input images into mild cognitive impairment (MCI). According to this study, deep learning can be improved by incorporating dropouts into the process. An image segmentation and fMRI AD detection method was developed by Sampath et al. [15]. AnFIS (Adaptive Neuro-Fuzzy Inference System) was utilised for feature extraction and segmentation, and Network was employed for classification. The results of this AD detection approach were significant.

In 2015, Li et al. [16] introduced a new method based on Principle Component Analysis (PCA). Permanent selection and dropout models are used as well as a deep learning approach called Restricted Boltzmann Machine (RBM). According to Tohka et al. [17], SVM and features-based classification algorithms were compared for their ability to detect the extent of dementia in patients using fMRI data and their performance. Alzheimer's Disease Neuroimaging (ADNI) database was used to classify AD and MCI patients against a "Normal Control" (NC). Feature selection with and without a filter and embedded features were examined in the study. Sample size and feature count have a significant impact on classification accuracy, according to a recent study. In order to improve classification efficiency, Zhang D et al. [18] presented a multi-kernel SVM. For MRI information, a deep learning framework based on 3D Convolutional Neural Networks (CNN) has been proposed. A sparse regression classifier is used in conjunction with the MRI Voxel-wise grey matter density map and PET intensity data to arrive at a multi-modal AD classification.

Sarraf S et al. [19] used CNN to develop a new method for distinguishing between an Alzheimer's-affected brain and a healthy brain. An important function of medical dataset classification is to aid in the development of predictive models and mechanisms for the detection and diagnosis of illness using clinical datasets and its associated phases. It has always been difficult to classify clinical information such as Alzheimer's disease, and identifying the most discriminating traits has always been the most difficult component. CNN and the LeNet-5 architecture were utilised to diagnose Alzheimer's disease. Brain MRI of normal controls yielded a 88 percent success rate. In this experiment, CNN and deep learning classification were shown to be the most effective methods for discriminating between clinical and healthy fMRI data using invariant shift and scale characteristics.

Ju R [20] developed a new method for detecting Alzheimer's disease based on neural networks and medical data. Classification of fMRI pictures and text using model training and classification is carried out. Deep Neural Network (DNN) classification was used by Gulhare K K et al. [21] to identify Alzheimer's illness. Non-demented and demented older adults were included in the longitudinal MRI dataset. A system for image segmentation with customizable features was devised. Finally, categorization based on the DNN is used to look for signs of Alzheimer's disease. 89.6% accuracy and a low mistake rate were achieved by using DNN to detect AD correctly. Using a deep learning model, Luo S et al. [22] established a new technique for automated identification of Alzheimer's disease. It made use of 3D brain scans to do CNN-based categorization. In this case, the invention was certified and experienced relying on MRI data obtained from the ADNI dataset. The data revealed that the increased sensitivity detection of Alzheimer's disease accuracy is 92 percent and the specificity is 93 percent.

For the novel deep learning-based strategy, Lu D and his colleagues [23] found a new method to improve its performance efficiency. When it comes to identifying MCI patients who may go on to develop Alzheimer's disease (AD) within the next three years (86.4 percent combined conversion accuracy in the time period from one to three years), 94 percent of this method is accurate, while the specificity in identifying non-demented controls is an impressive 86%. An effective whole-brain hierarchical network was built by Liu J [24] for MRI-based categorization of Alzheimer's disease (AD). The texture properties of ROI were included into the hierarchical network in order to improve classification accuracy. The high-dimensional features generated from raw feature spaces during AD classification were also given by computing the features' F-scores using this approach. The classification performance on the photos was enhanced by using a Multiple Kernel Classifier (MK-C). Proposed MRI-based AD diagnostic approach was tested using ADNI database MRI data and found to be effective and promising for clinical use. The summary of review given in this research covers the traditional methods and traditional CNN deep learning approaches for AD diagnosis. The above mentioned all the machine learning based models are not saturating in the terms of accuracy. In order to tackle the issue, we have used various transfer learning model like AlexNet, ResNet-50, Google Net model and VGG-16 Net model.

Proposed Methodology

The goal of this research is to compare the various transfer learning deep learning models namely AlexNet, VGG-16 Net, ResNet-50 and Google Net model for improving the classification and recognition of AD diseases. There are four primary parts to the system, which are: dataset gathering, Deep feature extraction, training, and testing. Pre-processing and extraction of features from the dataset is done using scikit learn [25] and Keras [26] with TensorFlow [27] as backend libraries for the deep learning modelling. Train the all models independently and compare the performance of each model respectively. Finally, predict the results for each transfer learning model.

Contribution of the Research

The overall methodology/algorithm implemented in the proposed system is broken down into the following steps:

- Image acquisition is being done.
- Load the image files into the programme as a folder directory.
- Divide the dataset into three groups namely training, validation and testing with 70%, 20% and 10% respectively.
- To train the four transfer learning deep learning models independently and obtain the results of each models individually.
- In order to predict the results we compare the four models (AlexNet, ResNet-50, Google Net and VGG-16 Net Model).
- Predict the outcomes as confusion matrix including true positives and false positives as well as true negatives and false negatives.

Dataset Collection

Open Access Series of Imaging Studies (OASIS) provided the data for this study on Alzheimer's disease [28, 29]. Tests on the model were carried out on the dataset. It has a total of 4 classes with a total of 8,980 Magnetic Resonance Imaging (MRI) images, with each class including 2245 images. Each image has a resolution of 176x208 pixels in the grey colour scheme. In our proposed work, Mild Dementia is labelled as 0, moderate Dementia is labelled as 1, non-demented is labelled as 2, and very mild Dementia is labelled as 3.

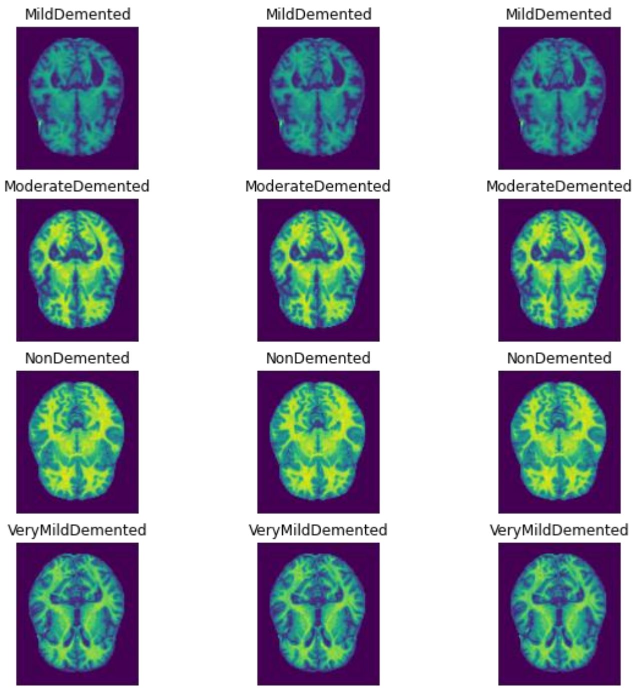

Fig. 2. Sample images from OASIS dataset

Figure 2 shows several examples of images from the OASIS dataset for Alzheimer's disease identification and recognition in MRI images. Each row displays a selection of images from each class. Separate training and testing sets were created from the dataset. As shown in Table 1, 70% of the dataset is employed to train the model, 20% of the dataset is employed to validate the model, while 10% is used to test it.

Table 1
Description about the Alzheimer's disease images

S. No.	Disease Type	Total No. of Images	Training Images	Validation Images	Testing Images
1.	Mild Demented	2245	1575	448	222
2.	Moderate Demented	2245	1575	448	222
3.	Non Demented	2245	1575	448	222
4.	Very Mild Demented	2245	1575	448	222

CNN Model

Deep learning algorithms, such as CNNs, are broadly applied in computer vision because of their likeness to human brains. CNNs are used for a variety of applications, including image recognition, image categorization, and so on. A CNN-based image categorization system is employed here. The layers of a CNN model are comprised of an input layer, numerous hidden layers, and an output layer, which is often separated into four categories as shown in Figure 3:

- Feature Extraction (Convolutional layer)
- Feature Reduction (Pooling layer)
- Flatten and Fully connected
- Prediction results (Soft-max)

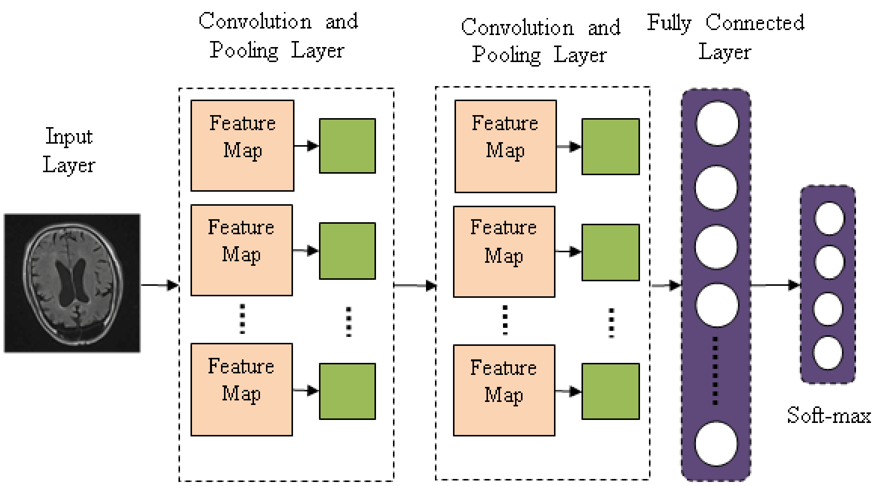

Fig. 3. Architecture of CNN model

Feature Extraction

Feature extraction or feature maps are created via convolution in CNNs, which can use the original image or another feature map as the input. It is the primary purpose of convolution in ANNs to exploit the unique structure of the input and learn how to turn it into the most informative form. A dot product multiplication is performed between a 3x3 sized filter matrix and a 3x3 sized section of the input image matrix in Figure 4.

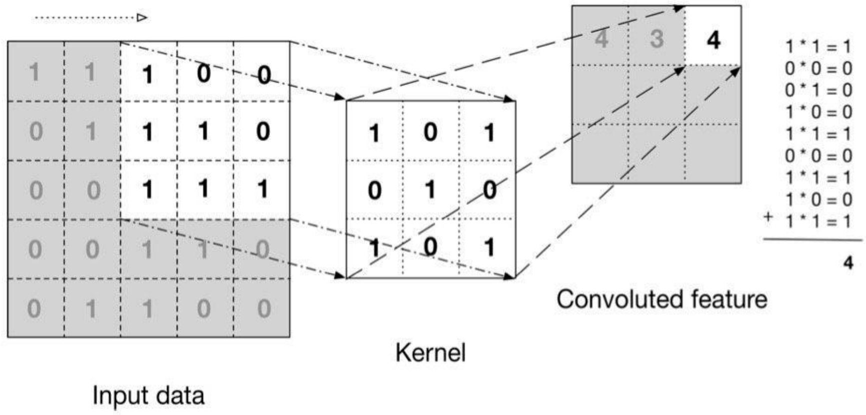

Fig. 4. Convolutional layer

It is the total of all of the resultant matrix components that is used to determine the "target pixel" on the map. Using the input matrix as a guide, it does the dot product multiplication on each of the remaining 3x3 sized sections, thereby completing the feature map. As a final step, the feature maps from each of the different filters are combined into a single convolutional layer. Additionally, convolutional layers have strides and padding. Input matrix strokes are the number of pixels a kernel or a filter moves over the input matrix. In cases when the filter does not match the input matrix, padding is utilised to compensate. Both "valid" and "zero/same" padding exist.

Feature Reduction

The pooling layers also sometimes called as feature reduction. Because, the height and width of feature maps are reduced by pooling layers, but the depth is retained. Reducing the amount of work necessary to process the data while still extracting the most important characteristics in feature maps is an advantage. Max and average pooling layers are the two types of pooling layers. As shown in Figure 5, Max pooling returns the maximum value of the elements in the section of the image covered by the filter, whereas average pooling provides the average value of the elements in the area of the image covered by the filter. Max pooling is more effective at extracting dominating characteristics and is consequently seen as more performance-enhancing.

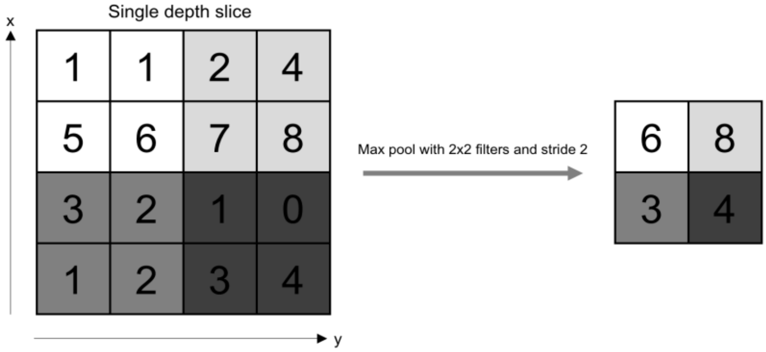

Fig. 5. process of feature reduction

Flatten and Fully connected Layer

When convolution/pooling results are sent into the fully connected layer, it flattens the data and then predicts which label best describes the image. It is common practise in a feed-forward neural network to multiply and total inputs before passing them on to the fully connected layer. The output is then generated using an activation function. The next fully connected layer receives the findings of the previous one. The final one includes a neuron for each class label, and it generates the probability distribution for each class label.

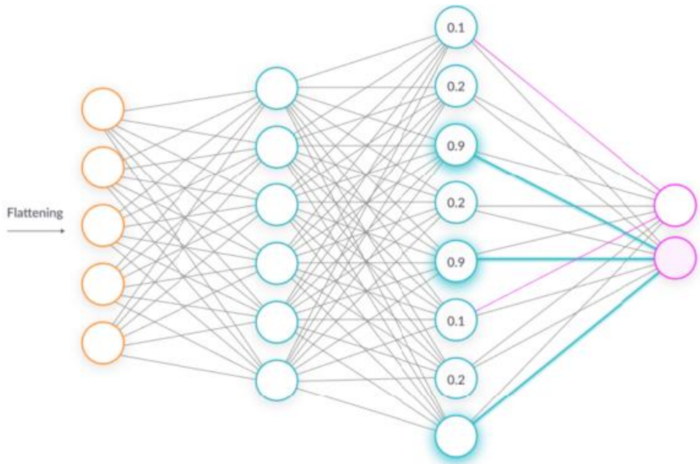

Fig. 6. process of converting 2D data into 1D vector

Finally, for prediction there are N classes to pick from, and the Softmax function outputs an N-dimensional vector. In this N-dimensional vector, each value shows the likelihood that a image falls into a certain category. As shown in Figure 6, the likelihood that a image belongs to class 1 is 10%, that it belongs to class 3 is 90%, that it belongs to class 4 is 2%, and that it belongs to class 8 is 0%, for example, if the output vector is [1. 2. 9. 2. 9. 1. 2. 0].

Alex Net

AlexNet is an eight-layer CNN with five convolution layers, three maximum pooling layers, and three fully linked layers. Over one million images and more than 1,000 categories from the ImageNet database were used to train AlexNet. It can take images up to 227x227x3 pixels in size as input: The input image's width and height are represented by the resolution of 227×227, while the digit 3 indicates that the images are RGB colour images. The first convolution layer has 96 filters with an 11x11 filter size and four strides.

Table 2
Information about Alex Net model

Layer	Filters	Filter Size	Stride
1	96	11×11	4
2	256	5×5	1
3	384	3×3	1
4	384	3×3	1
5	256	3×3	1

The second convolution layer is made up of 256 filters, each with a filter size of 5x5 and a stride of one. Third convolution layer has 384 filters with a 3x3 and a single stride filter size. In the fourth convolution layer, 384 filters with a filter size of 3x3 and a stride of one are used. Each of the 256 filters in the fifth convolution layer has a filter size of 3x3 and a one-stride length. Table 2 depicts the information about the number of convolution, filter size and stride respectively. A 3x3 pool size is used for ReLU and max pooling to normalise each convolutional layer thereafter [29,30]. Figure 7 depicts the AlexNet system's overall design layout.

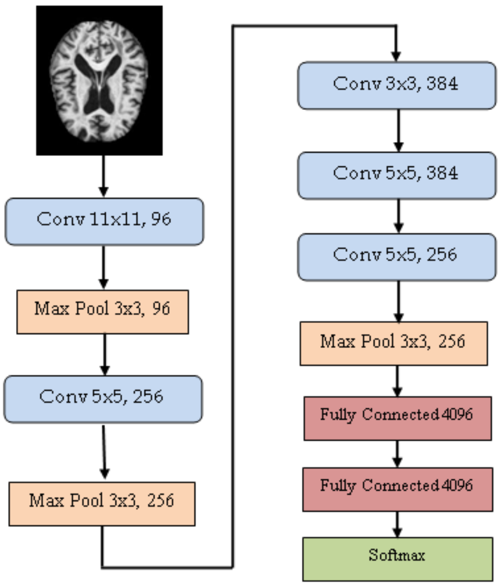

Figure 7. Architecture of Alex Net Model

VGG-16 Net Model

The Convolutional Neural Network evolved into the Deep Convolutional Neural Network, which has a greater number of convolutional layers than the original CNN. AlexNet is one of the most popular Deep CNN models, however there are a number of others. In the ILSVRC-2014 competition, Krizhevsky et al. [2015] offered the VGG-16 model (Visual Geometry Group), which is a strong deep convolutional neural network. As shown in Figure 8, the VGG-16 Net model consist of 13 convolution layer, 5 pooling layer, two fully connected layers and one soft-max classifier. The total layer distributed into five blocks. The two blocks contains two convolution and one pooling layer. Rest of the three blocks contains three convolution and one pooling layer respectively.

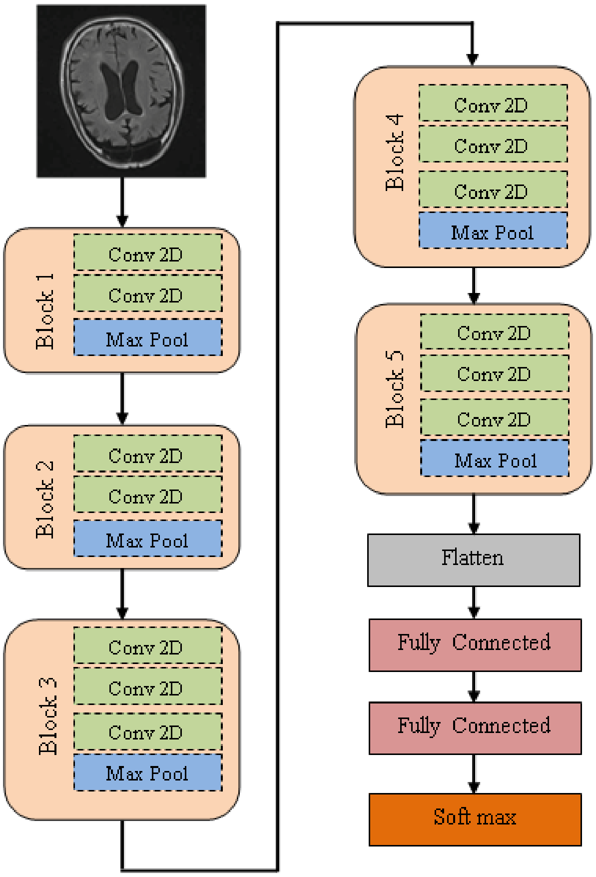

Fig. 8. Workflow of VGG-16 Net deep learning architecture

Res Net Model

ResNet-50 is a CNN with fifty levels of nested sub networks. There are 16 bottleneck blocks, 48 convolution layers, and one fully linked layer in the design [31,32]. There are a variety of both the same and distinct bottleneck components, as seen in Diagram 9.

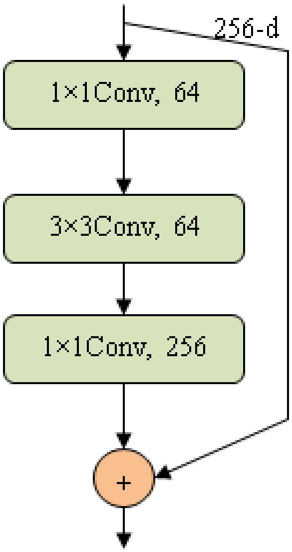

Fig. 9. Bottleneck building blocks

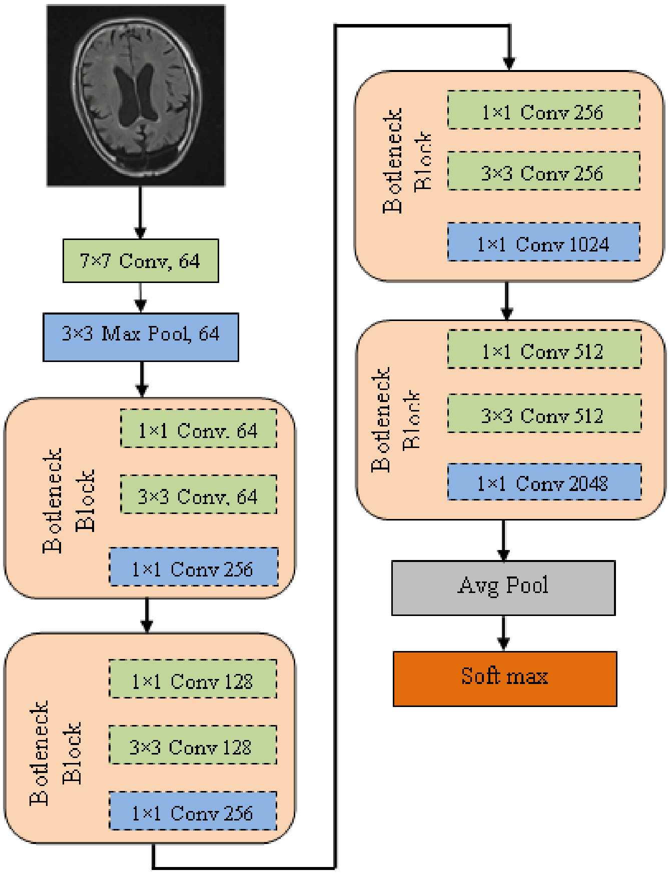

Fig. 10. Building block of ResNet- 50 Model

In the first three bottleneck blocks, there are convolution layers with 64 filters each with a size of 1x1 and a 3x3 size, as well as 64 filters with a 1x1 size. Convolution layers with 512 filters and 128 filters are found in building blocks 4 to 7, with the last two having filter sizes of 1x1 and 3 3 correspondingly. There are two convolution layers with 256 filters each, one with a filter size of 1x1 and the other with a filter size of 3x3, in addition to a third layer with 1024 filters, each with a filter size of 1x1. Filter sizes range from 1x1 to 3x3 in the convolution layers of building blocks 14 to 16, whereas layer 2048 has 2048 filters, all with filter sizes of 1x1. There are several ResNet models, including the ResNet-18, ResNet-50, and ResNet-101, to name a few. Figure 10 depicts the design of the ResNet-50 network.

Google Net Model

When Szegedy and colleagues (2014) launched the Inception model, popularly known as Google Net, in 2014, it surpassed all of the other contestants in the ILSVRC'14 challenges. When it comes to image scene classification, the model outperforms VGGNet and AlexNet by a factor of 5million weights, which is 28 times smaller than VGGNet and 12 times smaller than AlexNet. Figure 11 depicts a block diagram of the inception module's architecture. A conventional convolution is followed by pooling, two consecutive convolutions, and pooling, and the model proceeds with a series of nine inception module blocks until reaching the end.

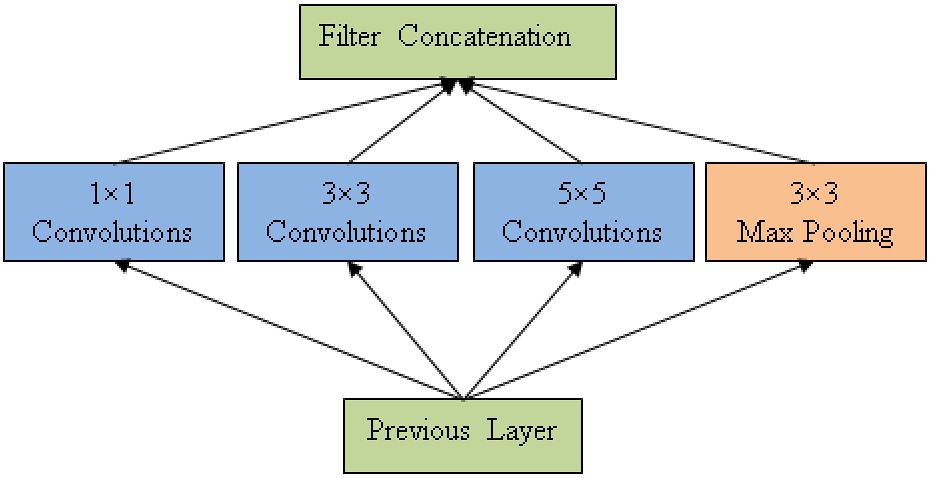

Fig. 11. Inception module with dimension reduction

A 3x3 pooling operation precedes a depth-wise filter concatenation in the Inception model, which then runs three convolutional operations with varying filter sizes (1x1, 3x3, and 5x5) in parallel. In terms of calculation, this structure is quite expensive. Thus, the preceding layer's activation volume is decreased to 1x1 "bottleneck" convolutional layers. Next, the convolution and pooling layers' outputs are combined and sent on to the inception module that follows them. GoogleNet employs 48 convolutional layers and nine linearly stacked inception modules. Global average pooling was used towards the conclusion of the preceding inception module. There are 19,085,738 total parameters, 19,054,634 of which are trainable and 31,104 of which are non-trainable.

Experimental Discussions and Analysis

Using transfer learning methodologies, this section evaluates the proposed earlier identification and recognition of Alzheimer's disease in MRI images and the results of that evaluated. An i5 processor with 8GB of RAM, and a 1TB hard disc drive were used to build the suggested model using Python and the Anacondo IDE.

Performance Metrics

To assess the proposed model's performance, performance assessment metrics are employed. Traditional machine learning methods can be evaluated using a variety of performance metrics, including Precision (Pr), Recall (Re), F1-measure (F) and Accuracy (A). The confusion matrix, as shown in Figure 12, is used to compute these measures. Actual classes are listed in the row, whereas predicted classes are listed in the column. The TP denotes a result in which the models accurately predict the positive class of variables. The TN is the result of successfully calculating the negative class by the models, which is the outcome. When the models incorrectly predict the positive class, this is referred to as the FP. When the models predict the negative class incorrectly, this is referred to as the FN.

Predicted Class

Actual Class

	Positive	Negative	
Positive	True Positive (TP)	False Negative (FN)	$R = \frac{TP}{(TP + FN)}$
Negative	False Positive (FP)	True Negative (TN)	
	$P = \frac{TP}{(TP + FP)}$		$A = \frac{TP + TN}{Total\ \mathrm{Im}\,ages}$

Fig. 12. Confusion Matrix

Precision (Pr): Precision is one of the most common ways to measure how far a metrics will work. It is used to find out how many correctly predicted events there were out of all predictions. In this way, we can measure the precision:

$$Pr = \frac{tp}{tp+fp} \tag{2}$$

Recall (Re): Recall is the percentage of occurrences that were successfully predicted over the total number of occurrences.

$$Re = \frac{tp}{tp+fn} \tag{3}$$

Accuracy (A): Accuracy is measured by the number of instances that were correctly classified. The accuracy of a classification system is equal to the ratio of the correct classification divided by the total number of classifications.

$$A = \frac{tp+fp}{tp+fp+tn+fn} \tag{4}$$

F1-Score (F): The measures of precision and recall are balanced by using the F1-measure (harmonic mean). The formula for calculating an F1-score is as follows:

$$F = 2 \times \frac{Pr \times Re}{Pr+Re} \tag{5}$$

Results Analysis of transfer learning model

In this section, we have evaluated the various transfer learning models namely AlexNet, ResNet-50, Google Net and VGG-16 Net model. Dropout and Adam optimizers were employed to avoid the problem of overfitting. The pre-trained deep learning model was trained and verified up to a maximum of 15 epochs in length. From Figure 13 (a-d), the confusion matrix for the four models is displayed. The majority of the classes in the OASIS dataset are correctly categorised with good results. The moderated demented is categorised as having bad performance in the workplace. The moderated demented are mostly misclassified as mild demented, while the non-demented are mostly misclassified as mild demented.

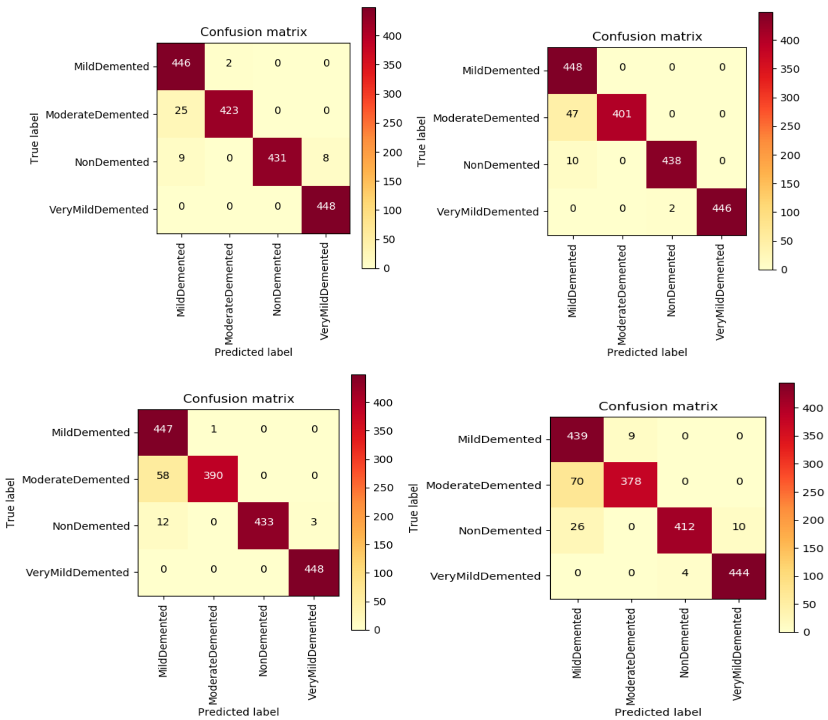

Fig. 13(a-d). Confusion matrix of different transfer learning models

Table 2
Traditional classifiers performance analysis

S. No.	Classifier	A	Pr	Re	F1- S
1.	Alex Net	93.35	94.14	93.36	93.42
2.	VGG-16 Net Model	95.87	96.38	95.87	95.89
3.	Res Net-50	96.70	97.06	96.71	96.73
4.	Google Net	97.54	97.67	97.54	97.55

In this sub section, various transfer learning techniques are evaluated and tested with same datasets and same configurations. Table 2 corresponds to Figure 14, which is a comparison chart of the various transfer learning models. It should be mentioned that the Google Net model beats the other transfer learning models such (Alex Net, VGG-16 Net and ResNet-50 model) in terms of accuracy and efficiency.

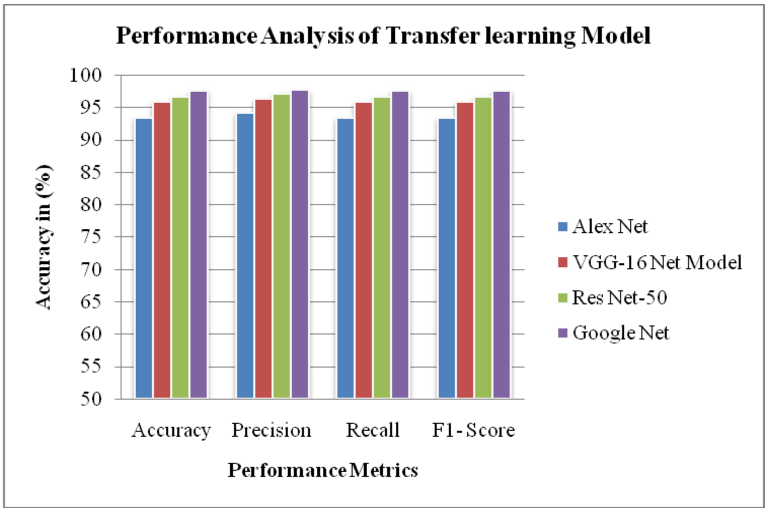

Fig. 14. Performance analysis of various transfer learning models

Conclusion

Using OASIS dataset, we investigated the performance of various deep convolutional neural networks such as AlexNet, VGG-16 Net, ResNe-50 and Google Net models for classifying the alzheimer's disease in earlier stages. In summary, we can observe from the experimental findings that a deep learning-based classification network is capable of extracting features from a images while also accomplishing hierarchy abstraction and classifying the AD disease using MRI images. The accuracy of AlexNet, VGG-16 Net, ResNet-50 and Google Net is 93.35%, 95.87%, 96.70% and 97.54 respectively. The performance and classification of Google Net models are superior to other transfer learning (like AlexNet, VGG-16 net and ResNet-50) models when they are compared. In the future, we must consider doing the AD disease work in a GPU configuration in order to reduce the time complexity. And also we have to plan ensemble the two deep learning models for improve the accuracy of AD disease systems.

References

1. J. Gaugler, B. James, T. Johnson, A. Marin, and J. Weuve, "2019 Alzheimer's disease facts and figures," Alzheimers & Dementia, vol. 15, no. 3, pp. 321-387, 2019.
2. T. Altaf, S. M. Anwar, N. Gul, M. N. Majeed, and M. Majid, "Multi-class Alzheimer's disease classification using image and clinical features," Biomedical Signal Processing and Control, vol. 43, pp. 64-74, 2018.
3. G. M. McKhann et al., "The diagnosis of dementia due to Alzheimer's disease: Recommendations from the National Institute on Aging-Alzheimer's Association workgroups on diagnostic guidelines for Alzheimer's disease," Alzheimer's & dementia, vol. 7, no. 3, pp. 263-269, 2011.
4. S. G. Mueller et al., "The Alzheimer's disease neuroimaging initiative," Neuroimaging Clinics, vol. 15, no. 4, pp. 869-877, 2005.
5. J. Islam and Y. Zhang, "Early Diagnosis of Alzheimer's Disease: A Neuroimaging Study with Deep Learning Architectures," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2018, pp. 1881-1883.
6. A. Farooq, S. Anwar, M. Awais, and S. Rehman, "A deep CNN based multi-class classification of Alzheimer's disease using MRI," in 2017 IEEE International Conference on Imaging Systems and Techniques (IST), 2017, pp. 1-6.
7. Garali, I., Adel, M., Bourennane, S., and Guedj, E. (2016). "Region-based brain selection and classification on pet images for Alzheimer's disease computer aided diagnosis," in Proceedings of the IEEE International Conference on Image Processing (Lausanne: IEEE), 1473–1477.
8. Jack, C. R. Jr., Bernstein, M. A., Fox, N. C., Thompson, P., Alexander, G., Harvey, D., et al. (2008). The Alzheimer's Disease Neuroimaging Initiative (ADNI): MRI methods. J.Magn. Reson. Imaging 27, 685–691. doi: 10.1002/jmri.21049
9. Chaplot, S., (2006) Classification of magnetic resonance brain images using wavelets as input to support vector machine and neural network. Biomedical signal processing and control, 1(1):86–92.
10. El-Dahshan, E.S.A., Hosny, T. and Salem, A.B.M., 2010. Hybrid intelligent techniques for MRI brain images classification. Digital Signal Processing, 20(2), pp.433-441.
11. Joshi, S., Simha, V., Shenoy, D., Venugopal, K.R. and Patnaik, L.M., 2010. Classification and treatment of different stages of alzheimer's disease using various machine learning methods. International Journal of Bioinformatics Research, 2(1), pp.44-52.
12. Filipovych, R., Davatzikos, C., and Alzheimer's Disease Neuroimaging Initiative, 2011. Semi-supervised pattern classification of medical images: application to mild cognitive impairment (MCI). NeuroImage, 55(3), pp.1109–1119.
13. Herrera, L.J., Rojas, I., Pomares, H., Guillén, A., Valenzuela, O. and Baños, O., 2013, September. Classification of MRI images for Alzheimer's disease detection. In 2013 International Conference on Social Computing (pp. 846-851). IEEE.

14. Li, F., Tran, L., Thung, K.H., Ji, S., Shen, D. and Li, J., 2015. A robust deep model for improved classification of AD/MCI patients. IEEE journal of biomedical and health informatics, 19(5), pp.1610-1616.
15. Sampath, R. and Saradha, A., 2015. Alzheimer's Disease Image Segmentation with Self Organizing Map Network. JSW, 10(6), pp.670-680.
16. Li, M., Lan, W., Wu, F.X., Pan, Y. and Wang, J., 2016. Classification of alzheimer's disease using whole brain hierarchical network. IEEE/ACM transactions on computational biology and bioinformatics, 15(2), pp.624-632.
17. Tohka, J., Moradi, E., Huttunen, H. and Alzheimer's Disease Neuroimaging Initiative, 2016. Comparison of feature selection techniques in machine learning for anatomical brain MRI in dementia. Neuroinformatics, 14(3), pp.279-296.
18. Zhang, T., 2018. Optimized fuzzy clustering algorithms for brain MRI image segmentation based on local Gaussian probability and anisotropic weight models. International Journal of Pattern Recognition and Artificial Intelligence, 32(09), p.1857005.
19. Sarraf, S. and Tofighi, G., 2016. Classification of Alzheimer's disease structural MRI data by deep learning Convolutional Neural Networks. arXiv preprint arXiv:1607.06583, pp.1-14.
20. Ju, R., Hu, C., Zhou, P. and Li, Q., 2019. Early diagnosis of Alzheimer's disease based on resting-state brain networks and deep learning. IEEE/ACM Transactions on Computational Biology and Bioinformatics (TCBB), 16(1), pp.244-257.
21. Gulhare, K.K., Shukla, S.P. and Sharma, L.K., 2017. Deep Neural Network Classification method to Alzheimer's Disease Detection. International Journals of Advanced Research in Computer Science and Software Engineering, 7(6), pp.1-4.
22. Luo, S., Li, X. and Li, J., 2017. Automatic Alzheimer's disease recognition from MRI data using deep learning method. Journal of Applied Mathematics and Physics, 5(09), pp.1892-1898.
23. Lu, D., Popuri, K., Ding, G.W., Balachandar, R. and Beg, M.F., 2018. Multimodal and multiscale deep neural networks for the early diagnosis of Alzheimer's disease using structural MR and FDG-PET images. Scientific reports, 8(1):5697, pp.1-13.
24. Liu, J., Pan, Y., Li, M., Chen, Z., Tang, L., Lu, C. and Wang, J., 2018. Applications of deep learning to MRI images: A survey. Big Data Mining and Analytics, 1(1), pp.1-18.
25. https://scikit-learn.org/stable/
26. https://keras.io/ (2017) Keras: The python deep learning library.
27. https://www.tensorflow.org/ (2017) An open-source software library for machine intelligence.
28. OASIS Brains. Open Access Series of Imaging Studies. Accessed: Jul. 13, 2020. [Online]. Available: https://www.oasisbrains.org
29. ADNI. Alzheimer's Disease Neuroimaging Initiative: ADNI. Accessed: Jul. 13, 2020. [Online]. Available: http://adni.loni.usc.edu/data-samples/access-data.
30. Rinartha, K., & Suryasa, W. (2017). Comparative study for Gede Budasi, I. & Wayan Suryasa, I. (2021). The cultural view of North Bali community towards Ngidih marriage reflected from its lexicons. *Journal of Language and Linguistic Studies*, *17*(3), 1484–1497

31. Kustina, K.T., Dewi, G.A.A.O., Prena, G.D., Suryasa, W. (2019). Branchless banking, third-party funds, and profitability evidence reference to banking sector in indonesia. *Journal of Advanced Research in Dynamical and Control Systems, 11*(2), 290-299.
32. Bawaningtyas, B. B., Perizade, B., Zunaidah, Z., & Soebyakto, B. B. (2021). Effect of e-learning and organizational commitment on nurse performance: (case study for intensive and outstanding nurses at Siloam Sriwijaya Hospital Palembang). International Journal of Health & Medical Sciences, 4(1), 169-181. https://doi.org/10.31295/ijhms.v4n1.1675