Performance Evaluation of CNN Models for Alzheimer's Disease Detection with MRI Scans

T.S.Sindhu[1],N.Kumaratharan[2], P.Anandan[3],P.Durga[4]

[1,4]Electronics and communication Engineering, C. Abdul Hakeem College of Engineering and Technology, Ranipet, India

[2]Electronics and communication Engineering, Sri Venkateshwara Engineering college, Sriperumbudur, Chennai, India.

[3]Electronics and communication Engineering, Saveetha School of Engineering, Saveetha University Chennai, India.

E-mail: [1]sindhuts1992@gmail.com, [2]kumaratharan@rediffmail.com, [3]anandanvp2000@gmail.com, [4]pdurga82001@gmail.com

Abstract

The primary symptom of Alzheimer's disease is memory impairment, which is a neurodegenerative condition. The manifestation of these symptoms can be attributed to the impairment of the cerebral nerve responsible for cognitive functions such as learning, thinking and memory. Alzheimer's disease is a prominent cause of mortality and lacks a definitive curve. However, appropriate medicinal interventions have demonstrated the potential to mitigate the progression and severity of the condition. This study presents the comparison of Convolutional Neural Network (CNN) models, namely ResNet50, VGG19 and VGG16 architectures, as an approach to construct an automated classification system for Alzheimer's disease in future. The study utilises Magnetic Resonance Imaging (MRI) datasets to identify MRI datasets of individual with Alzheimer's disease (AD), Cognitively normal (CN), mild cognitive impairment (MCI), early mild cognitive impairment (EMCI), and late mild cognitive impairment (LMCI). In the conducted experiment, the study achieved accuracy rates of 91.18% and 94.56% while utilising an epoch size of 2. The accuracy results indicate that the

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VGG16 model outperforms the ResNet50 model. The utilisation of automated Alzheimer's disease classification holds potential as an auxiliary tool for healthcare professionals in determining the stage of Alzheimer's disease hence facilitating the administration of suitable medicinal interventions.

Keywords: Alzheimer's Disease, ResNet50, VGG16, VGG19, and Accuracy.

1. Introduction

Alzheimer's disease is a neurological condition of the brain that develops gradually due to the death of nerve cells in certain areas of the brain. It starts with the patient being unable to carry out daily tasks due to memory loss, language difficulties, and other cognitive impairments. The disease damages the brain permanently, impairing cognition, memory, and other functions. If brain failure occurs, the person can even succumb. Because Alzheimer's disease causes a large loss of nerve cells throughout the brain, it can negatively affect one's ability to execute everyday tasks related to health, such speaking, writing, and reading. Individuals with AD may occasionally encounter difficulties in distinguishing their family members. It can be challenging to accurately diagnose Alzheimer's disease due to the gradual emergence of symptoms. Patients in the cognitive stage are at a higher risk of developing anomalies, while those in the later stages may suffer from heart failure. Nonetheless, early diagnosis and treatment can improve a patient's overall health.

The Alzheimer's Association has reported that in the United States, it ranks as the sixth leading cause of death. A recent poll indicates that there will be approximately 131.5 million individuals worldwide who will be living with dementia, with a significant portion of them being at higher susceptibility due to their advanced age. The patient's hippocampus section of the brain shrinks and wrinkles, affecting thinking, memory, and reasoning. This is the primary factor causing AD symptoms. The illustration of an AD brain and a healthy brain in figure (1) [15] below suggests that memory and language skills have deteriorated. Another possible cause of AD is genetic mutation, which is thought to afflict 1% or fewer people.

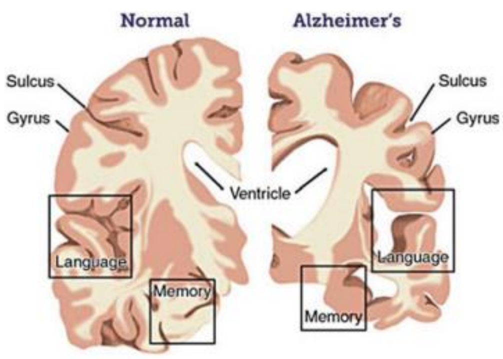


Figure 1. Visualize the Contrast between a Healthy Brain and an Alzheimer's Brain Through Cross-Sectional Imaging [15].

A thorough clinical evaluation that takes into account the patient's medical history, a variety of tests related to the neuropsychological disorders (including the analysis of the mental state of the patients, questions to examine the neuropsychiatric symptoms in individuals, tools to identify the severity of dementia, and other tests to identify the pathology in the brain) is necessary for an early diagnosis of this disease. Apart from these clinical procedures, there exist a plethora of other methods for the identification of AD, such as the use of biomarkers, analysis of cerebrospinal fluid (CSF), brain imaging using MRI and PET scans, and blood protein analysis. As CNNs have shown substantial advancements in processing of the medical images automatically. As a result, a variety of CNN models, including VGG, Residual Network (ResNet), SqueezeNet, EfficientNet, DenseNet etc have emerged as promising methods for the detection as well as the segmentation of the object. In spite of its ability in processing the images, the performance of the CNN is still limited due to the lack of sufficient training data from the medical imaging. On such cases transfer learning (pretrained models) are best suited for training eluding overfitting. These techniques are built over the top of the neural networks that are pre-trained (over a large dataset) and fine-tuning it on a small dataset. The proposed study aims in comparing the performance of the transfer learning architectures for the MRI scan dataset of individual with AD, CN, MCI, EMCI, and LMCI.

2. Related Work

Jayanthi Venkatesan performed the classification of Alzheimer illness using pre-trained deep networks [1]. The primary focus of the research was on the identification of early indicators of AD and distinct stages of decline in cognitive capacities of brain through the use of neuroimages and transfer learning. MRI scan reports from the ADNI (“Alzheimer's Disease Neuroimaging Database”). They pretrained models like GoogleNet, AlexNet, and ResNet-18, were used and tested on 6000 images gathered from the ADNI database. Computer-aided diagnostic system for Alzheimer's disease that requires real-time diagnosis has been developed by Nawaz and Muazzam Maqsood [2]. They have put up a taxonomy of the AD stages. Machine learning models like support vector machine (SVM), K-nearest neighbor (KNN), and Random Forest (RF) are used in the proposed system. To prevent overfitting issues, very large datasets were required. In contrast to earlier methods, real time deep learning models were also used in order to achieve the highest accuracy and an early diagnose.

Some of the AD categories like protein symptoms, and early identification of AD are very challenging. Presently, as there is not much treatment for AD utilizing any medical reasoning techniques. In order to obtain high accuracy, “Ketki Tulpule and V.P. Subramanyam Rallabandi” [3] focused on RBF (radial basis function) using SVM while evolving an automated ML strategy for classifying AD stages. Manohar Madgi and Vineeta Patil [4] talked about utilising CNN to predict AD early on. They proposed a paradigm that clarifies current research and exposes its difficulties and potential for innovation. It demonstrates that for the Alzheimer Disease Neuroimaging dataset, machine learning works well. The 18-layer convolutional network and the 3d convolutional network are thus the two techniques that are highlighted. As a result, multi-layered CNNs produce findings that are more accurate than 3D CNNs.

Transfer learning has been suggested as a method for classifying Alzheimer disease by Heta Acharya, Rutvik Mehta, and Dheeraj Kumar Singh [5]. gathering datasets for the four different types of AD and training them with the use of sophisticated systems like CNN, VGG16, ALEXNET, and RESNET50. AlexNet has outperformed rivals by a wide margin.

Nabila Abraham and Naimul Mefraz Khan [6] To address these issues utilising transfer learning, the most recent VG model was constructed with a large dataset of natural images.

They suggest employing transfer learning to diagnose AD utilizing MRI imaging. A transfer learning approach being investigated by Muzzam Maqsood and Faria Nazir[7] to spread Alzheimer's disease. They recommended creating distinct divisions within each AD class.

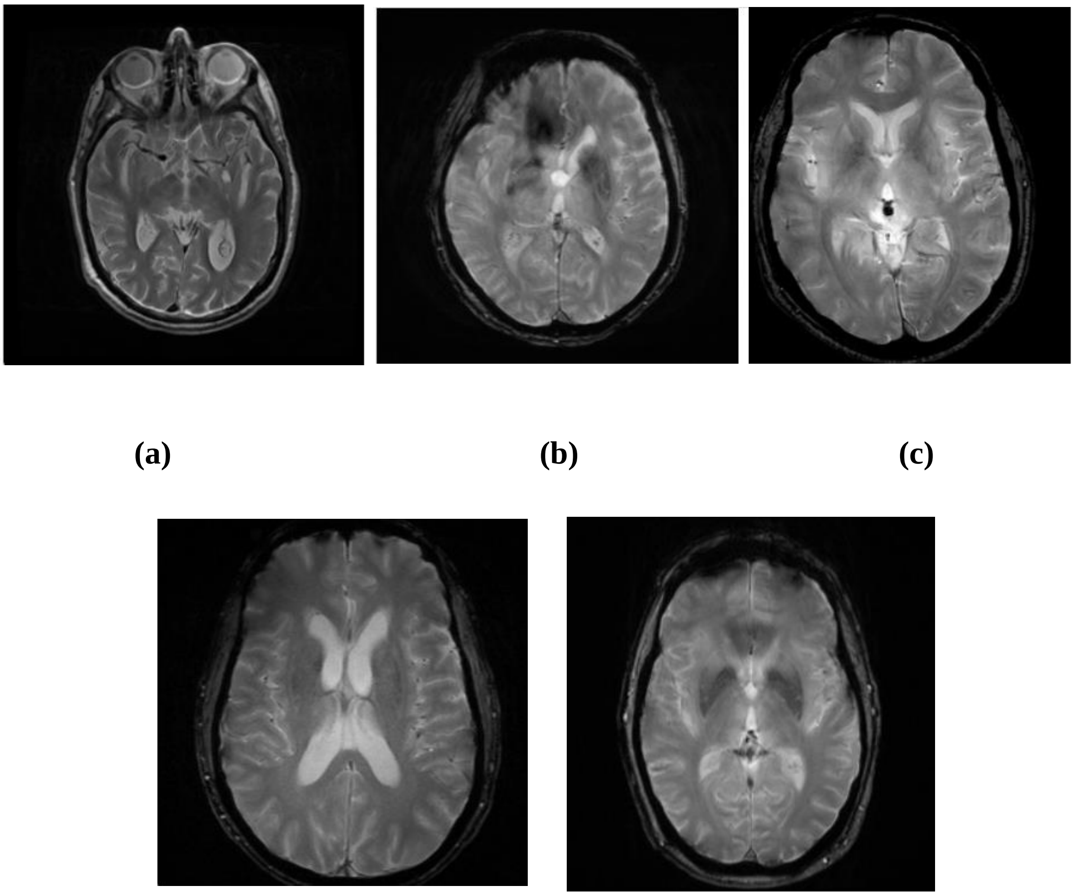
Liu M, Cheng D, and Yan W [8] suggested a novel method for diagnosing AD that combines CNN and RNN. CNN features are classified with an accuracy of 91.2% for one-vs-all of three classes using CNN and RNN trained on 2D slices of 3D PET data. "Wang S-H, Phillips P, Sui Y, Liu B, Yang M, and Cheng H" [9] suggested an eight-layer CCN that can distinguish between two different classes by using a variety of activation algorithms and pooling techniques. The model's remarkable 97.65% accuracy was attained. "Cui R, Liu M, and Li G" [10] analysed the longitudinal progression in order to do a sequential-analysis of an MRI image along the time axis. The spatial properties of MLP-multilayer perceptron are trained using a recurrent neural network (RNN). The preprocessing task for such a method is stiff segmentation. For NC and AD, the two-way classification accuracy is 89.69%.

A DCNN model was put up by Islam J. and Zhang Y. [11] for four classes. This involved training five models of DCNN, and combining the features of its output, allowed for the prediction of disease. This method is distinctive in that each model provides distinct traits that set it apart from the others, allowing it to be generalised for the prediction of unknown data with an accuracy of 93.18%. "Mahmoud Badawy, Amira Y. Haikal, and Hadeer A. Helaly" [12] described two methods for recognizing AD and categorizing medical images. The first approach analyzes images of brain structure from the "ADNI" dataset using straightforward CNN architectures with 3D and 2D convolutions. In contrast, the second strategy leverages the pretrained neural network models to perform the classification.

Four classes were described in the multimodal classification of AD by "Shi J, Zheng X, Li Y, Zhang Q, and Ying S" [11]. PET and MRI feature learning both use stacked autoencoders, or SAEs. These properties were combined and trained using SVM, although the accuracy of the system was significantly lower than that of earlier multimode classification techniquesThe CNN method for AD detection has been the subject of several works. Rajapakse RN, Kodikara ND, and Gunawar-dena KANNP conducted the early-detection of AD issue for three classes [12]. The achieved 84.4% accuracy.

3. Proposed Work

In the proposed study the transfer learning with different architectures is used to identify the different of stages of the AD in an individual. The proposed study compares the performance of the CNN models like VGG16, VGG19 and ResNet50, the pretrained neural network models with the MRI datasets of ADNI from Kaggle [https://www.kaggle.com/datasets/madhucharan/alzheimersdisease5classdatasetadni], the MRI dataset with five different stages of AD is displayed in the Fig.2 below.



(a) (b) (c)

(d) (e)

Figure 2. MRI Images from ADNI Dataset (a) AD, (b) CN (c) MCI, (d)EMCI, (e) LMCI

The comparative study begins with the collection of the different samples with different classes of AD, MCI, EMCI, LCMI and CN. Then the collected datasets are preprocessed and trained by using keras library with Tensorflow backend with different architectures like VGG16, VGG19 and Resnet50 by using ADAM (Adaptive Moment Estimation) optimizer. The flowchart in figure.3shows the stages of the proposed study. The obtained accuracy of VGG16, VGG19 and ResNet50 are 94.5%, 91% and 94% respectively.

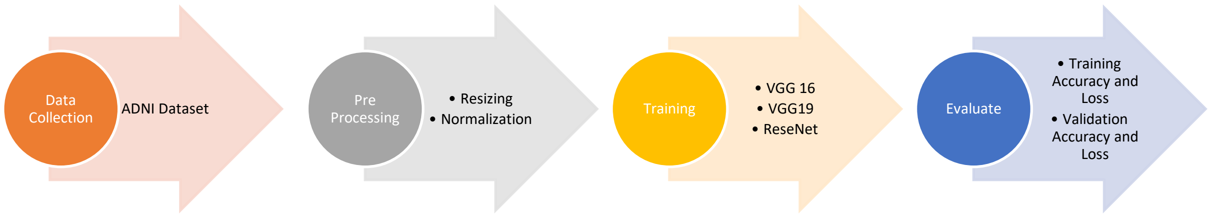


Figure 3. Flow Diagram

The process of training the deep neural networks like VGG16, VGG19, ResNet-50 using the keras library and tensor flow includes several steps. Initially the libraries necessary in performing the task are imported and the ADNI dataset is loaded. The dataset is resized to a standard resolution in order to ensure its consistency in the input sizes, the most standardized resolution set followed for the VGG16, VGG19, and ResNet50 are (224, 224) or (256, 256) the method utilizes the bilinear interpolation to resize the images to the required dimensions. The voxel intensities are normalized to a standard range to mitigate the variations in pixel values across different images. The pixel values of the images are normalized to a specific range, often between 0 and 1 or -1 and 1 to ensure that the neural network weights converge efficiently during training. The pretrained models are loaded and the final classification model is developed including a custom fully connected layers on the top of the pretrained models, the model is compiled specifying the optimizer, the study uses the Adam optimizer, the loss function (binary cross entropy) and the metric (accuracy and loss)

4. Results and Discussion

Tensorflow backend and the Keras library are used to implement the proposed model. For each CNN neuron, ReLU activation is used. The categories for output include AD, CN, LMCI, EMCI, and MCI. A total of 14,751 images are utilised to train the network, while another 3701 images are used for testing. The pretrained networks weights for the transfer learning models were obtained from ImageNet. All the three models were trained with 2 epochs with the batch size of 128. The entire dataset was passed through the model in batches of 128 samples for a total of 2 times. . of The Adam optimizer was set up with the learning rate of 0.0001 initially and was adjusted automatically during training. There is a 0.5 likelihood of dropout. Binary cross-entropy is employed as the loss function. Softmax is the function used for dense activation. Two epochs are used to train the network. The hyperparameters of the CNN model are displayed in the following Table.1

Table 1. Hyperparameters Used

Hyperparameter	
Activation Function (hidden layer)	ReLu
Activation Function (output Layer)	SoftMax
Learning Rate (initial)	0.0001
Learning Rate (adjusted)	0.0002
Dropout	0.5
Optimizer	ADAM
Loss Function	Binary cross entropy
Epoch	2
Batch size	128

Accuracy and loss are used to gauge performance for both the training and validation sets. The best indicator of a model's fit is loss. By utilising the Adam optimizer, VGG16 provides the best accuracy with the least amount of loss since it automatically adjusts the learning rate, making tiny updates for often occurring parameters and large updates for rarely occurring parameters. Figure 4(a, b) below displays accuracy achieved against number of epochs and loss against the number of epoch graphs for training as well as validation. As accuracy reaches 94.56% for the training set, loss is shown to decline to zero. This provides the model's training phase progress measurement. The measurement of model's quality is achieved by the validation set.

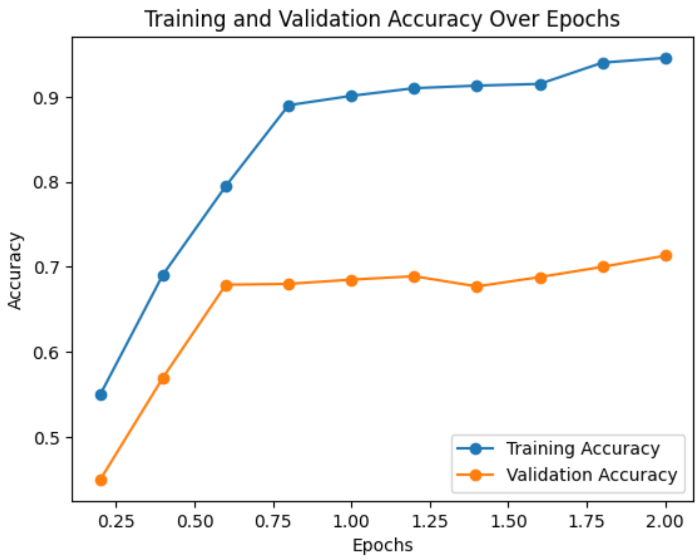


Figure 4 a. Training Accuracy with ADAM Optimizer

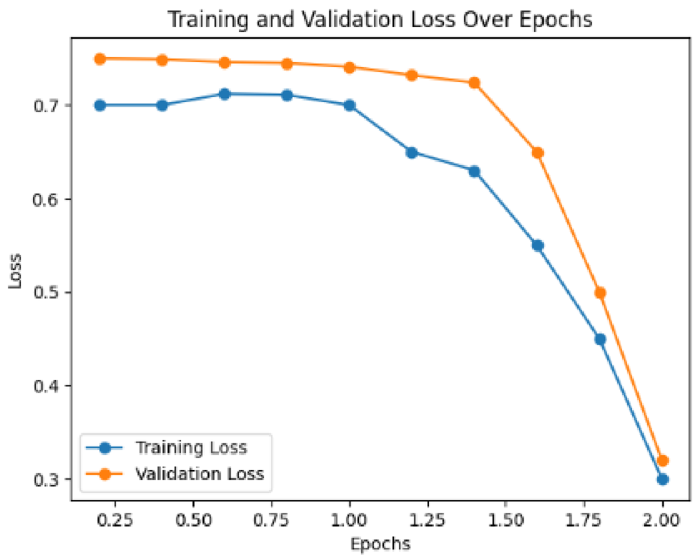


Figure 4 b. Training Loss with ADAM Optimizer

The increase in the training accuracy and the decrease in the training loss shows that the model is likely improving in its generalization to unseen data. Table.2 below shows the comparison of the accuracy and the loss observed during the training accuracy and loss for 2 epochs with 128 samples

Table 2. Performance Assessment

Evaluation	Metrics	Epoch 1			Epoch 2		
		ReseNet 50	VGG1 6	VGG1 9	ReseNet5 0	VGG1 6	VGG1 9
Training	Accuracy	0.90	0.92	0.89	0.94	0.95	0.91
	Loss	0.54	0.38	0.55	0.3	0.23	0.35
Validation	Accuracy	0.69	0.713	0.65	0.70	0.715	0.67
	Loss	0.50	0.35	0.48	0.32	0.20	0.33

5. Conclusion

In this work, the methodology for accurately detecting Alzheimer's disease based on deep convolutional neural networks is presented. On our dataset, we were able to obtain 94.56% training accuracy without utilising any manually created features to train the network. The validated accuracy is 71.31%. Additional research will concentrate on the testing process by using the CNN model to achieve better performance-scores on unseen dataset. In the future, DCNN features will be classified using support vector machines.

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Author's biography

Sindhu.T.S received his B.E. Degree in Electronics and Communication Engineering from Thanthai Periyar Government Institute of Technology,Anna University,Chennai , Tamil Nadu in the year 2014. M.E., in Applied Electronics from Kingston Engineering College, Anna University, Chennai, Tamil Nadu in the year 2016. Currently she is a Ph.D (Research Scholar), Anna University, Chennai, Tamil Nadu. Her area of research includes Image Processing and IOT. She is working as Assistant Professor in C.Abdul Hakeem College of Engineering and Technology,Melvisharam,Tamilnadu. She has about 3 journal publications in reputed journals and about 11 international conference proceedings.

N. Kumaratharan obtained his Ph.D. in the field of Wireless Communication from Pondicherry University in 2010. His area of research includes spread spectrum techniques, broadband communication and wireless sensor networks. He has more than 17 years of teaching and research experience. He has guided seven Ph.D. scholars of Anna University, Chennai. He has published 39 peer-reviewed international journals indexed by Clarivate Web of Science, Scopus, SCI and SCI-E. He has 43 international conference proceedings indexed by IEEE and Elsevier Academia.

Dr.P. Anandan received his B.E. Degree in Electrical and Electronics Engineering from Vellore Engineering College, University of Madras, Vellore, Tamil Nadu in the year 2002. M.E., in Applied Electronics from CEG, Anna University, Chennai, Tamil Nadu in the year 2004 and Ph.D. in VLSI and Nano Electronics in Anna University, Chennai, Tamil Nadu in the year 2015. His research interest includes VLSI and Nano Electronics. Currently he is working as Professor in Saveetha school of Engineering, Saveetha University, Chennai. He has about 28 international journal publications in reputed journals and about 40 international conference proceedings.