International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 6 Volume No.7 November - December – 2023
DOI:10.46647/ijetms.2023.v07i06.048 ISSN: 2581-4621

Alzheimer Detection and Classification using Deep Learning Techniques.

Ashweka Naik[1], Amita Dessai[2]
[1] PG - Student, Electronics Communication and Instrumentation Engineering, Goa College of Engineering, Farmagudi, Goa
[2] Assistant Professor, Electronics Communication and Instrumentation Engineering, Goa College of Engineering, Farmagudi, Goa
Corresponding Author Orcid ID : https://orcid.org/0009-0009-8302-2662

ABSTRACT
Alzheimer’s is progressive neurological disorder which causes brain shrinkage and death of brain cells which results in loose connections between neurons ultimately leading to memory-related problems. Symptoms of Alzheimer’s develop slowly, but its effects on brain are severe. Large population suffer from this disease and as estimated by 2050, 1 out of 85 people in world will have Alzheimer’s.
Alzheimer has no cure, Medication can slow symptoms progression if detected during initial stages. We classified Alzheimer into 4 classes Very mild, Mild, Moderate and No Alzheimer's for early detection and diagnosis using Residual Network-50-pretrained CNN model which has shown high accuracy in Recognizing images. Residual Network-50 architecture performance for MRI images was evaluated in this paper. Model was trained on google colab and showed testing accuracy of 80.14%.
Keywords— Alzheimer, MRI, Deep learning, CNN, ResNet-50.

1. Introduction

Human brain has billions of neurons which process and transmits information through chemical, electrical signals. Neurons transmits information among different parts of brain and from brain to muscles, organs of body.
Alzheimer's interrupts this mechanism between neurons which results in functions loss and ultimately cell death.
Many cellular, molecular alterations occur in brain of person with Alzheimer such as Amyloid plaques deposition between neurons, Neurofibrillary tangles, Atherosclerosis, chronic inflammation, vascular issues etc [12]. Investigations are yet to find which changes can cause Alzheimer's and which are results of it.

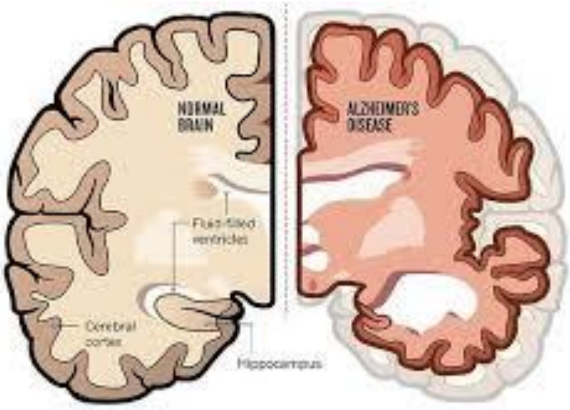

Fig 1. Image showing Normal Brain vs Alzheimer Disease Brain [21]

DOI:10.46647/ijetms.2023.v07i06.048 ISSN: 2581-4621

Alzheimer disease damages neurons, their network in brain utilized for memory including entorhinal cortex, hippocampus etc. Later it affects areas in cerebral cortex involved in language, reasoning, social behavior etc. Eventually, many brain areas are damaged. A person having Alzheimer's loses gradually her or his ability to function and live independently. Ultimately disease is fatal.

Average life expectancy after Alzheimer's diagnosis is only about 4 to 8 years [4]. A 2022 Lancet report estimates that globally, the population suffering from Alzheimer's will triple by 2050.

Alzheimer has no cure but progression of symptoms can be slowed with proper medication if early detected. Proper diet, exercise, music, frequent interaction with people etc may improve brain health [4].

1.1 Related Work

Previous work showed that several researchers have identified development of AI-based methods for diagnosis and stage classification of Alzheimer's Disease using Deep Learning techniques. Following is a quick insight into the work completed to date.

Brindha et al. [2] implemented ANN (Artificial Neural Network) and CNN (Convolutional Neural Network) for catogorizing normal, tumor brain. CNN model accuracy on applying the testing data is 89% and of ANN is 65.21%.

Pradhan et al. [4] used VGG-19 and DenseNet169 architectures for classifying MRI brain images into mild, moderate or no Alzheimer's disease categories, providing a comparative analysis of which architecture shows promising results. Accuracy of VGG-19 and DenseNet-169 is 82.6% and 80% respectively.

Chaihtra et al. used MRI data to identify Alzheimer and DL techniques to classify disease stage. Neural Networks MobileNet, DenseNet121, Xception, InceptionV3 are trained using same Kaggle Alzheimer Diseases dataset to analyze their performances. Highest accuracy of 91% is given by DenseNet-121 model.

Author Hussain et al. [5] compared proposed CNN and pre-trained CNN models Xception, InceptionV3, MobilenetV2, VGG. 12-layer CNN model they proposed for Alzheimer binary classification, detection using brain MRI data. An accuracy of 97.75% was shown by 12-layer CNN model, which is higher than pretrained CNN models (Xception-84.37%, InceptionV3-90.62%, MobileNetV2-81.24% and VGG19-50%) published on Open Access Series of Imaging Studies (OASIS) dataset.

Author optimized Deep Convolutional Neural Network with a complex activation function for 3D whole-brain images using ADNI data to automatically take features from whole-brain MRI scans and with an isotropically repeated convolutional block network architecture good accuracy was obtained.The proposed pipeline has 3 steps: brain volume resizing, 3D volume slicing, and CNN processing. Inspired by the architectural pattern of ResNet and ConvMixer they proposed a simple yet effective convolutional method that simultaneously performs standard convolution, depthwise convolution, point-wise convolution, skip convolution layer to learn brain MRI image multi-level features. Model proposed gave 96.12% accuracy.

Manzak et al. [6] used Decision tree learning (ML) for dividing training set into sub-clusters according to various characteristics, Random Forest provides information on importance of properties, making it easier to sort the properties according to high estimation rates. Classified Alzheimer's using Deep Neural Network. Model accuracy obtained was 67%.

Hasanah et al. proposed a method having following steps: median filter pre-processing, removal of non-cerebral tissues by skull stripping segmentation by thresholding, detected tumor feature extraction is realized using statistical first order features, from the histogram of the image and the Gray Level Cooccurrence Matrix (GLCM) is used to extract second-order features, classification technique used is SVM (Support Vector Machine). The model achieved total accuracy, sensitivity precision, specificity of 95.83%,93.33%, 94.08%, 96.87% respectively.

Sharma et al. used Computer Assisted Diagnostic framework. for recognizing illness during initial phase, they utilized three segments Corpus Callosum, Hippocampus and Cortex. Support Vector

International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 6 Volume No.7 November - December – 2023
DOI:10.46647/ijetms.2023.v07i06.048 ISSN: 2581-4621

Machine was used for classification. The model yields 91.67% exactness in finding of early Alzheimer's disease.

Four machine learning models were designed by author for identifying disease. Models include logistic regression, support vector classifier, decision tree, random forest classifier. The models are fine-tuned by choosing optimal values for parameters that influences model accuracy. The optimal parameters are found using a K-fold cross validation score, and the models used Longitudinal cross-sectional data from OASIS dataset. It was concluded that random forest classifier performs well than the other models.

After going through various research papers, I thought of observing Residual Network-50 deep CNN performance for detection, classification of Alzheimer MRI grayscale images and observe model Accuracy, Loss etc.

2. Methodology

DL (Deep Learning) uses Neural Networks to mimic human brain-like behavior. DL algorithms focuses on information processing patterns mechanism to identify patterns just like our human brain does and classifies the information accordingly.

Initially, dataset was loaded and applied to the ResNet-50 model introduced in computer vision research paper-2015 titled Deep Residual Learning for Image Recognition with padding at the initial layer, preserving information which improved accuracy and loss to some extent.

2.1. Block Diagram

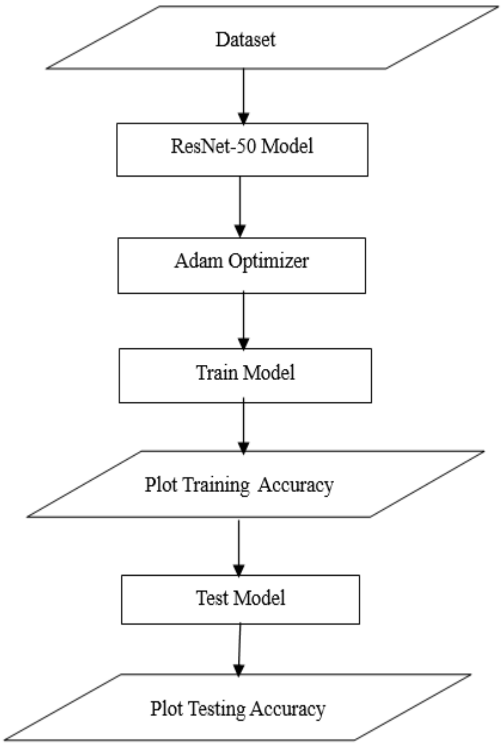

Fig 2. Proposed Architecture

2.2 Dataset

Open source online Kaggle dataset library is used to extract data. Dataset images are distributed over 4 classes namely Very mild, Mild, Moderate and No Alzheimer's. It contains 33984 images splitted for Training and Validation respectively in ratio of 8:2 and 6400 images were used for Testing. The dataset contains augmented images for various feature learning and better training and testing accuracies.

International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 6 Volume No.7 November - December – 2023
DOI:10.46647/ijetms.2023.v07i06.048 ISSN: 2581-4621

2.3 CNN Model: ResNet-50

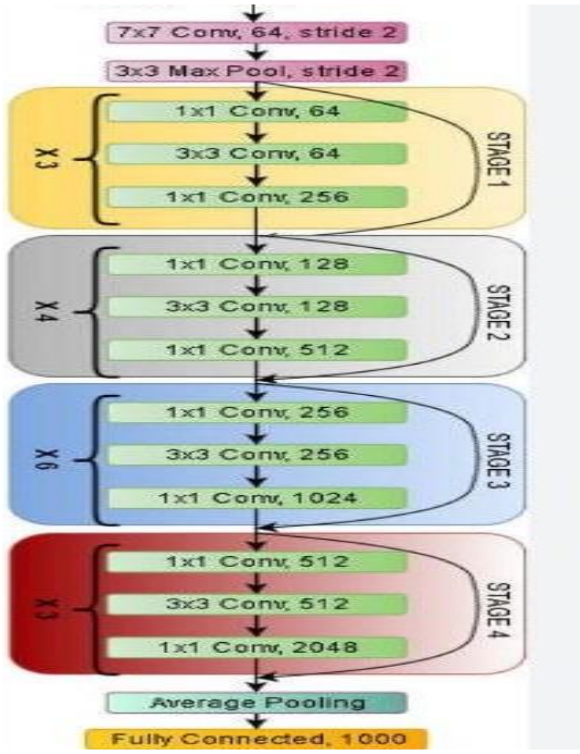

Fig 3. CNN Model: ResNet-50

Residual Networks (ResNet-50) is 50- layer CNN introduced by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. During backpropagation, gradient value reduces significantly, thus little change comes to weight leading to gradient vanishing problem. ResNet-50 overcomes this problem using skip connection and allows model to learn identity function which ensures that the higher layer will perform at least good as lower layer and not worse.

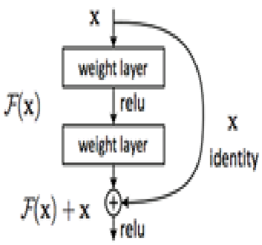

Fig 4. Skip Connection [17]

Skip Connection
Output is **F(X)+x**
Hence ResNet-50 has 2 types of blocks
Identity Block:
Value of x added to output layer if
Input size = Output size

Convolutional Block:
When input size not equal to output size, it is used in shortcut path to make them equal
All algorithms use output Y for training but ResNet-50 trains on F(X). ResNet-50 tries to make F(X)=0 such that Y=X.

International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 6 Volume No.7 November - December – 2023
DOI:10.46647/ijetms.2023.v07i06.048 ISSN: 2581-4621

Table.1. Size and parameters of Residual Network-50

Models	Size (MB)	Parameters
ResNet-50	98	25.6M

2.4 Adaptive Moment Estimation (Adam) Optimizer

Adam algorithm adjusts Neural Network parameters in real time for accuracy and speed improvement. Learning rate of each parameter are updated based on its historical gradients and momentum.

3. Results and Discussion

ResNet-50 model showed training, validation, testing accuracy of 84.60 %, 80%, 80.14% and training, validation, testing loss of 37.61%,48.21%,46.56%, respectively when trained for 20 epochs.Training the model for more epochs can improve accuracy. Following are graphs obtained.
Plots obtained for the accuracy and Loss.

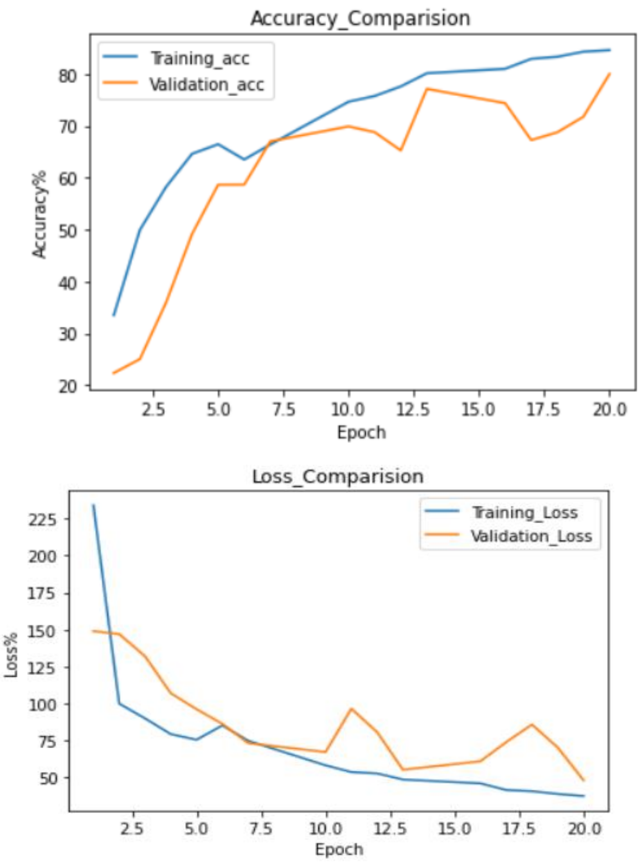

Fig 5. Accuracy and Loss Plot of ResNet-50 Model

CONCLUSION AND FUTURE WORK

ResNet-50 model has successfully classified MRI images into allocated 4 classes and gave us an effective solution of identifying disease automatically at early stage
Other deep learning models can be implemented in future, for early detection and classification of Alzheimer and their performance can be compared.
ResNet-50 gave testing accuracy of 80.14%. To improve accuracy, processed MRI images can be provided to model.

Awareness of disease should be spread among people and they should be motivated to get themselves examined for detection at initial stages, improving health care against this specific disease. Model can also be used to detect other Diseases.

References

1. Rashed, Baidaa Mutasher, and Nirvana Popescu. "Critical Analysis of the Current Medical Image-Based Processing Techniques for Automatic Disease Evaluation: Systematic Literature Review." *Sensors* 22, no. 18 (2022): 7065.
2. Brindha, P.G., Kavinraj, M., Manivasakam, P. and Prasanth, P., 2021, February. Brain tumor detection from MRI images using deep learning techniques. In *IOP conference series: materials science and engineering* (Vol. 1055, No. 1, p. 012115). IOP Publishing.Faisal,
3. Fazal Ur Rehman, and Goo-Rak Kwon. "Automated Detection of Alzheimer's Disease and Mild Cognitive Impairment Using Whole Brain MRI." *IEEE Access* 10 (2022): 65055-65066.
4. Pradhan, A., Gige, J. and Eliazer, M., 2021. Detection of Alzheimer's disease (AD) in MRI images using deep learning. *Int. J. Eng. Res. Technol. (IJERT)*, *10*, pp.580-585.
5. Hussain, Emtiaz, Mahmudul Hasan, Syed Zafrul Hassan, Tanzina Hassan Azmi, Md Anisur Rahman, and Mohammad Zavid Parvez. "Deep learning based binary classification for alzheimer's disease detection using brain mri images." In *2020 15th IEEE Conference on Industrial Electronics and Applications (ICIEA)*, pp. 1115-1120. IEEE, 2020.
6. Manzak, Dilek, Gökçen Çetinel, and Ali Manzak. "Automated Classification of Alzheimer's disease using deep neural network (DNN) by random forest feature elimination." In *2019 14th International Conference on Computer Science & Education (ICCSE)*, pp. 1050-1053. IEEE, 2019.
7. Aruchamy, Srinivasan, Veeramachaneni Mounya, and Ankit Verma. "Alzheimer's disease classification brain MRI using modified kNN algorithm." In *2020 IEEE International Symposium on Sustainable Energy, Signal Processing and Cyber Security (iSSSC)*, pp. 1-6. IEEE, 2020.
8. Alshammari, M. and Mezher, M., 2021, March. A modified convolutional neural network for MRI-based images for detection and stage classification of alzheimer disease. In *2021 National Computing Colleges Conference (NCCC)* (pp. 1-7). IEEE.
9. Arafa, D.A., Moustafa, H.E.D., Ali-Eldin, A.M. and Ali, H.A., 2022. Early detection of Alzheimer's disease based on the state-of-the-art deep learning approach: a comprehensive survey. *Multimedia Tools and Applications*, *81*(17), pp.23735-23776.
10. Salunkhe, S., Bachute, M., Gite, S., Vyas, N., Khanna, S., Modi, K., Katpatal, C. and Kotecha, K., 2021. Classification of Alzheimer's disease patients using texture analysis and machine learning. *Applied System Innovation*, *4*(3), p.49.
11. Salehi, A.W., Baglat, P. and Gupta, G., 2020. Alzheimer's disease diagnosis using deep learning techniques. *Int. J. Eng. Adv. Technol*, *9*(3), pp.874-880.
12. Patro, S. and Nisha, V.M., 2019. Early detection of Alzheimer's disease using image processing. *Int. J. Eng. Res. Technol. (IJERT)*, *8*(05).
13. S. Sarraf, D. D. DeSouza, J. Anderson, G. Tofighi, and for the A. D. N. Initiativ, "DeepAD: Alzheimer's Disease Classification via Deep Convolutional Neural Networks using MRI and fMRI," bioRxiv, no. August 2016, p. 070441, 2017, doi: 10.1101/070441.
14. Rohini Paul Joseph, C.Senthil Singh, M.Manikandan,"Brain Tumor MRI Image Segmentation and Detection in Image Processing". International Journal of Research in Engineering and Techonology.eISSN:2319-1163|PISSN:2321-7308.
15. Asim, Yousra, Basit Raza, Ahmad Kamran Malik, Saima Rathore, Lal Hussain, and Mohammad Aksam Iftikhar. "A multi-modal, multi-atlas- based approach for Alzheimer detection via machine learning." International Journal of Imaging Systems and Technology 28, no. 2, 2018, pp. 113-123.
16. S. Luo, X. Li, and J. Li, "Automatic Alzheimers disease recognition from MRI data using deep learning method," Journal of Applied Mathematics and Physics, vol. 5, pp. 1892-1898, 2017.

DOI:10.46647/ijetms.2023.v07i06.048 ISSN: 2581-4621

17. https://www.google.com/imgres?imgurl=https%3A%2F%2Fiq.opengenus.org%2Fcontent%2Fimages%2F2020%2F03%2FScreenshot-from-2020-03-20-15-26-38.png&tbnid=qX1VC6s07Re7VM&vet=12ahUKEwj29KHXxPzAhWR_DgGHejNCYcQMyhCegUIARCFAQ..i&imgrefurl=https%3A%2F%2Fiq.opengenus.org%2Fresnet50architecture%2F&docid=tA_gEQEkdHAgSM&w=748&h=454&q=resnet50&ved=2ahUKEwj29KHXxPz-AhWR_DgGHejNCYcQMyhCegUIARCFAQ

18. g Liu, Chong-Yaw Wee, Huafu Chen, and DinggaShen.Intermodality relationship constrained multi-modality multi-task feature selection for alzheimers disease andmild cognitive impairment identification. NeuroImage, 84:466-475, 2014.

19. L.Khedher, J. Ramírez, J. M. Górriz, A. Brahim, and I. A. Illán, ''Independent component analysis-based classification of Alzheimer's disease from segmented MRI data,'' in Proc. Int. Work-Conf. Interplay Between Natural Artif. Comput. Cham, Switzerland: Springer, 2015, pp. 78–87.

20. S.Zhang, S. Zhang, T. Huang, W. Gao and Q. Tian,"Learning Affective Features with a Hybrid Deep Model for Audio–Visual Emotion Recognition," IEEE Transactions on Circuits and Systems for Video Technology,vol. 28, no. 10, pp. 3030-3043, 2018.

21. https://www.google.com/imgres?imgurl=https%3A%2F%2FFwww.nia.nih.gov%2Fsites%2Fdefault%2Ffile%2Finlineimages%2Fbrain_slices_alzheimers_0.jpg&tbnid=Eu06vygpeHx5BM&vet=12ahUKEwimmrzF7_nAhX2znMBHbWyD6QQMygMegUIARD0AQ..i&imgrefurl=https%3A%2F%2Fwww.nia.nih.gov%2Fhealth%2Falzheimers-disease-fact-sheet&docid=A80zj1k4V30_BM&w=300&h=296&q=alzheimer%27s%20disease&ved=2ahUKEwimmrzF7_nAhX2znMBHbWyD6QQMygMegUIARD0AQ

22. https://www.google.com/imgres?imgurl=https%3A%2F%2Fopen-instruction.com%2Floading%2F2021%2F05%2Fq.png&tbnid=Ecm602pdKg3qSM&vet=12ahUKEwj29KHXxPzAhWR_DgGHejNCYcQMygtegUIARCAg..i&imgrefurl=https%3A%2F%2Fopen-instruction.com%2Fdl-algorithms% 2Foverview-of-residual-neural-networkresnet%2F&docid=JHwAxqBFzdZIKM&w=711&h=214&q=resnet50&ved=2ahUKEwj29KHXxPz-AhWR_Dg GHejNCYcQMygtegUIARC_Ag