VOLUME - 12, ISSUE - 08, AUGUST - 2023 • PRINT ISSN No. 2277 - 8160 • DOI : 10.36106/gjra

Original Research Paper

Computer Science

ALDO INTELLIGENT SYSTEM FOR EARLY DETECTION OF ALZHEIMER'S DISEASE

Anjaly G Nair	B.Tech Student, CSE, Valia Koonambaikulathamma College of Engineering and Technology, Trivandrum, Kerala, India
Archana Sajeev	B.Tech Student, CSE, Valia Koonambaikulathamma College of Engineering and Technology, Trivandrum, Kerala, India
Aryanandha A B	B.Tech Student, CSE, Valia Koonambaikulathamma College of Engineering and Technology, Trivandrum, Kerala, India
Reshmi Radhakrishnan	B.Tech Student, CSE, Valia Koonambaikulathamma College of Engineering and Technology, Trivandrum, Kerala, India
Dr L C Manikandan*	Professor, CSE, Valia Koonambaikulathamma College of Engineering and Technology, Trivandrum, Kerala, India *Corresponding Author

ABSTRACT Alzheimer's disease is a neurodegenerative affliction that can be identified through behavioral syndromes or neuroimaging. By utilizing deep learning, we can detect Alzheimer's disease. In this study, we implemented two pre-existing models to learn characteristics from MRI images and subsequently concatenate them for Alzheimer's disease classification. Upon inputting data, the system accurately produces one of the stages of Alzheimer's disease, including mild cognitive impairment or cognitive normalcy. The purpose of this project is to utilize deep learning to detect Alzheimer's disease.

KEYWORDS : Alzheimer disease, Mild cognitive impairment, ML, CNN, ANN, LMCI, EMC

INTRODUCTION

Utilization of industrial waste products in concrete has attracted attention all around the world due to the rise of environmental consciousness. The malady of Alzheimer's disease (AD) is characterized by degeneration of brain cells, and as such, it poses a challenge to identify changes to brain function that precede the onset of the disease. Machine learning (ML) and artificial neural networks (ANN) may assist in the early detection of Alzheimer's disease. Algorithms such as DenseNet and its variants demonstrate potential in predicting Alzheimer's disease via analysis of test images. The focal contribution of this research, as outlined in [6], comprises a hybrid pre-trained Convolution Neural Network (CNN) model designed for the early diagnosis of Alzheimer's disease. Additionally, a deep feature concatenation method is employed to amalgamate deep features extracted from diverse pre-trained CNNs. To reduce the gap between feature maps within the concatenation of fully connected layers, weight randomization is employed. Finally, a gradient-weighted class activation map is utilized to visualize the discriminatory regions of the image with the purpose of elucidating the model's decision.

Literature Survey

Maqsood introduced a unique classification algorithm that distinguishes patients with AD, Mild Cognitive Impairment (MCI), and CNN. This is accomplished via an ensemble of hybrid deep learning architectures that utilize spatial information captured in the MRI data. Although the ensemble classifiers are essential in the final product, the disadvantage of this system is that it lacks validation using multiple datasets [1].

Odusami presented a classification framework that incorporates structural MRI and Resting-state functional Magnetic Resonance Imaging (RS-fMRI) metrics to differentiate MCI non-converters (MCInc)/AD from MCI converters (MCIc), combining graph theory and machine learning. The system reduces feature redundancy across different classification groups by utilizing graph theory to extract features; however, the brain region analysis is computationally complex [2].

D. Popuri tackled the issue of automatic prediction of AD based on MRI images and proposed unsupervised learning methods with CNN and SVM (Support Vector Machine) implementations. The disadvantage of this system is that it is weak in terms of deep neural framework and relies on old PCA (Principal Component Analysis), a fully unsupervised deep learning technology for AD diagnosis [3].

Bae conducted a systematic review of published works in the field of AD, with particular emphasis on computer-aided diagnosis. The deep learning techniques and support vector machine demonstrate higher accuracy in identifying Alzheimer's disease in this review. Although the paper reviews different MRI methods and PET, there is no computational method proposed [4].

Ruiz proposed an open-source framework for the reproducible evaluation of AD classification using CNNs and T1w MRI. The framework assesses various CNN approaches rigorously and studies the impact of key components on system performance. The study aims to provide a more objective evaluation of AD classification. Although the proposed CNN-based models perform well, disadvantageously, feature scaling issues arise when training multiple datasets [5].

Proposed System

In this paper, we present our proposed system, the "ALDO Alzheimer Detection System." Our approach utilizes Deep features extracted by Resnet18 & Densnet121 models to diagnose Alzheimer's disease. Our method classifies AD into four different clinical statuses. Our proposed model improves on the DenseNet architecture by incorporating more max pooling, dense, and dropout layers. Furthermore, the system is augmented by DNGAN (DenseNet Generative Adversarial Network) to enhance accuracy and performance. We anticipate that our proposed system will generate more accurate Alzheimer's diagnoses with improved precision.

Methodology Convulation Neural Network

In the field of deep learning, Convolutional Neural Networks (CNNs) are a class of Artificial Neural Networks (ANNs) that are predominantly utilized for visual image analysis. CNNs, also referred to as Shift Invariant or Space Invariant Artificial Neural Networks (SIANN), are structured with a collective set of convolution kernels or filters that move along input features to produce translation-equivariant responses known as feature maps [7]. Despite their name, CNNs are often not invariant to translations due to the down sampling operation they apply to the input. Applications of CNNs are versatile and include image and video recognition, image segmentation, recommender systems, medical image analysis, natural language processing, brain computer interfaces, and financial time series analysis.

CNNs are essentially regularized Multilayer Perceptrons that are susceptible to over fitting data. Since Multilayer Perceptrons are fully connected networks, where each neuron connects with all neurons in the subsequent layer, they have a tendency to over fit.

Models are typically regularized in the form of penalizing parameters during training, trimming connectivity using skipped connections, dropout, etc. CNNs differentiate this approach by utilizing the hierarchical pattern found in data, and assembling larger patterns of increasing complexity by using smaller and simpler patterns contained in their filters. Consequently, CNNs fall on the lower extreme of the scale of connectivity and complexity.

While CNNs are known to produce high diagnostic accuracy for Alzheimer's disease dementia detection using magnetic resonance imaging scans, they are not yet used in clinical routine partly due to a lack of model comprehensibility. CNNs are capable of picking out and detecting patterns from images and text, thus making sense of them. The unique architecture of CNNs is depicted in Figure 1.

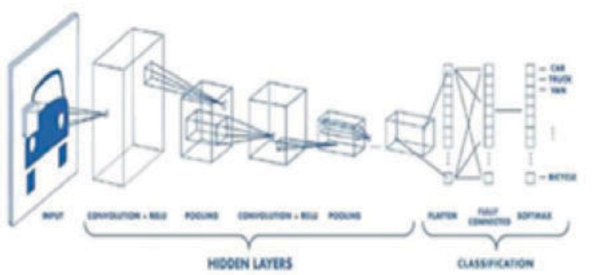

Fig.1: CNN Architecture

DENSENET

DenseNet (Densely Connected Convolutional Networks) is a deep learning architecture that was propounded by Huang et al. in 2016. It has gained momentum in computer vision tasks, specifically image classification, as a result of its distinct connectivity pattern and associated advantages [8].

The underlying principle of DenseNet is to overcome the vanishing gradient problem and promote feature reuse by densely connecting layers in a feed-forward neural network. In a traditional CNN, each layer takes input from the prior layer and transfers its output to the subsequent layer.

Conversely, in DenseNet, each layer obtains supplementary inputs from all preceding layers and subsequently passes on its feature maps to all subsequent layers by concatenation. Each layer is receiving a collective knowledge from all preceding layers. Since each layer receives feature maps from all preceding layers, the network can be thinner and more compact, i.e., with fewer channels.

The growth rate k, which is the additional number of channels for each layer, improves computational efficiency and memory efficiency. The DenseNet architecture is presented in Figure.2.

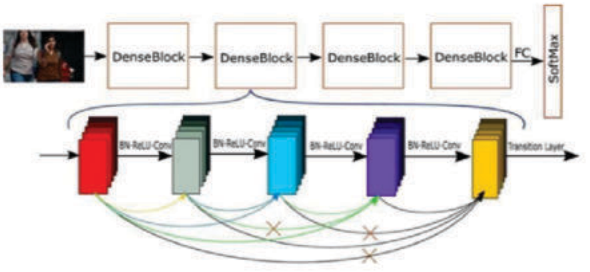

Fig.2: DenseNet Architecture

DNGAN

Due to the constant advancements in computer vision, high-quality images that contain substantial information have great potential for research in both our daily lives and scientific endeavors. However, image quality can differ due to various reasons, such as differing lighting conditions and surrounding noise, severely impacting the ability for individuals to interpret the information conveyed by the image, leading to unnecessary conflicts and outcomes. Specifically, in low-light conditions, images captured by cameras can be challenging to identify, and smart systems rely heavily on high-quality input images. Images collected in low-light environments have the characteristic of high noise and color distortion, which makes it difficult to utilize the image and more importantly, makes it challenging to fully explore the rich value of information that an image may hold.

To overcome these challenges, we propose a Heterogeneous Low-Light Image Enhancement method based on a DenseNet Generative Adversarial Network (DNGAN). The Generative Adversarial Network's generative network is created using the DenseNet framework and then learns to feature maps from a low-light image to replicate the normal-light image using a Generative Adversarial Network. DNGAN uses the combined power of Deep Neural Networks (DNNs) and Generative Adversarial Networks (GANs) to create a generative model. The DNN architecture is typically used as the generator in DNGAN, which learns to generate realistic and high-quality samples by capturing the complex patterns and distributions present in the training data. The discriminator component, also based on DNNs, learns to differentiate between the generated samples and real samples from the training data.

In our work, we retain four Block modules based on the Densenet-121 network, and we change the number of neurons in the fully connected layer to 64, while adding a Softmax classifier. The four Block modules learn the image features from low to high levels and then integrate the essential features through a fully connected layer automatically. Finally, the Softmax classifier is used to enhance and contextualize the image. Figure 3 illustrates the architecture of DNGAN.

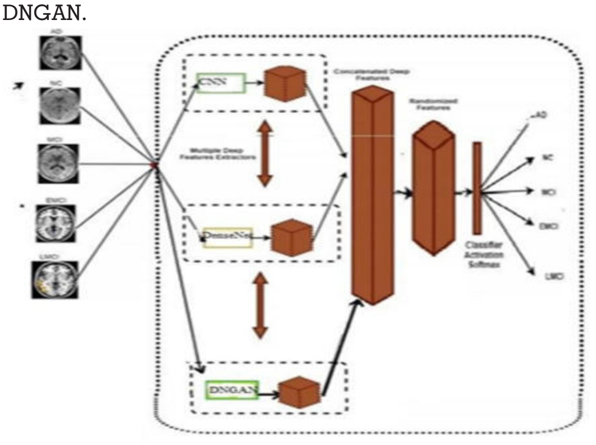

Figure 3: DNGAN Architecture

Aldo Architecture

The ALDO Alzheimer detection method relies on diagnosing through deep features extracted from the Densenet128 models. This method classifies Alzheimer's Disease (AD) into four clinical status variants. To improve the accuracy and effectiveness of the ALDO model, we modified the DenseNet architecture by adding more max pooling, dense, and dropout layers. Additionally, we enhanced the performance using DNGAN. Figure 4 illustrates the architecture of ALDO, and the system's modules are explained below.

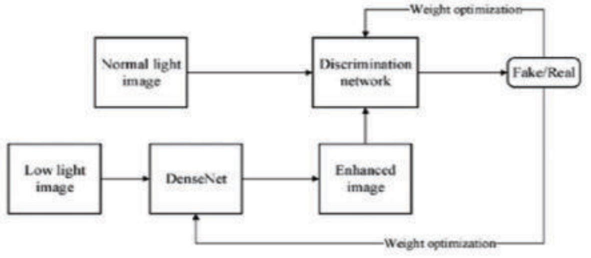

Figure 4: ALDO Architecture

A. Exploring the Dataset:

The ADNI (Alzheimer's Disease Neuroimaging Initiative) database contains images that can be utilized for detecting Alzheimer's Disease. The database is divided into training and testing datasets with a 60:40 ratio, containing 5256 and 2253 images, respectively. The training dataset is made up of 5256 images and is classified into four separate classes. The testing dataset, containing 2253 images, is used for validation purposes and will be used to evaluate the model. The class labels include MCI, LMCI, EMCI, and CN.

B. Pre-processing:

The grayscale is a range of gray shades from white to black, which is commonly used in monochrome displays or printouts. Rotation is used to improve the visual appearance of an image, and Image Augmentation is utilized to extend the dataset by adjusting the brightness, scaling, flipping, etc.

C. DenseNet Model Implementation:

The test set is predicted using the DenseNet121 algorithm. The Dense model is modified by adding additional layers to enhance its ability to make multiclass predictions. The Dense121 is improved by adding a global average pooling layer and a sequence of BN (Batch Normalization), Dr (Dropout rate), and ReLU activation layer. DenseNet121 is set with weights that have been pre-trained using natural photos from ImageNet.

D. Modified DenseNet121 (DNGAN):

The low-light images are improved using DNGAN, in which the images are divided into blocks, and each block is separately passed through the Dense model.

E. Evaluation:

The Dense model and the DenseNet DNGAN model are evaluated using the given test set, and accuracy, precision, and recall will be tabulated and evaluated.

RESULTS AND DISCUSSION

Table 1 presents a comparative analysis of the existing systems, indicating that the Convolutional Neural Network (CNN) used for classifying Alzheimer's Disease provides better results than the previous systems.

This study focuses on the DNGAN-based Alzheimer's classification using neural networks capable of handling low light images. The experiment was conducted on 1024 images from various categories of Alzheimer's, using three different models: CNN, DenseNet121, and DNGAN. The CNN model generated the feature map array with an accuracy of 0.78 and a validation loss of 1.359, while the DenseNet model predicted more cases of Alzheimer's with an accuracy of 0.95 and a validation loss of 0.135. The enhanced model successfully handled low light images by adding the activation classification results, yielding an accuracy of 0.95. The overall result of this work is 95%, which highlights the importance of DenseNet-based networks in Alzheimer's diagnosis. Figures 5 and 6 display the CNN accuracy and validation loss and the DenseNet accuracy and validation loss, respectively.

Table Comparison Of Existing Systems

Sr No	*TOPICS*	*ADVANTAGES*	*DISADVANTAGES*
1.	Classification ofAlzheimer's Disease from MRI data using anEnsemble of Hybrid Deep Convolutional Neural Networks	Ensemble classifiers are usedfor final prediction.	Not validated withdifferent dataset.
2.	Predicting MCI to AD Conversation using Integrated sMRI and RsfMRI MachineLearning and Graph Theory Approach	Feature redundancy is reduced within different classification groups usinggraph theory to extract features.	Brain regionanalysis is too complex in computation.
3.	Computer Aided Alzheimer's Disease Diagnosisby an Unsupervised Deep learning Technology	Unsupervised learning methods with CNN & SVM implemented.	The method is weak in terms of deepneural framework & uses old PCA (principal component analysis.
4.	Alzheimer Disease Detection Techniques and Methods: A Review	Review of different MRImethods and PET (Positron emission tomography).	No computational method is proposed.
5.	Convolutionalneural networks for classificationof Alzheimer's disease: Overview and Reproducible Evaluation.	Different CNN based models proposed to analysis performance.	Feature scaling makes problem when multiple datasets are trained.

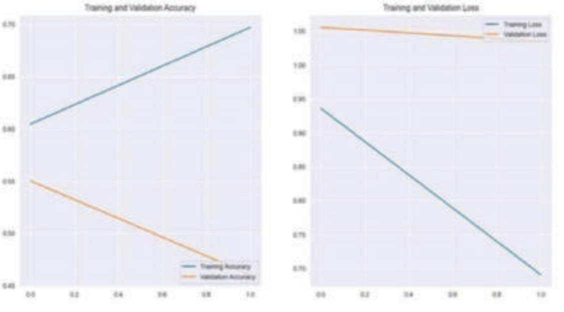

Figure.5: CNN Accuracy and Validation loss

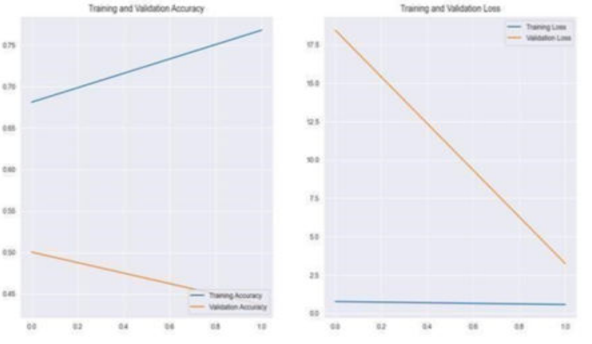

Figure 6: DenseNet Accuracy and Validation loss

CONCLUSION

Alzheimer's Disease (AD) plays a significant role in medical diagnosis, as it allows doctors to easily detect patients with AD syndrome by scanning their images. This study employs multiple experiments, using two CNN models, namely DenseNet and DNGAN, to achieve higher classification accuracy than basic machine learning techniques. The researchers use pre-trained deep convolutional neural networks to extract deep features from brain MRI images, which are then evaluated by several machine learning classifiers. The paper covers all important aspects and the latest developments so far, along with their limitations and challenges. It will help researchers gain an understanding of conducting new research with greater efficiency and accuracy. The accuracy of this study can be improved by applying optimization algorithms, adopting transfer learning models, and tuning hyper-parameters. In the future, image sequencing datasets can be considered for classifying and predicting AD, compared to static images.

REFERENCES:

[1] Maqsood, S Damasevicius, R, Shah F.M. "An efficient approach for the detection of brain tumor using fuzzy logic and U-NET CNN classification", In Proceedings of the International Conference on Computational Science and Its Applications, ICCSA 2021, Cagliari, pp.105–118,September 2021.

[2] Odusami, M.Maskeliunas, R. Damaševiˇcius, R. Misra, "Comparable study of pre-trained model on alzheimer disease classification", 13- 16 , In Proceedings of the International Conference on Computational Science and Its Applications, ICCSA 2021, Cagliari, Italy, pp.63–74, September 2021.

[3] Lu, D. Popuri, K. Ding, G.W.Balachandar, R. Beg, "Multiscale deep neural network based analysis of FDG-PET images for the early diagnosis of Alzheimer's disease, Med. Image Anal, pp.26–342, 2020.

[4] Bae, J.B. Lee, S. Jung, W. Park, S.Kim, W. Oh, H.; Han, J.W. Kim, G.E. Kim, J.S.Kim, J.H.Yadav, K.S.Miyapuram, "A Novel Approach Towards Early Detection of Alzheimer's Disease using Deep Learning on Magnetic Resonance Images", In Proceedings of the International Conference on Brain Informatics", Padova, Italy, pp.486– 495, September 2021.

[5] Ruiz, J. Mahmud, M. Modasshir, M. Shamim Kaiser, "Alzheimer's Disease Neuroimaging Initiative, 3D DenseNet Ensemble in 4-Way Classification of Alzheimer's Disease", In Proceedings of the International Conference on Brain Informatics, Padova, Italy, pp.85–96, September 2020.

[6] Mohamed, T.M. Youssef, M.A.M. Bakry, A.A. El-Keiy, 'Alzheimer's disease improved through the activity of mitochondrial chain complexes and their gene expression in rats by boswellic acid', Metab. Brain Dis. 2021, pp.255–264.

[7] Tadokoro, K. Yamashita, T. Fukui, Y. Nomura, E. Ohta, Y. Ueno, S. Nishina, S. Tsunoda, K. Wakutani, Y. Takao, Y. et al., 'Early detection of cognitive decline in mild cognitive impairment and Alzheimer's disease with a novel eye tracking test", J. Neurol. Sci. 2021.

[8] Zhang, T. Liao, Q. Zhang, D. Zhang, C. Yan, J. Ngetich, R. Zhang, J. Jin, Z. Li, "Predicting MCI to AD Conversation using Integrated sMRI and rs-fMRI: Machine Learning and Graph Theory Approach", Front. Aging Neurosci. 2021.

[9] Hojjati, S.H. Ebrahimzadeh, A. Khazaee, A. Babajani-Feremi, "Predicting conversion from MCI to AD using resting state fMRI, graph theoretical approach and SVM", J. Neuro sci. Methods, pp.69–80, 2017.

[10] Dai, Z. Lin, Q. Li, T. Wang, X. Yuan, H. Yu, X. He, Y. Wang, "Disrupted structural and functional brain networks in Alzheimer's disease", Neuro biol Aging, pp.71–82, 2019.