ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 9, Issue 8, August 2022

MDL-EAD: Multimodel Deep Learning Approach For Early Detection of Alzheimer's Disease

Mrs. SUJA G P [1]

[1]Research Scholar, Department of Computer Science, Muslim Arts College, Thiruvithancode, Kanyakumari , India.

sujamaran89@gmail.com

Abstract: Alzheimer's Disease (AD) is the most progressive neurodegenerative illness. It is primarily defined by neuronal shrinkage, amyloid deposition, and cognitive, behavioral, and psychiatric abnormalities. In the last decade, various machine learning (ML) algorithms have been investigated and applied to AD diagnosis, with a particular emphasis on the subtle prodromal stage of mild cognitive impairment (MCI), to assess critical features that characterize the disease's early manifestation and plan for early detection treatment. However, diagnosing early MCI (EMCI) remains problematic since it is very difficult to distinguish from cognitively normal individuals (CN). Consequently, the majority of classification algorithms for these two categories provide results with poor classification accuracy. The Multimodel Deep Learning Approach for Early Detection of Alzheimer's Disease (MDL-EAD) was proposed in this study as a method for EAD using multimodal imaging, which combines magnetic resonance imaging (MRI), positron emission tomography (PET), and standard neuropsychological test scores. The suggested methodology updates the learning weights to increase accuracy using Adam's optimization method. The system has an unparalleled accuracy of 98.5% in classifying cognitively normal controls from EMCI. These results imply that deep neural networks may be trained to automatically discover imaging biomarkers indicative of AD and use them to achieve accurate early identification of the illness.

Keywords: Alzheimer's disease, MDL-EAD, EMCI, PET, CNN, Deep learning

I. Introduction

The most frequent kind of dementia is AD. It is connected with brain deterioration, which results in memory loss and disorientation. The exact source of this deterioration is unknown at the moment [1]. However, it is obvious that AD does not hit suddenly but is a slow-moving degenerative process that may take decades to manifest in a way that interferes with everyday activities. This suggests that those diagnosed with MCI may be experiencing the early stages of AD.

According to recent research, 1 in every 85 persons might be impacted by this AD condition by 2050 [3]. It is critical to detect and treat AD patients in their early stages. There are numerous methods available for identifying and predicting this dementia, including MRI, PET (Positron Emission Tomography), and CT (Computed Tomography) scans; however, the most often used neuroimaging modality for diagnosing AD patients is MRI [5]. Earlier research studies have used MRI-based classification techniques with machine and DL algorithms. This paper's purpose is to develop the finest prediction and detection methods possible with the assistance of radiologists, clinicians, and carers to save time and aid patients suffering from this condition [7][8].

In artificial intelligence, DL is a subset of ML. Its numerous layered and structured structures enable the computer to learn categorization jobs from raw data. Network structure [9], [10]. CNN's extract high-level information from picture categorization and prediction in a neural network. Additionally, it is the most extensively used DL method because of its excellent success rate in picture analysis and classification [12, 13, and 14].

This article discusses how to optimize the performance of a neural network for classifying sliced MRI data. The primary emphasis of this study is on the network's use of various channels. In other words, the network will use all slices simultaneously rather than just one. The enhancement should come from common characteristics across numerous slices [16].

This article presents a novel paradigm for Convolutional network transformation using spectral graph theory. We generate MCI-graphs utilizing a variety of data gathering technologies and gender information. This solution successfully addresses the issue of individual variances, and the linkage of data between participants enhances the discriminability of various stages of MCI. The findings demonstrate that this strategy produced substantial prediction results after comprehensive validation.

II. Background Study

Data preprocessing before using the CNN model is the study's primary goal. One technique for diagnosing Alzheimer's disease (AD) was reported in [1]. The ADNI

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 9, Issue 8, August 2022

dataset, which includes fMRI and PET scans of Alzheimer's patients and healthy individuals, is used to train the model. Integration of data from several sources and retrieval of expert knowledge were the study's goals. The stacking layer's fundamental classifiers are evaluated using a nonlinear feature-weighted technique derived from deep belief networks. Conditional independence is violated by this method. To categories AD, the DL method is bein g used as advised. The researchers used data from the National Alzheimer's Coordinating Center. The results show that this approach has a classification accuracy advantage of 4% over six other well-known ensemble approaches.

The adoption of ML and DL techniques that generate diagnostic output comparable to humans in [3] has dramatically increased medical imaging applications for AD. An MRI dataset and a two-dimensional deep Convolutional neural network (2D-DCNN) were combined in this article to create a model for detecting Alzheimer's disease. The ADNI (MRI images) dataset is a good fit for the 2D-DCNN model. The model's accuracy, efficiency, and durability are evaluated. Classification accuracy for unbalanced groups was 97.89% when using the model to classify the input MRI pictures into three categories: Alzheimer's disease, mild cognitive illness, and normal control.

Transfer learning is used in [5] to train high-dimensional Deep Neural Network (DNN) models to obtain reliable findings while identifying Alzheimer's disease (AD) using fMRI data. They used three deep neural network models: VGG19, Inception v3, and ResNet50 to identify individuals with Alzheimer's disease, mild cognitive impairment (MCI), and chronic neuropathic pain (CN). With a total of 15 preparation epochs, VGG19 obtained a 90% accuracy rate, Inception v3 an 85% accuracy rate and ResNet50 a 70% accuracy rate. A 12-layer CNN binary classification model trained on brain MRI data is described in [5]. This model was built using data from the OASIS project. Many CNN models compare its accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve. More accurate than any other CNN model on this dataset, this one achieved 97.75% accuracy.

For the article in [15], three distinct photographs are juxtaposed. 4D fMRI scans, which are 3D images that change over time, are essential for the DL process. The progression measurements were important to have a better knowledge of fMRI brains scanning the most distinct characteristics. Deep pre-trained models are used in the Transfer Learning classification technique. The information gained during ImageNet Dataset training accelerates and strengthens the learning process by building a new resolution network [15].

III. PROPOSED MODEL

A specific study strategy was designed for each phase, which comprised MRI data collection, data preparation, training, and data assessment. Finally, the model development process is discussed.

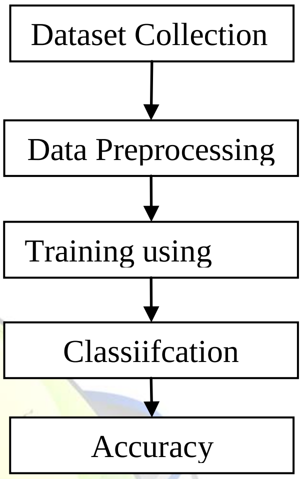

Figure 1: System Architecture

3.1 Dataset:

The dataset is collected from the kaggle.com website. There are three classes of images with 1512 mild, 2633 normal, and 2480 AD.

3.2 Data Preprocessing

For our part, we were given the jpg image format as input to the CNN model, which implies that the photographs must be in the jpg format as well. However, the data we obtained from the Kaggle website included photos with the nii extension, which required us to convert all of those images to jpg.

3.3 Method and Classification Algorithm

Often employed in image processing, pattern recognition, and classification, CNNs are a feedforward neural network. Based on biological processes, the visual cortex is designed. The weights and biases associated with each item in an image are stored in neurons in a CNN. Following is a list of the CNN model's most important features.

3.4 Convolutions

Convolution is applied to a picture with a block size of eight and a kernel size of 45*45*45; steps 1,2,3 used two Convolutional layers, with the first filter comprising 32 kernels of 3*3. Convoluted with the image, the kernels perform the function of feature finders, generating a collection of convolved features. The size of the kernel in a neural network is proportional to the size of the receptive neuron field, strengthening the neurons'

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 9, Issue 8, August 2022

regional connectivity to the previous volume. [2] discussed that In surgical planning and cancer treatment, it is crucial to segment and measure a liver tumor's volume accurately. Because it would involve automation, standardisation, and the incorporation of complete volumetric information, accurate automatic liver tumor segmentation would substantially affect the processes for therapy planning and follow-up reporting. [4] discussed that Liver tumor division in restorative pictures has been generally considered as of late, of which the Level set models show an uncommon potential with the advantage of overall optima and functional effectiveness. The Gaussian mixture model (GMM) and Expected Maximization for liver tumor division are introduced. [6] emphasized that Security is an important issue in current and next-generation networks. Blockchain will be an appropriate technology for securely sharing information in next-generation networks. Digital images are the prime medium attacked by cyber attackers. In this paper, a blockchain based security framework is proposed for sharing digital images in a multi user environment. [11] discussed about diabetic retinopathy from retinal pictures utilizing cooperation and information on state of the art sign dealing with and picture preparing. The Pre-Processing stage remedies the lopsided lighting in fundus pictures and furthermore kills the fight in the picture. Although the Disease Classifier step was used to identify arising wounds and other data, the Division stage divides the image into two distinct classes.

3.5 Rectified Linear Unit and Softmax

Softmax and the ReLU activation function are used to build a discrete probability distribution for the model's inputs. ReLUs need a lot less training time compared to sigmoid or hyperbolic tangents.

3.6 Pooling Layer

Maximizing is used in an area to obtain the maximum value determined by k, kernel size, input size, and stride s. This is done by using max-pooling. Using a pooling technique makes input smaller, but the outputs of nearby input groups are also efficiently summed. Downsampling occurs when the image size is exceptionally large, reducing the spatial dimensions while retaining significant information and reducing the number of parameters; in this investigation, one max-pooling layer is applied.

3.7 Dropout

Neurons with a probability of r, known as ratio dropout, are used in the hidden layers to convert the output to 0. Dropped neurons don't take part in the forward pass or backward propagation. The proposed architecture has two dropout layers, one following the pooling layers, with ratios of 0.25 and 0.5, respectively.

3.8 Fully Connected Layer

The final layer is FC which is a linked layer. Layers one and two are interconnected via synapses between neurons. As a bonus, since we vectorized and sent this matrix to the fully connected layer, the training performance of CNN models has improved.

IV. Results And Discussion

We employed CNN to identify and predict AD using MRI images in this study. We got a test accuracy rate of 0.985% and a low percentage of test loss of 0.0571 with this model after training and testing it on 7635 photos.

We trained and evaluated the model using four different epoch sizes, 25, 15, and 10, to compare the findings and get a more precise result. We improved accuracy by employing 25 epochs and reducing test loss over four epochs.

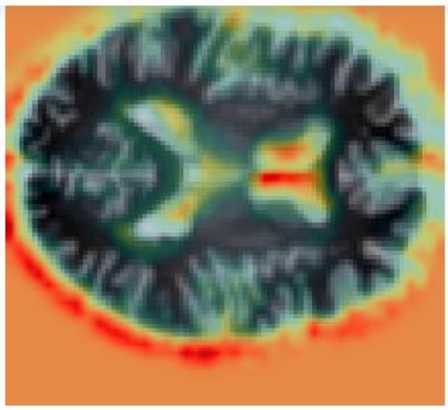

Figure 2: Preprocessed image

While noise removing the images and getting the original image for data is displayed in figure 2.

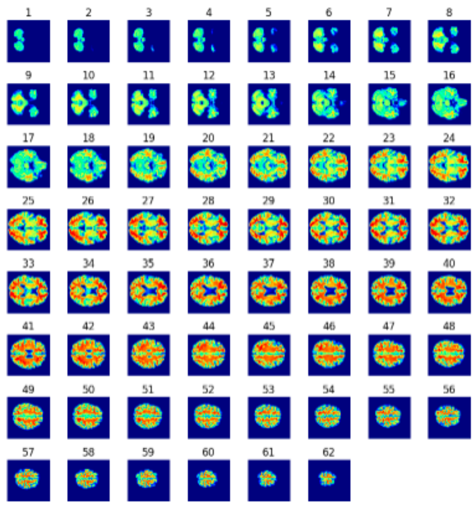

Figure 3: MCI classification using CNN

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 9, Issue 8, August 2022

The classification of CNN output is displayed in figure 3.

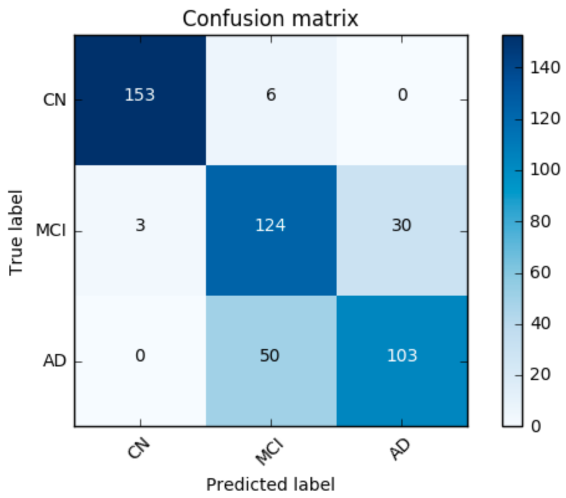

Figure 4: Confusion matrix

As seen in Figure 4, no clinically normal patient (CN) is identified as having AD, and vice versa. Additionally, the confusion matrix indicates a significant degree of doubt between individuals with MCI diagnosed as having AD and those with AD who are classified as having MCI.

V. Conclusion

Recent advances in biomedical engineering have elevated the study and interpretation of medical pictures to critical research fields. the AI-based technology that satisfies One of the reasons for this advancement in medical image analysis is the usage and use of DL. Classification by DL has been mostly employed during the last year. Automatic early detection of AD is physicians' major aims. Thus, an automated framework and classification system for AD based on MRI images are critical for the early diagnosis of AD patients. In this research, we devised a CNN classification technique for AD utilizing MRI data. The three photographs were employed in this investigation, totaling 1512 mild, 2633 normal, and 2480 AD. The accuracy level has been increased to 98.5%. Among the findings obtained with various epoch sizes, a significant result was achieved with an epoch size of 25 and an accuracy rate of 98.5%.

In the future, we anticipate and encourage more effort. Thus, the outcome might be enhanced further by using a deep CNN, which has lately shown promise in neuroimaging research. Thus, utilizing deep CNN to process massive MRI scan pictures might considerably increase the algorithm's capacity to identify AD. Additionally, this technique to DL benefits physicians, caretakers, radiologists, and patients suffering from one condition while also providing invaluable information to the researcher for diagnosing the other sort of sickness.

References

1. Janghel, R.R., Rathore, YK..: Image-based state-of-the-art techniques for the identification and classification of brain diseases. A review Medical and Biological Engineering and Computing, vol. 58 (2020).
2. Christo Ananth, S. Amutha, K. Niha, Djabbarov Botirjon Begimovich, "Enhancing Segmentation Approaches from Super Pixel Division Algorithm to Hidden Markov Random Fields with Expectation Maximization (HMRF-EM)", International Journal of Early Childhood Special Education, Volume 14, Issue 05, 2022,pp. 2400-2410.
3. Nawaz, S., Anwar, R., Liaqat, J. Iqbal.: Deep Convolutional Neural Network based Classification of Alzheimer's Disease using MRI Data. In: 2020 IEEE 23rd International Multitopic Conference (INMIC), Bahawalpur, Pakistan, pp. 1-6(2020).
4. Christo Ananth, M Kameswari, Densy John Vadakkan, Dr. Niha.K., "Enhancing Segmentation Approaches from Fuzzy-MPSO Based Liver Tumor Segmentation to Gaussian Mixture Model and Expected Maximization", Journal Of Algebraic Statistics, Volume 13, Issue 2, June 2022,pp. 788-797.
5. Hussain, E,Hasan, M.F., Hassan, S.Z., Hassan Azmi, T., Deep Learning Based Binary Classification for Alzheimer's Disease Detection using Brain MRI Images. In: 2020 15th IEEE Conference on In-dustrial Electronics and Applications (ICIEA), Kristiansand, Norway, pp. 1115-1120 (2020).
6. Christo Ananth, Denslin Brabin, Sriramulu Bojjagani, "Blockchain based security framework for sharing digital images using reversible data hiding and encryption", Multimedia Tools and Applications, Springer US, Volume 81,Issue 6, March 2022,pp. 1-18
7. Jabason, E., Ahmad, M.O., Swamy, M.N.S.: Classification of Alzheimer's Disease from MRI Data Using an Ensemble of Hybrid Deep Convolutional Neural Networks. In: 2019 IEEE 62nd Interna-tional Midwest Symposium on Circuits and Systems (MWSCAS), Dallas, TX, USA,pp.481-484 (2019)
8. Acharya, U.R., Fernandes, S.L., WeiKoh, J.E.: Automated Detection of Alzheimer's Disease Using Brain MRI Images. Journal of Medical Systems, vol. 43 (2019).
9. Rachna Jaina., Nikita Jain.: Convolutional neural network based Alzheimer's disease classification from magnetic resonance brain images. In: Computer Science and Engineering, Bharati Vidyape-eth's College of Engineering, New Delhi, India.(2020)
10. Simon, B.C., Baskar, D., Jayanthi, VS: Alzheimer's Disease Classification Using Deep Convolutional Neural Network. In: 2019 9th International Conference on Advances in Computing and Commu-nication (ICACC), Kochi, India, 2019, pp. 204-208, (2019).
11. Christo Ananth, D.R. Denslin Brabin, Jenifer Darling Rosita, "A Deep Learning Approach To Evaluation Of Augmented Evidence Of Diabetic Retinopathy", Turkish Journal of Physiotherapy and Rehabilitation, Volume 32,Issue 3, December 2021,pp. 11813-11817

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 9, Issue 8, August 2022

12. Laura Mc Crackin.:Early Detection of Alzheimer's Disease Using Deep Learning. In: Department of Electrical and Computer Engineering University of Waterloo. Waterloo, Canada (2018).

13. Khagi, B., Lee, C.G., Kwon, G.: Alzheimer's disease Classification from Brain MRI based on transfer learning from CNN.In: 2018 11th Biomedical Engineering International Conference (BMEiCON), Chiang Mai, Thailand, pp. 1-4. (2018).

14. Jabason.,Ahmad. .: Classification of Alzheimer's Disease from MRI Data Using an Ensemble of Hy-brid Deep Convolutional Neural Networks. In: 2019 IEEE 62nd International Midwest Symposium on Circuits and Systems (MWSCAS), Dallas, TX, USA,pp.481-484(2019).

15. Puranik, M., Shah, F.H.: Intelligent Alzheimer's Detector Using Deep Learning. In: 2018 Second In-ternational Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, pp. 318-323 (2018).

16. Suganthe, RC., Latha, RS, Geetha, M., Sreekanth, GR.: Diagnosis of Alzheimer's Disease from Brain Magnetic Resonance Imaging Images using Deep Learning Algorithms. Advances in Electrical and Computer Engineering 20 (3), pp.57-64, (2020).

SUJA G P., has completed her M.Sc., M.Phil., M.Ed.,M.Phil. She is currently pursuing Doctorate in Computer Science. Her area of Interest is Digital Image Processing, Soft Computing. She has presented many papers in the National and International conferences and has published papers.

