Section A-Research paper
ISSN 2063-5346

Prediction of Alzheimer's Disease Using MRI Data Utilizing a Deep Learning Model

TANGI DILEEP KUMAR[#1], T. RAVI KUMAR[#2] ,
[#1] Final Year M.Tech Student, Department of Computer Science and Engineering,
[#2]Associate Professor, Department of Computer Science and Engineering,
Aditya Institute of Technology and Management(AITAM),
Tekkali, K Kotturu, Andhra Pradesh 532201.

ABSTRACT

The most common form of dementia, Alzheimer's Disease (AD), is an irreversible neurological disorder that causes progressive mental decline. Although a clear diagnosis of Alzheimer's disease is challenging, in practise, the diagnosis of Alzheimer's disease is mostly dependent on clinical history and neuropsychological data, including magnetic resource imaging (MRI). In recent years, there has been an increase in study on applying machine learning to AD recognition, but this was not efficient for large datasets. This article presents our most recent contribution to the field and also try to propose automatic Alzheimer's disease identification method based on deep learning and 3D brain MRI. In order to achieve more accuracy, we used a Inception V3 Model. This study's CNN is made up of three groups of processing layers, two completely connected layers, and a classification layer. Each of the three groups in the structure is made up of three layers: a convolutional layer, a pooling layer, and a normalization layer. The Alzheimer's Disease Neuroimaging Initiative MRI data was used to train and test the algorithm. The data used included MRI scans of approximately 47 Alzheimer's patients and 34 healthy controls. The experiment demonstrated that the proposed method provided high AD recognition accuracy with a sensitivity of 1 and a specificity of 1.By conducting various experiments on our proposed model, we can able to test MRI image to the system and check the exact condition of the patient.

Keywords: Alzheimer's Disease, Magnetic Resource Imaging (MRI), Deep Learning, Neuroimaging Initiative, Machine Learning.

1. INTRODUCTION

Dementia is a term used to describe a group of symptoms produced by brain abnormalities. Dementia affects more than 46.8 million individuals globally today, with 131.5 million expected by 2050 [1]. There are several forms of dementia, the most common of which is Alzheimer's Disease (AD)[1]. Despite significant attempts to understand the pathophysiologic processes of dementia and create effective therapies, reliable diagnosis of dementia remains difficult. Some computer-aided systems have been investigated to diagnose AD in the hunt for an effective method of diagnosis. These systems rely on machine learning and clinical history information, as well as neuropsychological data from magnetic

resource imaging (MRI), structural MRI (sMRI), functional MRI (fMRI), and positron emission tomography (PET) (PET). Advanced neuroimaging techniques, such as magnetic resonance imaging

(MRI) and positron emission tomography (PET), in particular, have been developed and are being employed to uncover AD-related structural and molecular biomarkers (Veitch et al., 2019). Rapid advancements in neuroimaging techniques have made it difficult to combine large-scale, multimodal neuroimaging data. As a result, interest in computer-aided machine learning methodologies for integrative analysis has developed fast. Well-known pattern analysis methods, such as linear discriminant analysis (LDA), linear programme boosting method (LPBM), logistic regression (LR), support vector machine (SVM), and support vector machine-recursive feature elimination (SVM-RFE), have been used and show promise for the early detection of Alzheimer's disease and the prediction of Alzheimer's progression (Rathore et al., 2017).

In order to use such machine learning algorithms, relevant architectural design or pre-processing processes must be developed ahead of time (Lu and Weng, 2007). Machine learning classification studies typically involve four steps: feature extraction, feature selection, dimensionality reduction, and feature-based classification algorithm selection. These processes necessitate specialised knowledge and many optimization steps, which can be time-consuming. The reproducibility of these approaches has been a problem (Samper-Gonzalez et al., 2018). In the feature selection process, for example, AD-related features from various neuroimaging modalities are chosen to derive more informative combinatorial measures, which may include mean subcortical volumes, grey matter densities, cortical thickness, brain glucose metabolism, and cerebral amyloid- accumulation in regions of interest (ROIs), such as the hippocampus (Riedel et al., 2018).Hence this motivated me to develop the automatic AD using deep learning model[2] in which there will be less overhead and more accuracy for small or large datasets.

2. LITERATURE SURVEY

In this section we discuss about some related work that is carried out by several authors in order to detect the Alzheimer's Disease at the early stages.

MOTIVATION

1) "Early diagnosis of Alzheimer's disease based on deep learning: Challenges," in PMID: 35605488 with DOI: 10.1016/j.compbiomed.2022.105634 , by Sina Fathi.

This study examined the present state of employing deep learning methods on neuroimaging data for the prompt diagnosis of Alzheimer's disease. The authors investigated various deep models, modalities, feature extraction methodologies, and parameter initialization methods to determine which model or strategy could provide superior performance. Our evaluation results show that comparative analysis is difficult in this domain due to the lack of a benchmark platform; however, convolutional neural network (CNN)-based models, especially when used in an ensemble, appear to perform better than other deep models. The transfer learning strategy could also significantly enhance performance and time complexity. More research towards developing a benchmark platform to aid in comparative analysis is recommended[3].

2) "Early diagnosis of Alzheimer's disease using machine learning: A multi-diagnostic approach", in BMC part of Springer Nature, by Hugo Alexandre Ferreira.

The authors present a multi-diagnostic and generalizable strategy to diagnosing moderate cognitive impairment (MCI) and Alzheimer's disease (AD) using structural MRI and ML. Subjects from the AD Neuroimaging Initiative (ADNI) database[9] (n = 570) and the Open Access Series of Imaging Studies (OASIS) project database (n = 531) were used to train and test classifiers. Several classifiers are compared and integrated for a decision via voting. Furthermore, we present generalizability tests across datasets and protocols (IR-SPGR and MPRAGE), the impact of using graph theory measures on diagnostic classification[4] performance, the relative importance of different brain regions on classification for better interpretability, and an assessment of the classifier's clinical applicability.

3) "Deep Learning in AD: Diagnostic Classification and Prognostic Prediction Using Neuro Imaging Data", in Frontiers,2019, by Taeho Jo.

The application of deep learning to the early identification and automated categorization of Alzheimer's disease (AD) has recently received a lot of interest, thanks to rapid advancements in neuroimaging techniques[5] that have generated a lot of multimodal neuroimaging data. A thorough review of articles using deep learning techniques and neuroimaging data for Alzheimer's disease diagnostic classification was conducted. Deep learning studies on AD published between January 2013 and July 2018 were identified using a PubMed and Google Scholar search. The findings of these publications were summarised after they were examined, analysed, and categorised by algorithm and neuroimaging type. Four research employed a combination of deep learning and classic machine learning methodologies, while the other twelve used exclusively deep learning approaches.

4) "Generalizable deep learning model for early Alzheimer's disease detection from structural MRIs," Scientific Reports,2021, by Sheng Liu, and Arjun V. Masurkar,

Early Alzheimer's disease detection is critical for patient care and clinical studies. In this study, we used structural MRIs to develop a new approach based on 3D deep convolutional neural networks to accurately distinguish mild Alzheimer's disease dementia from mild cognitive impairment and cognitively normal individuals. We created a reference model based on the sizes and thicknesses of previously described brain areas thought to be involved in illness progression. Both models were validated using an internal hold-out cohort from The Alzheimer's Disease Neuroimaging Initiative (ADNI) and an external independent cohort from The National Alzheimer's Coordinating Center (NACC). When differentiating between cognitive normal patients and subjects with cognitive deficits, the deep-learning model attained an area-under-the-curve (AUC) of 85.12[6].

3. EXISTING SYSTEM

In the existing system there was no proper method to identify the Alzheimer's disease prediction using any ML or DL algorithms. The following are the main limitations in the existing system.

LIMITATIONS OF THE EXISTING SYSTEM

1. More Time Delay in finding the root cause of Alzheimer's Disease(AD).
2. There is no prevention technique due to late prediction.
3. There is no early prediction of Alzheimer's disease due to lack of knowledge
4. All the existing systems try to predict the AD based on manual approach by learning strong knowledge about the concept.
5. There is no method to identify the Alzheimer's disease based on ML and DM Methods

4. PROPOSED SYSTEM

In this proposed system we try to find out the Alzheimer's disease detection based on Inception V3 model by considering all the possible factors which are required for disease prediction. In this application we try to find out the accuracy and which stage of disease the patient is presently suffering with. Here in our application we have some possible stages such as: Very Mild Demented, Non Demented, MildDemented, and ModerateDemented.

ADVANTAGES OF THE PROPOSED SYSTEM

1) By using proposed Inception V3 model, we can get accurate Alzheimer's disease detection with more accuracy.

2) In this paper we survey different papers in which one or more algorithms are used for efficient prediction of AD.

3) Results clearly state that it is very accurate in identification of AD.

5. PROPOSED MODELS

In this proposed application, we used Pre-trained CNN model such as Inception V3 to automatically predict the AD from MRI images[7].

CNN Model

To recognize AD, the method uses a convolutional neural network (CNN). This study's CNN architecture consists of three convolutional layers[10], each followed by normalization and spatial max-pooling [10]. The network's final layers are made up of completely linked layers and a classification layer. Figure 1 depicts the network architecture. In each convolutional layer, the filter size was 5 5. After the convolutional layers, max-pooling of size 2 2 was applied, halving the feature map sizes after the operations. Max-pooling minimises the number of free parameters in the network and introduces minor spatial invariance. The completely connected layers are followed by a sigmoid logistic regression, which produces a score between 0 and 1, indicating the likelihood.

Inception V3 Model

The convolutional neural network (CNN) has been demonstrated to be a very powerful DL model that is appropriate for grid-like data such as RGB and MR images. Beginning with AlexNet's remarkable achievement on the natural image classification problem18, the application of CNNs has swiftly spread into a wide range of applications. Early successes in medical image analysis were gained in 2D images such as retinal and chest X-ray images19, and then extended to 3D [8] images such as MRI. Existing CNN-based MRI approaches are commonly classified as Level 2.

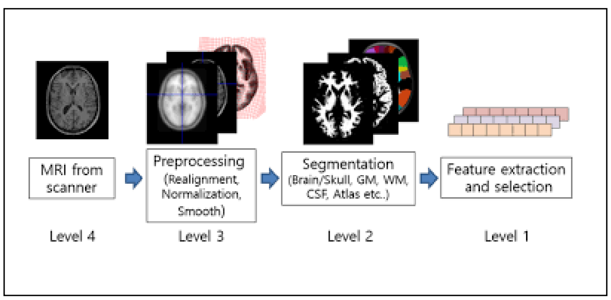


Figure 1. Inception V3 Architecture for AD

Some studies20,21 use preprocessing to partition the grey matter (GM) region and then use it as an input to the CNN. Rieke et al.22, Yang et al.23, and Korolev et al.24 developed 3D-CNN-based systems with various regularization techniques such as dropout (DO), batch normalization (BN), and residual module. Although these approaches produced outstanding results by employing proper regularization techniques, there was no unsupervised learning. When faced with data scarcity and high dimensionality, unsupervised learning is recognised as a key component in the field of DL. Strategies based on scratch training may introduce bias by randomly initializing weights for small quantities of data. Multimodal DL approaches have attempted to improve the classification accuracy of AD by incorporating multiple inputs and DL models. Lee et al.16 used an RNN to predict AD by extracting multimodal characteristics from MRI, Cohort data, and CSF data. Furthermore, Suk et al.27 used MRI, PET, MMSE, and CSF data to differentiate AD from MCI. Feng et al.28 established an integrated architecture for 3D-CNN and LSTM and supplied MRI and PET data to the network simultaneously. They demonstrated that multimodal data can be used to improve classification performance.

6. IMPLEMENTATION PHASE

The theoretical concept is transformed into a programmatically-based approach during the execution stage. At this phase, the application will be broken into several components and then programmed for deployment. The front end of the programme makes use of Google Collaboratory, while the back end database makes use of the dataset emotion text. Python is being used in this case to implement the existing programme, which is essentially divided into the five modules shown below. They are as follows:

1) Import Necessary Libraries
2) Load Dataset Module
3) Data Pre-Processing
4) Train the Model Using Inception V3
5) Result Analysis

1) Import Necessary Libraries Module

In this module, we must first import all of the necessary libraries for constructing the model. Here, we attempt to use all of the libraries that are used to convert data into intelligible formats. Because the data is divided into numerical values that the system can easily identify, we try to import the numpy module and use the matplot library to plot the data in graphs and charts.

2) Load Dataset Module

In this module, the user attempts to load a dataset downloaded or collected from the KAGGLE repository. The dataset names are stored here as 'alzheimers-dataset-4-class-of-pictures.rar'. This dataset provides a collection of human brain images.

3) Data Pre-Processing Module

In this step, we attempt to pre-process the incoming dataset and determine whether there are any missing values or incomplete data in the dataset. If such data is included in the dataset, the application will disregard it and load only valid information. In our proposed application, all input images will be MRIs, and no other images will be used as input images.

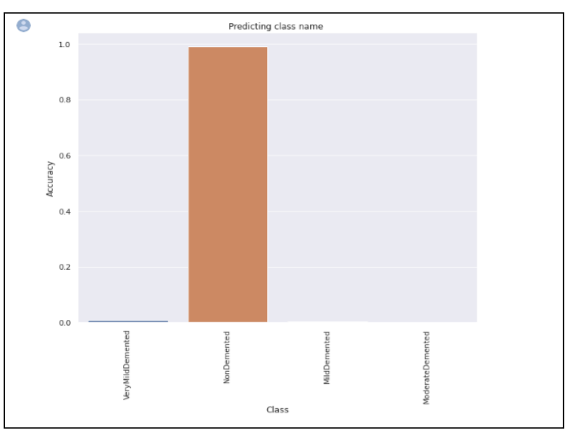
4) Train the Model Using Inception V3

In this section, we attempt to train the current model on a given dataset using the Inception v3 model in order to identify and classify the input dataset accurately and efficiently, and then we attempt to determine which algorithms suit best in order to identify and classify the input dataset accurately and efficiently. Here, we attempt to apply the Inception V3 method to forecast Alzheimer's disease and the class to which it belongs.

5) Performance Analysis Module

In this module, we attempt to compare the given dataset using the Inception V3 model and determine which of the following categories the data falls into:

1. VeryMildDemented
2. NonDemented
3. MildDemented
4. ModerateDemented



By reviewing the information, we were able to extract the following case.

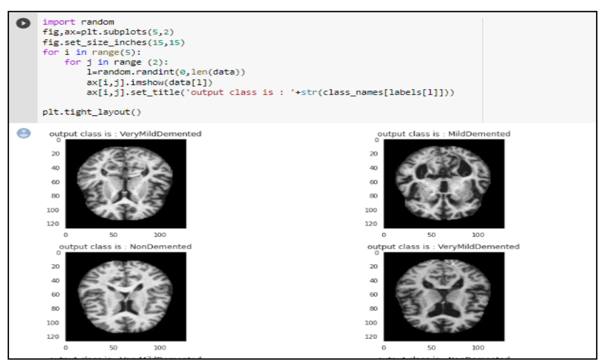
7. EXPERIMENTAL REPORTS

In this section we try to design our current model using Python as programming language and we used Google Collab as working environment for executing the application. Now we can check the performance of our proposed application as follows:

Data Set Loaded

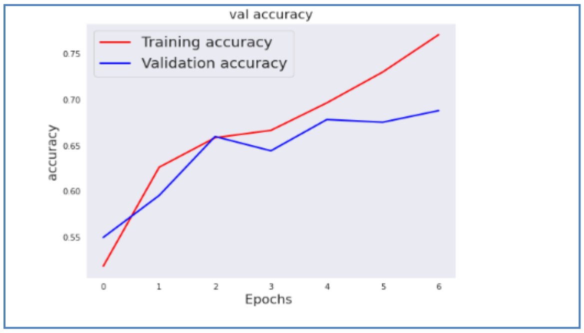
From the above window we can clearly see that data set is loaded and packages are imported. Now we can zip file is extracted to see what is present in that dataset.

Display some Random Input



From the above window we can clearly once the dataset is extracted we can see some sample images which are collected for training the model.

Validation Graph for Accuracy



From the above window we can clearly see the test and training validation accuracy is clearly seen in the above window.

8. CONCLUSION

This research describes an automatic AD identification technique based on 3D brain MRI and deep learning. To recognise AD, the method use a convolutional neural network (CNN). It is unusual in that it considers the 3D topography of the brain as a whole in AD recognition, resulting in correct recognition. This study's CNN is made up of three groups of processing layers, two completely connected layers, and a classification layer. Each of the three groups in the structure is made up of three layers: a convolutional layer, a pooling layer, and a normalisation layer. The Alzheimer's Disease Neuroimaging Initiative MRI data was used to train and test the algorithm.By using Inception V3 as our proposed model we can achieve almost 93.5 % accuracy in order to detect the AD from MRI images.As a future work we can extend the same topic on some more CNN models to increase the accuracy and reduce the time delay.

9. REFERENCES

[1] Alzhemer's Australia. https://fightdementia.org.au/

[2] Arnold, L., Rebecchi, S., Chevallier, S. and Paugam-Moisy, H. (2011) An Introduction to Deep Learning. ESANN 2011 Proceedings , European Symposium on Artificial Neural Networks , Computational Intelligence and Machine Learning, Bruges, Belgium, 27-29 April 2011, 477-488.

[3] Najafabadi, M.M., Villanustre, F., Khoshgoftaar, T.M., Seliya, N., Wald, R. and Muharemagic, E. (2015) Deep Learning Applications and Challenges in Big Data Analytics. Journal of Big Data, 2, No.1. https://doi.org/10.1186/s40537-014-0007-7

[4] Liu, P., Su, S. and Chen, M. (2015) Deep Learning and Its Application to General Image Classification. International Conference on Informative and Cybernetics for Computational Social Systems (ICCSS), 7-10.

[5] Payan, A. and Montana, G. (2015) Predicting Alzheimer's Disease: A Neuroimaging Study with 3d Convolutional Neural Networks. arXiv preprint arXiv:1502.02506.

[6] Liu, S., Liu, S., Cai, W., Che, H., Pujol, S., Kikinis, R., Feng, D. and Fulham, M.J. (2015) Multimodal Neuroimaging Feature Learning for Multiclass Diagnosis of Alzheimer's Disease. IEEE Transactions on Biomedical Engineering , 62, 1132-1140.https://doi.org/10.1109/TBME.2014.2372011.

[7] Sarraf, S., Anderson, J. and Tofighi, G. (2016) Deep AD: Alzheimer's Disease Classification via Deep Convolutional Neural Networks Using MRI and fMRI. bioRxiv, p. 070441.

[8] Hosseini, E., Asl, R.K. and El Baz, A. (2016) Alzheimer's Disease Diagnostics by Adaptation of 3D Convolutional Network. IEEE International Conference on Image Processing (ICIP).

[9] The Alzheimer's Disease Neuroimaging Initiative (ADNI).http://www.adni-info.org/

[10] Krizhevsky, A., Sutskever, I. and Hinton, G.E. (2012) ImageNet Classification with Deep Convolutional Neural Networks. International Conference on Neural Information Processing Systems , 1097-1105.