International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

A Survey on Early Detection and Classification of Alzheimer's Disease Using Machine Learning and Deep Learning Techniques

Rashmi V[1], Sankhya N Nayak[2]

[1]Assistant professor, Department of CS & E, Jawaharlal Nehru New College of Engineering
[2]Associate Professor, Department of CS & E, Jawaharlal Nehru New College of Engineering

Abstract

Alzheimer's disease is a disease that is caused due to depositions of protein around the brain cells. These depositions will distort the regular working of the brain, slowly making the patient unable to think, talk or even do regular chores. People of age more than 60 are prone to Alzheimer's. This disease has several stages which finally leads to dementia. In this regard, early detection of Alzheimer's can help doctors to properly treat and to delay the further protein depositions in the brain. In order to do so, many machine learning and deep learning techniques have been employed, out of which linear regression, decision trees, CNN and support vector machine are some of them to name. This paper provides a detailed review on dissimilar works proposed by different authors and also discusses the performance analysis of each proposed model.

Keywords: Alzheimer's, Dementia, Support vector machine (SVM), CNN architecture.

1. Introduction:

Alzheimer's disease is a degenerative disease that affects the human nervous system. It is caused due to the accumulation of proteins around the brain cells. A protein called amyloid will accumulate forming plaques and accumulation of protein called tau will forms tangle due to which normal functioning of the brain will be disturbed. Alzheimer's disease usually affects people of age more than 60 years. Persons suffering from Alzheimer's will gradually decline and later worsens the conditions. It majorly affects the normal working of brain cells which results in decline in memory and thinking abilities which can finally lead to dementia in early adults. People of age more than 60 are prone to this disease which slowly kills the confidence of the affected person as it gradually makes him/her unable to carry out his/her daily routine activities. It has been surveyed that over 55 million people have been diagnosed with this disease and there is increase in this count by a large number every year. So, finding right and accurate measure to control this becomes too prominent.

Alzheimer's disease distorts the daily activities and can also observe impairments in communication for them making it difficult to deal with, for the patients and even to their family. The cause of this deadly disease is still not deterministic. It can be caused through hereditary conditions, environmental or lifestyle factors. This disease shrinks the brain of the person suffering from Alzheimer's, giving small portions to remember things, tasks and language. Even though, there are medicines that are developed to treat Alzheimer's, they can only delay the progress between its stages. Over time, as the brain shrinks, brain cells will die which leads to further damage.

Dementia can be divided into majorly four stages, mild cognitive impairment, mild dementia, moderate dementia and severe dementia. In this connection, if it is can be detected at an early stages, it is possible to reduce the development between these different stages by slowing down the degeneration of brain. To detect Alzheimer's disease accurately, neuroimaging has proved to be very reliable, with the aid of machine learning and deep learning techniques. To employ these techniques, proper architectural development and performing necessary preprocessing of data becomes a prominent task.

2. Related work

Suriya Murugan M. G. Sumithra, Chandranvenkatesan, Xiao-Zhi Gao and S.Manoharan [1] has proposed a work that has made use of about 6400 magnetic resonance images of four classes as dataset. The four classes were taken to be mild demented, moderate demented, non-demented and very mild demented. Dataset comprised of images of size 176*208. Images were resized to 176*176 for this proposed work. From dataset, 80% images were used to train the model, 10% images were used to validate and remaining portion of dataset was used to test the trained data.

Proposed model was developed to classify among the dissimilar stages of Alzheimer's disease from the scratch. Architecture consists of two convolutional layers, a max pooling layer, four DEMNET blocks, two dropout layers, three dense layers and a softmax classification layer.

a. Input layer: in this layer, images were normalized and enlarged MRI images were taken as an input. This layer acts a preprocessing step that makes the work easier.
b. Convolutional layers: these layers provide the greatest support for the proposed model. These layers can be accounted as the core layer which does the ample amount of work. This layer performs convolution between input image and the various filters or mask accompanied by weights. The result of this convolution fetches the response, which will be then carried to the subsequent layers.
c. Pooling layers: The main reason of utilizing pooling layers was to reduce the computation space. So, this layer was positioned between all the convolutional layers. To reduce the cost of computation, the pixel which has the highest value in the given kernel was selected. Max pooling depends on stride as well as window size of pooling.
d. DEMNET block: This block makes use of four dissimilar filters in order to bring out the differential features which will be fruitful to distinguish between the stages of Alzheimer's disease. Each filter will contribute in getting dissimilar features. Model makes use of four DEMNET blocks. At every stage, batch normalization was carried out to diminish the hassle and to make sure all factors are in the same unit.
e. Dropout layer: in this layer, randomly some neurons present in the hidden layer will be dropped in the training phase. This is a crucial step to avoid any problem of overfitting.
f. Dense and softMax layers: this method makes use of three dense layers. This layers performs same mathematical operations that are carried out by artificial neural network. Subsequent layer is the softMax layer, which makes use of same number of neurons as that of classes. To calculate likelihood for every image on classes, categorical cross entropy was employed as loss function.

The performance of this proposed model was proved to be very high and is as follows. The work has utilized

Synthetic Minority Oversampling Technique (SMOTE). Due to which this model has become sensitive and specific to every minute detail and has given awesome results. This model attained F1 score of 95.27, accuracy of 95.23 and precision being 96 when evaluated for DEMNET with SMOTE and when without SMOTE, the model was evaluated, it attained F1 score of 83, accuracy of 85 and precision of 80.

Hadeer A. Helaly, Mahmoud Badawy, Amira Y. Haikal [2] suggested that detection of Alzheimer's disease at an early stage is crucial. In this regard, a framework was developed called as E^2AD^2C framework. This framework is primarily helpful for picture classification purpose and involves majorly six steps.

a. First and foremost step is data accession step. Trained data was acquired from ADNI dataset which comprises coronal, sagittal and axial in DICOM format. Trained data involves images of 300 patients, which were categorized into four groups, Alzheimer's disease (AD), Early Mild Cognitive Impairment (EMCI), Late Mild Cognitive Impairment (LMCI) and clinically stable or normal control (NC). Image set size acquired for Alzheimer's disease was 75 for each category making it a total of 300 image set.
b. Subsequent step is the preprocessing step, where the imbalanced classes of images will be treated by resampling them, for which two methods have been incorporated i.e., oversampling and undersampling. The proposed work carry out oversampling on Alzheimer's disease(AD), Early Mild Cognitive Impairment (EMCI), Late Mild Cognitive Impairment (LMCI) and undersampling on clinically stable or normal control (NC) class. All the acquired images will fetch about 6000 MRI images after resampling, resulting in a total of 24000 images. After this, subsequent step was to perform normalization, standardization and also resizing and de-noising procedures will be carried out.
c. Third step is the amplification step. As the medical dataset is too scarce, traditional amplification techniques were employed which includes rotation and flipping, finally bringing the size of the dataset to 48000 MRI images. This dataset of 48000 images was randomly shuffled and categorized into training, validation and test data set with 80:10:10 ratio on the basis of random selection for every category.
d. Subsequent step is the classification of medical images. This work considers four classes. To classify the current stage into either one the four considered stages, two separate binary classifications were employed between each two pair classes. This can be accomplished in two methods. First method was to make use of CNN architecture by building it from scratch and another method was to use transfer learning techniques, by making use of already trained weights called VGG19 model.
e. Further step is evaluation step where every method was tested for nine metrics which comprises of accuracy, loss, F1 score, recall, precision, ROC and AUC cures, MCC coefficient and confusion matrix.
f. Final step is the application step. Alzheimer's disease checking web application was proposed which helps both doctors and patients to check Alzheimer's remotely and determine the stage and take action accordingly.

The model attained experimental results with accuracy if 93.16% and 95.17% for 2D and 3D multiclass Alzheimer's disease stage classification.

Waleed Al Shehri [3] proposed a work where study of diagnosing and classifying Alzheimer's disease was done using DenseNet-169 and ResNet-50 model.this model involved following steps:

Primordial step is preprocessing, where dataset of images will be collected. Dataset that was available was i8nsufficient and so amplification step was very much required. Amplification was achieved by applying various transformations on the images. Once the images were amplified, validation was accomplished. Final dataset was classified into four categories namely non dementia, very mild dementia, mild dementia and moderate dementia.

Second step is model building. Proposed model was mainly based on DenseNet-169 and ResNet-50 CNN models. Its layers are,

a. Input layer: this is first layer of CNN. It is responsible for defining the size of the images which was used in the dataset. Image size was defined to be 240 * 240 * 3 (width * height * channels).
b. Convolutional layer: the second layer will be the convolutional layer which is the core of the CNN architecture. This layer comprises of feature maps. One of the feature maps used was padding, which was set to one. This layer is crucial for addressing the performance of the system.
c. Batch normalization layer: in this layer, gradients were subjected to normalization process. This step will then move forward in the network. This layer is kept in between non linearity and convolutional layers.
d. ReLU layer: this layer is used as a trigger to initiate the process.
e. Max-pooling layer: this layer helps to cut down the cost by eliminating the redundant data from spatial data as they occupy a large space due to its huge information.
f. Fully connected layer: all the above said layers will be merged together in this layer in order to provide the classification of model by the final layer. Outputs will be proportionate to the classes in the image dataset, four in this case.
g. Softmax layer: fully connected layer gives the output, which will not be normalized. To normalize, softmax layer was used. Output after normalization will be positive integer and will be utilized for classification purpose.
h. Classification layer: this layer is the last layer of CNN architecture. This classifies the data into given labelled classes and gives the probabilities for every image. This layer also provides the count of loss values.

The two algorithms used in this model were DenseNet-169 and ResNet-50. Minor modification were done to obtain accurate results. All the fundamentals remains same. Only change in DenseNet-169 was that it consisted of 6, 12, 32, 32 layered model. By this alteration and usage of shorter connections for layers, it achieved higher accuracy in training the dataset. ResNet-50 had originally 48 layers. In this study, two more layers were added, they are maxpool and average pool layers, which makes it perfect for training purpose.

Third step is model training. Once the model was ready, it must be trained, for which DenseNet-169 and ResNet-50 were used separately. Training was carried out by jumbling all dataset with epoch for 100. Among the image dataset, 70% data was used for training and 30% for testing the proposed model. Once the model was trained, it was rendered for testing the input data.

Final step testing model. Once the model was trained, it has to be tested. For this purpose, various images will be taken as input. Output from this model was cross-matched with the true values and thus the model was evaluated for its performance check.

Both the algorithms were evaluated and it was found that DenseNet169 attained 0.977 AUC for training and 0.887 for testing, whereas ResNet50 attained AUC of 0.838 for training and 0.819 for testing.

Sang Won Park, Na Young Yeo, Jinsu Lee, Suk-Hee Lee, Junghyun Byun, Dong Young Park, Sujin Yum, Jung-Kyeom Kim, Gihwan Byeon, Yeshin Kim, Jae-Won Jang [4] developed a model that involved a classification method done by three algorithms and gives the performance for each algorithm.

Primordial step is data accession and pre-processing. To achieve improved performance of machine learning model, normalization was carried out for all image set collected from ADNI dataset. F-flortaucipir 3D dynamic PET scan images were extracted through F-flortaucipir radioisotope. To have better image collection, interpolation was carried out at the time of preprocessing.

Subsequent step is measurement of SUVR and definition. Measured SUVR and region of interest definition using PET images were acquired bby the method of co registration. In this study, region of interest comprises of sixty eight cortical and twelve subcortical regions were separated in order to measure SUVR.

Subsequent step is to determine the status of amyloid protein. To get to know the amount of deposition of amyloid, a threshold value was set to 1.11. If SUVR was more than threshold value for F-florbetapir, that patient was counted under positive. For F-florbetaben, in order to take into account of SUVR, four dissimilar regions of brain was considered with threshold value set to 1.1. The four regions of brain includes frontal cortex, posterior cingulate cortex and lateral temporal cortex.

Different machine learning algorithms were employed to check the performance of each algorithms.

a. Logistic regression: It is one of the most commonly used method for classification purposes in the field of medicine. This methods can find correlation between continuous and categorical variable and can combine them as probability between 0 and 1. This was due to the sigmoid function. Predicted value will be between -∞ and ∞.
b. Support vector machine: It is utilized for classification purpose. It can classify the given data, after specifying decision factor in two dimension minimally. It usually considers optimal value, from which a huge gap was made between two groups. The groups were separated using margins either soft or hard margins.
c. XGB: It is an algorithm based on trees, it makes use of a technique that reduces errors by grouping many classification and regression trees. In this algorithm, more weight was given for weak learners and at that time strong learners will be in training phase. Thus, wrongly classified data can be accurately classified in subsequent round. Ultimately, results from both strong and slow learners will be counted for classification.
d. MLP: This algorithm involves about two to thousand layers of perceptrons. Through this, even non linearly separable data can be classified. As it contains too many layers, it can lead to overfitting. But to avoid this, many different methods can be employed which includes activation functions like sigmoid, softmax etc.,

Final step involves splitting of data and its validation. Input data was split into 80:20 ratio for training and testing purpose. For validation, k-fold cross validation was used to avoid disturbance in labelling. In this validation, stratified sampling was employed. Proposed method performed validations repeatedly for five times with no alterations in order to accurately validate the given data.

The proposed method has shown best results with mean AUC of more than 0.96 for all the algorithms specified. Among them, for SVM algorithm, AUC was found to be 0.88 and for MLP it was 0.75 and 0.73 for XGB algorithm.

3. Conclusion

Early detection and classification among the various deadly stages of Alzheimer's disease is too crucial. To do so, machine learning and deep learning techniques have been employed to achieve fruitful result. In this concern, many proposed model have been discussed that has yielded good performance result of the system. By reviewing recent works whose models have been discussed before says that linear regression, decision trees and CNN architecture can yield accuracy rate up to 95% and AUC of about 0.977.

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