International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
www.ijarst.in
ISSN: 2457-0362

ALZHEIMER'S DISEASE PREDICTION USING DEEP LEARNING ALGORITHMS

1. Dr. T Shyam Prasad, Assistant Professor, Department of CSE, Anurag Group of Institutions, Telangana, India. shyamprasadcse@anurag.edu.in

2. Pamu Vaishnavi, Department of CSE, Anurag Group of Institutions, Telangana, India. 19h61a05n1@cvsr.ac.in

3. Mandhalapu Sai Mohan , Department of CSE, Anurag Group of Institutions, Telangana, India. 19h61a05m1@cvsr.ac.in

4. Vatti Tharun Reddy, Department of CSE, Anurag Group of Institutions, Telangana, India. 19h61a05n8@cvsr.ac.in

Abstract : Alzheimer's disease is the extremely popular cause of dementia that causes memory loss. People who have Alzheimer's disease suffer from a disorder in neurodegenerative which leads to loss in many brain functions. Nowadays researchers prove that early diagnosis of the disease is the most crucial aspect to enhance the care of patients' lives and enhance treatment. Traditional approaches for diagnosis of Alzheimer's disease (AD) suffers from long time with lack both efficiency and the time it takes for learning and training. Lately, deep-learning-based approaches have been considered for the classification of neuroimaging data correlated to AD. In this paper, we study the use of the Convolutional Neural Networks (CNN) in AD early detection.VGG-16 trained on our datasets is used to make feature extractions for the classification process. Experimental work explains the effectiveness of the proposed approach.

Keywords : *Alzheimer's Disease (AD) , CNN , VGG 16.*

1. INTRODUCTION

This study is to introduce the Intelligent Healthcare Prediction and Classification System for AD Based on Deep learning with Big data Analytics. The main objective is to enhance classification accuracy to get the high-performance prediction of disease that helps us for early detection of disease and thus reducing the occurrence of dementia. Many kinds of research still don't achieve high performance of classification so we will seek to improve the accuracy of the model by using Deep Learning. Deep Learning is the most recent technique that allows the machine to distinct representation from raw data. In traditional machine learning technique is required to identify most of the feature by the expert to minimize data complexity and make it more visible for working with a learning algorithm. Unlike Deep Learning algorithms aims to learn high-level features extraction from data. This removes the need for domain expertise. In previous study another research focuses only on the performance of the pre-trained models for Alzheimer's detection, but they did not propose any new model. The proposed model has been used for binary classification and detection of Alzheimer's disease.

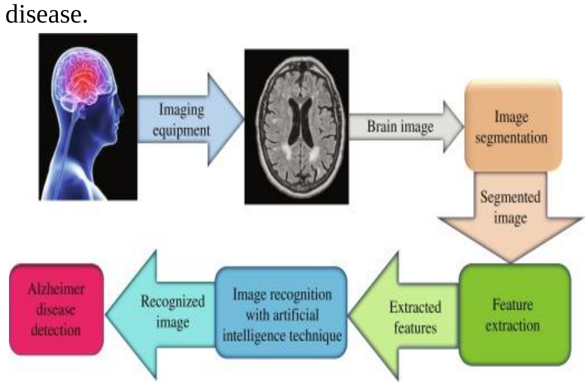

Fig 1 Example Figure

Alzheimer's disease (AD), the most common form of dementia, is a major challenge for healthcare in the twenty-first century. An estimated 5.5 million people aged 65 and older are living with AD, and AD is the sixth-leading cause of death in the United States. The global cost of managing AD, including medical, social welfare, and salary loss to the patients' families, was $277 billion in 2018 in the United States, heavily impacting the overall economy and stressing the U.S. health care system (Alzheimer's Association, 2018). AD is an irreversible, progressive brain disorder marked by a decline in cognitive functioning with no validated disease modifying

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
IJARST
ISSN: 2457-0362

treatment (De strooper and Karran, 2016). Thus, a great deal of effort has been made to develop strategies for early detection, especially at pre-symptomatic stages in order to slow or prevent disease progression (Galvin, 2017; Schelke et al., 2018). In particular, advanced neuroimaging techniques, such as magnetic resonance imaging (MRI) and positron emission tomography (PET), have been developed and used to identify AD-related structural and molecular biomarkers (Veitch et al., 2019). Rapid progress in neuroimaging techniques has made it challenging to integrate large-scale, high dimensional multimodal neuroimaging data. Therefore, interest has grown rapidly in computer-aided machine learning approaches for integrative analysis. In order to overcome these difficulties, deep learning, an emerging area of machine learning research that uses raw neuroimaging data to generate features through “on-the-fly” learning, is attracting considerable attention in the field of large-scale, high-dimensional medical imaging analysis (Plis et al., 2014). Deep learning methods, such as convolutional neural networks (CNN), have been shown to outperform existing machine learning methods (Lecun et al., 2015).

2. LITERATURE SURVEY

[1] Karen Parsons-Suhl , Mary E Johnson, Judy J McCann, Shirley Solberg was proposed a paper “Losing one's memory in early Alzheimer's disease”. In this paper A Heideggerian hermeneutical phenomenological research method was used to investigate the experience of memory loss in twelve individuals with early Alzheimer's disease or mild cognitive impairment. Data analysis proceeded as described by Diekelmann, Allen, and Tanner (1989), and incorporated the methods of Benner (1994), Thomas and Pollio (2002), and van Manen (1990). Three constitutive patterns with relational themes were identified. The first pattern, experiencing breakdown, consisted of two themes: awakening to breakdown and living with forgetting. The second pattern, temporality, consisted of three themes: being in the nothing, forgetting the past, and looking ahead. The third pattern, managing forgetting, consisted of the themes: remembering with cues, writing things down, recognizing what made remembering better or worse, and using laughter. The finding show that early Alzheimer's disease is more than an illness of cognitive losses and that forgetting is significant in light of the meaning that it has within everyday life.

[2] Hazel MacRae were implemented a topic based on “Managing Identity While Living With Alzheimer’s Disease” proposed a paper although any illness can negatively affect the self, Alzheimer’s disease poses a special threat. Based on interviews with nine Canadians diagnosed with early-stage Alzheimer’s disease, and adopting a symbolic interactionist perspective, this study examines the impact of the illness on identity. Findings indicate that, given the necessary resources, persons with Alzheimer’s can live meaningful, purposeful lives and creatively manage to protect and preserve identity. In contrast to previous research, participants did not reveal a great deal of concern about potential loss of self.

[3] Liang Zou; Jiannan Zheng; Chunyan Miao; Martin J. Mckeown; Z. Jane Wang was analyzed a research “3D CNN Based Automatic Diagnosis of Attention Deficit Hyperactivity Disorder Using Functional and Structural MRI”. In this research attention deficit hyperactivity disorder (ADHD) is one of the most common mental health disorders. As a neuro development disorder, neuroimaging technologies, such as magnetic resonance imaging (MRI), coupled with machine learning algorithms, are being increasingly explored as biomarkers in ADHD. Among various machine learning methods, deep learning has demonstrated excellent performance on many imaging tasks. With the availability of publically-available, large neuroimaging data sets for training purposes, deep learning-based automatic diagnosis of psychiatric disorders can become feasible. In this paper, we develop a deep learning-based ADHD classification method via 3-D convolutional neural networks (CNNs) applied to MRI scans. Since deep neural networks may utilize millions of parameters, even the large number of MRI samples in pooled data sets is still relatively limited if one is to learn discriminative features from the raw data. Instead, here we propose to first extract meaningful 3-D low-level features from functional MRI (fMRI) and structural MRI (sMRI) data. Furthermore, inspired by radiologists' typical approach for examining brain images, we design a 3-D CNN model to investigate the local spatial patterns of MRI features. Finally, we discover that brain functional and structural information are complementary, and design a multi-modality CNN architecture to combine fMRI and sMRI features. Evaluations on the hold-out testing data of the ADHD-200 global competition shows that the proposed multi-modality 3-D CNN approach achieves the state-of-the-art accuracy of 69.15% and outperforms reported classifiers in the literature, even with fewer training samples. We suggest that multi-modality classification will be a promising direction to find potential neuroimaging biomarkers of neuro development disorders.

[4] Chang Liu; Yu Cao; Marlon Alcantara; Benyuan Liu; Maria Brunette; Jesus Peinado; Walter Curioso was studied based on a paper "TX-CNN: Detecting tuberculosis in chest X-ray images using convolutional neural network". This paper explains about in Low and Middle-Income Countries (LMICs), efforts to eliminate the Tuberculosis (TB) epidemic are challenged by the persistent social inequalities in health, the limited number of local healthcare professionals, and the weak healthcare infrastructure found in resource-poor settings. The modern development of computer techniques has accelerated the TB diagnosis process. In this paper, we propose a novel method using Convolutional Neural Network(CNN) to deal with unbalanced, less-category X-ray images. Our method improves the accuracy for classifying multiple TB manifestations by a large margin. We explore the effectiveness and efficiency of shuffle sampling with cross-validation in training the network and find its outstanding effect in medical images classification. We achieve an 85.68% classification accuracy in a large TB image dataset, surpassing any state-of-art classification accuracy in this area. Our methods and results show a promising path for more accurate and faster TB diagnosis in LMICs healthcare facilities.

[10] Ossama Abdel-Hamid; Abdel-rahman Mohamed; Hui Jiang; Gerald Penn was proposed a paper "Applying Convolutional Neural Networks concepts to hybrid NN-HMM model for speech recognition". In this paper Convolutional Neural Networks (CNN) have showed success in achieving translation invariance for many image processing tasks. The success is largely attributed to the use of local filtering and max-pooling in the CNN architecture. In this paper, we propose to apply CNN to speech recognition within the framework of hybrid NN-HMM model. We propose to use local filtering and max-pooling in frequency domain to normalize speaker variance to achieve higher multi-speaker speech recognition performance. In our method, a pair of local filtering layer and max-pooling layer is added at the lowest end of neural network (NN) to normalize spectral variations of speech signals. In our experiments, the proposed CNN architecture is evaluated in a speaker independent speech recognition task using the standard TIMIT data sets. Experimental results show that the proposed CNN method can achieve over 10% relative error reduction in the core TIMIT test sets when comparing with a regular NN using the same number of hidden layers and weights. Our results also show that the best result of the proposed CNN model is better than previously published results on the same TIMIT test sets that use a pre-trained deep NN model.

3. METHODOLOGY

In previous study All the research mentioned above works have been done in recent years and have achieved better results on the OASIS dataset. However, there are some limitations in the existing research works mentioned as follows: (1) some of them have lower accuracy than others, (2) some models achieve higher accuracy but the performance of them have not been appropriately demonstrated against the pre-trained models, (3) another research focuses only on the performance of the pre-trained models for Alzheimer's detection, but they did not propose any new model.

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
ISSN: 2457-0362

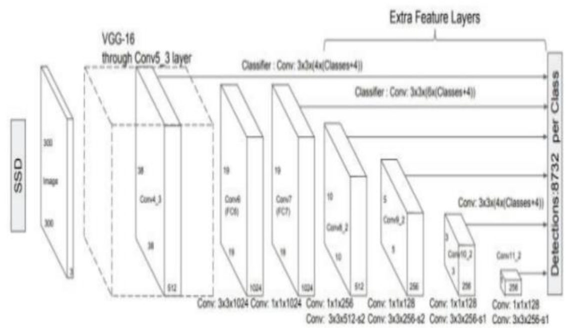

Fig 2 Proposed Architecture

in this paper, we propose a model to overcome the above limitations. Our proposed CNN model is based on a 12-layer architecture, which consists of convolutional, max pooling, dense, and flatten layers and three activation functions, namely Sigmoid, ReLU, and Leaky ReLU. Our proposed model has been used for binary classification and detection of Alzheimer's disease. The performance of our proposed model is compared with some existing CNN models that demonstrate the superiority of our proposed model over the existing models. The main contribution of the paper is as follows: 1) A 12-layer CNN architecture, which has achieved an accuracy of 97.75%, which is higher than any other previous studies that have been done before on the OASIS dataset. 2) The performance of our proposed model is better than some pre-trained models, namely InceptionV3, Xception, MobilenetV2, and VGG19.

Modules

Dataset Description:

We have collected our data from the OASIS dataset [20]. OASIS stands for Open Access Series Of Imaging Studies. This dataset contains a cross-sectional collection of 416 subjects. These subjects are aged from 18 to 96 years. For every subject, 3 or 4 individual T1-weighted MRI scans are included that were acquired in single scan sessions. The subjects include both men and women, and all of them are right-handed. 100 out of the 416 subjects that are aged over 60 years have been diagnosed with Alzheimer's disease (AD), ranging from very mild to moderate level. In addition, for 20 Non-Demented subjects, a reliability data set is included that contains images of the following visit within 90 days of their initial session.

Data pre-processing:

There are different sizes of images in the dataset. The different sizes of images can influence the architecture towards low accuracy.That's why we performed data pre-processing. There are two parts in our data pre-processing: a) Image resizing, and b) Image denoising. Image resizing reduces the time of neural network model training. We resized the images using OpenCV python. One of the fundamental challenges in image processing and computer vision is image denoising. What denoising does is to estimate the original image by suppressing noise from the image. We did image denoising on the brain MRI images from our OASIS dataset to get better performance of our model.

Data labeling:

After pre-processing, we labeled our data for binary classification and fixed our sample size. As we are doing binary classification, therefore we have labeled the records of the dataset with Clinical Dementia Ratio(CDR) 0 or 1. Note that CDR 0 indicates healthy (i.e., Non-Demented), and CDR 1 indicates severe Alzheimer's (i.e., Demented). There are 28 patients with CDR 1. For classification purposes, we considered 28 Alzheimer's patients and 28 Non-Demented patients. For every patient, there are two images. Then we divided the dataset into an 8:2 ratio based on random selection. That means 80% of data are used for training, and 20% of data are used for testing purposes.

Our Proposed 12-layer CNN model:

In this section, we discuss our proposed 12-layer CNN model for the detection and classification of Alzheimer's disease using brain MRI images. Our 12-layer CNN model has five steps: 1) Convolutional layer selection: In our proposed CNN model, we used Conv2D. We have used four conv2D layers in our model. 2) Pooling layer selection: In this model, we have used Maxpooling2D. For every Conv2D layer, we have used a Maxpool2D layer. Therefore, we have used four MaxPool2D layers. 3) Flatten Layer: In our model, after using the pooling layer, we used a flatten layer to flatten the whole network. 4) Dense Layer: After the flatten layer, we have used two dense layers. The dense layers are also known as fully connected layers. 5) Activation Function: We have used Sigmoid function as shown in Eq. 1 with another dense layer and ReLU function, as shown in Eq. 2. We have also used a Leaky ReLU activation function as it has proved to give the best performance with Maxpooling2D. The three activation functions are shown as follows:

Demonstrate performance of our proposed model:

In order to analyze the performance of our proposed CNN model, we calculated precision, recall, F1 score, accuracy, and ROC curve. The equations of accuracy, f1-score.

4. IMPLEMENTATION

Algorithms

Three supervised learning approaches are selected for this problem. Care is taken that all these approaches are fundamentally different from each other, so that we can cover as wide an umbrella as possible in term of possible approaches. For example- We will not select Random Forest and Ada Boost together as they come from the same family of 'ensemble' approaches:

For each algorithm, we will try out different values of a few hyper parameters to arrive at the best possible classifier. This will be carried out with the help of grid search cross validation technique. The algorithms are described below:

CNN :

A convolutional neural network (CNN or convnet) is a subset of machine learning. It is one of the various types of artificial neural networks which are used for different applications and data types. A CNN is a kind of network architecture for deep learning algorithms and is specifically used for image recognition and tasks that involve the processing of pixel data. There are other types of neural networks in deep learning, but for identifying and recognizing objects, CNNs are the network architecture of choice. This makes them highly suitable for computer vision (CV) tasks and for applications where object recognition is vital, such as self-driving cars and facial recognition.

CNN layers

A deep learning CNN consists of three layers: a convolutional layer, a pooling layer and a fully connected (FC) layer. The convolutional layer is the first layer while the FC layer is the last. From the convolutional layer to the FC layer, the complexity of the CNN increases. It is this increasing complexity that allows the CNN to successively identify larger portions and more complex features of an image until it finally identifies the object in its entirety.

Convolutional layer. The majority of computations happen in the convolutional layer, which is the core building block of a CNN. A second convolutional layer can follow the initial convolutional layer. The process of convolution involves a kernel or filter inside this layer moving across the receptive fields of the image, checking if a feature is present in the image. Over multiple iterations, the kernel sweeps over the entire image. After each iteration a dot product is calculated between the input pixels and the filter. The final output from the series of dots is known as a feature map or convolved feature. Ultimately, the image is converted into numerical values in this layer, which allows the CNN to interpret the image and extract relevant patterns from it.

Pooling layer. Like the convolutional layer, the pooling layer also sweeps a kernel or filter across the input image. But unlike the convolutional layer, the pooling layer reduces the number of parameters in the input and also results in some information loss. On the positive side, this layer reduces complexity and improves the efficiency of the CNN.

Fully connected layer. The FC layer is where image classification happens in the CNN based on the features extracted in the previous layers. Here, fully connected means that all the inputs or nodes from one layer are connected to every activation unit or node of the next layer. All the layers in the CNN are not fully connected because it would result in an unnecessarily dense network. It also would increase losses and affect the output quality, and it would be computationally expensive.

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
ISSN: 2457-0362

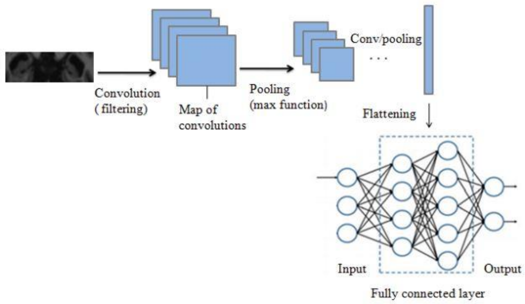

Fig 3 CNN

VGG 16:

VGG16 refers to the VGG model, also called VGGNet. It is a convolution neural network (CNN) model supporting 16 layers. K. Simonyan and A. Zisserman from Oxford University proposed this model and published it in a paper called Very Deep Convolutional Networks for Large-Scale Image Recognition.

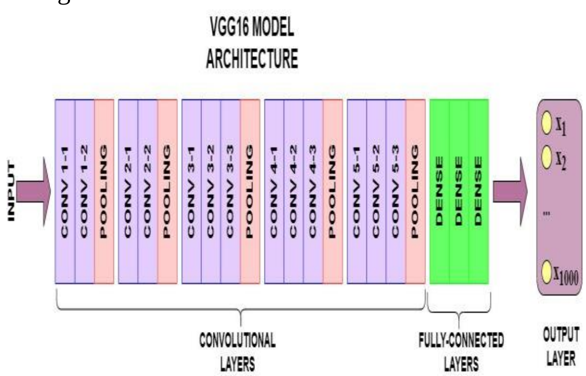

Fig 4 VGG 16

5. EXPERIMENTAL RESULTS

Alzheimer's is a progressive disease, where dementia symptoms gradually worsen over a number of years. In its early stages, memory loss is mild, but with late-stage Alzheimer's, individuals lose the ability to carry on a conversation and respond to their environment. Although current Alzheimer's treatments cannot stop Alzheimer's from progressing, they can temporarily slow the worsening of dementia symptoms and improve quality of life for those with Alzheimer's and their caregivers. Image Processing plays an important role in the early detection of Alzheimer's disease so that patients can be prevented before irreversible changes occur in the brain.

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
xception (Functional)        (None, 10, 10, 2048)      20861480
_________________________________________________________________
flatten_1 (Flatten)          (None, 204800)            0
_________________________________________________________________
dense_2 (Dense)              (None, 2)                 409602
=================================================================
Total params: 21,271,082
Trainable params: 409,602
Non-trainable params: 20,861,480
_________________________________________________________________
```

ACCURACY :

Accuracy refers to how close a measurement is to the true or accepted value. Precision refers to how close measurements of the same item are to each other.

Accuracy represents the number of correctly classified data instances over the total number of data instances.

To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN}$$

PRECISION:

Precision refers to the amount of information that is conveyed by a number in terms of its digits; it shows the closeness of two or more measurements to each other. It is independent of accuracy.

Now we will find the precision (positive predictive value) in classifying the data instances. Precision is defined as follows:

$$Precision = \frac{TP}{TP + FP}$$

Precision should ideally be 1 (high) for a good classifier. Precision becomes 1 only when the numerator and denominator are equal i.e TP = TP +FP, this also means FP is zero. As FP increases the value of denominator becomes greater than the numerator and precision value decreases (which we don't want).

RECALL :

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
www.ijarst.in
ISSN: 2457-0362

By definition recall means the percentage of a certain class correctly identified (from all of the given examples of that class). So for the class cat the model correctly identified it for 2 times (in example 0 and 2) Now we will introduce another important metric called recall. Recall is also known as sensitivity or true positive rate and is defined as follows:

$$Recall = \frac{TP}{TP + FN}$$

Recall should ideally be 1 (high) for a good classifier. Recall becomes 1 only when the numerator and denominator are equal i.e TP = TP +FN, this also means FN is zero. As FN increases the value of denominator becomes greater than the numerator and recall value decreases (which we don't want).

F1 SCORE :

F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

F1 Score becomes 1 only when precision and recall are both 1. F1 score becomes high only when both precision and recall are high. F1 score is the harmonic mean of precision and recall and is a better measure than accuracy.

So ideally in a good classifier, we want both precision and recall to be one which also means FP and FN are zero. Therefore we need a metric that takes into account both precision and recall. F1-score is a metric which takes into account both precision and recall and is defined as follows:

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

```
<CNNexplainer>
  Public:
    clone: function (deep = FALSE)
    explain: function (input_imgs_paths, class_index = NULL, methods = c("V",
    id: Xception_brain_MRI_reading
    initialize: function (model, preprocessing_function, id = NULL)
    model: function (object, ...)
    preprocessing_function: function (x)
    show_available_methods: function ()
  Private:
    available_methods: tbl_df, tbl, data.frame
```

Fig 5 CNN explainer

Fig 6 Input Image

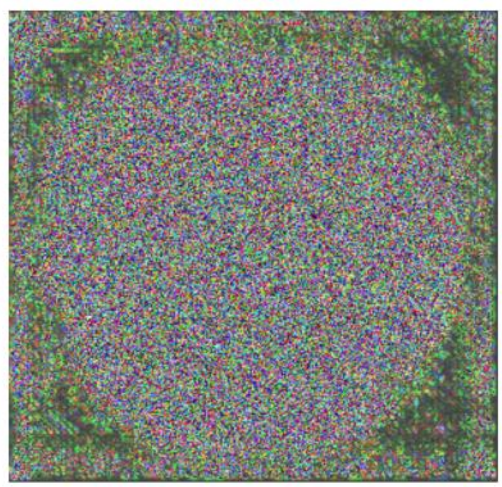

Fig 7 Vanilla gradient

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
ISSN: 2457-0362

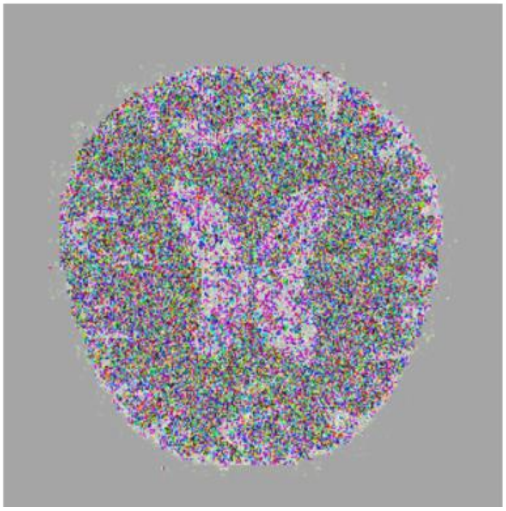

Fig 8 Gradient x input

Fig 9 Smooth Grad

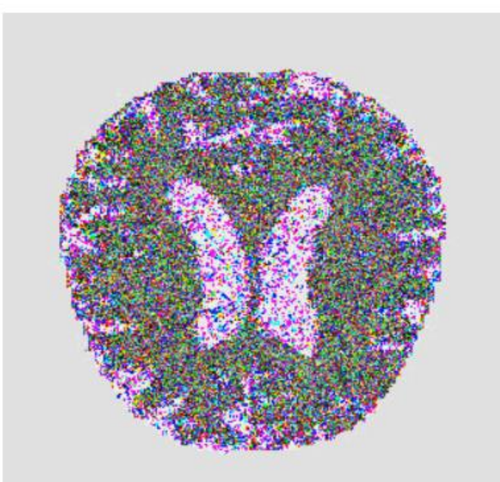

Fig 10 Smooth grad x input

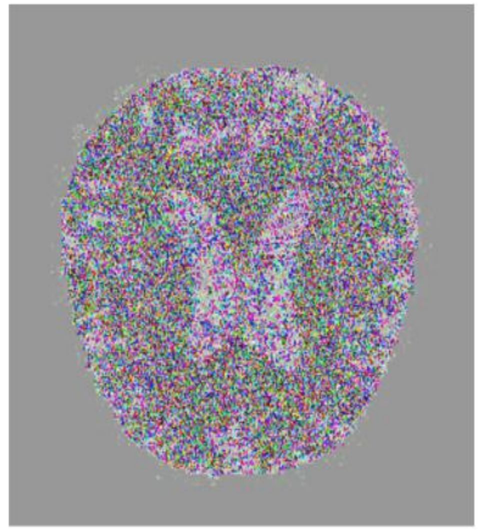

Fig 11 Integrated Gradients

ALGORITHM	ACCURACY
CNN	98
VGG 16	95

Table 1 Accuracy of algorithms

6. CONCLUSION

In this paper, we presented a 12-layer CNN model for binary classification and detection of Alzheimer's disease. We performed our study on the OASIS dataset. We used data pre-processing techniques, namely, Image resizing and Image denoising. Our proposed 12-layer CNN model is based on deep learning and machine learning algorithms. Our proposed model performs better than an existing 8-layer CNN model, and four pre-trained CNN models. Our future research plan is to perform multi-class classification on the OASIS dataset and early detection of Alzheimer's disease.

REFERENCES

[1] K. Parsons-Suhl, M. E. Johnson, J. J. McCann, and S. Solberg, "Losing One's Memory in Early Alzheimer's Disease", Qualitative Health Research, vol. 18, no. 1, pp. 31–42, 2008.

[2] H. MacRae, "Managing Identity While Living With Alzheimer's Disease", Qualitative Health Research, vol. 20, no. 3, pp. 293–305, 2010.

[3] L. Zou, J. Zheng, C. Miao, M. J. Mckeown and Z. J. Wang, "3D CNN Based Automatic Diagnosis of Attention Deficit Hyperactivity Disorder Using

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
www.ijarst.in
ISSN: 2457-0362

Functional and Structural MRI," in IEEE Access, vol. 5, pp. 23626- 23636, 2017.

[4] C. Liu et al., "TX-CNN: Detecting tuberculosis in chest X-ray images using convolutional neural network", 2017 IEEE International Conference on Image Processing (ICIP), Beijing, pp. 2314-2318, 2017.

[5] X. Zhao, L. Liu, S. Qi, Y. Teng, J. Li and W. Qian, "Agile convolutional neural network for pulmonary nodule classification using CT images", Int J Comput Assist Radiol Surg, Vol. 13, no. 1, pp. 585–595, 2018.

[6] Liu J. et al. "Integrate Domain Knowledge in Training CNN for Ultrasonography Breast Cancer Diagnosis," in Proc. International Conference on Medical Image Computing and Computer-Assisted Intervention, pp. 868-875, 2018.

[7] A. M. Alayba, V.Palade, M. England and R. Iqbal, "A Combined CNN and LSTM Model for Arabic Sentiment Analysis." in Proc International Cross-Domain Conference for Machine Learning and Knowledge Extraction, pp. 179-191, 2018.

[8] X. Penga and C. Schmid, "Multi-region Two-Stream R-CNN for Action Detection." in Proc. European Conference on Computer Vision, pp. 744-759, 2016.

[9] 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.

[10] O. Abdel-Hamid, A. Mohamed, H. Jiang and G. Penn, "Applying Convolutional Neural Networks concepts to hybrid NN-HMM model for speech recognition," in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Kyoto, pp. 4277-4280, 2012.

[11] G. V. Polanczyk, E. G. Willcutt, G. A. Salum, C. Kieling and L. A. Rohde, "ADHD prevalence estimates across three decades: An updated systematic review and meta-regression analysis", Int. J. Epidemiol., vol. 43, pp. 434-442, 2014.

[12] A. Eloyan et al., "Automated diagnoses of attention deficit hyperactive disorder using magnetic resonance imaging", Frontiers Syst. Neurosci., vol. 6, pp. 61, 2012.

[13] X. Peng, P. Lin, T. Zhang and J. Wang, "Extreme learning machine-based classification of ADHD using brain structural MRI data", PLoS ONE, vol. 8, no. 11, pp. e79476, 2013.

[14] Y. Zang et al., "Altered baseline brain activity in children with ADHD revealed by resting-state functional MRI", Brain Develop., vol. 29, no. 2, pp. 83-91, 2007.

[15] H. Yang et al., "Abnormal spontaneous brain activity in medication-naive ADHD children: A resting state fMRI study", Neurosci. Lett., vol. 502, no. 2, pp. 89-93, 2011.

[16] Y. Zang, T. Jiang, Y. Lu, Y. He and L. Tian, "Regional homogeneity approach to fMRI data analysis", Neuroimage, vol. 22, no. 1, pp. 394-400, 2004.

[17] D. Long et al., "Automatic classification of early Parkinson's disease with multi-modal mr imaging", PLoS ONE, vol. 7, no. 11, pp. e47714, 2012.

[18] H.-I. Suk, S.-W. Lee and D. Shen, "Hierarchical feature representation and multimodal fusion with deep learning for AD/MCI diagnosis", NeuroImage, vol. 101, pp. 569-582, Nov. 2014.

[19] C.-W. Chang, C.-C. Ho and J.-H. Chen, "ADHD classification by a texture analysis of anatomical brain MRI data", Frontiers Syst. Neurosci., vol. 6, pp. 66, Sep. 2012.

[20] M. Kobel et al., "Structural and functional imaging approaches in attention deficit/hyperactivity disorder: Does the temporal lobe play a key role?", Psychiatry Res. Neuroimag., vol. 183, no. 3, pp. 230-236, 2010.