ALZHEIMER DISEASE PREDICTION USING DEEP LEARNING TECHNIQUE

ABSTRACT- The most common kind of dementia in every region of the world is Alzheimer's disease (AD). From mild to severe, rendering all work impossible without assistance, it worsens with time. There has been a rise in this, and it's largely attributable to the ageing of the population and delayed diagnoses. Medical history, cognitive testing, and magnetic resonance imaging (MRI) are being used to try to identify individuals, however these methods have their limitations and are not always reliable. Here, we build on prior work by using CNN to identify anomalies in MRI images associated with AD. High-resolution illness-probability maps are constructed, linking specific brain regions to multi-layered perceptron models, and the proposed method takes into account the four stages of dementia and individual diagnoses. Offers visual aids that are simple to interpret. Distribution of samples across the four MRI image types should be even to prevent the issue of class imbalance. According to the DenseNet169 method, the spectrum of mental instability ranges from "very slightly deranged" through "slightly demented" to "moderately insane," with "not demented" being the least disturbed. Data on MRI scans downloaded from Kaggle indicates a serious problem with class imbalance. It has been proposed to use a DenseNet169 classification method on MRI data to identify the various phases of dementia. AD classes were predicted using the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset to evaluate the efficacy of the proposed approach.

Keywords: Magnetic Resonance Imaging, Alzheimer’s disease, Demented, Convolutional Neural Network.

I INTRODUCTION

The ability to employ computational neuroscience for translational purposes has been tremendously helpful to epidemiological studies of mental health. To better understand the mechanisms underlying clinical symptoms, this interdisciplinary field of study may prove useful in simulating the biological processes that occur in the human brain in both healthy and sick states. Neurodegenerative and neuropsychiatric diseases have profited from the expansion of machine learning (ML) and big biological datasets in the recent decade. The fundamental impetus for this effort is the use of magnetic resonance imaging, which is both easy to learn and offers a precise location for calcification and foreign masses. MRI is the gold standard for visualizing AD and its associated environments. AD is a form of dementia that can be both sudden and devastating. Every four seconds, a new case of AD is discovered, and it is a tragedy for the person diagnosed and their loved ones. Dementia is characterized by a decline in cognitive capacities such as reasoning, social and emotional coping, and independent functioning; Alzheimer's disease (AD) is the most common form of dementia. As the condition progresses, the sufferer will forget everything they have ever experienced, starting with recent events. Thus, an early diagnosis of the condition is crucial. A model that can take an MRI scan of the brain as input and output a diagnosis of dementia at the mild, moderate, very mild, or absence levels. Dementia is defined by severe difficulties in everyday life that hinder independence, much as mild dementia is defined by cognitive impairment and poor performance on an objective cognitive testing that reflects a decrease from the past. In the intermediate stage of AD, individuals are more confused and forgetful and require more help with activities of daily living and self-care. Intermediate-stage dementia patients with AD may: show worsening judgment and increasing confusion. Alzheimer's patients who do not have dementia A "neuropathology" is a situation in which a person exhibits the neuropathology often associated with the onset of full-blown AD symptoms yet retains cognitive capacity (NDAN). Intermediate dementia is a form of the disease that occurs between the normal aging-related decrease in memory and cognition and severe dementia. There are 12,500 improved photographs in the collection (JPEG) Each of the four AD types has its own separate file containing around 3,000 pictures (according to AD type). Degeneration of brain tissue might be classified as mild, moderate, very mild, or no dementia at all.

II.LITERATURE SURVEY:

Abol Bosher, Kunholee, etc. [1] sMRI Volumetric Feature-Based Data Detection for Alzheimer's Using Convolutional and Deep Neural Networks AD is a neurodegenerative disease that primarily

affects those over 65. The hippocampus is examined in relation to memory, stress, and neurological disorders. Training and validation of classification networks utilised volumetric features. The weighted classification accuracies for the left and right hippocampi using the suggested method were 94.82% and 94.02%, respectively. All of us, including Kai Li, Jiang Wang, Shanshan Li, etc. Latent Component of Feature Extraction from Multi-Channel EEG for AD Diagnosis, Proposed [2]. Extraction of Latent Factor Features from Multi-Channel EEG for Alzheimer's Disease Identification. Studies the role of brain activity decoding in the study of cognitive impairment and the role of default brain variables (latent factors) in illness processes. A quick look at the power spectrum shows that the two groups are mostly interested in different frequencies. Further research indicates that the distribution of latent factors in AD differs from that of the normal group in the theta frequency range. Yan Zhao, Baoqiang Ma, etc. MIGAN predicts AD. AD requires long-term forecasting. sMRI can detect AD-related cortical atrophy. 3D multi-information generative adversarial networks predict brain alterations for illness progression. Zhenyuan Ning, Qing Xiao, and others [4]. Relationship-based AD multi-modal shared representation learning. MRI and PET are utilised to diagnose AD because they provide complementing structural and functional information. Unfortunately, most techniques concatenate multi-modal features in the original space and ignore their underlying connections, which could help identify AD. Overcoming high-dimensional multimodal data overfitting is desirable. Bumshik Lee, Jae Young Choi, and others Classifying AD with MRI images using several deep networks and ensemble generalisation loss. MRI scans classify AD using a deep convolutional neural network ensemble (DCNNs). Principles and Current Developments in Machine Learning and Deep Learning Techniques for Brain Disease Detection was written by Protima Khan, Md. F. Kader, et al. The brain governs the body. Brain illnesses have been identified throughout history. Thus, the diversity of brain illnesses makes present diagnostic or detection technologies more complicated and research a priority. Early discovery of brain diseases may improve treatment. Nora Shoaip, Amira Rezk, and others put forward a proposal[7]. Comprehensive AD Diagnose Decision Support System Based on Fuzzy Ontology This research creates, implements, and assesses the AD Diagnose Ontology (ADDO). It is a comprehensive semantic knowledge basis for developing a CDSS for AD diagnosis based on fuzzy ontology. ADDO may be necessary for CDSS to represent, annotate, and provide access to AD research and diagnosis elements. Early Alzheimer Disease and Dementia Detection Using Deep Learning MRI was proposed by Suriya Murugan, Chandran Venkatesan, et al. The proposed method generates high-resolution disease probability maps from local brain structure to a multilayer perceptron and provides accurate, understandable visualizations of an individual's AD risk by taking into account four stages of dementia and making a precise diagnosis. [9] Tian Zhu, Chongfeng Cao, etc. AD influenced the development of Anatomical Landmarks and DAG Network Learning. Diagnosis Analyses of the morphology and statistics of grey matter imaging revealed anatomical feature regions. Second, a fundamental, efficient DAG convolutional neural network extracts discriminative deep image representation characteristics. Resting-State Functional Magnetic Resonance Imaging for the Detection of AD. Haibing Guo et al. The use of imaging for diagnosis and machine learning have benefited digital healthcare. Using the Improved Deep Learning Algorithm (IDLA) and statistically significant text data, early AD diagnosis was proposed.

III METHODOLOGY

Here we explore DL Algorithms to identify Alzheimer disease in the Medical Industry in this model. It uses two deep learning Algorithms for detecting the convolutional channel feature (CCF). However, in this model we choose the model of CNN and its layers to determine the mild, very mild, moderate and non-demented stage of the disease. We collect datasets from an open-source website called Kaggle. The dataset holds MRI images of the AD affected person. There were 400 images in total were 200 images of each category is taken and analysed. Resizing the MRI image into 200X200. As per the after the dataset collection and pre-processing methods, we apply the following machine and ensemble learning algorithm. Densenet and VGG16 are transfer learning, which is a neural network for classification and feature learning. It can be used with one or more invisible nodes. Parameters of invisible nodes are set. We are building a convolutional sequence model of 30 epochs. Convolutional sequences are an approach to inter-sequence learning in which an input sequence is mapped to a variable-length output sequence through a recurrent neural network. Then subsequently convolutional layer, Flatten layer, and Dense Layer. The layer is a set of filter, Prameters of which are to be Learned throughout the training. Flatten Layer collapses the facial dimension of the input into the channel dimension. Dense layer helps in changing the dimensionality of the ouput from the preceding layer. In this process relu and softmax Utilized are activation functions. Most neural networks, especially CNNs and multilayer perceptrons, use the Relu activation function. Softmax activates the last layer of a classification network because the output is a probability distribution.

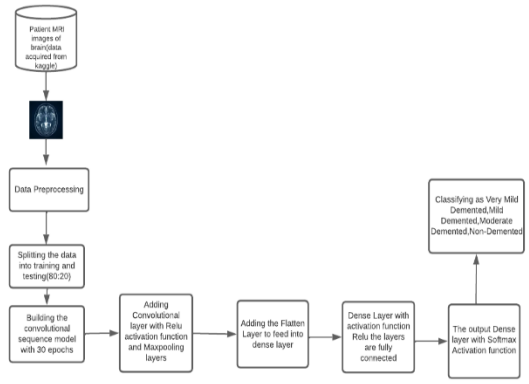

Fig 1 Proposed Architecture

1.Data acquisition

The initial step is to gather images. To create a classification model, the computer must learn by doing. To recognize an object, the computer must examine a large number of images. Deep learning models can also be trained using other types of data, such as time series data and voice data. Images are important information needed to identify AD in the context of the work discussed in this article. This step produces images that will be used to train the model later.

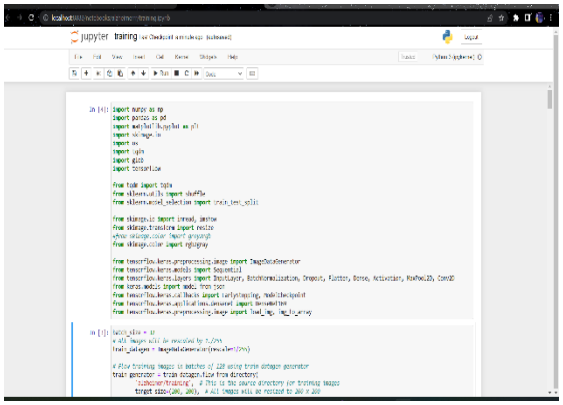

Fig 2 Representation of Data Acquisition

2.Data preprocessing

The image classification task assigns a class to a given MRI image. It is a basic high-level image comprehension task that can be divided into two and multi-classification tasks. The image is classified according to the requirements to the output layer after several convolution and fusion operations through CNN. The only difference between binary and multiclassification tasks is function of activation of the output layer. The job of image classification for MRI image analysis is readily recognised, allowing the essential steps to be made for determining the kind of dementia for which natural picture classification is high, including the usage of Convolutional Neural Network (CNN) to categorise JPG/PNG images.

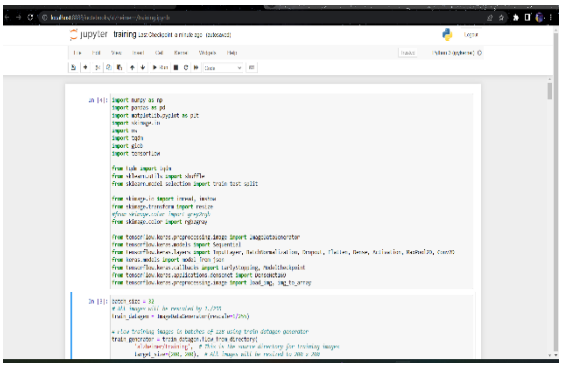

Fig 3 Representation of Data Preprocessing

3.Feature extraction

Feature extraction is done to reduce features in the dataset, In this module, we perform some additional operations on the segmented image. In this module, we will use feature extraction to obtain all of the detailed information about a brain image. In the fields of computer vision and machine learning, feature extraction and reduction have played a crucial role in the classification of tumour areas. The main problem with feature extraction is determining which features are the most active or robust for classification, resulting in an efficient performance. Feature extraction is used in dimensionality reduction.

4.Magnetic resonance imaging classification

Radio waves and magnetic fields are used to create high-quality 2D and 3D brain images. No radioactive tracers or X-rays are produced. Structural MRI, which assesses brain volume in vivo to detect brain deterioration, is most commonly used in AD (loss of tissue, cells, neurons, and so on). Alzheimer's causes brain degeneration. Structural MRI detects brain atrophy. Functional magnetic resonance imaging is another popular method for examining the primary visual cortex and brain topography (fMRI). fMRI provides crucial brain function data. Arterial blood oxygen level-dependent brain imaging technologies detect cerebral oxygen consumption and CBF metabolic rate contrasts and spin labelling (ASL).

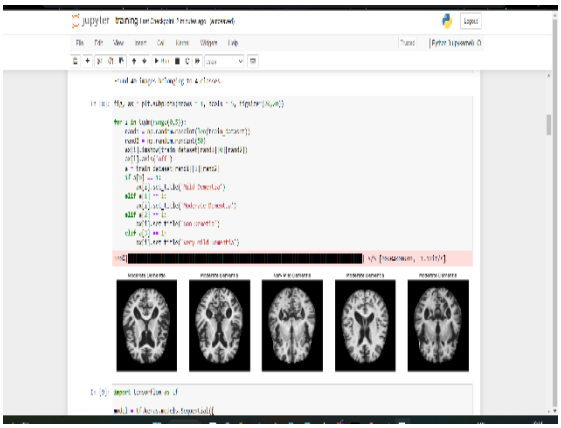

Fig 4 Representation of MRI Image Classification

5.CNN Model

Classifying a picture requires extracting features from the image to recognize dataset patterns. ANN's high parameter training makes photo classification computationally expensive. For example, a typical ANN can be trained to classify a 50 × 50 cat picture as either a dog or a cat using width and height. –(50*50) * 100 image pixels times hidden layer + 100 bias + 2 * 100 output neurons + 2 bias = 2,50,30 Filters use a local connection pattern across neurons to leverage a picture's spatial localization. Convolution is point wise multiplication of two functions to create a third. Hence, a filter and a matrix of picture pixels are functions. Gliding the filter across the picture yields the dot product of the two matrices. "Activation Map" or "Feature Map" describes this matrix.

Step 1: Choose a Dataset

You may choose a dataset of interest or construct your own picture dataset to solve your own image classification challenge. On kaggle.com, selecting a dataset is simple. The dataset I will be using may be found here.

12,500 enhanced photos of (JPEG) There are roughly 3,000 photos for each of the four categories of AD organised into four distinct files (according to AD type). Mild, Moderate, Very Mild, and No Dementia are the cell kinds. Here, we use a number of t libraries that need their importation code.
Step 2: Prepare Training Dataset

Assigning paths, labels, and resizing photographs will prepare our dataset for training. Resizing photographs to 200x200

Step 3: Training data is an array of picture pixel values and the image's CATEGORIES index.

Step 4: Shuffle Dataset

step5: Label and Feature

NEURAL NETWORKS will classify these listings.

Step 6: Normalizing X and categorizing labels.

Step 7: Separate CNN-use X and Y.

Step 8: Define, build, and train CNN Model

Step 9: Model score and accuracy.

The Dense net and VGG16 models classify AD type.

6.Dense Networks (Dense Net)

Gradients that disappear or erupt make training very deep neural networks problematic. A skip link can solve this problem by feeding a layer's activation unit to a deeper network layer. Dense networks start here. As neural networks add layers, training error should monotonically decrease. Yet, a typical neural network will eventually increase training error. Dense Nets are unaffected. More network layers will reduce training error. Dense Nets can train 1000-layer networks. Dense Network for image categorization Let's build a 50-layer Keras Dense Net for image categorization. TensorFlow, CNTK, and Theano-compatible Keras. It was designed for fast experimentation. The backend is TensorFlow. Please import all notebooks before starting.

Algorithm 2. Pseudo code of the used preprocessing method.

Input: The raw 1D sensor signal (S) with size of 5625

Output: Graylevel image (Im) with size of 125 x 45

1: *count* = 1;
2: **for** i=1 to 125 **do**
3: **for** j=1 to 45 **do**
4: *Im*(*i*, *j*) = *S*(*count*);
5: *count* = *count* + 1;
6: **end for** j
7: **end for** i
8: Normalize *Im* by using min-max normalization.

Fig 5 Pseudocode Representation of the Algorithm

7.VGG16 Implementation

The entire architecture uses convolution and max pool layers. Two FC (fully connected layers) and a SoftMax output finish it. VGG16 means 16 weighted layers. 138 million parameters make this network large. Importing all VGG16 libraries here. Creating a sequential model requires the Sequential technique. Sequential model organises model layers consecutively. Keras preprocessing loaded Image Data Generator. Image Data Generator adds labels to the model. This class has many useful methods for resizing, rotating, zooming, and flipping. This class does not affect disk-stored data. This class alters data supplied to the model.

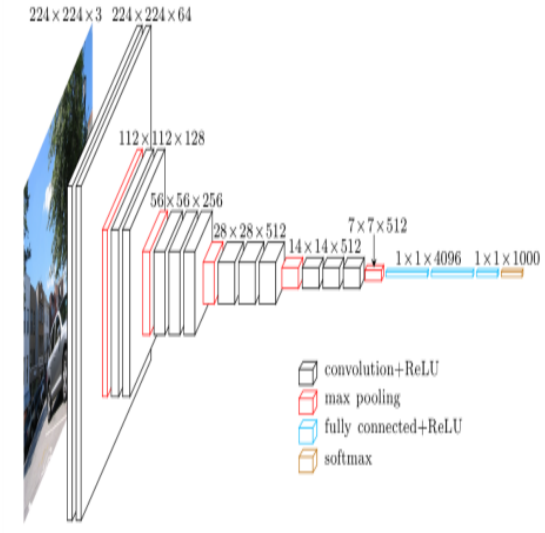

Fig 6 VGG16 Architecture Diagram

RESULTS:

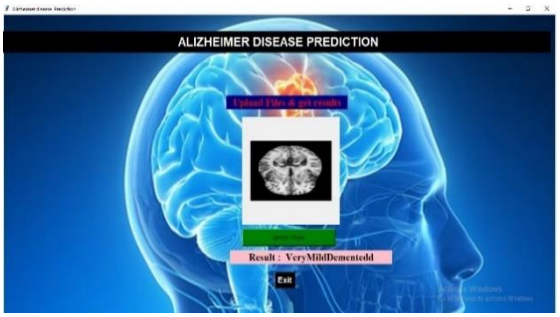

Fig 7 Representation of Very Mild Dementia

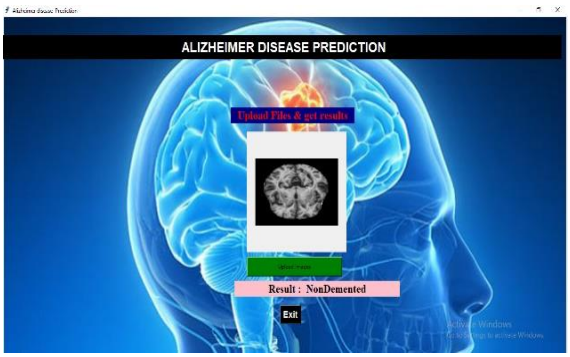

Fig 8 Representation of Non Dementia

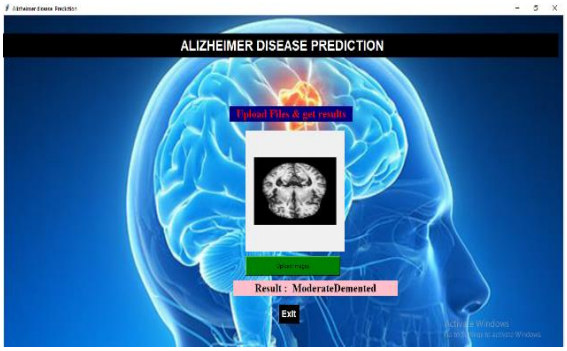

Fig 9 Reprsentation of Moderate Dementia

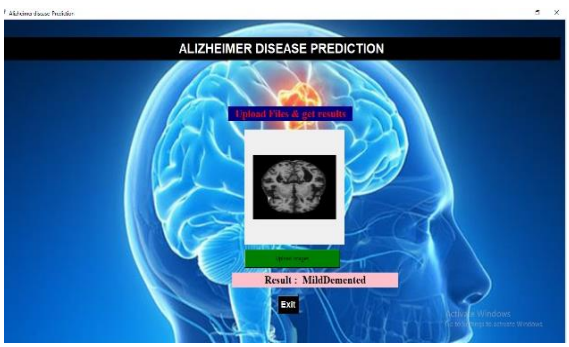

Fig 10 Reprsentation of Mild Dementia

IV.Experimental Analysis

A part of the test data was evaluated to determine how well the classifiers predicted AD patients following cross-validation. Visualizing the uncertainty matrix allowed classifier evaluation. to test machine learning classifiers Adult-onset dementia's brain shrinkage and cognitive decline substantially damage people's lives. About 60–70% of dementia cases in adults worldwide are related to AD, the most frequent form of dementia. As mentioned in the introduction, clinical and exclusion criteria were used to diagnose AD, which can only be proven postmortem. On the other hand, an accurate and early diagnosis of AD is critical for the prompt adoption of therapies to enhance brain health. Preclinical screening of AD-vulnerable individuals may help identify the disease's mechanism and improve treatment. Existing AD biomarkers required MRI data or sample collection (such as serum or fluid) (such as serum or fluid).

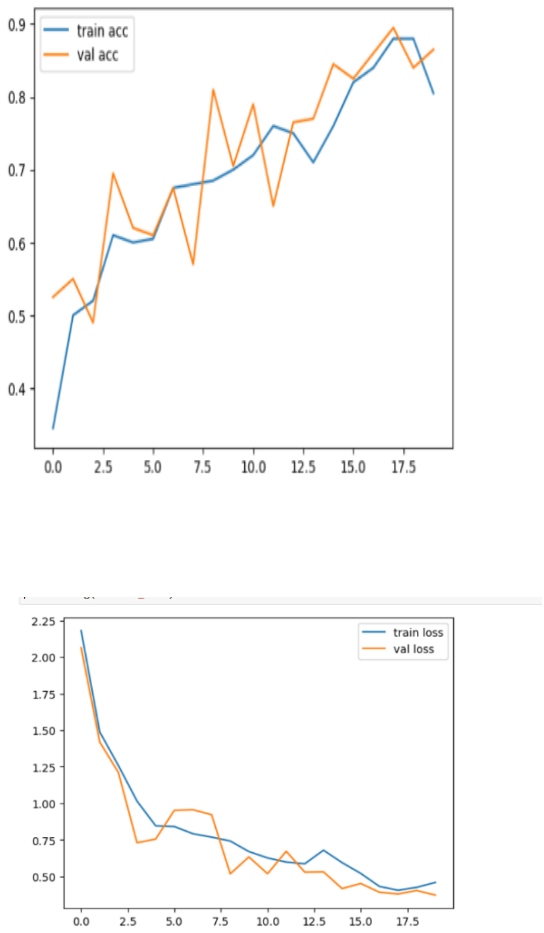

Fig 11 Graphical analysis

V.CONCLUSION

In this paper, we proposed a straightforward and reliable classification method for AD MRI scans. The method is based on a visual content description of the hippocampal region, a brain region associated with AD. We suggested fusing the classification outcomes with the hippocampus and CSF as two biomarkers. Studies revealed that combining hippocampal characteristics with CSF volume classification improved accuracy, particularly when separating AD from MCI, compared to using either visual characteristics or CSF volume calculation alone. Comparing the proposed method to other volumetric methods, we showed that it offers a higher level of classification accuracy. We intend to make use of various ROIs and MRI techniques within the pre-existing classification framework in this work.

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