Alzheimer's Disease Diagnosis using Deep Learning Approach

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Abstract-- Alzheimer's Disease (AD) is a long-term neurodegenerative condition that kills brain cells, leading to dementia and irreversible decline in cognitive abilities. There is no cure for it, and its underlying causes are still poorly understood. However, neuro imaging tools now help with clinical diagnosis, and deep learning techniques have lately developed as a crucial paradigm applied with these tools. Machine learning algorithms, in particular analytical modelling and sample detection in biomedical sciences from the deliverance of drugs to medicinal visioning; have emerged as the one among the key techniques that are helping researchers to gain a deeper accepting of the overall problem and to solve challenging clinical issues. Deep learning is a dominant machine learning approach for classifying and retrieving the characteristics. In this paper, the distinction between a brain affected by Alzheimer's disease and a healthy brain has been made using Convolutional Neural Networks (CNN). The significance of categorising this type of medical information is to ultimately establish a expect form or model to distinguish the kind of illness from healthy people or to expect the state of the illness. This study has effectively identified MRI data of individuals with Alzheimer's disease (AD) by using Convolutional Neural Network (CNN) and the well-known architecture of LeNet-5 model has been utilized on the trained data to obtain the maximum accuracy of distinguishing the AD affected brain and normally functioning brain.

Keywords-- Alzheimer's disease, Deep Learning, Convolutional Neural Networks (CNN), LeNet-5, Accuracy and Loss.

I. INTRODUCTION

Alzheimer's disease (AD) is a nervous, progressive, irreversible brain condition that manifests itself in a variety of ways. It steadily destroys brain cells, affecting memory and cognition and, eventually, the ability to do even the most basic tasks [1]. Dementia is finally brought on by this disorder's effects on cognitive deterioration. Alzheimer's disease has been discovered in 1 in 85 people. Even a one-year delay in the onset of the disease could result in a reduction of eleven million people diagnosed, greatly lessening its global impact [2]. Alzheimer's disease (AD) patients gradually lose their ability to think or remember things, as well as their ability to carry out daily tasks. A little deterioration in mental capabilities along the spectrum of normal cognitive function to AD is represented by moderate cognitive impairment (MCI), and more than 33% of people with MCI will eventually develop AD in five or more years. There are typically two types of MCI: stable MCI (sMCI), which does not proceed to Alzheimer's disease, and progressive MCI (pMCI), which does [3]. About fMRI in the resting state, there are two key ideas. The vast majority of scientists are enthusiastic in analysing brain networks and retrieval from rs-fMRI data along the spectrum of normal cognitive function to AD and during a clinical scan, rs-fMRI data gathering can be performed. First of all, compared to a typical fMRI, the technique will be more comfortable because patients don't need to perform any task, and there isn't any simulation.

Different neuroimaging techniques, including resting-state functional magnetic resonance imaging (rs-fMRI), structural magnetic resonance imaging (sMRI), and positron emission tomography (PET), can distinguish the histopathological changes linked to these diseases [4]. Figure 1 shows the MRI image of the brain with Alzheimer's disease (AD). As a result, they are being used more frequently for the medical analysis of AD and MCI. We can differentiate between standard and deep learning-based image analysis approaches, which are the foundation of a CAD system. The first stage of the pipeline consists of pre-processing, segmentation, feature extraction, and classification. Before analysis, the image is prepared by image pre-processing to eliminate any potential distortions, extraneous data, or to emphasise and toughen key aspects for subsequent processing [5, 6]. The segmentation process and then separates the important regions into collections of pixels that share traits like colour, strength, or quality that

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will be extracted in the segmentation step. The goal of segmentation is to make the visual illustration more understandable and straightforward to study. The final phase is classification, which entails giving objects a label by using either supervised or unsupervised machine learning techniques [6].

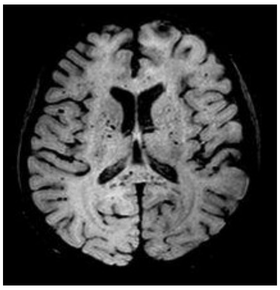


Fig. 1. MRI of brain with Alzheimer's disease

Deep learning techniques are different from traditional machine learning techniques. Without the need for feature selection, they can invariably imply an ideal data structure from raw images, making the process more objective and less prone to bias. They also require little to no image pre-processing. As a result, deep learning algorithms are more effective at identifying subtle and widespread anatomical anomalies [7]. For the study of a variety of medical imageries, such as those from MRI, CT, ultrasound, microscopy X-ray, and mammography, Deep Learning (DL) prototypes are successfully utilized. Deep models achieved notable outcomes in the areas of physiology, including the abdomen, lungs, bone, heart, brain, heart, breast, and retina as well as the segmentation of various organs and substructures, illness detection, and disease classification. However, there isn't much research available on applying deep learning models to detect AD. It has been established through prior medical studies that MRI scans data can have an important role in the premature diagnosis of Alzheimer's disease. It is remarkable to note that deep learning approach seems to represent a development in the field of computer-aided diagnosis [8]. It primarily differs from machine learning in that it requires little to no picture pre-processing and may automatically incorporate the best data representations from raw photos without the need for manual feature selection in advance [17]. The outcomes of which are more unbiased, reliable, and less subject to bias. Convolutional Neural Networks (CNN) is a sub-type of supervised Deep Learning (DL) technique which has achieved significant success in various numbers of medical domains, including speech recognition and imaging as well as natural language processing [8,9].

II. DATA PROCESSING AND ALGORITHMS

A. Data Acquisition

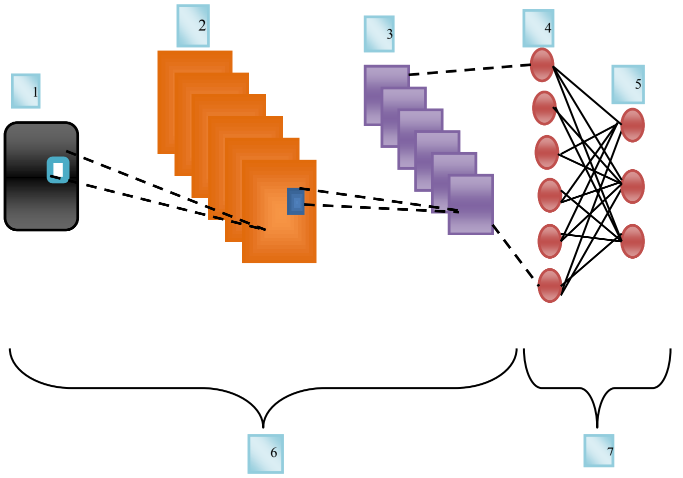
From the Kaggle dataset, 15 senior normal control subjects with a mean age of 75, 6.8 years and 30 female Alzheimer's disease (AD) patients were chosen. All normal volunteers were fit and had no past of medical or neurological disorders, while the AD patients had MMSE scores of less than 20 as reported by ADNI (Alzheimer's disease Neuroimaging Initiative) dataset. As part of the pre-processing steps for the structural data, the Brain Extraction Tool was required to extract T1 structural images of non-brain tissue. The preparation for practical data included the following: skull-stripping, motion correction (MCFLRIT), and spatial smoothing (Gaussian kernel of 5-mm FWHM). With the use of a high-pass temporal filter, low-level noise was eliminated. T1-weighted scans with high resolution of the subject were next registered using affine linear registration to the Montreal Neurological Institute standard space (MNI152), and the functional images were denoised at 2mm cubic voxels. 3845 images were the final result of the preprocessing step; the initial 10 slices of every image were eliminated since they lacked efficient knowledge.

B. Deep Learning

A modern version of machine learning that draws inspiration from the human brain is called hierarchical or structured deep learning. It was created using complex procedures those system top-level properties and extracts those details from information using analogous but more complex neural network architecture. The neocortex is a region of the cerebral cortex that controls hearing and eyesight in animals, was discovered to precede sensory inputs by producing them through a complicated order through time [10]. That was the main driving force for the development of deep machine learning, which concentrated on computer systems for representing data that displays traits resembling those of the neocortex.

C. Convolutional Neural Networks (ConvNets)

Similar to traditional neural networks, Convolutional Neural Networks (CNN) are motivated by the human eye system. We can encode some features and reduce the number of hyper parameters because this architecture explicitly assumes that original data are two-dimensional (images). In order to obtain the best possible recognition impact for such pictures, CNN mimics the human visual system to memorise and learn the edges and features of the visuals [10]. Local connection, parameter sharing, and invariant representation are the three unique characteristics of CNN drastically reduce computational complexity and simplify the networks. Convolutional layer, pooling layer, fully connected layer, and classifier are the four essential requirements of CNN. In order to create the feature maps, the convolutional layer was employed to extract picture features. The amount of features from the convolutional layer was decreased using the pooling layer [18]. We decreased and moved the feature maps into a column feature map once the feature maps had been optimally minimised, which further streamlined the parameter into an ideal number [11]. The classifiers were then utilised to detect AD. The CNN topology, which is an advance over conventional feed-forward back propagation is training, employs spatial relationships to reduce the number of parameters that must be learned. Figure 2 illustrates the architecture of Convolutional Neural Networks (CNN). Small sections of the image are considered as inputs to the graded structure's base layer in CNNs. among the most crucial. The complex architecture of CNN provides some degree of steady to move, range, and revolution, while the local receptive field provides access to fundamental qualities like aligned edges or corners for the neuron or processing unit [11, 12].



1-INPUT, 2-CONVOLUTION, 3-POOLING, 4-FULLY CONNECTED, 5-OUTPUT, 6-FEATURE EXTRACTION, 7-CLASSIFICATION

Fig. 2. Convolutional Neural Network (CNN) Architecture

The volume of the image is not altered by this layer. The class scores are calculated by the Fully-Connected Layer (FC) layer that generates a large number of classes. Each neuron in this layer will be connected to every number in the previous volume, as implied by the name, just like in traditional neural networks. In ConvNet architecture, a Pooling layer is typically introduced in between succeeding Convolutional layers. Its purpose is that in order to decrease (down sample) the representation's dimensional size so as to lessen the number of high-level parameters for networks and, as a result, manage over fitting [13]. Each input slice, regardless of depth is independently processed by the pooling layer, which then applies the MAX operation to resize each slice spatially.

D. LeNet 5

This network's use was broadened to additional challenging issues, and its hyper parameters were modified for the novel challenges. However, more advanced LeNet-5 iterations have undergone successful testing. In this paper, we dealt with a binary categorization of normal and Alzheimer's data that was highly difficult. To put it another way, we required a complex system for distinct types, which prompted us to select LeNet-5 and modify its structural design for MRI data [13]. Lenet-5 is the name of the network since it has five layers with learnable parameters. It combines three sets of convolutional layers and average pooling. Following the convolution and average pooling layers are two completely linked layers [14]. Then the images are divided into the relevant classes by a Softmax classifier. The figure 3 shows the Schematic diagram of proposed model.

Fig. 3. Schematic diagram of proposed model

The input layer, which is the initial layer of the architecture, is typically not counted because there is no learning taking place in this layer. The MNIST dataset is made up of 28x28 images, despite the fact that the input layer is designed to accept 32x32 images. Therefore, a pre-processing phase is incorporated where the images are padded to fulfil the specifications in order to obtain the MNIST images' dimensions to suit the input layer [14, 15]. The normalised gray scale images utilised in the study have an average of 0 and a standard deviation of reduced training times is a benefit of normalising images. The Figure 4 shows the architecture of LeNet-5 Model.

A-INPUT, B-CONV1, C-POOL1, D-CONV2, E-POOL2, F-FC1, G-FC2, H-OUTPUT,

I-MILDDEMENTED, ii-MODERATEDEMENTED, iii-NONDEMENTED, iv-VERYMILDDEMENTED

Fig. 4. Architecture of Lenet-5 Model.

In this architecture, the convolutional layer is essentially composed of neurons with trainable biases and weights. Other network architectures like the Pooling Layer, Normalization Layer, and Fully-Connected Layer are also included. The CONV layer, which calculates the output of neurons connected to specific input areas, does a scalar product calculation for each neuron between their mass and the position they are related to in the key volume. Pooling, also referred to as the POOL Layer, is used to down sample along the spatial dimensions. A zero-based element-wise activation function, such as the max (0, x) thresholding, is applied by the Normalization Layer or RELU layer.

There are seven levels in the LeNet-5 CNN architecture. The layer composition consists of three convolutional layers, two sub sampling layers, and two fully linked layers. The input layer, which is the initial layer, is typically not thought of as part of the network because nothing is learned there. The following layer receives photos that are 32x32 in size since the input layer is designed to accept images of that size [16]. LeNet-5 was used to recognise handwritten digits, and it easily outperformed all previous techniques. LeNet's design, which only had 5 layers and was made up of 5*5 convolutions and 2*2 max pooling, was fairly simple but opened the door to more advanced and intricate models. The following table 1 shows the details of size and measurements of the LeNet-5 Model.

TABLE.I SIZE AND MEASUREMENTS OF THE LENET-5 MODEL

Layer	**Filters**	**Filter Size**	**Stride**	**Size of Feature Map**
Input	-	-	-	32x32x1
Conv 1	6	5*5	1	28x28x6
Avg Pooling		2*2	2	14x14x6
Conv 2	16	5*5	1	10x10x16
Avg Pooling 2		2*2	2	5x5x16
Conv 3	120	5*5	1	120
Fully Connected1	-	-	-	84
Fully Connected2	-	-	-	10

III. RESULTS AND ANALYSIS

Deep Learning approaches mainly use the AE, DNN, DBN, and 2D/3D CNN algorithms. In order to create a stack of 2D images in JPEG, the pre-processed MRI 4D data in Nifti format were concatenated across the z and t axes using Python OpenCV. Binary picture categorization was accomplished using the LeNet model, which is based on the Convolutional Neural Network architecture from the Caffe DIGITS 0.2 deep learning framework. Figure 5 shows the classified output of the dataset loaded into the model.

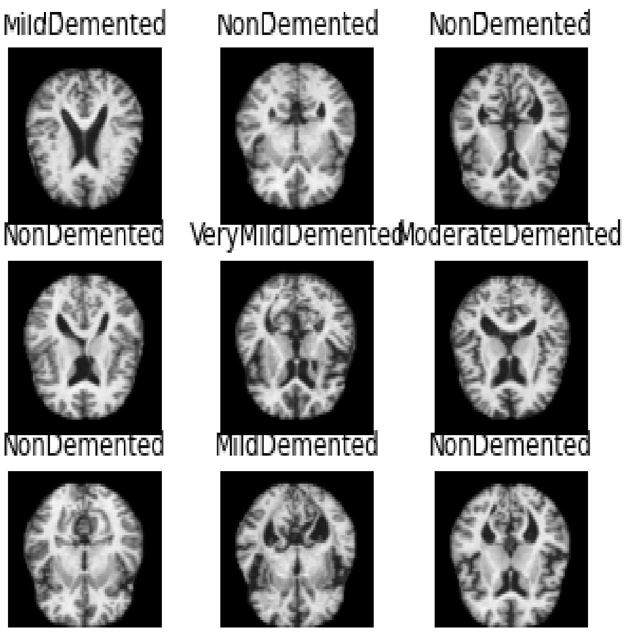


Fig. 5. Classified Output of the Alzheimer's disease dataset

The cross validation procedure was conducted five times (5-fold cross validation) to ensure the deep neural network's robustness and reproducibility. The following table 2 shows the accuracies achieved from CNN over 5 runs.

TABLE.II ACHIEVED ACCURACIES FROM CNN OVER 5 RUNS.

Run 1	**Run 2**	**Run 3**	**Run 4**	**Run 5**	**Average**
97.66	98.5	98.92	99.04	99.2	98.664

The average number of images eliminated during the pre-processing stage of deep learning. The accuracy of the validation data, as well as the loss of training and testing, was measured during the training phase. Training made up 60% of the data, followed by validation at 20% and testing at 20%. There were 297750 iterations since there were 47 epochs and 150 batches. The LeNet was trained by 3076 samples and validated and tested by 769 images. Deep Learning LeNet model successfully recognized the Alzheimer's data from Normal Control and the averaged accuracy reached 98.664%. The following figure 6 shows the Model accuracy. The loss of the proposed model was initially high and after 30 epochs the loss is started to decrease. The model loss is plotted in figure 7.

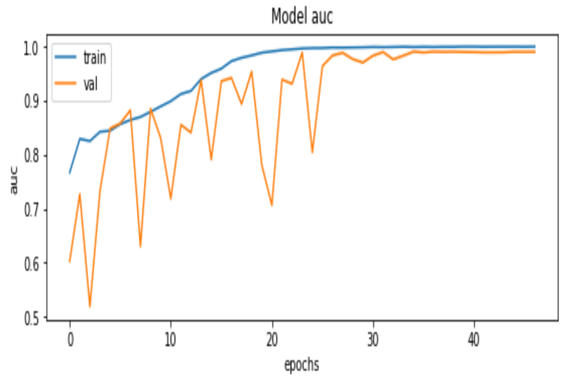


Fig. 6. Mapping of Model Accuracy

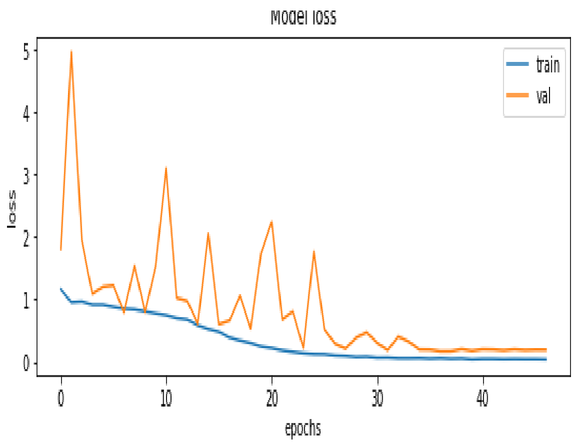


Fig.7. Mapping of Model Loss

IV. CONCLUSION

Using CNN's deep learning architecture (LeNet), which was tested and validated, we have successfully differentiated the AD data from the normal control in this study with a classification accuracy of 98.664% that has a vast quantity of pictures. This deep learning approach and our suggested model not only gives new possibilities for clinical picture analysis, but they also give scientists and doctor the ability to perhaps predict any future data. This method can be used to forecast different Alzheimer's disease stages for various age groups. Additionally, this deep learning-based system offers researchers a distinctive architecture for feature selection and categorization. The accuracy obtained in this study was extremely high, indicating that the network architecture was properly chosen.

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