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Diagnosis of Alzheimer’s Disease Using Deep Learning

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Abstract- Alzheimer's disease is the most frequent cause of dementia in adults 65 years of age and older. It is a neurological condition that progresses and cannot be reversed. Prodromal Alzheimer's disease detection is crucial because it can stop the patient's brain from suffering significant damage. In this study, a Deep Learning methodology is suggested for a technique to identify Alzheimer's disease from MRI. In the proposed approach, the Hippocampus region's texture and shape features are extracted from MRI scans and used as multi-class classifiers to identify different phases of Alzheimer's disease. The proposed strategy is being put into practice and is anticipated to provide greater accuracy when compared to traditional strategies. A degenerative brain condition that cannot be repaired, Alzheimer's disease. Someone in the globe gets an Alzheimer's disease diagnosis every four seconds. The outcome is fatal since it causes death. Therefore, it's critical to identify the illness as soon as possible. The most common cause of dementia is Alzheimer's. Dementia impairs people's capacity for autonomous functioning through reducing their capacity for reasoning and interpersonal coping. In the beginning, the patient will forget earlier events. As the condition worsens, individuals will eventually lose memory of entire incidents. The disease must be identified as soon as feasible. This study suggests a model that may determine whether a person has mild, moderate, or no Alzheimer's disease based on brain MRI sample pictures as input. For this categorization, we compare the resnet50 designs and indicate which one exhibits the most promising outcomes.

Keywords- MRI scan, Resnet50, Alzheimer, Deep Learning, dementia

I. INTRODUCTION

One of the most important organs in our body is the brain. The brain directs and facilitates all the actions and reactions that allow us to think and believe. Additionally, it strengthens our memories and emotions. Brain impairment caused by Alzheimer's disease is progressive in nature and irreparable. Alzheimer's disease has been identified in someone somewhere in the world every four seconds. It slowly improves while destroying the memory cells. Consequently, impairing one's capacity for thought.

It is a degenerative neurological condition that causes. Neuronal dysfunction or possibly death. On average, 1 in 10 persons over the age of 65 have this disorder, however it can occasionally develop earlier in life and has been identified in a number of people in their 20s.

The main cause of dementia in older persons is the condition itself.60 to 80% of people with dementia see a deterioration in their cognitive abilities needed for daily tasks. Alzheimer’s causes dementia instances. This condition is connected to plaque

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buildup and tangles in the brain, along with harm and degeneration of brain cells. Dr. Alois Alzheimer was the first to notice it after witnessing a woman die as a result of internal brain tissue alterations. When the doctor examined her brain after she passed away, he saw the development of Several Clumps.

These were determined to be the main factors causing this illness. They damaged the coordination between the brain and other sections of the body. Thus, those who have this ailment find it difficult. Very difficult to carry out daily tasks like driving, cooking, etc.

The initial stages of the symptoms may not be noticeable and include forgetting names and losing vital items, having difficulty planning, etc. The longest stage of Alzheimer's is the middle stage, which has symptoms including extreme mood swings, disorientation, impulsivity, lack of focus, trouble recognizing objects, etc.

The final phase is the most challenging. The most noticeable signs include poor communication skills, a higher risk of infections, poor decision-making, a bad sense of direction, short-term memory loss, and visual issues. According to a recent poll, there are estimated to be 50 million Alzheimer's patients globally.

Due to the fact that patients' cognitive symptoms are commonly attributed to aging, this ailment presents scientists and doctors with a significant issue today because it is frequently not discovered until patients have reached the terminal stages of the disease. The threat posed by this illness will persist until better care is given. As a result, the disease has a significant risk of affecting the elderly.

There is currently no treatment for this illness, however early intervention can decrease the progression of dementia. A number of good diet, exercise, and stress reduction have all been linked to lowering the risk of Alzheimer's disease. Exercising, interacting with others, avoiding head traumas, reading, and performing musical instruments, engaging in intellectual pursuits and using instruments can improve general brain health mentally& physically.

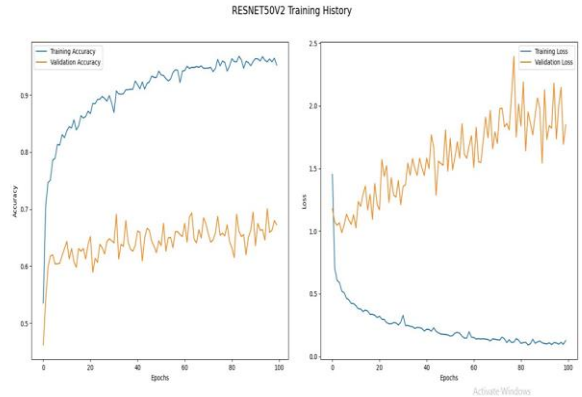

Fig-1.Training History

II. LITERATURE SURVEY

Suresha et al. [1] classified images into Normal, AD, and MCI, respectively, using a deep neural network and a rectified Adam optimizer. They used a Histogram of Oriented Gradients to extract features, and this resulted in a high accuracy of 99.5%. Physicians could identify Alzheimer's with the use of a new model developed by Lan et al. [2]. Diffusion tensor images, which are employed in brain network deployment, were utilized by him. He used the graph theory method to capture those details. After that, he used three different algorithms to verify the accuracy and recommended an improved strategy. He employed SVM, random forest, and CNN algorithms that were trained using SPL features. The three models have respective accuracy percentages of 90%, 98%, and 90%. The model's sensitivity was 92%, 96%, and 72%, and its specificity was 88%, 100%, and 94%, in that order.

According to Zubair et al. [3], there is a way to identify Alzheimer's disease. He used a five-stage machine learning pipeline process for the detection, with a sub-stage for each step. This pipeline was used with several different classifiers. His conclusion was that the performance metrics of the random forest classifier were superior. The Random-Forest classifier was used by Khan et al. [4] to compare the performance of imputation and non-imputation techniques. They found that 87% accuracy is obtained by the imputation method and 83% accuracy is obtained by the non-imputation method.

It additionally categorized the participants as either non-demented or demented, accordingly. In order to identify Alzheimer's disease, Asim et al. [5] suggested a multi-atlas method that combined the distinct features extracted from each atlas template with the combined attributes of the two atlases using PCA and cast-off SVM for classification. They were 94% accurate in the AD vs. CN test, 76.5% accurate in the CN vs. MCI test, and 75.5% accurate in the MCI vs. AD test. They noticed that compared to the single-atlas approach, the multi-atlas approach produced better results.

In his paper, Alam et al. [6] claimed that disease transmission can be stopped at an early stage of detection. He used structural magnetic resonance imaging (MRI) to pull brain scans from the repository. He proposed projecting the data onto the available linear space using kernels. He then used a Support Vector Machine (SVM) to categorize the information. For his classification, he achieved a good accuracy of 93.85% with high specificity and sensitivity. Voxel morphometry analysis was initially used by Moein et al. [7] to obtain some of the most important MRI pictures. Subsequently, he performed a principal component analysis on the extracted features. Next, in the designated subspace, a hybrid manifest learning framework was shown. Next, using a portion of the training data, a label propagation model was used to classify the data into two categories: mild and normal. The model yielded an astounding 93.86% accuracy rate for the specified classification.

A collaborative approach was used by Kumar Lama et al. [8] to differentiate AD from various other diseases. He used SMRs to assess AD in relation to health control and mild cognitive impairment. Three algorithms RELM, SVM, and IVM were employed by him in this segregation procedure. Furthermore, a discriminative method utilizing kernels is offered to address a variety of intricate data distributions. He came to the conclusion that RELM had superior performance metrics based on his classification strategy. Dr. Bryan et al. [9] observed that differences in inter site and multivendor estimations limited the use of AI in cerebral blood flow imaging techniques for Alzheimer's disease. These kinds can be rigorously standardized in human vision, but they still require a great deal of progress in understanding how to avoid dangers caused by measurable errors that are underrepresented and often missed.

In their work, Scuddero et al. [10] suggested an ML strategy utilizing biomarkers. They used a method learning locally weighted and biomarkers to test a personalized classifier for the disease. The approach first aims to categorize the subject and then determines which biomarker to order. They divided the patients into those with MCI who progressed to AD within a year and those without. A hybrid multi-class DL framework for the early diagnosis of AD by Paul et al. [11] was proposed. They employed a refined k-Sparse autoencoder (KSA) classification to identify brain regions that had undergone passive degradation. 150 MRI scan images, along with CSF and PET images from the ADNI study, were used in the experiments. According to the published results, modified KSA performed more accurately overall than both zero-masking strategy and traditional KSA. The accuracy of enhanced pair predictions using 100 classifier combinations was 83.143%, while the accuracy using 50 classifier combinations was 71.327%.

Chiyu et al. [12] introduced a 3D-CNN framework for AD diagnosis that made use of both MRI and PET images. They employed FSBI-LSTM. The diagnosis accuracy results for AD, PMCI, and SMCI classification from NC were 94.82%, 86.36%, and 65.35%, respectively. The two types of MCI, the previous state of AD, are progressive (PMCI) and stable (SMCI) (i.e., SMCI). A deep CNN-based pipeline was proposed by Islam et al. [13] in an attempt to diagnose AD and categorize its stages. Three deep CNNs, each with a slightly different structure, make up their method. The accuracy, precision, recall, and F1-score were 93.18%, 94%, 93%, and 92%, respectively, after technique validation using the OASIS. But there are only 416 SMRI data in the validation database. More recently, Liu et al. [14] created a multi-model deep CNN framework for the automatic segmentation and classification of the hippocampal regions in AD. First, hippocampal segmentation was performed using a deep CNN model. Subsequently, a 3D Dense Net was developed to learn discriminating image features for disease categorization, starting with the segmented hippocampal region. T1-weighted SMRI data (97 AD, 233 MCI, and 119 NC subjects) from the ADNI database comprised the evaluation dataset. They discovered that their method had an accuracy of 88.9%, an area under the receiver operating characteristics (ROC) curve (AUC) of 92.5%, and an accuracy of 76.2% for classifying AD vs. NC participants; additionally, their method had an AUC of 77.5% for detecting MCI vs. NC subjects. An ML-based AD classification algorithm was created by Neffati et al. [15].

III. EXISTING SYSTEM

Alzheimer's is typically the longest stage and can last for many years. During this stage, damage to nerve cells in the brain can lead to difficulty in expressing thoughts and performing routine tasks. The symptoms are also noticeable to others during this stage. In the last stage of the disease, the patient loses the ability to respond to their environment, carry out conversations, and, eventually, even control movements. As memory and cognitive skills continue to worsen, individuals need extensive help with daily activities. Unfortunately, very few AD patients are diagnosed at an early stage. Imaging modalities such as Magnetic Resonance Imaging (MRI) scan, Positron Emission Tomography (PET) scan, and Single-photo Emission Computed Tomography (SPECT) scan are used to track changes in the brain and diagnose Alzheimer's before irreversible neural damage is done. The current non-automated methods for diagnosis include cognitive impairment testing, mini-mental state examination (MMSE), and Clinical Dementia Rating (CDR).
The disadvantages are

- Less accuracy
- Prediction rate is low

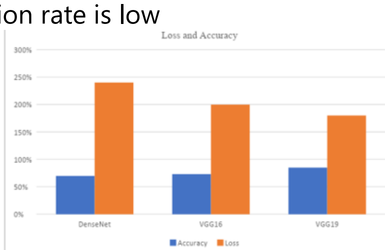

Fig-2. Model Comparison

IV. PROPOSED METHODOLOGY

In this study, we proposed an intelligent methodology for building a convolutional neural network (CNN) from scratch to detect AD stages from the brain MRI images dataset and to improve patient care. It is worth mentioning that training a deep-learning model requires a large amount of data to produce accurate results and prevent the model from over fitting problems. Therefore, for a better understanding of classifiers and to overcome the model over fitting problem, we applied data augmentation to the minority classes to increase the number of MRI images in the dataset. All experiments were conducted using an Alzheimer's MRI dataset consisting of brain MRI scanned images. The performance of the proposed model determines the detection of the four stages of AD. Experimental results show the high performance of the proposed model in that the model achieved a 99.38% accuracy rate, which is the highest so far. The advantages are.

- Where feasible, networks of specialist diagnostic centers should be established to confirm early-stage dementia diagnoses and formulate care management plans.

The VGG (Visual Geometry Group) CNN (Convolutional Neural Network) is a popular architecture known for its deep layers and strong performance in image classification tasks. The system architecture of VGG CNN can be summarized as follows:

- **Input Layer:** Receives an image, typically of size 224x224 pixels.
- **Convolutional Layers:** Apply learnable filters to extract features from the image.
- **Pooling Layers:** Reduce the spatial dimensions of the feature maps.
- **Fully Connected Layers:** Capture higher-level representations for classification.
- **Activation Function:** Introduce non-line arities, commonly RELU activation.
- **Soft Max Layer:** Produces probability scores for different classes.
- **Training and Optimization:** Update weights using back propagation and gradient descent.

The VGG CNN is characterized by its depth, ranging from 16 to 19 layers, allowing it to extract intricate features and achieve high performance in challenging image recognition tasks. The VGG CNN architecture is characterized by its depth, with configurations ranging from 16 to 19 layers. The increased depth allows for the extraction of intricate features and enables better performance on challenging image recognition tasks. However, deeper architectures also require more computational resources for training and inference.

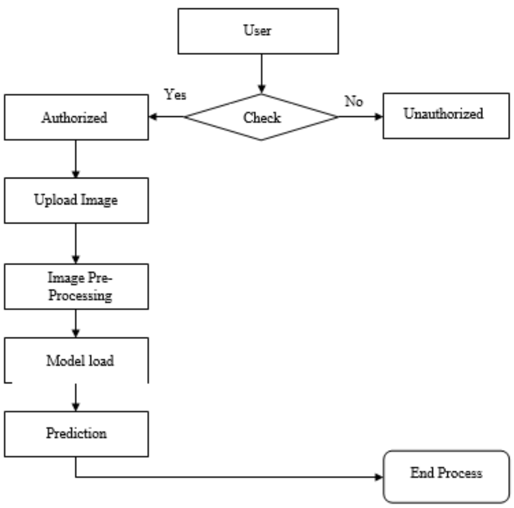

Fig.3-System Architecture

Upload Image

Give the user the option to choose an MRI image file to upload by providing a button.

Image Pre-Processing

Read the uploaded image, alter its size to 224 by 224 pixels, and change its color space to RGB.

Model Load

To make an Alzheimer's prediction, load the pre-trained model ('model_final.h5') and assemble it using the RMS prop optimizer with a learning rate of 1e-4, the categorical cross-entropy loss function, and accuracy as the evaluation metric

Prediction

Apply the model's predict function to the picture data and use the loaded model to predict the Alzheimer's disease category of the pre-processed image

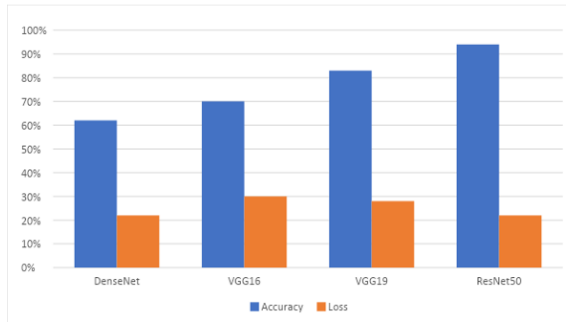

Fig-4.Res Net50 Accuracy and Loss

V. RESULTS

The below table shows the accuracy of two different models, VGG16 and ResNet50. The accuracy is measured as the percentage of correct predictions made by the model. The loss is a measure of how well the model is doing. A lower loss value indicates that the model is doing better. In this case, the VGG16 model has a lower loss value (0.22) and a higher accuracy (91%) than the ResNet50 model (loss = 0.30, accuracy = 82%). This means that the VGG16 model is doing a better job of predicting the correct outcome than the ResNet50 model.

Table 1.Accuracy

	Loss	Accuracy
DENSENET	0.28	88%
VGG16	0.70	96%
VGG19	0.28	88%
ResNet50	0.70	96%

VI. CONCLUSION

In conclusion, the use of Convolutional Neural Networks (CNN) in conjunction with machine learning has proven to be a highly successful method for the early diagnosis of diabetic retinopathy. This method has demonstrated great effectiveness in precisely recognizing and categorizing retinal pictures, enabling early diagnosis and intervention. It does this by utilizing deep learning and machine learning algorithms. We used a Convolutional Neural Network; each input image will be classified with the greatest degree of precision possible. There will be a hope that there won't be any no misclassification because of the accuracy of our model. We started with the basics. In conclusion, we found that MRI was highly predictive in mid-term pMCI, correctly classifying most of them. As a consequence, specificity and discriminative power increased at 5-year follow-up, outperforming complex machine learning approaches of incipient AD detection with shorter follow-up times. The unexpected good performance of MRI in the mid-term revealed the problem that an insufficient follow-up time may create for machine learning algorithms, given that these algorithms regard as non-diseased an important proportion of patients actually affected by AD and with evident a trophies. This may result in poor performance and lack of generalizability, as well as in non-interpretability of algorithm predictions. If sample enrichment for short-term clinical trials is required, other variables that predict short-term conversion must be included along with MRI .A Short follow-up might be also problematic when deriving biomarker cut-points from MCI samples, especially for those representing the early stages of the disease.

VII. FUTURE SCOPE

However, despite the progress made, there are still challenges to address. The development of robust algorithms requires large and diverse datasets, including data from different ethnicities and age groups. Additionally, the integration of AI systems into existing healthcare workflows and the acceptance of these technologies by healthcare providers are crucial for successful implementation. Ensuring the privacy and security of patient data is another important consideration that must be carefully addressed. In conclusion, the development of AI-based systems for Alzheimer's detection holds great promise in revolutionizing and improving patient outcomes. With continued research, technological advancements, and collaborations between healthcare providers, researchers, and technology developers, the future of Alzheimer's detection looks bright. By harnessing the power of AI, we can make significant strides in combating this brain-threatening disease and enhancing the quality of care for individuals with brain neurons. The program will improve the accuracy of Alzheimer's detection identification without causing pain to the patient. It can be turned into open-source software and has a lot of potential for use in hospitals. The software can assist clinicians in determining a link between type of dementia and indeed the likelihood of Alzheimer's detection.

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