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MRI Image Based Diagnosis Model for Alzheimer's Disease Using VGG16

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***Abstract*—People over the age of sixty are disproportionately affected by Alzheimer's disease (AD), making a few of the most typical kinds of dementia. Very few reliable diagnostic methods exist at this time for detecting AD in its earliest stages in clinical practice. There is currently no treatment or cure for Alzheimer's disease, and clinical trials for potential treatments are very likely to fail. Very mild dementia, mild dementia, and moderate dementia are all distinct stages of Alzheimer's disease. It's not easy to see the decline into absolute health lessness, memory loss, and dependence on others that comes with these early stages of dementia. By training the network using a collection of brain imaging data, VGG 16 may be used to generate predictions for the diagnosis of Alzheimer's disease (AD). This method relies on the observation that people with AD exhibit distinct patterns of brain activity and structural change. An extensive database of MRI scans from people with Alzheimer's disease (AD) and healthy controls may be employed to demonstrate VGG 16 network to recognize tell-tale signs of the illness. After the image has been trained, it can categorize people as having or not having AD based on brain imaging data. Patients can also make appointments with these doctors who specialize in dementia, and doctors can also recommend the best medications for the disease which have been found.**

Keywords—Machine Learning, Deep Learning, MRI, Visual Geometry Group, CNN.

I. Introduction

Alzheimer's disease (AD), often known as dementia, is caused by permanent damage to the brain's memory cells. Deterioration of the visual cortical tissues and problems in the nerve cells are to blame for memory loss. Normal brain function is severely impaired in people with AD, making it hard for them to carry out routine tasks like speaking, writing, and reading effectively. In the later stages of this condition, patients may have life threatening symptoms include difficulty breathing and heart failure. Although life expectancy may be increased, it is very difficult to establish an early and accurate diagnosis of AD. Although AD symptoms emerge slowly, the situation for patients deteriorates as the disease advances. The search estimates that by 2050, one in every 85 individuals would be living with Alzheimer's disease. According to studies, this disease is the second most serious brain ailment in the globe. This disease destroys neurons and often manifests in the hippocampus region before spreading to the rest of the brain and spreads over. However, AD development and negative consequences may be mitigated with early diagnosis and therapy. Both mental and physical well- being are essential for a fulfilled human existence. Using MRI scans and a Deep Learning model [8], CNN is suggested for the diagnosis of Alzheimer's disease. VGG16, the features utilized in the CNN-based- trained model, are used to remove the features from trained model, are used to remove the features from the MRI scan picture shown in Fig 1.

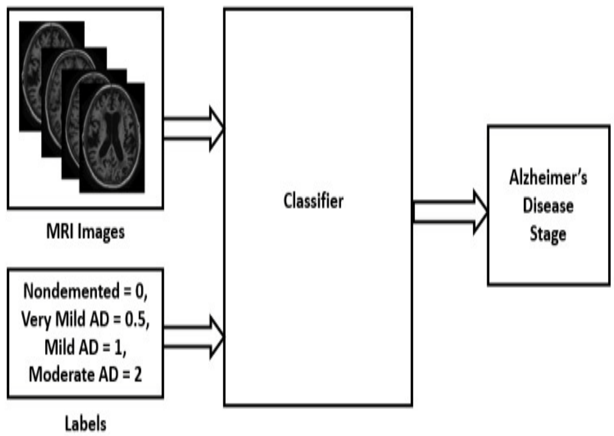

Fig.1. Detection of Alzheimer Disease

II. Literature Survey

Abrol, Anees, et al. [1] suggested research utilizes transfer learning with VGG16 and Fast as to conduct multilevel categorization of Alzheimer's disease, separating cases into four distinct categories: mild dementia, moderate dementia, non-demented, and very mild dementia. Prediction accuracy for this method is 99%, which is a substantial increase over that achieved in past studies and provides enough proof of the effectiveness of the proposed tactics.

Rakesh Reddy M [2] proposed a system to identify AD using MRI scans from the ADNI database, this study examined the results and performances of two distinct

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convolution neural network models, namely VGGNet-16 and VGGNet-19. Different slice ranges, a random validation split, a cross validation, and leaving out the hippocampus all played roles in the CNN models' training.

The findings demonstrate that the models are effective at recognizing true-negatives or correctly identifying a healthy patient. The two CNN models' AD classification accuracy varied from 66.6% to 74.8%, depending on the training approach used.

De Silva, S., S. Dayarathna, and D. Meedeniya [3] showed a 3D axial brain pictures from an MRI which is retrieved and fed into a convolutional neural network for multiclass categorization (CNN). Comparisons were made between a custom-built CNN, a VGG-16 model, and a ResNet-50 model. In order to diagnose Alzheimer's disease and classify the patient's severity of memory deterioration using the VGG-16.

E. Loveman, C. Green, J. Kirby et al. [4] Axial Sagittal or Coronal slices of the 3D pictures are provided as input in [9], with each slice having the size of a single image pixel (176x220) axial slicedimension. As dimension reduction gets extremely complicated for classification, they used PCA+TSNE.The reduced dimension is now 609x3=1827, which is derived from a single RAW MRI scan using created CNN features. The outcome will thus be determined by which of two separate working principles—Navies Bayes and KNN—has the maximum accuracy.The Trained CNN with the proposed concept has the maximum accuracy in this instance, at 88.2%.

Jeny Benios [5] developed a model in Python, and its implementation provides a system that is very useful to physicians for the classification of Alzheimer's disease. Using70% photos from the training set and 30% images from the validation set, our trained model achieved perfect accuracy on a separate, held-out test set.

Garcia-Gutierrez, Fernando, et al. [6] In this publication, the authors proposed using a VGG-Twin former model built on Transformer and convolutional neural network (CNN) for short-term longitudinal studies of MCI. This model progressively fuses far-flung spatial feature representations by superimposing attention windows of varying widths, with sliding window attention being employed for fine-grained fusion of spatially adjacent feature representations.

R.G.DeSouza, W.P.Dos Santos [7] proposed a low-level spatial characteristics of longitudinal sMRI images are extracted using a VGG-16-based CNN, and then mapped to high-level feature representations via temporal attention. In order to ensure the accuracy of their results, consulted the ADNI dataset. The sMCI vs. pMCI classification job has an accuracy of 77.2%, sensitivity of 79.97%, specificity of 71.59%, and area under the curve (AUC) of 0.8153. Lei et al. detected the connection among the data and the brain areas using a multi-layered independently RNN model. The experiment by the authors uses the ADNI dataset, and extraction of features and image processing are also carried out to obtain the clinical score from the dataset.

III. Proposed System

The proposed approach consists of three parts: image acquisition. pre-processing, model training, feature Extraction, classification shown in Fig 2.

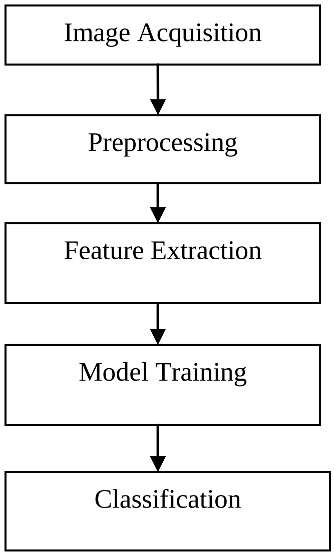

Fig.2. Workflow Of Proposed System

The system adheres to the step-by-step process of data preprocessing and classification depicted in Fig 3.

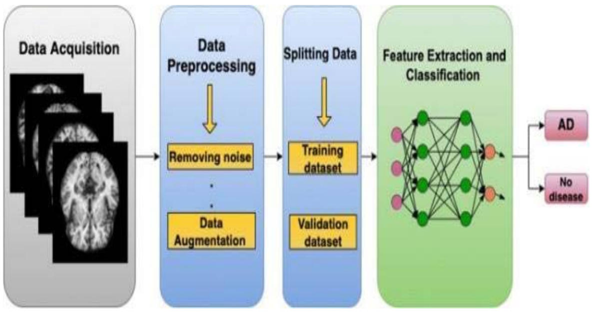

Fig.3. Module Flow

A. Image Acquisition

Magnetic resonance imaging [5] is a diagnostic tool used in the medical field to identify and see anatomical structures at a microscopic level. There is no better method than this one for identifying tissue differences. Brain photos taken from public sources on the Internet may be uploaded using this module. In terms of file size and format, images may be anything. An image must first be recorded by a camera and transformed into a controllable entity before any video or image processing can start. The "Image Acquisition" procedure entails the conversion of an optical image (Real World Data) into a collection of numerical data that can then be processed by a computer as shown in Fig 4.

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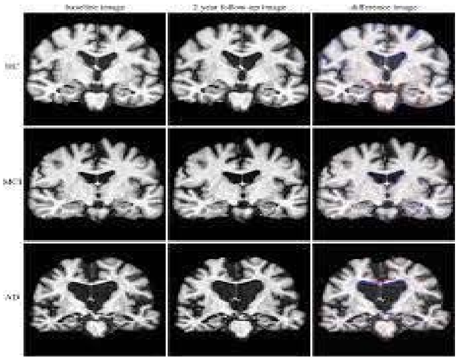

Fig.4. Structural Brain Imaging

B. Preprocessing

This section allows to adjust the picture size so that it fits on the page. In order to clean up the photos, use the median filter method. Each output sample in a median filter, a kind of nonlinear filter, is calculated as the middle value after all input values have been sorted according to the window. The purpose of preprocessing [4] is to enhance the picture data by reducing artefacts and highlighting certain details that will be useful in the analysis and processing that follows. After that, it uses the median filter technique to clean up the photos as shown in Fig 5.

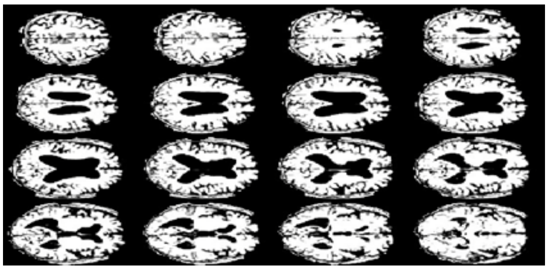

Fig.5. Pre-Processing

C. Feature Extraction

By effectively reducing the amount of data feature extraction [7] enables the selection and fusion of variables into features, enabling the acquisition of the best feature from such enormous data sets. Moreover, it may help cut down on duplicate information in an analysis. The time it takes for the machine to learn something new and for that learning to generalize to other situations is reduced by the data reduction and the work it puts into constructing variable combinations.

D. Classification

An Example of Magnetic Resonance Biomedical imaging techniques allow for the detection and visualization of anatomical features previously undetectable to the plain sight [9]. There is no better method than this one for identifying tissue differences. Gather diagnostic information by extracting features and matching them against a model file. Predictions from a model trained with all training instances except those used to estimate feature selection values [6] were used to measure the model's performance on the validation set. When in beta, the user may input a brain picture and offer information about a diagnosis based on the illnesses indicated by the system as depicted in Fig 6.

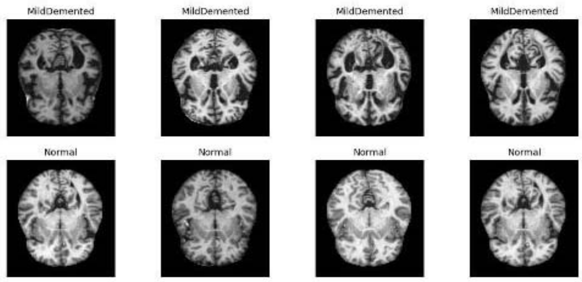

Fig.6. Classification Of MRI

IV. Algorithm

A. Visual Geometry Group 16

The very compact VGG16 design consists of convolution, a fully connected layer, and a pooling layer. This architecture is also featured in the Alex Net model[3]. There are a total of 16 levels, if the pooling layer is not included. The size of this structure grows as more layers are added to it. The standard input size for this network is 224x224 pixels, and the standard filter size is 3x3. Class probabilities are sent to the network's output layers through an activation function at the network's final stage.

To perform image classification tasks, VGG16 is a deep learning model [10] that was trained on a huge dataset of pictures. Features from MRI of the brain may be extracted using VGG16 for the purpose of Alzheimer's disease prediction. The collected characteristics may be fed into a different classifier neural network [1,2], to make predictions about Alzheimer's disease and its severity. The rationale behind employing VGG16 for Alzheimer's disease prediction is that it has already learnt to detect patterns and characteristics in pictures with the value for image classification, and these features may be reused for a new job.

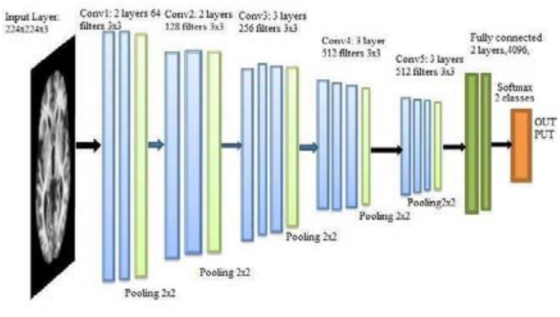

Fig.7. CNN Layer

The VGG16 network's first layer has been fed the 224x224 pixel pictures for feature extraction. The images then pass through further convolutional layers shown in Fig 7.

A stack of two convolutions with a receptive area of 3x3 is used immediately after the ReLU activation functions to convey the 224 x 224-pixel image. Each of these levels has 64 individual filters. With the stride value fixed at 1, the

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padding is also fixed at 1 pixel. The spatial resolution is preserved in full, and the dimensions of the activation at the output are identical to those at the input in this design. Activations with a stride value of 2 pixels are sent to the pooling layer because the window size is 2 by 2. The VGG16 network's first layer has fed the 224 x 224-pixel pictures for feature extraction. The images then pass through further convolutional layers. A stack of two convolutions with a receptive area of 3x3 is used immediately after the ReLU activation functions to convey the 224x224-pixel image. Each of these levels has 64 individual filters. With the stride value fixed at 1, the padding is also fixed at 1 pixel. The spatial resolution is preserved in full, and the output activation dimensions match those of the input pictures thanks to this design. Activations with a stride value of 2 pixels are sent to the pooling layer due to the fact that the window size is 2 by 2. Using the SoftMax function [11], the number of storage nodes in the final layer is proportional to the number of classification task divisions.

B. Softmax Classifier

For classification, SoftMax employs the cross-entropy loss. The SoftMax classifier gets its name from the SoftMax function, which converts the raw class scores into normalized positive values that amount to one in order to employ the cross-entropy loss.

$$\sigma(z)i = \frac{e^{z}i}{\sum_{j=1}^{k} e^{z^{j}}} \qquad (1)$$

For a k-class multiclass classifier given in (1), the SoftMax function is defined as Z, the input vector. where z^{i} is a component of the input vector, and it may take any real value. Assuming a uniform probability distribution, the normalization factor at the end of the equation ensures that the function's output values add up to 1. An input vector to the SoftMax function consists: (z0, ... zK) The standard exponential function is applied to each element of the input vector. The resulting number is positive and bigger than zero, albeit how much greater depends on whether the input was little or large. A probability, by definition, must lie between zero and one, yet it is still not constrained to that interval. Each component of the input vector is multiplied by the universal exponential function.

The result is a non-negative number greater than zero, which is very small if the input is negative and extremely huge otherwise. To be meaningful, the range of a probability has to be restricted to (0, 1). The conditional probability of each class is determined by the SoftMax function [12], which is given the input picture. In a similar vein, it details the probabilities of each category. The goal of the model is to maximize the conditional probability of the class that is assigned to a given feature vector in the fully connected layer.

The VGG16 network was modified by adding a new unskilled dense layer at the very end. Next, the entire network is trained using the dataset provided. The categorical cross entropy is the cost function for multiclass classification. One way to characterize the classification entropy is as follows: where z^{i} is a segment of the input vector for z and j is the jth class were halted in order to produce our CNNs' models because to the fact that filters in the foundation layers [15] search for low-level components in pictures, such as angles and lines. Only the fifth block, where the filters check for abstract traits, was trained.

Convolutional neural network (CNN) VGG-16 is one that was suggested in this model. To do this, normalize the input photos and create the training and validation sets. The regulation in the fully linked layer is another feature of the VGG-16 concept. Before training, the VGG-16 model architecture on the brain, database is removed when completely linked, producing meaningful vector pictures.

V. Results and Experiments

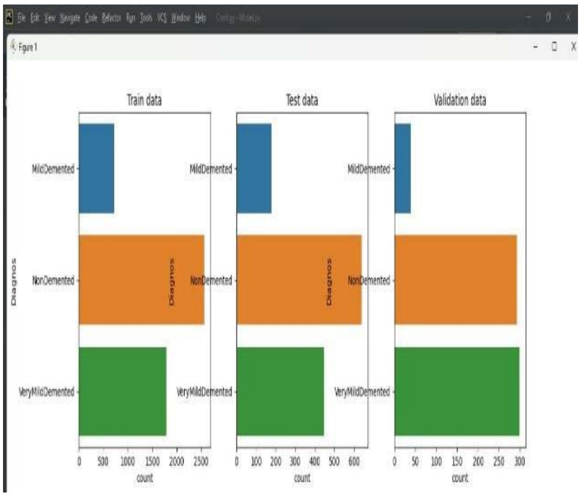

Fig.8. ccuracy Loss

The quality and size of the training dataset, the selection of hyperparameters, and the algorithm's performance on the validation set are some of the variables that affect the accuracy loss in Alzheimer's disease prediction using VGG16 shown in Fig 8. However, it is well known that deep learning models, like VGG16, may do extremely well in image classification tasks, such as predicting Alzheimer's disease from brain scans. It can further optimize the model by adjusting the hyper parameters [14], adding or removing layer, or using a different optimization approach if the accuracy loss is significant.

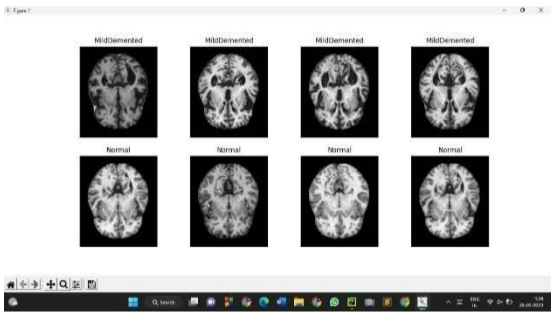

Fig.9. Classification of MRI

Gather the brain MRI scans and the associated diagnosis, then separate the data into training, validation, and testing sets. Prepare the data for use in the model by preprocessing it, as by normalizing the intensity values and shrinking the photos to a specific size. Fig 9 shows as a starting point, can be utilized a convolutional neural network (CNN) architecture like VGG16.

These pretrained models can be adjusted using the data, or create a new architecture from start. Utilize the training set to develop the model, then by using the validation set to test it. After training, assess the model on the test set to determine how well it performs in separating healthy from Alzheimer's MRI scans. Metrics like accuracy can be evaluated. (AD) research is increasingly using positron emission tomography (PET) imaging that focuses on neurofibrillary tau tangles [13], however its value may be restricted by traditional quantitative or qualitative assessment methodologies in early disease phases. When it comes to recognizing and learning from spatial patterns in images, VGG16 performs well. Fig 10 depicts the training and validation accuracy for each epoch and Fig 11,12 shows the results for Alzheimer's Disease Prediction.

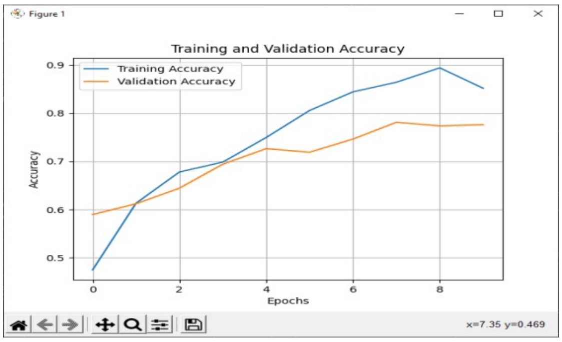

Fig.10. Training and Validation Accuracy

Fig.11. AD Prediction

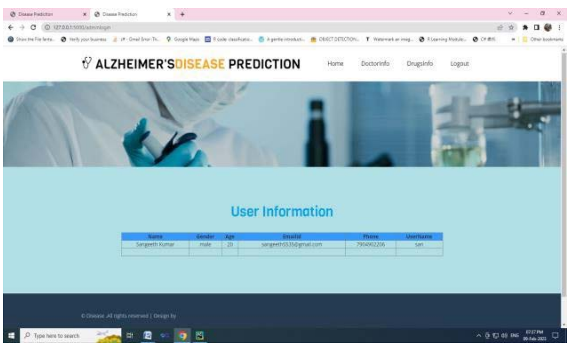

Fig.12. User information

VI. Conclusion and Future Enhancement

With further time and thorough investigation, the suggested system may be improved in the future. To further expand the diagnostic choices available to the physician employing PET, new Alzheimer's disease detection algorithms may be implemented. Alzheimer's disease (AD) research is increasingly using positron emission tomography (PET) imaging that focuses on neurofibrillary tau tangles; however, its value may be restricted by traditional quantitative or qualitative assessment methodologies in early disease phases. When it comes to recognizing and learning from spatial patterns in images, VGG16 performs well.

The most prevalent type of late-stage dementia, Alzheimer's disease (AD) is a progressive neurological condition. In this research, by comparing conventional ML with DL, then moved on to the AD diagnostic phase. Demonstrated a picture preprocessing approach used in Alzheimer's disease diagnosis to improve learning quality. And also showed other DL approaches that are often used in the classification process, including CNN, RNN, DNN, AE, and DBN. Disease categorization using DL is crucial, yet there are difficulties in working with the dataset. Hence, included a literature study for each difficulty and illustrated their proposed solutions. In this review, integrated preprocessing methods with the most popular DL approaches, compare distinct state-of-the-art research with their obstacles in dealing with datasets and classification stages, and present several preprocessing methods that were processed on neuroimaging.

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