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Alzheimer Disease Prediction using Deep Learning Algorithms

B. V. Ramana1, B. R. Sarath Kumar2
1Dept of IT, Aditya Institute of Technology and Management, Tekkali, AP, India.
2Dept of CSE, Lenora College of Engineering, Rampachodavaram, A.P, India.
*Corresponding Author: iamsarathphd@gmail.com

ABSTRACT
Alzheimer's disease, the most prevalent neurodegenerative illness, exhibits initially mild symptoms that worsen over time. It is a common form of dementia, and its lack of a cure poses treatment challenges. Diagnosis often occurs at later stages, making early prediction crucial for potentially slowing down the disease's progression. This study employs a machine learning algorithm, specifically a Convolutional Neural Network (CNN), to forecast the onset of Alzheimer's disease. The algorithm utilizes psychological indicators such as age, visits, MMSE scores, and educational level, along with MRI images, to make predictions. Detecting Alzheimer's at an early stage is vital to prevent severe brain damage, especially among individuals aged 65 and above, for whom the disease can become dangerous and even fatal. The primary objective of this research is to build a useful model for Alzheimer's prediction using machine learning techniques, including CNN and feature extraction/selection. Alzheimer's disease is now the sixth leading cause of mortality in the US, and projections suggest it may rank third among seniors, following heart disease and cancer. Early diagnosis and treatment are critical for forecasting the disease's progression and halting its advancement. However, the diagnosis of Alzheimer's relies on various medical tests and extensive multivariate heterogeneous data, making manual comparison, visualization, and interpretation of the data laborious and complex.

Keywords- Alzheimer disease, mild cognitive impairment, machine learning algorithms, psychological parameters.

1.INTRODUCTION
Alzheimer The most prevalent kind of dementia that frequently affects those over 65 is Alzheimer's disease (AD), which is distinguished by the gradual deterioration of cognitive and memory abilities. Early AD diagnosis is necessary for prompt treatment, which can help reduce the course of dementia [1]. Deep learning approaches that can account for interregional correlation have recently emerged as an appealing and essential component of computer-assisted analytical procedures and are now often used for the automated diagnosis and analysis of neuropsychiatric illnesses. This initiative focused on Alzheimer's disease categorization and prediction. We aimed to develop a very accurate model that predicts the stage of Alzheimer's disease based on MRI scans to aid clinicians in diagnosis. If MRI pictures are not yet available, provide the doctor with a preliminary evaluation of the patient's dementia risk based on patient data.

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2.LITERATURE SURVEY

psychiatrist Alois Alzheimer reported the first instance of the condition in 1906[2]. AD first appeared. This imaging method uses magnetic fields and radio waves to create high-quality, high-resolution 2D and 3D pictures of the brain's structural components. Neither radioactive tracers nor X-rays produce any hazardous radiation. The structural MRI, which assesses brain volumes in vivo to identify brain degeneration, is the type of MRI that is most frequently employed in AD patients. Alzheimer's disease (AD) will inevitably lead to gradual brain damage. AD first appeared [3].

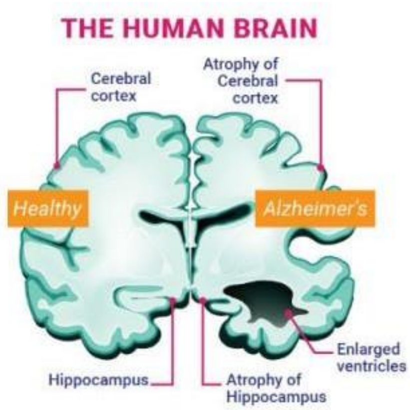

FIGURE 1: Progress of AD from MCI to severe AD.

3.Machine Learning to Deep Learning in Alzheimer Disease

In the last ten years, machine learning (ML) has been more important in identifying MRI biomarkers of Alzheimer's disease (AD) and in enhancing the diagnosis and prognosis of AD. To distinguish between stable moderate cognitive impairment (MCI) and progressing MCI, researchers have used a variety of ML techniques. For instance, Haller et al. classified the two groups precisely after using a support vector machine (SVM) to analyses 35 cases of normal controls and 67 cases of MCI [4]. The recovery of robust texture descriptions from entire pictures has frequently been disregarded, despite the fact that the majority of ML algorithms for bio-image classification have prioritized segmentation. However, picture segmentation may not be necessary if compelling qualities can be extracted from the complete image. Traditional texture descriptors like Gabor filters and Haralick texture features were used in early studies in this area.

To get machine learning (ML) closer to artificial intelligence, deep learning (DL), a new area of ML study, has arisen. To better interpret text, sound, and picture data, DL structures often use numerous layers of abstraction and representation. Generative architecture and discriminative architecture are two categories for DL. Both machine learning (ML) and deep learning (DL) have been widely used in Alzheimer's disease (AD) research, but DL has recently come to be seen as a particularly potent strategy. By utilizing its capacity to automatically train hierarchical representations from big datasets, DL has revolutionized the area by enabling more precise and

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reliable AD detection, diagnosis, and prediction.

In AD research, machine learning techniques have been used to analyses a variety of data sources, including neuroimaging, genetic, and clinical information. These methods often entail creating algorithms that can recognize correlations and patterns in data to help with classification and prediction tasks. Support vector machines (SVM), random forests, and logistic regression are ML techniques that have been used to find AD biomarkers, differentiate between distinct disease stages, and forecast disease development. Due to its capacity to automatically build hierarchical representations from unstructured data, DL, a branch of ML, has attracted a great deal of interest. Deep neural networks (DNNs), in particular, have displayed astounding performance in a variety of AD-related activities. In order to help in the diagnosis and categorization of AD, convolutional neural networks (CNNs) have been effectively used in the processing of neuroimaging data by extracting features and patterns from brain pictures. In order to anticipate how an illness would develop over time, recurrent neural networks (RNNs) have proved successful in modelling the temporal relationships in longitudinal data [5].

4.SYSTEM OVERVIEW

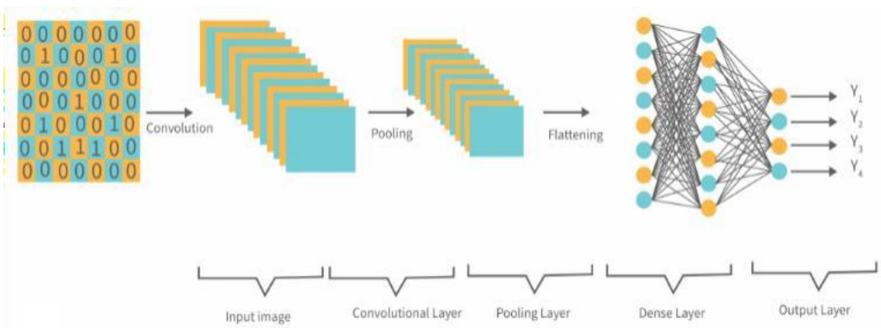

Figure 2: Convolutional Neural Network (CNN) Architecture

Multimodal analysis has also been helpful for DL in AD studies. DL models can make use of the complimentary nature of these sources for better AD diagnosis and prediction by combining data from many data modalities, including neuroimaging, genetic, and clinical data. CNNs and RNNs are used in multimodal DL architectures to integrate and fuse data from several modalities, enabling a more thorough knowledge of AD pathophysiology. The accessibility of huge datasets, such as the Alzheimer's Disease Neuroimaging Initiative (ADNI), has made the use of DL in AD research even easier [6]. These datasets give researchers access to a wealth of labelled data, enabling the construction of deep learning models on vast and varied datasets pertaining to AD. Overall, the shift from machine learning (ML) to deep learning (DL) in AD research has revolutionized the discipline by enabling the creation of complex models that can automatically learn detailed patterns and representations from unstructured data. CNNs and RNNs are two deep learning (DL) algorithms that have considerably improved the detection, classification, prediction, and multimodal analysis of AD. These advancements present intriguing opportunities for early diagnosis, individualized care, and a deeper knowledge of the illness.

The most prevalent kind of dementia that frequently affects those over 65 is Alzheimer's disease (AD), which is distinguished by the gradual deterioration of cognitive and memory abilities. Early AD diagnosis is necessary for prompt treatment, which can help reduce the course of dementia. Deep learning approaches that can account for interregional correlation have recently

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emerged as an appealing and essential component of computer-assisted analytical procedures and are now often used for the automated diagnosis and analysis of neuropsychiatric illnesses. This initiative focused on Alzheimer's disease categorization and prediction. We aimed to develop a very accurate model that predicts the stage of Alzheimer's disease based on MRI scans to aid clinicians in diagnosis. If MRI pictures are not yet available, provide the doctor with a preliminary evaluation of the patient's dementia risk based on patient data.

CNN is short for Convolutional Neural Network. It is a deep learning model used to analyze visual data such as photos and videos. CNN revolutionized the field of computer vision, achieving significant success in tasks such as image classification, object detection, and image segmentation [7]. A convolutional layer is a central component of a CNN that applies filters to the input data to extract features. Also known as kernels, these filters scan the input data using convolution functions, allowing the network to learn local patterns and spatial correlations. The output of the convolutional layer is then passed through activation functions and combined to reduce dimensionality and capture the most important features.

CNNs are frequently composed of numerous convolutional layers, which are followed by a fully connected layer that performs the final classification or regression operation. Convolutional layers collect low-level information like edges and textures, whereas fully connected layers learn higher-level representations and generate predictions based on them [8].

One feature of CNNs is their capacity to learn hierarchical data representations automatically. CNNs may extract features at multiple levels of abstraction using convolutional layers with distributed weights, allowing the capture of complex patterns and connections in visual data.
Training a CNN entails feeding it tagged data and employing backpropagation and gradient descent to optimize network parameters (weights and slopes).

i) Data preparation: First, the CNN needs to train the data list. This document contains a collection of pictures and notes about their class or classes.
ii) Data processing: The images in the data are often modified to some extent and can be pre-processed in other steps such as normalization or data addition to improve the imaging model, quality and detail.

iii) Model Architecture: A CNN model is defined by defining its architecture, which includes convolutional, network and all layers. The architecture varies depending on the complexity of the task and the size of the data.

iv) Training: During training, the CNN learns the patterns and features of the input image by adjusting its weights and weights. This is done through an iterative process where the model predicts a training image, compares it to the ground reality map, and updates the model without using optimization methods such as gradient descent or vice versa.

v) Forward propagation: Once a CNN is trained, it can be used to classify images. In the next step, the input image is fed to the CNN, and the network performs integration, activation and fusion to extract features from the image.

vi) Evaluation: After subtraction, the subtraction is flattened and passed through one or more seams. All levels highlight and emphasize functions and deliver the final result. The results can

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be interpreted as an estimatedprobability for each class.

vii) Post-processing: Convert the probability estimate to alist of classes, usually choosing the class with the highest probability. Depending on the specific application, additional post-processing steps such as authentication orfiltering are rarely possible.

viii) Evaluation: Evaluate the performance of CNN models by comparing predictions with the truth of experimental data. Metrics such as precision, accuracy, recall, and F1 score are often used to evaluate model performance.

ix) Fine-tuning and optimization: Depending on the performance of the model, fine-tuning techniques such as hyperparameter tuning, adding optimization techniques or using pre-trained models can be used to improve theaccuracy and reliability of the image distribution.

5.SYSTEM DESIGN

CLASS DIAGRAM

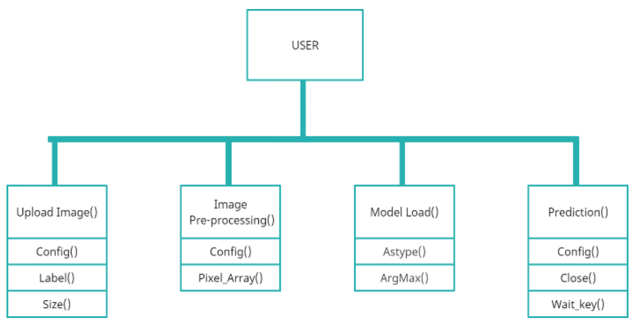

Figure 3: Class diagram

SEQUENCE DIAGRAM:

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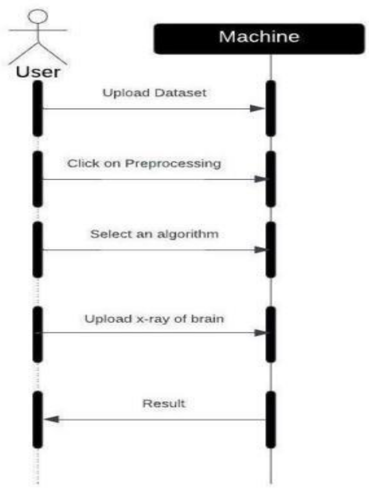

Figure 4: Sequence Diagram

6.USES CASE DIAGRAM

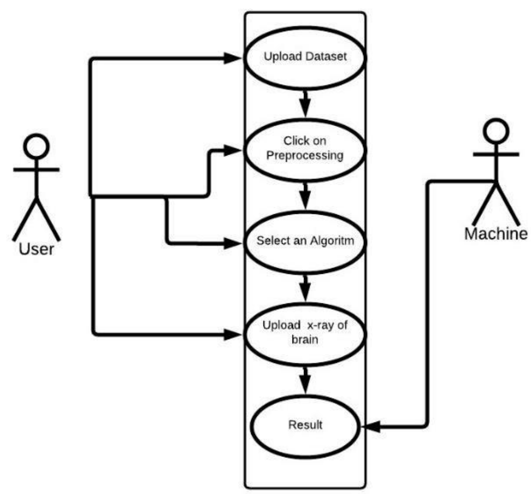

Figure 5: Uses Case Diagram

Activity Diagram:

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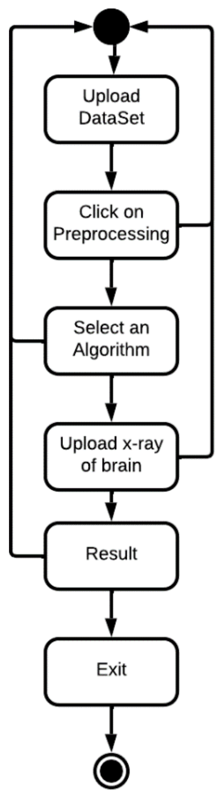

Figure 6: Activity Diagram

7.PSEUDO CODE:

1. Import the necessary libraries (eg tkinter, cv2, numpy,keras, etc.)

2. Create a main tkinter window with appropriatedimensions and title.

3. Define global variables for filename, classifier, labels, X, Y, X_train, y_train, X_test, y_test, vgg16_model.

4. Create functions for different functions:

uploadDatafile()
- Open the file window to select the folder for the dataset.
- Save the selected folder in the "filename" variable.
- Show the path of the selected folder in the sticker widget.
- Extract and display the tags found in the data folder.

processDataset()

- Restore empty lists of labels and images (X, Y).
- Browse the dataset folder and read each image file.
- Preprocess images by resizing them, converting them to atable and normalizing them.

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- Attach the image table to X and the corresponding title toY.
- Mix and split datasets into training and testing.
- Show a summary of datasets.

trainVGG16()

- Load the VGG16 model with previously learned weights.
- Freezes previously learned layers and adds new layers forclassification.
- Build a model with a suitable optimizer and loss function.
- Train the model on the training dataset using the validationset and model checkpoints.
- Estimate the model from the test dataset.
- Calculate and display precision, accuracy, recall and F-scores.
- Display confusion matrix using seaborn and matplotlib.
-

trainVGG19()

- Load the VGG19 model with previously learnedweights.
- Freezes previously learned layers and adds new layersfor classification.
- Build a model with a suitable optimizer and loss function.
- Train the model on the training dataset using thevalidation set and model checkpoints.
- Estimate the model from the test dataset.
- Calculate and display precision, accuracy, recall and F-scores.
- Display confusion matrix with seaborn and matplotlib.

diagram ()

- Download training history for VGG16 and VGG19models.
- Graph and display the training accuracy of both modelsby epoch.

predict tumor ()

- Open the file window to select a test image.
- Read and preprocess the image.
- Predict tumor grade with a trained VGG19 model.

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- Show image with predicted tumor grade.

Closed ()

- Close the main tkinter window.

5. Create and customize tkinter widgets (stickers,buttons, text box) in the main window.
6. Configure button event handlers to perform the appropriate actions.
7. Set the background color of the main window and run the tkinter main event loop.

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8.Testing

	Description	**Expected Result**	**Actual Result**	**Status**
	Testing trained model with Brain MRI image of .mp4 type	Alzheimer	Error	Fail
	Testing trained model with normal Brain image	Normal	Normal	Pass
	Testing trained model with Brain MRI image	Alzheimer	Alzheimer	Pass
	Testing trained model with normal Brain image	Normal	Normal	Pass
	Testing trained model with normal of .pdf type	Normal	Error	Fail
	Testing trained model with Brain	Alzheimer	Alzheimer	Pass

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	MRI image			
	Testing trained model with normal Brain image	Normal	Normal	Pass
	Testing trained model with Brain MRI image	Alzheimer	Alzheimer	Pass
	Testing trained model with Brain MRI image	Alzheimer	Alzheimer	Pass

9.EXECUTION

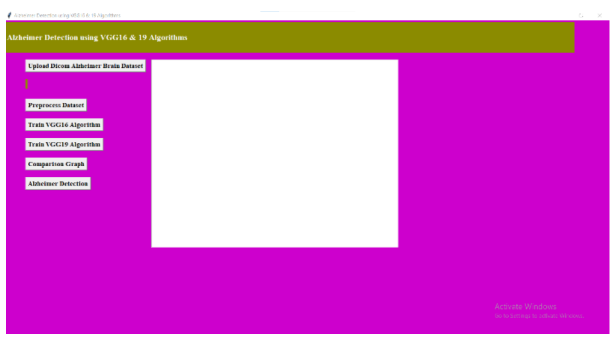

Figure 7: Home Page

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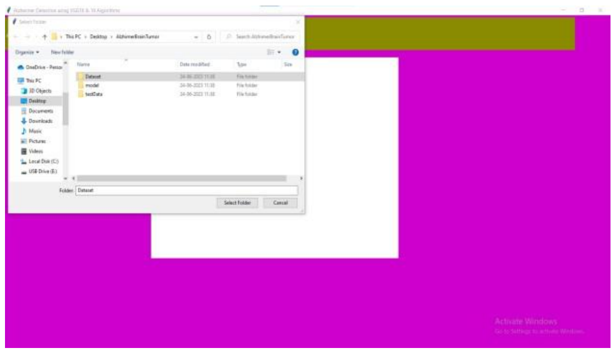

Figure 8: Upload Dataset

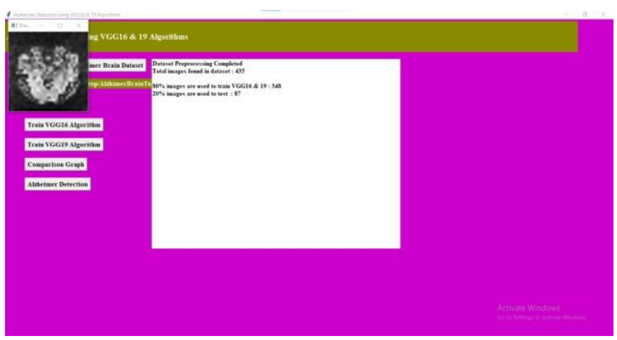

Figure 9: Preprocess Dataset

Figure 10: VGG16 Algorithm

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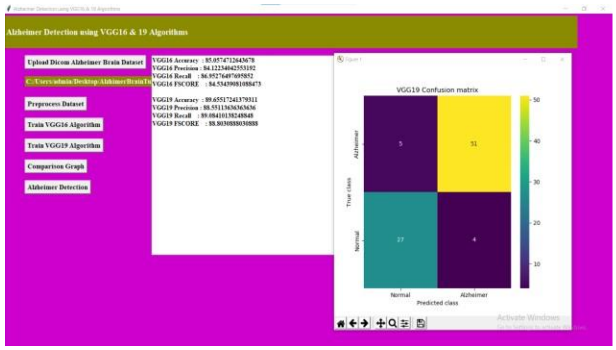

Figure 11: VGG19 Algorithm

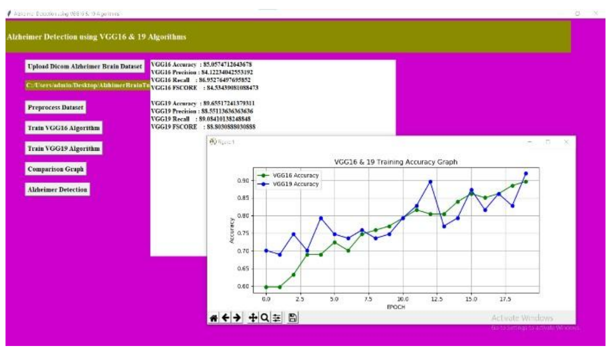

Figure 12: Comparison Graph

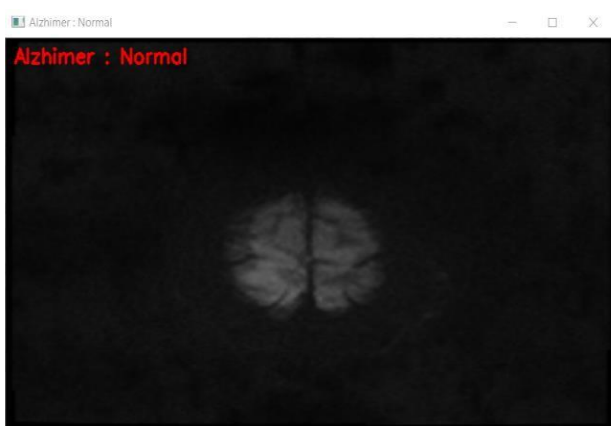

Figure 13: Alzheimer

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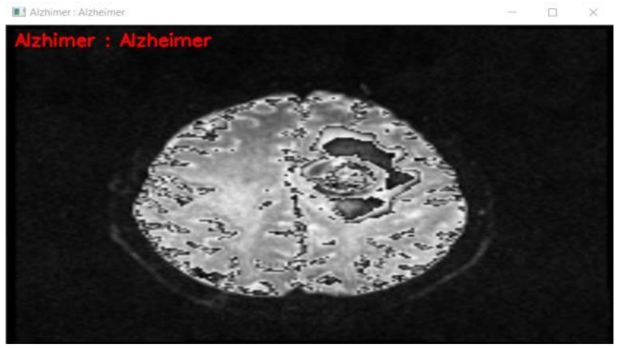

Figure 14: Normal

CONCLUSION

The deep learning model is accurate, with an area under the curve (AUC) of 85.12, when distinguishing between cognitively normal subjects and subjects with either MCI or mild Alzheimer's disease dementia. In the more difficult task of detecting MCI, it reaches an AUC of 62.45. It is also significantly faster than the volume/thickness model, where volumes and thickness must be extracted beforehand. The model can also be used to predict progression: according to the model, subjects with mild cognitive impairment progressed to dementia more quickly over time. An analysis of the features learned from the proposed model shows that it is based on several domains related to Alzheimer's disease. These findings suggest that deep neural networks can automatically learn to recognize image biomarkers that predict Alzheimer's disease and use them to achieve accurate early detection of the disease.

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