A project report on

Early Detection of Alzheimer's Diseases Using Convolutional Neural Network

Submitted in partial fulfillment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

In

ELECTRONICS AND COMMUNICATION ENGINEERING

By

CH. HARI SIVA KRISHNA	**20A81A0476**
L. LAKSHMI SAILAJA	**20A81A0497**
M. SRIVALLI DEVASENA	**20A81A04A0**
K. SUJITHA	**20A81A0486**
M. P.RAM MADHUKAR	**20A81A04A5**
S. NAGASAI VEERA VENKATA RATNAM	**20A81A04B8**

Under the guidance of

Dr. M.Thamarai, M.E.,Ph.D

Professor

Department of ECE

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

SRI VASAVI ENGINEERING COLLEGE

(Affiliated to JNTUK, Kakinada, Accredited by NBA and NAAC-A)

Pedatadepalli,Tadepalligudem-534101**,**AndhraPradesh**(2020–2024)**

SRI VASAVI ENGINEERING COLLEGE

DEPARTMENTOF

ELECTRONICS AND COMMUNICATION ENGINEERING

CERTIFICATE

This is to certify that the project report entitled **“Early Detection of Alzheimer's Diseases Using Convolutional Neural Network”** is submitted by **K. SUJITHA (20A81A0486), L.LAKSHMI SAILAJA (20A81A0497), M.SRIVALLI DEVASENA (20A81A04A0), CH. HARI SIVA KRISHNA (20A81A0476), M.P.RAM MADHUKAR (20A81A04A5), S.NAGASAI VEERA VENKATA RATNAM (20A81A04B8)** in partial fulfillment of the requirements for the award of the Degree of **Bachelor of Technology** in **Electronics and Communication Engineering**, from **Sri Vasavi Engineering College**, Tadepalligudem affiliated to **JNTUK**, Accredited by **NBA** and **NAAC** with “**A”** grade, is a record of bonafide work carried out by them under my guidance and supervision

.

PROJECT GUIDE	**HEAD OF THE DEPARTMENT**
Dr. M. Thamarai,,	Dr. E. Kusuma Kumari,
M.E., Ph.D, Professor	M.Tech, Ph.D , Professor & HOD

EXTERNAL EXAMINER

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Project Associates

K. SUJITHA	**20A81A0486**
L. LAKSHMI SAILAJA	**20A81A0497**
M.SRIVALLI DEVASENA	**20A81A04A0**
CH. HARI SIVA KRISHNA	**20A81A0476**
M. P.RAM MADHUKAR	**20A81A04A6**
S. NAGASAI VEERA VENKATARATNAM	**20A81A04B8**

DECLARATION

We hereby declare that the project entitled **"Early Detection of Alzheimer's Diseases Using Convolutional Neural Network"** is submitted in partial fulfillment of the requirements for the award of **BACHELOR OF TECHNOLOGY in Electronics and Communication Engineering** under the esteemed supervision of **Dr. M.Thamarai, M.E., Ph.D, Professor, Departmentof ECE**. This is record of work carried out by us and results embodied in this project report have not been submitted to any other university for the award of any degree.

Project associates

K. SUJITHA	**20A81A0486**
L. LAKSHMI SAILAJA	**20A81A0497**
M.SRIVALLI DEVASENA	**20A81A04A0**
CH.HARI SIVA KRISHNA	**20A81A0476**
M. P.RAM MADHUKAR	**20A81A04A5**
S. NAGASAI VEERA VENKATA RATNAM	**20A81A04B8**

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ABSTRACT

Alzheimer‟s disease (AD) is a progressive neurological condition characterized by the gradual deterioration of memory and cognitive functions, with no definitive cure currently available. Early detection is crucial for ensuring patients receive appropriate care. Numerous studies have utilized statistical and deep learning techniques to diagnose AD. In recent times, deep learning, particularly Convolutional Neural Networks (CNNs), has gained traction for early AD detection. However, many existing CNN models, often employed through transfer learning, exhibit high computational complexity and large memory footprints. This project proposes an efficient CNN model for early AD detection, aiming to reduce computational complexity and memory footprint. The model is designed to predict AD across four categories: mild dementia, very mild dementia, nondementia, and moderate dementia. The proposed model's performance is compared against established pre-trained models to assess its efficiency in terms of classification accuracy and memory size. Specifically, our model achieves an accuracy of 98.77%, surpassing the accuracies of existing pre-trained models, including InceptionV3, VGG16, and ResNet50, by approximately 57.81%, 48.89%, and 48.74%, respectively. Also the proposed model significantly reduced the memory requirements to 8.09MB, when compared to InceptionV3 (83.17MB), VGG16 (56.13MB), and ResNet50 (89.98MB). This comparison shows the efficacy of our proposed model in improving accuracy for early AD detection while addressing concerns regarding classification accuracy and memory usage.

CHAPTER -1
INTRODUCTION

Alzheimer‟s disease (AD) is a chronic neurodegenerative disease. It is the major cause of dementia, which is a more general term that defines a group of symptoms that affect cognitive tasks, such as memory, thinking, and behavior. In 2018, it was estimated that over 50 million people worldwide were living with dementia, and this number is expected to reach 152 million by 2050. 1 in 85 people worldwide will suffer from AD. The application of machine learning techniques in AD diagnosis has given promising results and currently is a hot topic of research, aided by publicly available data from websites like Alzheimer‟s Disease Neuroimaging Initiative (ADNI), Australian Imaging Biomarker & Lifestyle Flagship Study of Ageing (AIBL) and Open Access Series of Imaging Studies (OASIS). Before progressing to the full-blown AD stage, normal control (NC) subjects experience mild cognitive decline which includes problems with memory, language, judgment, and thinking. This onset of cognitive decline is termed as Mild Cognitive Impairment (MCI). MCI patients have a high chance of advancing to AD with an estimated annual conversion rate of rate 15%. The average life expectancy after AD diagnosis is 3-9 years, as currently, there is no cure for AD.
more neurons die, additional parts of the brain are affected and begin to shrink. By the final stage of Alzheimer‟s, damage is widespread, and brain tissue has shrunk significantly. Alzheimer's disease is a progressive neurodegenerative disorder that primarily affects the brain, leading to a gradual decline in cognitive functions such as memory, thinking, and reasoning. It is the most common cause of dementia in older adults and is characterized by the accumulation of abnormal deposits in the brain, including beta-amyloid plaques and tau tangles. These deposits interfere with communication between brain cells and cause cell death, resulting in the characteristic symptoms of Alzheimer's disease.

1.1 Need for Early Detection of Alzheimer's Diseases

Alzheimer's disease is the leading cause of dementia. However, neither Alzheimer‟s disease nor Alzheimer‟s dementia are an inevitable consequence of aging. This review provides an overview of the issues involved in a diagnosis of Alzheimer‟s disease before an individual meets the criteria for Alzheimer‟s dementia. It examines how Alzheimer‟s disease diagnosis rates can be improved, the implications of an early diagnosis for the individual, carer, and society, and the importance of risk reduction to prevent or delay progression. Although no disease-modifying agents capable of reversing the initial pathological changes are currently available, it may be possible to prevent or delay the development of dementia in a proportion of the population by modifying exposure to common risk factors. In other individuals, diagnosing the disease or risk of disease early is still valuable so that the individual and their carers have time to make choices and plan for the future, and to allow access to treatments that can help manage symptoms. Primary healthcare professionals play a pivotal role in recognizing individuals at risk, recommending lifestyle changes in mid-adult life that can prevent or slow down the disease, and in timely diagnosis. Early intervention is the optimal strategy because the patient‟s level of function is preserved for longer.

1.2 Key points about Alzheimer's disease

1. Symptoms: Alzheimer's disease typically begins with mild memory problems and confusion and gradually progresses to more severe cognitive impairment. Common symptoms include forgetfulness, difficulty completing familiar tasks, language problems, disorientation, poor judgment, and personality changes.

2. Stages: Alzheimer's disease is often categorized into three main stages - mild, moderate, and severe. In the mild stage, symptoms are relatively subtle, while in the severe stage, individuals may lose the ability to communicate and perform basic self-care tasks.

3. Risk Factors: Age is the most significant risk factor for Alzheimer's disease, with the risk increasing as people get older. Other risk factors include genetics (a family history of the disease), certain genes (e.g., ApoE4), cardiovascular factors (e.g., high blood pressure, diabetes), and lifestyle factors (e.g., lack of physical activity, poor diet, smoking).

4. Diagnosis: Alzheimer's disease is diagnosed through a combination of medical history, cognitive assessments, neurological exams, and sometimes brain imaging or cerebrospinal fluid analysis to rule out other conditions. A definitive diagnosis can only be confirmed through a post-mortem examination of the brain tissue.

5. Treatment: Currently, there is no cure for Alzheimer's disease, but there are treatments and interventions that can help manage symptoms and improve the quality of life for affected individuals. These may include medications to temporarily alleviate cognitive and behavioral symptoms, as well as non-pharmacological approaches such as cognitive rehabilitation, occupational therapy, and support for caregivers.

6. Research: Ongoing research is focused on understanding the underlying causes of Alzheimer's disease and developing effective treatments or preventive strategies. Some promising areas of research include investigating the role of inflammation, genetics, and lifestyle factors in the development of the disease. Alzheimer's disease is a devastating condition that not only affects individuals but also places a significant burden on their families and caregivers. Early diagnosis and appropriate management can help individuals with Alzheimer's disease maintain a better quality of life for as long as possible. It's essential to seek medical advice if you or a loved one is experiencing symptoms of cognitive decline. The difference between a Healthy brain and a Severe Alzheimer‟s brain is shown in Fig 1.1 and the MRI images of a healthy and Alzheimer‟s brain are shown in Fg 1.2 and Fig 1.3.

Fig 1.1. Difference between Healthy and Alzheimer‟s brain

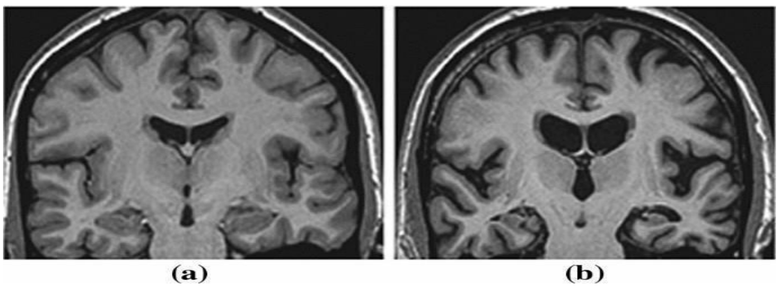


Fig 1.2. MRI Image of Healthy Brain Fig 1.3. MRI Image of Alzheimer‟s Brain

Therefore, having an accurate computer-aided system for early AD detection would significantly contribute to preventive treatment. Generally, diagnosis of this disease requires a series of examinations: cognitive tests, blood tests, behavior assessments, brain imaging, and medical history analysis. This increases the diagnosis cost and time. As a result, a more efficient and cost-effective diagnostic system is crucial. Deep learning helps to process and analyze various types of data, such as brain images (MRI, PET scans), genetic data, and clinical data, to aid in early diagnosis and disease progression monitoring. In this proposed work we have designed an efficient CNN architecture and model to predict Alzheimer‟s Disease along with that we tested the model performance by comparing pre-trained models such as InceptionV3, VGG16, and ResNet50.

1.3 Deep Learning

Deep learning is a subset of machine learning where artificial neural networks, inspired by the structure and function of the human brain, learn to perform tasks by analyzing vast amounts of data. It's used for tasks like image and speech recognition, natural language processing, and more. Deep learning excels in finding patterns and features in data that are difficult for humans or traditional machine learning algorithms to extract.

1.4 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are analogous to traditional ANNs in that they are comprised of neurons that self-optimize through learning. Each neuron will still receive an input and operate (such as a scalar product followed by a non-linear function) - the basis of countless ANNs. From the input raw image vectors to the final output of the class score, the entire network will still express a single perceptive score function (the weight). The last layer will contain loss functions associated with the classes, and all of the regular tips and tricks developed for traditional ANNs still apply., CNNs primarily focus on the basis that the input will be comprised of images. This focuses on the architecture to be set up in a way that best suits the need for dealing with the specific type of data.

CNNs are comprised of three types of layers. These are convolutional layers, pooling layers, and fully-connected layers. When these layers are stacked, a CNN architecture has been formed. The convolutional layer will determine the output of neurons that are connected to local regions of the input through the calculation of the scalar product between their weights and the region connected to the input volume. The rectified linear unit (commonly shortened to ReLu) aims to apply an "elementwise" activation function such as sigmoid to the output of the activation produced by the previous layer. The pooling layer will then simply perform down-sampling along the spatial dimensionality of the given input, further reducing the number of parameters within that activation. The fully-connected layers will then perform the same duties found in standard ANNs and attempt to produce class scores from the activations, to be used for classification. It is also suggested that ReLu may be used between these layers, as to improve performance. Through this simple method of transformation, CNNs can transform the original input layer by layer using convolutional and down-sampling techniques to produce class scores for classification and regression purposes. Convolutional Neural Networks differ from other forms of Artificial Neural Networks in that instead of focusing on the entirety of the problem domain, knowledge about the specific type of input is exploited. This in turn allows for a much simpler network architecture to be set up.

The proposed project work describes the Early Detection of Alzheimer's Diseases Using Convolutional Neural Networks. And tested the model performance by comparing pre-trained models such as InceptionV3, VGG16, and ResNet50. The project report is organized as follows. The literature survey is presented in Chapter 2. In Chapter 3, the proposed work methodology is discussed. Chapter 4, describes the pre-trained models. Chapter 5 describes various machine learning libraries and software tools used in the project work. The results are discussed in Chapter 6. The conclusion is presented in Chapter 7.

CHAPTER – 2
LITERATURE SURVEY

2.1 Study of Related Papers

The following research papers are studied in detail to understand the proposed recommendation technique and experimental result for predicting the output.
Here we have gathered several periodicals that have researched our connected work, which is based on the rice plant, and we have separately summarized each work as shown below.

A. Gamal, M. Elattar, and S. Selim [1] proposed a content-based image retrieval system that relies on 3D Capsules Network (CapsNets), a 3D CNN, and a pre-trained 3D auto- encoder technology to detect AD at its initial stages. They used SVM with kernels that allowed for the switching of amnestic MCI to AD while removing the other subtypes of the prodromal phase of AD. This paper also discusses several potential future directions for AD detection using deep learning algorithms, including the use of multimodal data, transfer learning, and the prediction of disease progression and treatment response. An end-to-end system to recognize the three AD stages using four classification tasks and another aim of thisstudy was to set a clear, simple, and fast preprocessing pipeline for images.

M. Fabietti et al., [2] developed a methodology that allows understanding AD via the discovery of biomarkers, for which a robust model was needed. A multimodal approach was used to label and structure the neuronal recordings, which subsequently had different features of each domain extracted from them as input for the classification models. It also introduces an ensemble mechanism that combines the top-performing models.The system is designed to improve the accuracy of Alzheimer's disease detection and aid in its early prediction. The machine learning models and fusion techniques optimize performance and the study identifies higher frequency bands as important in detecting AD in spectral analysis and validates the role of the hippo campus using spatial mode.

C. M. Chabib, L. J. Hadjileontiadis, and A. A. Shehhi, [3] introduced a new approach for the early detection of Alzheimer's Disease using MRI images, called DeepCurvMRI. The model combines curvelet transform and convolutional neural networks to improve the accuracy of AD diagnosis in its early stages. The process involves the preprocessing of MRI images, feature extraction using curvelet transform, and classification using a convolutional neural network. These results were obtained using the leave- one-group-out (LOGO) cross-validation approach. It uses MRI images to improve the diagnostic accuracy in medical centers and DeepCurvMRI efficiently identify brain regions associated with AD MRI images,serving as a fast and easy to implement the tool for assisting physicians in AD diagnosis.

Q. Dao, M. A. El-Yacoubi and A. -S. Rigaud, **[4]** proposed a new approach to detect and classify early-stage Alzheimer's patients using loop patterns in online handwriting. To cope with the lack of training data, the authors investigate several data augmentation techniques, including a variant of Generative Adversarial Networks (GANs), DoppelGANger, which is specifically tailored for time series and is suitable for synthesizing realistic online handwriting sequences. This was obtained by using DoppelGANger for data augmentation. It tackles the problem of limited data through synthetic data generation, based on the application of of Generative Adversarial Network adapted to time series, namely Doppelganger.

Al-Shoukry, T. H. Rassem and N. M. Makbol, [5] explained about MRI, PET, and SPECT can be used for non-invasive visualization of the brain's structure and function, and can help in the early detection of Alzheimer's Disease. The paper has used deep learning algorithms for AD detection, including convolutional neural networks (CNNs), Capsule Networks (CapsNets), and auto-encoders. The content-based image retrieval system relied on a 3D Capsules Network (CapsNets), i.e. a 3D CNN, and a pre-trained 3D auto-encoder technology to detect AD at its initial stages. Increasing interest in image analysis leads to improved diagnostic accuracy and Efficient, capable of identifying initial AD and capable to differentiating AD from different forms of dementia, Reliable, non-invasive, easy to implement, and inexpensive.

Ahmed et al. [6] proposed a system in the research paper is an ensemble of patch-based classifiers for diagnosing Alzheimer's disease using SMRI. The system uses simple convolutional neural networks (CNNs) ensembles as feature extractors and softmax cross-entropy as the classifier. The patch-based approach is used to overcome the scarcity of data. The final decision-making procedure is a weighted voting strategy, where each model's decision score can be considered a weighted vote. The system consists of 3 models for generating decision scores on individual patches. Here the patch generation technique used in the deep learning-based approach reduces the scarcity of training data. The ensemble technique helps to build a robust model while avoiding overfitting.

M. M. S. Fareed et al., [7] explained that ADD-Net is built from scratch using a deep CNN architecture and is designed to classify the stages of Alzheimer's Disease by decreasing parameters and calculation costs. Each block is specifically designed with many layers named ADD-block, which is used to classify Alzheimer's Disease in its early stages for all the specific classes. The SMOTETOMEK method is employed for handling dataset imbalance problems for generating new instances to balance the number of samples for each category. The Grad-CAM algorithm provides insight into CNN layers' working by visualizing class activation heat-map. The ADD-Net achieved high accuracy. In comparison state-of-the art models such as ADD-Net demonstrated superior performance in evaluation metrics like precision, recall F1-score.

H. Guo and Y. Zhang [8] proposed a system using an Improved Deep Learning Algorithm (IDLA). The methodology involves processing raw resting-state functional MRI (R-fMRI) data using the DPABI toolbox, which is based on the SPM8 program and the REST (Resting- State fMRI Data Analysis Toolkit). The data is preprocessed by regressing out confounding factors before performing functional connectivity (FC) analysis to identify the impact of physiological artifacts. Then it involves building a network of the brain using the time-series matrix of blood level changes in each brain region. This matrix shows how different brain areas relate to a strong brain connectivity network, which accurately and effectively represents the health situation of the brain. Finally the time series data and matrices are used indifferent models of extraction and comparison easy to classify Alzheimer‟s Disease. The specialized network of autoencoders allows for efficient processing of high-dimensional data in healthcare, making it a reliable & efficient tool for AD diagnosis.

R. A. Shah, D. Lalakiya, S. Desai, Shreya and V. Patel, [9] Propoed a system includes a wearable electronic device equipped with sensors that support patients with AD and improve their lifestyles. The device enables locating the patient on the map, reminding them of medication times, and providing a button for requesting assistance in case of emergency. The system also includes a facial recognition prototype based on CNN that extracts the points of interest of the eyes, nose, and mouth for classifying the input image as a family member/ not a family member. Steganography encryption has been integrated to protect the identity of the person who is not registered in the database and hence, supporting the person with AD to recognize more people during future conversations. The proposed system also includes a psychological monitoring system through Google Assistant.

Ninon Burgos, Simona Bottani, Johann Faouzi, Elina Thibeau-Sutre, Olivier Colliot [10] They first focused on data processing, covering image reconstruction, signal enhancement and cross-modality image synthesis and on the biomarkers that can be extracted from spatio-temporal neuroimaging data, such as the volume of normal structures or of lesions. They describe how DL can be used to detect diseases, predict their evolution, improve their understanding and help develop treatments. For those applications, they emphasize the types of architectures and data used, as well as the concerned disorders. Finally, they highlight trending applications and provide guidelines to bridge the gap between research studies and clinical routine. CNN have been successfully applied to imaging and genetic data in numerous brain disorders. RNN showed encouraging results with longitudinal clinical data and sensor data.

F. U. R. Faisal and G. -R. Kwon, [11] system included a wearable electronic device equipped with sensors that support patients with AD and improve their lifestyles. The device enables locating the patient on the map, reminding them of medication times, and providing a button for requesting assistance in case of emergency. The system also includes a facial recognition prototype based on CNN that extracts the points of interest of the eyes, nose, and mouth for classifying the input image as a family member/not a family member. Steganography encryption has been integrated to protect the identity of the person who is not registered in the database and hence, supporting the person with AD to recognize more peopleduring future conversations. The proposed system also includes psychological monitoring system through Google Assistant.

Sina Fathi, Ali Ahmadi, Afsaneh Dehnad, et al. [12] present a deep learning-based ensemble method for early diagnosis of Alzheimer's disease using MRI images. The main objective of this study is to address the growing prevalence of Alzheimer's disease and its associated costs. The proposed approach combines multiple deep learning models to improve the accuracy of early diagnosis of Alzheimer's disease. The methodology used in this study involves preprocessing the MRI images, training multiple deep learning models, and combining them using a weighted probabilistic ensemble method. The proposed ensemble approach was selected and evaluated using a large dataset of MRI images from multiple sources. Overall, this study provides a promising approach for improving the accuracy of early diagnosis of Alzheimer's disease using deep learning-based ensemble methods. it also provides precious information to the researcher to diagnosis the other type of disease and high success achieved in analysis and image classification.

Zouaoui, Brik, Attallah, Djeriuoi, and Belkhelfa (2022) [13] present a novel approach for diagnosing Alzheimer‟s disease (AD) utilizing transfer learning with MRI images. Their work, presented at the 2022 International Conference of Advanced Technology in Electronic and Electrical Engineering (ICATEEE), focuses on leveraging pre-trained neural network models to extract relevant features from MRI scans. By adopting transfer learning, the authors aim to enhance the accuracy and efficiency of AD diagnosis, which is critical for early detection and intervention. Their method likely involves utilizing knowledge gained from solving related tasks to improve the classification performance of AD diagnosis. The paper likely discusses the methodology, experimental setup, results, and conclusions drawn from applying transfer learning to AD diagnosis using MRI images. Overall, their work contributes to the advancement of diagnostic techniques for AD and holds promise for improving patient outcomes through early detection and treatment.

Shastry KA, Vijayakumar V, V MKM, B A M, B N C. [14] They covered a various approaches used for predicting Alzheimer's Disease, including supervised and unsupervised learning, and discusses the challenges associated with using deep learning for Alzheimer's Disease prediction. The article also provides a detailed analysis of the most promising deep learning techniques for predicting Alzheimer's Disease, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and autoencoders. It discusses the accuracy of these techniques in predicting the onset of Alzheimer's Disease and highlights the importance of using multimodal data for improving prediction accuracy. Overall, this article provides valuable insights into the latest advancements in deep learning techniques for predicting Alzheimer's Disease and offers a detailed analysis of the various approaches used for predicting Alzheimer's Disease.

In conclusion, considering the various aspects such as memory space, time efficiency, accuracy, computational requirements, and trainable parameters, it is essential to evaluate the proposed model against these existing approaches. By leveraging the strengths and insights gained from the literature survey, the proposed model aims to surpass the benchmarks set by previous studies, offering a comprehensive solution for AD detection with superior performance metrics across multiple dimensions.

CHAPTER – 3
METHODOLOGY

3.1. CNN

The name “convolutional neural network” indicates that the network employs a mathematical operation called convolution. Convolutional networks are a specialized type of neural networks that use convolution in place of general matrix multiplication in at least one of their layers. A convolutional neural network consists of an input layer, hidden layers and an outputlayer. Inany feed-forward neural network, any middle layers are called hidden because their inputs and outputs are masked by the activation function and final convolution. In a convolutional neural network, the hidden layers include layers that perform convolutions. Typically this includes a layer that performs a dot product of the convolution kernel with the layer‟s input matrix. As the convolution kernel slides along the input matrix for the layer, the convolution operation generates a feature map, which in turn contributes to the input of the next layer. This is followed by other layers such as pooling layers, fully connected layers, and normalization layers. Figure 3.1 shows typical convolutional neural network . Last layer predicts the output.

The number of neurons in output layer depends upon numbers of classes.

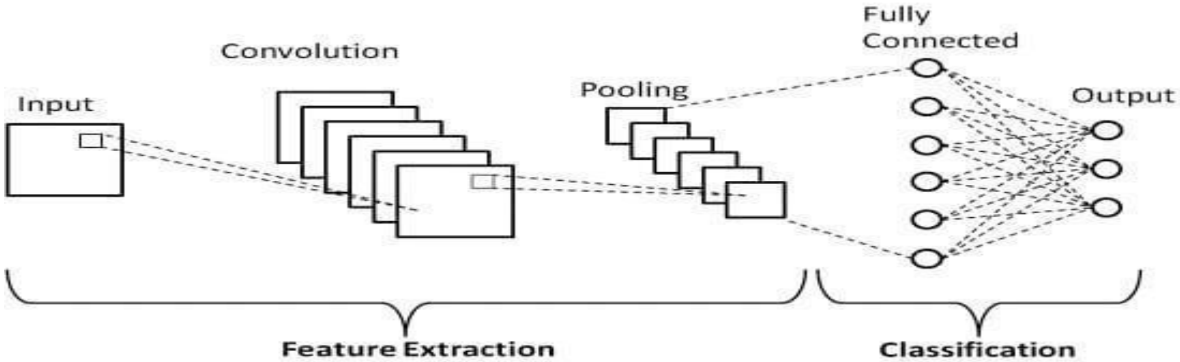


Fig 3.1 Architecture of Convolution Neural Network

3.1.1. Convolutional Layer -The Kernel

The element involved in carrying out the convolution operation in the first part of a

Convolutional Layer is called the Kernel/Filter, K. The Kernel shifts 9 times because of Stride Length = 1 (Non-strided), every time performing a matrix multiplication operation between Kand the portion P of the image over which the kernel is hovering. The filter moves to the right with a certain Stride Value till it parses the complete width. Moving on, it hops down to the beginning (left) of the image with the same Stride Value and repeats the process until the entire image is traversed. The objective of the Convolution Operation is to extract the high-level features such as edges, from the input image.

3.1.2. Pooling Layer

Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature. This is to decrease the computational power required to process the data through dimensionality reduction. Furthermore, it is useful for extracting dominant features which are rotational and positional invariant, thus maintaining the process of effective training of the model. Max Pooling returns the maximum value from the portion of the image covered by the Kernel.

3.1.3. Fully Connected Layer

A fully connected layer in a neural network, also known as a dense layer, is one where each neuron in the layer is connected to every neuron in the preceding layer. In this type of layer, each neuron receives input from every neuron in the previous layer and produces a single output, which is then fed into the next layer. This type of connectivity allows for complex relationships to be learned between features in the input data. Figure3.2 shows fully connected internal working.

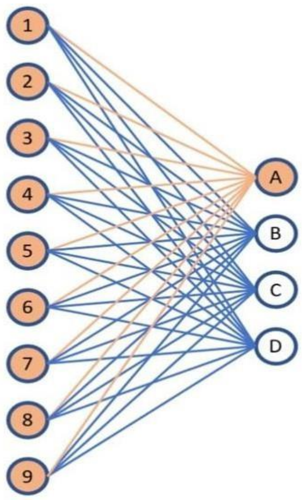


Fig3.2 Fully Connected Internal Working

3.2. Role of MRI :

MRI (Magnetic Resonance Imaging) is widely used in the detection and diagnosis of Alzheimer's disease.

It helps by:

Structural Imaging: MRI can detect structural changes in the brain associated with Alzheimer's, such as shrinkage of the hippocampus and other regions affected by the disease.

Visualization of Brain Abnormalities: MRI can reveal abnormalities like amyloid plaques and neurofibrillary tangles, which are hallmarks of Alzheimer's disease, although these may not be visible at early stages.

Tracking Disease Progression: Serial MRI scans over time can track changes in the brain's structure, providing insights into disease progression and response to treatment.

Differential Diagnosis: MRI can help distinguish Alzheimer's disease from other forms of dementia or neurological disorders by identifying specific patterns of brain atrophy or pathology.

Research and Clinical Trials: MRI is essential in research studies and clinical trials aimed at understanding the underlying mechanisms of Alzheimer's disease and testing potential therapies. Overall, MRI plays a crucial role in the early detection, differential diagnosis, monitoring, and research of Alzheimer's disease. However, it's often used in combination with other diagnostic tools, such as cognitive and biomarker tests, for a more comprehensive evaluation.

3.3. Dataflow Diagram:

Input Data is where brain imaging data, such as MRI scans or PET scans, would be fed into the CNN model. Preprocessing Stage involves steps like normalization, resizing, and possibly augmentation to prepare the input data for the CNN. Feature Extraction layers within the CNN extract relevant features from the preprocessed data. In the case of Alzheimer's disease detection, the Features could be patterns indicative of brain Classification Layers follows feature extraction, the model's architecture includes layers responsible for classifying the input data into categories such as "Alzheimer's positive" or "Alzheimer's negative.". The final output of the CNN model would be the predicted diagnosis or classification of the input brain imaging data.

The data flow diagram visualizes how data moves through these stages, illustrating the transformations and computations to occur within the CNN model to arrive at its predictions. The below figure 3.3 is the data flow diagram for Alzheimer‟s disease detection.

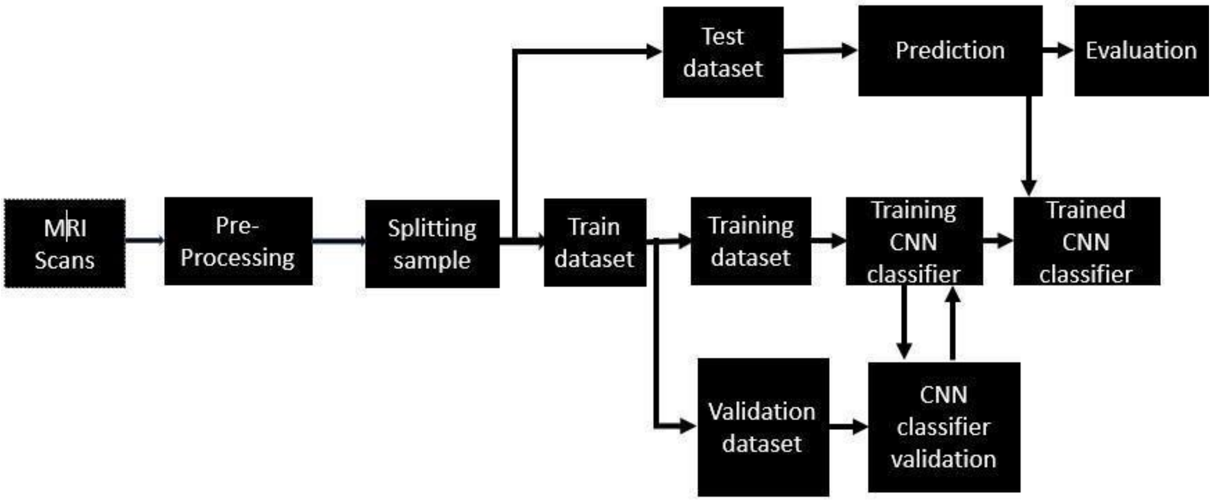


Fig 3.3. Dataflow diagram for Alzheimer‟s disease detection.

3.4 Mathematical Operations:

The CNN modal has the following two parts:

1. Features Learning
2. Classification

Feature Learning

Feature learning involves the techniques that are used to extract the features from input images and make the machine learn those features automatically.

Convolution Layer

The convolution layer is used for the feature extraction.

Here, dim of I=m1 x m2 x mc dim of K=n1 x n2 x nc

dim of F=(m1-n1+1) x (m2-n2+1) x 1

And, $F[i, j] = (I * K)_{[i,j]}$

The ij-th entry of the feature map is given as:

$$f[i,j] = \sum_{x}^{m_1} \sum_{y}^{m_2} \sum_{z}^{m_c} k_{[x,y,z]} I_{[i+x-1,j+y-1,z]} \quad \ldots\ldots\ldots\ldots\ldots \text{eq (1).}$$

Here,

dim = dimension of input image.
K = kernal size.
F = feature map.

Padding

The procedure described above has one drawback The applied filters focus more on the center of the image rather than its corner. It could be compensated by padding.

Activation Function

$$c = F + b$$
$$c = I * K + b \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{eq(2)}$$

$$\text{Conv}(I,K) = \phi_a(c)$$
$$= \phi_a(I * K + b) \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{eq(3)}$$
Where ϕ_a *is an activation function.*

The most commonly used activation function is ReLU which eliminates the negative values:

$$R(x) = \max(0, x) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathit{eq}(4)$$

The below figure 3.4 shows the ReLU Activation function operation and figure 3.5 shows ReLU activation function Graph.

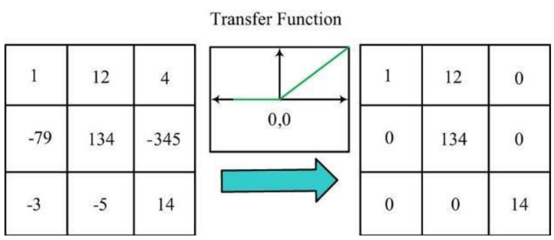


Fig 3.4. ReLU Activation Function Operation

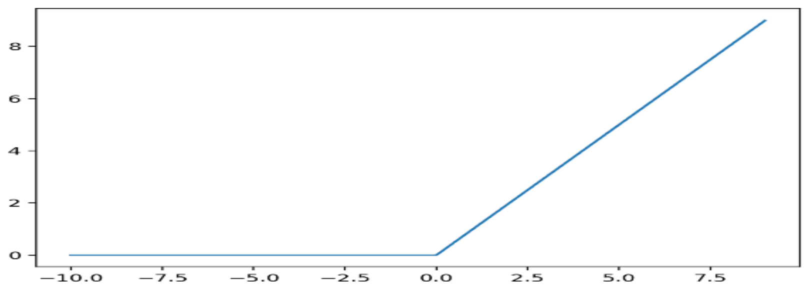


Fig 3.5. ReLU Activation Function Graph

Pooling Layer

In the pooling layer, the spatial size of convoluted features is reduced. In this way we get the dominant feature of the image. In the pooling layer, a pooling function is applied on the result obtained from the convolution layer. Let us assume that:

$$Conv(I,K) = C$$
$$P = \phi_p(C)$$
Where ϕ_p *is an pooling function* .

The dimension of the pooled part is given as :

$$\text{dim of P} = \left(\frac{m_1+2p-n_1}{s}\right) \text{ X } \left(\frac{m_2+2p-n_2}{s}\right) \text{ X } m_c \qquad \text{........eq(5).}$$

where,

m_1x m_2 = the dimensions of input image.

n_1 x n_2 = the dimesions of padding Kernal.

Here,„s" stands for stride and p stands for padding.

There are different types of pooling such as average pooling, and max pooling. An example of max pooling is given below figure 3.6.

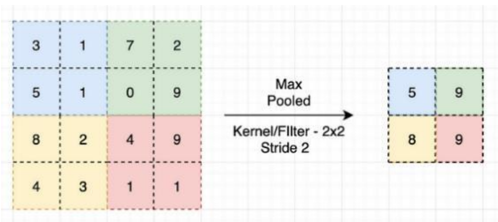


Fig 3.6. Max Pooling Operation

Classification

In this way, several hidden layers (convolutional layer + pooling layer) has been used for the feature extractions. Once the feature extraction is done, the resultant is flattened into a single vector. Now, this single vector would be used as the input for the fully connected layer where the classification is done.

Fully Connected Layer

The fully connected layer receives the flattened vector and results into another vector. In machine learning models, there is also the possibility of one class to occur higher as compared to other classes. So, to eliminate this problem the balanced weights are combined with the pooled part, a biased term has been added and then the activation function is applied.

The mathematical description is as below

$$X = \sum_i \omega_i p_i + b' \qquad \text{.......eq (7)}$$

$$z = g(X) \qquad \text{......eq (8).}$$

Where g is an activation function for fully connected layer.

In this way, on each layer the weights are added to the pooled parts and the activation function is applied. Several hidden layers are used here and the last layer would use the activation function which performs the classification by calculating the probability for each class.

Softmax Activation function

The softmax activation function transforms the raw outputs of the neural network into a vector of probabilities.

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \qquad \text{......eq (10).}$$

3.5. Architecture Of Proposed Model:

The proposed model architecture comprises several layers designed for effective feature extraction and classification in image data. Initially, the input images are rescaled to a range between 0 and 1 for normalization. Subsequently, a series of convolutional layers are applied, each followed by a max-pooling layer, which serves to extract hierarchical features while reducing spatial dimensions. Dropout regularization is then employed to prevent overfitting by randomly deactivating a portion of neurons during training.

Following the convolutional layers, the feature maps are flattened into a one-dimensional array to be fed into fully connected layers. The first dense layer consists of 128 neurons with ReLU activation, facilitating the extraction of high-level features. Finally, the output layer utilizes softmax activation to produce class probabilities, enabling multi-class classification. This architecture is well-suited for image classification tasks, leveraging convolutional operations for feature extraction and fully connected layers for classification.

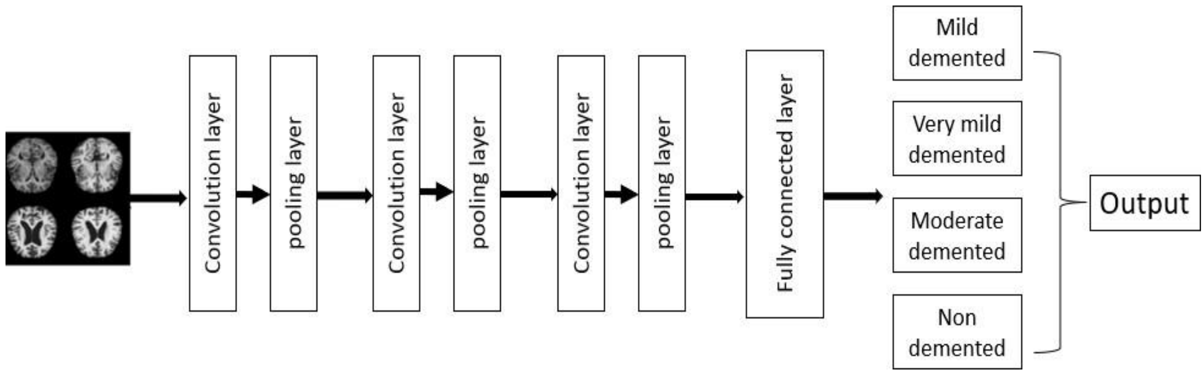


Fig.3.7. Flow chart

3.6. Algorithm Of Proposed Model:

Step 1: Loading Input Data Set from Kaggle and Adding Required Libraries

In this initial step, we source our dataset from Kaggle, a prominent platform for datasets covering various domains. This dataset serves as the foundation of our project, providing the information necessary for model training and evaluation. Additionally, we import essential libraries that facilitate data manipulation, visualization, and machine learning tasks. These libraries typically include Pandas for data manipulation, NumPy for numerical computations, Matplotlib and Seaborn for visualization, and TensorFlow or PyTorch for implementing machine learning models.

Step 2: Defining a Model

Once we have our dataset and libraries in place, we proceed to define the architecture of our machine learning model. This involves designing the structure of the neural network, specifying the number of layers, types of activation functions, and other architectural considerations. The model definition phase is crucial as it lays the groundwork for subsequent steps such as model compilation and training.

Step 3: Preprocessing the Data

Before feeding the data into our model, it is essential to preprocess it to ensure compatibility and improve model performance. This preprocessing step involves several tasks such as handling missing values, scaling numerical features to a standard range, encoding categorical variables into numerical representations, and splitting the data into training and testing sets. Preprocessing ensures that the data is in a suitable format for training and evaluation.

Step 4: Building a Model

With the model architecture defined and the data preprocessed, we proceed to build the model by compiling it. Compilation involves specifying additional parameters such as the loss function, optimizer, and metrics to monitor during training. These choices have a significant impact on the model's learning process and ultimately its performance on unseen data.

Step 5: Training the Model

Once the model is compiled, we train it using the training data. Training involves feeding the model with input data and corresponding labels, allowing it to learn patterns and relationships within the data. During training, the model adjusts its parameters iteratively to minimize the specified loss function, thereby improving its ability to make accurate predictions. Training is typically performed over multiple epochs, with the training data being repeatedly presented to the model.

Step 6: Test Output Prediction

After training the model, we evaluate its performance by making predictions on the test data. The model's predictions are compared against the ground truth labels to assess its accuracy and generalization capability. This step provides insights into how well the model performson unseen data and helps identify any potential issues such as overfitting or underfitting.

Step 7: Classification Results and Report

Finally, we analyse the classification results obtained from the model predictions. This involves generating various metrics such as precision, recall, and F1-score to assess the model's performance across different classes. Additionally, we may visualize the results usingtools such as confusion matrices to gain a deeper understanding of the model's strengths and weaknesses. The classification report summarizes these findings, providing valuable insights into the model's overall performance and areas for improvement.

The proposed model performance is compared with pretrained model such as Inception v3, VGG16, ResNet50. We have implemented the pretrained models also , that are explained in chapter 4.

CHAPTER-4
PRETRAINED MODELS

In this chapter we are dicuss about implementation of Pre - trained models

4.1 Transfer Learning Concept

Pretrained models in deep learning can be highly beneficial for Alzheimer's disease research. Researchers can leverage pre-trained models, such as convolutional neural networks (CNNs) trained on large image datasets like ImageNet, and then fine-tune them on Alzheimer's disease-specific data. This approach helps in two main ways:

Transfer Learning: Pretrained models capture generic features from vast datasets. By fine-tuning these models on Alzheimer's disease images or other relevant data, researchers can adapt the model's learned features to the specific characteristics of Alzheimer's disease, potentially improving performance with less labeled data.

Reduced Training Time and Data Requirement: Training deep learning models from scratch requires large amounts of labeled data and computational resources. By starting with pretrained models, researchers can significantly reduce the amount of data and time needed for training, accelerating the research process.

Furthermore, pretrained models can be used for various tasks related to Alzheimer's disease research, such as image classification, segmentation, and even predicting disease progression or treatment response from medical imaging data. Overall, leveraging pretrained models can enhance the efficiency and effectiveness of deep learning research in Alzheimer's disease detection, diagnosis, and understanding.

4.2 Pre-Trained models:

4.2.1. Inception v3:

Inception v3 is a convolutional neural network architecture used for image classification tasks. It was developed by Google Research as part of the Inception family of models.

Inception v3 is known for its efficiency in terms of computational resources and its performance on various image recognition benchmarks.

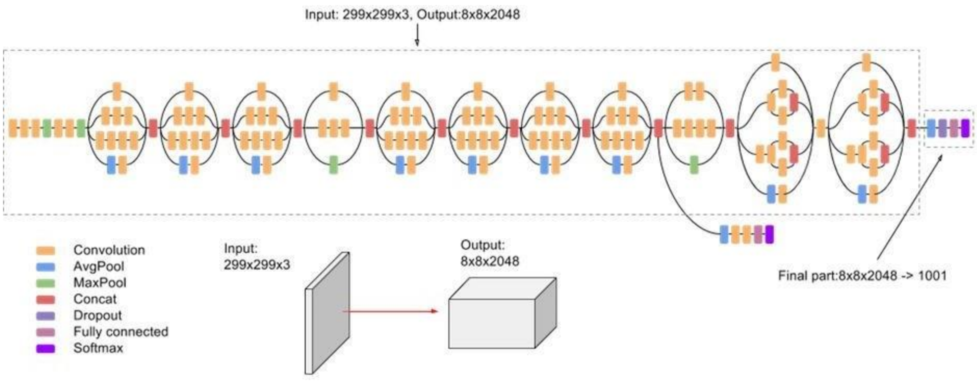


Fig 4.1. Architecture of Inception V3

The above figure 4.1 represents InceptionV3 is a deep CNN architecture known for its ability to extract features from images. It uses inception modules with parallel convolutional branches of different sizes to capture features at various scales. Pre-trained on datasets like ImageNet, it's fine-tuned for Alzheimer's detection, adapting to MRI or PET scans. Its auxiliary classifiers aid training, and a final classification layer outputs probabilities for Alzheimer's presence. It's effective for early detection by identifying subtle patterns in medical images.

4.2.2. VGG16:

VGG-16 is a convolutional neural network architecture proposed by the Visual Geometry Group (VGG) at the University of Oxford. It consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. VGG-16 is known for its simplicity and uniform architecture, with 3x3 convolutional filters and max-pooling layers used throughout the network. It has been widely used as a base model for various computer vision tasks, including image classification and object detection.

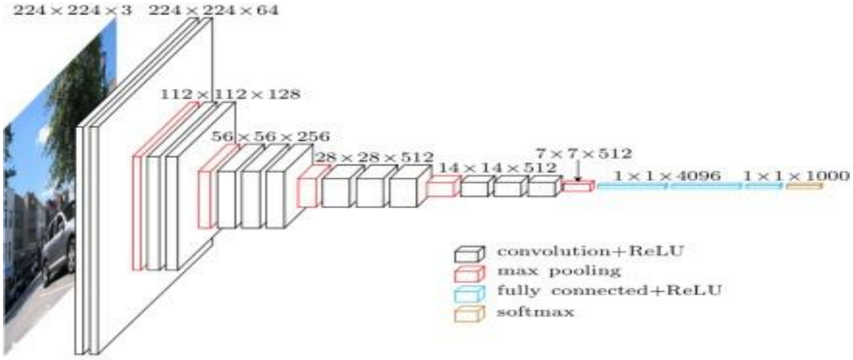


Fig 4.2. Architecture of VGG16

The above figure 4.2 represents VGG16 is a deep convolutional neural network consisting of 16 weight layers, including convolutional and fully connected layers. It's effective for image classification tasks, including Alzheimer's disease detection. By fine-tuning VGG16 on brain image data, it can learn to detect patterns associated with Alzheimer's disease, making it suitable for early detection.

4.2.3. ResNet50:

ResNet50 is part of the ResNet (Residual Network) family of neural network architectures, introduced by Microsoft Research in 2015. It's known for its deep structure, which allows it to learn complex features from images effectively. The "50" in its name refers to the number of layers it has. ResNet50 has been widely used and adapted in both research and practical applications due to its performance and efficiency. It's often used as a pre-trained model for transfer learning, where it's fine-tuned on specific datasets for tasks like image recognition and object detection.

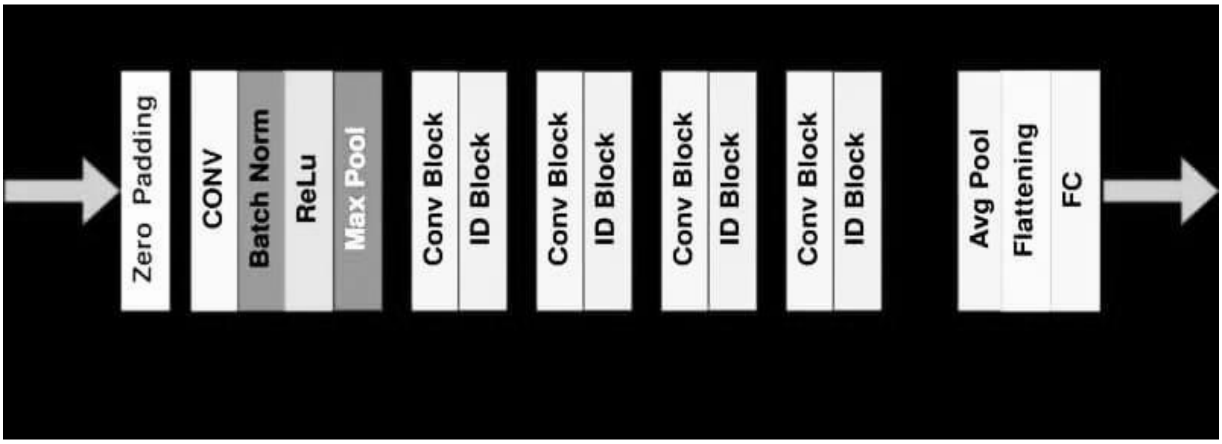


Fig 4.3 Architecture of ResNet50

The above figure 4.3 representsResNet50 is a deep convolutional neural network architecture designed for image classification tasks. It employs residual blocks with skip connections to enable training of very deep networks. With its ability to capture intricate patterns in images, ResNet50 is effective for early detection of Alzheimer's disease using brain imaging data like MRI or PET scans.

4.3 Algorithm

An Alzheimer's disease detection algorithm using Inception V3, VGG16, and ResNet50

Data Preparation: Gather and preprocess brain MRI/CT scan images, including resizing, normalization, and augmentation.

Model Selection: Choose Inception V3, VGG16, and ResNet50 as potential models based on their performance in similar tasks.

Modifying the top layer fully connected layer according to the tumor classification process.

Build and compile the model

Training: Split data into training, validation, and test sets. Train the models using the training set, validate with the validation set, and adjust hyperparameters to prevent overfitting.

Evaluation: Evaluate model performance using metrics like accuracy, precision, recall, and F1-score on the test set.

Fine-Tuning: Optionally, fine-tune the best-performing model using techniques like transfer learning or hyperparameter tuning.

Deployment: Deploy the optimized model for Alzheimer's disease detection, potentially integrating it into a user-friendly interface for practical use.

We compared the proposed model with other pre-trained models such as Inceptionv3, VGG16, and ResNet50. According to the project, we changed the last line of code in the pre- trained model.

CHAPTER 5

SOFTWARE REQUIREMENTS

In the proposed work we have implemented CNN model using Python software and libraries like Matplotlib, NumPy, Keras and TensorFlow used are discussed in this chapter.

5.1 Python:

Python is an object-oriented, high-level language, interpreted, dynamic, and multipurpose programming language.

Python is an easy to learn yet powerful and versatile scripting language which makes it attractive for Application Development.

Python's syntax and dynamic typing with its interpreted nature, make it an ideal language for scripting and rapid application development in many areas.

Python supports multiple programming pattern, including object-oriented programming, imperative and functional programming, or procedural styles.

Python is not intended to work in special areas such as web programming. That is why it is known as multipurpose because it can be used with web, enterprise, 3D CAD, etc.

We don't need to use data types to declare variables because it is dynamically typed so we can write a =10 to declare an integer value in a variable.

Python makes the development and debugging fast because there is no compilation step included in python development and edit-test-debug cycle is very fast.

5.2 Python Features

Easy to Use:

Python is easy to very easy to use and a high-level language. Thus, it is a programmer-friendly language.

Expressive Language:

Python language is more expressive. The sense of expression is the code is easily understandable.

Interpreted Language:

Python is an interpreted language i.e. interpreter executes the code line by line at a time. This makes debugging easy and thus suitable for beginners.

Free and Open Source:

Python language is freely available (www.python.org). The source code is also available. Therefore, it is open source.

5.3 Python use CNN for Alzheimer‟s detection

Python is a popular programming language that is often used in conjunction with deep learning libraries like TensorFlow and Keras to implement CNN for Alzheimer's detection. In Python, you can write code to define the architecture of the CNN model, preprocess the brain scan images, train the model using labeled data, and make predictions on new brain scans.

Using Python, you can import the necessary libraries, such as TensorFlow and Keras, to create and train the CNN model. You can define the layers of the model, including convolutional layers, pooling layers, and fully connected layers. Python provides a user-friendly syntax that allows you to easily configure the parameters of these layers, such as the filter sizes, activation functions, and strides.

Python also enables you to preprocess the brain scan images before feeding them into the CNN model. You can use libraries like NumPy and OpenCV to resize, normalize, and augment the images, enhancing the model's ability to detect Alzheimer's-related patterns.

Once the model is defined and the images are preprocessed, you can train the CNN model using a labeled dataset. Python allows you to iterate through the dataset, calculate the loss, andupdate the model's weights using optimization algorithms like stochastic gradient descent.

After the model is trained, you can utilize it to make predictions on new brain scans. Python provides functions to preprocess the new images in the same way as the training data, and then you can feed them into the trained model to obtain predictions.

Python's flexibility and extensive libraries make it a popular choice for implementing CNN for Alzheimer's detection. It allows researchers and developers to leverage the power of deep learning and easily build and train models to assist in early diagnosis.

5.4 Libraries

Matplotlib: Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python. Matplotlib makes easy things easy and hard things possible. A large number of third-party packages extend and build on matplotlib functionality, including several higher-level plotting interfaces (seaborn, HoloViews, ggplot,
...), and a projection and mapping toolkit (Cartopy).
"matplotlib" uses CNN for Alzheimer's detection. However, matplotlib is actually a popular library in Python for creating visualizations, not specifically for Alzheimer's detection.

CNNs (Convolutional Neural Networks) are commonly used in the field of deep learning for image classification tasks, such as Alzheimer's detection. While matplotlib can be used to visualize the results or performance of a CNN-based model, it is not directly involved in the training or implementation of the CNN itself.

Numpy: NumPy is a Python library used for working with arrays. It also has functions for working in domain of linear algebra, fourier transform, and matrices. NumPy was created in 2005 by Travis Oliphant. It is an open-source project and can be used freely. NumPy, which stands for Numerical Python, is a library consisting of multidimensional array objects and a collection of routines for processing those arrays. Using NumPy, mathematical and logical operations on arrays can be performed. NumPy is a Python package. Numpy is a powerful library in Python that provides support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays.

Keras: Keras is a powerful and easy-to-use free open-source Python library for developing and evaluating deep learning models. It wraps the efficient numerical computation libraries Theano and TensorFlow and allows to definition and training of neural network models in just a few lines of code. Keras is actually a high-level neural networks API that can be used with Tensorflow. It provides a user-friendly interface for building and training deep learning models, including CNNs for Alzheimer's detection.

With Keras, you can easily define and configure the layers of your CNN model. You can specify the number of convolutional layers, pooling layers, and fully connected layers, along with their respective parameters such as filter sizes, activation functions, and dropout rates.

Keras also simplifies the process of training the CNN model. You can compile the model with an optimizer, a loss function, and evaluation metrics. Then, you can fit the model to yourlabeled dataset, specifying the number of epochs and batch size for training.

Once the CNN model is trained, you can use it to make predictions on new brain scans by feeding them into the model. Keras provides simple functions to preprocess the input images and obtain the predicted probabilities or class labels.

TensorFlow: It is a free and open-source software library for machine learning and artificial intelligence. It can be used across a range of tasks but has a particular focus on training and inference of deep neural networks.

It was developed by the Google Brain team for Google's internal use in research and production. TensorFlow can be used in a wide variety of programming languages, including Python facilitating its use in a range of applications in many sectors.

Tensorflow uses CNN for Alzheimer's detection by leveraging the power of deep learning algorithms. With CNN, the framework can analyze brain scans and detect patterns that may indicate the presence of Alzheimer's disease. The CNN model is trained on a large dataset of brain images, allowing it to learn and recognize specific features associated with Alzheimer's. By feeding new brain scans into the trained model, Tensorflow can make predictions on whether a person is likely to have Alzheimer's at an early stage. It's an exciting use of technology to potentially improve early diagnosis and treatment!

CHAPTER 6
RESULTS

The proposed project work described an efficient CNN model for the early detection of AD with less computation complexity and less memory size.

This model performance will be measured using classification accuracy and computation complexity and also the performance of the proposed work will be compared with existing pre-trained models.

6.1. DATASET:

The selected dataset focuses on Alzheimer's disease and was sourced from Kaggle. Following access to the dataset on the Kaggle platform, the dataset was downloaded and its contents were extracted. Through meticulous exploration, a comprehensive understanding of the dataset's structure and contents was obtained. Leveraging the Python programming language and the panda"s library, the dataset was successfully loaded into the machine learning environment. Subsequently, essential preprocessing steps, such as data cleaning and handling missing values, were executed. Additionally, the dataset was partitioned into distinct subsets for training, validation, and testing, facilitating subsequent machine learning model training. The training subset comprises 5,123 images, while the test subset contains 1,279 images. Furthermore, both subsets are divided into four categories.

Here are the counts for each category within the training dataset:

- Mild Demented: 719 images
- Moderate Demented: 52 images
- Non-Demented: 2,560 images
- Very Mild Demented: 1,792 images

Here are the counts for each category within the test dataset:

- Mild Demented: 179 images
- Moderate Demented: 12 images
- Non-Demented: 640 images
- Very Mild Demented: 448 images

For validation, 20% of the training dataset is reserved, while the remaining 80% is utilized for training purposes. The dataset can be split using a subset function. And sample Alzheimer‟s dataset image shown in Fig 6.1

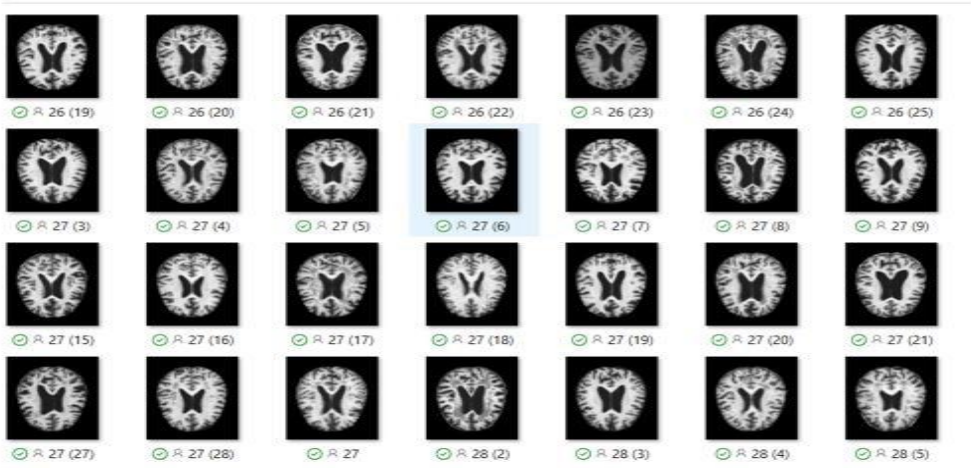


Fig 6.1. Alzheimer‟s Data Set

6.2. Parameters:

Precision: It measures the percentage of predictions made by the model that are correct.

Precision=(TP)/ (TP + FP)

Recall: It measures the percentage of relevant data points that were correctly identified by the model.

Recall=(TP)/ (TP + FN)

F1 Score: It is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model.

F1=2 ((precision x recall)/ (precision + recall))

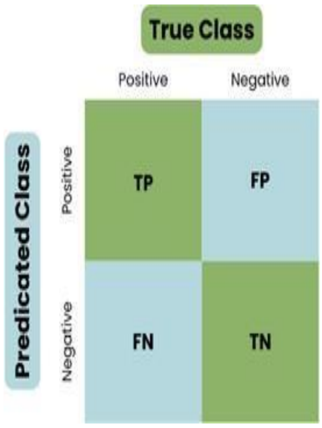
Accuracy: It is a metric that computes how many times a model made a correct prediction across the entire dataset.

Accuracy = (Correct predictions)/ (All predictions)

Confusion matrix:

It is a performance evaluation tool in machine learning, representing the accuracy of a classification model.

For 2 x 2 metrix **For 4 x 4 metrix**



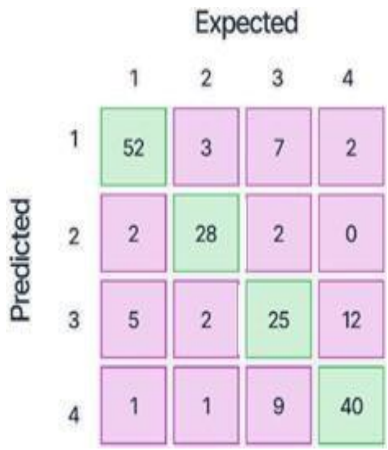


Fig 6.2 Confusion Matrix

6.3. Pre-trained model output:

6.3.1. Inception V3:

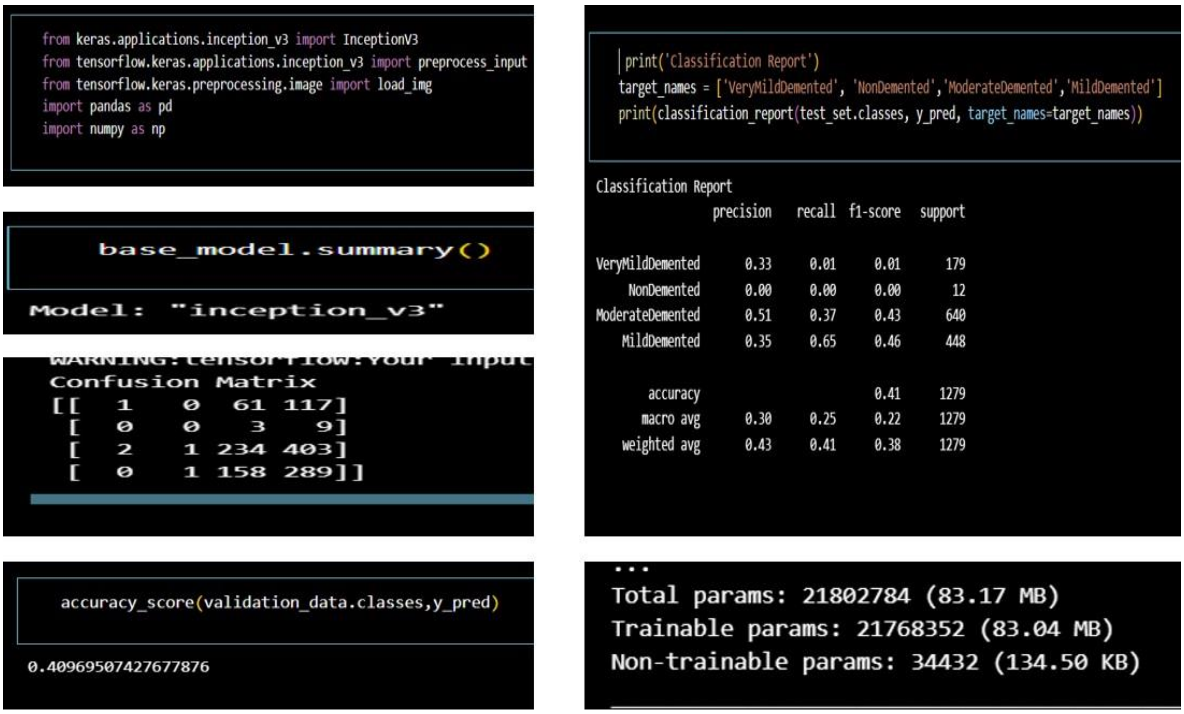


Fig 6.3 Output of Inception V3

6.3.2. VGG16:

```
import tensorflow as tf
from tensorflow.keras.applications import VGG16
from tensorflow.keras.applications.vgg16 import preprocess_input
from tensorflow.keras.preprocessing.image import load_img
import pandas as pd
import numpy as np
```

```
base_model.summary()

Model: "vgg16"
```

```
WARNING:tensorflow:Your in
Confusion Matrix
[[   2    0  175    2]
 [   0    0   12    0]
 [   3    0  628    9]
 [   5    0  435    8]]
```

```
accuracy_score(validation_data.classes,y_pred)

0.4988272087568413
```

Classification Report

	precision	recall	f1-score	support
VeryMildDemented	0.20	0.01	0.02	179
NonDemented	0.00	0.00	0.00	12
ModerateDemented	0.50	0.98	0.66	640
MildDemented	0.42	0.02	0.03	448
accuracy			0.50	1279
macro avg	0.28	0.25	0.18	1279
weighted avg	0.43	0.50	0.35	1279

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_class
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_class
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_class
  _warn_prf(average, modifier, msg_start, len(result))
```

```
...
Total params: 14714688 (56.13 MB)
Trainable params: 14714688 (56.13 MB)
Non-trainable params: 0 (0.00 Byte)
```

Fig 6.4 Output of VGG16

6.3.3. ResNet50:

```
import tensorflow as tf
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.applications.resnet50 import preprocess_input
from tensorflow.keras.preprocessing.image import load_img
import pandas as pd
import numpy as np
```

```
base_model.summary()

Model: "resnet50"
```

```
y_pred = baseline_model.predict
WARNING:tensorflow:Your input ran
Confusion Matrix
[[   0    0  179    0]
 [   0    0   12    0]
 [   0    0  640    0]
 [   0    0  448    0]]
```

```
accuracy_score(validation_data.classes,y_pred)

0.5003909304143862
```

Classification Report

	precision	recall	f1-score	support
VeryMildDemented	0.00	0.00	0.00	179
NonDemented	0.00	0.00	0.00	12
ModerateDemented	0.50	1.00	0.67	640
MildDemented	0.00	0.00	0.00	448
accuracy			0.50	1279
macro avg	0.13	0.25	0.17	1279
weighted avg	0.25	0.50	0.33	1279

```
...
Total params: 23587712 (89.98 MB)
Trainable params: 23534592 (89.78 MB)
Non-trainable params: 53120 (207.50 KB)
```

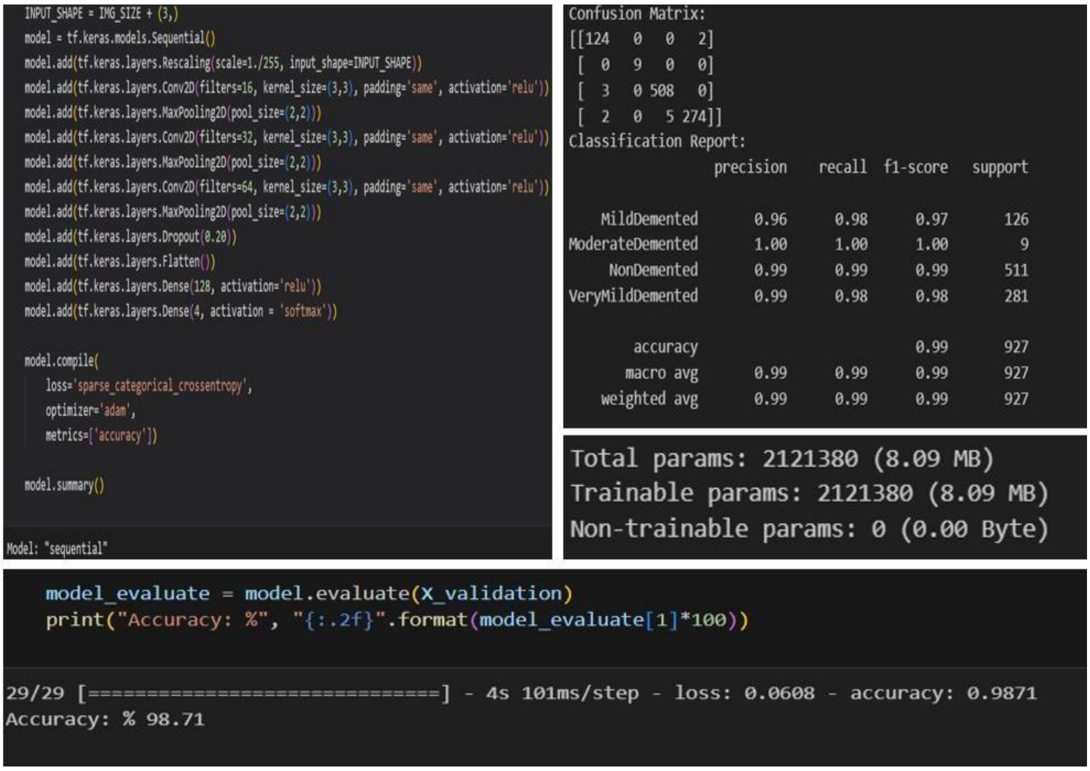
Fig 6.5 Output of ResNet50

6.4. Implementation of Proposed Models

The addition of a dropout rate of 0.20 to our CNN model for early AD detection enhances its robustness by preventing overfitting, ensuring better generalization to new data. This regularization technique helps in learning more generalized representations from the dataset. With an alpha value of approximately 0.00013, our model's L2 regularization parameter controls complexity and prevents memorizing noise during training.

Our model has around 2,121,380 learned parameters, totaling approximately 8.09 MB in size. These parameters include weights and biases across convolutional and fully connected layers, highlighting the model's complexity in capturing relevant features for accurate AD detection. This setup optimizes computational efficiency while maintaining high accuracy and memory optimization.

6.4.1 Proposed model output:



```
INPUT_SHAPE = IMG_SIZE + (3,)
model = tf.keras.models.Sequential()
model.add(tf.keras.layers.Rescaling(scale=1./255, input_shape=INPUT_SHAPE))
model.add(tf.keras.layers.Conv2D(filters=16, kernel_size=(3,3), padding='same', activation='relu'))
model.add(tf.keras.layers.MaxPooling2D(pool_size=(2,2)))
model.add(tf.keras.layers.Conv2D(filters=32, kernel_size=(3,3), padding='same', activation='relu'))
model.add(tf.keras.layers.MaxPooling2D(pool_size=(2,2)))
model.add(tf.keras.layers.Conv2D(filters=64, kernel_size=(3,3), padding='same', activation='relu'))
model.add(tf.keras.layers.MaxPooling2D(pool_size=(2,2)))
model.add(tf.keras.layers.Dropout(0.20))
model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(128, activation='relu'))
model.add(tf.keras.layers.Dense(4, activation = 'softmax'))

model.compile(
    loss='sparse_categorical_crossentropy',
    optimizer='adam',
    metrics=['accuracy'])

model.summary()

Model: "sequential"
```

```
Confusion Matrix:
[[124   0   0   2]
 [  0   9   0   0]
 [  3   0 508   0]
 [  2   0   5 274]]
Classification Report:
                  precision    recall  f1-score   support

    MildDemented       0.96      0.98      0.97       126
ModerateDemented       1.00      1.00      1.00         9
     NonDemented       0.99      0.99      0.99       511
VeryMildDemented       0.99      0.98      0.98       281

        accuracy                           0.99       927
       macro avg       0.99      0.99      0.99       927
    weighted avg       0.99      0.99      0.99       927
```

```
Total params: 2121380 (8.09 MB)
Trainable params: 2121380 (8.09 MB)
Non-trainable params: 0 (0.00 Byte)
```

```
model_evaluate = model.evaluate(X_validation)
print("Accuracy: %", "{:.2f}".format(model_evaluate[1]*100))

29/29 [==============================] - 4s 101ms/step - loss: 0.0608 - accuracy: 0.9871
Accuracy: % 98.71
```

Fig 6.6 Output of Proposed model

6.4.2 Comparison of accuracy of the proposed model with pre-trained models:

	Pre-Trained Model			Proposed Model
	InceptionV3	**VGG16**	**ResNet50**	
Number of trainable Parameters	21802784	14714688	23587712	2121380
Memory size	83.17 MB	56.13 MB	89.98 MB	2121380
Classification Accuracy	83.17 MB	49.88%	50.03%	98.77%

Table 6.1 Performance of the proposed model with pre-trained models

The proposed model achieves remarkable accuracy, surpassing InceptionV3 by 2.41 times, VGG16 by 1.98 times, and ResNet50 by 1.97 times. Additionally, it consumes significantly less memory, approximately 10.31 times less than InceptionV3, 6.94 times less than VGG16, and 11.11 times less than ResNet50, demonstrating its efficiency in memory usage compared to established pre-trained models which are shown in above Table 6.1.

6.4.3 Comparison of performance of Proposed Model with Pre-trained Models:

	Precision	Recall	F1-score
InceptionV3	0.43	0.41	0.38
VGG16	0.43	0.50	0.35
ResNet50	0.25	0.50	0.33
Proposed Model	0.99	0.99	0.99

Table 6.2 Performance matrix of the proposed model with pre-trained models

The proposed model outshines the pre-trained models in every aspect of evaluation. It exhibits remarkably higher accuracy, precision, recall, and F1-score compared to InceptionV3, VGG16, and ResNet50. Moreover, it consumes significantly less memory and boasts a smaller parameter matrix size. These findings underscore the superiority of the proposed model in terms of both performance and efficiency, making it a compelling choice for classification tasks, particularly in domains where accuracy and resource utilization are paramount which are shown in above Table 6.2.

6.5. Proposed Model Graph of Training and Validation Accuracy:

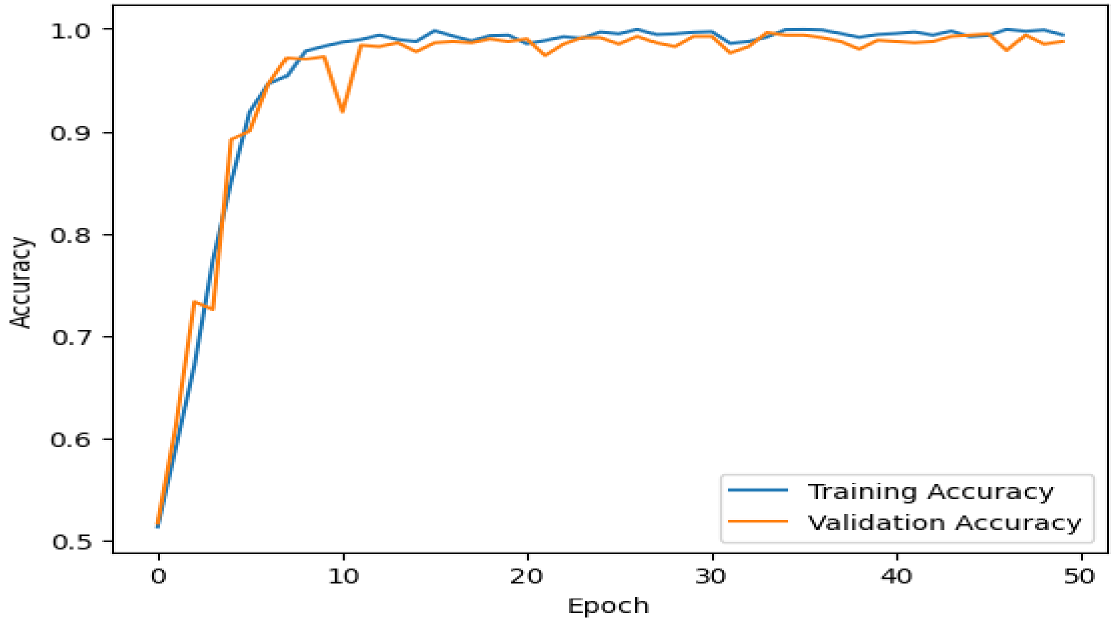


Fig 6.7 Proposed Model Graph of Training and Validation Accuracy

The depicted graph presents the accuracies and validation accuracies for each epoch throughout 50 epochs shown in Fig 6.7

6.6. Pre-trained Model Graph of Training and Validation Accuracy:

The depicted graph presents the accuracies and validation accuracies for each epoch throughout 5 epochs for pre-trained models such as Inceptionv3, VGG16, and ResNet50 are shown in Fig 6.7, Fig 6.8, and Fig 6.9

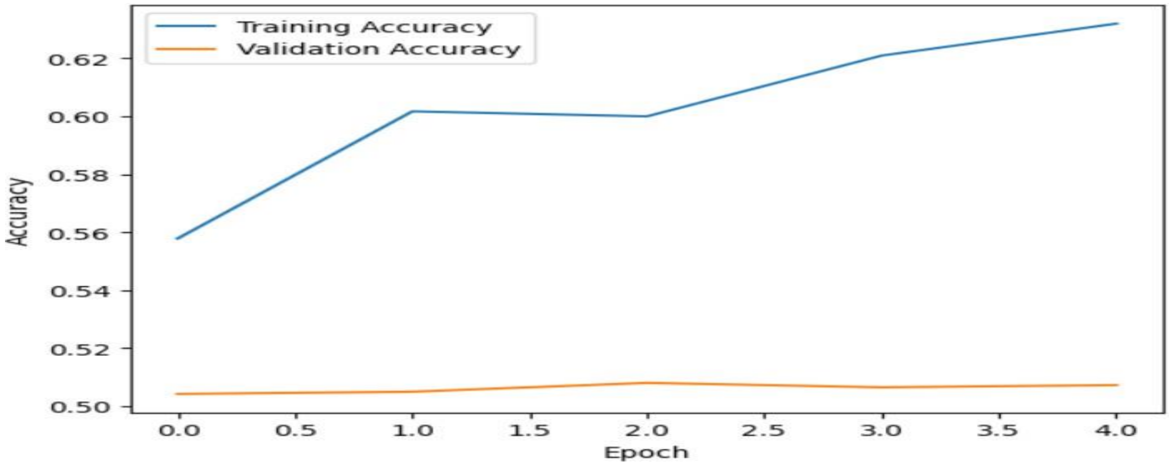


Fig 6.8.1 Graph of Inceptionv3

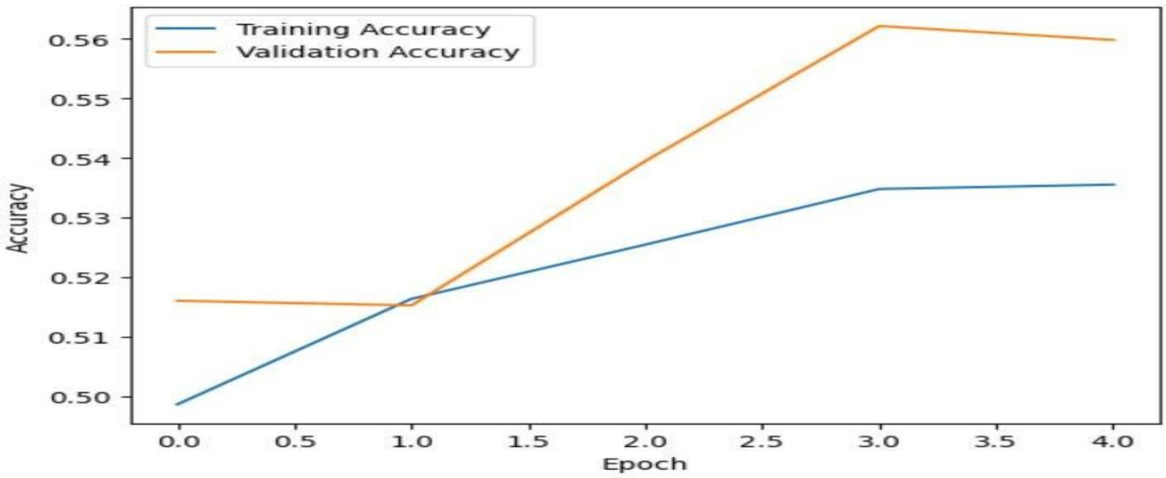


Fig 6.8.2 Graph of VGG16

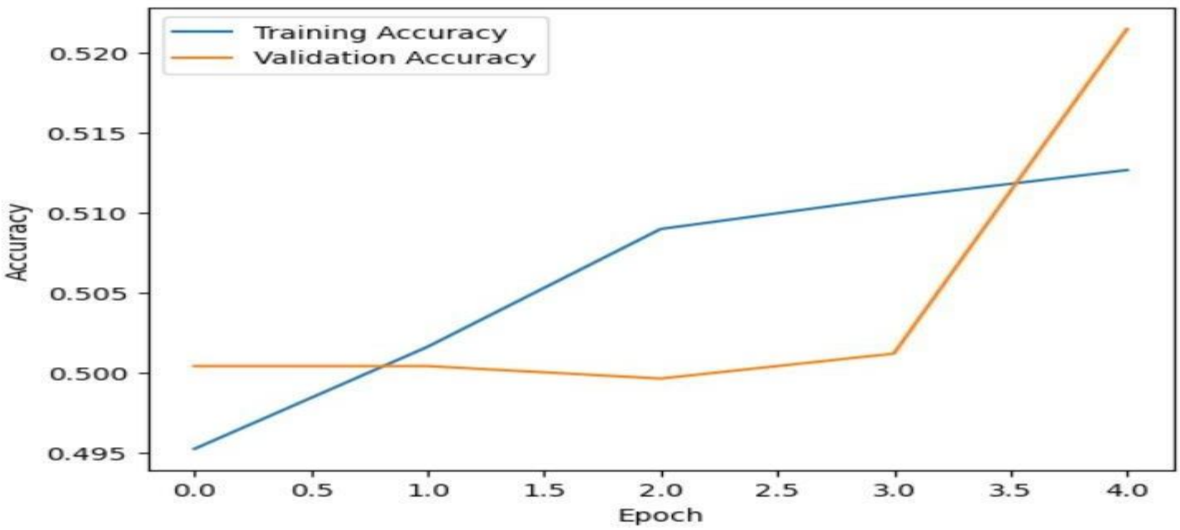


Fig 6.8.3 Graph of ResNet50

6.7. Sample Prediction of Alzheimer"s Disease:

To test the performance of a machine learning model on user-provided images, the user will first be prompted to provide the path of the image they wish to test. The image will then be loaded, resized to match the model's input size, and converted into an array. The array will be expanded to form a batch and passed to the model for prediction. Finally, the image, along with the predicted class label, will be displayed to the user. This entire process will enable theuser to test the model's performance on their images. The output of the proposed CNN model for various stages such as NonDemented, VeryMildDemented, MildDemented, and ModerateDemented are shown in Fig 6.9.1, Fig 6.9.2, Fig 6.9.3, Fig 6.9.4

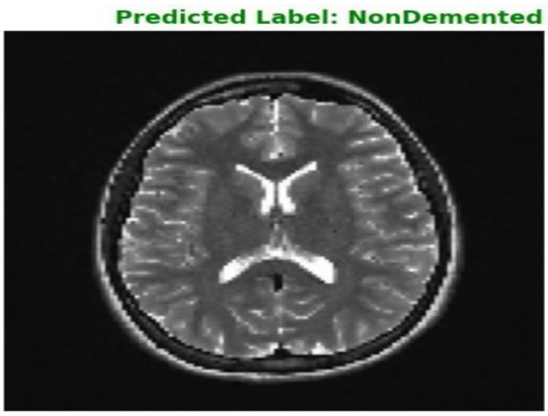


Fig.6.9.1 Prediction of Non-Demented

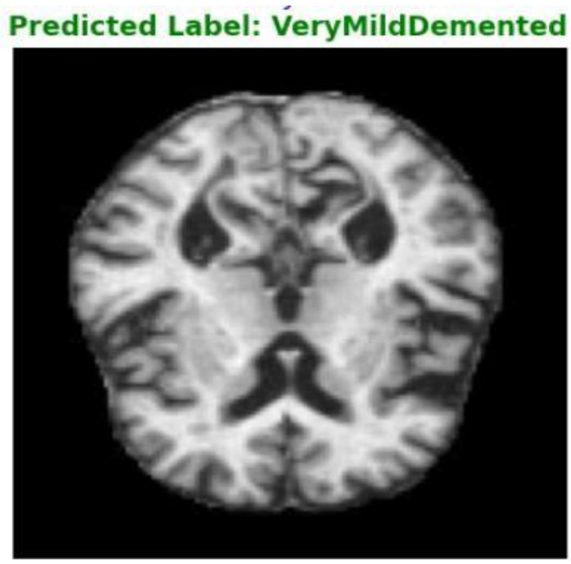


Fig.6.9.2 Prediction of Very Mild Demented

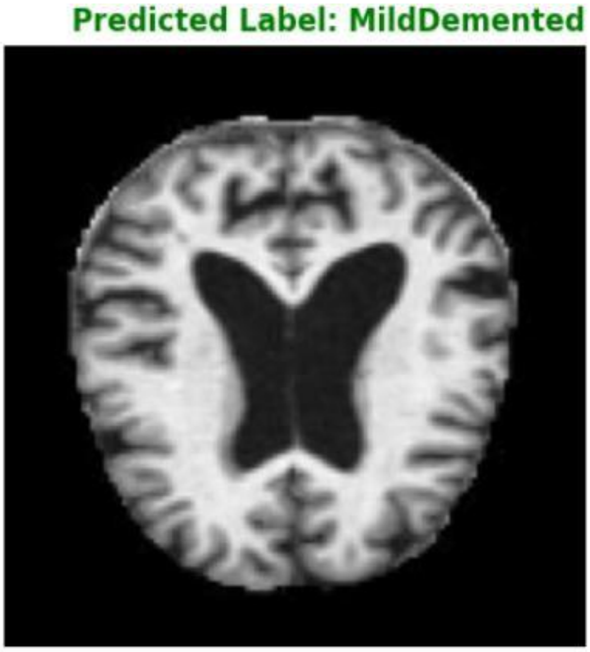


Fig.6.9.3 Prediction of Mild Demented

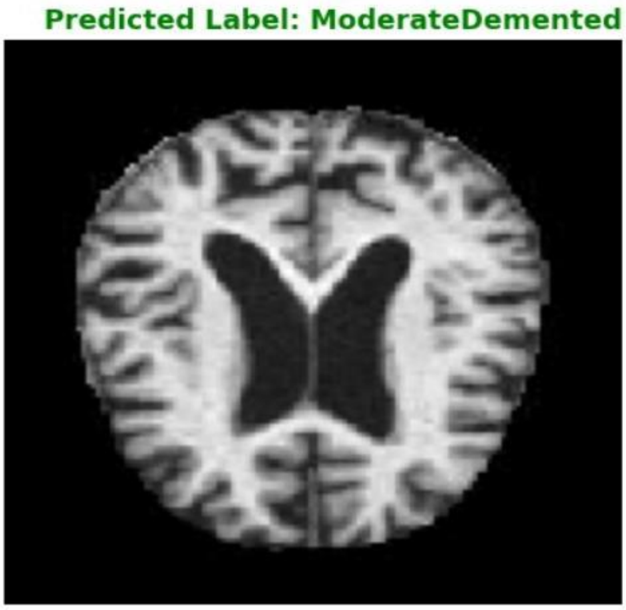


Fig.6.9.4 Prediction of Moderate Demented

CHAPTER-7
CONCLUSION

Hence proposed project work described an efficient CNN model for the early detection of AD with less memory size and high classification accuracy. This model performance of the proposed model was compared with the standard benchmark pretrained models such as VGG16, Inception V3 and ResNet 50. The proposed CNN model produced an accuracy of 98.77%, surpassing the accuracies of existing pre-trained models, including InceptionV3, VGG16, and ResNet50, by approximately 57.81%, 48.89%, and 48.74%, respectively. Also the proposed model significantly reduced the memory requirements to 8.09MB, when compared to InceptionV3 (83.17MB), VGG16 (56.13MB), and ResNet50 (89.98MB). Thus the proposed CNN model was efficient in improving accuracy for early AD detection while addressing concerns regarding classification accuracy ,computational complexity and memory usage.

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