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Alzheimer's Disease Diagonisis At An Early Stage Using Deep Learning Techniques)

[1]Dr.R.M.Mallika, [2]P.Navyasai, [3]P.Lakshmi Harshitha, [4]J.N.Mohan Sai, [5]B.Muni Siva Sandeep

[1]Associate Professor, Department of Computer Science and Engineering, Siddharth Institute of Engineering & Technology J.N.T.U Anantapur, Tirupati , Andhra Pradesh, India,

[2-5]student Department of Computer Science and Engineering, Siddharth Institute of Engineering & Technology J.N.T.U Anantapur, Tirupati , Andhra Pradesh, India.

Abstract: **Alzheimer's infection is a neurological sickness that bit by bit kills off synapses and makes the cerebrum decay. It's the main source of dementia, which is described by a continuous loss of mental, conduct, and social capacities and at last prompts reliance on others. Early and correct identification of Alzheimer's Disease (AD) is crucial to effective patient care because it empowers individuals to take preventative actions before any permanent brain damage has been done. Early-stage AD may be identified, but not predicted, since prediction is only useful before symptoms appear. Alzheimer's disease (AD), mild cognitive impairment (MCI), and non-AD data are categorised using biomarkers such amyloid PET and cerebrospinal fluid (CSF) biomarkers, among others. In order to detect Alzheimer's disease (AD) in its earliest stages, deep learning (DL) is an excellent method. In this article, we investigate how early illness detection may be facilitated by Deep Learning methods.**

Index Terms - **Alzheimer's Disease, Deep Learning, Computer Aided Diagnosis, Pathologically Proven Data, Early Diagnosis, Class Imbalance.**

I. INTRODUCTION

A sort of dementia, Alzheimer's disease (AD) is portrayed by steady beginning of mental and conduct decrease in late middle age or later. Degeneration of specific synapses and the presence of neuritic plaques are the pathologic trademarks. Most people have a gradual worsening of symptoms until they become very disruptive to daily life. In 1906, a German doctor named "Dr. Alois Alzheimer" initially characterised the condition now known as Alzheimer's disease.

Generally speaking, Alzheimer's disease (AD) appears as a steady decrease in mental capacities over the long run. 60% to over two thirds of all examples of dementia might be followed back to this. Memory problems, especially regarding recent events, are a prominent early indicator of dementia. Language troubles, bewilderment (counting effectively getting lost), mind-set swings, absence of want, selfdisregard, and conduct issues are among signs that might show up as the condition advances. As somebody's wellbeing falls apart, they commonly disconnect themselves from companions and family members. Steadily, physical processes are lost, eventually prompting passing.

The typical future after analysis is somewhere in the range of three and nine years, but this could fluctuate relying upon the speed of improvement. While advanced age is the strongest predictor of developing AD, it is not exclusively a disease of the elderly. Gentle carelessness portrays the illness' most memorable stages, while cutting edge stages are described by an obvious decrease in the patient's ability for correspondence and responsiveness. While there is presently no solution for Alzheimer's disease (AD),an early conclusion might assist with reducing the sickness' effect and give victims a superior personal satisfaction. According to projections, by 2050, 1 in 85 people would have AD, and that figure is expected to quadruple in the following 20 years (Zhang, 2011). (Ron Brookmeyer, 2007).

That's why it's crucial to have a precise diagnosis, particularly in the beginning stages of Alzheimer's disease. Infectious pneumonia symptoms include a hacking cough, high body temperature followed by shivering chills, difficulty breathing, chest discomfort that is acute or stabbing on deep inhaling, and rapid breathing. The elderly may have the most noticeable symptoms of bewilderment. Information interpretation and analysis are performed through machine learning. It can also model data and identify patterns. It saves time (Mitchell T, 1997) and effort (by allowing judgements that would have been impossible to make using conventional methods) (Duda RO, 2001).

The field of computer-assisted diagnostics has made substantial use of machine learning techniques, particularly in the identification and categorization of brain disorders utilising CRT images (Cruz, 2006) and x-rays (Bookheimer, 2000; Supekar, 2008; Cruz, 2006). (Patrician, 2004) Professionals in the field of Alzheimer's disease have just recently started to try to use machine learning for AD prediction. So, there is not a lot written on using machine learning for Alzheimer's disease predictions. However, current imaging methods and high-throughput diagnostics have left us with a plenty (frequently many) cell, clinical, and sub-atomic qualities to consider. In today's world, tried-and-true metrics and common sense are often useless. This is why we have to rely on nonconventional and computationally-intensive methods like machine learning. Disease prediction and visualisation using machine learning is part of a larger trend towards foresight (Weston, 2004) and individualised treatment (Cruz, 2006). This shift is significant for patients looking to improve their quality of life and way of living, doctors trying to figure out what treatments to provide their patients, and health economists trying to figure out how much money they can save by reducing unnecessary medical care.

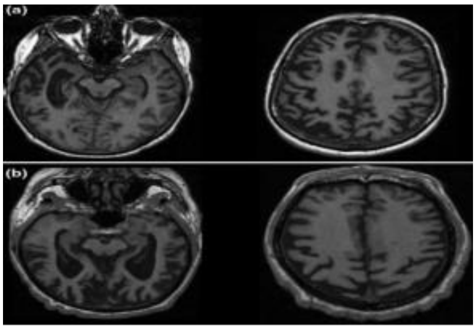


Fig 1 Early onset Alzheimer's

Many recurring patterns and knowledge gaps have emerged from the analysis of the already available research. One of the most noticeable developments is the increasing use of machine learning techniques for early diagnosis and prognosis of AD. Overtraining, a lack of external testing or validation, a class imbalance (wherein some classes have too few instances while others have too many), and the use of a pathologically untested data set (which causes uncertainty in outcomes) were among the most glaring omissions. Better planned and validated studies did show, however, that machine learning approaches, as opposed to traditional statistical methods, may enhance AD prediction accuracy.

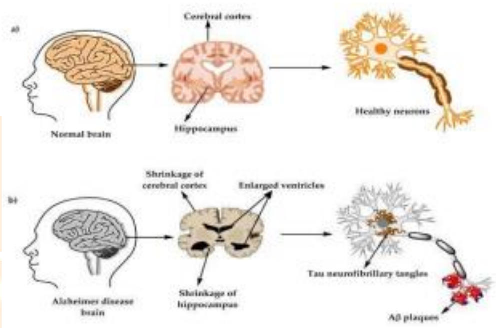


Fig 2 Alzheimer's disease pictorial representation

These are the symptoms of Alzheimer's disease:

– Memory loss
– Cognitive deficits
– Problems with spatial awareness
– Problems with speaking, reading and writing
– Personality or behavior changes Complications:
– Restlessness and agitation
– Bladder and bowel problems
– Depression
– Infections

Moreover, machine learning has a substantial impact on the forecasting and prognosis of AD. A methodology is developed to address these obstacles to accurate early-stage AD diagnosis. The proposed approach consolidates a prehandling stage for settling the class unevenness issue in the obsessively confirmed informational collection. The "scourge of dimensionality" happens when there are too couple of cases and such a large number of characteristics, albeit this issue might be stayed away from by the cautious choice of significant highlights using an AI approach (Cruz, 2006). The informational collection is parted into two classes, preparing and testing, by the model. When training data is based on a small sample of test data, over-training occurs (Chaves, 2010). In light of this, it is important to choose a training set that encompasses a substantial subset of the whole dataset. The model provides low-confidence, low-support categorization utilising association rule mining.

II. LITERATURE SURVEY

The following publications and research on Alzheimer's disease were evaluated for our own work.

Backstom, K., Nazari, M, et al., [1] A quick three-layered profound convolutional network for identifying Alzheimer's sickness in X-ray filters. The paper was introduced at the 2018 IEEE fifteenth Worldwide Conference on Biomedical Imaging (ISBI 2018), held in April 2018, and is distributed on pages 149-153. Alzheimer's disease (AD) diagnosis and automatic feature extraction from MRI brain images are still difficult. In this review, we present a clear and powerful three-layered convolutional network (3D ConvNet) design for superior execution Promotion identification on an enormous dataset. For include extraction, the proposed 3D ConvNet utilizes five convolutional layers, and afterward for Promotion/NC arrangement, it utilizes three completely associated layers. The essential commitments of this paper are as per the following: (a) the proposition of a novel and viable 3D ConvNet engineering; (b) the examination of the impact of hyper-boundary determination on the viability of Promotion order; (c) the examination of the impact of prehandling; (d) the examination of the impact of information parceling; and (e) the examination of the impact of dataset size.

Carneiro, T., Medeiros Da NóBrega, et al., [2] We evaluate Google Collaboratory's effectiveness as a tool to speed up deep learning programmes. In: IEEE Access, Volume 6, Issues 61677-61685 (2018). Google Colaboratory, or Colab for short, is a cloud administration based on Jupyter Note pads that plans to scatter AI guidance and exploration. The powerful GPU and deep learning-optimized runtime are provided at no cost. In this article, we take a close look at the hardware requirements of Colaboratory and examine its performance, capacity, and potential bottlenecks. Colaboratory, an accelerator for deep learning used in computer vision and other GPU-centric applications, is used for this investigation. Two applications from the realm of computer vision—one concerned with the identification and categorization of objects and the other with their location and segmentation—have been selected as test cases.

Cheng, D., Liu et al., [3] for the determination of Promotion in light of a multi-methodology order framework. Article shows up on pages 1-5 of 2017's tenth Conference on Image and Signal Processing, BioMedical Engineering, and Informatics (CISP-BMEI). Alzheimer's disease (AD) patients would benefit greatly from prompt and precise diagnosis, as would the research community's pursuit of effective treatments for the condition. Neuroimaging strategies like positron emission tomography (PET) and attractive reverberation imaging (X-ray) might be important in the analysis of Alzheimer's illness. Late years have seen a lot of investigation into the utilization of AI calculations for examining multi-methodology neuroimages for quantitative evaluation and PC supported finding (computer aided design) of Promotion. After picture preprocessing steps including enlistment, division, and element extraction, most of current methodologies remove the hand-created highlights to prepare a classifier to recognize Promotion from different gatherings. Utilizing the recommended strategy, general attributes for Promotion arrangement might be consequently gained from X-ray and PET imaging information. To preprocess and segment the MRI pictures, this study suggests using neural networks.

Cui, R., Liu, M, et al., [4] To better diagnose Alzheimer's illness, researchers have used 3-D DenseNet with geometric forms to analyse the hippocampus. 23(5):2099-2107 IEEE Journal of Biomedical and Health Informatics (2019). The hippocampus is among the brain areas affected first by Alzheimer's disease (AD) and its precursor, moderate cognitive impairment (MCI). Hippocampal atrophy is a frequently utilised biomarker for the diagnosis of AD that has been shown to be reliable and accessible. Existing approaches typically use structural magnetic resonance images to calculate hippocampal shape and volume characteristics (MRI). As a means of bettering categorization, the suggested technique is able to make use of both local visual data and global form characteristics. In this work, we present a profound learning-based classification framework for Alzheimer's disease.

Vasco Sá Diogo,Hugo Alexandre Ferreira et al,. [5] Machine learning for early Alzheimer's disease diagnosis: a multi-diagnostic, generalizable strategy. Alzheimer's disease (AD) must be diagnosed as soon as possible so that effective treatment may be started. Albeit however clinical utility, interpretability, and generalizability of the classifiers across datasets and X-ray systems stay limited, AI (ML) methods have been broadly investigated in endeavors to fabricate calculations for precise early recognition of Promotion. Utilizing primary Xray and ML, we give a multi-symptomatic and generalizable technique for distinguishing MCI and Promotion.

G. Palacios-Navarro , J. Buele, et al., [6] Identifying cognitive impairment in Alzheimer's patients using a routine task (adl). Standardized screening measures exist for the diagnosis of cognitive impairment, however they have limited ecological validity and the data they provide may be skewed. The purpose of this research was to determine how well an ADL-based test might identify cognitive impairment in a group with Alzheimer's disease (AD). There were a total of 24 people that took part in the research. Twelve elderly people (81.757.8 years old), all diagnosed with AD, made up the AD group (ADG). Twelve seniors (five men, 77.7 6.4 years old) made up the Healthy group (HG). At two points in time around 3 weeks apart, both groups received an ADL-based intervention.

Abolbasher , byeong c.Kim, et al., [7] Detection of Alzheimer's Disease using sMRI Volumetric Features using a Deep Neural Network with a Convolutional layer for improved accuracy. Alzheimer's disease (AD) is a neurological ailment that mostly affects the elderly (those over the age of 65). The hippocampus is a very popular ROI for the study of memory, stress, and neurological disorders. In addition, shrinkage of the hippocampus is associated with the onset of dementia and Alzheimer's. Nonetheless, various biomarkers are now being utilised to identify AD, including amyloid beta (a42) protein, tau, phosphorylated tau, and hippocampus volume atrophy. We have presented an approach to the diagnosis of AD that utilises volumetric characteristics taken from the left and right hippocampi using structural magnetic resonance imaging (sMRI) data.

ShuangshuangGaoa,b, DimasLima. [8] A look at how deep learning has been used to help diagnose Alzheimer's illness. The predominance of Alzheimer's disease (AD) is marvelously high, making it the most pervasive age-related persistent ailment. The area of clinical imaging has seen an ascent in the utilization of profound learning lately. It has gotten a great deal of interest in the field of Alzheimer's illness ID and is currently the standard methodology for surveying clinical photos. The profound model is better than conventional AI strategies as far as precision and proficiency when used to the location of Promotion.

Shashi Rekha, Gangula Rekha, et al.,[9] Utilizing AI to Make a Location Model for Alzheimer's. Alzheimer's disease (AD) is a dynamic degenerative cerebrum problem that causes moderate cognitive deterioration, in the long run prompting passing. Alzheimer's sickness is a neurological problem that causes moderate cognitive decline and a decrease in regular working. Diagnosing Alzheimer's disease at an early stage is crucial for the development of more effective therapies. A brain imaging report and human skills are needed to complete the arduous and time consuming job of detecting Alzheimer's disease. It goes without saying that the standard method of Alzheimer's disease diagnosis is both expensive and prone to mistakes. A different method has been explored in this project that is quicker, cheaper, and more trustworthy. Medical care and treatment may benefit from the use of artificial intelligence technologies.

Anza Aqeel, Ali Hassan,Muhammad Antique Khan,et al., [10] An Expectation Structure for Alzheimer's Sickness In light of Long haul and Transient Memory Biomarkers. Alzheimer's disease (AD) is a dynamic neurodegenerative problem, and early determination might be a distinct advantage for patients' personal satisfaction and a supportive instrument for specialists. The suggested study introduces a mechanised predictive framework for AD forecasting, one that relies on machine learning (ML) techniques. Deduced biomarkers from neuropsychological tests (NM) and magnetic resonance imaging (MRI) scans are fed into a recurrent neural network (RNN).

III PROPOSED METHODOLOGY

The term "existing model" is used to highlight a pre-existing approach developed with the use of deep learning algorithms.

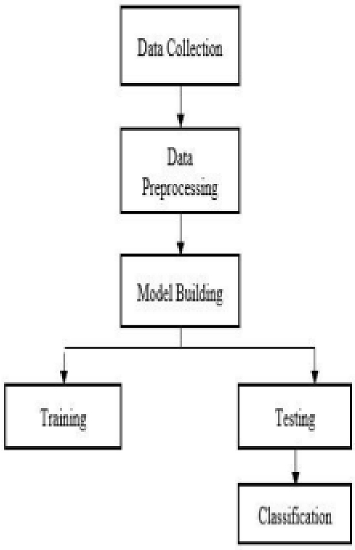


Fig 3 Block diagram

Here the process is performed using the Google Net, which is one of the transfer learning method, but this could not get the high accuracy. The disadvantages of existing system is less feature compatibility and low accuracy. So, We plan to propose a new approach.

In proposed system we are using Modified CNN, MobileNet, and VGG16 for the Alzheimer's disease classification. By using these algorithms we can get better accuracy with CNN and mobilenet. Here we will have accurate classification, less complexity and high performance.

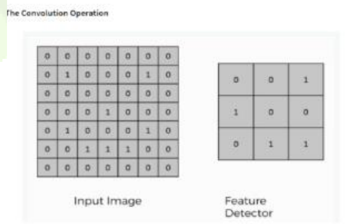
Fig 3 illustrates the proposed methodology in block diagram.Initially, the data will be collected, and the data will be preprocessed.The data cleaning, normalization, splitting, transformation, etc. will take place here.Next comes model building, which involves generalizing and learning from training data in order to create a mathematical representation.Here we have 2 internal steps training and testing.After testing classification will be done.

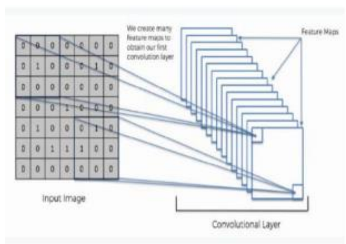
IV MATERIALS AND METHODS

In this part, we lay out the procedures we followed and discuss the suggested methodology's underlying model in depth.

Convolutional Neural Network:

Our first building block is the convolution operation. We use this analyze brain MRI images which comes from the data. The progression of the illness is also mapped out in this study. The strategy is also effective with the skewed data. Deep neural layers, a batch processing layer, a pooling layer, and a ReLU layer are the four types of layers used in the CNN.





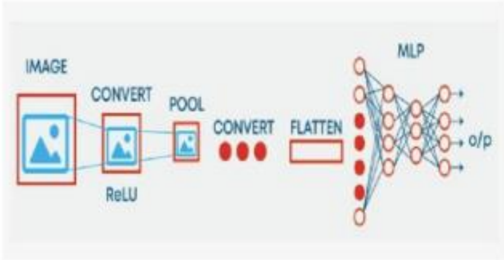


Fig 4 CNN Algorithm

ReLU Layer:

The second piece of this step will include the Rectified Linear Unit or Relook. In this article, we'll go through Relook layers in Convolutional Brain Organizations and explore the job linearity plays in this sort of organization. ReLU helps keep the figuring expected to dramatically run the brain network from developing. The computational expense of including more ReLUs develops directly with the size of the CNN.

Pooling Layer:

Third, we'll combine all of the information into a single set, or pool. By pooling the data from numerous neurons in the former layer into a solitary neuron in the following layer, we might limit the quantity of aspects in the secret layer. Towards the conclusion, you'll see an example created with an interactive visual tool that will undoubtedly help you grasp the full idea.

Flattening:

At the point when we work with Convolutional Brain Organizations, we will momentarily go through the leveling system and how we change from pooling to smoothed layers. At the point when many element maps are consolidated into one, a smoothing activity is performed to change the subsequent 2-layered clusters into a solitary, long, constant direct vector. For order purposes, the image, in the wake of being smoothed, is given as contribution to a completely associated layer. After this is complete, we will combine the aforementioned parts into one.

VGG16:

The accuracy of this object recognition and classification system is 92.7%, as measured by its ability to sort 1000 photos into 1000 distinct categories. One of the most wellliked picture categorization techniques, it employs transfer learning with relative ease. This network is unique in that it consists of just three 3x3 convolutional layers layered one on top of the other. Max pooling takes care of reducing volume size.

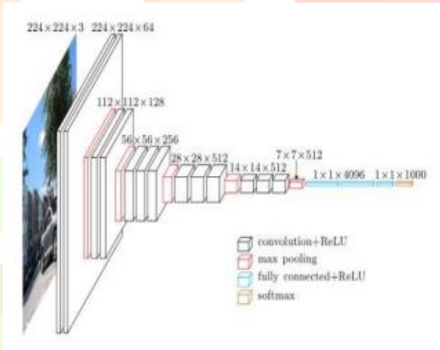


Fig 5 VGG Architecture

MobileNet:

The MobileNet CNN architecture has been extensively utilised for image classification and object recognition. In this case, MobileNet may be utilised as a feature extractor for brain scans to spot Alzheimer's disease in its early stages. Convolutions that can be separated in depth are used by MobileNet. As compared to a network built using ordinary convolutions of the same depth, the number of parameters in such architecture is drastically reduced. This results in light weight deep neural networks. Because of its computational efficiency, the MobileNet architecture is ideal for use on mobile devices or edge devices with constrained resources. The network may learn to discover patterns in the data that are important to Alzheimer's disease by fine-tuning the pretrained MobileNet weights on a data set of brain pictures. For image-based Alzheimer's disease diagnosis, the MobileNet model's output may be fed into a deeper neural network or support vector machine.

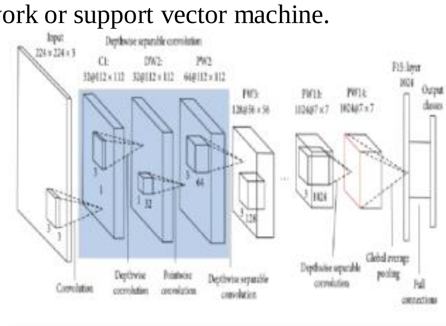


Fig 6 MobileNet

AlexNet:

It is also same as MobileNet and here the specialty of AlexNet is would be its ability to learn complex patterns in brain images that are relevant to the disease. In particular, the AlexNet has shown outstanding performance when using the transfer learning method, which makes use of the weights from the previously-trained network on the Image Net data set.

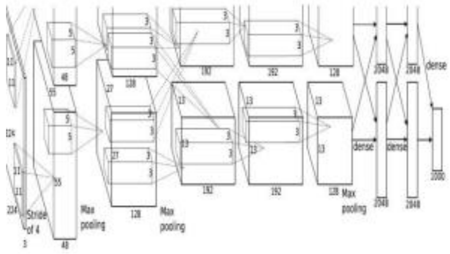


Fig 7 AlexNet

Modules:

There are two modules in our paper. They are:

– System

– User

System Module:

1. Create Dataset: Dataset of MRI scans of patients with Alzheimer's disease, includes 7600 pictures used for training and 3800 used for testing.
2. Pre-processing: Changing the dimensions and orientation of the photos so that our model may be properly trained.
3. Training: Our model is trained utilising the preprocessed training dataset and the Modified CNN technique in combination with other deep learning models.
4. Classification: The results will be displayed are which type of Alzheimer’s diseases.

– Mild Demented

– Moderate Demented

– Non Demented

– Very Mild Demented

User Module:

1. Upload Image: For this to work, the user must submit a picture for analysis.
2. View Results: The user examines the categorised images.

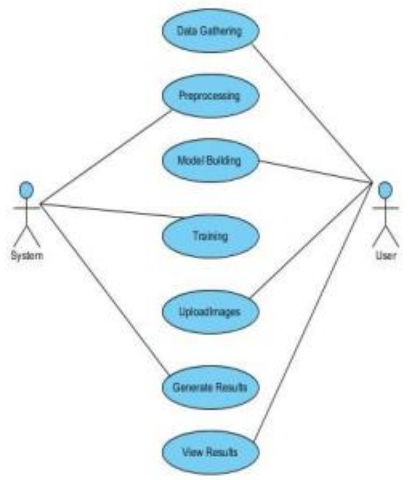


Fig 8 Use case Diagram

In Fig 7, First we will gather all the images and we will pre process them.After pre processing we will build a model which will fit for the system.for this the training phase is needed where we will refer all the needed methods. Then it needs to be tested.After all the system based work user’s work will get involved. User needs to upload an image of brain to get results where it shows the brain is affected with Alzheimer disease or not.Now, system will take the image and will go through all the methods like CNN, AlexNet, MobileNet etc to generate results, and the system will send results to user as expected.

IV RESULT ANALYSIS

Training without using any data augmentation strategies yielded encouraging and statistically meaningful outcomes. The neural network was trained using MRI scans of the reference images; this method ensured perfect correctness. It should be made clear, however, that there are limits to the study. It has not been confirmed if these correlate to the degree of severity of the disease, but first, the new coefficient provides a stratification of the individuals that corresponds to their nature . And there's no clinical evidence to back up these numbers, so additional research is needed to confirm their accuracy. Second, the study could only use data from one central location, which is likely not diverse enough for the purpose of the inquiry. Some research topics are also left open by this experimental design, which might be investigated in further studies. Without taking into account the fact that each approach was applied independently, the methods enabled us to achieve this remarkable level of performance. As a result, it would be helpful to investigate if the combination of the approaches would result in higher performance, or to ask whether there may be a mix of ways that enhances the performance of convolutional networks. Last but not least, while MOBILENET, VGG16,Alexnet and CNN exhibited good results, it contains many training parameters; hence, it would be interesting to evaluate whether the dementia categories of mild dementia, moderate dementia, non-dementia and very mild dementia .

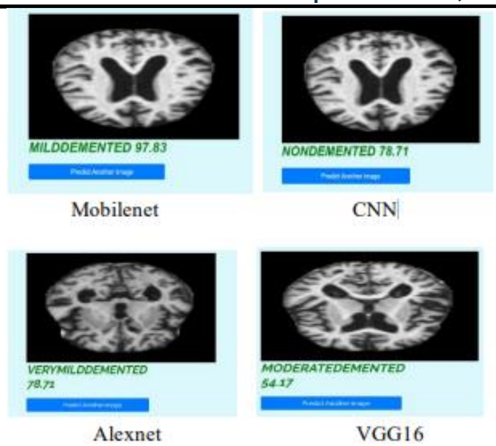


Fig 9 Output Results

V CONCLUSIONANDFUTUREENHANCEMENT

In this article, we use deep learning algorithms to correctly classify MRI scans of people into four distinct dementia categories: mild dementia, moderate dementia, nondemented, and very mild dementia. Here, we've taken into account a dataset of MRI images that will include four distinct kinds and be trained with the help of the Modified CNN, MobileNet, and VGG16 algorithms. Tests have been run after training, with images being uploaded and labelled.

Based on a survey of the relevant literature, we have concluded that the majority of the articles published in this field are concerned with either biomarkers or neuroimaging, with a growing emphasis on image analysis. The bulk of the chosen individuals already had a diagnosis of AD, hence the study didn't contribute much to the initial discovery of the disease. In this article, we take a look back at some of the most important Alzheimer's disease (AD) datasets, diagnostic tools, and detection methods.0

For preliminary studies in the field of neuroimaging, this method is practical. This can be utilized in future to classify the types of different classifications easily that which can tend to easy to find out the infections in early stages and can be cured in the initial stages only. Bio markers that predict disease progression before to the formation of overt dementia are being used in conjunction with the novel approaches to investigate the possible neuro protective effect of disease-modifying medications in the pre symptomatic phases of AD.

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