



IJITCE

ISSN 2347- 3657

International Journal of Information Technology & Computer Engineering

www.ijitce.com



Email : ijitce.editor@gmail.com or editor@ijitce.com

DETECTION OF ALZHEIMER'S DISEASE

Amaragani Lohith¹, DR. K. Irfan babu²

Article Info

Received: 17-01-2023 Revised: 12 -02-2023 Accepted: 06-03-2023

ABSTRACT :-

Alzheimer's disease is a progressive brain condition that cannot be reversed. Someone in the world is diagnosed with Alzheimer's disease every four seconds. It is a disease of the brain that worsens with age. Alzheimer's disease is the leading contributor to dementia. Because it reduces a person's capacity for reasoning and interpersonal coping skills, dementia affects their ability to live independently. The patient won't be able to recall details until it is too late in the course of their illness. They will eventually forget entire events as the illness progresses. Because Alzheimer's is a disease that changes all the time, early detection and organization can greatly aid in infectious prevention. Recent studies have utilized voxel-based brain MR image feature extraction methods and machine learning algorithms for this purpose. Since Alzheimer's impacts and damages the white and faint matter of the frontal cortex, focusing on these two areas turns out to be all the more remarkable at expecting the infection. It is essential to eradicate the disease as soon as possible. A model that takes sample MRI images of the brain as input and determines whether a person has Alzheimer's disease as an output is the subject of this project. For this request, we are differentiating the VGG19 and DenseNet169 structures with sort out which one offers promising outcomes.

Keywords:- *deep learning, CNN DENSE, CNN VGG19, mri dataset*

INTRODUCTION:-

The most common cause of dementia in elderly people is Alzheimer's disease (AD). There is currently a lot of interest in using machine learning to learn more

about metabolic diseases like diabetes and Alzheimer's that affect a lot of people worldwide.

¹Student, Mahatma Gandhi Institute of Technology, Hyderabad, Telangana.

²Assistant Professor, Mahatma Gandhi Institute of Technology, Hyderabad, Telangana.

Each year, their incidence rates rise alarmingly. Neurodegenerative changes affect the brain in Alzheimer's disease. Diseases that impair memory and function will affect an increasing number of people, their families, and healthcare providers as our aging population grows. Both socially and monetarily, these impacts will be huge. Alzheimer's disease is difficult to predict in its early stages. When it is dealt with promptly, promotion is more potent

programmed arrangement of neurodegenerative diseases like MCI and Promotion. For early AD or MCI, proper examination of the cerebrospinal fluid (CSF), medial temporal lobe atrophy (MTL), and other brain biomarkers is possible. On MRI images, abnormal concentrations of the aforementioned biomarkers may suggest MCI or AD. Clinicians can use the existing classification system to diagnose these diseases. Subsequently, gathering Advancement normally requires a lot of effort and time. To increase precision, CNN models like VGG16, VGG19, and ResNet were utilized. Notwithstanding, their precision is as yet battling at 90%. To revive the precision other than a searing

and has fewer minor repercussions than when it is dealt with later. The best boundaries for Alzheimer's sickness expectation have not set in stone using Choice Tree, Irregular Woodland, Backing Vector Machine, Slope Helping, and Casting a ballot classifiers. High-layered grouping techniques have typically been used when looking into Attractive Reverberation Imaging (X-ray) for the

CNN model DenseNet169 has been proposed. Because these methods were mostly carried out without any prior planning, it was really hard to get any important results done in a short amount of time. As a result, we trained high-dimensional Deep Neural Network (DNN) models in order to quickly obtain meaningful results.

EXISTING SYSTEM :-

Finishing Alzheimer's sickness (Advancement) can be troublesome, particularly toward the start of the illness cycle, when gentle mental impedance (MCI) is normal. Alzheimer's disease, the most prevalent type, may account for 60 to 70% of dementia cases. It has been shown that the improvement of ideal

administration requires early investigation. Nonetheless, further improvement of the end cycle would be incredibly useful given that treatment is probably going to find success as of now. To receive an Alzheimer's diagnosis, the patient must undergo a number of costly and time-consuming procedures, which require both money and time. It is challenging to determine whether a person has Alzheimer's disease using the current framework. Only by examining the patient's medical history and determining whether they have a genetic disorder can this be accomplished. Likewise, it's conceivable that the specialist will not generally have the option to let you know the sickness. A PC based knowledge approach has been acquainted with address the recently referenced issues and take a gander at Alzheimer's disorder at its earliest stages to diminish the sickness' earnestness and help patients in achieving individual satisfaction. In addition to assisting patients in overcoming these issues, these AI models also contribute to outcomes that are more precise and free of errors.

Several medical professionals have investigated Alzheimer's disease in various ways over time. The fundamental areas of focus for all experts in this field are the movements in a patient's prosperity, the

clinical course of the sickness, and their response to therapy. In general, they are looking for significant biomarkers that adequately address MCI and promotion. In addition to determining who is most likely to develop AD, they want to make an early diagnosis. Alluring resonance imaging (X-beam), a harmless clinical tool, is utilized by specialists to identify subtle disorders or clinical issues. In most cases, X-ray machines make use of a computer and a powerful magnetic field to take precise pictures of every body part. For the multiclass grouping of Alzheimer's infection (Promotion) and gentle mental weakness (MCI), underlying X-ray biomarkers like the hippocampus' shape and surface, cortical estimations, and volume estimations are used. Promotion, MCI has recently been characterized using support vector machines (SVM), KNN (K-closest neighbour) calculation, NN (Brain Organization), trio, and relapse models. It was possible to distinguish Alzheimer's disease, as Zubair [3] pointed out. For the conspicuous verification, he used a five-stage ML pipeline with sub-stages for each stage. Classifiers were used to process this pipeline. He reasoned that the exhibition measurements of the irregular backwoods classifier were predominant. Khan and others (4) investigated the Arbitrary Woodland classifier's application to both ascription and non-attribution approaches.

The accuracy of the ascription strategy was found to be 87%, while the accuracy of the non-attribution strategy was 83%. It also freely coordinated the subjects as either inconsistent or normal.

PROPOSED SYSTEM :-

A hierarchical set of representations is used by Deep Learning to acquire low-, middle-, and high-level features. Deep neural networks can handle more complicated data sets. It is better at summarizing data that has already been covered because of its various layers. Different datasets are used to prepare and test various calculations that make use of the fundamental skill of Profound Learning. Like neurons in humans, deep learning has layers that help the model or algorithm learn and process the data. By dealing with the data that is given to them as information, these layers advance as they progress through the request. The predicted output from the deep learning model is obtained after the final layer is removed using an activation function. The learned deep learning model can be used to predict or detect anything given a comparable dataset, giving us the accuracy needed for training. This is what deep learning does in layman's terms. Both the advantages of training a deep learning model from scratch and transfer learning are subjective. The problem you're

attempting to solve, the amount of time you have, the amount of data you have, and the amount of computing power you have all play a role. A classifier, like a two-layered mind association, can be prepared on top of a pretrained model, like DenseNet169 or VGG19, as an establishment. Here, you just permit the classifier's boundaries to change while keeping the pre-prepared model's center unaltered. When preparing a model quickly or with limited computational resources, this method is ideal. Due to the possibility of area variation, the exhibition probably won't be ideal for this situation. A problem-specific deep learning model like VGG19 or DenseNET169 can be trained from scratch. This recommends that the model's underlying boundaries are shiny new instead of coming from a model that had been pretrained. Despite the increased preparation time and computational resources, preparing information yields all boundaries. If the training data are sufficient, a model that is comparable to the model in approach 1 should perform better when trained using this method.

Proposed Methodology :-

The framework's applied and conduct point of view is the proposed technique. This is just a view that shows how the dataset is retrieved from the database and

how it is used to train various models in our project modules. In the chart above, we can see the data is being taken from the readiness dataset and a while later provided for the models. After that, the test dataset and the accuracy of the validation or testing are compared. The sick images from the dataset are taken after the precision has been analyzed. The arrangement is of two types—maniacal and non-unbalanced. In addition, the architecture diagram demonstrates how the various modules of the project work together to produce the desired output. Additionally, it demonstrates how the project's modules must be interconnected to function properly.

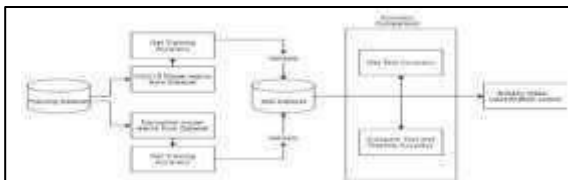


Figure1:-block diagram of Alzheimer's Disease

VGG19:- A. Zisserman and K. Simonyan from the University of Oxford came up with the idea for VGG19. The design of VGG19 is one of the convolutional cerebrum system models. It has 16 convolutional layers and three totally related layers, as shown in Fig.3.3. Regardless of the way that there are various gatherings to characterize, creating incredible results has been illustrated. The

evaluation by A. Zisserman and K. Simonyan demonstrates that the model correctly depicted a dataset of approximately 1000 classes with a precision of 92.7%. Numerous clinical examination projects use the well-known VGG19 grouping model, which can be used to order a wide range of classes. It can accurately predict trees and automobiles. In clinical datasets, VGG19 is currently being used to predict smaller groups like the location of breast cancer, macular edema, cerebrum cancer, and so on. This is one of the reasons why the classification model used in this study was the same. It also provides a standard method for building a classifier, which is helpful in the majority of studies, because it uses straightforward Convolutional and Max Pooling layers in its model construction.

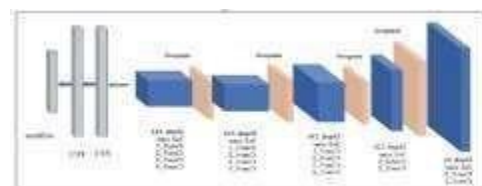


Figure2:- Layers in VGG19 Architecture.

The VGG model has 19 layers, 16 of which are convolution layers, 3 of which are Fully Connected, 5 of which are MaxPool layers, and 1 of which is SoftMax. Convolution layer: The

convolutional layers of a convolutional brain organization purposefully apply learned channels to the information pictures in order to produce highlight maps that indicate the presence of those elements in the data. Convolutional layers are exceptionally viable, and when they are stacked in profound models, layers near the info can learn low-level highlights like lines, while layers further in the model can learn higher-request or more unique elements like shapes or explicit articles.

The layer MaxPool: A common ordering pattern for layers in a convolutional neural network that can be repeated one or more times in a given model is the addition of a pooling layer following the convolutional layer. Two typical capabilities are frequently utilized by the pooling system: Pooling In like manner: Conclude the component guide's run of the mill motivator for each fix. Maximum Pooling, on the other hand: Determine the feature map's maximum value for each patch. Completely interconnected layer: The brain's forward-moving organizations are basically the Completely Associated Layer. A legitimate RGB picture of size (229 x 229) was added to this association, showing that the matrix was in the shape (229,229,3).

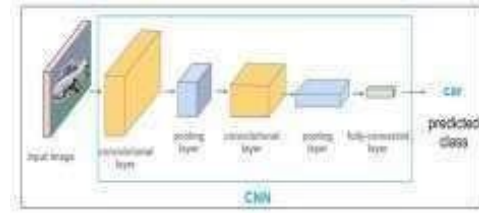


Figure3:- CNN

All convolutional layers, with the exception of the first, which takes the image as its input, produce output feature maps from the output of the previous layer before passing them on to the next layer. DenseNet-169 was chosen because, despite having 169 layers of depth, it was able to effectively deal with the vanish gradient problem and had a relatively low parameter count compared to other models.

With the exception of the principal layer, each convolutional layer contributes to the result through the next convolutional layer and produces an element map yield that is sent to the main convolutional layer. The layers are firmly associated in those blocks: All feature maps from the layer before it are input into each layer. Each subsequent layer's guide can serve as information for that layer, and its own planning component can be promoted as a contribution to the main layers.

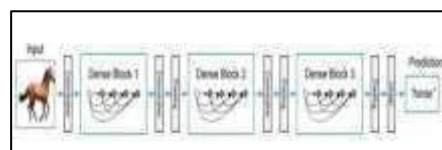


Fig 4: A DenseNet Architecture with 3 dense blocks.

Separating the organization into blocks with thick connections, as shown in Fig.

3.6 addresses the issue. By and by, the Convolution and pooling exercises outside

the thick blocks can play out the down analyzing movement and inside the thick

block we can guarantee that the size of the component maps is something basically

the same as have the choice to perform feature connect. The transition layers that

are situated in between the dense blocks perform the convolution and pooling. The

DenseNet architecture's transition layers are a batch-norm, 1x1 convolution, and

2x2 average pooling layer. Instead of summing the residual like ResNet does,

DenseNet combines all feature maps. Although some resizing might work,

feature maps of different sizes cannot be combined. As a result, the element guides

for each layer in each thick block are the same size. CNN, on the other hand,

heavily uses downsampling. This job is guaranteed by progress layers between two

thick blocks. A change layer comprises of Normalization of a Batch 1x1

Convolution.

3. Normal pooling DenseNet's advantages include:

- Densenet alleviates the disappearing inclination problem.
- Improved feature propagation, reduced

parameter count, and enhanced feature reuse result.

3.1.3 Dataset

The data are from Kaggle, a free online dataset library; There have been no other studies or projects utilizing the dataset yet.

It is an open-source dataset. Almost 6,000 pictures are remembered for this dataset, which is separated into two classifications:

Both normal and insane.

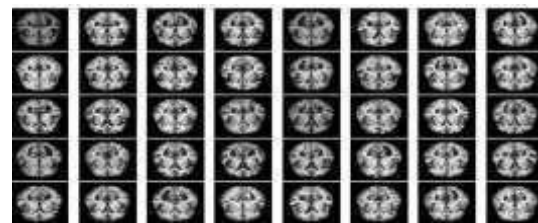


Figure 4:- Demented Alzheimer's Scan.

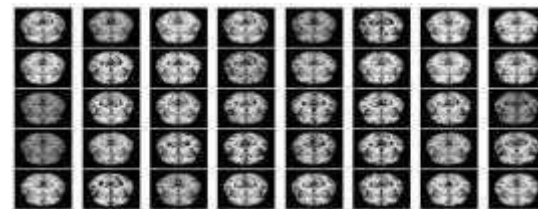


Figure 5:- Non-Demented Alzheimer's Scan.

The features are then divided between an 80% train dataset and a 20% test dataset.

Every profound learning model goes through two stages since preparing takes up 80% of the information: training and

testing, where it makes predictions based on the data it has. Both the demented and

non-demented models make use of the same dataset, which has been separated

from the original Kaggle dataset and is

divided in an 8:2 ratio, with the training dataset accounting for 80% and the validation dataset accounting for 20%. If either model used a different kind of input, there won't be any difference in the prediction because the dataset distributions must be the same. Consequently, the query is removed from both models and they are reset to the same inspection level—not the same dataset—as they were during training and testing. The fundamental target of this dataset is to cultivate a significantly exact model for predicting Alzheimer's sickness stage.

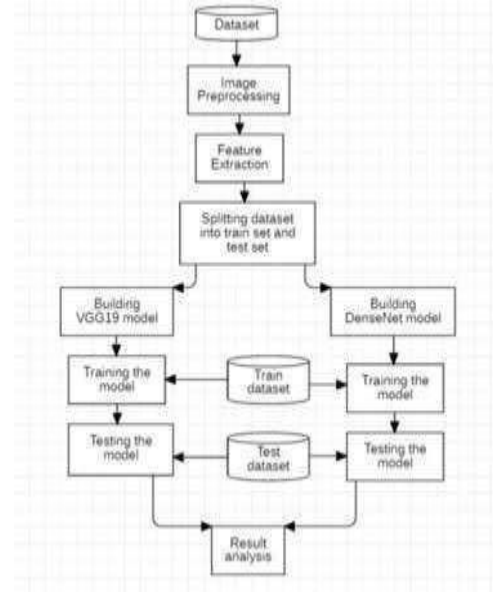


Figure6:- architecture diagrams

Result:

DenseNet169

Fig-5.11: Classification

	precision	recall	f1-score	support
0	0.93	0.97	0.95	100
1	0.97	0.93	0.95	100
accuracy			0.95	200
macro avg	0.95	0.95	0.95	200
weighted avg	0.95	0.95	0.95	200

report of DenseNet169

VGG19

Fig-5.12: Classification report of VGG19

In the above figures 0 represents No Alzheimer's whereas 1 represents

	precision	recall	f1-score	support
0	0.82	0.99	0.90	100
1	0.99	0.79	0.88	100
accuracy			0.89	200
macro avg	0.91	0.89	0.89	200
weighted avg	0.91	0.89	0.89	200

Alzheimer's disease.

From Fig-5.11 we observe that accuracy of DenseNet169 is 95% and from Fig-5.12 we observe

that the accuracy of VGG19 is 89%.

Conclusion:

The architecture diagram, which also shows the system's architecture, shows the major components and their connections.

Resizing and reshaping images are two of the most important steps in picture pre-handling. The proposed model's performance is also affected by the diversity of each CNN model's architecture.

BIBLIOGRAPHY:-

- [1]. Maskeen kaur and Amanjot kaur, "Machine Learning Based Approach for Detection of Alzheimer's Disease", International Journal of Scientific and Research Publications 2022 IJSRP, Volume 11, Issue 11, November 2021 Edition [ISSN 2250-3153]
- [2]. Mahmoud Seifallahi, Afsoon Hasani Mehraban, James E. Galvin, and Behnaz Ghoraan, "Alzeimers disease

detection using comprehensive Analysis of
Timed Up and Go test via Kinect V.2
Camera and Machine Learning” , IEEE
TRANSACTIONS ON NEURAL
SYSTEMS AND REHABILITATION
ENGINEERING, VOL. 30, 2022

[3]. CHIYU FENG , AHMED ELAZAB,
PENG YANG , TIANFU WANG , FENG
ZHOU , HUOYOU HU , XIAOHUA
XIAO , AND BAIYING LEI , “Deep
Learning Framework for Alzheimer’s
Disease Diagnosis via 3D-CNN and FSBi-
LSTM”, 10.1109/ACCESS.2019.2913847

[4]. Nianyin Zenga, Hong Qiu ,Zidong
Wang, Weibo Liu,Hong Zhang, Yurong
Li, “A new switching-delayed-PSO-based
optimized SVM algorithm for diagnosis of
Alzheimer’s disease”, Volume 320,
December 2018

. Asim, Yousra, Basit Raza, Ahmad
Kamran Malik, Saima Rathore, Lal
Hussain, and Mohammad Aksam Iftikhar,
“A multi-modal, multi-atlas- based
approach for Alzheimer detection via
machine learning.” November 2017
International Journal of Imaging Systems
and Technology
28(2)DOI:10.1002/ima.22263