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NeuroScan: Deep Learning based model for Early Detection of Alzheimer's Disease for Health Care Sector

E. Lalitha[1], Jaya Prakash Sunkavalli[2], Chunduru Anilkumar[3], A Naga Kalyani[*4], Naresh Tangudu[5]

[1]Dept of CSE- (CyS, DS) and AI&DS, VNR Vignan Jyothi Institute of Engineering and Technology, Nizampet, Hyderabad, T.S, India

[2]Department of Information Technology, Siddhartha Academy of Higher Education (Deemed to be University), Vijayawada, Andhra Pradesh.

[*4]Dept of CSE(AI&ML), BVRIT HYDERABAD College of Engineering for Women, Hyderabad, Telangana, India.

[3,5]Department of Computer Science Engineering (Data Science), Aditya Institute of Technology and Management, Tekkali, Srikakulam, Andhra Pradesh 532201

***Corresponding Author:**

Email ID: nkalyani.a@gmail.com

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ABSTRACT

Alzheimer's disease has become a silent epidemic, supported by serious records and long-term predictions, and is currently the seventh biggest cause of mortality. Memory, behaviour, and language are all severely damaged in those who suffer from this terrible illness. Early detection is essential for expanding treatment options, but it is still a difficult undertaking because there aren't enough effective cures and precise diagnoses. Although classic machine learning methods and deep learning approaches been employed in numerous research investigations, their diagnostic abilities are frequently constrained by underlying limitations. In order to overcome this, we suggest a unique deep learning-based paradigm for Alzheimer's disease early detection. Utilizing deep learning techniques, our NeuroScan framework analyses a variety of data sources, including brain imaging. We also look at relevant research on Alzheimer's illness and consider how deep learning can help with early-stage diagnosis. We enhance the Alzheimer Disease Neuroimaging Initiative (ADNI) dataset to highlight the effectiveness of our method and its exceptional performance. With the aid of a sizable MRI dataset that includes both healthy and diseased people, this research proposes a state-of-the-art, user-friendly, automated deep learning method for predicting Alzheimer's disease.

Keywords: *NeuroScan framework, Deep learning algorithms, Brain imaging, Traditional machine learning techniques, Alzheimer's disease.*

1. INTRODUCTION

An ongoing neurodegenerative condition is Alzheimer's disease (AD). It is the main contributor to dementia, a more generic term for a collection of symptoms that impair mental processes like memory, thinking, and behaviour. More than 50 million individuals worldwide were estimated to be living with dementia in 2018, and by 2050, that number is projected to rise to 152 million. Around the world, AD will affect 1 in 85 people. The use of machine learning methods in AD diagnosis has shown hopeful outcomes and is currently a hot research topic thanks to publicly accessible data from websites like the Alzheimer's Disease Neuroimaging Initiative (ADNI), Bio-marker & Lifestyle Flagship Study of Ageing (AIBL). The moderate cognitive deterioration in normal control (NC) participants involves memory, language, judgement, and thinking issues, before the AD stage fully developed. Mild Cognitive Impairment (MCI) is the noun that refers to the beginning of cognitive deterioration. 15% annualised anticipated conversion rate, Patients with MCI are at greater danger of getting AD. Since there is no known cure for AD yet, the average life expectancy after an AD diagnosis person is 3 to 9 years.

How does Alzheimer's affect the brain?

Researchers are still trying to comprehend the complex changes in the brain related with Alzheimer's disease. 10 years or more prior to the development of symptoms, changes in the brain may start. Amyloid plaques and tau tangles are both products of aberrant accumulations of proteins that occur in the early stages of Alzheimer's disease. Formerly Functioning neurons stop operating and lost synapses to nearby neurons, and eventually die. Alzheimer's disease is also thought to be affected by numerous more factors and complex brain alterations. The two areas of the brain that are essential for memory formation is the entorhinal cortex and the hippocampal-apparently suffer damage promptly. Many areas of the brain are impacted and begin diminishing while additional neurons die. By the time Alzheimer's illness is fully cured, Brain tissue has drastically decreased and has sustained extensive injury.

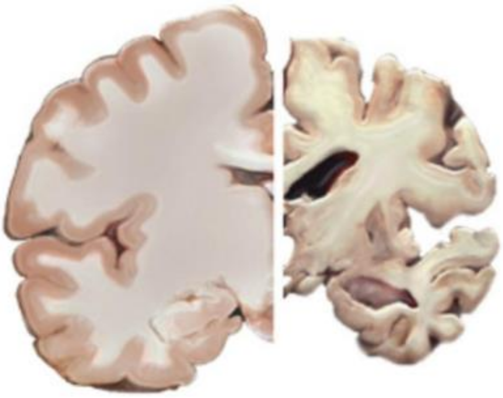
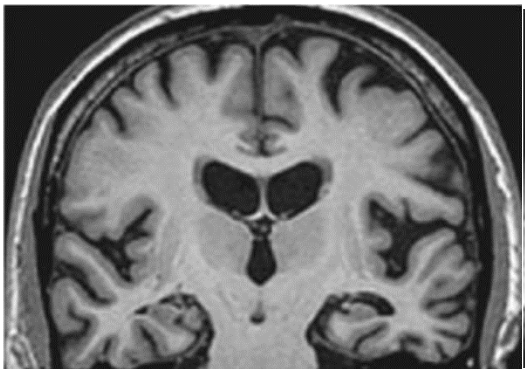


Fig 1 Difference between Healthy and Alzheimer's brain



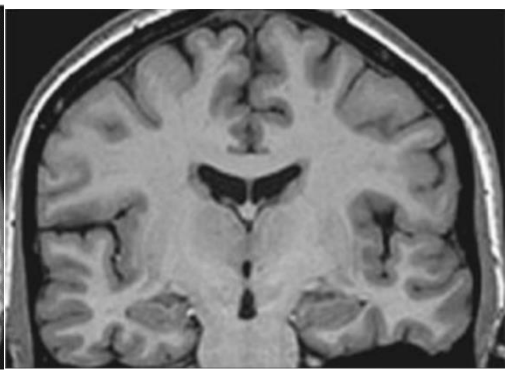


Fig 2 MRI Image of Healthy Brain **Fig 3 MRI Image of Alzheimer's Brain**

Fig 1 explains about the difference between healthy brain and alzheimer's brain. As a result, establishing a reliable computer-aided approach for early AD identification would greatly benefit in the prevention of disease. **Fig 2** represents the MRI Image of healthy brain and **Fig 3** represents the MRI Image of Alzheimer's brain. Typically, this disease must be diagnosed with a battery of tests, including ones for cognition, blood, behaviour, brain imaging, and medical history. This raises the price and duration of the diagnosis. Therefore, a more effective and economical diagnostic system is essential. To assist in early diagnosis and disease progression tracking, deep learning processes and analyses a variety of data sources, including clinical data, genetic data, and brain pictures (MRI, PET scans). ResNet is used in this to help extract useful characteristics from brain pictures, which are then fed to a classifier to help identify between people without Alzheimer's disease and those who have the condition with the help of MRI(Magnetic Resonance Imaging).

2. LITERATURE SURVEY

The method that is suggested in this paper is a content-based image retrieval system that uses a pre-trained 3D auto-encoder, a 3D CNN, and 3D Capsules Network (CapsNets) to find early signs of AD. They employed SVM with functional kernels them to eliminate the other subtypes of AD's initial phase while transitioning amnestic MCI to AD. Using a content-based picture retrieval system that used the 3D Capsules Network (CapsNets), the highest accuracy for identifying AD was 70.33%. The utilisation of multimodal data, transfer learning, and the prediction of disease progression and treatment response are some of the additional potential future paths for AD detection using deep learning algorithms that are covered in this work. The third mission of this project is to supply a clear, straightforward, and speedy image preprocessing pipeline. An complete system was developed to recognise the three AD stages utilising 4 classification tasks**[1]**. The goal of this effort was to provide a technique for discovering biomarkers that can be used to explain AD, which required a strong model. The neural recordings were labelled and organised using a multimodal method, after which various properties of each domain were retrieved from them and used as input for the classification models. The top-performing models are combined through an ensemble process that is also introduced. The system's goal is to increase the detection precision and support early prognosis of Alzheimer's disease. The ensembled machine learning model with explainability (EXML) that is suggested in this paper had an accuracy of 99.4% as its highest value. The work uses fusion approaches, machine learning models, and higher frequency bands to detect AD in spectral analysis, and it supports the function of the hippocampus using spatial models**[2]**.

The research introduces DeepCurvMRI, a novel method for MRI images-based early identification of Alzheimer's disease. To be able to increase the accuracy of AD diagnosis in its early stages, the model integrates curvelet transform with convolutional neural network. Preprocessing of the MRI images, feature extraction using the curvelet transform, are all phases in the process, as well as classification using a convolutional neural network. For the multi-classification challenge, the DeepCurvMRI model's maximum accuracy was 98.62% 0.10%, while for the binary classification task, it was 98.71% 0.05%. The leave-one-group-out (LOGO) cross-validation method was used to get these results. DeepCurvMRI effectively identifies brain regions linked to AD MRI images, providing as a quick and simple-to-use tool to aid doctors in AD diagnosis. It uses MRI scans to increase the diagnostic accuracy in hospitals**[3]**. Using loop patterns in online handwriting, the author suggests a novel method for identifying and categorising people with early-stage Alzheimer's disease. The authors research a number of data augmentation methods to make up for the lack of training data, including DoppelGANger, a version of Generative Adversarial Networks (GANs) that is well-suited for time series and can be used to create sequences of realistic online handwriting. The study's highest accuracy mark is 89%. This resulted from data augmentation using DoppelGANger. Synthetic data production, based on the use of the Generative Adversarial Network applied to time series, especially Doppelganger, is employed to deal with the issue of incomplete data**[4]**.

Here, non-invasive methods like MRI, PET, and SPECT are used to visualise the anatomy and function of the brain. These methods can also aid in the early diagnosis of Alzheimer's disease. In the article, convolutional neural networks (CNNs), capsule networks (CapsNets), and auto-encoders were employed as deep learning techniques for AD identification. A 3D CNN, or 3D Capsules Network, and a previously trained 3D auto-encoder were used by the content-based picture retrieval system to identify AD in its earliest phases. Out of all the approaches, the following content-based picture retrieval system had the highest accuracy, at 98.42%. Growing interest in image analysis has increased diagnostic efficiency and accuracy, making it possible to distinguish early-stage AD from other types of dementias. dependable, non-intrusive, simple to use, and reasonably priced**[5]**. An ensemble of patch-based classifiers is the suggested approach in the research report for SMRI-based Alzheimer's disease diagnosis. The technique employs simple convolutional neural network (CNN) clusters as feature extractors and softmax cross-entropy as a classifiers. The patch-based strategy is employed to get over the lack of data. A weighted voting technique is used for the final decision-making process, in which each model's decision score functions as a weighted vote. Three models make up the system, which generates decision scores for individual patches. Using the GARD group dataset, they were succeeding in achieving consistency of 90.05%. Here, the deep learning-based approach's patch generation planning decreases the lack of training data. A robust model can be created using the ensemble technique without overfitting**[6]**.

In this paper, By reducing parameters and calculation expenses, the ADD-Net classification system was created from the ground up utilising a deep CNN architecture. The ADD-block, a specially created block with numerous layers, is used to categorise Alzheimer's disease in its early stages for each of the distinct groups. When dealing with dataset imbalance issues, the SMOTETOMEK technique is used to create new instances in order to balance the quantity of samples for each classification. By displaying a heat map of class activation, the Grad-CAM technique sheds light on how CNN layers function. The accuracy of their suggested ADD-Net system with SMOTETOMEK was 97.05%. High precision was attained using the ADD-Net. ADD-Net displayed greater performance in evaluation measures like precision, recall, and F1-score which is compared to cutting-edge models**[7]**.

The Improved Deep Learning Algorithm (IDLA) was employed by the suggested system. The method entails using the DPABI toolbox, which is built on the SPM8 programme and the REST (Resting-State fMRI Data Analysis Toolkit), to handle unprocessed resting-state functional MRI (R-fMRI) data. To determine the impact of physiological artefacts, the data is preprocessed by regressing out confounding variables before functional connectivity analysis (FC). After that, a network of the brain's regions is constructed using a time-series matrix of changes in blood levels. This matrix demonstrates how various brain regions contribute to a robust brain connection network, which precisely and effectively depicts the state of the brain's health. Finally, various methods of extraction and comparison are utilised to classify the time series data and matrices for Alzheimer’s disease. It is a reliable and effective technique for diagnosing AD since the specialized network of autoencoders enables efficient processing of high-dimensional data in healthcare**[8]**. The study includes a number of experiments with various parameters and contrasts the outcomes with those provided by earlier investigations. To comprehend the connections between the various features in the dataset, the paper uses the correlation matrix. The data cleaning chores, such as eliminating missing values and using the one hot encoder to convert non-numeric values into numeric values. The experiments by Islam and Zhang to propose a deep convolutional neural network in Alzheimer's diagnosis employing brain Magnetic Resonance Imaging (MRI) data analysis with the Open Access Series of Imaging Studies (OASIS) dataset**[9]**.

The system consists of a wearable electronic gadget with sensors that supports AD patients and enhances their quality of life. The gadget lets you find the patient on a map, remind them when to take their medications, and give them a button to push to get help in an emergency. In order to categorise input image as belonging to a family or not, the system also incorporates a face recognition prototype based on CNN that disables the areas of interest of the eyes, nose, and mouth. To help the person with AD recognise more persons during future discussions, steganography encryption has been added to safeguard the person's detect who isn't listed in the database. The suggested system also features a Google Assistant-based psychological monitoring system**[10]**. They start out by concentrating on data processing, including image reconstruction, signal augmentation, cross-modality picture synthesis, and the biomarkers that can be retrieved from spatio-temporal neuroimaging data, considering the amount of tumours or healthy tissues. They explain how DL is used to identify diseases, forecast their evolution, advance our understanding of them, and aid in the creation of remedies. They place a strong emphasis on the types of architectures and data employed in those applications, as well as the relevant illnesses. Finally, they describe popular applications and offer suggestions for bridging the gap between clinical practise and research studies. Numerous brain illnesses have effectively used CNN to analyse genetic and imaging data. With both longitudinal clinical data and sensor data, RNN demonstrated good outcomes**[11]**.

This study uses an ensemble of deep neural networks that have been transfer learning-trained to classify Alzheimer's disease. The ADNI baseline dataset and a smaller dataset of only 100 people are used by the authors to extensively evaluate their suggested model in a variety of experimental conditions. They contend that deep neural networks' extremely non-convex loss surfaces pose a variety of local optima that can incorporate a variety of predictions to create a robust ensemble model, and that transfer learning computationally speeds up the training of individual models. They demonstrate how significantly better than other models their model performs. They also demonstrate how significantly better than the actual ensemble performs their suggested ensemble. Images from Alzheimer's Disease Neuroimaging Initiative (ADNI) database was used in the research. Materials and methods, experimentation details, experiment findings, and conclusions are only a few of the elements that make up the paper's structure. prevents the lengthy training period needed for typical deep neural network ensembles**[12]**. In this study, a deep learning-based ensemble method for MRI-based early Alzheimer's disease diagnosis is presented. This study's major goal is to address the rising incidence of Alzheimer's disease and its consequences. The suggested method integrates many deep learning models to increase the accuracy of Alzheimer's disease early diagnosis. Preprocessing the MRI data, training several deep learning models, and merging them using a weighted probabilistic ensemble method make up the methodology used in this study. Using a sizable dataset of MRI scans from various sources, the proposed ensemble technique was chosen and assessed. Using deep learning-based ensemble approaches, this work offers a promising strategy for enhancing the precision of early Alzheimer's disease detection. A great degree of success was attained in the analysis and image categorization, and it also offers priceless information to the researcher to diagnose different types of disease**[13]**.

The paper addresses recent developments in neuroimaging and machine learning for dementia diagnosis and the extraordinary progress made by computer-aided algorithms in tackling the problem of precise and prompt dementia diagnosis. The effectiveness of deep learning methods in the early identification of dementia is also extensively evaluated in this research. The review is divided into sections that cover medical imaging analysis in dementia care, traditional and contemporary machine learning algorithms to categorise dementia, performance measurement, problems and opportunities of current dementia research, and future research objectives. Patients receive real-time notifications to judge the effectiveness of treatment early on. reduces the rate of degenerative changes and helps the patient keep their quality of life**[14]**. The paper explores the difficulties of utilising deep learning for Alzheimer's Disease prediction as well as different methods for doing so, such as supervised and unsupervised learning. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and autoencoders are among the most promising deep learning methods for predicting Alzheimer's disease that are thoroughly examined in this article. It explores how well these methods work at predicting when Alzheimer's disease may manifest and emphasizes the value of utilising multimodal data to increase prediction accuracy. Overall, this article contains insightful information on recent developments in deep learning methods for Alzheimer's disease prediction and presents a thorough examination of the many methods employed to do so. They produce excellent results and are utilised for computer-aided diagnosis because they can effectively extract patterns from vast amounts of neuroimaging data**[15]**.

3. METHODOLOGY

Dataflow Diagram:

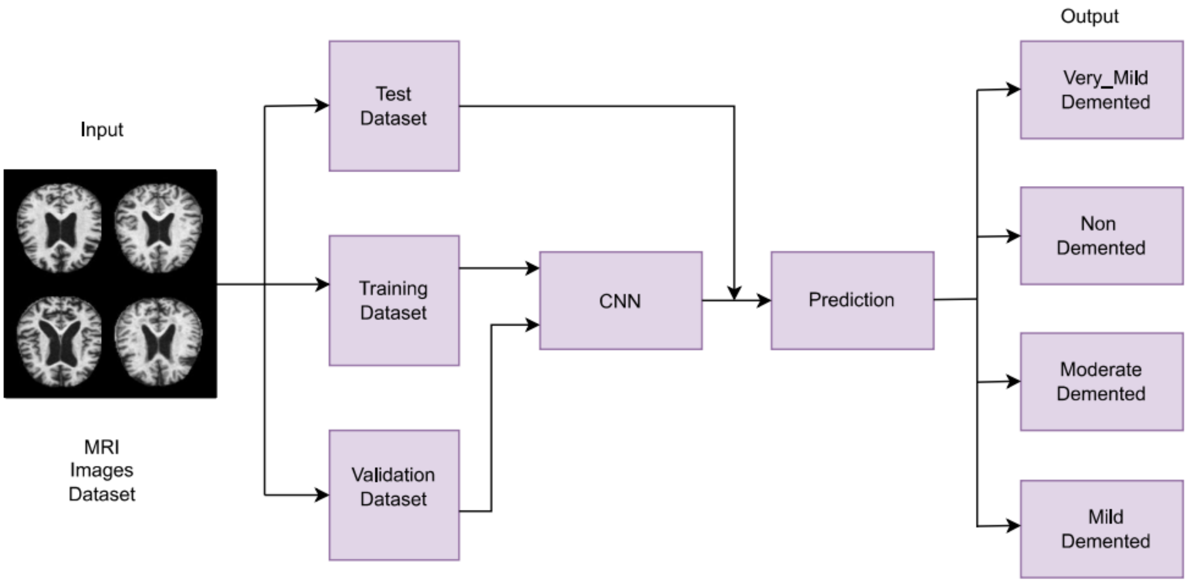


Fig 4 Dataflow diagram for Alzheimer's disease detection

Fig 4 represents the dataflow diagram for alzheimer's disease detection. The MRI images are taken as the input and the images are resized and preprocessed for better quality so that we can analyze more effectively and then they are given for training, testing and validation and then the model evaluation takes place and then the output of the image is obtained.

Dataset: The dataset is made up of four files, Mild_Demented, Moderate_Demented, Non_demented, Very_Mild_Demented which has a total of about 6000 photos which is given for testing and training. **Fig 5** represents the ADNI dataset.

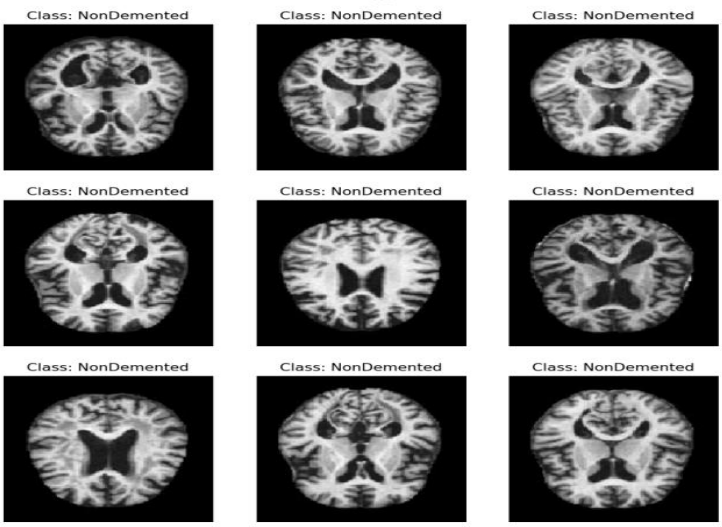


Fig 5 Alzheimer's dataset

Convolutional neural networks:

A particular kind of artificial neural network called a convolutional neural network (CNN) is made for processing structured grid-like data, like photos, movies, and other sorts of grid-based data. The key technological accomplishment of CNNs is the capacity to learn on their own and retrieve hierarchical properties from the input data. Natural language processing, picture classification, video and image analysis for healthcare purposes, and image and video recognition are some of their applications. The CNN consists of three different kinds of layers: fully-connected (FC), pooling, and convolutional layers. CNNs been put to use for tasks like Alzheimer's disease identification and classification utilising MRI (Magnetic Resonance Imaging) scan data. To determine if a patient has Alzheimer's disease or not, these networks are used to automatically learn and extract pertinent information from brain pictures.

1. Convolutional Layer: On the input image, convolutional filters are used in this layer. These filters apply element-wise multiplications and summations as they move across the image, creating feature maps that draw attention to patterns or features like edges, corners, textures, etc.
2. Pooling Layer: The physical dimensions of the feature maps are smaller but vital data is preserved via pooling layers. Pooling decreases the computational load and helps the network be more resilient to little fluctuations in the input data.
3. Fully connected Layer: For classification or regression tasks, fully connected layers are utilised after a number of convolutional and pooling layers. These layers link every neuron in the layer below and the layer above together. On the basis of the learnt representations, they combine the extracted features and generate final predictions

CNN Architecture:

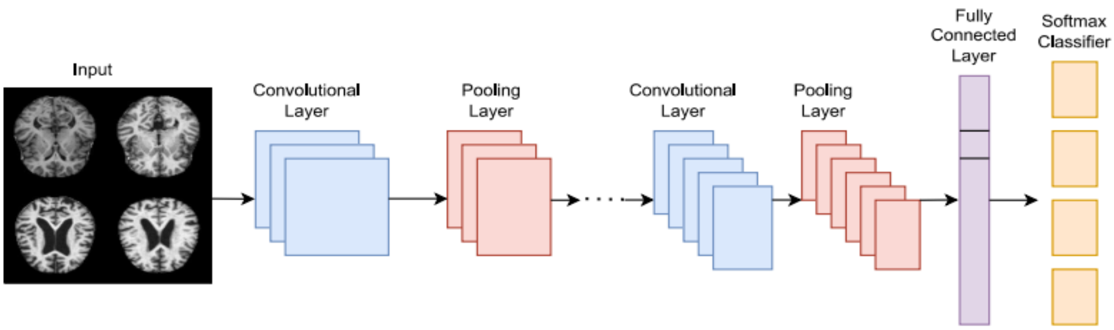


Fig 6 Convolutional Neural Network Architecture for Alzheimer’s Disease Detection

We created a unique inception model to increase the model accuracy. Dropout, Flatten, Batch Normalisation, and Global Average Pooling are new layers that we have added. **Fig 6** represents the Convolutional Neural Network Architecture for Alzheimer’s Disease Detection.

- **Dropout**- The training dataset may get overfit if every single attribute have been connected to the FC layer. A dropout layer, which reduces the size of the model by removing a few synapses from the neural network during training, solves this issue.
- **Flatten**- the data is transformed into a 1-D array before it is entered into its subsequent layer.
- **Batch Normalization**- Regulates the results of the preceding layer and supplies it as input to the following layer. As an outcome, deep networks may be taught using a significantly less number of training epochs and the learning process becomes more stable.
- **Global Average Pooling**- It computes a single average value for each of the input.

Inception V3:

Inception V3 is a 42-layer model. It has been demonstrated that the Inception v3 image recognition model achieves greater accuracy. A convolutional neural network (CNN) architecture called Inception v3 was created by Google researchers as a member of the Inception architectural family. It is primarily made for jobs involving image categorization and recognition. Image categorization, object recognition, and feature extraction have all benefited from the widespread adoption of Inception v3, which represents a substantial leap in deep learning for computer vision. The actual model is composed of convolutions, average pooling, maximum pooling, concatenations, dropouts, and fully connected layers. **Fig 7** represents the Inception V3 Architecture for Alzheimer’s disease detection

Inception V3 architecture:

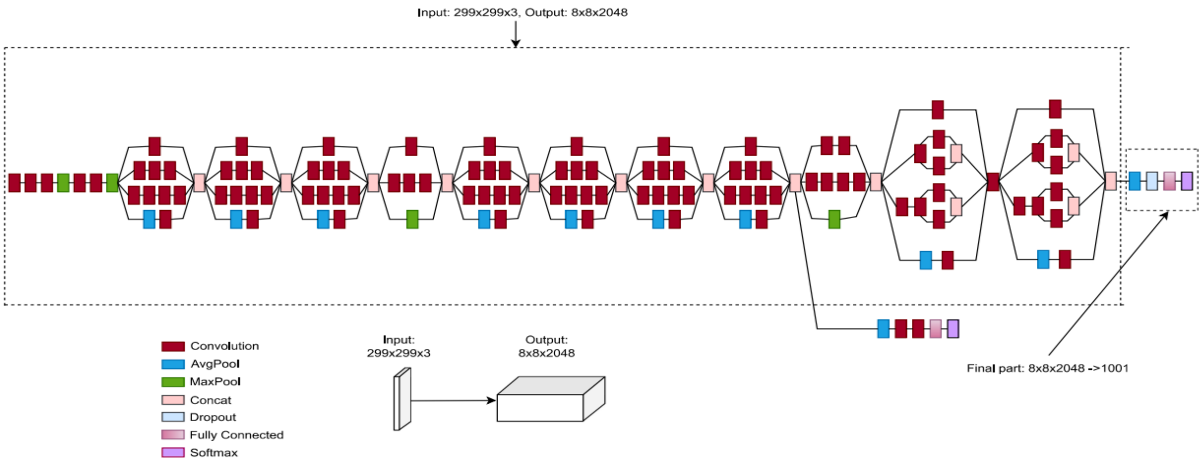


Fig 7 Inception V3 Architecture for Alzheimer's disease detection

Major features of InceptionV3 architecture:

1. Factorizing into Convolutions

   1.Factorizing into Smaller Convolutions

2.Factorizing into Asymmetric Convolutions

In order to reduce the total amount of contacts and parameters without affecting network performance, convolutions are factorised.

2. Auxiliary Classifier

Auxiliary classifiers are used to accelerate the convergence of very deep neural networks. A regularizer in the Inception V3 model architecture is provided by auxiliary classifiers. Regularization is a method for calibrating machine learning models that reduces a modified loss function and guards against overfitting and underfitting.

3. Reduction of Efficient Grid Size

Although it has a deeper network and is more productive than the Inception VI and V2 models, its response time is unchanged. Calculation is less expensive.

Performance metrics:

1) **Categorical Accuracy class:** Determines how frequently forecasts and labels match. To calculate the regularity with which the prediction matches the actual label, this metric generates the 2 local variables that is total and count.

2) **tf.keras.metrics.AUC:** This curve (AUC) is a statistical metric used to analyse a classifier's ability to differentiate between classes. The greater the AUC, the more effectively the model does in distinguishing between the positive and negative classifications.

3) **Matthew's correlation coefficient(MCC)**: It is a statistic that we may use to evaluate how well a categorization model is working.

4) **Balanced accuracy**: It is a metric that we are able to employ to evaluate the ability of a classification model. When there is an unbalance between the two classes—that is, when one class appears much more frequently than the other—this statistic is extremely useful.

It is calculated as: $Balanced\ accuracy = \frac{sensitivity+Specificity}{2}$

Sensitivity: The "true positive rate"—the proportion of positive cases the model is able to identify.

Specificity: the proportion of negative cases the model manages to recognise, or the "true negative rate."

4. RESULTS AND DISCUSSION

In this study, we introduced a custom inception model for detection of Alzheimer's disease into 4 stages. In this model we rescaled the images from 1-255 to 0-1 that means all images are treated effectively. The dataset is splitted into test, validation, and training data. When we carried out the project using inception V3 we got accuracy around 70% but by using custom inception model by adding few more layers to the existing model to increase the accuracy and for better performance. For hidden layers, we opted for the RELU activation function, whereas for output layers, we applied the Softmax activation function because softmax activation function gives better accuracy for multiclass predictions. The reason for callback function used is if the accuracy goes above 99% out training must be stopped then the metrics which we are used is categorical accuracy and AUC. After we carried out about 20 epochs our custom model gave the accuracy around 79.06%.

The graphs for model accuracy, model AUC and model Loss is

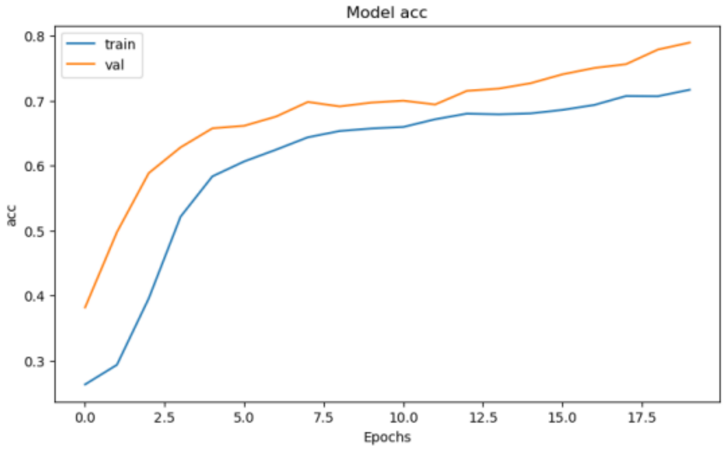


Fig 8 Model Accuracy graph

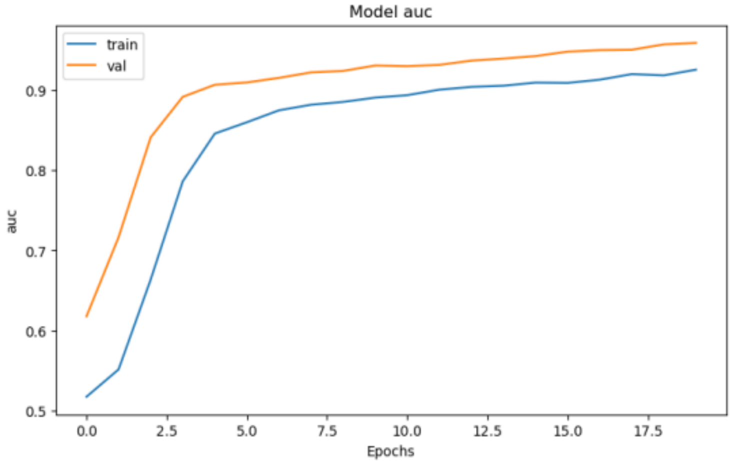


Fig 9 Model AUC graph

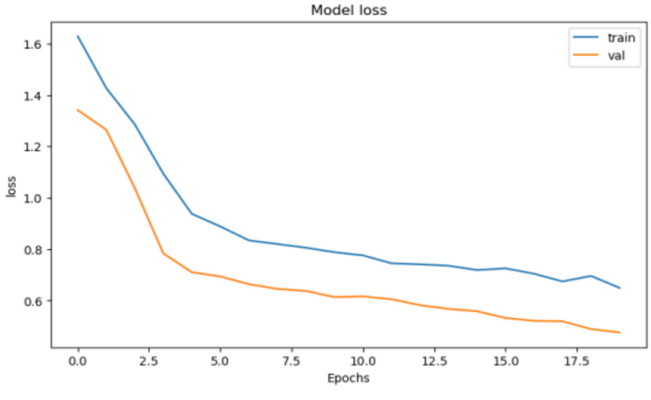


Fig 10 Model loss graph

Fig 8 represents the model accuracy graph, Fig 9 represents the model AUC graph and Fig 10 represents the model loss graph. Evaluating our model and test our custom model by providing the testing data. **Table 1** represents the Comparison table for Performance metrics The testing accuracy obtained is 91.25%. Since the labels are softmax arrays we need to roundoff in the form of 0's and 1's, so we have printed the classification report. Y-axis shows the truth value and X-axis shows the prediction. All green boxes represent the correct number of classification also used other metrics like Balanced accuracy score with accuracy of 91.37% and Matthew's correlation coefficient of 88.48%. **Fig 11** represents the Confusion matrix of the model and **Fig 12** represents the comparison line chart for performance metrics.

The confusion matrix is shown below:

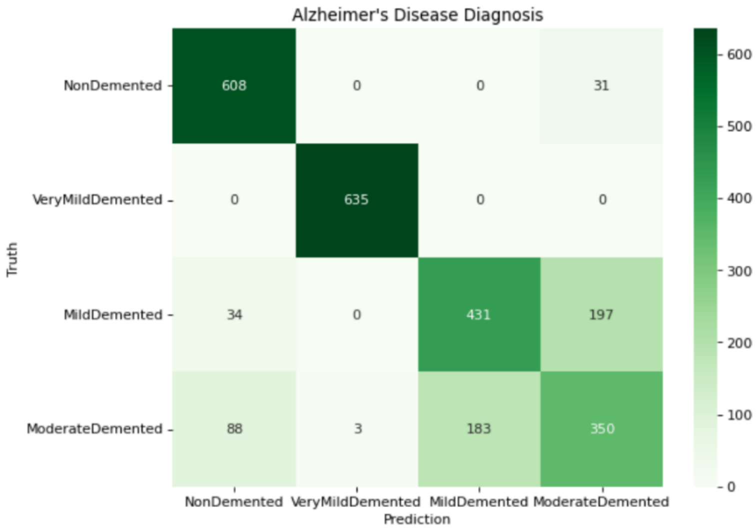


Fig 11 Confusion matrix of the model

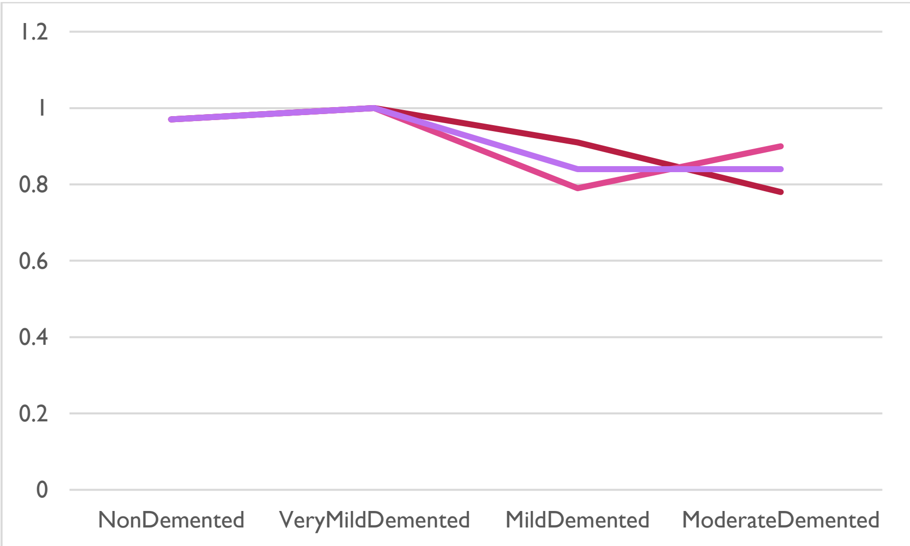


Fig 12 Comparison graph for Performance metrics

	Precision	Recall	F1-Score	Support
Non Demented	0.97	0.97	0.97	639
Very Mild Demented	1.00	1.00	1.00	635
Mild Demented	0.91	0.79	0.84	662

Moderate Demented	0.78	0.90	0.84	624
Micro avg	0.91	0.91	0.91	2560
Macro avg	0.92	0.91	0.91	2560
Weighted avg	0.92	0.91	0.91	2560
Samples avg	0.91	0.91	0.91	2560

Table 1 Comparison table for Performance metrics

5. CONCLUSION

Our project was successfully implemented using Inception v3 architecture and achieved better accuracy The model developed was successfully able to detect and classify Alzheimer's disease into four stages – Non_Demented, Very_Mild_Demented, Mild_Demented and Moderate_Demented. Alzheimer's disease is a prevalent neurological illness that affects the elderly. As a result, early discovery is critical for adequate treatment and to avoid mishaps. Using deep learning, this effort assists in the automated identification of Alzheimer's disease The primary purpose of this research is to devise a practical method for people to take the required and appropriate safeguards against developing Alzheimer's disease. If a brain MRI scan is available, we may use this initiative to make its diagnostic accessible to everyone. Deep Learning is a fast-expanding area, and its use in the healthcare industry can be very beneficial to patients Deep neural networks, particularly CNNs, can give useful information for diagnosing Alzheimer's disease Picture processing, particularly image categorization. is better served by CNN. This model uses brain MRI data to forecast Alzheimer's Disease affected-brain vs a normal ageing brain. Our suggested network might be extremely useful in detecting early-stage Alzheimer's disease.

6. FUTURE WORK

Future research will be able to mix various datasets with cutting-edge deep learning algorithms to enhance the accuracy of AD prediction at earlier stages. The purpose of deep learning-based AD research is to increase performance and transparency. however, it is still in its early phases. However methods for integrating entirely various types of input into deep learning networks need to be established, research on using deep learning to diagnose Alzheimer's disease is moving toward a model that uses only deep learning algorithms rather than hybrid methods as the amount of Data and computing capabilities for multifunctional scanning grows.

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