DETECTION OF ALZHEIMERS DISEASE

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BONAFIDE CERTIFICATE

Certified that this project report entitled **ALZHEIMERS DISEASE DETECTION,** is a bonafide work **of P KHYATHI REDDY (19BEC1118) DUVVADA MEERA (19BEC1264) P PENCHALA MOHAN(19BEC1047) and C JOSHANSAI REDDY (19BEC1031)** who carried out the project work under my supervision and guidance.

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ABSTRACT

Alzheimer's disease is an ever-evolving dementia that causes neuropathy that causes mental degradation and cognitive decline. Side effects of AD steadily progress and become more serious over the long run. By 2050, one out of 85 individuals overall is supposed to be impacted by the illness. Early finding of AD is viewed as a compelling treatment, however early recognition of AD is a troublesome undertaking. Since different examinations have inferred that most AD patients lose their discourse work, neuropsychological evaluations are generally performed for early discovery of AD. The exactness of the Psychological Cognitive Test relies completely upon the expertise of the specialist. You really want to carry out a programmed discovery and grouping model to recognize AD. Longitudinal investigation of constant MRI is vital for measure sickness movement for precise outcomes. Various clinical experts dissect and decipher clinical information. Accordingly, the use of profound learning gave magnificent experiences and precise clinical outcomes. The profound learning approach is utilized to effectively order and concentrate the general elements of that can be utilized to analyze AD patients.

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TABLE OF CONTENTS

1. INTRODUCTION

Because of the development and improvement in computing procedures of higher speed DL algorithms have prevailed in computer vision and examination of neuroimaging, empowering a wide scope of chances which brought about an endeavor on the DL-based approaches for distinguishing and foreseeing the neurological issue from the MRI scans[3]. Despite the fact that there are countless DL algorithms like Recurrent Neural Network and Long-Short Term Memory, Deep Neural Network, and Auto encoder, researchers have been depending on the Convolutional Neural Network based way to deal with distinguish the neurological issue from MRI information.

2. LITERATURE SURVEY

This paper[9] is primarily concerned with the early detection of Alzheimer's disease (AD) using magnetic resonance imaging and convolutional neural networks (ConvNets) (MRI). As inputs for categorization, MRI image slices of grey count and white remember were used. Following the convolutional challenges, group learning procedures were used to improve the order by combining the results of deep learning on classifiers. In this paper, three basic ConvNets were planned, implemented, and reversed. This technique was previously evaluated primarily based on a dataset from the Alzheimer's Disease Neuroimaging Initiative for the early exploration of this disease. In particular, the arrangements' accuracy rates have reached up to 97.65% for AD/mild mental impairment and 88.37% for gentle mental impedance/normal control.

A recent deep learning method [4] can identify patients with MCI who are at a higher risk of transitioning completely to AD within three years. The ADNI data set is being used to combine the baseline underlying MRI, neuropsychological, segment, and APOe4 hereditary information. The goal is to distinguish between a quiet AD and a sound

gathering. This procedure yielded a normal of 0.924 AUC, with forecast exactness of 86%, responsiveness of 87.5%, and explicitness of 85%.

The convolutional network is an artificial neural network used for various analyses, such as for analyzing images, sounds, and so on. Two-layered data are best handled by this approach. A pooling layer and a standardization layer are available for pooling and standardization. Each layer has an input layer, a result layer, and a secret layer that all have convolutional layers. [3]

Using bidirectional FSBi-LSTMs (totally stacked bidirectional long momentary recollections), the author of the paper[10] discusses a structure based on 3D-CNNs and bidirectional FSBi-LSTMs. Every MRI and PET output is intended to be analyzed using a 3D-CNN engineering. By further developing its presentation on the basis of profound trademark maps, the FSBi-LSTM is applied. Data from the AD neuroimaging initiative (ADNI) was used to test the strategy. For identifying AD from normal control (NC), pMCI from NC, and sMCI from NC, this approach yields normal accuracy of 94.82%, 86.36%, and 65.35 %, respectively.

C3d-LSTM, one of the deep models proposed [6,] combines 3D CNN and LSTM. The 3D CNN can be used to deal with fMRI data, and LSTM is an improvement of RNN that effectively eliminates the inclination evaporating issue when compared to RNN. The primary advantage of this model is that it accepts 4D data as contribution without cutting, making it easier to use. Furthermore, this model outperforms other 2D and 3D models in terms of accuracy.

The ISDL model is used to eliminate undesirable districts from the diagnosis in order to obtain a precise determination of Alzheimer's infection in this paper[7]. The minor relapse is associated with a complicated configuration module. In the AD-CN configuration and MCI change forecasting, this model outperforms a few existing techniques. The dataset for this model was made up of T1-weighted sMRI examinations recovered from the ADNI data set.

This paper[11] proposes a profound distinguishable convolutional brain network model for AD characterization to address this issue and improve the proficiency of the DL algorithm. In this paper, depthwise separable convolution (DSC) is used instead of conventional convolution. The proposed brain network, in contrast to traditional brain organisations, has lower boundaries and registration costs. The proposed brain organization's boundaries and computational expenses are significantly lower when compared to regular brain organisations. The proposed model is ideal for installed devices due to its low power consumption. The DSC calculation has proven to be extremely effective for distinguishing Alzheimer's disease in light of the OASIS appealing reverberation imaging dataset.

Methodology [8] is based on a deep convolutional autoencoder using brain MRI images, with two sections: an encoder that packages participation into an idle representation and a decoder that uses idle states to replicate information into an information collection. It is divided into. Expression. A 26-layer deep CAE method is required to get a representation of the lower layer information. This model looks for the most transparent dataset, also known as the "open access sequence of imaging tests". This model uses one MRI slice at a time and combines the indicated predictions with a single understanding to achieve 74.66 percent accuracy.

This paper [12] aims to achieve a high level of automatic classification. Seven morphological features captured from 240 ADNIs MRIs using SegNet, gray matter, white matter, cortical surface, gyrus and groove contours, cortical thickness, hippocampus, and CSF space train ResNet in an array. Used to, the classifier achieved 96 percent responsiveness and 95 percent accuracy compared to the other 240 ADNI-sMRIs used in preparation.

In this study [17], we essentially use a PCA (principal component analysis) strategy for layered feature space reduction and an SVM (Support Vector Machine) approach to improve AD inference accuracy using SPECT-based images. Introduced a computational visualization device based on. The best image is selected under PCA printing to diagonalize the covariance grid, and the separated data is used to create an SVM classifier that ranks the new objects individually.

This article uses [18] deterioration of the medial temporal lobe (MTL) to find early neurodegenerative changes in the area of Alzheimer's disease (AD). Strategies were established and studied using reference references of 144 AD patients and 189 age-matched controls. It was subsequently used in a group of 302 MCI subjects, of which 136 had clinically plausible AD (MCI converter) and 166 recovered normally after 2 years of treatment (MCInon converter). All subjects were taken from the ADNI database.

The paper[23] infers that PiB and FDG can distinguish early AD obsessive strategies and resulting neuro degeneration Imaging with PiB and FDG has health advantages, comprehensive of preclinical location of AD. PiB and FDG permit the analyze of connections of Aβ to changes in insight and neurodegeneration. The present audit centers around utilization of PiB and FDG-PET and their relationship to one another.

[27] Consideration is given here to deep learning verification of AD detection. According to this study, forced standardisation and adoption are important pretreatment techniques

for Alzheimer's disease detection. In highlight extraction, complex patching strategies related to disease-related areas are more valuable. Transfer learning and data expansion are beneficial for certain patient populations.

They[28] proposed a 3D multichannel CNN architecure to recognize patients with Alzheimer's from normal controls, then, at that point, proposed an augmentation of their architecture to integrate multiple scans from a patient's set of experiences to further develop arrangement exactness and anticipate future prognosis.

The architecture used is a crossover model in which the profound elements extracted from the BiLSTM [29]model are used to train various ML classifiers. It consists of 1371 ADNI subjects. The trial results based on ADNI data demonstrated the viability and reasonableness of the proposed profound learning model.

A deep learning model based on a stacked CNN and BiLSTM network is proposed in this paper[30]. This multimodal perform multiple tasks model predicts various factors based on a combination of five types of multimodal time series data and a background (BG) data. Anticipated factors include an AD multiclass proposed model that focuses on nearby and longitudinal features. The ADNI database is used to generate a dataset of 1536 subjects.

Reference	**Technique**	**Modality**	**Data source type**	**Accuracy**
[13]	CNN model with inception blocks	MRI	ADNI, OASIS	Classification |Accuracy CN-MCI 98.73% CN-AD 100% AD-MCI 93.72% CN-MCI-AD 92.11% At 10-fold cross validation using ADNI CN-MCI 92.92 ± 3% CN-AD 98 ± 2%, AD-MCI 90 ± 4% CN-MCI-AD 94.9 ± 2% 135 MRI volumes selected from OASIS data set CN-AD 92% MCI-AD 91.76% CN-MCI 88.23% three-way classification 81.48%

[4]	Novel profound learning design, in light of double learning and an impromptu layer for 3D divisible convolutions	▪ structural MRI ▪ Demographic ▪ Neuropsychological ▪ APOe4 genetic data	ADNI MRI - 785 (AD - 192 MCI - 409(counting both MCI patients who convert to AD and MCI patients who don't convert to AD), HC – 184)	10-fold cross-validation Accuracy - 86% sensitivity - 87.5% specificity - 85% area under the curve (AUC) – 0.925
[5]	recurrent Neural Networks (RNN) with flowed three bidirectional gated recurrent units (BGRU) layers is built on the results of CNN	MRI	ADNI 830 MRI (198 AD, 403 MCI, 229 NC)	Classification Accuracies AD vs NC - 91.33% pMCI vs sMCI - 71.71%
[9]	convolutional neural networks (ConvNets)	MRI	ADNI	Classification Accuracy AD/MCI - 97.65% MCI/NC - 88.37%
[10]	3D-CNN and fully stacked bidirectional long short-term memory (FSBi-LSTM)	MRI, PET	ADNI	Average Accuracies AD vs NC - 94.82% pMCI vs NC - 86.36% sMCI vs NC - 65.35%
[11]	Deep separable convolutional (DSC) neural network model	MRI	OASIS	Average Classification Rates AlexNet - 91.40% GoogLeNet - 93.02%
[12]	Differential Evolution-Multiclass Support Vector Machine (DE-MSVM) for classification and AlexNet for feature extraction	MRI, PET	ADNI	Accuracy DE-MSVM - 98.3% MSVM - 95.23%

[2]	Deep Convolutional Neural Networks	MRI and fMRI	ADNI 144 subjects of fMRI and 302 subjects of MRI data,	Accuracy fMRI- 97.7% MRI pipelines- 100% LeNet : 99.9% GoogleNet. :98.84%
[19]	Computer aided brain diagnosis (CABD) with ST+KNN(Spatial Temporal KNN)	MRI	ADNI	Test Accuracy: 94.54% Test Precision: 88.33%, Sensitivity:96.30% Specificity: 93.64%.
[33]	CNN and RNN with cascaded three bidirectional gated recurrent units (BGRU) layers	MRI (Longitudinal T1-weighted MRIs)	ADNI 830 participants including 198 AD, 403 MCI, 229 normal controls (NC) subjects	Accuracy AD vs. NC - 91.33% pMCI vs. sMCI - 71.71%
[32]	Three-dimensional convolutional network (3D ConvNet)	MRI	ADNI 340 subjects , 1198 MRI brain scans	Test accuracy : 98.74%, AD detection rate : 100% False alarm: 2.5%
[20]	Deep convolutional neural networks	MRI	OASIS 416 data samples	Accuracy: 93.18% Precision: 94% Recall: 93% f1-score: 92%
[18]	SVM Classifier	MRI	ADNI 144 AD subjects, 302 MCI subjects, 136(AD-MCI converters),166 NC subjects	NC vs AD AUC: 0.97 Specificity:94% Sensitivity:89% NC vs MCI AUC: 0.92 Specificity:80% Sensitivity:89%
[8]	Deep Convolutional Auto encoders (Deep CAEs)	MRI	OASIS	Classification accuracy : 74.66%

TABLE I

Comparision of different deep learning models from the literature survey

3. PROBLEM STATEMENT

In 2020, there will be more than 55 million people living with dementia around the world. Every 20 years, this number will nearly double, reaching 78 million in 2030 and 139 million in 2050. The prevalence of Alzheimer's disease is expected to rise in the coming years. As a result, developing strategies for detecting Alzheimer's disease is critical. Therefore it is essential to devise methods for detection of Alzheimer's. The purpose is to explore some deep learning techniques for discerning between Alzheimer's magnetic resonance imaging (MRI) and healthy control reference data.

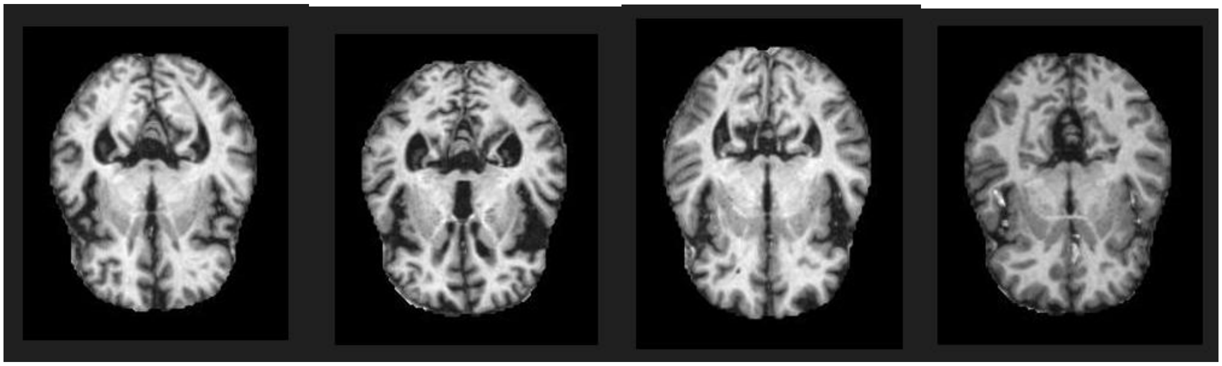
4. METHODOLOGY

4.1 DATA ACQUISITION

Data found in this study was taken from the ADNI database, which can be accessed at adni.loni.usc.edu. ADNI was created specifically for gathering, validating, and using blood biomarkers as predictors of Alzheimer's disease. It was founded in 2003 with the purpose of collecting and analyzing brain scans from people with Alzheimer's disease, Parkinson's disease, and other forms of dementia. 615 MRI pictures were allocated to 179 AD, 254 MCI, and 182 NC. In each group, the proportion of male to female controls are about equivalent. The information is oftentimes isolated into three classes: training, validating, and testing, in a 3:1:1 proportion.

		Train	Test	Validation	Total
1	Mild Demented	717	179	143	1039
2	Moderate Demented	52	12	10	74
3	Non Demented	2560	640	512	3712
4	Very Mild Demented	1792	448	358	2598
	Total				7423

TABLE II
Tabulation of the splitting of data for different classes



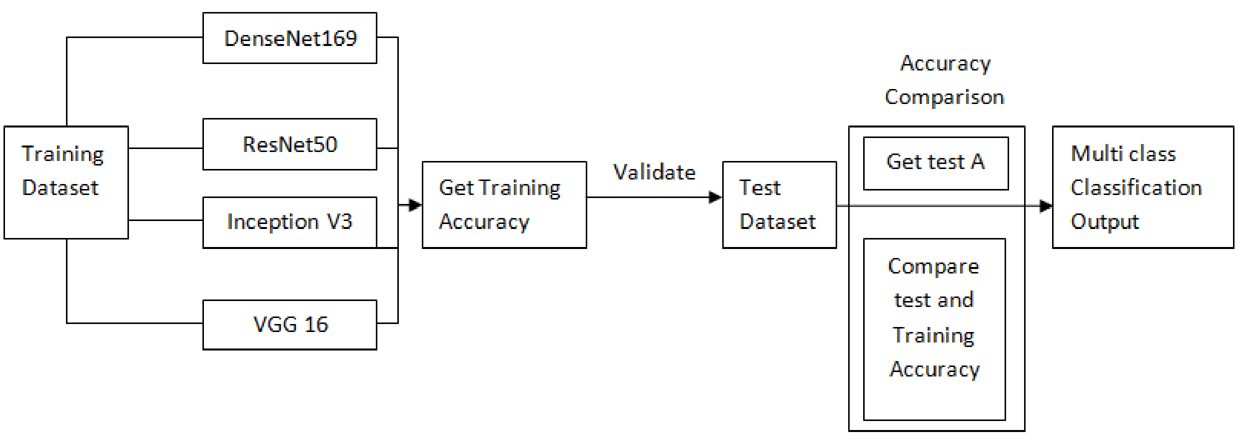
(a) (b) (c) (d)

Figure 1: various brain MRI images presenting various AD stages. (a) Mild demented; (b) Moderate demented; (c) Very mild demented; (d) Non demented

4.2 MODEL TRAINING

This research reviews and assesses existing state technology models with a range of hyper-parameter variations on a dataset. These designs comprise various Convolutional neural networks such as DenseNet169, ResNet50, Inception v3 and VGG16.

4.3 PROPOSED METHODOLOGY



Architecture of the deep learning models for detection of AD

The system architecture defines the framework's theoretical and functional perspectives. A view essentially demonstrates how to use a dataset to create a dataset and how to use that information in a module to prepare various models. As shown, information is gathered from the preparation dataset and sent to the model. Because of the comparison with the test dataset, the accuracy of testing and approval is not completely determined. Following an accuracy analysis, pathogenic photographs are extracted from the dataset. There are four types of dementia: mild dementia, moderate dementia, non-dementia, and very mild dementia. The blueprint also demonstrates the various modules that are used, how to integrate them to achieve important results, and how to connect and work with each module.

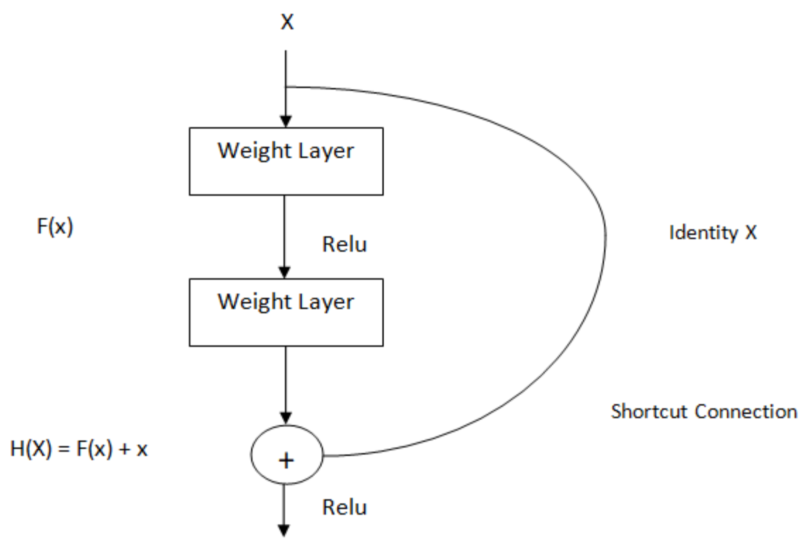
DenseNet169

DenseNet169 is a CNN that employs no-delay close relationships between layers. To achieve feedforward behaviour, each layer receives additional contributions from all previous layers and passes its component skeleton to all or some other layer. Densenet is a typical CNN application. There are L (L + 1) / 2 connections in the L layer. All subsequent shift schedules for each shift can be used as input to promote unique planning capabilities to contribute to the primary shift. Densenet169 is one of the most popular Densenet bundle models for image classification. This model is well-known for its large size and precision. This is a result classification object with 1,000 different image net characteristics. As a result, when the image is input, it goes through a series of layers of thick squares based on the design. There is a progress layer after each thick square layer that adds and shrinks the image's pixels and is passed to the layer that accompanies the modified rendering of the image. The model places the image after passing through a specific layer. They are performed in four different orders: mild dementia, moderate dementia, non-dementia, and very mild dementia. With respect to the dataset, the model had an accuracy of approximately 79.88 percent.

Resnet50

ResNet50 is a ResNet model variant with 48 convolution layers located near one MaxPool layer and one AveragePool layer. There is a floating element activity of 3.8 x 10 9 units. The ResNet model, which is widely used.The stack is built directly, with each layer of the remaining learning modules weighing x. The relu operation is then non-linearly differentiated and weighted in the second layer before detecting F (x) + x. Because Relu usually causes long-term inactivation of neurons, these dormant neurons are still involved. The included calculated values imply that it is still difficult to exclude image features. Mish replaces Relu's capacitance in the model to compensate for its lack.The Mish enactment work is indicated in Equation 1 as follows:

f(x)=xtanh(ln(1+e^x))



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Inception v3

The inception v3 model debuted in 2015, with 42 layers and a lower error rate than previous models. Inception v3 is a convolutional mind community from the Inception family that makes multiple updates including the use of Label Smoothing, Factorized 7 x 7 convolutions, and the use of a classifier to reduce call data down the community.

The true version is made up of symmetric and deviated shape blocks, as well as convolutions, ordinary pooling, maximum pooling, connections, dropouts, and clearly associated layers. At some point in the version, group normalisation is extensively used and applied to incitation inputs. The use of Softmax causes misfortune.

The large modifications achieved at the Inception V3 version are

- Factorization into Smaller Convolutions
- Spatial Factorization into Asymmetric Convolutions
- Utility of Auxiliary Classifiers
- Capable Grid Size Reduction

In general, the start V3 model is made up of forty two layers, which is clearly superior to the previous initiation V1 and V2 models. The functionality of this version, on the other hand, is simply incredible.

TYPE	PATCH / STRIDE SIZE	INPUT SIZE
Conv	3×3/2	299×299×3
Conv	3×3/1	149×149×32
Conv padded	3×3/1	147×147×32
Pool	3×3/2	147×147×64
Conv	3×3/1	73×73×64
Conv	3×3/2	71×71×80
Conv	3×3/1	35×35×192
3 × Inception	Module 1	35×35×288
5 × Inception	Module 2	17×17×768
2 × Inception	Module 3	8×8×1280
Pool	8 × 8	8 × 8 × 2048
Linear	Logits	1 × 1 × 2048
Softmax	Classifier	1 × 1 × 1000

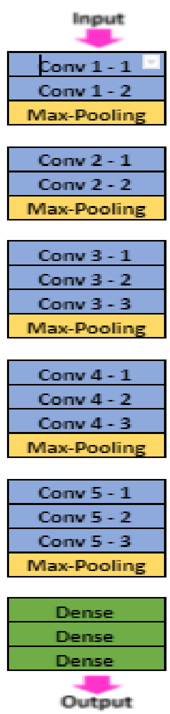
The above table portrays the system of the beginning V3 model. Here, the result size of each module is the information size of the accompanying module.

VGG 16

VGG16 is a convolutional neural network (CNN) plan used in 2014. It is still considered one of the overwhelming vision model plans. The worst thing about the VGG16 is that it focused on the phase 1 3x3 channel convolution layer and used the overall equivalent padding and stage 2 2x2 channel maxpool layer, rather than the uncalculable hyperlimits. This ensures that the entire array follows this convolution and maximum pool tier approach. Ultimately, there are two FCs (fully related layers) followed by a softmax of the result. The 16 on the VGG16 indicates that there is a 16-layer load. This attribution is an immeasurable relationship with about 138 million borders.

The commitment to convnets is a fixed size 224x224 RGB image. Subtracting the average RGB resources contained in the action set from each pixel is a fair pre-management done here. It is more important and has more non-linearity and less cutoff points. One of the plans is to use a 1x1 convolution channel like this. This should be recognizable (using subsequent non-linearity) as a rapid distinction between information channels. Spatial attenuation of convolution steps and conv. The level input is fixed at 1 pixel for a 3 x 3 convolution level. This ensures that the spatial target is preserved after convolution. Five maxpooling layers that follow part of the convolution layer are useful for spatial pooling. Maxpooling runs in a level 2 2x2 pixel window.

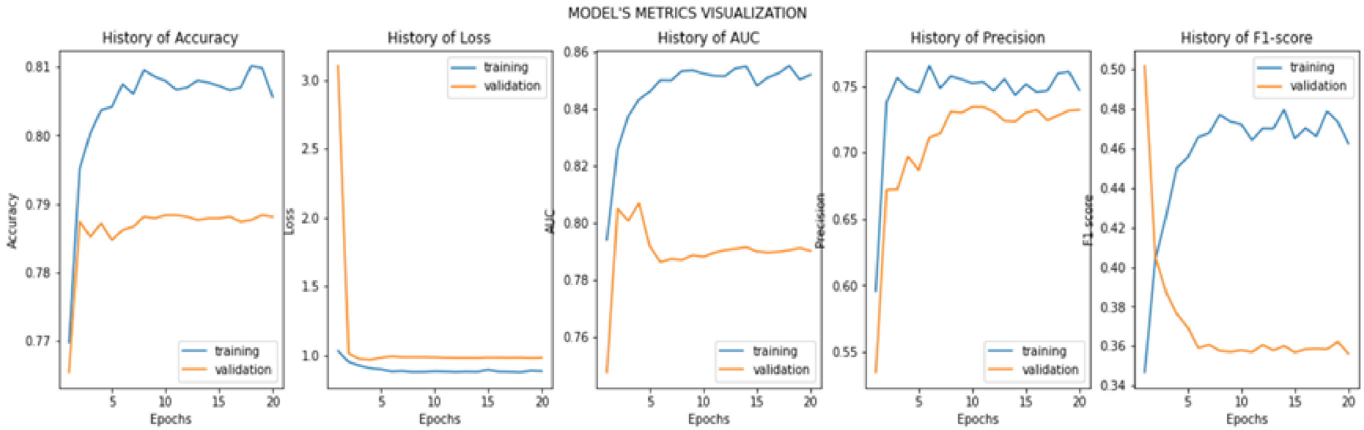
There are three fully connected (FC) layers following a bunch of convolutional layers (these have different depths with different plans): the basic two each have 4096 channels and the third is a 1000-way ILSVRC representation. And include 1000 such channels (per class). The last layer is the delicate Max layer. Fully related layer approaches are virtually indistinguishable by all affiliations. Figure 1 shows VGG16 engineering. It is as follows:



5. RESULTS

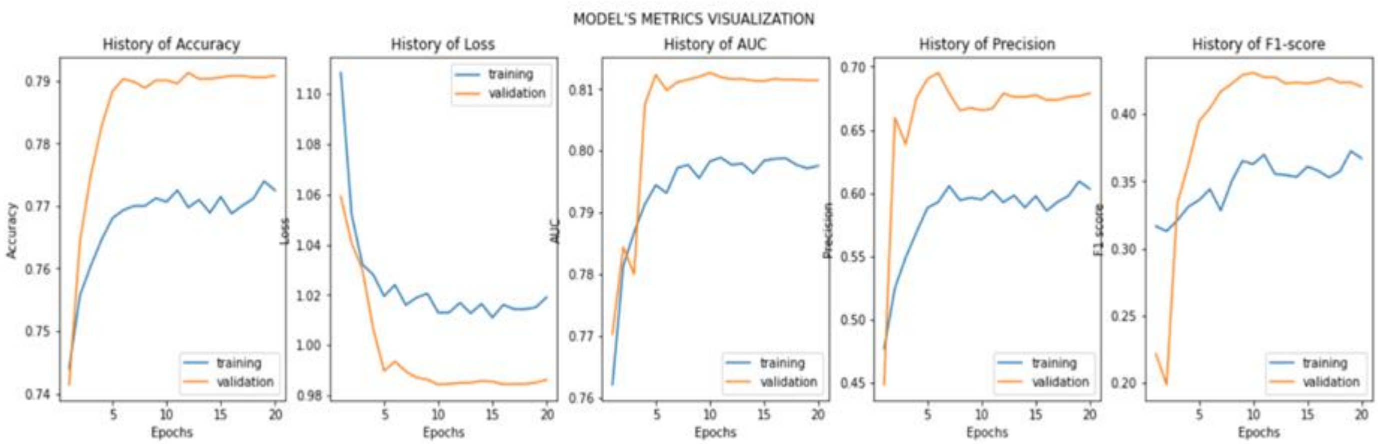
DenseNet169 Model

The Densenet model has been found to be very accurate in image characterization. Examining the generated charts, they seemed encouraging. The model results in an accuracy of approximately 79.88% of the information. This model achieves 88% AUC and about 84.38% in mobile data, and its damage is also very low. The graphic is as follows:



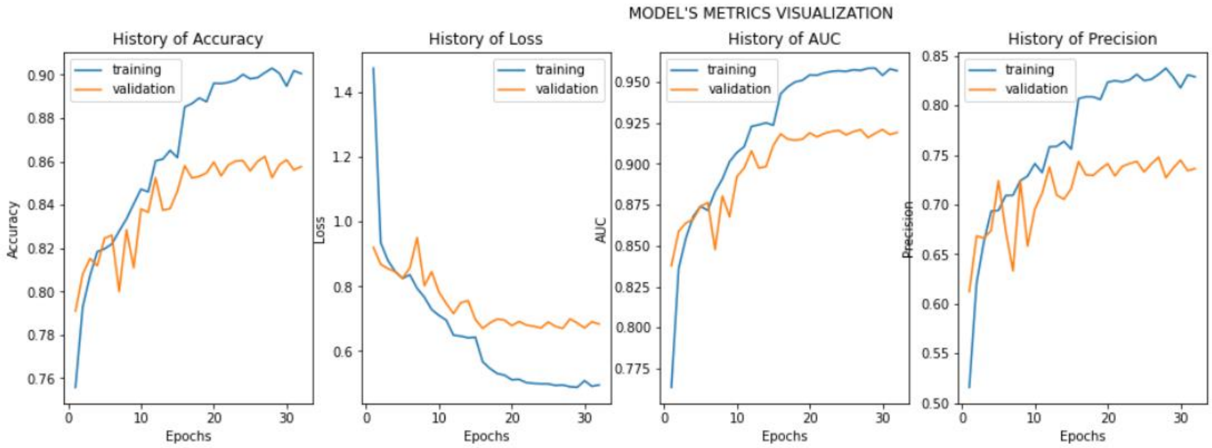
Resnet50 Model

The Resnet model turned out to be fairly accurate in the definition of the image. Examining the generated graphics, I found that it looked promising. This model provided about 75.7% data accuracy. This model achieves 88% AUC and about 80% in train data, and its loss is also very low. The graphic is as follows:



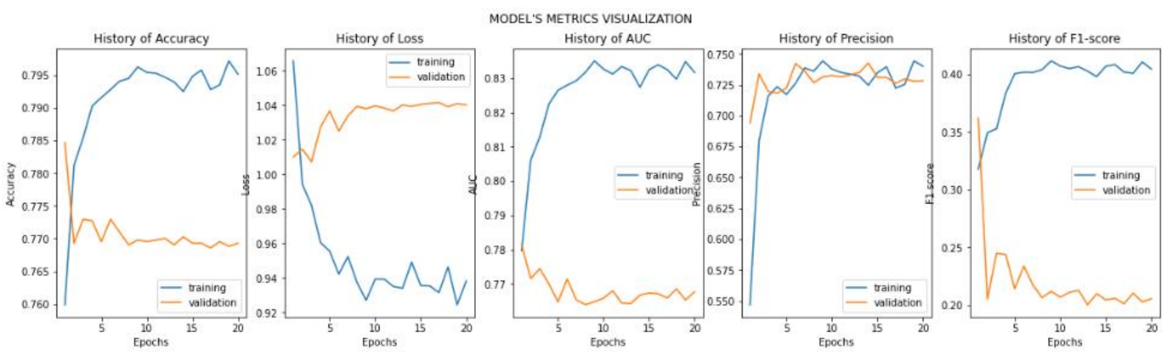
VGG16 Model

The VGG16 model turned out to be fairly accurate in the definition of the image. Examining the generated graphics, I found that it looked promising. This model provided about 53.91% data accuracy. This model achieves 90% AUC and about 95% in train data, and its loss is also very low. The graphic is as follows:



InceptionV3 Model

The InceptionV3 model turned out to be fairly accurate in the definition of the image. Examining the generated graphics, I found that it looked promising. This model provided about 79% data accuracy. This model achieves 77% AUC and about 83% in train data, and its loss is also very low. The graphic is as follows:



S. No	Model	Accuracy	Precision	Recall	AUC	F1-Score
1	DenseNet169	0.798	0.673	0.370	0.843	0.48
2	ResNet50	0.757	0.583	0.098	0.800	0.166
3	VGG16	0.54	0.754	0.090	0.090	0.165
4	InceptionV3	0.775	0.761	0.147	0.810	0.242

TABLE III

Analysis of performance measures for different deep learning models

From the graphs shown above and Table III, it can be observed that the training performance of ResNet50 and VGG16 were appreciable, but DenseNet169 and InceptionV3 have performed well with the test set.
There is a significant difference between the test accuracies of these networks. Hence, it was concluded that Densenet169 based deep architecture can be employed for reflection scene category classification from input images. The compound scaling method in Densenet169 architectures carefully balances network width, depth, and resolution for achieving better accuracy and efficiency.

6. CONCLUSION

This research helps in providing model weights to classify the Alzheimers disease which can act as supporting blocks for detection of the dymentia. The key objective of this work is to examine the performances of the state-of-the-art deep convolutional networks for classfication of the stages of the Alzheimers disease.
Extensive analysis was performed with different deep architectures like Densenet169, Resnet50,VGG16 and InceptionV3. The performance of these models was analyzed with metrics like ROC curve, AUC score, Accuracy, Loss and confusion matrix. Observations from different architectures revealed that Densenet169 based deep convolutional network performs better than other architectures in this classification, with an average of 80% accuracy.

7. FUTURE WORK

The future work of this research is that nearly all the research papers have used different models with similar datasets and used less models for comparing between the deep learning architectures. We can used advanced deep learning models with data different from different sources which will be helpful in classifying the AD accurately and efficiently.

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