DOI: https://doi.org/10.52756/ijerr.2024.v46.007 *Int. J. Exp. Res. Rev.*, Vol. 46: 85-99(2024)

Original Article | Peer Reviewed | Open Access

International Journal of Experimental Research and Review (IJERR)
© Copyright by International Academic Publishing House (IAPH)
ISSN: 2455-4855 (Online)
www.iaph.in

Performance Comparison Between Different Per-trained Models with Resnet-53 Using MRI and PET Scan Alzheimer's Disease Image Dataset

Rama Lakshmi Boyapati* and Radhika Yalavarthi

Department of Computer Science and Engineering, GITAM School of Technology, GITAM (Deemed-to-be University), Visakhapatnam-530045, Andhra Pradesh, India

E-mail/Orcid Id:

RLB, ramalakshmi.boyapati@gmail.com, https://orcid.org/0000-0001-7041-2260; *RY*, ryalavar@gitam.edu, https://orcid.org/0000-0001-6898-2467

Article History:

Received: 10th Jun., 2024
Accepted: 11th Dec., 2024
Published: 30th Dec., 2024

Keywords:
Bottleneck, Desnet121, Inception V3, Neuroimaging, RESNET 50, RESNET 101, VGG-16, c

How to cite this Article:
Rama Lakshmi Boyapati and Radhika Yalavarthi (2024). Performance Comparison Between Different Per-trained Models with Resnet-53 Using MRI and PET Scan Alzheimer's Disease Image Dataset. *International Journal of Experimental Research and Review*, *46*, 85-99.
DOI: https://doi.org/10.52756/ijerr.2024.v46.007

Abstract: In order to provide immediate support and medical care to identify Alzheimer's disease (AD) as early as possible. By analysing patterns and features in large datasets, these approaches can identify subtle changes in brain structure, function, or biomarkers that may indicate the presence of the Disease at an early stage. Early detection allows for timely intervention and treatment, potentially improving patient outcomes. Using MRI and PET scans image datasets particular to Alzheimer's disease. This study compares the performance of several pre-trained models, like VGG-16, VGG-19, RESNET 50, INCEPTION V3 and Desnet121 with the proposed model ResNet-53. The main goal is to assess and compare how well these models are able to discriminate between healthy people and people with AD. By comparing each model's accuracy and precision, we use transfer learning to optimize them all. The performance of the RESNET-53 is strong to classify the AD and the accuracy is 99.65%. Our findings showed significant differences in performance, with certain models exhibiting higher accuracy in particular imaging modalities. In the proposed model the preprocessing will be initialized by a zero centering process then combined Gaussian filter with bilateral filter. For feature extraction, ResNet is used for its residual connections. In the ResNet architecture first layers are freezed and the last 3 layers are customized for feature extraction. The study emphasizes how integrating deep learning approaches with a variety of imaging modalities may enhance diagnosis accuracy. The accuracy obtained using VGG 16, VGG 19, ResNet 101, RESNET 50, DenseNet 121 and Inception V3 models are 89.61%, 92.81%, 96.32%, 95.27%, 97.80% and 96.44%. The proposed model provides a classification accuracy of 99.65%. The proposed model ResNet 53 has more accuracy. "ResNet-53 outperforms baseline models, achieving a precision of 98.96%, recall of 95%, and an F1-score of 96.97%, which demonstrates its ability to handle class imbalance more effectively than previous approaches.

Introduction

Alzheimer disease (AD) is a neurodegenerative illness that worsens with time and has a major impact on cognitive function (Ambily and Immanuel, 2021; Roy et al., 2024). Presents enormous problems to people with AD, their families, and healthcare systems across the world. Managing the illness and creating successful treatment plans depend on an early and precise diagnosis (Alzheimer's Association, 2024). Because they provide comprehensive insights into the structure and function of the brain, medical imaging methods like Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI) have become essential in the early identification of Alzheimer's disease (Liu et al., 2024). Image analysis in the healthcare sector has undergone an overhaul because the pre-trained models have shown excellent performance in a variety of medical imaging applications. Hansen (2020) used these models, which are trained using large-scale datasets. Because ResNet (Residual Networks) can mitigate the vanishing gradient problem and preserve accuracy in deep networks. It has become one of the most popular architectures among

*Corresponding Author: ramalakshmi.boyapati@gmail.com

them. Convolutional Neural Networks (CNNs) automatically extract features from unprocessed picture input. Alzheimer's disease-related patterns can be identified by modifying models like as VGG, ResNet and DenseNet. Alzheimer's disease (AD) is a progressive neuro degenerative disease with high morbidity. Mild cognitive impairment (MCI), a transitional state between normal ageing and dementia, has been identified as a high-risk factor for AD. Epidemiological studies suggest that 15-20% of the MCI patients may progress to Alzheimer's disease. Elderly Patients with MCI who are not undergoing proper diagnostic procedures for progressing to AD may have risk factors. Early-stage detection in MCI patients may delay the progression to AD. MCI does not affect daily activities, and individuals with MCI have normal cognitive function. However, MCI exhibits heterogeneous features in cognitive function and clinical progression and the clinical outcomes remain uncertain. Some MCI patients remain stable or even revert to normal functions, whereas others progress towards AD. Therefore, there is an urgent need to define biomarkers that can identify and predict high-risk individuals with MCI who will progress to AD, as these individuals will require subsequent intervention (Haloi, 2024). Currently, biochemical changes in the cerebrospinal fluid (CSF) and neuroimaging measures of brain anatomy and function have been identified as reliable biomarkers of AD.

Alzheimer's disease can be distinguished from other forms of dementia or neurological illnesses with the use of MRI (Himabindu et al., 2024). With the use of magnetic resonance imaging (MRI), medical practitioners may track the advancement of Alzheimer's disease over time by obtaining precise pictures of the brain. With the introduction of residual connections, ResNet-50 enables data to bypass one or more levels in both forward and backward passes. Remaining connections help to keep gradients flowing across the network. This tackles the difficulties related to the problem of disappearing gradients. Representation learning can be done efficiently thanks to the residual architecture. CNNs are frequently utilized for MRI scan analysis related to the brain. To detect anatomical alterations in the brain that are suggestive of Alzheimer's disease, pre-trained models like as VGGNet, ResNet, and DenseNet have been modified. Deep learning models may be used to analyze PET scans in order to identify tau protein deposits or amyloid plaques. For this, models such as U-Net and other segmentation networks are used.

Alzheimer disease is a neurological cognitive disorder which requires early detection before the disorder progresses to a disease. So many factors influence the cognitive disorder to identify this at the earliest, analysis of cognitive information and also the internal factors such as the gene mutation or the nucleotide polymorphism to be analyzed at the earliest. Pre-identification of this mild cognitive disorder can be solved with the classification approaches of machine learning and further deep analysis of gene expression, deep learning approaches can be used. Early identification of mild cognitive disorders may stop turning the stage to Alzheimer's disease. As Alzheimer's disease has no cure, so we can stop turning these mild disorders into AD by early detection. Numerous methods have been proposed for this but the collected data for the study is less and the cause of the disease information is huge, either it's the MRI data that is responsible or the transcriptomic data. In this model, we used the ensemble machine learning approaches for the classification of genes which are responsible for the MCI to Alzheimer disease and predicting the probability of converting this MCI to AD rate. Also used Alzheimer disease neuroimaging initiative (ADNI), the 1500 cases of MRI image information collected from four regions of the brain. The approach followed by us outperforming the existing recent approaches.

Despite advancements in the field, several gaps persist in the research surrounding Alzheimer's disease detection and classification. One significant challenge lies in integrating various medical imaging modalities, such as MRI, PET, CT, and genomic data; effective fusion techniques are needed to leverage the complementary information offered by these diverse sources. Additionally, the scarcity of high-quality and diverse datasets poses a major obstacle to training and evaluating deep learning models (Pal et al., 2023). There is an urgent need for research focused on the creation of large-scale, annotated Alzheimer's disease datasets, particularly those that include longitudinal data capable of capturing disease progression over time. Furthermore, understanding the intricacies of Alzheimer's disease progression is crucial; however, there are notable gaps in developing models that can conduct longitudinal analyses of medical images to effectively monitor disease progression and assess treatment efficacy.

ResNet 53 is one of the architectures of ResNet (Residual Networks), it is the deep Convolutional neural network. It is one of the model consisting of 53 layers. ResNet family has different models like ResNet-18, ResNet-34, ResNet-50, ResNet-110 or ResNet-152. Here, the depth is represented by the layers. It consists of residual connections also called skip connections, which are used for vanishing gradient problems. It is one of the

DOI: https://doi.org/10.52756/ijerr.2024.v46.007

deep networks to reduce noisy data. All the layers need not to use full transformation from input to output. Because residual connections from input allow gradient flow during backpropagation (Rama Lakshmi and Radhika, 2024) Bottleneck Design is one of the important characteristics of ResNet 53, by using this bottleneck design a series of 1x1 convolutions is used to reduce before applying 3x3 convolutions. ResNet 53 decrease the computational cost. ResNet 53 is mainly used in Image classification, segmentation and object detection. The main advantages of ResNet 53 is more stable, improves the gradient flow, has better generalization, solves complex problems with large datasets and is scalable.

Identify the problem statement

#Early identification of mild disorders which lead to Alzheimer's disease is still a challenge.

#Existing approaches failed to Select appropriate gene expressions and phenotype information from gene banks related to AD.

#Existing approaches failed to collect information from MRI images of mild cognitive disorder patients.

#All existing approaches have followed the tree-based classification method like Random Forest where the number of cases predicted isn't accurate (Rao et al., 2024).

#The existing classification approaches failed to collect proper data and identification of redundancy is a problem.

Motivation of research work

#Late-Onset Alzheimer's Disease (LOAD) has become a formidable public health threat. Even though there are a lot of pathophysiology scientific advances but there is no cure for Alzheimer's disease.

#Its the need of the hour for the diagnosis of complicated molecular aetiology driving Alzheimer's disease (AD).

#AD is a multifactorial and heterogeneous irregularity interaction which requires a large genomic and neuroimaging data analysis.

#Dixit et al. (2024) Study on mild cognitive impairment and its role in disease progression and study on dementia pathologies, transcriptional bio regulation in the progression of the disease.

Aim of the Research Work

#Finding novel insights from the study of neurodegenerative disorder data.

#Study of multidimensional high-quality neuropathological and clinical data for progression to MCI-AD.

#Comparison between different pertained models with Resnet-53 using MRI and PET scan Alzheimer's disease image dataset.

#Study of data collected from OASIS Data.

#Finding the correlation of genes responsible for neurodegenerative disorders and finding the underlying molecular signatures and novel biomarker information for neuro disorder diseases.

Literature Survey

The research focuses on classifying MRI scans of AD patients using transfer-learning Methodology, specifically VGG16, ResNet-50, and AlexNet, in combination with CNN (Acharya et al., 2021). The proposed learning Methodology was tested on MRI images from a dataset at the Kaggle warehouse, with four categories. Transfer learning is a popular technique that utilizes pre-trained networks to reduce training time for neural network Methodology, especially when the available dataset is small. CNN is widely used in medical image analysis due to their effectiveness in extracting features from images. The VGG16 Methodology, initially trained on the ImageNet dataset, consists of 16 layers and can classify images into 1000 categories. ResNet 50 is a CNN architecture utilized in computer vision. It contains 50 layers and retrieves the issue of disappearing gradients through residual blocks. AlexNet was the first deep neural network to achieve significant improvement in ImageNet classification accuracy. It comprises 5 conv layers & three FC layers. AlexNet utilizes the ReLu, which is faster than the tanh function commonly used at the time. ReLU helped achieve faster training time and lower error rates. "Scattered pooling" refers to the effects of pooling layers in CNNs.

There is presently no treatment for the progressive neurological disease Alzheimer's or effective treatment to slow its progression (Raju et al., 2021). The proposed work utilizes transfer learning with the VGG16 Methodology and Fastai framework to perform multilevel classification of AD based on MRI. Pre-processing steps include intensity normalization and skull stripping of the MRI images obtained from Kaggle. The algorithm computes the brain-affected region for each class and projects it onto MRI images using GradCam. The fully connected layers of the VGG16 Methodology are trained on the ImageNet and are retrieved for the classification task. The convolutional layers, responsible for learning lower-level features, require minimal modification as they are common for all images.

According to Khan et al. (2023) the suggested method aids in the early identification and prevention of Alzheimer's disease and enables prompt therapeutic therapy. GM (gray matter) extraction is performed on the

Table 1. Merits and Demerit Analysis on Different Approaches.

Author	Algorithm	Merits	Demerits	Accuracy
Jain and Thada, 2024	Dual Noise Integrated Privacy Preservation (DNIPP)	Easy for implementation.	It works for a particular dataset.	96.10%
Mehmood et al., 2021	VGG19	Predicting images takes less time.	The images should have high quality.	98.73%
Yang et al., 2021	VGG16	The performance was efficient	The prediction of accuracy and precision was not accurate.	82.5%
Ramalakshmi, and Radhika, 2024	ResNet	Multiple problems can be solved at once by this model.	Neurological problems are not explained.	99%
Liu et al., 2022	DL	It is possible to automatically detect images.	Performances and analysis need to be enhanced.	83%
Bringas et al., 2020	CNN	There are patterns found for each step.	The dataset was small.	90%
He et al., 2016	VGG	Used ImageNet and COCO detection and segmentation well very.	Analysed using 100 to 1000 layers, so time complexity is more.	Achieves 3.57% error.

3D voxel data of the MRI scans, and the resulting GM slices are used to train VGG architectures. The pre-trained models VGG 16 and VGG 19 are trained on the ImageNet and are utilized, a layer-wise transfer learning approach is adopted with step-wise freezing of blocks. Data pre-processing is crucial to enhance the contrast and pixel intensity of the MRI scans. Operations such as skull stripping, registration, normalization, and segmentation are applied using tools like the SPM12. The dataset is split into three parts of ratio 7:1.5:1.5 to evaluate the proposed approach. VGG 16 and VGG 19 architectures are employed as they have shown superior performance in feature extraction and image processing tasks.

Li et al. (2021) have proposed a DL methodology for identifying AD at an initial stage. The relationship between simple MRI biomarkers and aspects of AD progression supports the use of these indicators in the early detection and monitoring of AD. Image characteristics that represent the course of AD may be derived using a transfer learning approach based on the 3-dimensional nature of CNN Methodology centred on structural MRI. The augmented CNN Methodology shows higher prediction accuracy compared to the Image CNN Methodology in distinguishing stable and progressive MCI. CNN-derived image phenotypes have associations with early-stage markers of AD, such as lipid metabolites and histamine metabolites involved in tau phosphorylation & insulin resistance. The CNN-derived phenotypes show better associations with AD-related processes compared to clinical labels, cognitive labels, & picture summary measurements. The transfer learning technique improves the robustness of CNN Methodology and reduces over-fitting. Case/control MCI is frequently left out of GWAS research, producing less accurate phenotypes, whereas CNN-derived picture phenotypes offer continuous and exact measurements. One of the compared global features extracted from Alzheimer’s images using deep Convolution Neural Network models like VGG-16, ResNet50, ResNet 101 and Inception V3. Their results showed better performance using ResNet50 for feature extraction compared to others.

Both verbal and nonverbal communication abilities frequently deteriorate in Alzheimer's disease patients (Sekhar et al., 2024). Individuals who are competent in sign language may experience difficulties with it, forget words, or lose the capacity to create cohesive phrases when they have Alzheimer's disease. For those who communicate primarily through sign language, alterations in fluency, such as a reduction in sign language vocabulary or problems with grammar and syntax, might be a precursor to cognitive decline.

The proposed

Initial step as Pre-processing to reduce the noise of the data and important features are extracted for image classification and all are accomplished by the AD Detection system through the use of an extensive DL model. Many designs, including VGG 16, VGG 19, RESNET 50, RESNET 101 and Inception V3, are included in this model. The time and computing resources needed to train models from scratch may be greatly decreased by using pre-trained CNN models, ResNet50, DenseNet121, and NASNetLarge. These models gain the capacity to categorize the pictures into predefined groups through supervised learning, which makes it possible to identify specific brain abnormalities and structures.

A. VGG 16

Convolution neural networks (CNNs) were used to recognize images, and transfer learning was used on the VGG16 (Visual Geometry Group 16) CNN model following training. VGG16 contains 14,714,688 parameters and 16 hidden layers. The model was trained using 1000 colored pictures from 1000 distinct categories. The VGG16 model's layers are frozen; a new input layer is added for the current input data and the input layer is sliced off to prevent the weights from changing during further training. The output is flattened and delivered to a fully connected layer with 64 neurons and Leaky ReLU (alpha = 0.1) as the activation function after the pre-defined model (VGG16).

Figure 1. Structure of VGG 16

which offer a reliable beginning point for a variety of computer vision tasks. For computer vision applications, such as deep learning model training for image identification, ImageNet is a sizable, freely accessible collection of annotated pictures. In order to identify the items in each of the more than 14 million photos in the collection, WordNet synset annotations are used. Aiming to provide 500–1,000 pictures for each of the 80,000 synsets in the database, ImageNet is structured in accordance with WordNet's semantic hierarchy (Yadav and Sharma, 2021). A minimum of one million of the quality-controlled, human-annotated photos also include boxes that define boundaries. Data gathering and magnetic resonance imaging images were used to create a new format. The preprocessing step included new information that was improved and might alter the 224 × 224 × 3 picture dimensions. This approach changed how pre-trained techniques like InceptionResNetV2, ResNet50V2, DenseNet121, Xception, VGG16 and MobileNetV2 were classified.

One of the biggest and most comprehensive resources for computer vision deep learning model training is ImageNet (Singh and Kumar, 2024). In addition, compared to other image datasets, it is more precise and wider in scope, and its hierarchical structure offers chances for computer vision researchers. In order to go from the data gathering stage to the analysis stage, the technique applies Convolutional Neural Network (CNN) models that have already been trained and selected to preprocess the dataset. The selected pre-trained models provide a strong basis for image classification tasks: EfcientNet0, AlexNet, GoogLeNet, MobileNetV2,

B. VGG-19

Visual Geometry Group with 19 weight layers, it consists of Convolutional layers with 3 × 3 filters, Activation Function ReLU (Rectified Linear Unit), Pooling layers as Max pooling and Global Average Pooling with 2 × 2 filter and 2 stride to reduce spatial dimensions, three Fully Connected Layers at the network's terminus for classification and final layer called as Softmax Layer. A simple 3 × 3 convolutional layer serves as the main example. The first and second convolutional layers each include 64 kernel features that handle filters with a 3x3 size. When converting the proportions, the Rigid Permeable image, which has a depth of 3, was placed over the first and second convolutional layers. The result will depend on the transfer of the topmost pooling layer with a tread of 2. The 3rd and 4th convolutional layers were utilized in a 124-feature kernel modified with a 3x3 pervade size. After adding pooling layers within thread 2, the result's total dimension is 56x56x128. The fifth, sixth, and seventh convolutional layers are composed of essence that is 3×3.

DOI: https://doi.org/10.52756/ijerr.2024.v46.007

C. RESNET 50

A member of the ResNet (Residual Network) family. ResNet50 has 50 layers, as the name would imply. It expands on the fundamental concept of residual learning presented in the first ResNet study. The introduction of skip connections, also known as shortcuts, allows the network to elide one or more layers, easing the gradient flow during training and is the main innovation of ResNet. This assists in training very deep neural networks successfully by minimizing the vanishing gradient problem. ResNet-50 is a member of the ResNet (Residual Networks) group and a 50-layer deep convolutional neural network (CNN). The vanishing gradient issue, typical of deep networks, may be avoided while training extremely deep networks by using ResNet topologies.

$y = F(x, \{Wi\}) + x$ -------- Equ (1)

Here, F(x,{Wi}) means the residual mapping and {Wi} are the weights of residual blocks.

In each residual block, ResNet-50 uses the important design called as bottleneck design, with three layers: 1 × 1, 3 × 3 and 1 × 1 convolutions.

Multiply-Accumulate Operation (MAC) = (Number of Parameters*Height*Weight)

Number of Parameters

1 × 1 Convolution layer with 1 × 1 filter size and it consists of number of parameters = C_{in}* C_{mid}

3 × 3 Convolution layer with 3 × 3 filter size and it consists of number of parameters = C_{mid}* C_{mid}*f_s*f_s

1 × 1 Convolution layer with 1 × 1 filter size and it consists of number of parameters = C_{mid}* C_{out}

Example: 1 × 1 Convolution layer

Number of parameters = C_{in}* C_{mid} = 3*16 = 48

Multiply-Accumulate Operation (MAC) = 48*256*256

3 × 3 Convolution layer

Number of parameters = C_{mid}* C_{mid}*f_s*f_s = 16*16*3*3=2304

Multiply-Accumulate Operation (MAC) = 2304*256*256

D. RESNET 101

ResNet-101 is one of the deep Convolutional neural networks in ResNet group, it has more layers and very deep models effectively. In ResNet-101, it consists of 33 bottleneck blocks. It was trained on the ImageNet dataset and consists of million of images with thousands of objects. It solves the vanishing Gradient problem and introduces residual learning. It uses shortcut connections that skip one or more layers and aggregate the input to the output of number of layers. The depth of these model is 101 layers and deeper than resNet-50.

INCEPTION V3: It is a member of the Inception model group, which was first created by Google. The concepts presented in Inception V1 (GoogLeNet) and Inception V2 architectures, in particular, are expanded upon in this version. The purpose of Inception V3 was to increase model accuracy and maximize the utilization of computing resources and improve the efficiency of deep networks.

DesNet121: DesNet consists of narrow filers and has a small set of new feature-maps. Due to the gradients and information flow, training very deep networks also presented challenges. Since each layer of DenseNets has direct access to the gradients from both the original input picture and the loss function, DenseNets addresses this problem. "Densely Connected Convolutional Networks", Zhang et al. (2020) presented DenseNet121, an architecture for convolutional neural networks. The dense connection pattern found in the network design is denoted by the word "Dense" in DenseNet. DenseNet creates direct connections between every layer, producing densely linked blocks, in conventional convolutional neural networks, where each layer is merely connected to the layers that come after it. Especially in situations when there is a shortage of training data, these dense connections increase learning efficiency and performance by facilitating feature reuse and gradient movement across the network.

DenseNet121 specifically refers to a DenseNet architecture with 121 layers. It comprises multiple dense blocks, each containing a series of convolutional layers with batch normalization and ReLU activation, as well as skip connections that concatenate the feature maps from all preceding layers (Aparna and Rao, 2023). Dense blocks are separated by transition layers, which include convolutional layers followed by pooling operations to reduce the spatial dimensions of the feature maps.

E. Steps of Workflow in Proposed System

a. Image Pre-processing: One of the most extensive and comprehensive resources for computer vision deep learning model training is ImageNet. In addition, compared to other image datasets, it is more precise and longer in scope, and its hierarchical structure offers chances for computer vision researchers. It involves techniques as Resizing as scaling and padding, Normalization, Data Augmentation as rotation, flipping, translation, scaling and contrast adjustment, Cropping as center and random, Color space conversion, Noise reduction and edge Detection.

DOI: https://doi.org/10.52756/ijerr.2024.v46.007

Preprocessing is one of the critical roles in handling medical images from MRI and PET images. OASIS datset includes both MRI and PET images. Skull Striping is one of the tools used to focus on brain tissues. Skull Striping is used by BET algorithm. After skull striping MRI images have varying intensity levels, so normalization is used to reduce the intensities using Zero centering. All the images are intensity normalized to [0,1] range to reduce intensity. And images are resized to 224x224. Motion correction technique is used for the images to stable across time. By combining MRI and PET scan data, multi-modal image registration allows the model to learn from alternative data sources. Gaussian and bilateral filters are used for the pre-processing. As shown in figure 2, Gaussian noise was added to the images to help the model become more robust to noisy data. Gaussian filter is used to protect the intensity of the image and bilateral filter is used to preserve the edge information of the image. These filters are often applied as pre-processing steps to improve the quality of input images before feeding them into deep-learning models like ResNet-53. Applying a Gaussian filter helps to smooth out random intensity fluctuations in tissues, improving the image's quality for model training. MRI scans contain important high-contrast boundaries between different tissues (e.g., gray matter, white matter, and cerebrospinal fluid). A bilateral filter helps reduce noise while maintaining these important structural details. Figure 2 explains about the architecture of my proposed model.

b. Selecting Pre-trained model: The pre-trained models and the decision of which to use relies on the particular application, the needed trade-off between computational effectiveness, accuracy, and precision, and the number of resources at hand. According transfer learning capabilities and the dataset, we have to select the type as if it is image classification for the image dataset and Object detection for identifying and locating objects in the images. Exploration based on model complexity and size.

c. Load the Pre-trained model: Loading a Pre-trained model that typically depends on the Deep Learning architecture. Loading process uses TensorFlow/Keras, PyTorch and funning Inference.

d. Modify the Model: Here the model typically involves adapting it for a new task as fine-tuning in different datasets and changing its model.

e. Freeze Base Layers: Freezing the base layers is used to retain the pre-trained weights for extraction of features.

f. Compile the Model: In the compilation process, the model optimize the appropriate model, metrics and loss functions.

g. Train the Model: Pre-trained models may be trained by loading them with pre-trained weights, adjusting them for your particular purpose, and then fine-tuning them using your fresh dataset.

h. Evaluate the Model: Analysing pre-trained model effectiveness on a dataset it hasn't seen before entails evaluating it using metrics like as accuracy, precision,

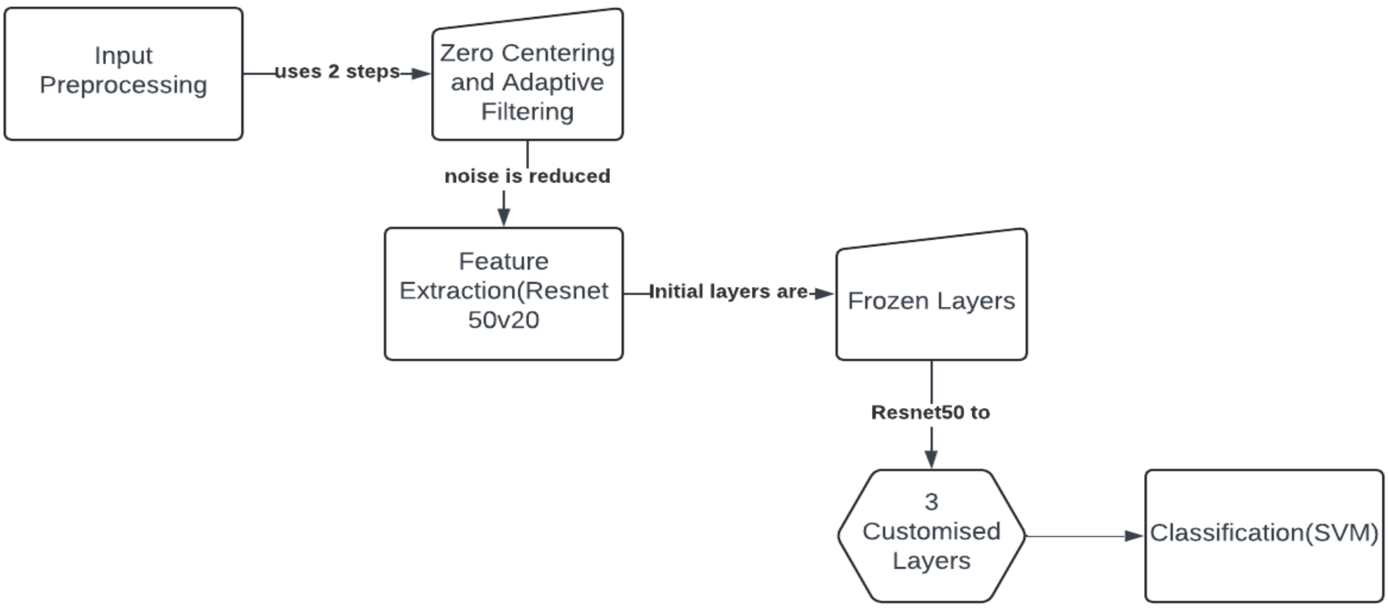

Figure 2. Basic Block Diagram of the Proposed System.

recall, or any other pertinent measure that may be necessary depending on the task.

i. Fine-Tuning: A pre-trained CNN can be improved by modifying a model that was developed on a big dataset (such as ImageNet) for a new, frequently smaller dataset. Usually, this method entails training the remaining layers of the model on a new dataset while freezing portions of the layers. To adjust a pre-trained CNN with PyTorch and TensorFlow/Keras.

f. Deploy the Model: Convolutional neural networks (CNNs) that have already been trained must be deployed. This is done by placing the learned model in a situation where it can make predictions, usually on an edge device, mobile app, or online service.

Data Augmentation

Data Augmentation is mainly used to increase the diversity of the training set to prevent overfitting. Some of the augmentation techniques are translation, rotation, cropping, zooming, adjusting elastic deformations and synthetic data. This technique is used to customize the images and to extract important features from the images. Highlight that augmentation helps to artificially increase the variety of the data, which keeps the model from overfitting to the short sample size because MRI and PET datasets are usually tiny. The parameters used for the data augmentation are maximum rotation angle, percentage of zoom and amount of noise added to the images. The vanishing gradient issue is lessened by ResNet-53's utilization of deep residual connections, particularly in deep networks. Explaining how the pre-processing processes enable the network to discover significant patterns across complex medical pictures is crucial when using ResNet-53 to MRI or PET data. The model benefits from clean, normalized data because of the depth of ResNet-53, as the residual connections will help maintain valuable information across layers. When working with high-dimensional medical pictures, which frequently include significant noise and fluctuation, this is extremely crucial. Data augmentation is essential for boosting data range and avoiding overfitting in small datasets like OASIS. In order to achieve effective generalization, augmentation enables the model to learn invariant information, such as varied orientations, anatomical differences, or intensity fluctuations.

Table 2. Accuracy of different models by various Authors and the proposed model.

Author/ Classifier	Methodology	Accuracy
Aderghal et al., 2020	CNN	91.86%
Mehmood et al., 2021	VGG19	98.73
Liu et al., 2022	DL	83%
Bringas et al., 2020	CNN	90%
Yang et al., 2021	VGG16	82.5%
Muhammed Raees and Thomas, 2021	SVM, DNN	80%
Ebrahimi et al., 2020	ResNet 18	96.88%
Acharya et al., 2021	AlexNet	95.70%
Sarawgi et al., 2020	Ensemble methods	88.0%
Proposed model	**RESNET-53**	**99.65%**

Table 2 shows the accuracy comparison of various authors, who used different pre-trained models for feature extraction and classification. These accuracies are from the different papers, which are explained by different authors. Here, table 2 shows the proposed model ResNet-53 has the highest accuracy than the other models.

Figure 3 explains about the graphical representation of the accuracy comparison of various authors with different models. Table 2 is converted to a graphical representation with its accuracy and different methodologies. The X-axis represents accuracy and the Y-axis represents different authors.

Dataset

In humans, Alzheimer's disease is a neurological disease that impairs thinking and memory. Although Alzheimer's disease cannot be cured, its progression can be slowed down if detected early. The Open Access Series of Imaging Studies (OASIS) provides data including MRI (Magnetic Resonance Imaging) scans that can help identify structural changes in the brains of those who have been diagnosed with the illness. OASIS (Open Access Series of Imaging Studies): The OIASIS dataset contains precise 3D geometry annotations for 140,000 photos and is for single-image 3D in the real world. Rama Lakshmi et al. (2024) The MRI scans provide detailed images of the brain, allowing researchers to study brain structure and detect changes associated with aging and Alzheimer's disease. Figure 4 describes the biomarkers extracted from 3D images.

Brain imaging MRI images from OASIS, together with associated clinical data and neuroimaging, are openly accessible for study and analysis. It provides information on the brain and aids in the development of treatment plans for a number of disorders linked to the brain, such as Alzheimer's disease. Alzheimer disease is

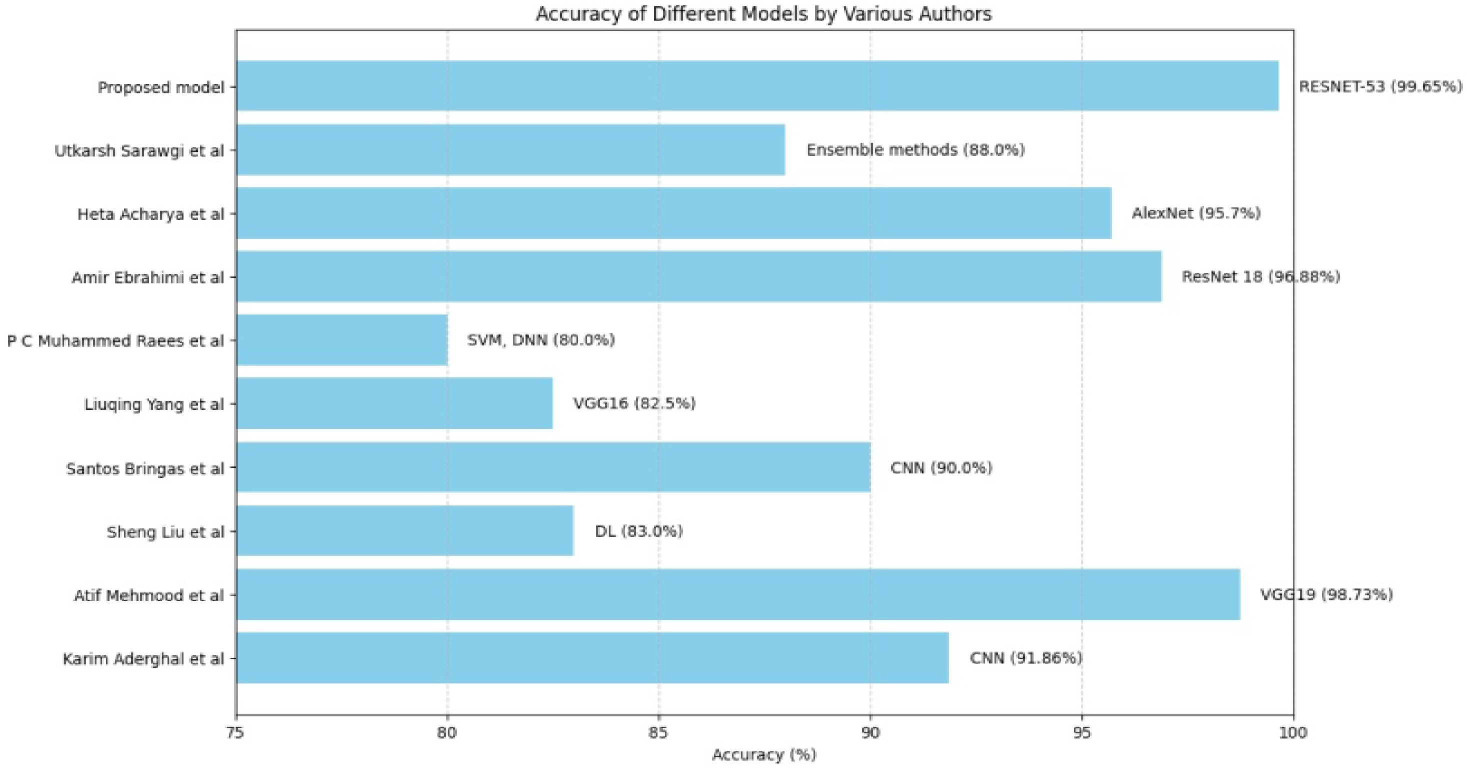

Figure 3. Accuracy Comparison among different Authors with different models.

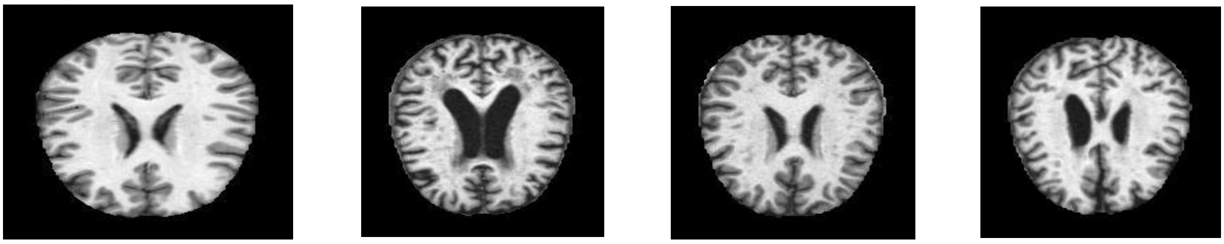

Figure 4. Four Labels in the Dataset (1) Mild Demented (2) Moderate Demented.

currently diagnosed using a mix of neuroimaging methods, clinical exams, and cognitive tests. However, particularly in the stages of the disease, the accuracy and dependability of the current diagnostic techniques may be reduced. Sample images of MRI and PET Scan representing different labels of Alzheimer's disease.

In Figure 4 explains about the labels in the dataset. The dataset contains 4 labels as Mild Demented, Moderate Demented, Non-Demented and Very Mild Demented. And those labels are from both training and test data.

Results and Discussion

VGG-16, VGG-19, DenseNet121, ResNet50, Inception V3 and ResNet101 which are trained on a training dataset of 6 images and tested on a test dataset of 6470 images, where both the training and test dataset contain 4 labels as Mild Demented, Moderate Demented, Non-Demented and Very Mild Demented.

Total Training Milddemented Images: 737
Total Training Moderatedemented Images: 52
Total Training Nondemented Images: 2610
Total Training Verymilddemented Images: 1792
Total Test Milddemented Images: 179
Total Test Moderatedemented Images: 12
Total Test Notumor Images: 640
Total Test Verymilddemented Images: 448
--
Total Training Images: 5191
Total Test Images: 1279

```
Epoch 25/50
161/161 [==============================] - 1s 7ms/step - loss: 0.1542 - acc: 0.9433 - val_loss: 2.7415 - val_acc: 0.5684
Epoch 26/50
161/161 [==============================] - 1s 8ms/step - loss: 0.1470 - acc: 0.9427 - val_loss: 2.5944 - val_acc: 0.5770
Epoch 27/50
161/161 [==============================] - 1s 8ms/step - loss: 0.1381 - acc: 0.9490 - val_loss: 2.5439 - val_acc: 0.5778
Epoch 28/50
161/161 [==============================] - 1s 7ms/step - loss: 0.1172 - acc: 0.9563 - val_loss: 2.7770 - val_acc: 0.5770
Epoch 29/50
161/161 [==============================] - 1s 9ms/step - loss: 0.1310 - acc: 0.9538 - val_loss: 2.7735 - val_acc: 0.5528
Epoch 30/50
161/161 [==============================] - 2s 11ms/step - loss: 0.0923 - acc: 0.9639 - val_loss: 3.0410 - val_acc: 0.5708
Epoch 31/50
161/161 [==============================] - 2s 12ms/step - loss: 0.1474 - acc: 0.9478 - val_loss: 3.1757 - val_acc: 0.5645
Epoch 32/50
161/161 [==============================] - 1s 9ms/step - loss: 0.0642 - acc: 0.9783 - val_loss: 3.7577 - val_acc: 0.5692
Epoch 33/50
161/161 [==============================] - 1s 7ms/step - loss: 0.1483 - acc: 0.9449 - val_loss: 2.7805 - val_acc: 0.5364
Epoch 34/50
161/161 [==============================] - 1s 8ms/step - loss: 0.0726 - acc: 0.9720 - val_loss: 3.4897 - val_acc: 0.5645
Epoch 35/50
161/161 [==============================] - 1s 9ms/step - loss: 0.1015 - acc: 0.9643 - val_loss: 3.2495 - val_acc: 0.5778
```

Figure 5. VGG 16 Epoch Report.

```
Epoch 18/40
161/161 [==============================] - 1s 7ms/step - loss: 0.4051 - acc: 0.8364 - val_loss: 1.2082 - val_acc: 0.5481
Epoch 19/40
161/161 [==============================] - 1s 8ms/step - loss: 0.3879 - acc: 0.8459 - val_loss: 1.1875 - val_acc: 0.5559
Epoch 20/40
161/161 [==============================] - 2s 9ms/step - loss: 0.3645 - acc: 0.8566 - val_loss: 1.3203 - val_acc: 0.5348
Epoch 21/40
161/161 [==============================] - 2s 9ms/step - loss: 0.3195 - acc: 0.8789 - val_loss: 1.4952 - val_acc: 0.4988
Epoch 22/40
161/161 [==============================] - 1s 7ms/step - loss: 0.2970 - acc: 0.8849 - val_loss: 1.3600 - val_acc: 0.5410
Epoch 23/40
161/161 [==============================] - 1s 7ms/step - loss: 0.2750 - acc: 0.8987 - val_loss: 1.4045 - val_acc: 0.5543
Epoch 24/40
161/161 [==============================] - 1s 7ms/step - loss: 0.2523 - acc: 0.9119 - val_loss: 1.5830 - val_acc: 0.5098
Epoch 25/40
161/161 [==============================] - 1s 7ms/step - loss: 0.2302 - acc: 0.9227 - val_loss: 1.6308 - val_acc: 0.4996
Epoch 26/40
161/161 [==============================] - 1s 6ms/step - loss: 0.2152 - acc: 0.9319 - val_loss: 1.5774 - val_acc: 0.5371
Epoch 27/40
161/161 [==============================] - 1s 8ms/step - loss: 0.1796 - acc: 0.9451 - val_loss: 1.6032 - val_acc: 0.5317
Epoch 28/40
161/161 [==============================] - 1s 7ms/step - loss: 0.1988 - acc: 0.9334 - val_loss: 1.6551 - val_acc: 0.5301
Epoch 29/40
161/161 [==============================] - 1s 7ms/step - loss: 0.1821 - acc: 0.9424 - val_loss: 1.7000 - val_acc: 0.5348
Epoch 30/40
161/161 [==============================] - 1s 7ms/step - loss: 0.1517 - acc: 0.9540 - val_loss: 1.7000 - val_acc: 0.5270
```

Figure 6. ResNet 50 Epoch Report.

Figure 5 shows the accuracy and validation of the VGG 16. Accuracy is 96.435 and loss validation is 3.2%. Number of epochs used is 50.

Experimental Setup

The Tensorflow Federated effort is presently in initial development and may not work with a master. However, the Tensorflow_federated pip package 0.5.0 has been verified to work with collab. An example of training from the Modified National Institute of Standards and Technology (MNIST) is provided for the Federated Learning (FL) API layer of TFF. It is an assemblage of higher-level APIs that may be used to do typical federated learning tasks, such as federated training, on models that users have given and that have been constructed within TensorFlow.

Rama Lakshmi and Radhika (2024) In Gaussian filter sigma is generally selected randomly but in our work that sigma is calculated by using cross-validation. Cross-validation means the training data is divided into the

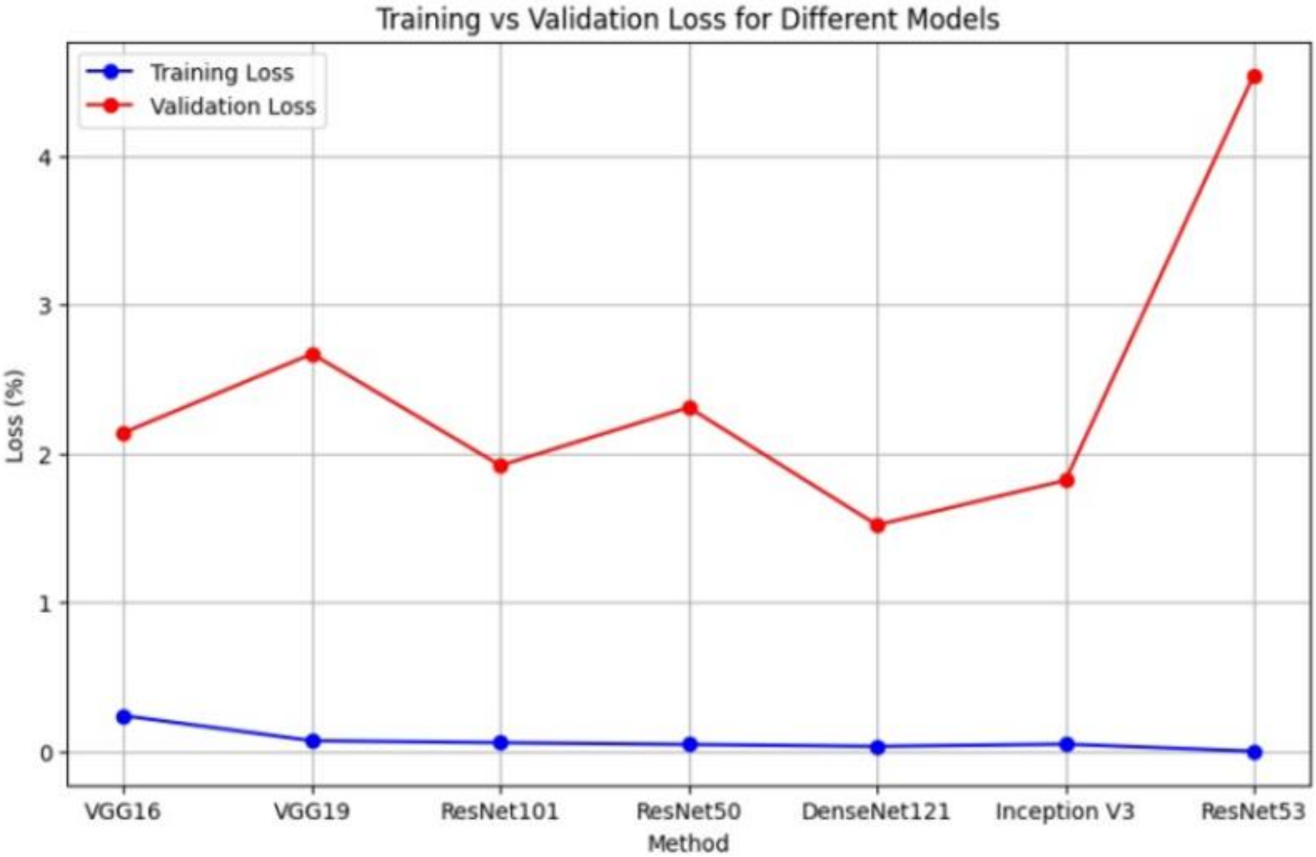

Figure 7. Training and Validation loss for different Models.

```
Epoch 45/50
161/161 [==============================] - 1s 8ms/step - loss: 0.0501 - acc: 0.9804 - val_loss: 3.4579 - val_acc: 0.5371
Epoch 46/50
161/161 [==============================] - 1s 8ms/step - loss: 0.0771 - acc: 0.9738 - val_loss: 3.4278 - val_acc: 0.5512
Epoch 47/50
161/161 [==============================] - 1s 7ms/step - loss: 0.0667 - acc: 0.9773 - val_loss: 3.4487 - val_acc: 0.5598
Epoch 48/50
161/161 [==============================] - 1s 7ms/step - loss: 0.1172 - acc: 0.9579 - val_loss: 3.2372 - val_acc: 0.5246
Epoch 49/50
161/161 [==============================] - 1s 8ms/step - loss: 0.0322 - acc: 0.9905 - val_loss: 3.8122 - val_acc: 0.5661
Epoch 50/50
161/161 [==============================] - 1s 8ms/step - loss: 0.0103 - acc: 0.9965 - val_loss: 4.5482 - val_acc: 0.5715
```

Figure 8. Epochs Report for proposed model ResNet-53.

Table 3. Experiment Results for Accuracy and Loss for both training and validation.

Sl.No	Method	Accuracy		Loss	
		Training	Validation	Training	Validation
1	VGG16	96.43%	57.00%	0.084%	3.10%
2	VGG19	92.81%	71.24%	0.072%	2.67%
3	ResNet101	96.32%	74.32%	0.059%	1.92%
4	ResNet50	95.40%	52.70%	0.151%	1.70%
5	DenseNet121	97.80%	73.58%	0.034%	1.52%
6	Inception V3	96.44%	64.33%	0.049%	1.82%
7	**ResNet53**	**99.65%**	**57.15%**	**0.0013%**	**4.54%**

number of parts from which the highest value is considered. And according to aspect-height and aspect-width, the aspect ratio is calculated. Based on accept ratio edges are preserved. In the classification process, SVM model is used. Here SVM is not directly used; hyperparameterization technique (hyperopt) is used. It is one of the techniques in optimization. By using this parameters are hypertunned, parameters like kernel, regularization and gamma. Creates hyperplane and compares the margin of the hyperplane then picks the largest margin and then makes predictions for the new data points. Root Mean Square is calculated and the number of epochs are 40.

Figure 6, shows the accuracy and validation of the ResNet 50. Accuracy is 95.40 and loss validation is 1.7%. Number of epochs used are 40. showcasing the convolutional blocks integrated with skip connections. This design is pivotal to the architecture's ability to facilitate efficient training while mitigating issues related to the vanishing gradient. The skip connections allow the model to retain essential information across layers, which is crucial for maintaining performance during deep learning processes.

Table 3. Experiment Results for accuracy and loss for both training and validation for different pre-trained methods and comparison between different models with proposed method ResNet-53.

Figure 7 shows the graphical representation of the Training and Validation loss for different Models. On X-axis different pre-trained models are placed. On the Y-axis loss percentage is mentioned. Validation loss is shown in red color and training loss is shown as blue.

Figure 8 shows the result of the ResNet 53 with 50 epochs with accuracy and loss. The proposed model ResNet-53 got a high accuracy of 99.65%, along high validation loss of 4.54%, which leads to be a sign of overfitting (Rama Lakshmi and Radhika, 2024). But in this case, the model performance will be well-trained data but the problem is to generalize to new data. We got that much accuracy because we consider uncontrolled images (i.e., different direction images), so, the preprocessing is done in several steps so we got that much accuracy. For example, if one image from the original dataset which is very mild demented and the predicted image is also very mild then the accuracy is 99.6% and if one image is moderate and my predicted image is non-demented, so is .1 %. In this case, we may have a chance to get the error. So in this type of situation we checked the error case also. Our main goal is to identify the disease correctly.

Conclusion

An innovation in the field of medical research is the utilization of deep convolutional neural networks (DCNNs) which employs Deep Learning CNN models such as VGG-16, VGG-19, DenseNet121, ResNet50, ResNet101, Desnet121 and Inception V3 for feature extraction and classification of the image to identify Alzheimer's disease from MRI and PET scan images. The diagnosis of AD has been made easier by these advanced CNN structures, which have shown promising results in identifying patterns and anomalies in brain pictures. In the future, segmenting tumors seen in brain scans will be a key component in detecting Alzheimer's disease. The advancement of segmentation algorithms based on CNN can facilitate identification. Defining abnormalities associated with Alzheimer's disease can help in a comprehensive diagnosis. The proposed model ResNet 53 has achieved the highest accuracy than the other models. Although ResNet-53 successfully captures complex visual characteristics, it would need more improving for robust expansion, as shown by the comparatively high validation loss, which raises the possibility of overfitting. ResNet-53's promising results suggest that it might help with Alzheimer's early diagnosis; however, further validation and improvement of its clinical applicability would require work with more datasets and regularization approaches.

Future work

Research Investigations on genetics have shown a number of risk factors connected to Alzheimer's. In order to possibly lower the risk or postpone the start of the

DOI: https://doi.org/10.52756/ijerr.2024.v46.007

disease, future studies may concentrate on creating gene treatments that target and change these genetic risk factors. Lifestyle therapies have demonstrated promise in preserving cognitive health and lowering the risk of Alzheimer's disease. These interventions include cognitive training, physical activity, and dietary changes. Researchers are attempting to create more readily available and reliable methods to recognize Alzheimer's early on. This involves the creation of biomarkers and neuroimaging methods that can identify the disease's early indicators before symptoms appear. Many clinical trials are being conducted to look at possible treatments that might change the condition. The root cause of Alzheimer's is tau tangles and beta-amyloid plaques in the brain, to delay the disease's progression. The immunotherapy techniques, like as monoclonal antibodies, to eliminate or neutralize beta-amyloid plaques are being investigated by researchers. Aliaa E1-Gawady et al. (2022) Study on different classification methods available for the disease-caused genes selection is required for accurate prediction of the new patients with MCI progressing to AD. Combining large-scale genomic data with a neuroimaging set may result in generating the required amount of molecular Biomarker information for the MCI to AD progression study.

Acknowledgement

I would like to thank my mentor Dr Radhika Yalavarthi, Diwakar Babu Kothapalli and Vinay Kumar Kottapalli for expert advice, encouragement and for their help.

Conflict of interest

There is no conflict of interest.

References

Acharya, H., Mehta, R., & Kumar Singh, D. (2021). Alzheimer Disease Classification Using Transfer Learning. *Proceedings-5th International Conference on Computing Methodologies and Communication* (ICCMC) *2021*, 1503–1508. https://doi.org/10.1109/ICCMC51019.2021.9418294

Aderghal, K., Afdel, K., Benois-Pineau, J., & Catheline, G. (2020). Improving Alzheimer's stage categorization with Convolutional Neural Network using transfer learning and different magnetic resonance imaging modalities. *Heliyon*, *6*(12). https://doi.org/10.1016/j.heliyon.2020.e05652

Aliaa, El-Gawady., Mohamed, A. Makhlouf., BenBella, S. Tawfik., & Hamed, N. (2022). Machine Learning Framework for the Prediction of Alzheimer's Disease Using Gene Expression Data Based on Efficient Gene Selection. *Symmetry, 2022*, 491. https://doi.org/10.3390/sym14030491

Ambily, F., & Immanuel, A.P. (2021). Early detection of Alzheimer's disease using an ensemble of pre-trained models. *2021 International Conference on Artificial Intelligence and Smart Systems* (ICAIS), *13*(1). https://doi.org/10.1109/ICAIS50930.2021.9395988

Aparna, M., and Rao, B.S. (2023). A novel automated deep learning approach for Alzheimer's disease classification. *IAES International Journal of Artificial Intelligence*, *12*(1), 451. https://doi.org/0.11591/ijai.v12.i1 .pp451-458

Bringas, S., Salomón, S., Duque, R., Lage, C., & Montaña, J. L. (2020). Alzheimer's Disease stage identification using deep learning models. *Journal of BiomedicalInformatics,109*. https://doi.org/10.1016/j.jbi.2020.103514

Dixit, A., Gupta, A., Chaplot, N., & Bharti, V. (2024). Emoji Support Predictive Mental Health Assessment Using Machine Learning: Unveiling Personalized Intervention Avenues. *International Journal of Experimental Research and Review*, *42*, 228-240. https://doi.org/10.52756/ijerr.2024.v42.020

Ebrahimi, A., Luo, S., & Chiong, R. (2020). Introducing Transfer Learning to 3D ResNet-18 for Alzheimer's Disease Detection on MRI Images. *2020 35th International Conference on Image and Vision Computing New Zealand* (IVCNZ), 1–6. https://doi.org/10.1109/ivcnz51579.2020.9290616

Haloi, R., & Chanda, D., (2024). Performance Analysis of KNN, Naïve Bayes, and Extreme Learning Machine Techniques on EEG Signals for Detection of Parkinson's Disease. *International Journal of Experimental Research and Review, 43*(Spl Vol), 32–41. https://doi.org/10.52756/ijerr.2024.v43spl.003

Hansen, B. (2020). Diffusion Kurtosis Imaging as a Tool in Neurotoxicology. *Neurotox Research, 37*(1), 41–47. https://doi.org/10.1007/s12640-019-00100-3

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp.770-778. https://doi.org/10.1109/CVPR.2016.90

Himabindu, D. D., Pranalini, B., Kumar, M. S., Neethika, A., Sree N, B., C, M., B, H., & S, K. (2024). Deep CNN-based Classification of Brain MRI Images for Alzheimer's Disease Diagnosis. *International*

Journal of Experimental Research and Review, 41(Spl Vol), 43–54. https://doi.org/10.52756/ijerr.2024.v41spl.004

Jain, P., & Thada, V. (2024). Securing the Data Using an Efficient Machine Learning Technique. *International Journal of Experimental Research and Review, 40*(SplVolume), 217-226. https://doi.org/10.52756/ijerr.2024.v40spl.018

Khan, R., Akbar, S., Mehmood, A., Shahid, F., Munir, K., Ilyas, N., Asif, M., & Zheng, Z. (2023). A transfer learning approach for multiclass classification of Alzheimer's disease using MRI images. *Frontiers in Neuroscience, 16*. https://doi.org/10.3389/fnins.2022.1050777

Li, Y., Haber, A., Preuss, C., John, C., Uyar, A., Yang, H. S., Logsdon, B. A., Philip, V., Krishna Murthy Karutur, R., & Carter, G. W. (2021). Transfer learning-trained convolutional neural networks identify novelmri biomarkers of Alzheimer's disease progression. *Alzheimer's and Dementia: Diagnosis, Assessment and Disease Monitoring, 13*(1). https://doi.org/10.1002/dad2.12140

Liu, S., Masurkar, A. V., Rusinek, H., Chen, J., Zhang, B., Zhu, W., Fernandez-Granda, C., & Razavian, N. (2022). The generalizable deep learning model for early Alzheimer's disease detection from structural MRIs. *Scientific Reports, 12*(1). https://doi.org/10.1038/s41598-022-20674-x

Liu, T., Xu, F., & Zhang, D. (2024). Alzheimer's disease classification using hybrid deep learning models with MRI and PET scan images: A comparative analysis. *Scientific Reports*, *14*, 5732. https://doi.org/10.1038/s41598-024-34735-9

Mehmood, A., Yang, S., Feng, Z., Wang, M., Ahmad, A. S., Khan C, R., Maqsood, M., & Yaqub, M. (2021). A Transfer Learning Approach for Early Diagnosis of Alzheimer's Disease on MRI Images. http://adni.loni.usc.edu/wp-content/

Muhammed Raees, P. C., & Thomas, V. (2021). Automated detection of Alzheimer's Disease using Deep Learning in MRI. *Journal of Physics: Conference Series, 1921*(1). https://doi.org/10.1088/1742-6596/1921/1/012024

Pal, R., Pandey, M., Pal, S., & Yadav, D. (2023). Phishing Detection: A Hybrid Model with Feature Selection and Machine Learning Techniques. *Int. J. Exp. Res. Rev.*, *36*, 99-108. https://doi.org/10.52756/ijerr.2023.v36.009

Raju, M., Thirupalani, M., Vidhyabharathi, S., & Thilagavathi, S. (2021). Deep Learning Based Multilevel Classification of Alzheimer's Disease using MRI Scans. *IOP Conference Series: Materials Science and Engineering, 1084*(1), 012017. https://doi.org/10.1088/1757-899x/1084/1/012017

Rama Lakshmi, Boyapati., & Radhika, Y. (2024). Multimodal Machine Learning for Early Alzheimer's Disease Detection: Leveraging Cognitive Features, and Resnet-Based Image Analysis with SVM Tuning. *International Journal of Intelligent Systems and Applications in Engineering (IJISAE)*, *12*(3), 56–70

Ramalakshmi, B., & Radhika, Y. (2024). RESNET-53 for Extraction of Alzheimer's Features Using Enhanced Learning Models. *International Journal of Computational and Experimental Science and Engineering (IJCESEN)*, *10*(4), 879-889. https://doi.org/10.22399/ijcesen.519

R. L. B., & R. Y. (2024). Resnet-53 for Alzheimer's Disease Detection from MRI Images and Analysis with SVM Tuning with Hyper Optimization Technique. *2024 4th International Conference on Sustainable Expert Systems* (ICSES), Kaski, Nepal, pp.1065-1072. https://doi.org/10.1109/ICSES63445.2024.10763183.

Rao, K. V., Devi, J. A., Anuradha, Y., G, K., Kumar, M. S., & Rao, M. S. (2024). Enhancing Liver Disease Detection and Management with Advanced Machine Learning Models. *International Journal of Experimental Research and Review, 42*, 100–110. https://doi.org/10.52756/ijerr.2024.v42.009

Roy, P., Ghosh, D., Sanyal, R., Madhu, N.R., Dey, A. (2024). The Controversy Surrounding Drugs Against Neurodegenerative Disorders: Benefit or Harm? In: Pathak, S., Banerjee, A. (eds) Neuroprotective Effects of Phytochemicals in Brain Ageing. Springer, Singapore. pp. 373-386. https://doi.org/10.1007/978-981-99-7269 2_17

Sarawgi, U., Zulfikar, W., Soliman, N., & Maes, P. (2020). Multimodal Inductive Transfer Learning for Detection of Alzheimer's Dementia and its Severity. http://arxiv.org/abs/2009.00700

Sekhar, C., Devi, J., Kumar, M., Swathi, K., Ratnam, P., & Rao, M. (2024). Enhancing Sign Language Understanding through Machine Learning at the Sentence Level. *International Journal of Experimental Research and Review, 41*(Spl Vol), 11-18. https://doi.org/10.52756/ijerr.2024.v41spl.002

Singh, A., & Kumar, R. (2024). Brain MRI Image Analysis for Alzheimer's Disease (AD) Prediction

Using Deep Learning Approaches. *SN Computer Science*, *5*, 160. https://doi.org/10.1007/s42979-023-02461-1

Yadav, A., & Sharma, N. (2021). A review of pretrained models for medical image classification: Applications to Alzheimer's disease. *Journal of Computational Biology*, *28*(5), 517-529. https://doi.org/10.1089/cmb.2020.0325

Yang, L., Wang, X., Guo, Q., Gladstein, S., Wooten, D., Li, T., Robinson, W. Z., Sun, Y., & Huang, X. (2021). Deep Learning Based Multimodal Progression Modeling for Alzheimer's Disease. *Statistics in Biopharmaceutical Research*, *13*(3), 337–343. https://doi.org/10.1080/19466315.2021.1884129

Zhang, Z., Yang, S., Zhang, X., & Zhao, Y. (2020). A comparative study of deep learning models for Alzheimer's disease classification using MRI and PET scans. *Medical Image Analysis*, *65*, 101794. https://doi.org/10.1016/j.media.2020.101794

How to cite this Article:

Rama Lakshmi Boyapatiand Radhika Yalavarthi (2024). Performance Comparison Between Different Per-trained Models with Resnet-53 Using MRI and PET Scan Alzheimer's Disease Image Dataset. *International Journal of Experimental Research and Review*, *46*, 85-99.

DOI : https://doi.org/10.52756/ ijerr.2024.v46.007