Alzheimer's disease Prediction using deep learning

21BIO211 INTELLIGENCE OF BIOLOGICAL SYSTEM

<u>Group 9</u>

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***Abstract*— Alzheimer's disease is a neurodegenerative disorder that affects millions of people worldwide. Early and accurate detection of the disease is crucial for timely intervention and treatment. In recent years, deep learning techniques, such as convolutional neural networks (CNNs) and transfer learning, have shown great promise in medical image analysis tasks, including Alzheimer's disease detection. This paper presents an approach for Alzheimer's disease detection using CNN and Transfer learning. Alzheimer's disease is a type of brain disease that indicate with memory impairment as the early symptoms. These symptoms occur because the nerve in the brain involved in learning, thinking and memory as cognitive function have been damaged. Alzheimer is one of diseases as the leading cause of death and cannot be cured, but the proper medical treatment can delay the severity of the disease. This study proposes the Convolutional Neural Network (CNN) and Transfer learning as a method to develop automated classification system of Alzheimer's disease. The experiment is conducted using Magnetic Resonance Imaging (MRI) datasets to classify Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented from 2 MRI datasets. The automated Alzheimer's disease classification can be helpful as assisting tool for medical personnel to diagnose the stage of Alzheimer's disease so that the appropriate medical treatment can be provided.**

Keywords*— *neurodegenerative, CNN, Transfer Learning

I. INTRODUCTION

Alzheimer's disease (AD) is a fatal irreversible, progressive neurodegenerative disorder that causes brain cells to waste away and die. Typically, AD begins in middle/old age, with protein accumulation inside/around neurons. The most prevalent and one of the early symptoms of AD is problems remembering new things, since AD-related changes usually begin in the brain parts charged with learning. Symptoms include, but are not limited to, behavioral changes; deep confusion regarding time, events, and places; and doubts about family members and friends. They usually develop slowly and worsen over time, leading to a continual deterioration in memory and difficulty in swallowing, talking, and walking.

Despite exploring various treatments for preventing or slowing AD, the success rate has been low, particularly in the latest phases of the disease.7 Studies indicate that AD-related changes in the brain might begin about 20 years before symptoms emerge.1 Therefore, there is a time gap that could be highly valuable to slowing AD's progression. Early detection of AD extends the independence of patients for a longer period. Recent research may enable greater comprehension of the disease and improvement of new treatments.

The rise in the computation capacity of graphics processing units (GPUs) has supported the evolution of modern and innovative deep learning algorithms. As a subgroup of machine learning, deep learning models analyze data processing and pattern recognition in the human brain to solve complicated decision-making tasks. Deep learning approaches have enhanced intelligent systems in numerous areas. Research on medical images has been encouraged by deep learning methods in applications using two-dimensional (2D) natural images. Among deep learning models, convolutional neural networks (CNNs) have recently demonstrated revolutionized outcomes in disease detection and organ segmentation. In contrast to traditional machine learning methods, CNNs can merge three main steps of classification: feature extraction, feature selection, and classification. It was recently stated that CNNs are the most frequently used method—about 70%—for AD detection.

II. ABOUT DATASET

We have used 2 datasets. Each Dataset contains 4 types of classes with each class containing different number of images. These datasets focuses on Alzheimer's disease and contains MRI (Magnetic Resonance Imaging) images of the brain. The images are classified into four different classes:

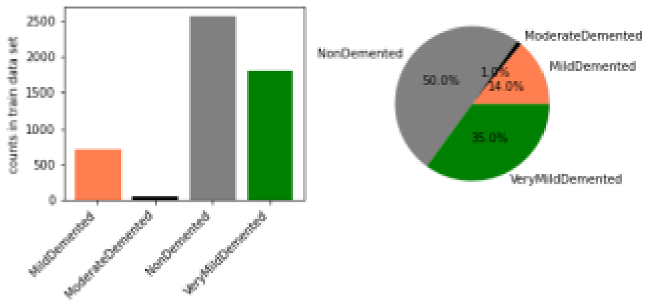
- Mild Demented: This class includes MRI images of individuals with mild symptoms of Alzheimer's disease.

- Moderate Demented: This class includes MRI images of individuals with moderate symptoms of Alzheimer's disease, indicating a more advanced stage of the disease compared to the "Mild Demented" class.

- Non Demented: This class includes MRI images of individuals who do not show any symptoms of Alzheimer's disease.

- Very Mild Demented: This class includes MRI images of individuals with very mild symptoms of Alzheimer's disease, potentially representing an early stage of the condition.

DATASET 1



The Above picture shows the number of Images present in train set of the dataset

DATASET 2

```
Mild_Demented 896
Moderate_Demented 64
Non_Demented 3200
Very_Mild_Demented 2240
```

The above picture Shows number of Images present in the Each class of the dataset.

```
Found 6400 images belonging to 4 classes.
```

It's important to note that MRI is a widely used imaging technique in medical diagnostics and research, especially for neurological disorders like Alzheimer's disease. By using MRI images in this dataset, the aim is likely to develop a highly accurate predictive model that can automatically classify patients into different stages of Alzheimer's disease based on their brain scans.

Given that the data was hand-collected from various websites and each label was verified, it suggests that efforts were made to ensure data quality and accuracy. The availability of both training and testing sets is crucial for building and evaluating machine learning models.

Here are some of the challenges that might be encountered when working with this dataset:

- The images are of varying quality, which could make it difficult to train a model that is robust to noise.

- The dataset is relatively small, which could limit the accuracy of the model.
- The labels for the images are not always accurate, which could also impact the accuracy of the model.

Despite these challenges, this dataset is a valuable resource for us as we are working on developing new methods for diagnosing Alzheimer's disease. With careful attention to these challenges, it is possible to train a model that can accurately predict the stage of the disease from MRI images.

III. LIBRARIES USED

1) **Pandas**: For the above dataset containing MRI images and labeled into four classes, Pandas can be used to perform various data management and analysis tasks. Although Pandas is primarily known for working with tabular data, it can still be beneficial in the analysis of image datasets like the one described.

2) **Numpy**: When working with image data, NumPy is an indispensable tool for handling and performing operations on the pixel values of the images. It complements Pandas, which can handle the accompanying metadata, by providing efficient array operations and numerical processing capabilities for the MRI images themselves.

3) **Matplotlib**: Matplotlib is a Python library widely used for creating visualizations and plots. In Alzheimer's disease prediction, Matplotlib can be employed to generate various types of plots and charts that help in understanding the data, evaluating the model, and presenting the results.

4) **Tensorflow**: TensorFlow is an open-source machine learning library developed by Google that is widely used for building and training deep learning models. For Alzheimer's disease prediction, TensorFlow can be instrumental in creating and training deep learning models to classify MRI images into different stages of Alzheimer's disease.

5) **Keras**: In the context of Alzheimer's disease prediction, Keras can be used as a front-end to TensorFlow to construct and train neural networks for classifying MRI images into different stages of Alzheimer's disease. Keras integration with TensorFlow also ensures high performance and the ability to leverage TensorFlow's GPU acceleration for faster training and inference on large MRI datasets.

6) **train_test_split**: is a function from the scikit-learn library used for splitting the dataset into training and testing sets. It enables the creation of separate subsets for training and evaluation, ensuring unbiased performance assessment of the model. These libraries collectively provide the necessary tools and functionalities to implement and evaluate the proposed deep learning model for dementia classification.

IV. RELATED WORK

Numerous studies have been conducted in the field of Alzheimer’s disease prediction using neuroimaging data. Various approaches have been explored, including traditional machine learning algorithms and deep learning techniques. Here, we provide a brief overview of some relevant studies:

Chen et al. [1] conducted a study that investigates the use of CNNs for Alzheimer's disease diagnosis based on MRI images. He proposed a multi-task CNN architecture that combines classification and regression tasks to predict the disease stage and cognitive scores, respectively. The model achieves promising results in terms of accuracy and correlation with clinical scores.

Li et al. [2] conducted a research that presents a symmetric two-stream CNN architecture for Alzheimer's disease diagnosis using both structural MRI and functional MRI (fMRI) data. The model leverages transfer learning by pretraining the CNN on a large non-neuroimaging dataset before fine-tuning on the Alzheimer's dataset. The approach achieves competitive performance in distinguishing Alzheimer's patients from healthy controls.

Liu et al. [3] conducted a study, that explores transfer learning techniques applied to CNNs for Alzheimer's disease diagnosis using MRI images. They used a pre-trained CNN model on a large natural image dataset and fine-tune it on the Alzheimer's disease dataset. The approach demonstrates improved classification performance compared to training CNNs from scratch.

Chandrashekara et al. [4] proposed a research that utilizes a transfer learning approach to build an Alzheimer's disease diagnostic model using MRI images. He employed a pre-trained CNN architecture and fine-tune it on the target Alzheimer's disease dataset. The study demonstrates the potential of CNNs and transfer learning for accurate and automated diagnosis.

These related works demonstrate the effectiveness of using CNNs and transfer learning techniques to improve the accuracy of Alzheimer's disease prediction based on brain MRI images. The application of deep learning and transfer learning in this field has the potential to assist healthcare professionals in early detection and management of Alzheimer's disease, leading to better patient care and treatment outcomes.

Some key conclusions and takeaways from these studies:

CNNs for Alzheimer's Disease Prediction: The application of CNNs to brain MRI images for Alzheimer's disease prediction is a powerful approach. CNNs can automatically learn relevant image features and patterns that are critical for distinguishing between different stages of the disease and healthy controls.

Multi-Modal Data: Some studies explored the use of multi-modal data, such as combining structural MRI and functional MRI (fMRI) data. Integrating information from multiple modalities can improve the accuracy and robustness of Alzheimer's disease prediction models.

Transfer Learning: Transfer learning is an effective strategy for leveraging pre-trained CNN models, initially trained on a large dataset of non-neuroimaging images, to improve the performance of Alzheimer's disease prediction. Fine-tuning a pre-trained model on the target Alzheimer's disease dataset helps in achieving better generalization and mitigates the need for large amounts of labeled medical imaging data.

V. METHODOLOGY

The methodology section plays a pivotal role as it sheds light on the strategies employed to investigate the research problem and provides a basis for the study's validity and reliability. This section guides readers through the process of data collection, data processing, and analysis, allowing them to understand the rigor and appropriateness of the research design.

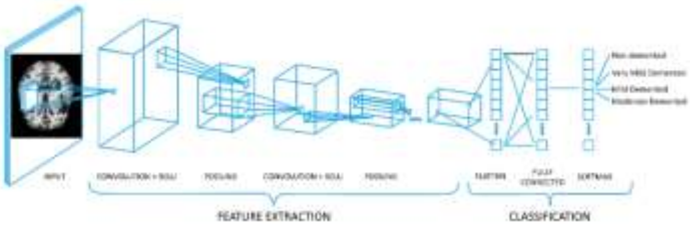
A) DATA PREPROCESSING:

The dataset used in this study consists of brain images representing different dementia stages. To ensure uniformity and eliminate potential noise, several preprocessing steps were performed. First, all images were resized to a resolution of 128x128 pixels. Images with dimensions other than 128x128 were excluded from the dataset to maintain consistency. To enhance the model's ability to generalize, data augmentation techniques were applied. These techniques include rotation, scaling, and horizontal flipping of the images. Data augmentation increases the dataset size and improves the model's robustness by exposing it to variations in the input data. The dataset was then divided into training and testing sets using an 85:15 split ratio. This division ensures an adequate amount of data for model training while allowing for unbiased evaluation of its performance. Shuffling and randomization were applied during the splitting process to prevent information leakage.

B) MODEL ARCHITECTURE:

MODEL 1: CNN

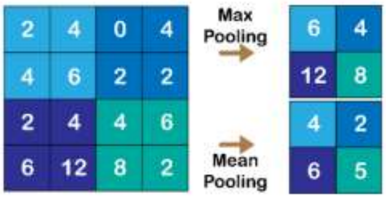
Convolutional Neural Network is one of the algorithms of deep learning as development of the Multilayer Perceptron (MLP) which is designed to process two-dimensional structure such as image. CNN is included in the type of Deep Neural Network because of the high network depth . Each layers of CNN learn to detect a variety of images. Image processing is applied to process image at a different resolution, and the output of each image is processed and used as input to the next layer.



Each convolutional layer in a CNN is created using the Conv2D() class that simply performs the convolution operation in a two-dimensional space. In other words, the movement of the kernel (filter) happens on the input image across a two-dimensional space. In Keras, a convolutional layer is referred to as a Conv2D layer.

Our model defines a convolutional block, which consists of a Conv2D layer (a 2D convolutional layer) followed by BatchNormalization and MaxPooling2D layers. The function takes the number of filters as input, which determines the depth of the output feature maps. The kernel size is set 3 which specifies height and with of kernel window. The strides is the number of steps that we move the filter over input image is set to 1 The padding parameter specifies the padding method for the Conv2D layer, with the default value being 'same' to preserve the spatial dimensions of the input. The default is no activation that is equivalent to the linear or identity activation. We used a 'relu' activation function in each convolutional layer.

Each pooling layer in a CNN is created using the MaxPooling2D()class that simply performs the Max pooling operation in a two-dimensional space.



Max pooling layers with a pool size of 2x2 are utilized to downsample the feature maps, reducing their spatial dimensions and extracting the most salient features. Dropout layers with a rate of 0.25 are introduced to prevent overfitting by randomly dropping out units during training

The model also defines a dense block, which consists of a Dense layer (a fully connected layer) followed by BatchNormalization and Dropout layers. The function takes the number of units as input, determining the number of neurons in the Dense layer. . Dropout with a rate of 0.2 is applied to this dense layer to prevent overfitting.

This Model contains a line that defines the main sequential model. It begins with an input layer of shape IMG_SHAPE, which represents the input images.

In Keras, a Sequential model can be built by using the Sequential()class. Here, we sequentially add layers to the model using the add()method. According to the Keras documentation, A CNN can be instantiated as a Sequential model because each layer has exactly one input and output and is stacked together to form the entire network.

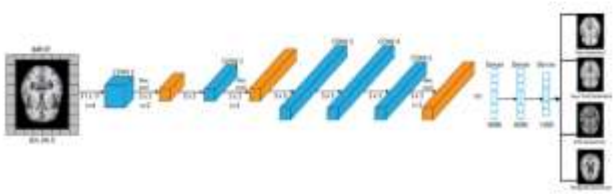
The model contains several convolutional blocks. Each convolutional block is added to the model using the conv_block function with increasing numbers of filters (16, 32, 64, 128, 256). The MaxPooling2D layer is used to reduce the spatial dimensions of the feature maps after each convolutional block.

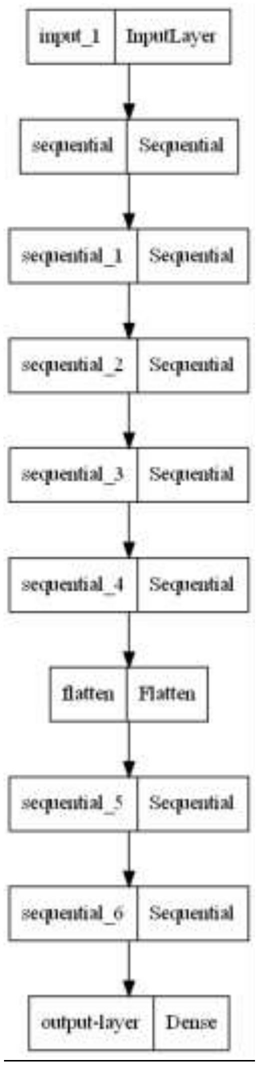
After the convolutional blocks, the feature maps are flattened into a 1D vector, preparing them for the fully connected layers.

The model includes two dense blocks with 128 and 64 units, respectively. The Dense layers are followed by BatchNormalization and Dropout layers to improve generalization and reduce overfitting.

The last layer of the model is a Dense layer with 4 units (one for each class: Mild Demented, Moderate Demented, Non Demented, Very Mild Demented). The activation function is set to 'linear' since this is a regression task to predict the stage of Alzheimer's disease.

At last we print a summary of the model architecture, displaying the number of parameters and the shape of the output at each layer.





The above plot Shows the different layers our model goes through in the Process

MODEL 2 : TRANSFER LEARNING

Transfer Learning is a machine learning technique where a model trained on one task is re-purposed and fine-tuned for a related, but different task. The idea behind transfer learning is to leverage the knowledge learned from a pre-trained model to solve a new, but related problem. This can be useful in situations where there is limited data available to train a new model from scratch, or when the new task is similar enough to the original task that the pre-trained model can be adapted to the new problem with only minor modifications.

The model takes a pre-trained base model, applies transfer learning to it, and adds some new layers on top to create the final model. The preprocess function is used to preprocess the input images before passing them through the base model.

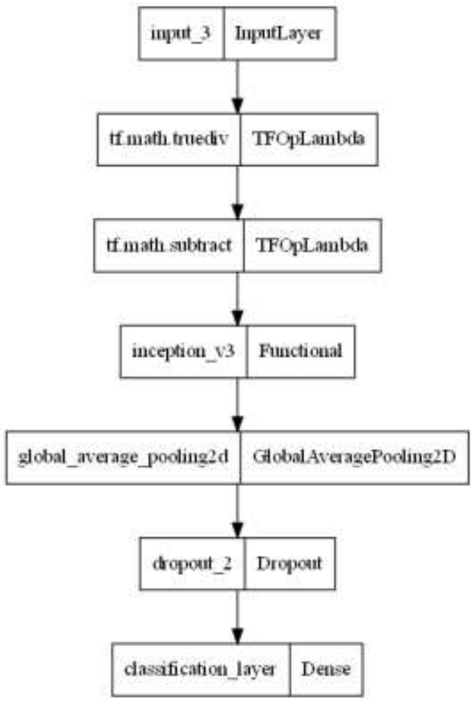
A function is defined to create the custom transfer learning model. It takes two parameters: trained_model, which is the pre-trained base model, and preprocess, which is the function to preprocess the input images.

A pre-trained base model is instantiated using the trained_model parameter. The input_shape is set to img shape, which represents the shape of the input images. The layers of the base model are set to be non-trainable, meaning that their weights will not be updated during training. This prevents the base model from being retrained and keeps its pre-trained features intact.

The input images are preprocessed using the preprocess function, which applies any necessary transformations or normalization to the images before feeding them into the base model. The preprocessed images are passed through the base model to obtain the extracted features. Since the base model is non-trainable, these features remain fixed during training.

A Global Average Pooling layer is added after the base model to reduce the spatial dimensions of the feature maps while retaining important spatial information. A Dropout layer is applied to the features to reduce overfitting during training. The dropout rate is set to 0.2, meaning that 20% of the neurons will be randomly dropped out during each training batch.

A Dense layer with 4 units is added as the final output layer. The final model is created by specifying the input and output layers.



Fine Tuning by training Deeper Layers

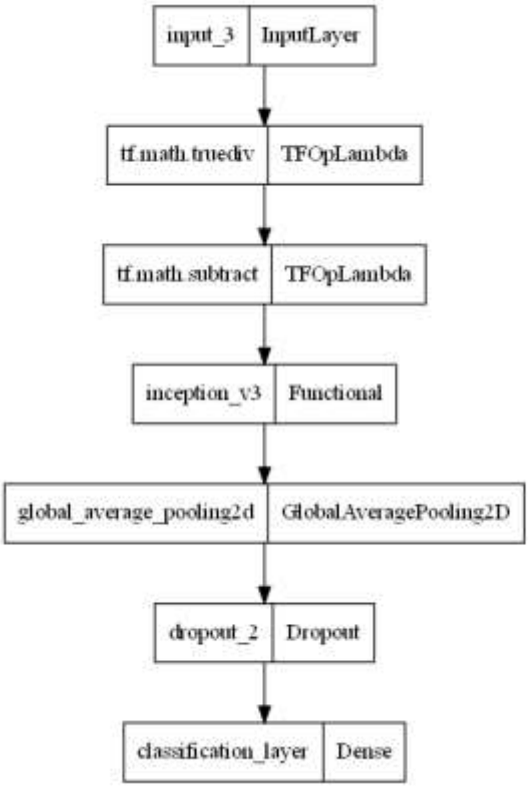
Fine tuning focuses on setting certain layers of the base model as trainable while freezing the rest of the layers to retain their pre-learned features.

We will set the index_base_model variable to 3, representing the index of the pre-trained base model within the larger model.

We will set the entire pre-trained base model to be trainable. This means that all layers within the base model will have their weights updated during the fine-tuning process.

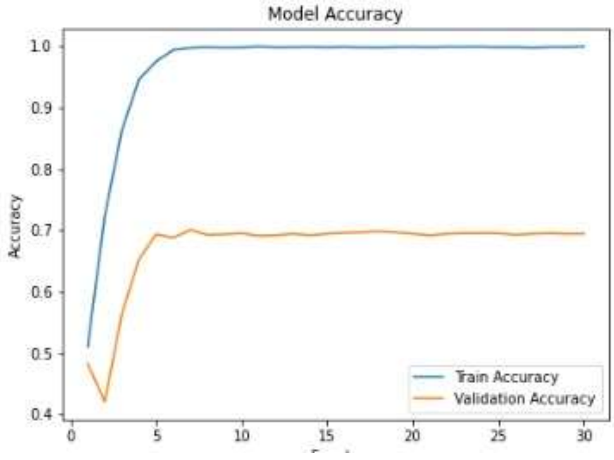
The num_finetuned_layers is set to 30. This represents the number of layers at the end of the pre-trained base model that will be fine-tuned during the transfer learning process.

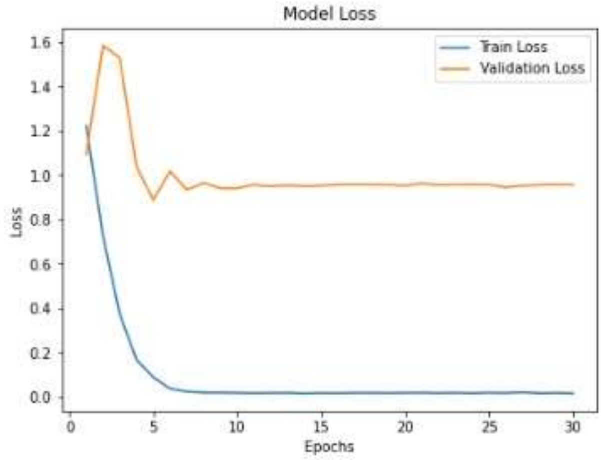
Fine-tuning allows the model to adapt and learn from the specific data in the target task (Alzheimer's disease prediction), while retaining the general features learned from the pre-trained base model, potentially leading to improved performance in the new prediction task.



VI) Results and performance

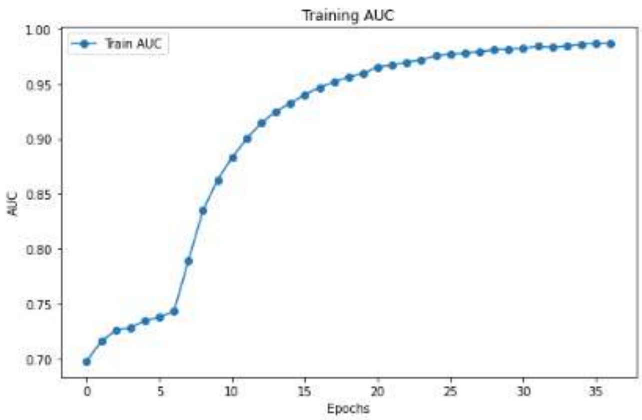
CNN DATASET 1:

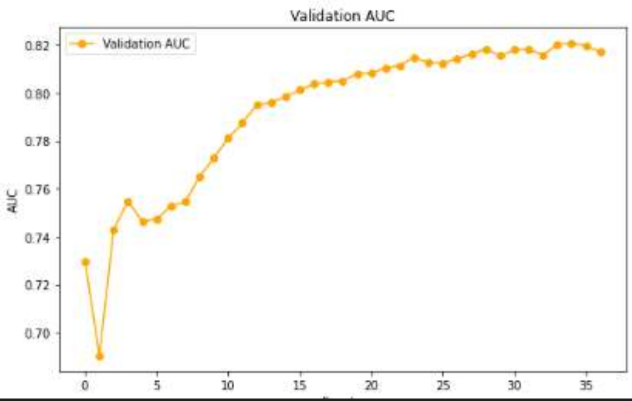




Dataset 1 CNN model is giving An Train accuracy of 100 % and valid accuracy of 73.42%

TRANSFER LEARNING DATASET 1:

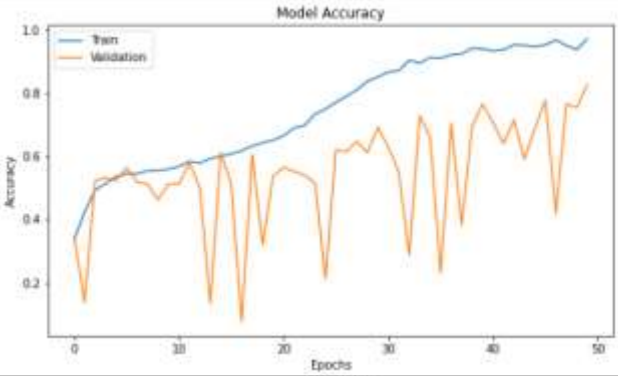


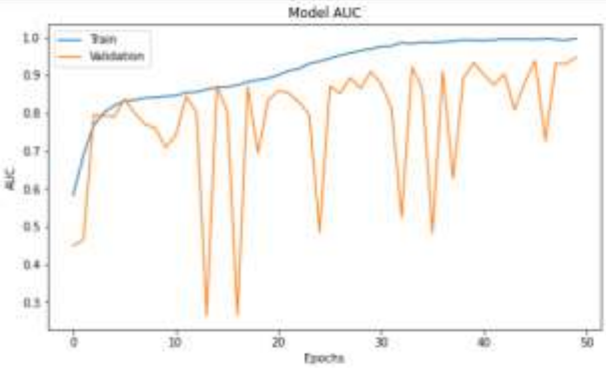


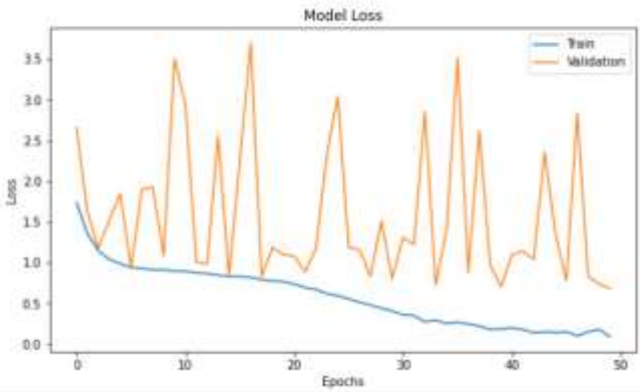

```
STARTING EPOCH: 36
EPOCH: 36, Trian AUC: 0.9898),Val Auc: 0.8130
Finished!
```

Here we have a train accuracy as 98.98 and Val accuracy as 81.30% after fine tuning our model

CNN DATASET 2:

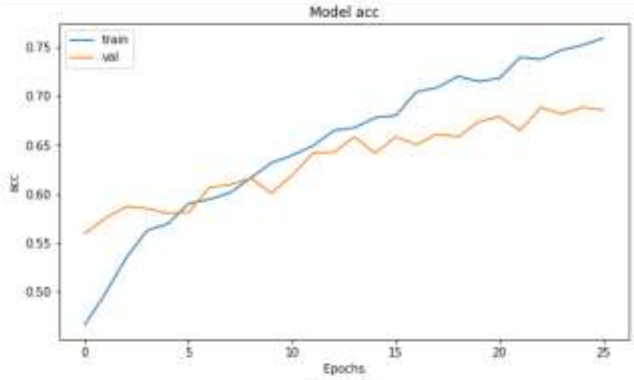


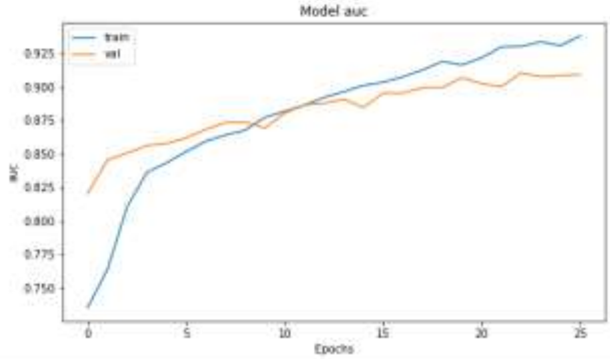




CNN model of Dataset 2 gives a Testing accuracy of 80.47%.

TRANSFER LEARNING DATASET 2:





We have a Testing accuracy of 71.56%

VII) CONCLUSION

In conclusion, the application of Convolutional Neural Networks (CNNs) and transfer learning in Alzheimer's disease prediction has shown great promise and potential. The use of deep learning techniques in medical image analysis, particularly in the context of MRI-based diagnosis, has become an active area of research. The combination of CNNs and transfer learning offers several key advantages for predicting Alzheimer's disease stages based on brain MRI images:

Highly Accurate Predictions: CNNs are powerful deep learning models capable of automatically learning relevant features from the input MRI images. When combined with transfer learning, where knowledge from pre-trained models is used, CNNs achieve high accuracy in Alzheimer's disease prediction.

Reduced Data Dependency: Transfer learning enables the fine-tuning of pre-trained models with limited labeled data, making it feasible to develop accurate prediction models even with small medical image datasets.

Feature Extraction: CNNs excel in automatically extracting intricate patterns and subtle variations in

MRI images. This feature extraction capability is crucial for identifying meaningful biomarkers associated with different stages of Alzheimer's disease.

Reduced Overfitting: Transfer learning helps in mitigating overfitting issues since the pre-trained model's learned features are generalized across diverse image data, improving the robustness of the prediction model.

Automated Diagnosis: The CNN and transfer learning-based models offer the potential for automated Alzheimer's disease diagnosis, which can significantly aid healthcare professionals in early detection and personalized treatment planning.

Time and Cost-Efficient: By leveraging pre-trained models and transfer learning, the time and computational resources required to train the model are reduced, making it cost-effective and accessible for researchers and medical practitioners.

However, despite these advantages, there are still challenges and opportunities for further research in Alzheimer's disease prediction Deep learning:

Interpretable Models: As deep learning models are often considered black boxes, efforts to interpret and explain model predictions for medical decision-making remain essential.

Data Quality and Quantity: The availability of high-quality and diverse MRI datasets is crucial for developing robust and generalizable prediction models.

Multi-Modal Data: Integrating multiple imaging modalities (e.g., MRI, PET, fMRI) and clinical data could improve prediction accuracy and provide a more comprehensive understanding of Alzheimer's disease progression.

In conclusion, the integration of CNNs and transfer learning holds great potential for revolutionizing the field of Alzheimer's disease prediction based on brain MRI images. With ongoing research and development, these techniques can contribute significantly to early diagnosis, personalized treatment planning, and ultimately, improved patient outcomes in the battle against Alzheimer's disease.

VIII) FUTURE PROSPECTS

- **Improving the interpretability of deep learning models:** One of the challenges of using deep learning models is that they can be difficult to interpret. Researchers are working on developing methods to make deep learning models more interpretable, so that clinicians can better understand how the models are making their predictions.

- **Early Detection:** One of the major challenges in Alzheimer's disease is its late diagnosis, which limits the effectiveness of available treatments. Deep learning models could aid in the early detection of the disease by analyzing a combination of diverse data sources, such as brain imaging (MRI, PET scans), genetic data, and cognitive assessments.

- **Multi-Modal Data Integration**: Deep learning techniques can effectively integrate data from various sources, such as neuroimaging, genomics, and clinical data. This integration may lead to a more comprehensive understanding of the disease's progression and could potentially identify biomarkers that are difficult to detect through traditional methods.

- **Remote Monitoring:** As technology advances, deep learning-based algorithms could enable remote monitoring of individuals at risk of Alzheimer's disease or those already diagnosed. This could involve continuous data collection from wearable devices or smartphone apps, allowing for real-time analysis and early detection of cognitive decline.

- **Drug Discovery:** Deep learning can play a crucial role in drug discovery for Alzheimer's disease. By analyzing vast amounts of biomedical data and identifying potential drug-target interactions, deep learning models can expedite the process of finding new therapeutic compounds and accelerate the development of novel treatments.

IX) ACKNOWLEDGEMENT

We wish to show our appreciation to Dr.Renuka Suravajhala., Anu Rohit Melge and Anandhu Presannan who guided us throughout this project.We would like to thank our friends and family for providing us with deep insights into this study

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