ALZHEIMER DISEASE PREDICTION USING DEEP LEARNING

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INTRODUCTION

- Alzheimer’s disease is an unpredictable degenerative brain disease.
- Every 4 seconds someone in the world is diagnosed with Alzheimer’s disease the result is fatal as it leads to death.
- The leading cause of AD Is dementia, dementia causes a reduction in reasoning abilities interpersonal coping skills, and abilities to function independently.
- The patient will forget the recent events in the early stage if the illness progresses they will gradually forget the whole event.
- Therefore, diagnosing the disease as soon as possible is essential.
- A model that takes a brain MRI sample image as input and determines whether a person has mild, moderate, very mild, or no dementia disease as output.

Abstract :

- Alzheimer’s disease (AD) is the most common cause of dementia globally. It steadily worsens from mild to severe, impairing one’s ability to complete any work without assistance.
- It begins to outstrip due to the population ages and diagnosis timeline. For classifying cases, existing approaches incorporate medical history, neuropsychological testing, and Magnetic Resonance Imaging (MRI), but efficient procedures remain inconsistent due to a lack of sensitivity and precision.
- By considering four stages of dementia and conducting a particular diagnosis, the proposed model generates high-resolution disease probability maps from the local brain structure to a multilayer perceptron and provides accurate, intuitive visualizations of individual Alzheimer’s disease risk. four stages of dementia and conducting a particular diagnosis, the proposed model generates high-resolution disease probability maps from the local brain structure to a multilayer perceptron and provides accurate, intuitive visualizations of individual Alzheimer’s disease risk.
- A DenseNet169 algorithm classification is proposed to detect the dementia stages from MRI. Which is superior to existing methods, we also used the Alzheimer’s disease Neuroimaging Initiative (ADNI) dataset to predict AD classes to assess the efficacy of the proposed model.

S. No	Year & Author name	Title	Description	Advantages	Disadvantages
8.	2021	“Prediction of future Alzheimer's disease dementia using plasma phospho-tau combined with other accessible measures” by Blennow K et al.	The first approach is based on traditional classifiers,the second approach utilizes deep neural networks.	Utilizes waikato environment for knowledge analysis (WEKA) tool.	The paper is focused only on the machine learning and the accuracy is low.
9.	2021	“Application of Artificial Intelligence techniques for the detection of Alzheimer’s disease using structural MRI images” by Candice Ke En Ang et al.	Provides essential features required to detect fraudulent.	Random forest algorithm is very stable.	Speed during testing and application will suffer.
10.	2021	“A Deep Learning Model for Early Diagnosis of Alzheimer Diseases and Dementia from MR Images” by Chandran Venkatesan et al.	Hybrid methods which use AdaBoost and majority voting methods are applied.	Algorithms for clustering and classification were used separately.	Lack of confidentiality and lack of security of data.
11.	2021	“Alzheimer Disease Detection using Correlation based Ensemble Feature Selection and Multi Support Vector Machine” by Jhansi et al.	Describes probability of fraudulent transactions in prevalence and context of credit card usage.	Can handle large datasets helps in predicting the disease efficiently.	The customers credit card passwords, cvv numbers and other vital information are always vulnerable.

S. No	Year	Title	Description	Advantages	Disadvantages
12.	2021	"Feature Extraction and Identification of Alzheimer's disease based on Latent Factor of Multi-Channel EEG" by Jiang Wang et al.	Here different machine learning algorithms on an imbalanced with ensemble classifiers using boosting techniques are implemented.	Random forest with boosting shows that it proves accurate in detecting disease.	By using the three algorithms we cannot determine the names of fraud and non-fraud transactions for the given dataset using machine learning.
13.	2021	"Detection and analysis of Alzheimer's disease using various machine learning algorithms" by Usha Kumari et al.	Several algorithms and neural networks were used.	Gradient boosting has the highest accuracy.	Gradient boosting can over emphasize outliers and cause overfitting.
14.	2021	"Relation-induced Multi-modal Shared Representation Learning for Alzheimer's disease Diagnosis" by Qing Xiao et al.	The GA was implemented with the RF in its fitness function.	GA selected attributes demonstrated that the GA-RF achieved an overall optimal accuracy of 99.98%.	The algorithm works accurately for a limited amount of dataset only.
15.	2021	"Resting State fMRI and Improved Deep Learning Algorithm for Earlier Detection of Alzheimer's Disease" by Haibing Guo et al.	The paper attempts to present a systematic literature review (SLR) on machine learning (ML)-based fraud detection.	The paper presented the key issues, gaps, and limitations in the area of financial fraud detection.	The paper fails to pay attention to unsupervised practices,which can uncover new insights.

Existing System :

- The Existing model used a Machine Learning algorithm with psychological parameters like age, number of visits, MMSE, and some other features, and by making use of all these they have created an ML model.
- Existing Systems used algorithms such as Support Vector Machine(SVM), and Decision Tree algorithms for classifying Alzheimer's disease.
- Using all the above approaches they ended up achieving low accuracy.
- In the existing, they also used the VGG19 model to classify Alzheimer's disease in which the vanishing gradient problem is raised.
- Also, Feature Propagation is not strengthened and the Reusability of the feature is not enhanced.
- They did not take a step to reduce the number of parameters.

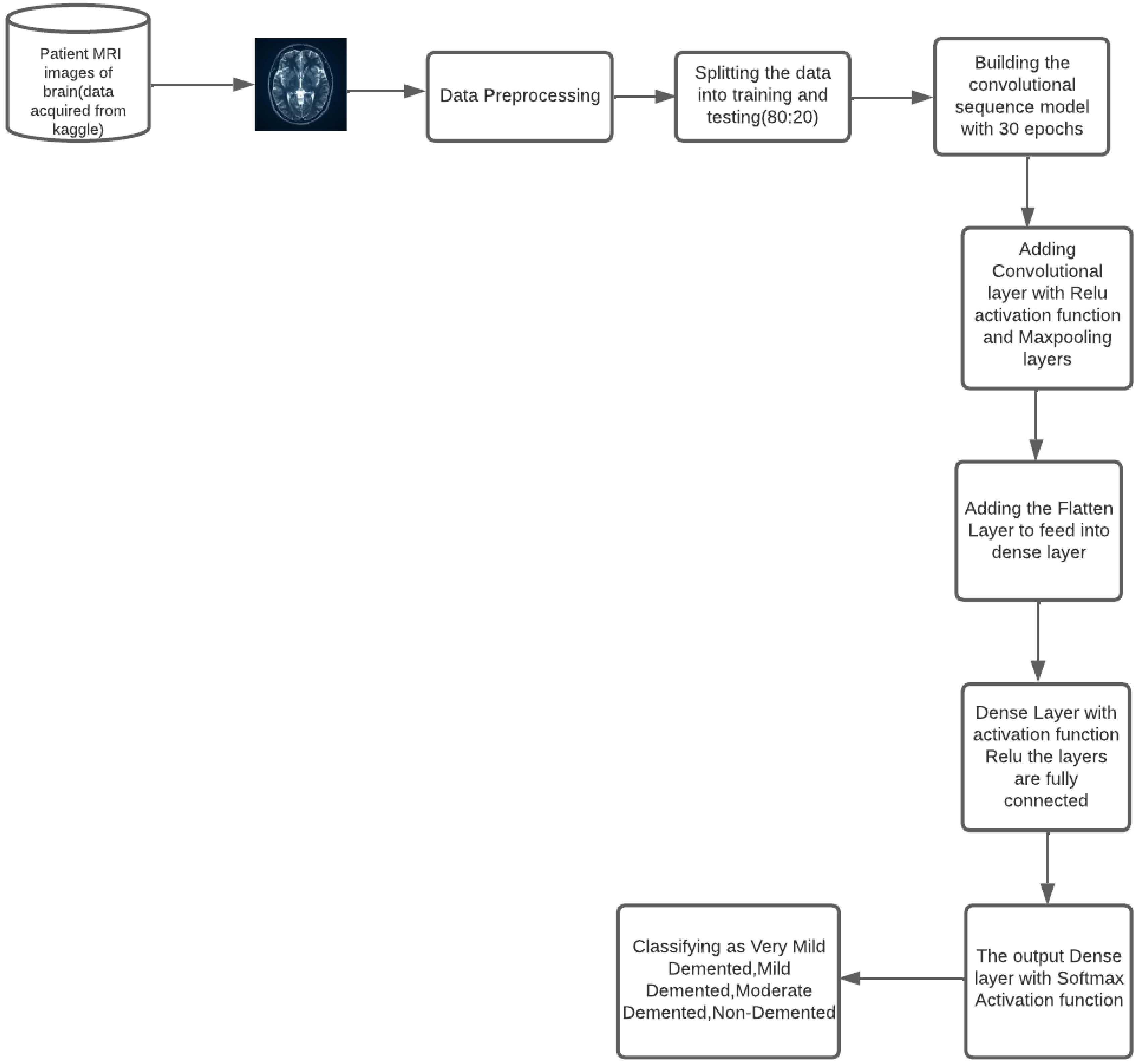
Proposed System :

- Here, we explore DL Algorithms to identify and diagnose Alzheimer's disease using MRI images of the human brain.
- We collect the datasets from an open-source website called Kaggle. The dataset holds MRI images of the human brain in the affected person. For each category, we use 50 datasets.so a total of 200 datasets have been taken.
- After the data set collection and pre-processing methods, we use and apply the following deep learning algorithms – Densenet169 algorithm classification for AD diagnosis.
- This is an effective algorithm due to its better size and accuracy.
- When the image is given as input It passes through a sequence of layers of dense blocks after every dense block layer there is a transition layer, convolutional layer, and Pooling layer which enhances the image pixels and reduce the size.

Proposed System Advantage:

- Vanishing Gradient problem is alleviated by Densenet
- Feature Propagation is strengthened
- Reusability of feature is enhanced.
- Number of the parameter is reduced.
- Making use of all these we built this project to achieve high accuracy.

Proposed System Architecture :



LIST OF MODULES :

- Data acquisition
- Image preprocessing
- Magnetic resonance imaging classification
- Densenet 169

MODULE 1-DATA ACQUISITION:

- The first step is to acquire images. To produce a classification model, the computer needs to learn by example. The computer needs to view many images to recognize an object. Other types of data, such as time series data and voice data, can also be used to train deep learning models.
- In the context of the work surveyed in this paper, the relevant data required to detect Alzheimer disease will be images. The output of this step is images that will later be used to train the model.

MODULE 2-IMAGE PRE-PROCESSING:

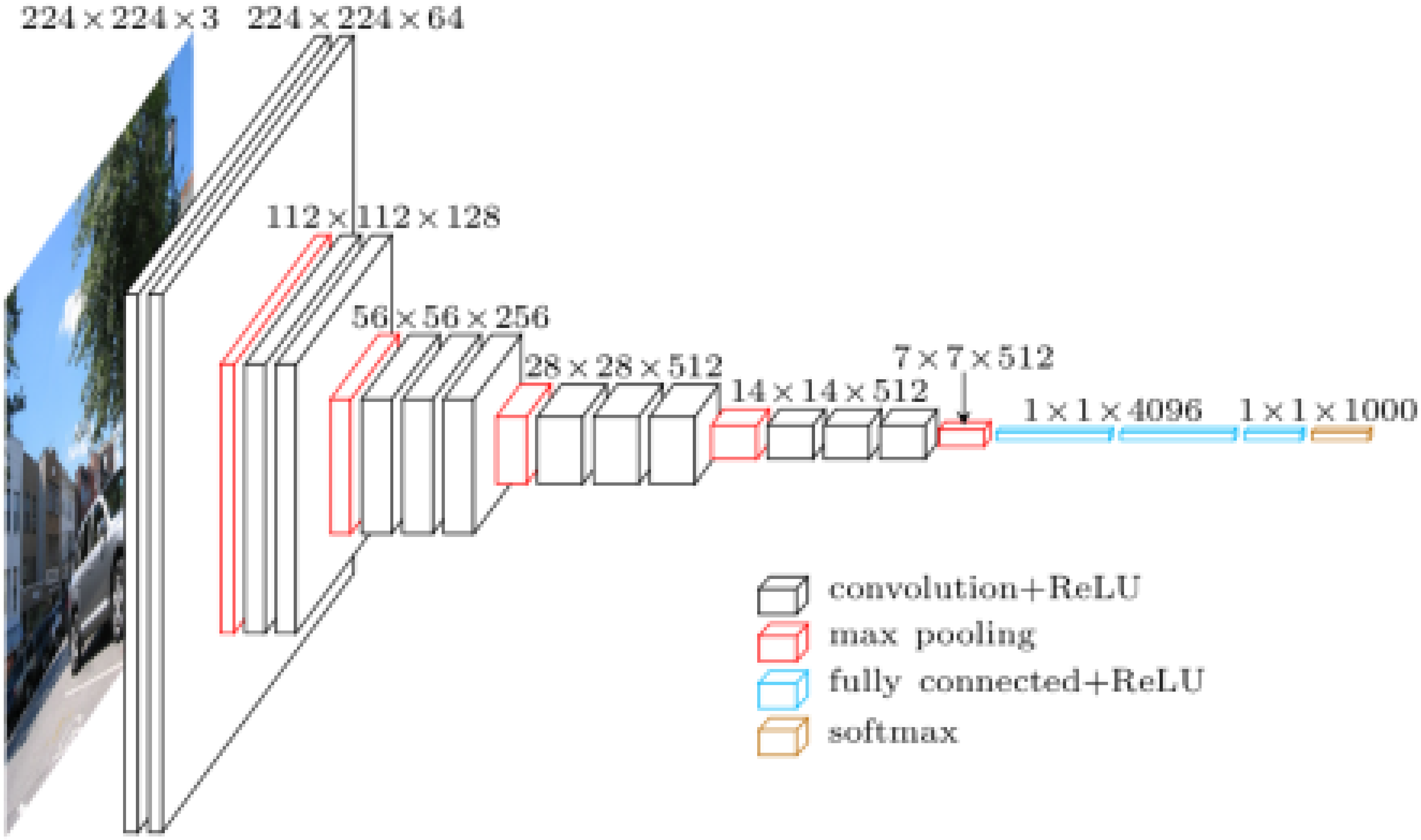
- An image classification task determines the category of a given input MRI image. It is a basic task in high-level image understanding and can be divided into binary- and multi classification tasks. After multiple convolution-and-pooling operations via a CNN, an image is classified in the output layer following the requirements.
- Activation function of the output layer is the only difference between binary and multi classification tasks. An image classification task for MRI image analysis easily identified and then necessary actions can be taken to which type of dementia, is a high performance in natural image classification, including Convolution neural network (CNNs) can be used in JPG/PNG image classification

MODULE 3 - MAGNETIC RESONANCE IMAGE CLASSIFICATION:

- This imaging technique utilizes radio waves and magnetic fields to generate high-quality and high-resolution 2D and 3D images of brain structures. No harmful radiations from X-rays or radioactive tracers are generated. The most commonly used MRI for AD cases is the structural MRI, which measures brain volumes in vivo to detect brain degeneration (loss of tissue, cells, neurons, etc.).
- Brain degeneration is an inevitable progressive component of AD. A structural MRI used to detect brain atrophy. Alternatively, Functional Magnetic Resonance Imaging (fMRI), a widely used method to measure human primary visual cortex and detect brain topography.
- fMRI provides useful information and data about the human brain’s activity, i.e., how the brain functions. fMRI methods, such as brain imaging based on arterial Blood Oxygenation Level Dependent (BOLD) contrasts and spin-labelling (ASL), are sensitive to the cerebral metabolic rate of oxygen consumption and cerebral blood flow (CBF).

MODULE 4 - DENSENET 169:

- Densenet169 is among the major models of the Densenet group for image classification. The model is fairly popular due to it is better to size and accuracy. It is an output classifier object for 1000 varying classifications present in the ImageNet. The Densenet model has shown decent accuracy in the classification of images. The model has displayed certain promising graphs. It used a batch size of 128. The model has run for 40 epochs.
- The model provided an accuracy of about 87% in the train data and about 80% in the test data. The model displayed an AUC of about 88% in train data and about 82% in the test data and the model loss obtained is also pretty low. After going through certain layers, the model classifies the images accordingly. The classification done is of four types namely Mild Demented, Moderate Demented, Non Demented and Very Mild Demented. The model displayed an accuracy of about 87% on the train dataset and an accuracy of about 78% on the test dataset.


224 × 224 × 3
224 × 224 × 64
112 × 112 × 128
56 × 56 × 256
28 × 28 × 512
14 × 14 × 512
7 × 7 × 512
1 × 1 × 4096
1 × 1 × 1000
convolution+ReLU
max pooling
fully connected+ReLU
softmax

jupyter training Last Checkpoint: 2 minutes ago (autosaved)

Logout

File Edit View Insert Cell Kernel Widgets Help Trusted Python 3 (ipykernel)

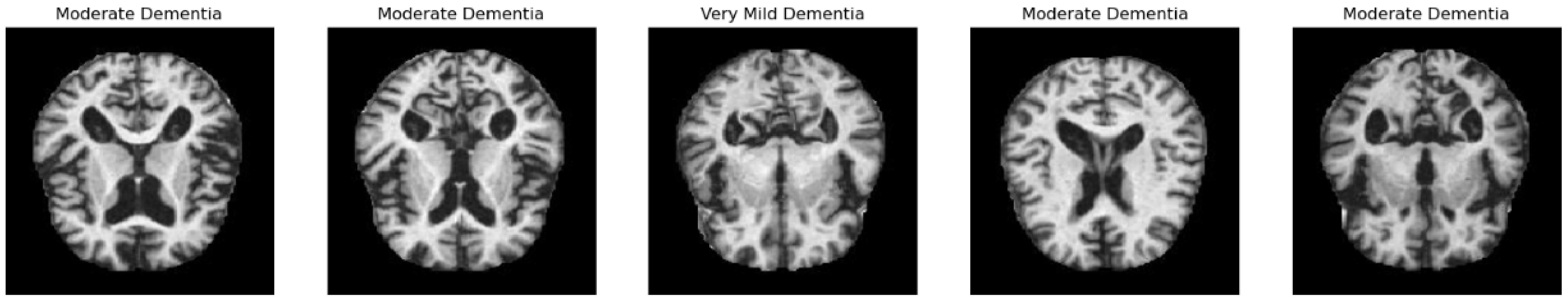
Run Code

```
Found 40 images belonging to 4 classes.
```

In [8]:

```
fig, ax = plt.subplots(nrows = 1, ncols = 5, figsize=(20,20))

for i in tqdm(range(0,5)):
    rand1 = np.random.randint(len(train_dataset))
    rand2 = np.random.randint(50)
    ax[i].imshow(train_dataset[rand1][0][rand2])
    ax[i].axis('off')
    a = train_dataset[rand1][1][rand2]
    if a[0] == 1:
        ax[i].set_title('Mild Dementia')
    elif a[1] == 1:
        ax[i].set_title('Moderate Dementia')
    elif a[2] == 1:
        ax[i].set_title('Non Demetia')
    elif a[3] == 1:
        ax[i].set_title('Very Mild Dementia')
```

```
100%|██████████| 5/5 [00:04<00:00,  1.12it/s]
```



localhost:8888/notebooks/alzheimerrr/training.ipynb

jupyter training Last Checkpoint: 5 minutes ago (autosaved)

Logout

File Edit View Insert Cell Kernel Widgets Help Trusted Python 3 (ipykernel)

Run Code

```
6/6 [==============================] - 5s 771ms/step - loss: 0.9023 - acc: 0.5595
Epoch 12/30
6/6 [==============================] - 5s 772ms/step - loss: 0.8610 - acc: 0.5893
Epoch 13/30
6/6 [==============================] - 5s 874ms/step - loss: 0.8275 - acc: 0.6369
Epoch 14/30
6/6 [==============================] - 5s 772ms/step - loss: 0.8425 - acc: 0.6488
Epoch 15/30
6/6 [==============================] - 6s 906ms/step - loss: 0.8365 - acc: 0.5990
Epoch 16/30
6/6 [==============================] - 5s 755ms/step - loss: 0.8059 - acc: 0.5833
Epoch 17/30
6/6 [==============================] - 5s 889ms/step - loss: 0.7217 - acc: 0.6667
Epoch 18/30
6/6 [==============================] - 5s 774ms/step - loss: 0.7988 - acc: 0.6190
Epoch 19/30
6/6 [==============================] - 5s 883ms/step - loss: 0.7199 - acc: 0.6667
Epoch 20/30
6/6 [==============================] - 5s 778ms/step - loss: 0.7017 - acc: 0.6726
Epoch 21/30
6/6 [==============================] - 5s 766ms/step - loss: 0.7260 - acc: 0.6786
Epoch 22/30
6/6 [==============================] - 5s 879ms/step - loss: 0.6418 - acc: 0.7321
Epoch 23/30
6/6 [==============================] - 5s 765ms/step - loss: 0.6099 - acc: 0.7083
Epoch 24/30
6/6 [==============================] - 5s 766ms/step - loss: 0.6288 - acc: 0.6905
Epoch 25/30
6/6 [==============================] - 6s 895ms/step - loss: 0.6401 - acc: 0.7188
Epoch 26/30
6/6 [==============================] - 5s 770ms/step - loss: 0.6885 - acc: 0.7202
Epoch 27/30
6/6 [==============================] - 5s 751ms/step - loss: 0.5882 - acc: 0.7917
Epoch 28/30
6/6 [==============================] - 6s 892ms/step - loss: 0.4794 - acc: 0.7760
Epoch 29/30
6/6 [==============================] - 5s 763ms/step - loss: 0.5284 - acc: 0.7798
Epoch 30/30
```

```
[1]: # Test Case 1: Non-Dementia
import numpy as np
from keras_preprocessing import image
import easygui

dic = test_dataset.class_indices
idc = {k:v for v, k in dic.items()}

img = load_img(r'C:/Users/SRI DHARSHINI/alzheimerrr/alzheimer/training/NonDemented/nonDem0.jpg', target_size = (224,224,3))
img = img_to_array(img)
img = img/255
imshow(img)
plt.axis('off')
img = np.expand_dims(img,axis=0)
test_image = image.load_img(r'C:/Users/SRI DHARSHINI/alzheimerrr/alzheimer/training/NonDemented/nonDem0.jpg', target_size = (200,
test_image = np.expand_dims(test_image, axis=0)
result = model.predict(test_image)
if result[0][1] == 1:
    prediction = "NonDemented"
elif result[0][0] == 1:
    prediction = "MildDemented"
elif result[0][2] == 1:
    prediction = "VeryMildDementedd"
elif result[0][3] == 1:
    prediction = "ModerateDemented"

print(prediction)
```

```
1/1 [==============================] - 0s 71ms/step
NonDemented
```

Run Code

In [22]:

```python
# Test Case 2: Mild Demented
import numpy as np
from keras_preprocessing import image
import easygui

dic = test_dataset.class_indices
idc = {k:v for v, k in dic.items()}

img = load_img(r'C:/Users/SRI DHARSHINI/alzheimerrr/alzheimer/training/MildDemented/mildDem0.jpg', target_size = (224,224,3))
img = img_to_array(img)
img = img/255
imshow(img)
plt.axis('off')
img = np.expand_dims(img,axis=0)
test_image = image.load_img(r'C:/Users/SRI DHARSHINI/alzheimerrr/alzheimer/training/MildDemented/mildDem0.jpg', target_size = (2(
test_image = np.expand_dims(test_image, axis=0)
result = model.predict(test_image)
if result[0][1] == 1:
    prediction = "NonDemented"
elif result[0][0] == 1:
    prediction = "MildDemented"
elif result[0][2] == 1:
    prediction = "VeryMildDementedd"
elif result[0][3] == 1:
    prediction = "ModerateDemented"

print(prediction)
```

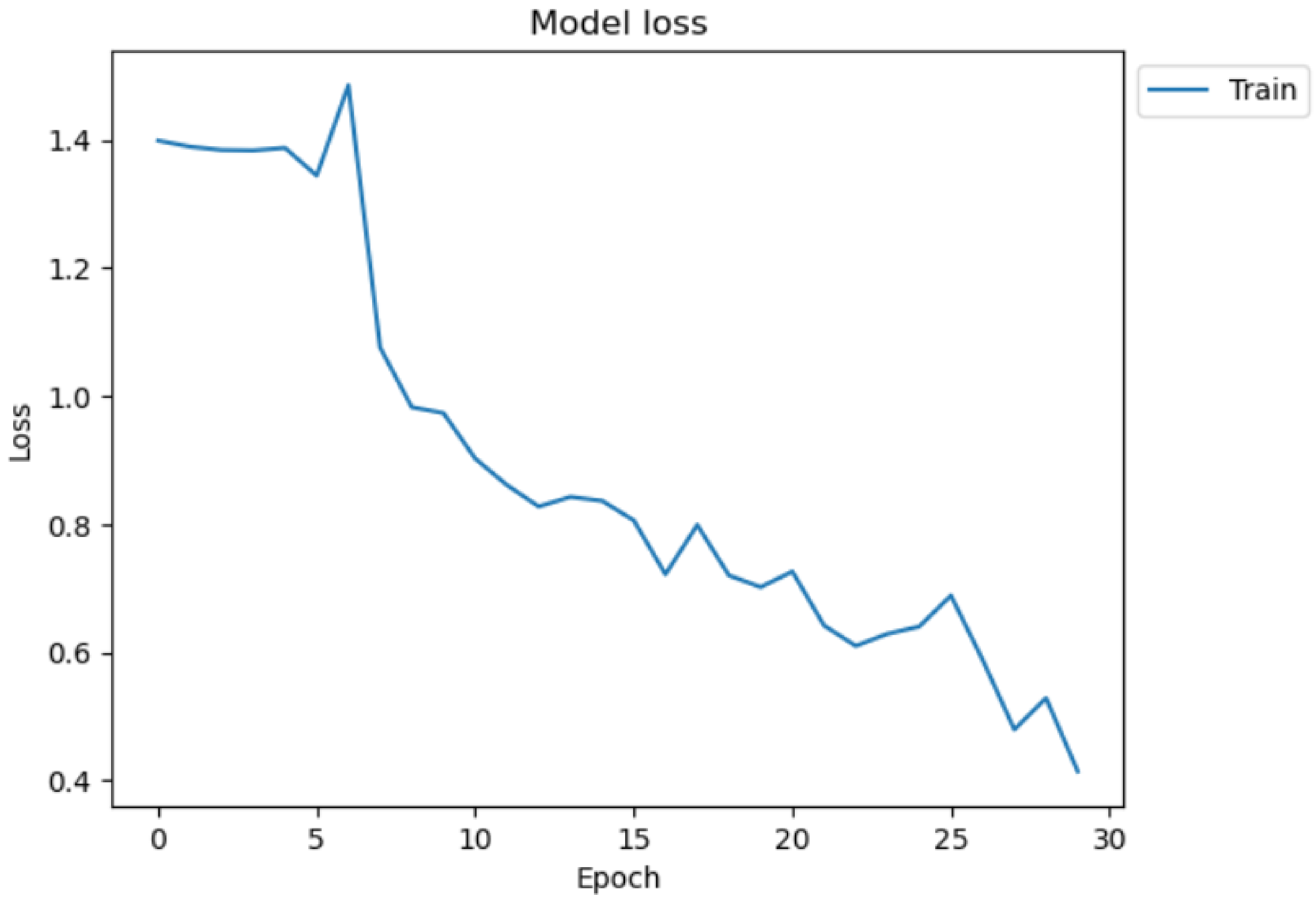
```
1/1 [==============================] - 0s 78ms/step
MildDemented
```

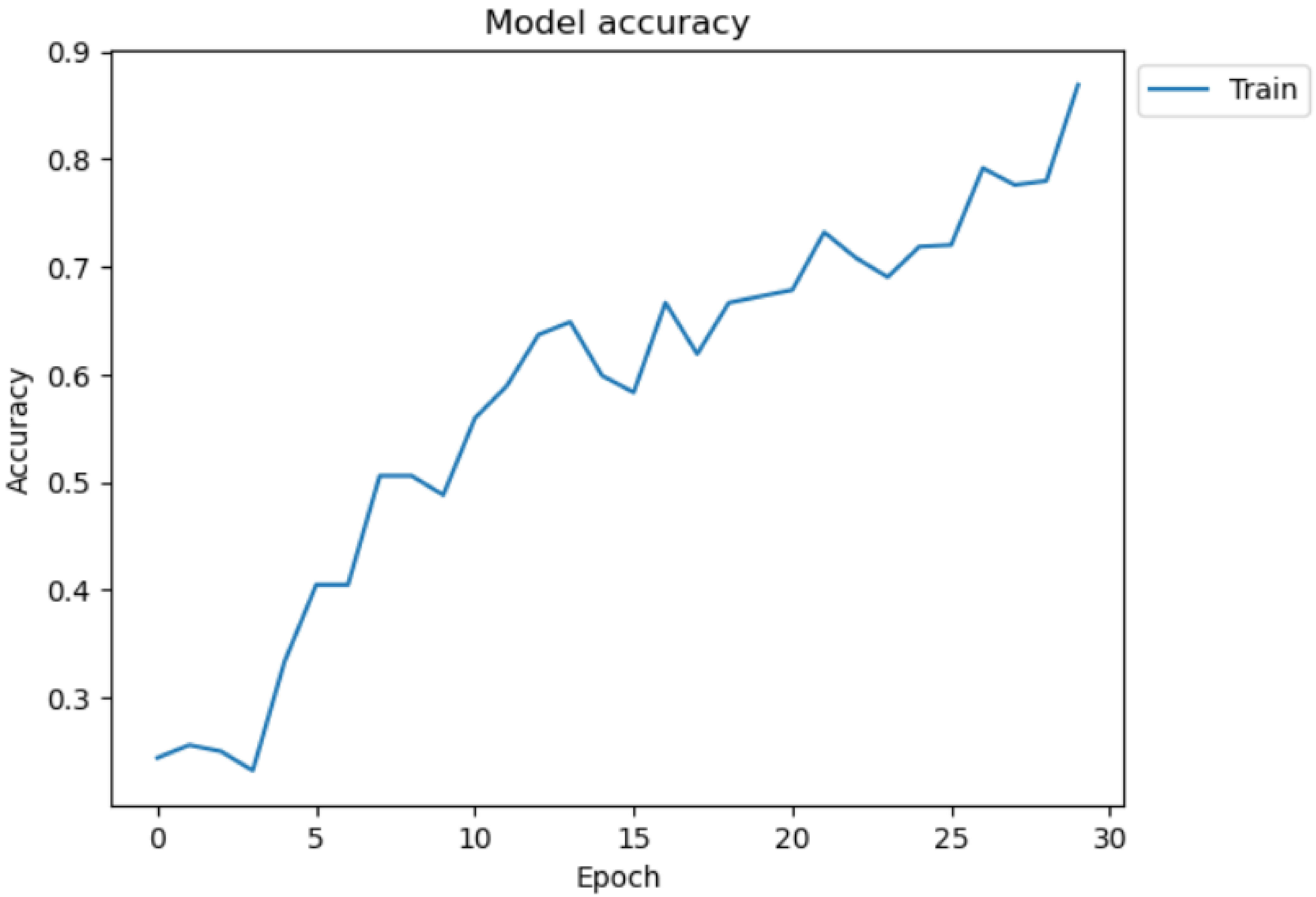
In [24]:

```python
# Test Case 3: Moderate Demented
import numpy as np
from keras_preprocessing import image
import easygui

dic = test_dataset.class_indices
idc = {k:v for v, k in dic.items()}

img = load_img(r'C:/Users/SRI DHARSHINI/alzheimerrr/alzheimer/training/ModerateDemented/moderateDem26.jpg', target_size = (224,22
img = img_to_array(img)
img = img/255
imshow(img)
plt.axis('off')
img = np.expand_dims(img,axis=0)
test_image = image.load_img(r'C:/Users/SRI DHARSHINI/alzheimerrr/alzheimer/training/ModerateDemented/moderateDem26.jpg', target_s
test_image = np.expand_dims(test_image, axis=0)
result = model.predict(test_image)
if result[0][1] == 1:
    prediction = "NonDemented"
elif result[0][0] == 1:
    prediction = "MildDemented"
elif result[0][2] == 1:
    prediction = "VeryMildDementedd"
elif result[0][3] == 1:
    prediction = "ModerateDemented"

print(prediction)
```

Performance Analysis :

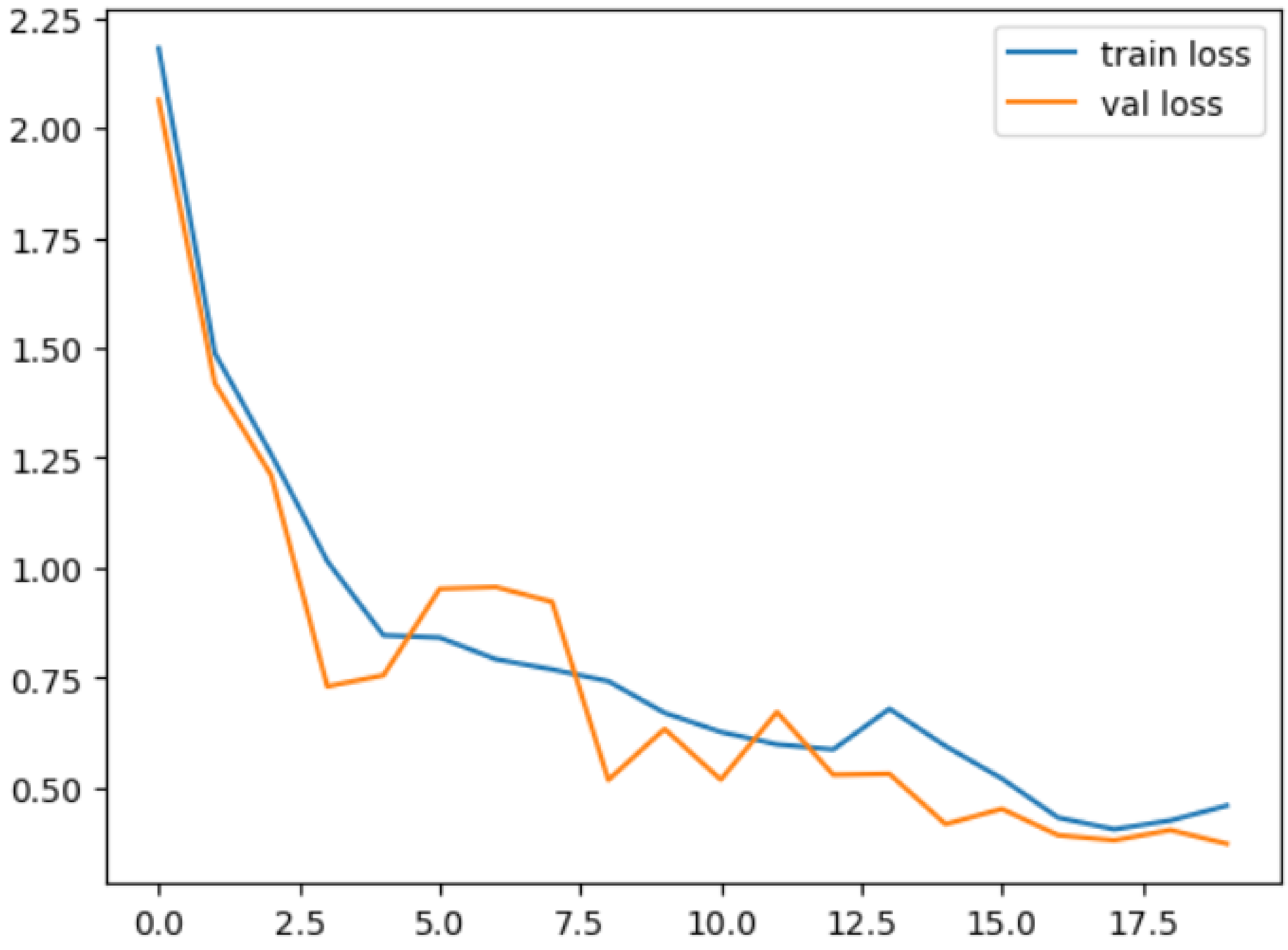
- The performance analysis of the DL algorithm are as follows :



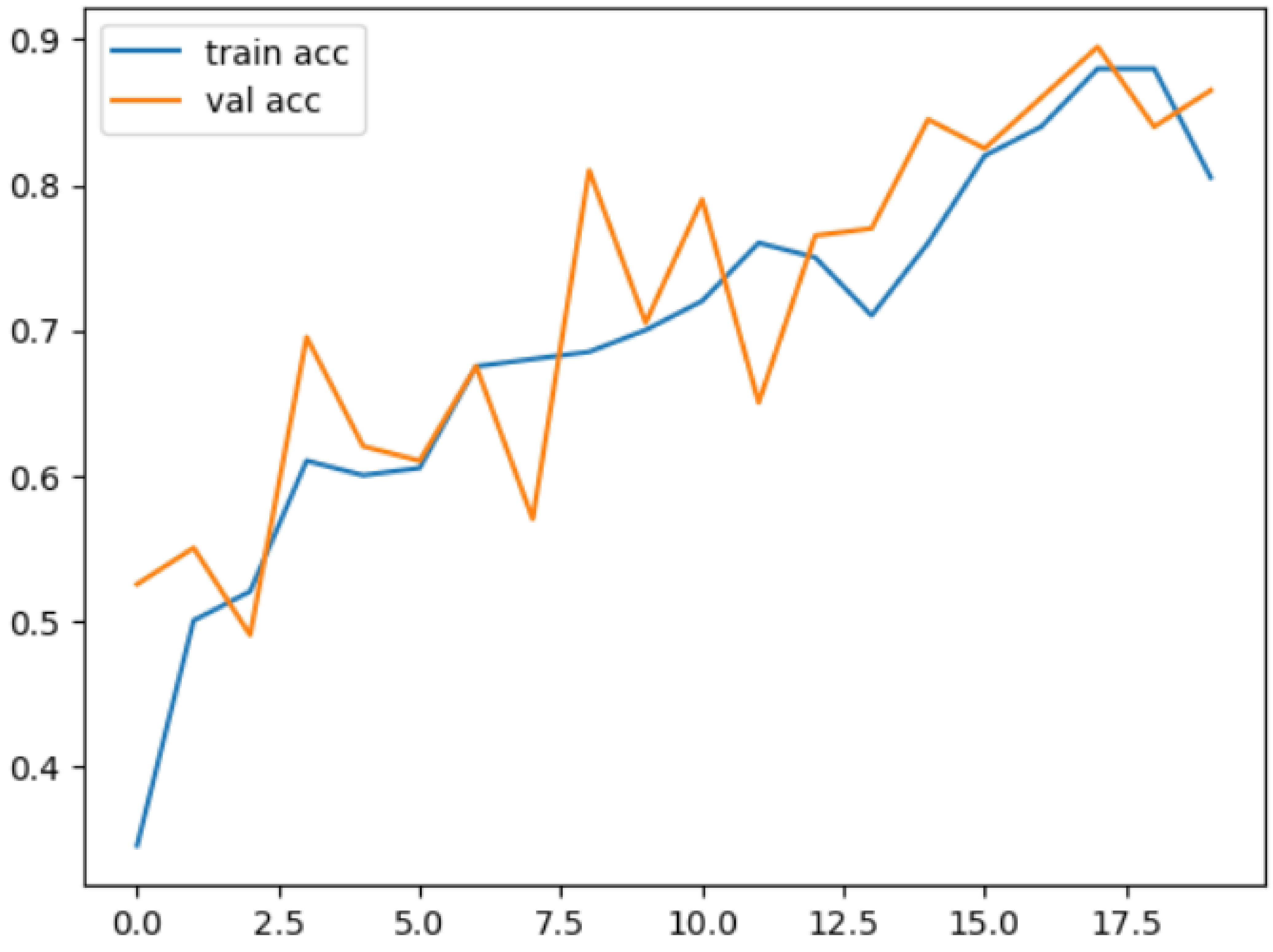


Model accuracy
Train
Accuracy
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0
5
10
15
20
25
30
Epoch

VGG16

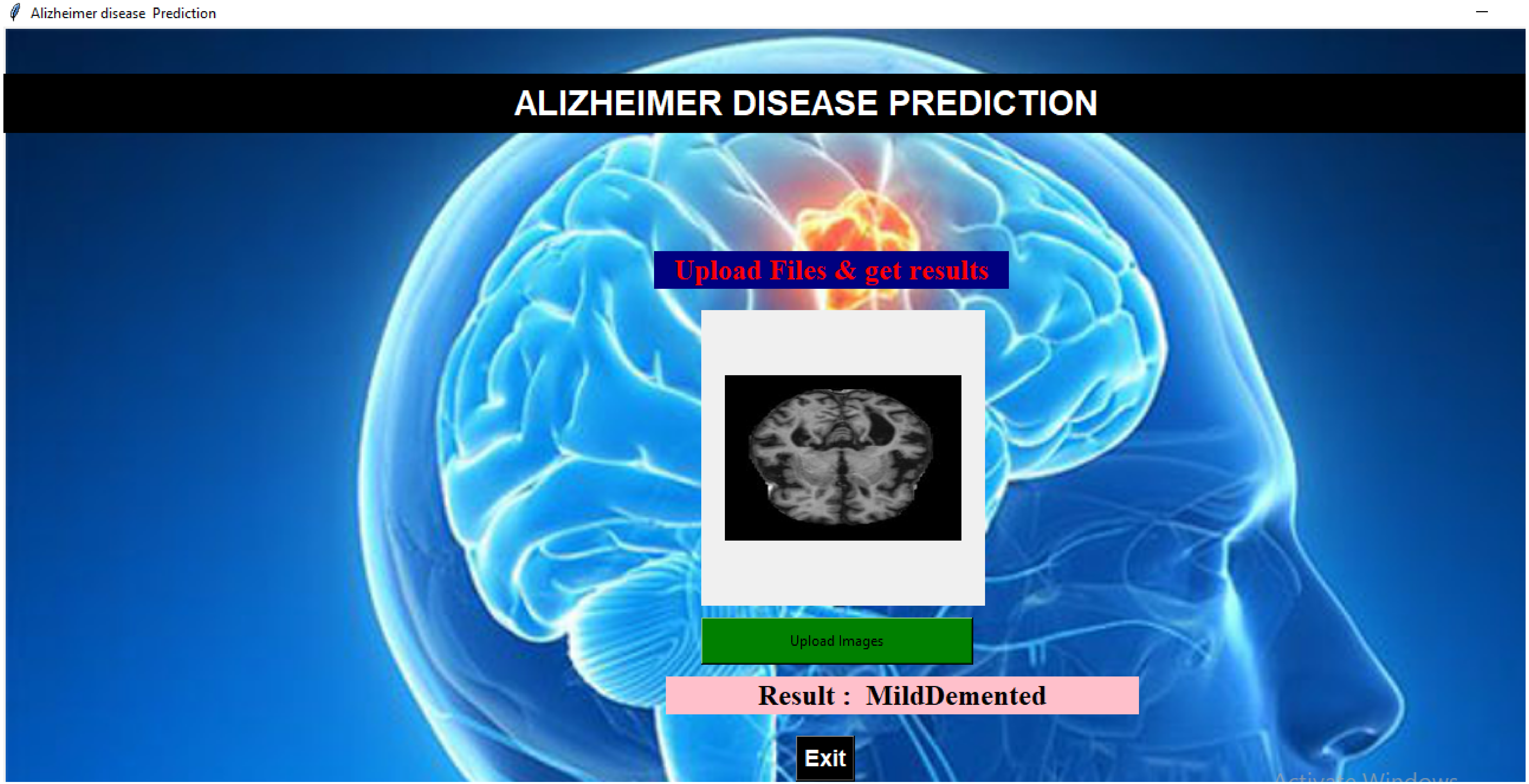


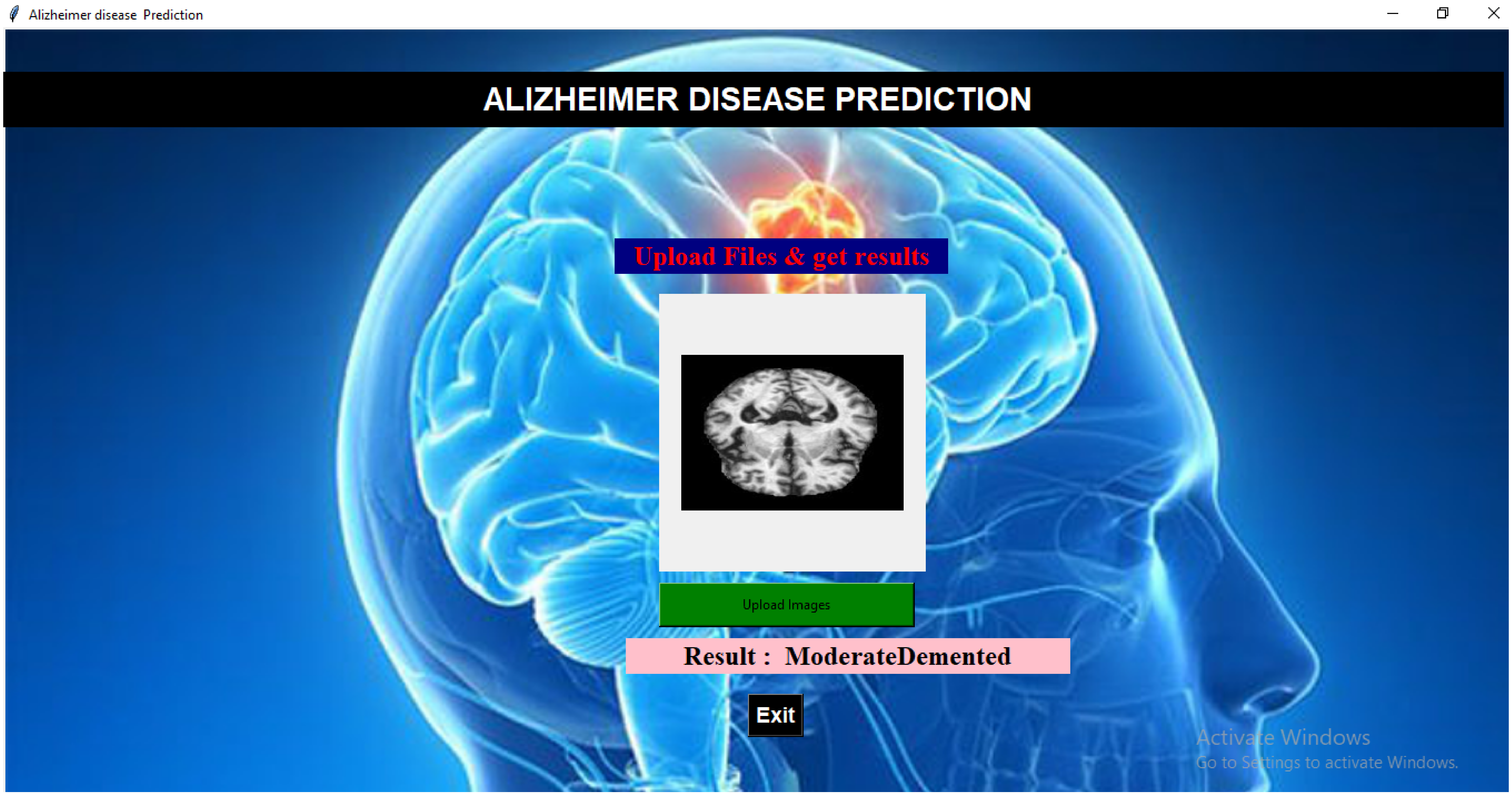
train loss
val loss
2.25
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

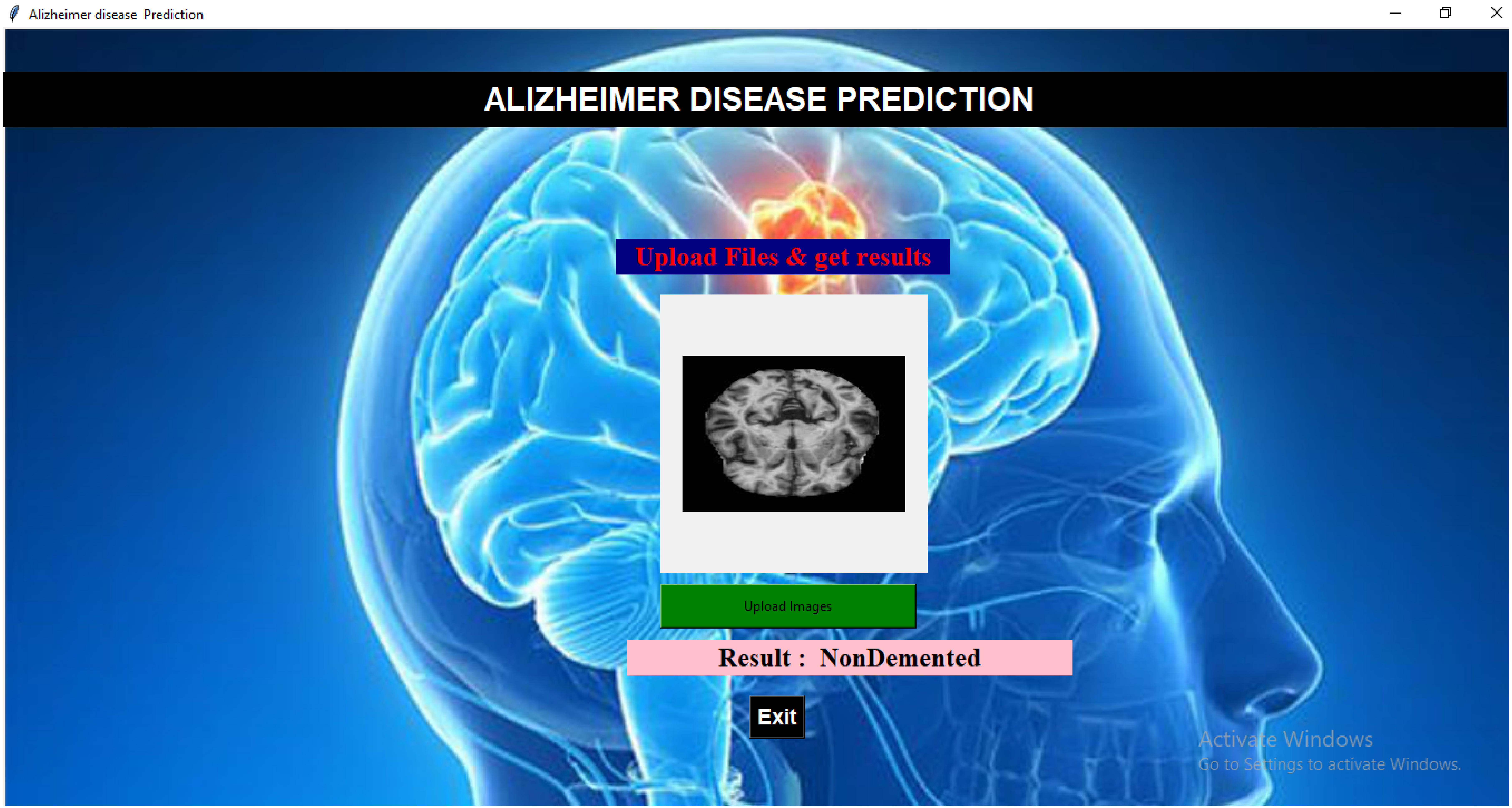


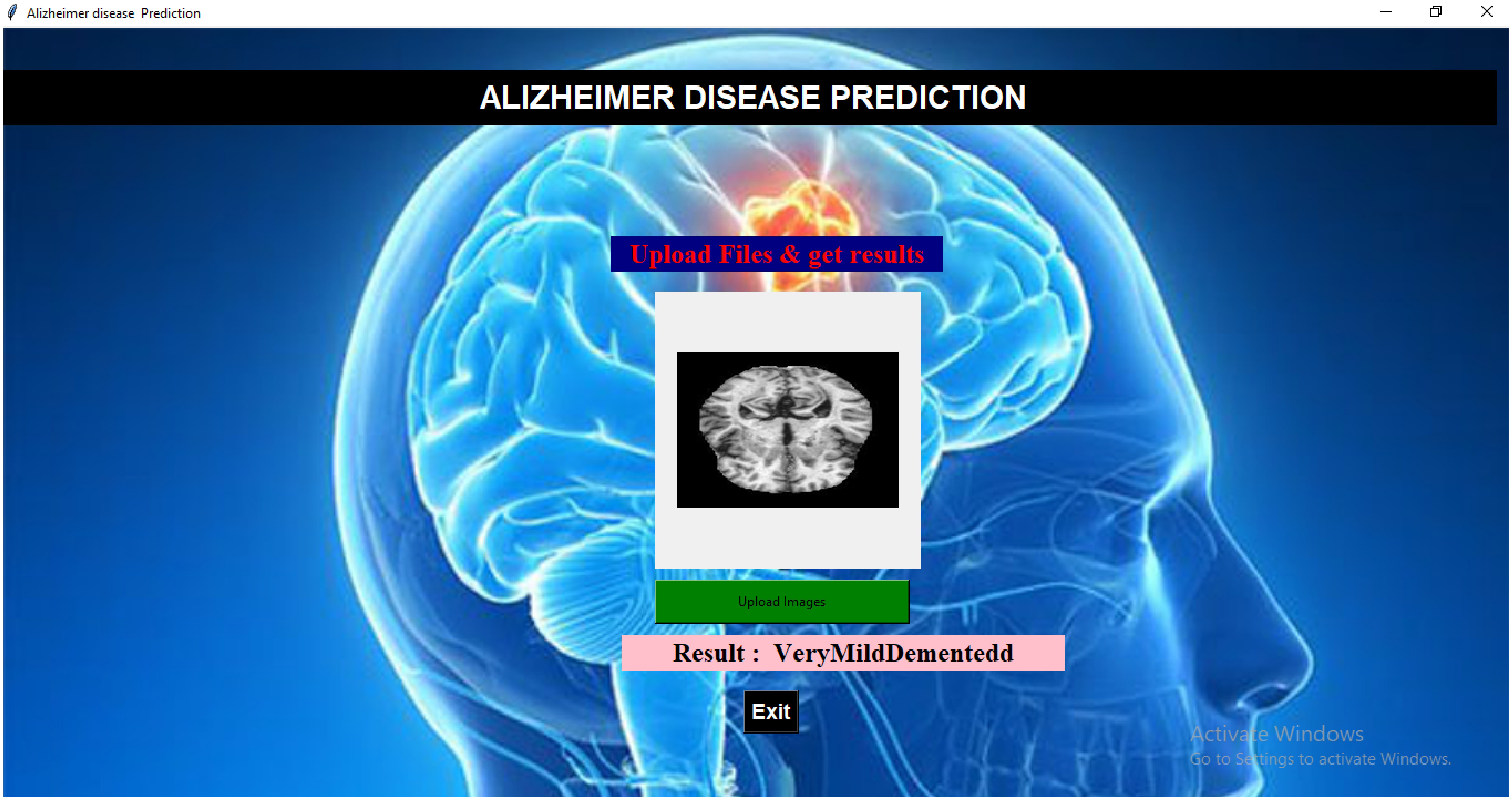
train acc
val acc
0.9
0.8
0.7
0.6
0.5
0.4
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

Output:


Alizheimer disease Prediction
ALIZHEIMER DISEASE PREDICTION
Upload Files & get results
Upload Images
Result : MildDemented
Exit


Alizheimer disease Prediction
ALIZHEIMER DISEASE PREDICTION
Upload Files & get results
Upload Images
Result : ModerateDemented
Exit
Activate Windows
Go to Settings to activate Windows.


Alizheimer disease Prediction
ALIZHEIMER DISEASE PREDICTION
Upload Files & get results
Upload Images
Result : NonDemented
Exit
Activate Windows
Go to Settings to activate Windows.


Alizheimer disease Prediction
ALIZHEIMER DISEASE PREDICTION
Upload Files & get results
Upload Images
Result : VeryMildDementedd
Exit
Activate Windows
Go to Settings to activate Windows.

Conclusion :

- In this paper we proposed a simple and robust classification approach of MRI scans for Alzheimer's disease diagnosis. The approach is based on visual content description of anatomical structure of a brain region involved in AD (hippocampal area). We proposed a late fusion of classification results on two biomarkers: hippocampus and CSF.

- The experiments showed that combining hippocampus features and CSF amount classification gave better accuracy especially when discriminating between AD and MCI than when using either visual features or CSF volume separately for discriminating between AD and MCI than using either visual features extraction or CSF volume computation separately.

- We also demonstrated that the proposed method provides better classification accuracy compared to other volumetric methods. In the perspective of this work we plan to use multiple ROIs, but also multiple MRI modalities in the established classification framework.

Future Work:

- Far greater expert optimism exists about breakthroughs in AD in the next 20 years than in the prior 20 years. In our assessment, 10 breakthroughs were judged as being at least 70% likely to occur by 2037, whereas in our 2001 study no breakthrough was judged as being even 50% likely by 2021.
- This optimism is reflected in the clinical pipeline for novel therapies, with a wide range of possibly disease-modifying biologics and small molecules now in Phase II and III clinical trials.
- However, challenges remain in delivering the predicted new AD therapies to patients, ranging from the use of appropriate cognitive screening tools to the preparedness of national healthcare systems to diagnose and treat large numbers of potentially eligible patients.

Thank You!