A Project Report

On

Alzheimer’s Disease Detection
USING DEPP LEARNING APPROACH

SUBMITTED IN PARTIAL FULFILLMENT

OF THE REQUIREMENTS

FOR B.TECH PROJECT

By

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Under The Supervision Of

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY, PATNA (JUNE 2023)

Certificate

NATIONAL INSTITUTE OF TECHNOLOGY PATNA
Department of Computer Science and Engineering

This is to certify that Mr. Ahmar Hasan Arish (Roll No. 2006110), Mr. Ankit Kumar (Roll no. 2006115) and Vishal Anand (Roll No. 2006181) are registered candidates for B.Tech program under department of **Computer Science and Engineering** of **National Institute of Technology Patna**.

I hereby certify that they have completed all other requirements for submission of the minor project and recommend for the acceptance of a minor project entitled, "**Alzheimer's Disease Detection Using Deep Learning**" in the partial fulfillment of the requirements for the award of B.Tech degree.

Dr. Krishan Kumar Sethi

Project Supervisor

Professor Department of CSE

Prof. Maheshwari Prasad Singh

Head of Department, CSE

May-2023

Declaration

We, Ahmar Hasan Arish (Roll No. 2006110) Ankit Kumar (Roll no. 2006115) and Vishal Anand (Roll No.2006116) registered candidates for B.Tech Program under department of **Computer Science and Engineering** of **National Institute of Technology Patna**, declare that this is our own original work and does not contain material for which the copyright belongs to a third party and that it has not been presented and will not be present to any other University/ Institute for a similar or any other degree award.

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ABSTRACT

Numerous approaches and practical for detecting Alzheimer's disease have been developed over time. Understanding the scanned images of the human brain is the initial stage in this procedure. This explain the extent to which the brain has been damaged.

To extract usable information from an image, Image Processing employs a number of algorithms. Each algorithm generates output in its own way. As a result, the efficiency of each method differs. A few image segmentation algorithms are employed to segment the photos in order to obtain the needed information, and ground truth is used to validate the results.

The purpose of this project is to develop a deep learning model that can accurately detect Alzheimer's disease from MRI scans of the brain. Three different types of deep learning models were utilized, including convolutional neural networks (CNN), recurrent neural networks (RNN), and Densely Connected Network (DenseNet-121) and Inception models. A dataset containing MRI scans from both healthy individuals and individuals diagnosed with Alzheimer's disease was used to train and validate the models. The models were evaluated based on their accuracy, precision, recall, and F1-score. Results show that the Inception model outperformed the other models, achieving an accuracy of 92.27% while the traditional CNN model achieved a respectable frequency of 75.02%. These findings demonstrate the potential of deep learning models in accurately diagnosing Alzheimer's disease from MRI scans and can help in early diagnosis of disease.

1. Introduction

Alzheimer's disease is a brain disorder that affects people of all ages. At first, the symptoms are modest, but as time passes, they get more severe. It was named after Dr. Alois Alzheimer, who described the illness for the first time in 1906 Trusted Source. Alzheimer's disease is a mild and progressive condition, meaning that the symptoms get severe over time. Memory loss is a flagship, and this will be one of the first symptoms to hit. The symptoms appear gradually, over months or years. If they being developed over long period, a person may require medical attention. One of the most affected part due to this Alzheimer's is Corpus Callosum which is responsible for communication in the brain.

Figure 1.1 An Alzheimer disease infected people

1.1 Statistics:

Alzheimer's disease affects over 5.5 million people in the US aged over 60. Eighty percent of those surveyed are over 75. Alzheimer's disease is expected to effect 60 to 70 percent of the approximately fifty million people globally who already suffered with dementia.

1.2 Symptoms:

1. Causes Anterograde Amnesia
2. Reduces speaking ability
3. Infects the frontal lobe of the brain
4. Causes Mood imbalance
5. Minimize Decision making ability.

1.3 Background:

Human brain consists of a main part called Neuron. Neuron which transfers information to body parts. There are nearly over 80 billion of Neurons in a human brain connect with each other as in picture. The linked part two neurons is called a Synapse, highlighted by circling in the below picture. The Synapse is the location where neurotransmitters such as glutamine are released and transmission of data or information takes place in between the neurons. In addition to neurotransmitters, it also releases a small peptide called beta amyloid.

Normally amyloid beta is cleared away by microglia, the cells of our brain. Due to hypertension release of amyloid beta increase to much of increase and less clearance of amyloid beta, they accumulate each other form sticky aggregate called amyloid plaques. These amyloid plaques block information transfer from one neuron to neuron, which the main reason for Alzheimer's disease. Due to rapid release of amyloid plaques, microglia set off hyper activated and emits chemical that ruin synapse. A necessary neuron called "tau" becomes hyper phosphated twisted themselves in order to form a structure named tangles, which squash the neurons from inside.

Figure 1.2 Neurons

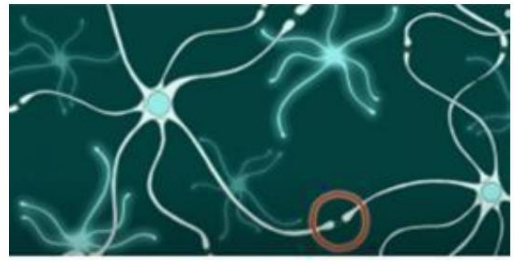

Figure 1.3 Synapse

1.4 Prevention:

At Present, there is no specific drug or medicine for healing AD. In general, the lower levels of acetylcholine in the brain leads to the initiation of AD. Cholinergic drugs are used to prevent AD. All these precautions measured are pertinent theoretically, but no practical way of curing AD.

1.5 Motivation:

With the current technological advancements in the medical sector, it has become possible to track and cure diseases. Even after this, there are certain diseases which are difficult to track and cure, one such disease is Alzheimer's. There are various organizations and research communities worldwide that are working hard to find a permanent cure for AD. This requires a lot of man hours to get a significant result.

1.6 Objective of Work:

This can be possible by Image Processing. The person's brain who are affected by AD are analyzed and, thereby generalizing a pattern in which a person is affected by AD. By observing the structure of the brain, several major differences can be found between a normal brain, Mild cognitive impairment (MCI) brain and AD brain. These differences form a way for the identification of AD at its early stages, which can be done by segmenting the affected part of the brain. It is not possible to cut a person's brain to find whether he has AD or not and can be only done through Image Processing. This helps in early detection of AD, which improves prevention process, since curing may not be possible. It is miserable for anyone to be affected by AD, but it has become one of the most common and unrecognized diseases, using several image processing techniques at least we can extend the time taken for going from MCI to AD.

1.7 Literature Survey:

[1]: This paper uses CNN to predict AD class.
84% accuracy was obtained when CNNs were used to segregate the progressive MCI patients from the stable MCI patients. They developed an algorithm that used MRI scans to evaluate the condition of a particular patient. They used a total of 2,265 cases, and they selected the ADNI dataset for their work.
[2]: They report the comparison with recent state-of-the-art approaches on two established medical data sets (OASIS).They obtained a classification accuracy, sensitivity and specificity of 77% and specificity of 79% when dealing with four classes.

2. Methodology

We have used following models to label a MRI image class as demented or not:

i) CNN
ii) RNN
iii) Inception-v3
iv) DenseNet-121

2.1 Tools Used:

Programming language- python
Image processing and machine learning libraries- keras, tensorflow

2.2 Data Collection:

The ADNI dataset is a collection of data obtained from participants in the Alzheimer's Disease Neuroimaging Initiative (ADNI) study launched in 2004 that aims to improve our understanding of Alzheimer's disease by identifying biomarkers and developing better methods of diagnosis, treatment, and prevention.
Dataset consists of two files - Training and Testing both containing a total of around ~5000 images each segregated into the severity of Alzheimer's classes.

2.3 Data Pre-Processing:

2.3.1 Augmentation:

Performed Image Data Augmentation on given MRI data. It is a technique that creates new images from the existing ones.
To do that we make some small changes to them such as adjusting the brightness of the image, or rotating the image, or shifting the subject in the image horizontally or vertically.
Image augmentation techniques allow us to artificially increase the size of our training set, thereby providing much more data to our model for training. This allows we to improve the accuracy of our model enhancing the ability of our model to recognize new variants of our training data.

2.3.2 Resize:

The input images are resized to 224x224 pixels before being fed into the model. Resizing the images to the fixed size ensures that input data is consistent and allow the model to process the images more efficiently.

2.3.3 Labels are **one-hot encoded.**

2.3.4 Batch Size:

Batch size used is of 32, it indicates that the generator will generate batches of 32 samples each. During training, the model will be updated after each batch of data is fed into the model.

3. Implementation

3.1 Using CNN

In our Alzheimer's disease detection model, we have used a convolutional neural network (CNN) architecture. A CNN is a type of deep learning neural network that is commonly used for image recognition and classification tasks. The key advantage of using CNNs over other traditional neural network architectures is their ability to automatically learn relevant features from images through the use of convolutional layers.
The CNN architecture consists of several layers, including convolutional layers, pooling layers, and fully connected layers. The convolutional layers perform feature extraction from the input images by applying a set of filters to the image. Each filter slides over the entire image, computing the dot product between the filter weights and the pixel values at each location. This process generates a feature map for each filter, highlighting specific features such as edges, corners, and shapes present in the image.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 224, 224, 25)      700

 conv2d_1 (Conv2D)           (None, 224, 224, 75)      16950

 max_pooling2d (MaxPooling2D  (None, 112, 112, 75)     0
 )

 flatten (Flatten)           (None, 940800)            0

 dense (Dense)               (None, 4)                 3763204

 dense_1 (Dense)             (None, 8)                 40

 dense_2 (Dense)             (None, 16)                144

 dense_3 (Dense)             (None, 4)                 68

=================================================================
Total params: 3,781,106
Trainable params: 3,781,106
Non-trainable params: 0
```

Figure 3.1 CNN model summary

The pooling layers reduce the size of the feature maps generated by the convolutional layers by performing a max or average operation over a small window. This reduces the number of parameters in the network and helps prevent overfitting.

The fully connected layers perform classification by taking the flattened output from the previous layer and mapping it to the output classes. The weights in these layers are learned through the process of backpropagation during training.

In our Alzheimer's disease detection model, we have used **dropout layers** to prevent overfitting and improve the generalization performance of the model. By randomly dropping out neurons in the fully connected layers, the model is forced to learn more robust features and prevent it from overfitting to the training data.

We have used multiple convolutional and pooling layers to learn complex features from the MRI scans of the brain. The outputs from these layers were then passed through fully connected layers for classification.

Thus, CNNs are a powerful tool for image classification and have been shown to be effective for diagnosing Alzheimer's disease from MRI scans of the brain.

3.2 Using RNN

In addition to the convolutional neural network (CNN) architecture, you have also used a recurrent neural network (RNN) in your Alzheimer's disease detection model. RNNs are a type of neural network that are commonly used for sequence modeling tasks such as speech recognition, language translation, and text generation.

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 reshape (Reshape)           (None, 224, 672)          0

 simple_rnn (SimpleRNN)      (None, 64)                47168

 dense (Dense)               (None, 4)                 260

 dense_1 (Dense)             (None, 8)                 40

 dense_2 (Dense)             (None, 16)                144

 dense_3 (Dense)             (None, 4)                 68

=================================================================
Total params: 47,680
Trainable params: 47,680
Non-trainable params: 0
```

Figure 3.2 RNN model summary

Unlike traditional feedforward neural networks, RNNs have loops in their architecture that allow them to process sequences of inputs one element at a time, while maintaining an internal state that captures information about the sequence seen so far. This makes RNNs well-suited for modeling sequences of variable length, such as time-series data, audio signals, and text.
The key component of the RNN architecture is the recurrent layer, which maintains a hidden state that is updated at each time step based on the current input and the previous hidden state. The hidden state serves as a memory that allows the network to capture information about the sequence seen so far and make predictions based on that information.
In our Alzheimer's disease detection model, we have used an RNN architecture with one or more recurrent layers to model the temporal dependencies present in the MRI scans of the brain. By processing the MRI scans as a sequence of images, the RNN can capture temporal changes and patterns that may be indicative of Alzheimer's disease.

3.3 Using DenseNet-121

DenseNet-121 is a type of deep convolutional neural network (CNN) that has several advantages over traditional CNNs and recurrent neural networks (RNNs).
The key feature of DenseNet-121 is its use of dense blocks, which are made up of multiple layers that are connected to all subsequent layers in the block. This allows each layer to have access to the feature maps generated by all previous layers in the block, leading to more efficient use of parameters and improved feature propagation through the network.
The DenseNet-121 architecture consists of several blocks of dense layers, followed by transition layers that reduce the spatial dimensions of the feature maps. The dense layers use a combination of convolutional, batch normalization, and activation functions to learn complex features from the input images. The transition layers use pooling or convolution operations to reduce the spatial dimensions of the feature maps, while preserving the depth of the feature maps.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
densenet121 (Functional)	(None, 7, 7, 1024)	7037504
dropout (Dropout)	(None, 7, 7, 1024)	0
flatten (Flatten)	(None, 50176)	0
batch_normalization (BatchNormalization)	(None, 50176)	200704
dense (Dense)	(None, 64)	3211328
batch_normalization_1 (BatchNormalization)	(None, 64)	256
activation (Activation)	(None, 64)	0
dropout_1 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 64)	4160
batch_normalization_2 (BatchNormalization)	(None, 64)	256
activation_1 (Activation)	(None, 64)	0
dropout_2 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 64)	4160
batch_normalization_3 (BatchNormalization)	(None, 64)	256
activation_2 (Activation)	(None, 64)	0
dropout_3 (Dropout)	(None, 64)	0
dense_3 (Dense)	(None, 32)	2080
batch_normalization_4 (BatchNormalization)	(None, 32)	128
activation_3 (Activation)	(None, 32)	0
dropout_4 (Dropout)	(None, 32)	0
dense_4 (Dense)	(None, 32)	1056
batch_normalization_5 (BatchNormalization)	(None, 32)	128
activation_4 (Activation)	(None, 32)	0
dense_5 (Dense)	(None, 4)	132

Figure 3.3: Summary of DenseNet Model

3.4 Using Inception-v3

In traditional CNNs, each convolutional layer typically has a fixed filter size, which limits the scale of the features that can be captured by that layer. In Inception-v3, each inception module consists of several parallel convolutional layers with different filter sizes, allowing the network to capture features at multiple scales and resolutions.

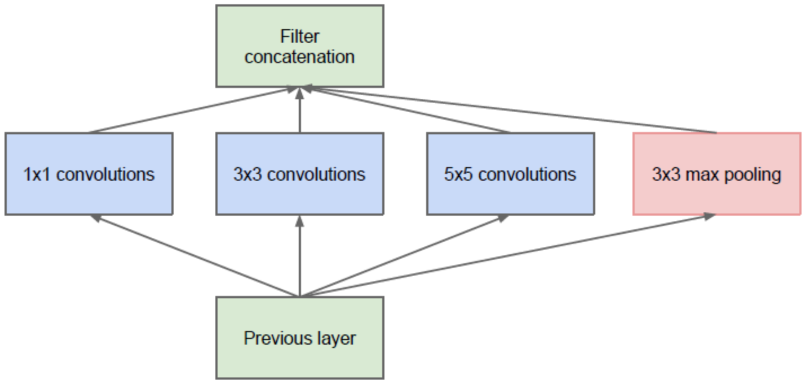

Figure 3.4 Inception V3 architecture

One of the key benefits of Inception-v3 is its ability to capture features at multiple scales and resolutions, which can lead to improved accuracy and reduced overfitting compared to other neural network architectures. Inception-v3 has been shown to be effective for image classification tasks, and has also been applied successfully to medical imaging tasks such as diagnosing Alzheimer's disease from MRI scans of the brain.

inception_v3 (Functional)	(None, 4, 4, 2048)	21802784
dropout (Dropout)	(None, 4, 4, 2048)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
flatten (Flatten)	(None, 2048)	0
batch_normalization_94 (BatchNormalization)	(None, 2048)	8192
dense (Dense)	(None, 512)	1049088
batch_normalization_95 (BatchNormalization)	(None, 512)	2048
dropout_1 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131328
batch_normalization_96 (BatchNormalization)	(None, 256)	1024
dropout_2 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 128)	32896
batch_normalization_97 (BatchNormalization)	(None, 128)	512
dropout_3 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 64)	8256
dropout_4 (Dropout)	(None, 64)	0
batch_normalization_98 (BatchNormalization)	(None, 64)	256
dense_4 (Dense)	(None, 4)	260

Figure 3.5 Inception Model Summary

4. RESULTS AND ANALYSIS

The results of the Alzheimer's disease prediction implemented using different models show varying levels of accuracy. The CNN model achieved an accuracy of 75.02% along with relatively lower F1 Score, Precision, and Recall values. In comparison, the Inception-v3 model demonstrated significantly higher accuracy of 92.27% with improved F1 Score, Precision, and Recall. The superior performance of Inception-v3 can be attributed to its deeper architecture and better feature extraction capabilities. Similarly, the DenseNet-121 model achieved a relatively higher accuracy of 76.83% but still fell short of Inception-v3. The variations in accuracy between these models could be due to differences in network architectures and feature extraction methods employed. On the other hand, the RNN model also achieved an accuracy of 75.02%, but it exhibited lower F1 Score, Precision, and Recall. This can be attributed to the inherent limitations of RNN in capturing long-term dependencies in the data, resulting in reduced performance in this particular task.

Models	**Accuracy(%)**	**F1Score(%)**	**Precision(%)**	**Recall(%)**
CNN	75.02	50.03	50.03	50.03
Inception-v3	92.27	85.38	86.29	84.50
DenseNet-121	76.83	53.79	52.07	52.90
RNN	75.02	36.59	50.06	29.24

Our observation has shown that accuracy can be improved by using Inception-v3 model and by using DenseNet-121 as compared to typical CNN and SVM. Introducing regularization technique has also worked in improving the accuracy of the model. Out of them all , Inception-v3 model has best performed with accuracy of 92.27%.

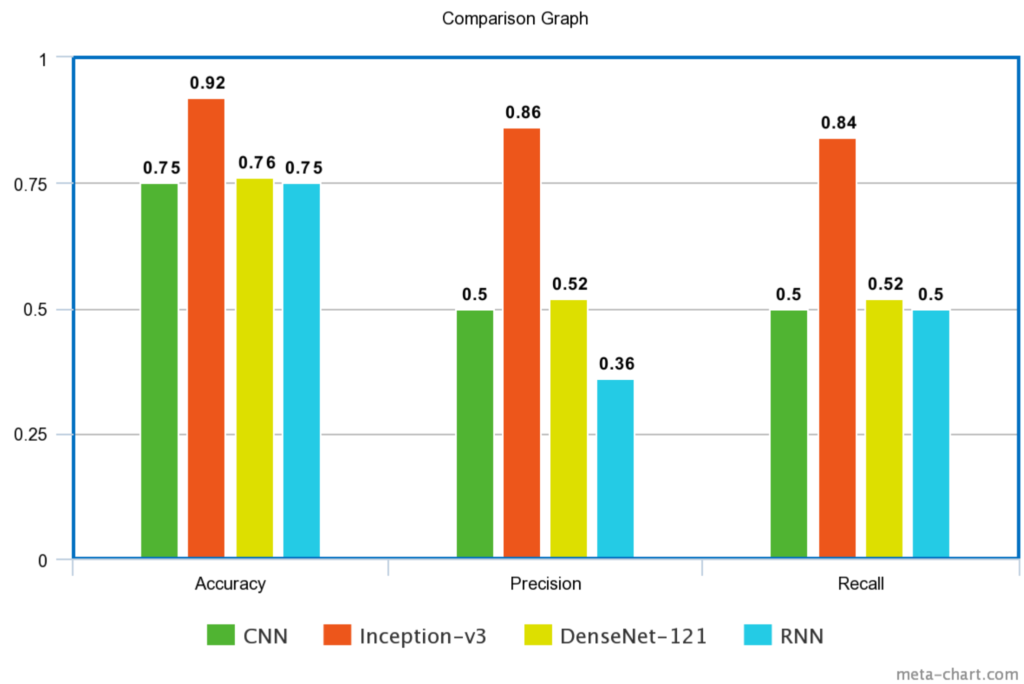

Figure 4.1 Graph Comparison of various models

SVMs are particularly useful when the number of features is relatively small compared to the number of samples and when the classes are well-separated.

RNN works well on sequential data where input data is a sequence.

5. Deployment and Testing

We deployed the model and created a simple yet beautiful front-end where one can upload the MRI-Scan of the Brain and test to get the corresponding class category of the image. We used **Streamlit to** build the user-interface.

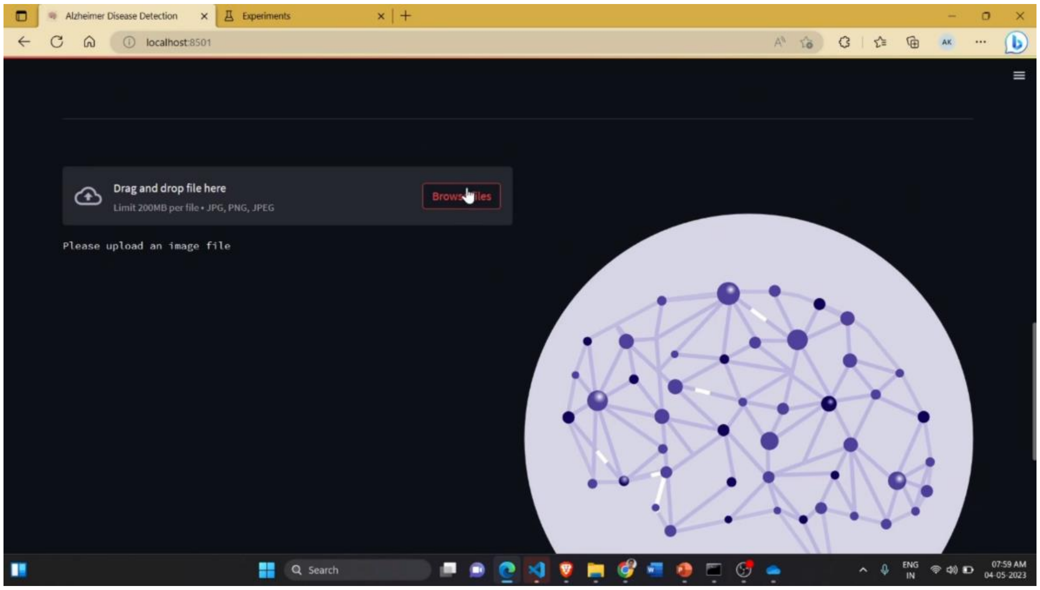

Fig. 4.2: Interface for the model

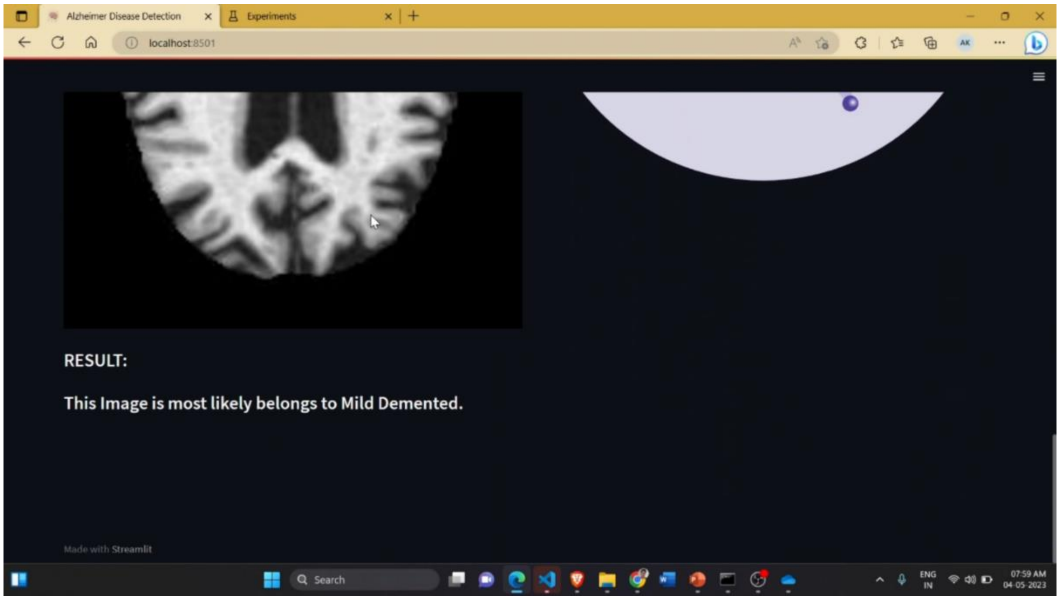

Fig.4.3: Result after the upload

6. CONCLUSION AND FUTURE SCOPE

A higher batch size can improve the accuracy, But due to the limitations of the machine and processing power the batch size could not be improved further.

In research paper "Towards Alzheimer's Disease Classification through Transfer Learning by Marcia Hon and Naimul Mefraz Khan, Ryerson University ,Toronto, ON" the batch size of 40 and 100 epochs was found to optimal for achieving accuracy of 96% on testing dataset. Increasing the dataset will only make this model better.

A 3-D CNN is observed to perform better in case of MRI images classification.
In 3-D CNN slices of image that contain more information are extracted and then passed to the convolutional network.
This extraction is performed using auto-encoders and image entropy function.

The U.S. National Institute on Aging (NIA) is funding a 6-year, up to **$300 million** project to build a massive Alzheimer's research database that can track the health of Americans for decades and enable researchers to gain new insights on the brain-wasting disease.[4]

7. References

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