Early Alzheimer Disease Detection and Classification based on CNN

A report submitted in partial fulfillment of the requirements for Mini Project (ITIT-3203)

Integrated Masters of Technology
in
Information Technology

by

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CANDIDATES DECLARATION

We hereby certify that the work, which is being presented in the report, entitled **ALZHEIMER DISEASE DETECTION USING CONVOLUTION NEURAL NETWORK**, in partial fulfillment of the requirement for mini project (ITIT-3203) for **Integrated Masters of Technology in Information Technology** and submitted to the institution is an authentic record of our own work carried out during the period *January 2024* to *April 2024* under the supervision of **Dr. Sunil Kumar**. We also cited the reference about the text(s)/figure(s)/table(s) from where they have been taken.

Date: Signature of the Candidate

This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Date: Signature of the Supervisor(s)

ABSTRACT

Alzheimer's disease (AD), an irreparable brain disease, impairs thinking and memory while the aggregate mind size shrinks which at last prompts demise. Alzheimer's is a neurodegenerative disease and leads to severe memory loss and inability to cope with daily life tasks. Early diagnosis of AD is essential for the progress of more prevailing treatments. Detecting Alzheimer's is a difficult and time consuming task, but requires brain imaging report and human expertise. Needless to say, this conventional approach to detect Alzheimer's is costly and often error prone. In this project an alternative approach has been discussed, that is fast, costs less and more reliable. Artificial intelligence systems can help in providing better health care and medical solutions. The performance of human diagnosis degrades due to fatigue, cognitive biases, systems faults, and distractions. However, artificial intelligence based diagnosis systems are less error prone and give safe support to clinicians in detection and decision making. This work presents a smart and reliable way of diagnosing Alzheimer's disease (AD) and its possible early stage i.e., mild cognitive impairment. The presented framework is based on deep learning and detects Alzheimer's and its initial stages accurately from structural MRI scans. Identifying mild cognitive impairment (MCI) subjects who will progress to Alzheimer's disease is not only crucial in clinical practice, but also has a significant potential to enrich clinical trials. This project proposes to combine MRI data with a neuropsychological test, Mini-Mental State Examination (MMSE), as input to a multi-dimensional space for the classification of Alzheimer's Disease (AD) and it's prodromal stages.

Keywords: Artificial Intelligence, Alzheimer's disease (AD), Machine learning, Accuracy, Classifier models

ACKNOWLEDGEMENTS

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Chapter 1

INTRODUCTION

Alzheimer's disease (AD) is a neurological illness that progresses over time and is characterized by memory loss and cognitive impairment. It is a major global health concern. Effective intervention in a population that is aging requires an early and accurate diagnosis.

In recent times, there have been encouraging advances in understanding and treating Alzheimer's disease (AD) thanks to the combination of medical research with machine learning (ML), namely using Convolutional Neural Networks (CNNs). Our initiative focuses on improving diagnostic accuracy through the application of machine learning techniques, particularly CNNs, which should improve patient outcomes and clinical decision-making.

An overview of AD is given in this chapter, with special attention to its clinical manifestations, underlying pathology, and diagnostic difficulties. Our examination of machine learning's application in medical research highlights the technology's capacity to decipher intricate data sets and facilitate the early identification of illnesses. Furthermore, we go over the significance of preprocessing and data preparation in ML-based methods, highlighting the requirement for high-quality datasets to train reliable models. By utilizing knowledge from both our research and the literature already in existence, we tackle the dynamic field of AD prediction and machine learning, with a strong emphasis on creative problem-solving and cross-disciplinary cooperation.

By combining conventional diagnostic approaches with state-of-the-art computational techniques, our project seeks to expand research on Alzheimer's disease and ultimately produce more effective early detection and intervention solutions.

1.1 MOTIVATION

Under the current conditions, human instinct and standard measurements do not often coincide. In order to solve this problem, we need to leverage innovative approaches such as machine learning, which are computationally intensive and non-traditional. Machine learning techniques are increasingly being used in disease prediction and visualization to offer prescient and customized prescriptions. In addition to improving patients' quality of life, this drift aids physicians in making treatment decisions and health economists in [?] making their analyses.[4] Viewing medical reports may lead radiologists to miss other disease conditions. As a result, it only considers a few causes and conditions. The goal here is to identify the knowledge gaps and potential opportunities associated with ML frameworks and EHR derived data.

1.2 OBJECTIVES

Develop and evaluate a CNN-based model for Alzheimer's detection using brain MRI images, assessing its performance in accuracy, sensitivity, and specificity, and comparing results with state-of-the-art methods.

1.3 LITERATURE SURVEY

1.3.1 ALZHEIMER'S DISEASE - AN OVERVIEW

Alzheimer's disease is a progressive neurodegenerative disorder that primarily affects memory, cognitive abilities, and behavior. It is the most common cause of dementia among older adults. The disease is characterized by the abnormal accumulation of two proteins in the brain: beta-amyloid plaques and tau protein tangles. These deposits lead to the degeneration and eventual death of nerve cells, causing a gradual decline in cognitive function.

In recent years, machine learning (ML) techniques, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools for automated AD detection using various types of data, including neuroimaging, genetic, and clinical data. Here's a comprehensive literature survey on the topic:

1. **Neuroimaging-Based AD Detection:** Neuroimaging methods, including positron emission tomography (PET) and structural magnetic resonance imaging (MRI), offer important insights into changes in brain morphology and function linked to AD disease. CNN-based methods get great accuracy in differentiating AD patients from healthy controls by extracting relevant characteristics from neuroimaging data.

2. **Genetic and Biomarker-Oriented Methods:** AD risk and pathology are linked to both genetic and biochemical indicators, such as the apolipoprotein E (APOE) genotype and the amounts of tau and amyloid-beta proteins in cerebrospinal fluid

(CSF). In order to create prediction models for early identification and risk assessment of AD, machine learning algorithms, such as CNNs, incorporate genetic and biomarker data.

3. **Clinical Data Integration:** Clinical Data Integration: Clinical characteristics are critical to the diagnosis and prognosis of AD. Examples of these aspects include demographic data, medical history, and results of cognitive tests. CNN-based models combine genetic and neuroimaging data with multimodal clinical data to improve the precision and dependability of AD identification.

4. **CNN Structures for Identifying AD:** For AD detection tasks, a number of CNN designs have been proposed, including 2D and 3D CNNs, recurrent neural networks (RNNs), and attention mechanisms. By including sophisticated variables like temporal and spatial correlations in neuroimaging data, these structures increase the ability of AD classifiers to discriminate.

5. **Validation and Performance Assessment:** Extensive validation methods, including as holdout validation, cross-validation, and external validation on separate datasets, are used in studies assessing CNN-based AD detection models. The diagnostic effectiveness of machine learning (ML) models is evaluated using performance measures, including area under the receiver operating characteristic curve (AUC-ROC), sensitivity, specificity, and accuracy.

6. **Obstacles and Prospective Paths:** Notwithstanding the noteworthy advancements in CNN-based AD detection, several obstacles persist, such as heterogeneity in data, interpretability of machine learning models, and applicability to a wide range of demographics. The creation of explainable AI methods, the integration of multimodal data sources, and long-term studies to monitor the course of illness and the efficacy of treatment are potential future research paths.

1.3.2 DETECTING ALZHEIMER'S DISEASE STAGES USING CNN AND MRI IMAGES

Convolutional Neural Networks (CNN) are a type of deep learning model particularly well-suited for image recognition and analysis tasks. They have been widely used in medical image analysis, including the detection and classification of diseases like Alzheimer's.

Thus a membership function $\mu_A(x)$ is associated with a fuzzy set $\tilde{A}$ such that the function maps every element of universe of disclosure X to interval [0,1].

Mathematically, mapping is written as:

$$\mu_{\tilde{A}}(x) : X \rightarrow [0,1] \tag{1.1}$$

1.4 METHODOLGY

The methodology involves collecting a diverse dataset of brain MRI scans with AD-positive and healthy samples. Data preprocessing ensures uniformity and quality. The dataset is split into training, validation, and test sets.[3] A CNN architecture is designed and trained using an optimizer and loss function. Model performance is evaluated on the validation set, and hyperparameter tuning is conducted. The final CNN model is evaluated on the test set for real-world performance. Ethical considerations and interpretability techniques are addressed, with a focus on potential research avenues for improved early AD detection.

1.4.1 DATA COLLECTION AND PREPROCESSING

1. Obtain a diverse and representative dataset of brain MRI scans, containing both AD-positive and healthy samples.

2. Ensure data quality by verifying proper labeling, resolution, and consistency across the dataset.

3. Normalize the MRI images to a consistent scale to ensure uniformity in pixel values

4. Perform skull stripping to remove non-brain tissues, reducing noise and irrelevant information.

1.4.2 Data Labeling and Splitting:

1. Divide the dataset into training, validation, and test sets in an appropriate ratio (e.g.,70-15-15) for model training, tuning, and evaluation.

1.4.3 CNN Model Architecture Design:

1. Design a CNN architecture suitable for Alzheimer's Disease detection.

2. Stack multiple convolutional layers to capture spatial features effectively

3. Use pooling layers for spatial downsampling to reduce computational load and prevent overfitting.

4. Introduce dropout layers to prevent overfitting by randomly deactivating neurons during training. Implement fully connected layers for classification.

1.4.4 Model Training

1. Gather a dataset of brain MRI[?] scans from individuals at different stages of Alzheimer's disease (e.g., normal, mild cognitive impairment (MCI), early-stage Alzheimer's, middle-stage Alzheimer's, and late-stage Alzheimer's).

2. Preprocess the MRI images to ensure uniformity in size, orientation, and resolution. Common preprocessing steps include normalization and image enhancement.

1.4.5 Model Evaluation and Testing:

1. Initialize the CNN model with appropriate weights and biases. Use a suitable optimizer (e.g., Adam, RMSprop) to minimize the chosen loss function (e.g., binary crossentropy) during backpropagation. Train the model on the training set for multiple epochs, fine-tuning hyperparameters as needed. base.

1.4.6 Alzheimer's Stage Detection:

The methodology for Alzheimer's stage detection using CNN involves several key steps. Firstly, a comprehensive dataset of brain MRI scans is collected, featuring individuals at different stages of Alzheimer's Disease, including mild cognitive impairment (MCI), early AD, and advanced AD stages. The dataset is carefully preprocessed, ensuring consistent quality and format across images. Normalization standardizes pixel intensities, while skull stripping removes non-brain tissues and minimizes noise interference. The dataset is then split into training, validation, and test sets, ensuring a balanced distribution of disease stages in each subset. A CNN architecture is designed, incorporating convolutional layers for spatial feature extraction, pooling layers for downsampling, and fully connected layers for disease stage predictions. The model is trained using an appropriate optimizer and loss function, with hyperparameter tuning to optimize performance. Performance evaluation on the validation set refines the model, and the final CNN is assessed on the independent test set for unbiased performance estimation. Interpretability techniques, such as Grad-CAM, aid in understanding the model's decisions. Ethical considerations regarding patient data privacy are addressed, and potential research avenues are explored to enhance Alzheimer's stage detection, contributing to improved diagnosis and treatment strategies for patients.

Chapter 2

DESIGN DETAILS AND IMPLEMENTATION

In this section, we outline the design details and implementation steps of the CNN-based Alzheimer's Disease stage detection system. We describe the CNN architecture, data preprocessing techniques, model training setup, and evaluation metrics used for assessing performance. The implementation is carried out using Python, leveraging popular deep learning libraries such as TensorFlow and Keras. The details provided here will offer a comprehensive understanding of the system's structure and how it addresses the challenges of Alzheimer's Disease stage detection effectively.

2.1 DATA COLLECTION

The code starts by collecting data from the Kaggle Alzheimer's Dataset, which consists of four classes of images representing different stages of dementia. The dataset is split into training and testing sets.

2.2 DATA PREPROCESSING

The images are preprocessed to ensure uniformity and prepare them for training the machine learning model. The following steps are applied to each image in the dataset:

2.2.1 IMAGE RESIZING

Each image is resized to a square with a side length of 150 pixels. This step is necessary to standardize the image dimensions and reduce computational complexity.

2.2.2 IMAGE-TO-ARRAY CONVERSION

After collecting the image arrays, they are converted into a numpy array format using np.array. This creates a multi-dimensional array where each row corresponds to an image, and the columns represent the pixel values.

2.2.3 LABEL GENERATION

When loading and processing images, we map each image to its corresponding class name. Then, converted these class names into the assigned numerical labels.

2.2.4 DATA SPLITTING

The dataset is divided into training and testing sets using the train_test_split function from scikit-learn. 90% of the data is used for training (X_train, y_train), and the remaining 10% is reserved for testing (X_test, y_test). The random_state parameter is set to 101 to ensure reproducibility.

2.2.5 DATA SHUFFLING

Before the data splitting, the X_train and Y_train arrays are shuffled using the shuffle function from scikit-learn. Shuffling helps prevent any bias that might arise from the original order of the data.

2.3 SUMMARY OF DATASET:

Total number of images: 6400
Image size: 128x128 pixels (each image is square)
Number of classes:(MildDemented, ModerateDemented, NonDemented, and VeryMildDemented)
Class distribution: The distribution of images among different classes in both the training and testing sets.
The preprocessed data (X_train, X_test, y_train, y_test) is now ready for use in training and evaluating a machine learning model to predict the stages of dementia based on brain images. This data can be utilized with various machine learning algorithms, such as convolutional neural networks (CNNs), to create a predictive model for Alzheimer's disease stages.

2.4 IMPLEMENTATION/EXECUTION OF PROJECT

After studying the network model we have identified the different parameters which affects our considered end to end delay output. [5]Now the work is to use fuzzy system over these parameters. The implementation of the project is discussed stepwise in below sections.

2.4.1 TRAINING SET LABEL ENCODING

The original y_train array has categorical stage labels. We create y_train_new to hold encoded numerical labels. For each label in y_train, we find its index in the labels list. This index becomes the numerical encoding. y_train_new now stores these numerical representations. Then, y_train is reassigned to its one-hot encoded version using Keras. This format represents each stage label as a binary vector, suitable for neural network training.[6]

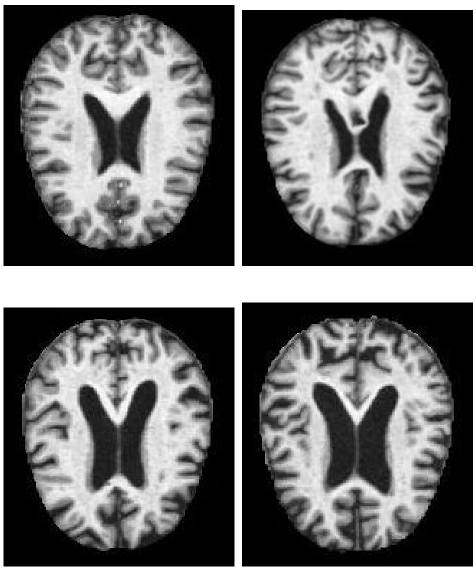


Figure 2.1: MRI scan images[1] from non-dimented, very mild, mild and moderate dimented respectively

2.4.2 TESTING SET LABEL ENCODING

The testing set labels (y_test) go through the same process. y_test_new stores encoded numerical labels by finding each label's index in the labels list. Afterward, y_test is reassigned to its one-hot encoded version using tf.keras.utils.to_categorical. Both training and testing sets are now represented as numerical one-hot encoded arrays, ideal for training and evaluating neural network models, especially for multi-class classification tasks. The presented model is a sequential-based neural network designed for

Alzheimer's disease stage prediction using brain images. Below is a summary of the key components of the model and the evaluation results:

2.4.3 MODEL ARCHITECTURE

1. The model consists of several layers:
   - Input layer rescales the pixel values of input images to a range of [0, 1].
   - Three sets of Convolutional (Conv2D) and MaxPooling layers, which learn features from the input images.
   - A Flatten layer to convert the 2D feature maps into a 1D vector.
   - Two Dense (fully connected) layers, with ReLU activation functions, to perform classification.
2. The model also includes data augmentation and dropout layers to improve generalization and reduce overfitting.
3. The final layer is a Dense layer with the number of units equal to the number of classes, which outputs logits to output probabilities for the 4 dementia stages.

Table 2.1: A Summary of our proposed CNN model

Model architecture layers		
	OutputShape	Param
rescaling$_2$($Rescaling$)	(None, 180, 180, 3)	0
conv2d$_3$($Conv2D$)	(None, 180, 180, 16)	448
max$_p ooling2d_3(MaxPooling2D)$	(None, 90, 90, 16)	0
conv2d$_4$($Conv2D$)	(None, 90, 90, 32)	4640
max$_p ooling2d_4(MaxPooling2D)$	(None, 45, 45, 32)	0
conv2d$_5$($Conv2D$)	(None, 45, 45, 64)	18496
max$_p ooling2d_5(MaxPooling2D)$	(None, 22, 22, 64)	0
dropout (Dropout)	(None, 22, 22, 64)	0
flatten$_1$($Flatten$)	(None, 30976)	0
dense$_2$($Dense$)	(None, 128)	3965056
dense$_3$($Dense$)	(None, 4)	516

2.4.4 DATA AUGMENTATION

Data augmentation is applied using the ImageDataGenerator from Keras to artificially increase the diversity of training samples. Augmentation techniques include rotation, width and height shifts, shearing, zooming, and horizontal flipping. Data augmentation is useful for training deep learning models when the dataset is limited, as it can prevent overfitting and improve model performance.

2.4.5 MODEL TRAINING

1. The model is trained using the Adam optimizer with a Sparse Categorical Crossentropy loss function.

2. Training is performed over multiple epochs, with the specified training and validation datasets.

3. The training loop records training and validation accuracy and loss metrics for visualization.

4. Data augmentation is applied to the training dataset to increase the diversity of training samples and improve the model's robustness.

5. Dropout regularization is employed to prevent overfitting by randomly dropping a fraction of the units during training.

2.4.6 MODEL EVALUTION AND TESTING

1. **Evalution :**

   - After training, the model's performance is evaluated using the validation dataset.
   - The training and validation accuracy and loss curves are plotted to assess the model's performance and identify overfitting.
   - Additionally, a confusion matrix is computed using the model's predictions on the validation dataset to evaluate its performance on each class.

2. **Testing :**

   - For testing, an image is imported, preprocessed, and fed into the trained model for prediction.
   - The predicted class label is obtained by selecting the class with the highest probability from the model's output.
   - The input image and predicted class label are displayed for visual inspection.

First time the model is trained for 10 epochs without data augmentation and adding dropout layer with a batch size of 32. The training and validation accuracy and loss are reported after each epoch.

Doing data augmentation and adding a Dropout layer before running the model training for the **second time**, it introduces a regularization technique aimed at reducing overfitting. Overfitting occurs when a model learns to memorize the training data

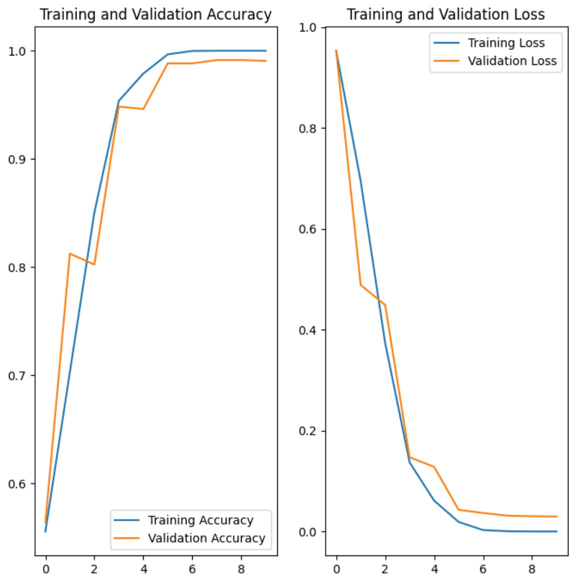


Figure 2.2: Before data augmentation and dropout layer

instead of generalizing well to unseen data.The Dropout layer randomly sets a fraction of input units to zero during training, which helps prevent overfitting by reducing the interdependence of neurons. The training and validation accuracy and loss are reported after each epoch.

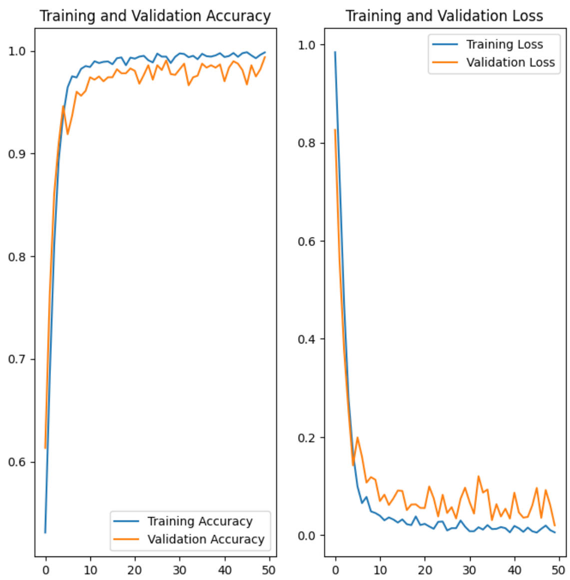


Figure 2.3: After data augmentation and dropout layer

The model's accuracy on the training dataset gradually improves as it learns from the data. However, it's essential to monitor the validation accuracy simultaneously. Validation accuracy measures the model's performance on a separate dataset (not used for training) and ensures that the model generalizes well to unseen data.

Chapter 3

RESULTS AND DISCUSSION

3.1 RESULTS

After training deep learning architectures for Alzheimer's disease stage prediction using MRI images, the individual accuracies achieved are as follows:

1. **Before data augmentation and dropout layer**
    - Accuracy : 98% accuracy
2. **After data augmentation and dropout layer**
    - Accuracy : 99% accuracy

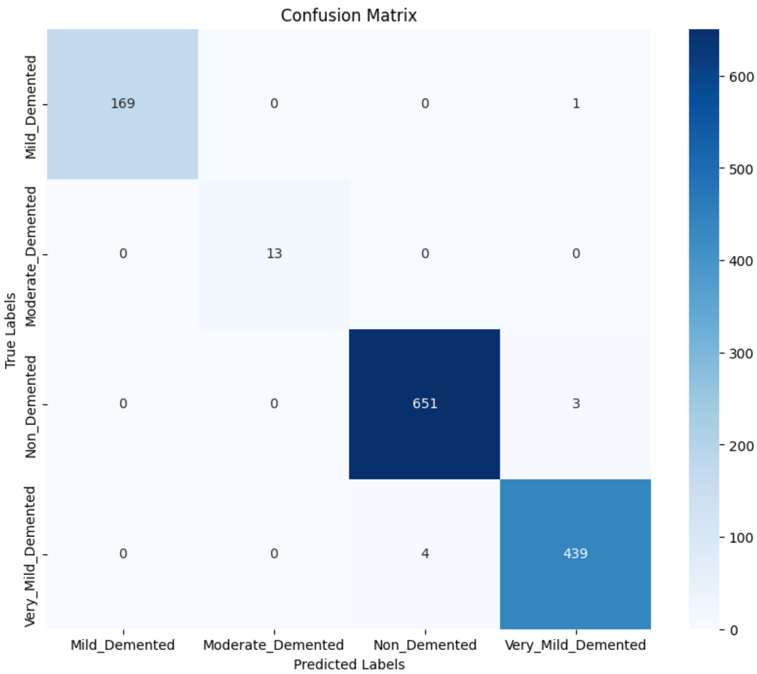


Figure 3.1

Table 3.1: Confusion Matrix For Architecture

Classification Report				
	Precision	Recall	f1-Score	Support
MildDemented	1.00	1.00	1.00	2
ModerateDemented	1.00	0.99	0.99	443
NonDemented	0.0	NaN	NaN	0
VeryMildDemented	1.00	0.01	0.99	654
Accuracy			0.99	640

3.2 COMPARISON OF TRAINING AND VALIDATION PERFORMANCE

1. **Before data augmentation and dropout layer**

   - **Accuracy:** The model achieves an accuracy of around 98.54% on the training data and 98.34% on the validation data after 10 epochs.

   - **Loss:** Both training and validation loss decrease steadily over epochs, indicating good convergence.

2. **After data augmentation and dropout layer**

   - **Accuracy:** The model achieves an accuracy of around 99.84% on the training data and 99.37% on the validation data after 50 epochs.

   - **Loss:** Both training and validation loss decrease steadily over epochs, indicating good convergence.

3.3 ACCURACY COMPARISON WITH OTHER MODELS

Table 3.2: Comparison with other models for accracy

Accuracy Report	
	Accuracy
Proposed Model	99%
Base Paper Model	97.75%
InceptionV3	90.62%
Xception	84.37%
MobileNetV2	81.24%

Chapter 4

CONCLUSION AND FUTURE SCOPE

4.1 CONCLUSION

In conclusion, the model created for this experiment showed promise in MRI image-based Alzheimer's disease stage prediction. A convolutional neural network (CNN) comprising three convolutional layers, max-pooling layers, dropout regularization, and fully connected layers made up the model architecture. A dataset of MRI pictures of Alzheimer's patients in various stages of the illness was used to train and assess the model.

The model yielded training accuracy of 99.84% and validation accuracy of 99.37% after 50 epochs of training. These findings suggest that the model has made good progress on generalizing to new data. Through the application of methods including batch normalization, dropout regularization, and data augmentation, the model was able to reduce overfitting and increase its resilience.

Furthermore, the study of the confusion matrix showed that the model functioned effectively across a variety of classes with very few misclassifications. This shows that using MRI pictures, the model can distinguish between Alzheimer's disease stages rather well.

In summary, based on MRI data, the created model shows potential in aiding medical professionals in the diagnosis and stage of Alzheimer's disease. More iterations and validation of the model on bigger and more varied datasets may improve its therapeutic usefulness and yield even more precise predictions.

4.2 FUTURE SCOPE

In the realm of Alzheimer's disease diagnosis and management through deep learning techniques applied to MRI imaging, several avenues for future exploration and development present themselves:

1. **Integration of Multimodal Data:** Future studies may examine the integration of additional modalities, such as genetic data, PET scans, and clinical information, however this experiment only looked at MRI pictures. Integrating data from several sources may improve prediction accuracy and offer a more thorough knowledge of how Alzheimer's disease develops.

2. **Pretrained models and transfer learning:** Using transfer learning from pretrained models trained on large-scale datasets might speed up model training and enhance performance, particularly in situations with a shortage of labeled data. It might be useful to fine-tune models that were pretrained on either particular Alzheimer's disease datasets or generic medical imaging datasets.

3. **Advanced Architectures:** By investigating more complex neural network architectures that are specifically designed to manage the spatial and temporal dependencies found in MRI sequences, such as attention mechanisms, graph neural networks, or recurrent neural networks, more advanced models with improved predictive power may be developed.

4. **Improved interpretability and explainability** of deep learning models are essential for the clinical uptake of these algorithms. Future studies might concentrate on creating methods for deciphering model predictions, finding pertinent biomarkers, and offering insights into the model's decision-making process.

5. **Clinical Validation and Deployment:** Before deep learning models can be implemented into clinical practice, extensive clinical investigations must be carried out to verify the models' efficacy in actual clinical situations. To achieve the effective deployment and uptake, industrial partners, doctors, and researchers must collaborate.

6. **tailored medicine:** By customizing diagnostic and prognostic models to each patient's unique attributes, such as genetic profiles, clinical history, and demographic data, it may be possible to conduct tailored risk assessments and treatment planning, which might eventually result in better patient outcomes.

Chapter 5

DEPLOYMENT

We have made the web application for ALZHEIMER DISEASE DETECTION using Streamlit and deployed it on huggingface which marks a significant milestone in bringing cutting-edge AI capabilities to a user-friendly interface[7]. This deployment process involved a series of essential steps, transforming our trained model into an interactive and accessible tool for users.

1. We have integrated our ensemble CNN MODEL into our Streamlit application's backend.

2. A key highlight of our deployment process is the interactive user interface crafted using Streamlit [2]. The interface empowers users, regardless of their technical background, to seamlessly interact with our ML model. Our application showcases data input and output fields, allowing users to input data and obtain predictions effortlessly.

3. After this we cloned our HUGGINGFACE repository to the local machine.Added the app file along with all it's dependencies and committed the changes to the repository.

4. Now the Alzheimer Disease Detection web application is live and up for the end users.

5.1 WEBPAGE SCREENSHOTS

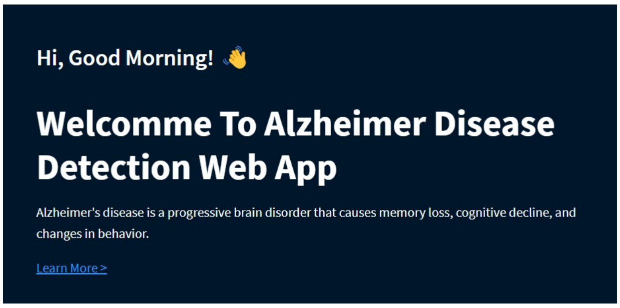


Figure 5.1: FrontPage of the WebApp

Real-Time Predictions: Following the upload of an image, the app processes it using the ensemble model to produce real-time predictions for the stage of Alzheimer's disease. A percentage indicating the degree of confidence in the outcome is included with the predictions.

Figure 5.2: Upload the Scan Images Section

Resources for Education: The app offers educational material on Alzheimer's disease to help users comprehend the disease's stages and its effects on different people. Users are given useful information that they might use for early identification and action.

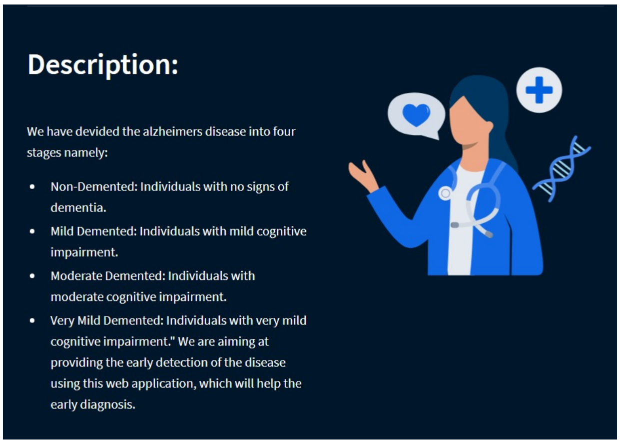


Figure 5.3: Info About Degree of Dementia

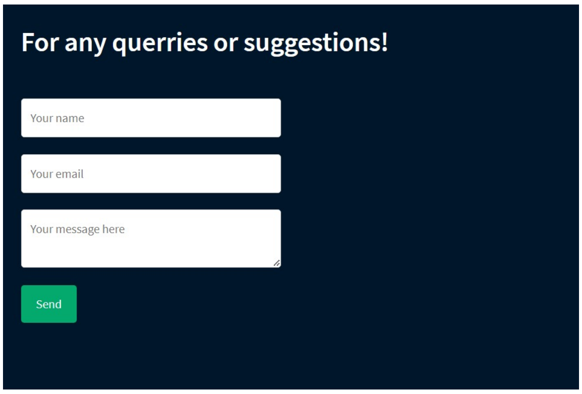
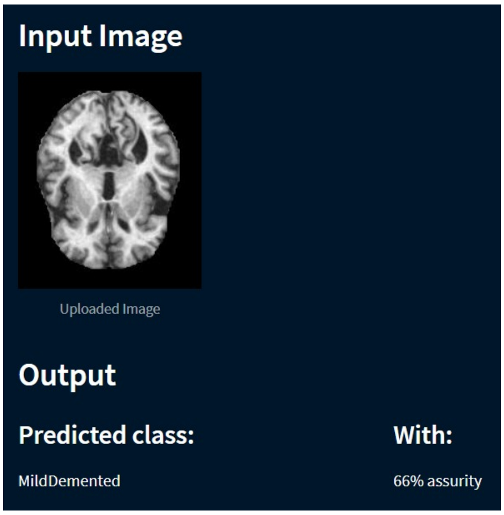
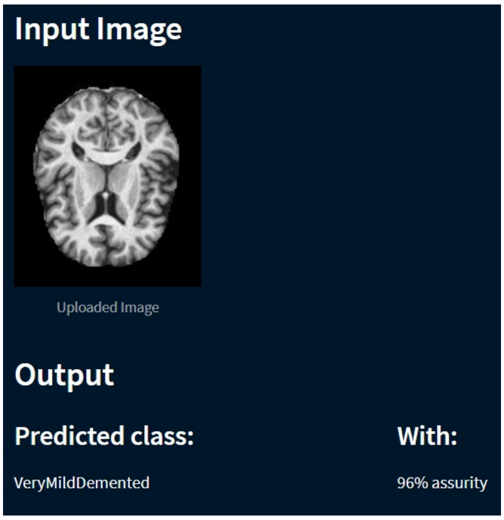


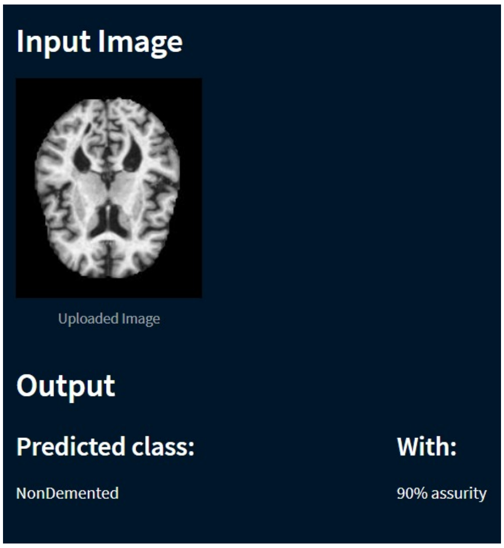
Figure 5.4: Contact Us Section



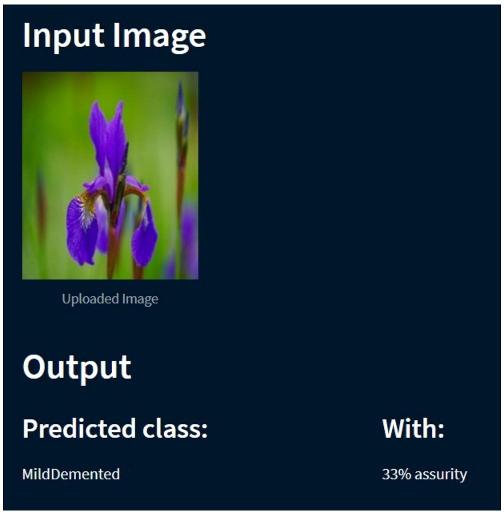
(a) Mild Demented



(b) Very Mild Demented



(c) Non Demented



(d) Low Accuracy Over Random Images

Figure 5.5: PREDICTED CLASS ALONG WITH ASSURITY OVER MRI

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