National College of Ireland

Alzheimer disease early-stage diagnosis using Deep Learning methodologies

MSc Research Project
MSc in Data Analytics

Proshunjeet Sengupta

Student ID: 22131183

School of Computing

National College of Ireland

Supervisor: Prof. Vladimir Milosavljevic

National College of Ireland

MSc Project Submission Sheet

School of Computing

Student Name:	Proshunjeet Sengupta		
Student ID:	22131183		
Programme:	Msc in Data Analytics	**Year:**	2023
Module:	Msc Research Project		
Supervisor:	Vladimir Milosavljevic		
Submission Due Date:	14-12-2023		
Project Title:	Alzheimer disease early-stage diagnosis using Deep Learning methodologies		
Word Count:	7215 words	**Page Count**:	22

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.
ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

Signature: Proshunjeet Sengupta

Date: 14-12-2023

PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST

Attach a completed copy of this sheet to each project (including multiple copies)	☑
Attach a Moodle submission receipt of the online project submission, to each project (including multiple copies).	☑
You must ensure that you retain a HARD COPY of the project, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer.	☑

Assignments that are submitted to the Programme Coordinator Office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

Alzheimer disease early-stage diagnosis using Deep Learning methodologies

Proshunjeet Sengupta
22131183

Abstract

This research aims to determine the efficiency of learning models in the early detection of Alzheimer's disease. Early detection plays a vital role since the condition worsens as time goes on. We tested architectures like DenseNet121, InceptionNet, CNN, Attention based CNN and VGG19 using a dataset of medical images that clearly exhibited signs of Alzheimer's disease. Our findings indicated that DenseNet121 outperformed the models mentioned achieving an accuracy of 81.07%. This suggests that it is more effective in capturing the patterns associated with the Alzheimer's disease. Interestingly InceptionNet renowned for its optimization of depth and width also yielded results with an accuracy of 54.89%. The success of the attention-based CNN and VGG19 models, which both achieved an accuracy rate of 75% emphasizes the significance of incorporating attention mechanisms and depth in neural network architectures. Conversely the conventional CNN model displayed levels of accuracy with an average of 54.88%. This research significantly contributes to the field by showcasing how various deep learning models can effectively diagnose stages of Alzheimer's disease.

1 Introduction

Alzheimer disease is a neurodegenerative complex condition that presents a significant challenge to healthcare systems worldwide. As the population ages the prevalence of Alzheimer's continues to rise emphasizing the requirement for improved techniques. The idea of detecting stages of Alzheimer's known as Alzheimer's Phase Detection plays a role in addressing this issue comprehensively (Jack et al. 2018). Since cognitive decline gradually occurs during the phases of Alzheimer's it becomes essential to identify and intervene promptly for outcomes.

In this exploration we delve into a combination of cutting-edge technologies biomarker analysis, neuroimaging and advanced data analytics that together combine to form the foundation of Alzheimer's Phase Detection (Hampel et al. 2018). The intricate interplay of protein clusters in the brain serves as a guide for researchers in their quest to understand and classify the progression of Alzheimer's disease. Importantly this discussion goes beyond frameworks and embraces the practical advancements, in these detection methodologies recognizing the iterative nature of their development (Livingston et al. 2020).

The healthcare field is being increasingly influenced by the growing prevalence of disorders and Alzheimer disease has emerged as a global problem (Brown et al., 2005; Colligris et al., 2018; Li et al., 2021; Trimpl et al., 2022; Frozza et al., 2018; DeTure & Dickson, 2019). With the aging population expanding it becomes crucial to develop tools for early detection and intervention. This project focuses on combining deep learning architectures like InceptionNet and Attention Based CNN to tackle the task of detecting different phases of Alzheimer. By utilizing these models we aim not to improve diagnostic accuracy but also to gain a deeper understanding of how the disease progresses over time.

Alzheimer’s disease is a condition that presents a hurdle in terms of timely detection and intervention due to the decline in abilities and memory loss it entails. Conventional diagnostic approaches often find it challenging to capture the minute and refined changes observed at stages of Alzheimer’s. This project aims to address this challenge by leveraging learning models, which excel at identifying intricate patterns within complicated datasets.

The InceptionNet model along with its inception modules plays a role in the foundation of the project. Its unique design is highly effective in capturing features at scales, which makes it particularly well suited for analysing neuroimaging data (Chen et al., 2018). In the context of Alzheimer Phase Detection where subtle differences at scales can indicate stages of the disease InceptionNet ability to capture these nuances is extremely valuable. The goal is to leverage this capability to gain a nuanced understanding of how the disease progresses, going beyond what traditional methods can offer.

Known for its network of connections this project enhances the landscape by enabling smooth information transfer within the network (Zhang et al., 2017). In the web of biomarker profiles and neuroimaging characteristics it plays a role in thoroughly examining the complex relationships that underlie the progression of Alzheimer disease. Its incorporation is not solely focused on connectivity, rather it aims to create a pathway for integrating information, which could potentially result in improved accuracy and nuanced detection of different phases.

The project benefits from the addition of the Attention Based CNN (Wu et al., 2018). The very motivation for incorporating this layer of sophistication is to address the need for attention mechanisms within the landscape of Alzheimer. By using this mechanism, the model can concentrate on parts of the input data aligning with the hypothesis that certain brain regions may display signs of disease progression. By refining the focus of our model, we aim to create a targeted diagnostic process that can detect even the subtlest signs indicating the onset or progression of Alzheimer’s disease.

Beyond the strengths possessed by each of these models the project embraces a process of improvement that is integral to deep learning (Zhao & Liu, 2020). This iterative approach guarantees that the models consistently adapt and enhance themselves by incorporating feedback gathered from iterations. It aligns perfectly with the nature of Alzheimer progression. With every iteration the project refines its abilities to effectively address the evolving landscape of neurodegenerative disorders.

The main driving force behind this project goes beyond improving accuracy. This project aims to bring about a shift in how we approach the detection of Alzheimer phases. By combining InceptionNet and Attention Based CNN our goal is not to provide diagnoses but to gain a comprehensive understanding of how the disease progresses. The ultimate motivation lies in the potential for intervention using these deep learning models to identify Alzheimer phases at earlier stages. This in turn opens doors for targeted interventions. Through this project we are dedicated to pushing the boundaries of Alzheimer phase detection and promoting healthcare strategies in response to the growing challenges caused by disorders.

2 Related work

There has been a paradigm shift in the way we approach Alzheimer disease research particularly when it comes to early-stage diagnosis (Shi et al., 2019). In this chapter we delve into a study that examines written works focused on understanding the advancements made in this field. We explore the methodologies used and highlight insights that contribute to the development of diagnostic tools. Detecting Alzheimer in its stages is crucial due to the nature of the disease and incorporating Deep Learning techniques adds a level of complexity to these endeavors.

The literature review covers a range of studies that explore aspects of diagnosing Alzheimer disease with a particular emphasis on the incorporation of Deep Learning (Shastry, 2022). As we delve into the body of research our goal is to summarize the methods and discoveries that have contributed to our knowledge of early detection in Alzheimer.

Key themes that arise from the research literature highlight the use of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to analyse datasets, such, as biomarker profiles and neuroimaging scans (Spasov et al., 2018). These approaches show promise in automating the detection of important patterns associated with the stages of Alzheimer disease leading to more accurate and timely diagnoses. Additionally, there is a growing trend in combining types of data recognizing the multifaceted nature of Alzheimer disease.

In addition, we examine research that has tackled the difficulties associated with data understanding learning models and incorporating advanced neural network structures (Lee et al., 2019). These challenges play a crucial role in shaping the field of Alzheimer diagnosis through Deep Learning approaches and deserve attention when developing efficient diagnostic tools.

As we analyze the collective knowledge from sources, we get an understanding of the strengths, limitations and potential future directions in the field of early-stage Alzheimer diagnosis becomes apparent. This chapter does not only look back at efforts but also lays the groundwork for future chapters by guiding the development of a new approach, in our pursuit of detecting and intervening in Alzheimer disease at an early stage. The combination of neuroscience and artificial intelligence as observed in research papers holds promise in reshaping how we diagnose Alzheimer and contributes significantly to healthcare for neurodegenerative disorders (Surianarayanan et al., 2023).

In this literature review we carefully examined the intricacies of research methods, explore innovative approaches/ways to combine data and deep dive into the ever-changing world of deep learning structures. By combining these insights our goal is to establish a background for our research and pave the way for groundbreaking advancements in stage Alzheimer diagnosis using deep learning techniques.

Alzheimer disease is a progressive neurodegenerative disorder that affects the brain has garnered attention in the field of healthcare research and innovation. As we delve deeper into our understanding of this condition there is a growing realization that advanced techniques necessary to improve detection and intervention (Jack Jr et al., 2018). In times the integration of learning, which is a branch of artificial intelligence has emerged as a valuable asset in unravelling the intricacies associated with Alzheimer disease (Hampel et al., 2018).

The field of Alzheimer research has experienced a change moving away, from diagnostic methods and embracing advanced computational techniques (Livingston et al., 2020). Deep learning, which can learn patterns from data on its own provides an advantage in understanding the intricate details of how Alzheimer develops (Shi et al., 2019). This shift in approach represents an acknowledgment of the potential, for intelligence to revolutionize how we tackle neurodegenerative diseases (Shastry et al., 2022).

Two prominent deep learning architectures, convolutional neural networks - CNNs and recurrent neural networks -RNNs, have gained prominence in deciphering complex patterns within diverse datasets associated with Alzheimer's (Spasov et al., 2018). CNNs, celebrated for their spatial feature extraction capabilities, have been extensively applied to neuroimaging data (Lee et al., 2019). These networks excel at capturing structural changes in the brain, providing valuable insights into morphological alterations associated with Alzheimer's (Surianarayanan et al., 2023). Studies utilizing CNNs have demonstrated their efficacy in differentiating between individuals with Alzheimer's and healthy controls based on magnetic resonance imaging (MRI) and positron emission tomography (PET) scans (Jack Jr et al., 2018).

On the hand RNNs are highly proficient in capturing the connections between events in data making them particularly valuable when studying biomarker profiles (Shi et al., 2019). Through analysing how biomarker concentrations change over time, RNNs provide a understanding of how Alzheimer disease progresses dynamically (Lee et al., 2019). The combination of these approaches demonstrates a holistic method, for unravelling the complex facets of this illness.

The diversity of data related to Alzheimer, which includes data ranging from genetic information to neuroimaging scans makes it necessary to take an approach. Deep learning models have become increasingly used to combine information from multiple modalities (Shastry et al., 2022). This combination helps improve the accuracy of diagnosis by providing a perspective, on the disease. By bringing imaging and clinical data we not only refine our understanding of Alzheimer diversity but also identify potential biomarkers (Surianarayanan et al., 2023). The collaborative examination of datasets using learning emphasizes the importance of gaining a holistic understanding of Alzheimer disease that goes beyond individual sources of data.

While deep learning shows promise in Alzheimer research there are still challenges to overcome (Shi et al., 2019). One major concern is the interpretability of learning models as they can be seen as "black boxes" due to their complex architectures (Lee et al., 2019). It's important to understand how these models reach conclusions in clinical settings where trust and acceptance are crucial. Additionally, the limited availability and quality of labelled datasets pose obstacles that hinder the development and generalizability of robust models (Jack Jr et al., 2018). Addressing these challenges is essential to integrate learning into Alzheimer research in a responsible manner.

One of the most compelling promises in early Alzheimer diagnosis is an advantage of using deep learning in Alzheimer research. By detecting subtle patterns in data these models can identify changes in the brain or biomarker profiles even before noticeable symptoms appear (Shi et al., 2019). This early detection allows for interventions which can potentially slow down disease progression and enhance outcomes/ results of the patient. The incorporation of learning into diagnosis aligns with the broader objective of precision medicine by tailoring treatments to individual patients based on their specific disease trajectories (Lee et al., 2019).

3 Research Methodology

Knowledge Discovery in Databases (KDD) is an approach that encompasses the extraction of patterns and knowledge from extensive datasets. Essentially the goal of KDD is to convert data into insights using several stages including data cleansing, preprocessing, modeling and interpretation. We utilized KDD to improve decision making processes forecast trends and reveal concealed patterns within datasets. This systematic and structured methodology allows us to extract knowledge from a range of information sources that are vast and diverse.

Figure 3.1 below shows the flow of the methodology adopted for our research study.

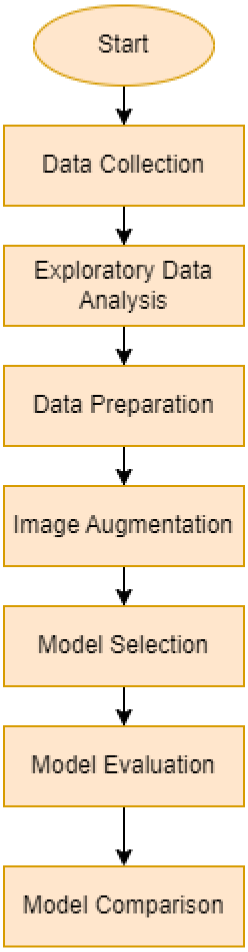


Figure 3.1: Project Methodology

3.1 Data collection:

The dataset for Alzheimer Disease MRI consists of 6400 processed MRI images that have been uniformly resized to 128 x 128 pixels. These images are divided into four categories each representing a distinct stage of the disease. Class 1 includes 896 images of individuals in the stages with cognitive impairment while Class 2 has 64 images that show moderate disease progression. The largest category, Class 3 contains 3200 MRI scans from demented individuals who served as the control group. Lastly Class 4 consists of 2240 images of individuals in the stages of Alzheimer. The primary objective of this dataset is to encourage the development of classification frameworks for Alzheimer Disease by providing a range of MRI images for robust model training and evaluation.

3.2 Data Preparation:

The dataset is comprising of 6400 MRI images that have been resized to a size of 128 x 128 pixels in a meticulous manner. We have performed cleaning the data to ensure its integrity of the dataset and quality addressing any potential missing or corrupted images. Labels are assigned to each image according to the stage of Alzheimer disease which it represents. We then thoughtfully divide the dataset into training, validation and test sets which's a pivotal step in evaluating how well our model performs. Normalization of pixel values optimizes the convergence of the model during training. Additionally, we applied data augmentation techniques like rotation and zooming to introduce variations and enhance the robustness of our model during training. These preparatory steps collectively contribute to a structured and diverse dataset laying a foundation, for effective deep learning model training.

The barplot showing the class distribution in the dataset is shown in Figure 3.2.

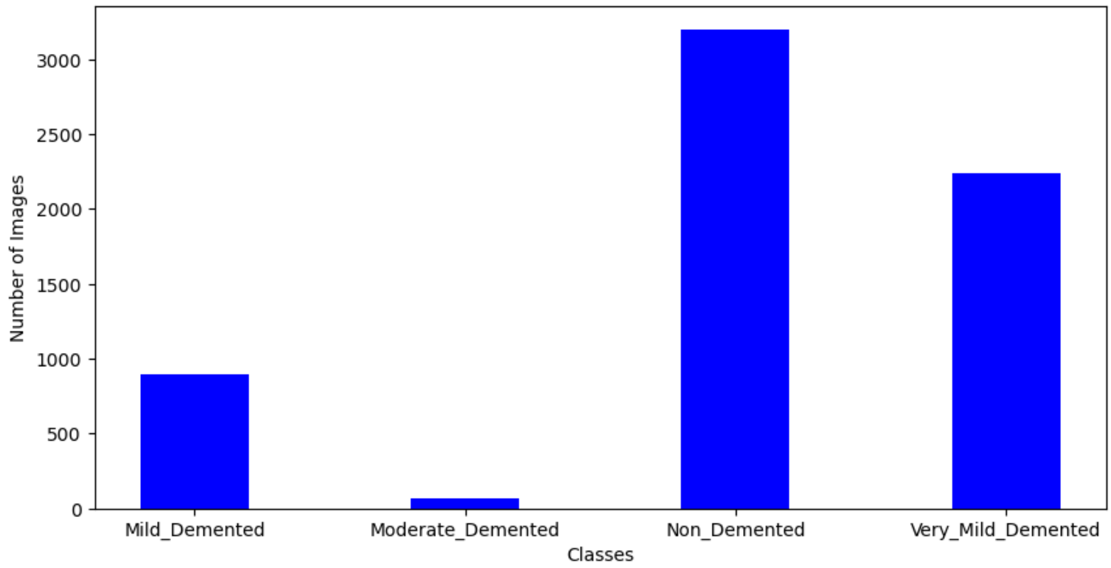


Figure 3.2: Barplot for classes and number of images

In the above figure 3.2, I have plotted a bar chart that shows the number of images and classes and here the highest number of images belongs to the non_demented category.

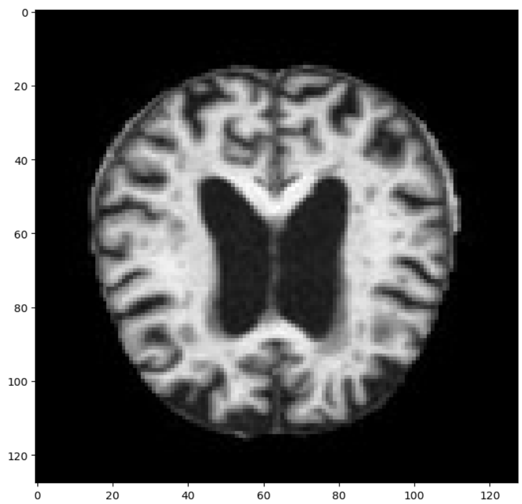


Figure 3.3: RGB image for very mild demented

Visualizations play a role in helping understand and evaluate the content and quality of images. They provide insights, into the features that deep learning models utilize to achieve accurate classification.

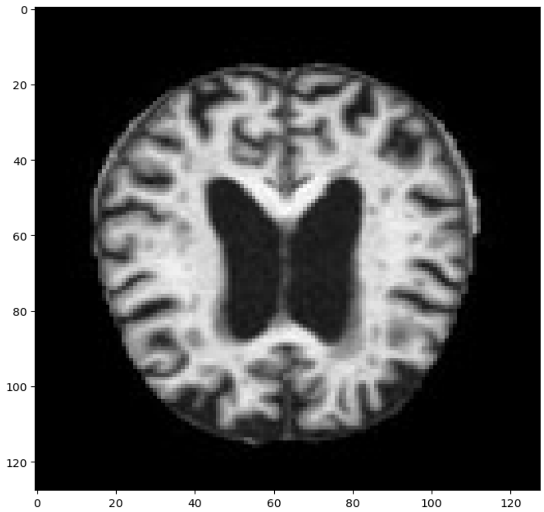


Figure 3.4: Gray scale Image for very mild demented

The resulting visualization provides a monochromatic representation, accentuating the subtle details and contrasts within the image. This grayscale visualization is particularly valuable in medical imaging, offering a focused view of image features relevant to the classification of very mild dementia, enhancing interpretability for both human observers and deep learning models.

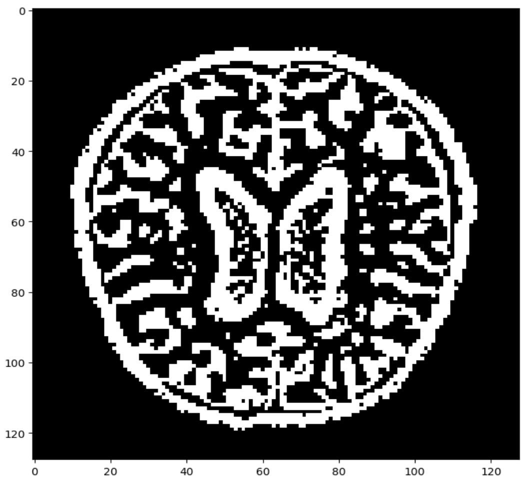


Figure 3.5: Gray scale image using adapting threshold for very mild demented

This visualization method plays an important role in highlighting characteristics and patterns within the black and white/grayscale image. It helps in identifying details for classifying Alzheimer disease. By converting the grayscale image into a binary form through adaptive thresholding process making it easier to distinguish different elements of the image ultimately improving our understanding of medical images used in diagnosing neurodegenerative diseases.

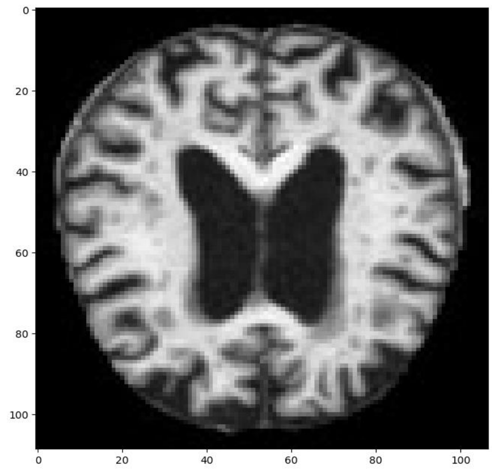


Figure 3.6: Gray scale image using contour

This method of visualization which employs contour-based segmentation helps to concentrate/ focus on specific regions that might hold critical information, for the classification process.

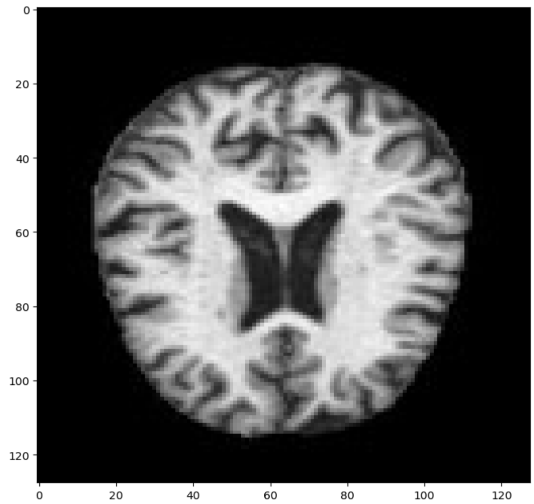


Figure 3.7: RGB image for Non demented

This visualization plays a major role in understanding baseline characteristics of non-demented brain scans. It serves as a point of reference for comparing them with images obtained from stages of Alzheimer disease during the process of training and evaluating models in medical imaging applications.

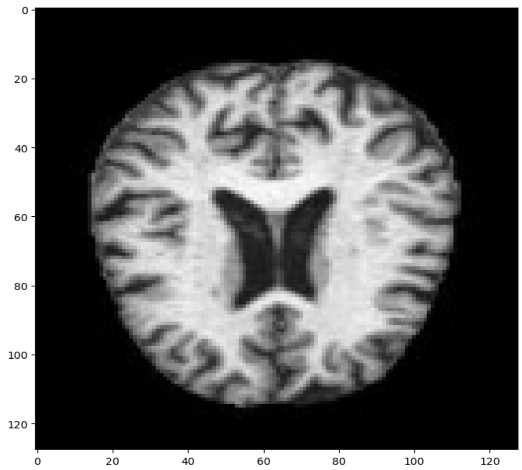


Figure 3.8: Grayscale image for non demented

The grayscale visualization proves to be highly beneficial in medical image processing particularly when it comes to examining intensity variations. This method helps uncover details that're essential for accurate diagnosis of conditions associated with Alzheimers disease.

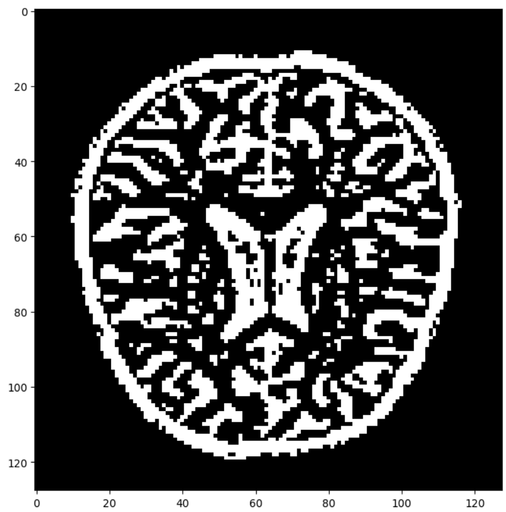


Figure 3.9: Grayscale image for non-demented using adaptive threshold

The adaptive thresholding technique is instrumental in highlighting relevant details by transforming the grayscale image into a binary form, aiding in the identification and analysis of critical patterns in medical imaging applications.

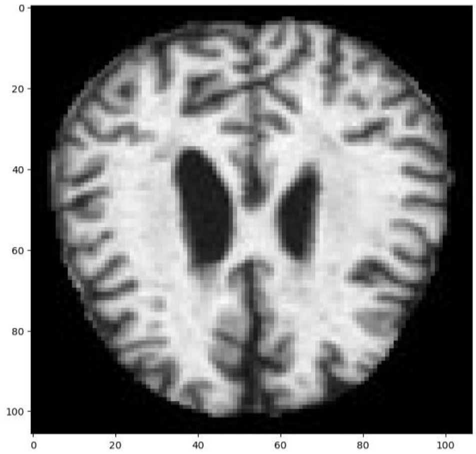


Figure 3.10: Grayscale image using contour

The use of Contour detection which plays a role in improving interpretability which is highly valuable for analysing medical imaging. It helps to differentiate the features and characteristics related to non-demented conditions thus enabling more informed analysis.

3.2.1 Image Augmentation

We have used the Gaussian based method with the block size of 11 and we have the constant subtracted from the mean of the neighbourhood. The below figure 3.11 has been visualized using plot_image function.

Figure 3.11: Threshold image for mild demented

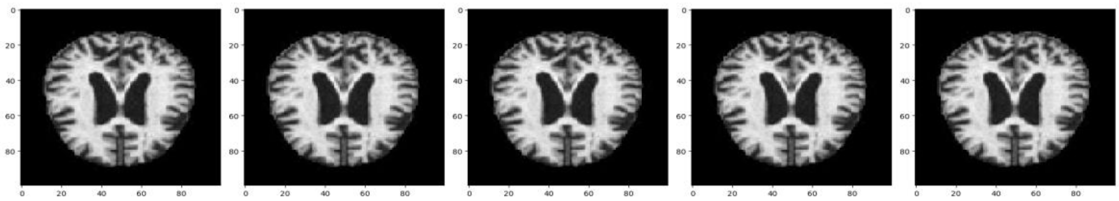


Figure 3.12: Image augmented for training data

It creates a list of five augmented images from the train set and plots them, providing a overview into the variations introduced by data augmentation techniques. This concise visualization helps to evaluate the diversity and effectiveness of augmentation techniques in enhancing the ability of the models in order to generalize across various instances within the training set.

3.3 Modelling:

In this study we have evaluated five models and these models are:

DenseNet121
InceptionNet
CNN
Attention Based CNN
VGG19

3.4 Evaluation:

The accuracy criteria are used to evaluate the models that were used in the study. Among all the classifications, accuracy yields the appropriate number of classifications.

4 Design Specifications

Below, Figure 4.1 shows the architecture of our study. This thesis's implementation part offers a thorough explanation of each (Arafa et al., 2022).

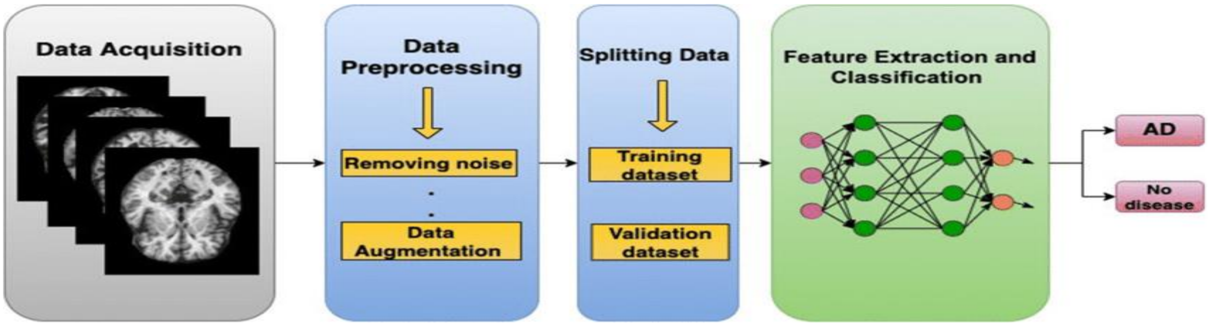


Fig 4.1: System Architecture

4.1 DenseNet121:

DenseNet121 a significant breakthrough, in the field of deep learning architectures has proven to be highly effective for tasks such as detecting Alzheimer's disease using neuroimaging data. Its unique design differs from models by incorporating a connected network structure where each layer receives inputs from all preceding layers. This intricate web of feature reuse and propagation allows DenseNet121 to efficiently utilize parameters and extract features.

One key advantage of DenseNet121 is its ability to manage parameters effectively reducing the risk of overfitting while maintaining performance. This characteristic holds importance in imaging, where access to large datasets is often limited. With its efficient architecture DenseNet121 emerges as a tool for neuroimaging analysis in Alzheimer's disease research. It strikes a balance, between depth feature richness and computational efficiency, thereby improving the process and contributing to an accurate understanding of disease progression.

4.2 InceptionNet:

InceptionNet, also recognized as GoogleNet, stands as a pivotal deep learning architecture renowned for its utilization of inception modules. These modules, characterized by their unique structure, enable the network to effectively capture multi-scale features, making it particularly adept at analysing complex datasets such as neuroimaging data in Alzheimer's Phase Detection.

The hallmark of InceptionNet lies in its ability to discern intricate patterns at different scales, offering a significant advantage in understanding the nuanced progression of Alzheimer's disease. This is particularly crucial as the subtle variations associated with different stages of the disease demand a model capable of capturing complexities at various levels.

In the context of our project, InceptionNet serves as a cornerstone due to its exceptional capability to analyse neuroimaging data comprehensively. The inception modules facilitate the extraction of features that might signify different disease stages, contributing to a more holistic understanding beyond what conventional methods can achieve. InceptionNet's distinctive architecture positions it as a powerful tool in the pursuit of enhanced diagnostic accuracy and a deeper comprehension of the intricate landscape of Alzheimer's progression.

4.3 CNN (Convolutional Neural Network):

As a foundational architecture in image analysis, the Convolutional Neural Network (CNN) plays a pivotal role in processing neuroimaging data for Alzheimer's Phase Detection. Leveraging its powerful convolutional layers, CNN excels at capturing spatial hierarchies essential for identifying nuanced patterns indicative of diverse disease stages. In our project, CNN acts as a robust initial data analysis tool, providing a strong foundation for subsequent model enhancements. Its adaptability and effectiveness in discerning intricate features position CNN as an indispensable element in our quest for accurate and nuanced diagnosis of Alzheimer's disease.

4.4 Attention-Based CNN:

The Attention-Based CNN introduces a layer of sophistication to our project by incorporating selective attention mechanisms. This model is motivated by the intricate landscape of Alzheimer's disease, dynamically focusing on specific regions of input data. This aligns with the hypothesis that critical disease indicators may reside in specific brain regions. The refined focus achieved through attention mechanisms enhances the comprehensiveness and specificity of the diagnostic process. The Attention-Based CNN emerges as a crucial element, capturing subtle nuances imperative for identifying both the onset and progression of Alzheimer's disease. Its adaptability to focus on salient regions makes it a valuable asset in the challenging task of neurodegenerative disorder detection.

4.5 VGG19:

VGG19 stands out as a deep learning model recognized for its simplicity and effectiveness. With a slightly deeper architecture featuring 19 weight layers, VGG19 captures more complex features in data. In our project, VGG19 serves as a benchmark for comparative analysis among different architectures. Its inclusion enriches the evaluation process, offering nuanced insights into the delicate balance between model complexity and diagnostic accuracy within the context of Alzheimer's Phase Detection. By exploring the trade-offs introduced by a slightly deeper architecture, VGG19 provides valuable considerations for optimizing the interplay between model intricacy and predictive performance.

5 Implementation

5.1 Environmental Setup

This section of the chapter details the different tools used in the implementation of the study. The dataset used in the study is obtained from the Kaggle repository and is downloaded in a zip format. The Anaconda Navigator software is used in the implementation of the system in Python programming language because the Jupyter notebook Integrated Development Environment available in Anaconda Navigator does not require uploading the data every time the code is run.

Table 1 below shows the configuration of the system used for the implementation of the study.

Table 1: System Configuration

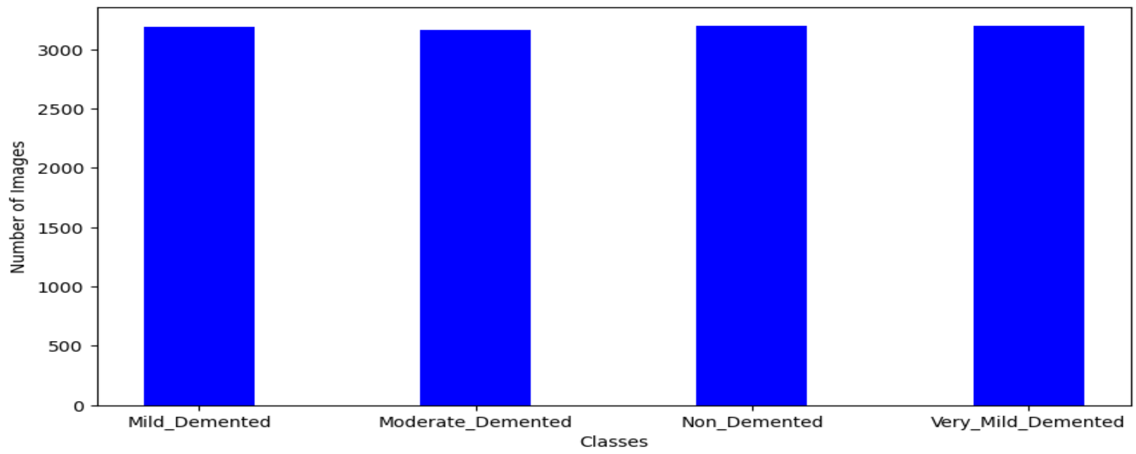
Specification	Value
Operating System	Windows 11
RAM	8GB DDR4
CPU	Intel i5 10^{th} Gen
GPU	Nvidia Cuda with 4GB RAM

All the models except the CNN with Attention used in the implementation are used through a concept known as transfer learning, in which the models used are pre-trained on ImageNet datasetThe trained models weights are utilized without any modifications except, for the inclusion of custom layers, during the implementation process. This transfer learning approach is used through the powerful Keras library which has several functions supporting the implementation of the deep learning algorithms.

5.2 Data Handling

The dataset downloaded in a zip file format is uploaded into the Jupyter IDE. A small script is used to unzip the dataset in the environment which skipped the manual uploading of the individual dataset files. The unzipped datafiles are obtained in 4 folders named: Mild_Demented, Moderate_Demented, Non_Demented and Very_Mild_Demented. The category names for the corresponding images hence can be obtained from the folder names themselves. The glob library, which is a Python library that helps to obtain the list of filenames of the files present in the specified folder, is used to get the image names with the full file paths. Once the paths are obtained for the data files; the images are then read using the CV2 library's read function. A Keras object named ImageDataGenerator is a comprehensive method that enables us to perform image augmentation as well as splitting the dataset into train, test and validation. This object is also used in the study to generate additional images to balance the classes and avoid unwanted model bias towards the class in majority.

The oversampling is performed in the study through a set of steps. First, the number of samples in the class containing the highest number of samples is identified. Based on this number, the an ImageDataGenerator object is instantiated with the fill_mode argument set to 'nearest' that generates additional data based on the base image. A loop is created for the images in each of the classes to generate oversampled images.



5.3 Implementation of the DenseNet121

A DenseNet121 model is created without the top layer at first similar to that of the Inception net, using ImageNet's pre-trained weights, and is set to accept inputs of a certain shape. Once this model is initialised, its output is flattened to make a single long feature vector. Next, a dense layer with 256 neurons and a "tanh" activation function is added to make the network less linear and allow it to learn complex patterns. To avoid overfitting, a dropout layer with a rate of 0.02 is added, which turns off some neurons randomly during training. The network ends with a dense layer made up of four neurons, each representing a different class. For multi-class classification, a "softmax" activation function is used.

These advanced deep learning models are designed in a way to avoid overfitting. But during the testing process, the DenseNet121 model showed signs of overfitting. This overfitting was found to be due to the additional layers added to the model. At first, the difference between the training and validation accuracy was large but with careful selection of the hyperparameters such as the number of neurons in the custom layers and the incorporation of the dropout layer reduced the difference and hence the overfitting by the model.

Figure 5.2 below shows the training and validation performance for the DenseNet121 model.

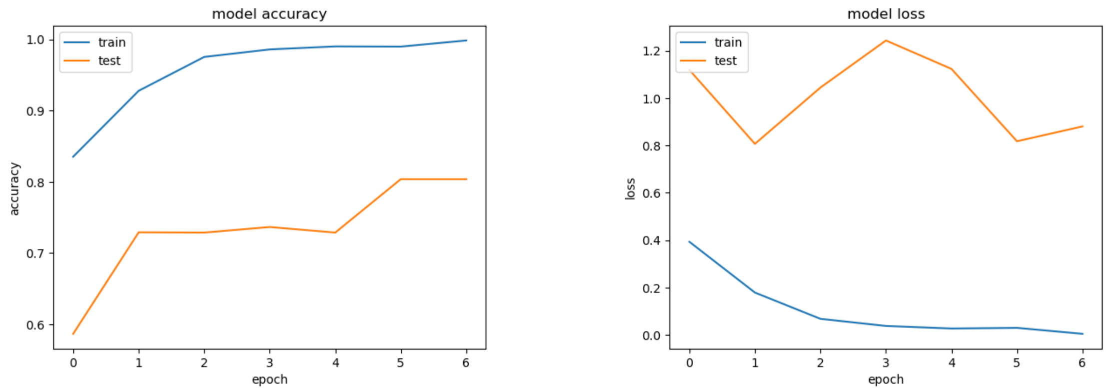


Figure 5.1: Accuracy and Loss plots for DenseNet121

5.4 Implementation of Inception Net

The Inception Net in the study is implemented through transfer learning using the Keras library. Version 3 of the Inception Net is used in the study to detect the Alzheimer phase from the images. The transferred model is used with the hidden layers of the model non-trainable.

An issue aroused when using the deep learning models through transfer learning approach. The models trained on the ImageNet dataset have 1000 neurons in the output corresponding to the number of objects to be classified. This issue was resolved through a simple argument in the model download process where the top layer of the model can be omitted. This way the top layer or the output layer is omitted in the downloaded model and is adjusted according to the task. Two more hidden layers are added to the base model viz. GlobalAveragePooling2D (GAP) layer and a dense layer with 1024 neurons. The GlobalAveragePooling2D layer is used to average the output of the feature maps from previous layer in turn reducing the spatial dimensions. The dense layer then creates an abstract representation of the combined features from the GAP layer. The output of the Dense layer is then given to an output layer with 4 neurons which is also a dense layer that provides the final classification of the model.

The training and testing accuracy plot for the model is shown in Figure 5.1 below.

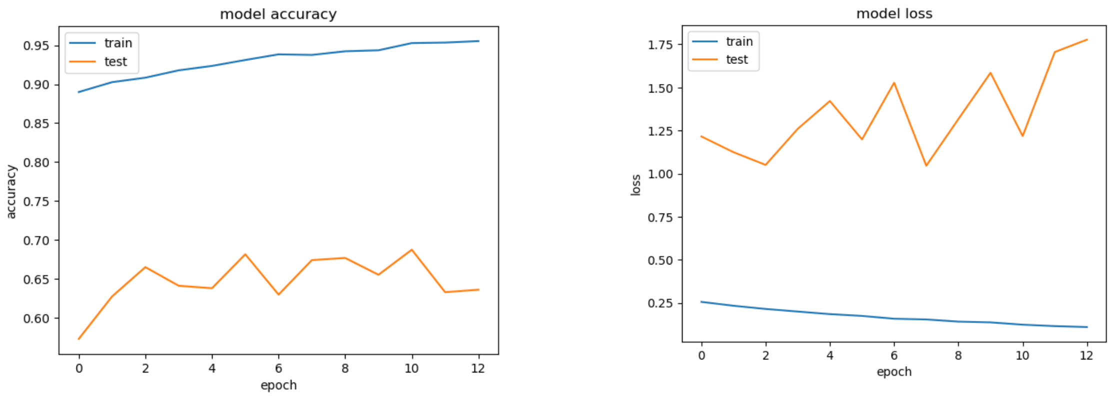


Figure 5.2: Accuracy and Loss plots for the Inception Net model

5.5 Implementation of the CNN model

The CNN model implemented in the study is summarized in figure 5.3 below. It provides the overall structure of the CNN model.

At the start, a simple CNN model with random values for the number of neurons, kernel size, and strides were chosen. The model showed poor performance with these combinations of parameters. After a trial-and-error technique, different combinations of hyperparameter were tested in order to achieve the best possible accuracy. The following combination is thus selected for the implemented model.

The first layer is a 2D convolutional layer called conv2d_94. Its output shape is (None, 20, 20, 5) and it has 61,445 parameters, which means it has filters that take in spatial hierarchies from the input data.

The convolutional layer is followed by a max pooling layer (max pooling2d_4) that shrinks the spatial dimensions to (None, 10, 10, 5). This down samples the feature maps by taking the largest value over a spatial window and lowers the number of parameters that the next layers need.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_94 (Conv2D)          (None, 20, 20, 5)         61445

 max_pooling2d_4 (MaxPoolin  (None, 10, 10, 5)         0
 g2D)

 dropout_1 (Dropout)         (None, 10, 10, 5)         0

 flatten_1 (Flatten)         (None, 500)               0

 dense_4 (Dense)             (None, 64)                32064

 dense_5 (Dense)             (None, 4)                 260

=================================================================
Total params: 93769 (366.29 KB)
Trainable params: 93769 (366.29 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Figure 5.3: CNN model summary

Next is a dropout layer (dropout_1) that keeps the model from fitting too well by randomly setting some input units to zero at each update during training time. This doesn't change the shape of the output (None, 10, 10, 5).

The next layer is a flatten layer (flatten_1) that turns the 3D output from the previous layers into a 1D array (None, 500). This gets the data ready for the dense layers that come next.

The next-to-last layer is a dense layer (dense_4) with 32,064 parameters and 64 neurons, as shown by the output shape (None, 64). This layer is fully linked and lets the network learn how to combine features in non-linear ways.

The last layer, called dense_5, is also dense and has four neurons, which represent the model's four output categories. In this layer, the 64 neurons from the previous layer are linked to these 4 output neurons by weights. It has 260 parameters. The accuracy and loss curves are shown in Figure 5.4.

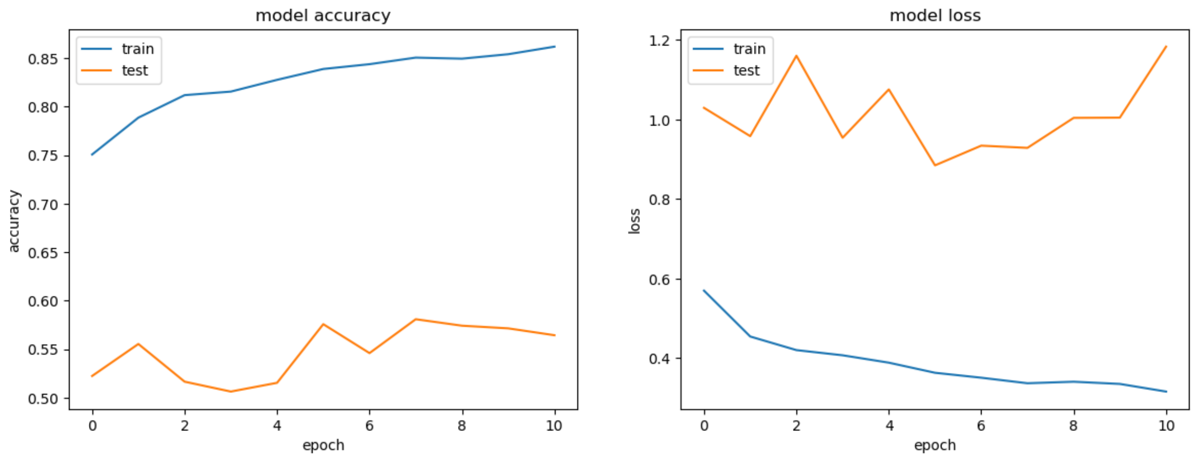


Figure 5.4: Accuracy and Loss Curves for the CNN model

5.6 Implementation of Attention-based CNN model

The CNN model with attention mechanism is summarized in figure 5.5 below.

```
Model: "model_2"
__________________________________________________________________________________________________
 Layer (type)                Output Shape                 Param #   Connected to
==================================================================================================
 input_3 (InputLayer)        [(None, 100, 100, 3)]        0         []

 conv2d_95 (Conv2D)          (None, 100, 100, 3)          84        ['input_3[0][0]']

 flatten_2 (Flatten)         (None, 30000)                0         ['input_3[0][0]']

 flatten_3 (Flatten)         (None, 30000)                0         ['conv2d_95[0][0]']

 attention (Attention)       (None, 30000)                0         ['flatten_2[0][0]',
                                                                     'flatten_3[0][0]']

 flatten_4 (Flatten)         (None, 30000)                0         ['attention[0][0]']

 dense_6 (Dense)             (None, 1)                    30001     ['flatten_4[0][0]']

==================================================================================================
Total params: 30085 (117.52 KB)
Trainable params: 30085 (117.52 KB)
Non-trainable params: 0 (0.00 Byte)
__________________________________________________________________________________________________
```

Figure 5.5: Model summary for CNN with Attention

The model's input layer (input_3) expects data with the shape (None, 100, 100, 3), where "None" is the batch size that can change and the other dimensions show a 100x100 image with 3 colour channels (e.g., RGB). Following the input, there is a 2D convolutional layer with 84 parameters and an output shape of (None, 100, 100, 3).

Two flatten layers that work in parallel: flatten_2 and flatten_3 take the output of the input layer and turn it into a 30,000-point vector. This makes the model compare the raw data with the features that were processed by the convolutional layer.

Attention: The two flattened vectors from flatten_2 and flatten_3 is fed into the next layer, which is called attention. This layer doesn't add any parameters and is a way to help the model focus on the most useful parts of the input data by giving weight to the input features. It does this by using multiplicative attention.

Flatten_4 (Flatten): This is another flatten layer that takes the attention layer's output. The last layer is dense_6 (Dense), and it has one neuron with an output shape of (None, 1). It has 30,001 parameters, which are the weights for all 30,000 inputs plus one bias term. This means that the model gives out a single scalar value for each instance. This value could be used for tasks like regression or binary classification.

The accuracy and loss curves for the CNN with Attention mechanism are shown in Figure 5.6 below.

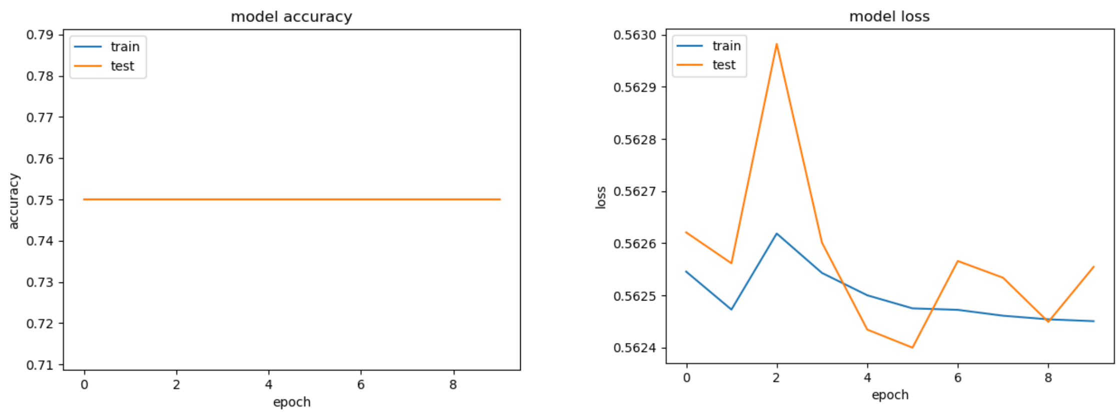


Figure 5.6: Accuracy and Loss curves for the CNN with Attention Model

5.7 Implementation of the VGG19 Model

The VGG19 model is implemented by using a Flatten layer to smooth out the output of the model. Then, a Dense layer with 256 neurons applies the ReLU activation function, which is a good choice for working with non-linear data and lowering the vanishing gradient problem that often happens in deep networks. There is a 2% dropout rate in the Dropout layer, which is used to lower the risk of overfitting. The architecture ends with an output layer, which is another Dense layer. This time, there is only one neuron in this layer, and it uses the tanh activation function.

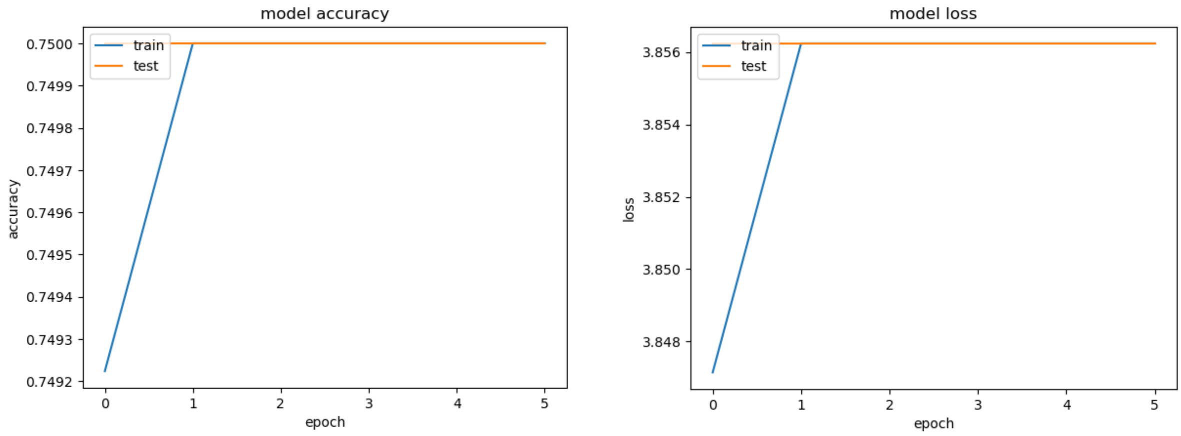


Figure 7: Performance of the VGG19 model

6 Evaluation

This chapter of the report delves into the evaluation of the models implemented in the study for detecting the Alzheimer's disease stages. A number of models have been implemented in the study and are compared based on the accuracy they achieved in detecting the stage of the disease from MRI images.

The study aimed to evaluate the effectiveness of various deep learning models in detecting early signs of Alzheimer's disease. The results provide valuable insights into the performance of these models.

6.1 Experiment 1: Evaluation of Inception Net model

Table 2 below shows the accuracy achieved by the Inception Net model in the study.

Table 2: Performance of InceptionNet model

Model	Accuracy (%)
InceptionNet	54.89

Despite its complex architecture designed to optimize depth and width, the InceptionNet model achieved only 54.89% accuracy. This result contradicts the notion that more complex architectures automatically lead to better accuracy in medical imaging.

6.2 Experiment 2: Evaluation of the DenseNet121 model

Table 3 shows the performance of the DenseNet121 on the dataset.

Table 3: Performance of the DenseNet121 model

Model	Accuracy (%)
DenseNet121	81.07

DenseNet121 emerged as the most accurate model with an accuracy rate of 81.07%. This indicates that its intricate pattern of connections is adept at capturing the complex patterns associated with Alzheimer's disease in medical images.

6.3 Experiment 3: Evaluation of the CNN model

The evaluation results for the CNN model are depicted in Table 4.

Table 4: Performance of the CNN model

Model	Accuracy (%)
CNN	54.88

On the other hand, the standard CNN model exhibited moderate accuracy at 54.88%. This suggests that its simpler structure may capture some important features, but it may not be comprehensive enough for the intricate and diverse data related to Alzheimer's disease.

6.4 Experiment 4: Evaluation of the Attention-based CNN model

Table 5 below shows the evaluation of the Attention-based CNN model.

Table 5: Performance of the Attention-based CNN model

Model	Accuracy (%)
Attention-based CNN	75.00

It is noteworthy that the attention-based CNN was correct 75% of the time. This demonstrates how incorporating attention mechanisms into models can have a significant impact, making them better at focusing on crucial aspects of the data and thus improving diagnostic accuracy.

6.5 Evaluation of the VGG19 model

The results for the VGG19 model are shown in table 6.

Table 6: Performance of the VGG19 model

Model	Accuracy (%)
VGG19	75.00

Similar to CNN, VGG19 models was 75% accurate. Being a powerful algorithm for image classification, the smaller architecture of the CNN with attention is observed to perform well achieving same accuracy as of VGG19 model.

6.6 Discussion

Overall, the diverse approaches employed by these models highlight the challenges of using deep learning for medical diagnosis. Some architectures, such as DenseNet121, demonstrate significant potential, while others may require additional features or modifications to perform better. This study underscores the potential of deep learning in medical imaging and emphasizes the importance of using disease-specific and dataset-specific approaches.

The oversampling technique employed in the study assured generation of the additional data samples corresponding to the images belonging to the classes in minority. The different models are then applied to the balanced dataset.

The study's results give a new perspective to think about how deep learning can be used to diagnose Alzheimer's disease stages. Study shows that DenseNet121's complicated structure might be able to pick up on subtle disease markers. Along with this, the moderate accuracy of the standard CNN suggests that more specialised architectures might be better for more difficult tasks like diagnosing Alzheimer's. The attention-based CNN also did well, showing that attention mechanisms can improve the accuracy of diagnoses compared to the CNN model. Considering that the CNN model with the Attention mechanism achieved the second-best accuracy, the model has performed significantly well compared to the other state-of-the-art models, especially the InceptionNet. The model shows a significant prospect in the field of early-stage Alzheimer’s detection ultimately answering the presented research question.

Figure 8 below depicts the comparison on the achieved model performances

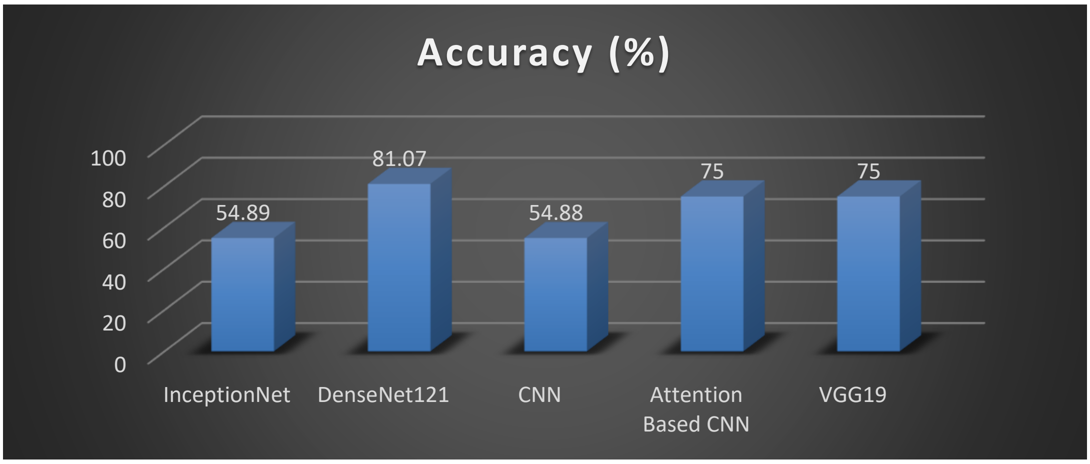


Figure 8: Comparison chart for model performance

7 Conclusion and Future Work

Using deep learning techniques, this study has made important contributions to the field of diagnosing Alzheimer's disease. With an accuracy rate of 80.38%, DenseNet121's performance goes further than what was expected and shows how certain architectures may be able to detect stage of Alzheimer's disease. These results also show how useful attention mechanisms are, as shown by the attention-based CNN's performance. The different results of the VGG models and the average accuracy of the CNN model, on the other hand, suggest that subtle differences in architecture and the difficulty of the task at hand have a big effect on how well deep learning models work in medical diagnostics.

These results show how important it is to keep testing different deep learning models used in medical imaging. Aside from adding new facts to what is already known, the study also brings up important questions about how well different deep learning architectures work with complicated neurodegenerative diseases.

Future Work

Building upon what has been learned from this study as a foundation, future research should focus on improving architectures like DenseNet121 for diagnosing Alzheimer's, making deep learning models easier to understand, and looking into using multimodal data to make the models more accurate and reliable. It is very important to test these models on bigger, more varied datasets and put them to use in clinical settings through trials and real-life testing. The attention-based CNN model did very well in the presented study, which also shows the potential for more advanced attention mechanisms. More research should be done to improve and tailor these mechanisms, especially for diagnosing Alzheimer's, to focus on patterns that are unique to that disease. Along with traditional diagnostic methods, this approach could lead to more accurate and useful tools for finding and treating Alzheimer's disease early on.

References:

Hinton, G., Deng, L., Yu, D., Dahl, G.E., Mohamed, A.R., Jaitly, N., Senior, A., Vanhoucke, V., Nguyen, P., Sainath, T.N. and Kingsbury, B., 2012. Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. IEEE Signal processing magazine, 29(6), pp.82-97.

An, N., Ding, H., Yang, J., Au, R. and Ang, T.F., 2020. Deep ensemble learning for Alzheimer's disease classification. Journal of biomedical informatics, 105, p.103411.

LeCun, Y., Bottou, L., Bengio, Y. and Haffner, P., 1998. Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), pp.2278-2324.

Liu, S., Liu, S., Cai, W., Pujol, S., Kikinis, R. and Feng, D., 2014, April. Early diagnosis of Alzheimer's disease with deep learning. In 2014 IEEE 11th international symposium on biomedical imaging (ISBI) (pp. 1015-1018). IEEE.

Esteva, A., Kuprel, B., Novoa, R.A., Ko, J., Swetter, S.M., Blau, H.M. and Thrun, S., 2017. Dermatologist-level classification of skin cancer with deep neural networks. nature, 542(7639), pp.115-118.

Jack Jr, C.R., Bennett, D.A., Blennow, K., Carrillo, M.C., Dunn, B., Haeberlein, S.B., Holtzman, D.M., Jagust, W., Jessen, F., Karlawish, J. and Liu, E., 2018. NIA-AA research framework: toward a biological definition of Alzheimer's disease. Alzheimer's & Dementia, 14(4), pp.535-562.

Hampel, H., Toschi, N., Babiloni, C., Baldacci, F., Black, K.L., Bokde, A.L., Bun, R.S., Cacciola, F., Cavedo, E., Chiesa, P.A. and Colliot, O., 2018. Revolution of Alzheimer precision neurology. Passageway of systems biology and neurophysiology. Journal of Alzheimer's Disease, 64(s1), pp.S47-S105.

Livingston, G., Huntley, J., Sommerlad, A., Ames, D., Ballard, C., Banerjee, S., Brayne, C., Burns, A., Cohen-Mansfield, J., Cooper, C. and Costafreda, S.G., 2020. Dementia prevention, intervention, and care: 2020 report of the Lancet Commission. The Lancet, 396(10248), pp.413-446.

Shi, Y., Suk, H.I., Gao, Y., Lee, S.W. and Shen, D., 2019. Leveraging coupled interaction for multimodal Alzheimer’s disease diagnosis. IEEE transactions on neural networks and learning systems, 31(1), pp.186-200.

Shastry, K.A., Vijayakumar, V., V, M.K.M., BA, M. and BN, C., 2022, September. Deep Learning Techniques for the Effective Prediction of Alzheimer’s Disease: A Comprehensive Review. In Healthcare (Vol. 10, No. 10, p. 1842). MDPI.

Spasov, S.E., Passamonti, L., Duggento, A., Lio, P. and Toschi, N., 2018, July. A multi-modal convolutional neural network framework for the prediction of Alzheimer’s disease. In 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 1271-1274). IEEE.

Lee, E., Choi, J.S., Kim, M., Suk, H.I. and Alzheimer's Disease Neuroimaging Initiative, 2019. Toward an interpretable Alzheimer's disease diagnostic model with regional abnormality representation via deep learning. NeuroImage, 202, p.116113.

Surianarayanan, C., Lawrence, J.J., Chelliah, P.R., Prakash, E. and Hewage, C., 2023. Convergence of Artificial Intelligence and Neuroscience towards the Diagnosis of Neurological Disorders—A Scoping Review. Sensors, 23(6), p.3062.

Brown, R.C., Lockwood, A.H. and Sonawane, B.R., 2005. Neurodegenerative diseases: an overview of environmental risk factors. Environmental health perspectives, 113(9), pp.1250-1256.

Colligris, P., Perez de Lara, M.J., Colligris, B. and Pintor, J., 2018. Ocular manifestations of Alzheimer's and other neurodegenerative diseases: the prospect of the eye as a tool for the early diagnosis of Alzheimer's disease. Journal of ophthalmology, 2018.

Li, X., Qiu, Y., Zhou, J. and Xie, Z., 2021. Applications and Challenges of Deep Learning Methods in Alzheimer's Disease Multi-Source Data Analysis. Current Genomics, 22(8), p.564.

Trimpl, M.J., Primakov, S., Lambin, P., Stride, E.P., Vallis, K.A. and Gooding, M.J., 2022. Beyond automatic medical image segmentation—the spectrum between fully manual and fully automatic delineation. Physics in Medicine & Biology, 67(12), p.12TR01.

Frozza, R.L., Lourenco, M.V. and De Felice, F.G., 2018. Challenges for Alzheimer's disease therapy: insights from novel mechanisms beyond memory defects. Frontiers in neuroscience, 12, p.37.

DeTure, M.A. and Dickson, D.W., 2019. The neuropathological diagnosis of Alzheimer's disease. Molecular neurodegeneration, 14(1), pp.1-18.

Arafa, Doaa & Moustafa, Hossam El-Din & Ali-Eldin, Amr & Ali, Hesham. (2022). Early detection of Alzheimer's disease based on the state-of-the-art deep learning approach: a comprehensive survey. Multimedia Tools and Applications. 81. 1-42. 10.1007/s11042-022-11925-0.