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entitled

Alzheimer's Disease Recognition Using Machine Learning

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Dedication

To my dearest parents, sisters, and husband Nejmeddine,

Your strong love and support have been a constant in my life.

I will be always thankful for all of the sacrifices you made to assure my fulfillment and achievement.

I would not be where I am now without your consistent support and confidence in me.

The present effort is dedicated to you as a symbol of my gratitude for everything you've done for me.

I hope it offers you happiness and reminds you of how great you are adored.

With all my heartfelt love and appreciation.



Thanks

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List of Acronyms

AD Alzheimer's Disease

AD Deep Learning

DNN Deep Neural Network

ANN Artificial Neural Network

MCI Mild Cognitive Impairment

AI Artificial Intelligence

ML Machine Learning

FE Features Extraction

MI Medical Images

MMSE Mini Mental State Examination

MRI Magnetic Resonance Imaging

PET Positron Emission Tomography

SVM Support Vector Machine

CNN Convolutional Neural Network

RBM Restricted Boltzmann Machine

DBN Deep Belief Network

ROI Region Of Interest

BP Back-Propagation

ADNI Alzheimer's Disease Neuroimaging Initiative

MLP Multi Layer Perception

FC Fully Connected

GUI Graphical User Interface

DA Data Augmentation

■ Introduction

"In 1906, Dr. Alois Alzheimer discovered Alzheimer's Disease (AD). The discovery was made through the examination of a patient named Auguste Deter, who had been experiencing memory loss and unusual behaviors since 1901. Auguste Deter passed away in 1906 at the age of 51. The pathological findings from her case were linked to clinical symptoms of dementia" [1].



Figure 1. *Dr Alois Alzheimer [2]*

Today, over 110 years later, AD is a devastating disease that affects more than 46.8 million people worldwide[1]. An estimated 6.7 million Americans age 65 and older are living with AD in 2023.

About 1 in 9 people age 65 and older (10.7%) has AD. Seventy-three percent are age 75 or older. Almost two-thirds of Americans with AD are women. Older Black Americans are about twice as likely to have AD or other dementias as older Whites. Older Hispanics are about one and one-half times as likely to have Alzheimer's or other dementias as older Whites[3]. The diagnosis can be established by detecting atrophy (shrinkage) in the hippocampus and entorhinal cortex, both of which are key brain areas for memory creation and consolidation. Furthermore, Medical Images (MIs) play a role in the process of diagnosing and analyzing medical conditions. This technique can identify modifications to cortical thickness, which may suggest neuronal damage or death. However, current Deep Learning (DL) and Machine Learning (ML) techniques are used in the analysis of MIs. The aim of this research is to develop an automatic system that can accurately identify and categorize AD through the analysis of MRIs. This report is organized as follows:

Chapter One serves as an introduction to various key aspects of AD. It delves into the factors that play a role in the development of AD, sheds light on the increasing number of AD cases, and on the resulting economic impact. Additionally, the chapter explores the research axes and domains relevant to AD, and the screening methods for AD. Finally, it describes the changes that occur throughout the progression of the disease.

Chapter two describes the related researches and introduces two Machine Learning methods and three powerful DL models. For each model, we presented two old studies showing theirs accuracy. These models have made great addition in this field and show great potential in different applications.

Chapter three presents the Proposed Model in this work. In this chapter, we presented the System Architecture, the Data Acquisition, Features extraction, Multi Layer Perceptron for classification, Evaluation Metrics, Experiments and evaluations. Additionally, two Graphical User Interfaces (GUIs) realised by Gradio library will be presented. Finally, the report will be concluded with a general conclusion.

Chapter

1

Alzheimer's Disease

1.1 *Introduction*

AD is a common and challenging form of dementia. We need to understand its causes, address the rising number of cases, represent its economic impact, and identify research and domains axes, and some of its screening methods. By studying the factors involved, responding to the increasing cases, evaluating the economic consequences, focusing research efforts, and improving screening techniques, we can make progress in dealing with AD.

1.2 *Factors Contributing to Alzheimer's Disease*

AD remains a prevalent and devastating form of dementia with no known cure, primarily affecting the elderly population. The lack of advancements in diagnosing and treating this disease compounds the issue. It is influenced by various factors, including an increased risk with age and genetic anomalies. However, wrong habits including a lack of physical activity and a bad diet were related to an elevated probability of the illness. Certain health issues, such as hypertension and diabetes, can lead to it too. Furthermore, scientific research has confirmed that modifications in the brain, such as the formation of beta-amyloid plaques and neurofibrillary tangles, are connected to the progression of AD. Although the exact cause of the disease is unknown, it is likely a combination of these factors.

1.3 *Rising Alzheimer's Cases and Economic Impact*

The prevalence of AD and related conditions is expected to significantly increase among individuals aged 45 to 65, reaching an estimated 13 million cases by the end of 2050. These predictions indicate a worrying surge in the occurrence of this severe ailment among adults in their middle age. Furthermore, the economic burden associated with Alzheimer's and its related conditions is predicted to surpass 321

billion USD by 2022, with estimates indicating a big increase of over 1 trillion USD by the year 2050. The increasing costs highlight the significant financial burden that healthcare systems, families, and society will face.

1.4 Research Axes

Several interesting paths of research in AD diagnosis and prediction have been explored. Computer aided methods for early AD prediction, for example, involve the deployment of neural networks, particularly Convolutional Neural Network (CNN), using MRI Datasets. Another potential technique is the use of Transfer Learning (TL) and pre-trained health data categorization models, such as MobileNet and InceptionV3, which have proven a rise in AD diagnosis. Researchers are also currently testing and comparing several models for Alzheimer's stage categorization using performance indicators to discover the best accurate technique for diagnosis. Furthermore, the creation of innovative frameworks for identifying distinct phases of AD has the potential to allow for earlier intervention and improved treatment results.

Finally, these study subjects clarify the ongoing efforts to enhance our ability to detect and treat AD, to enhance treatment results and quality of life for individuals impacted by this terrible disease.

1.5 Research Domains

Machine Learning is being utilized to diagnose AD from medical pictures in the domains of Artificial Intelligence(AI), ML, Medical Imaging(MI), and neuroscience.

In medical image processing, AI and ML are used to create algorithms that can automatically evaluate and categorize medical pictures, including brain scans. These algorithms are capable of detecting patterns and variations in brain imaging that might suggest AD. These methods produce comprehensive pictures of the brain that aid in the identification of anatomical and functional alterations associated with AD. Because of the widespread use of methods such as MRI and Positron Emission Tomography(PET) , MI is an essential tool in the diagnosis of AD. DL has considerable potential as a study topic for recognizing AD using ML algorithms. Researchers can explore brain scan images using Deep Neural

Networks(DNNs) such as CNNs to automatically extract significant characteristics and identify between healthy and Alzheimer's patients. Neuroscientific research also helps us understand AD, including biomarkers that can be used to diagnose it. This information may be utilized to create ML algorithms that can detect biomarkers in medical photos.

- **Artificial Intelligence:** It refers to machines that can take in and interpret data from the actual world to make judgments that help achieve a certain objective. Chatbots and image and speech recognition technology are examples of AI applications in use today.
- **Machine Learning:** It entails training algorithms and software to learn from data and complete tasks without explicit developer instructions. The efficacy of ML algorithms is closely related to the quality of the data on which they are trained. As a result, the quality and relevance of the data utilized in ML training are critical to the performance of the final algorithm.
- **Medical Imaging:** The use of different imaging methods, such as MRI, to create pictures of the internal structures and functioning of the human body. The fundamental goal of MI is to allow healthcare professionals to non-invasively evaluate the body's tissues, organs, and bones to collect important data for diagnosis, treatment, and monitoring of medical disorders.
- **Neuroscience:** It is the scientific study of the nervous system and its different components, including the brain, spinal cord, and nerves, to understand how they operate and how they link to behavior, cognition, and other aspects of human experience.

1.6 Screening Alzheimer's Disease

Screening for AD is employing several tests and evaluations to detect early indicators of the illness before it progresses. AD screening tests may involve cognitive evaluations such as memory and problem-solving tasks, as well as brain imaging studies to determine illness-related brain modifications.

It should be noted that AD screening is not a conclusive diagnostic process. Screening tests may help medical professionals in determining if additional examinations are required to confirm a diagnosis of AD or other cognitive disorders. There are many important screening procedures for AD like:

- **Cognitive Evaluations:**

These evaluations are used to assess a person's thinking abilities, like memory, problem-solving, attention, and language skills. One common test used for this purpose is the Mini Mental State Examination (MMSE), shown as an example in figure 2. It helps measure how well someone's brain is functioning and can detect any cognitive issues or changes over time. By looking at different aspects of cognition, these evaluations give useful information about a person's mental strengths and weaknesses, which can guide appropriate care and interventions if needed.

Screening Tool: The Mini-Mental State Examination (MMSE)

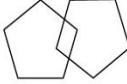
Patient _____	Examiner _____	Date _____
Maximum	Score	
5	5	Orientation <ul style="list-style-type: none">• What is the (year) (season) (date) (day) (month)?• Where are we (state) (country) (town) (hospital) (floor)?
3	5	Registration <ul style="list-style-type: none">• Name 3 objects: 1 second to say each. Then ask the patient all 3 after you have said them. Give 1 point for each correct answer. Then repeat until he/she learns all 3. Count trials and record. Trials _____
5	5	Attention and Calculation <ul style="list-style-type: none">• Serial 7's. 1 point for each correct answer. Stop after 5 answers. Alternatively spell "world" backward.
3	3	Recall <ul style="list-style-type: none">• Ask for the 3 objects repeated above. Give 1 point for each correct answer.
2	1	Language <ul style="list-style-type: none">• Name a pencil and watch.• Repeat the following "No ifs, ands or buts."
3	1	<ul style="list-style-type: none">• Follow a 3-stage command: "Take a paper in your hand, fold it in half and put it on the floor."• Read and obey the following CLOSE YOUR EYES.
1	1	<ul style="list-style-type: none">• Write a sentence.
1	1	<ul style="list-style-type: none">• Copy the design shown. 
Total Score		
ASSESS level of consciousness along a continuum _____		
Alert Drowsy Stupor Coma		
Used with permission.		
more information on reverse ➔		

Figure 2. Mini-Mental State Examination [4]

- **Brain Imaging:** Magnetic Resonance Image(MRI) and Positron Emission Tomography(PET) scans may be employed to detect brain abnormalities associated with AD.

– **Magnetic Resonance Image:** It is a medical imaging technique used in medicine that utilizes a strong magnetic field plus radio waves to produce detailed pictures of inside organs. It is currently among the most widely used imaging modalities for both diagnosing and tracking the advancement of AD. MRI could show abnormalities in the structure of the brain that are related to AD, such as shrinkage of certain parts of the brain. The figure 3 represents an MRI showing the structure of the brain in a normal person versus a person affected by AD.

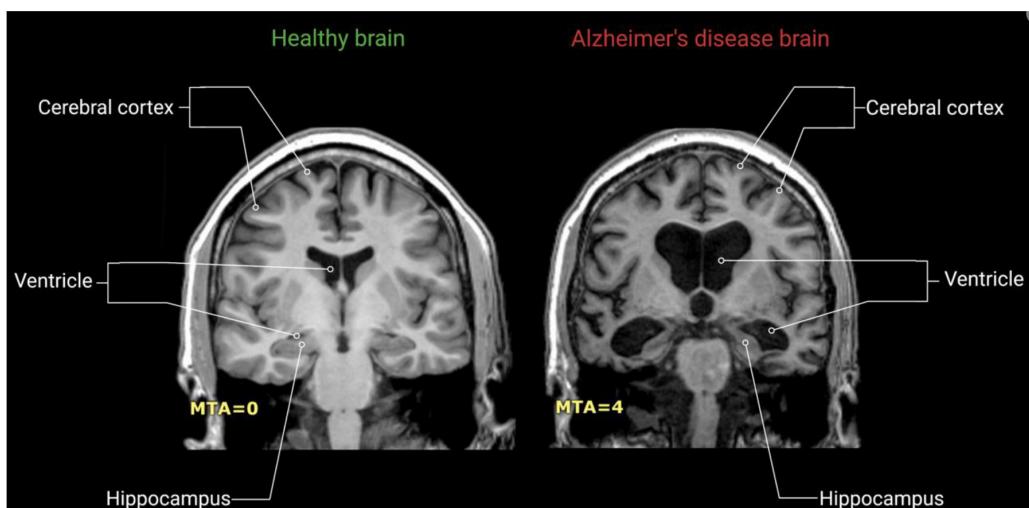


Figure 3. Normal person VS AD person [5]

– **Positron Emission Tomography:** It's a medical imaging technique that employs a small quantity of radioactive material to provide pictures of the body's interior structures and processes. A bit of radioactive material, termed the radiotracer, may be injected inside the human body or drank orally before a PET scan. It generates positrons, which have positive charge particles which interact with electrons in the human system to create gamma rays. A PET scanner detects these gamma rays and utilizes the data to build pictures of the body's interior structures as well as functions. This scan can identify variations in the structure and function of the brain, such as variations in the dimensions and forms of

brain areas, which are frequently linked with brain atrophy. The photo 4 represents two PET scans of 2 patients.



Figure 4. Normal Person VS AD Person

- **Pathological Changes in Alzheimer's Disease: Amyloid Plaques and Neurofibrillary Tangles**

- **Tau Protein and Beta-Amyloid Protein**

Tau Protein and Beta-Amyloid Protein are biological markers detected in the blood that can be utilized to identify early signs of AD. They are two common indications. Beta-amyloid is a protein that occurs naturally in the body when a bigger protein known as amyloid precursor protein is split. It is removed from the brain in several ways in healthy people.

However, for people whose affected by AD, their beta-amyloid builds up in the brain, producing clumps that can expand into bigger formations known as plaques. Tau protein is typically involved in the stabilization of the structure of nerve cells in the brain, however, it can become changed and lose its normal function in AD. The abnormal tau proteins can then group and create tangles, interfering with nerve cell function and ultimately damaging them. This is a figure 5 showing the pathological changes of Amyloid plaques and Neurofibrillary tangles.

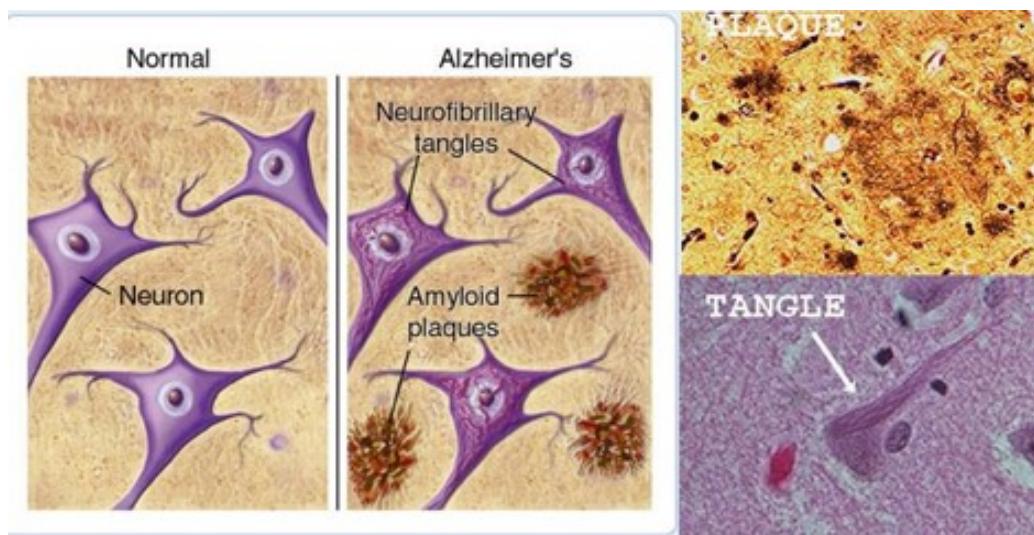


Figure 5. Identification of the Characteristic Pathological Changes of amyloid plaques and neurofibrillary Tangles[6]

– Neuronal Death and Brain Shrinkage

In AD, the accumulation of beta-amyloid plaques and tau protein tangles can lead to neuronal death. This neuronal death can result in brain tissue loss, resulting in a reduction in brain volume, which is commonly referred to as "Brain Shrinkage". Brain shrinkage often affects many sections of the brain, such as the hippocampus, entorhinal cortex, and other cerebral cortex regions. These parts of the brain are critical for memory, learning, and other cognitive function. Brain tissue loss is frequently connected with cognitive decline, including memory loss, disorientation, and difficulties with everyday tasks. The following figure 6 shows the changes that occur throughout the progression of the disease.

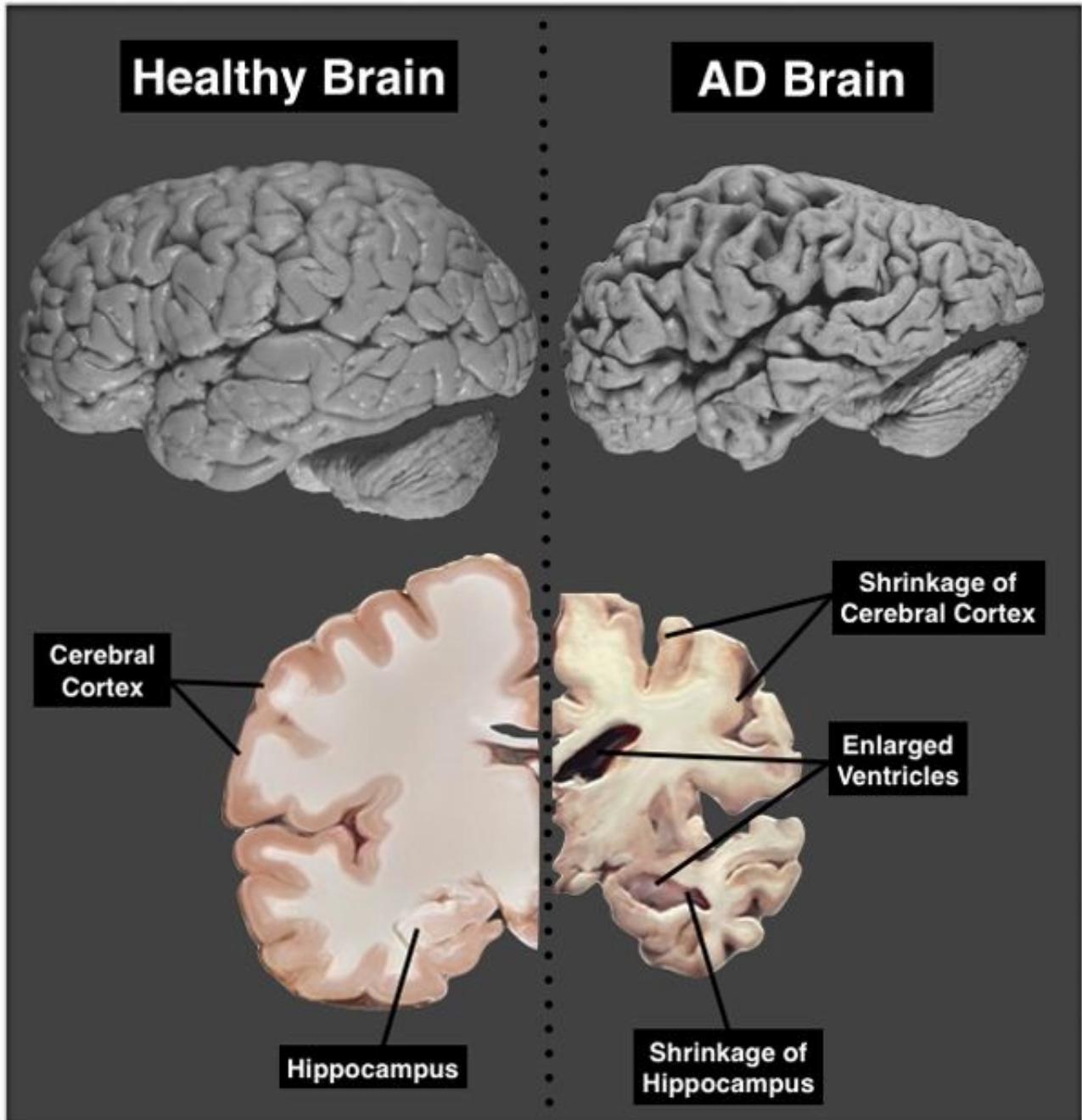


Figure 6. The changes that occur throughout the Progression of the Disease [7]

1.7 Conclusion

In conclusion, AD is a popular and severe form of dementia that has no known cure due to population aging and a lack of innovative discoveries to identify and cure this type of disease. Researchers in the field of Health and AI are working to make progress in developing computer-aided systems for early detection, also, scientists are working hard to create a cure for this phenomenal disease. They

are working on different research axes which are: Computer-aided methods for early AD prediction using AI, the use of Transfer Learning and pre-trained health data categorization models, testing and comparing different models for Alzheimer's stage categorization using performance indicators, also, the creation of innovative frameworks for identifying distinct phases of AD to allow for earlier intervention.

However, they are working to increase the capacity to identify and treat AD, as well as to improve the quality of life for those affected by the illness. To increase the accuracy and efficacy of diagnostic tools, researchers in the field of AD detection are integrating advanced technologies like AI, ML, DL, and neuroscience. The capacity of AI and ML algorithms to scan massive volumes of medical data and detect patterns allows for early detection of those at high risk of developing AD. Furthermore, DL, a subset of ML, can discover subtle patterns that standard analytic approaches may miss. Neuroscience research is looking at the fundamental causes of AD, which might lead to novel diagnostic tools. Finally, It is crucial to remember that AD screening is never a definite diagnostic method.

Chapter

2

Related Work

2.1 *Introduction*

In the field of AI, we note that there are two subsets named ML and DL models. However, ML is a subtype of AI that enables machines to learn through data and produce predictions or conclusions based on this data. Furthermore, the technique of DL, which is additionally referred to be deep structured study or hierarchical learning, employs an extensive amount of hidden layers to retrieve characteristics from input and turn the data into various degrees of representation [8]. The following figure 7 presents the techniques mentioned previously.

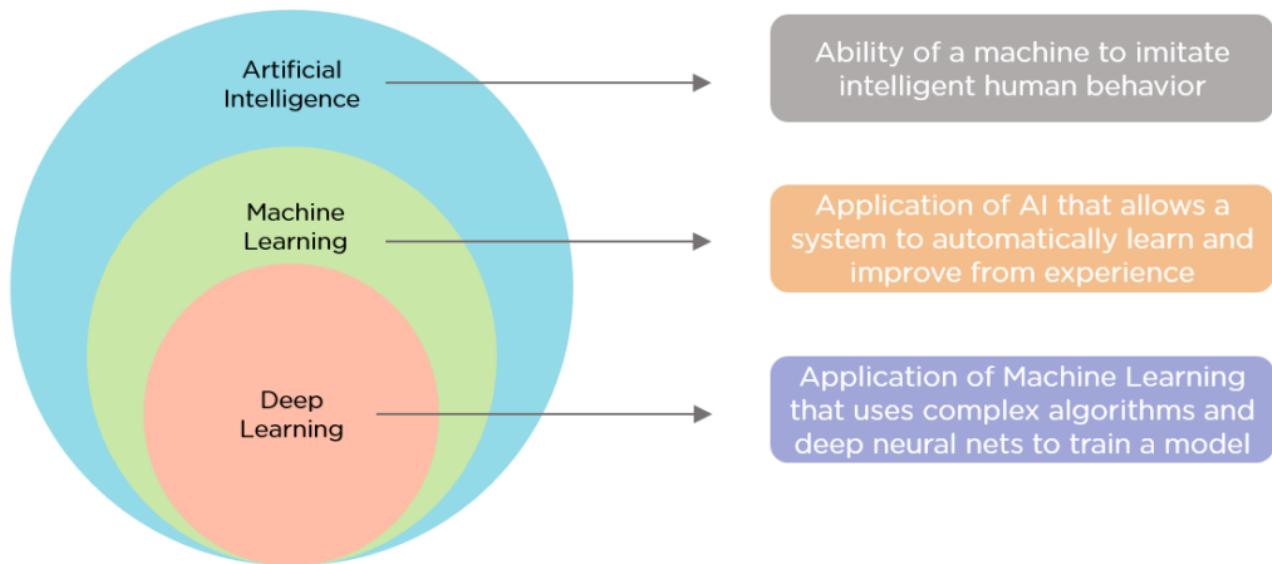


Figure 7. Artificial Intelligence: Machine Learning vs Deep Learning [9]

Now, we will explore these two terms better :

- **Machine Learning:** It is defined as a discipline of artificial intelligence (AI) that provides machines the ability to automatically learn from data and past experiences to identify patterns and make predictions with minimal human intervention[10].

- **Deep Learning:** This represents a subsection of ML where algorithms are trained to achieve complicated duties such as image recognition. Its algorithms are designed after the architecture and function of a person's brain, and they analyze and gain knowledge from vast volumes of data by employing layers of linked neurons. Its networks can learn data structure representations, which means they can discover patterns and characteristics at many levels of complexity.

2.2 Machine Learning Models

2.2.1 Support Vector Machines

Support Vector Machines(SVMs) are supervised learning algorithms that may be used for classification problems. The primary principle underlying SVMs is to identify a hyperplane that separates each class in the training data as much as possible. SVMs rely on specific points known as "support vectors" or "nodes" to effectively categorize and separate data points in complicated, high-dimensional domains. SVMs establish decision boundaries that maximize the margin between various classes by carefully inserting these support vectors, allowing for successful classification. To do this, SVMs find the hyperplane with the greatest margin, defined as the distance that exists that separates the hyperplane and the nearest data points from the various classes. After finding the hyperplane, fresh data may be categorized by determining which side of the hyperplane it appears on. This algorithm is very useful when the data contains numerous characteristics or has a clear margin of distinction, or when it has both. The following figure 8 shows an example of an SVM with several classes equal to 2.

"Bansal.D, Khanna.k, and Al, (2020), [12], using MRI, the authors proposed a technique for identifying Dementia brain trouble. They utilized the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. They used, also, the Bag of Features technique to extract features from MRI data. Using a multi class SVM, the scans are then classified into three groups: demented, mild cognitively impaired, and normal controls. The experimental findings show that the suggested technique performs competitively in terms of classification accuracy by 86%."

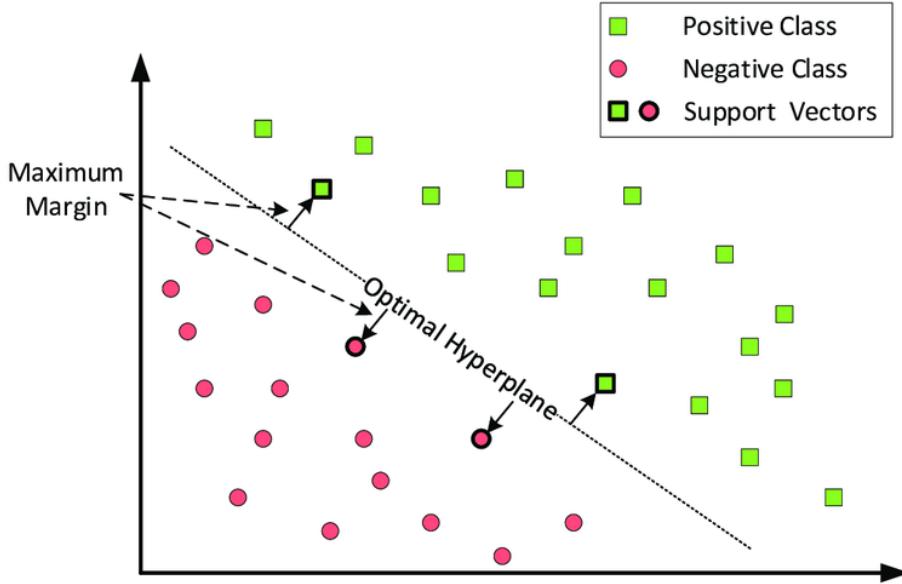


Figure 8. An example of SVMs with two classes [11]

” Tian.J, Smith.G, and Al, (2021) [13] employed a Convolutional Neural Network for feature extraction from retinal images and utilized an SVM classifier. The dataset used was the UK Biobank dataset. The machine learning achieved an average classification accuracy of 82.44%.”

2.2.2 Multi-Layer Perceptron

Multi-Layer Perceptron (MLP) is an artificial neural network with several layers. It is made up of many nodes. MLP is made up of an input layer that receives the feature vector, an output layer that makes a judgment or prediction about the input, and a choice of hidden layers that serve as the MLP’s real computational engine. They are frequently used to solve supervised learning challenges. They learn to predict the correlation between inputs and outputs by training on a collection of input-output pairings. Training entails modifying the model’s parameters, or weights and biases, to decrease errors. The input layer takes input data, which is later processed by the hidden layers via calculations conducted by nodes linked to one another with attached weights. Non-linearity is introduced into the model using activation functions. The ultimate result of the MLP is produced by the output layer, with the number of nodes based on the number of classes in the classification problem. MLP is extensively used for a broad range of applications, including image recognition, speech recognition, and many

others, but it has significant disadvantages, such as overfitting, which may be overcome by employing regularization techniques. The following figure 9 represents an MLP architecture.

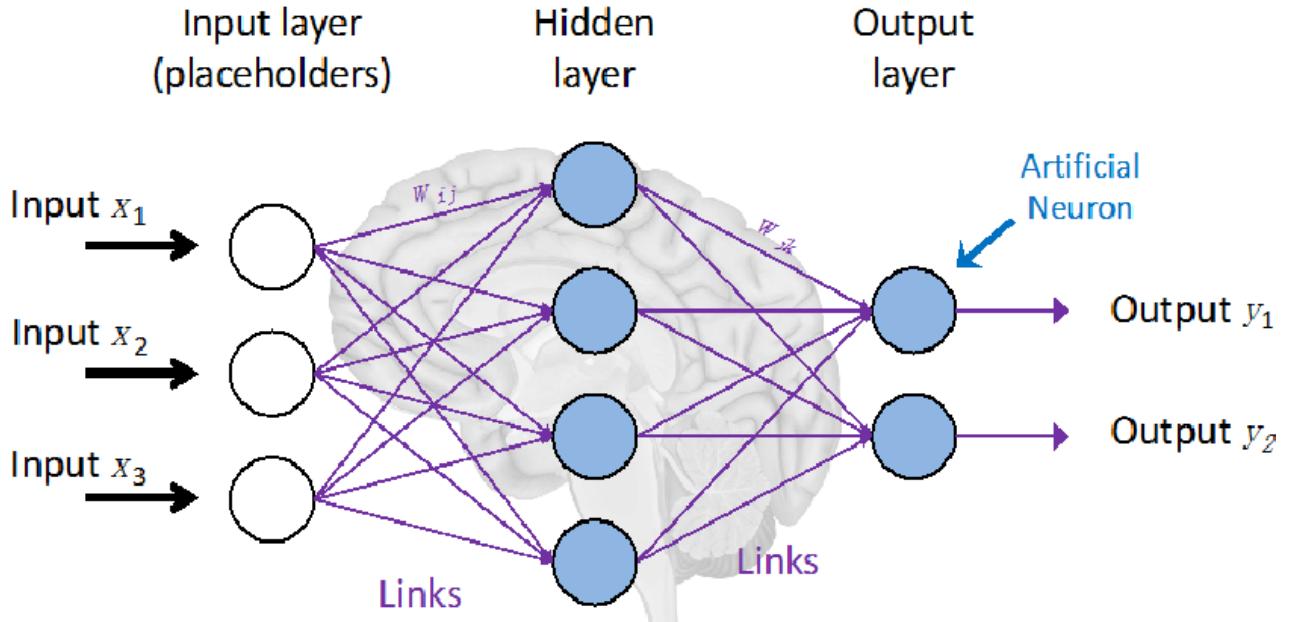


Figure 9. An example of MLP with two classes [14]

”Liu.M, Li.F and Al, (2020) [15], proposed a multi-model deep learning framework for joint hippocampal segmentation and AD classification using structural MRI data. The method incorporates a multi CNN model for hippocampal segmentation and disease classification, followed by a DenseNet for feature extraction from segmented regions. By combining the learned features from both models and using MLP as a classifier, the proposed method achieved an accuracy of 92.5% for AD vs NC classification, and an accuracy of 77.5% for MCI vs NC classification on ADNI database. The results demonstrate superior performance compared to single model methods and other competing approaches.”

”Raju.M, Gopi.V, and Al, (2021), [16] used the Convolutional Neural network for the features extraction, and an MLP classifier. The dataset utilized in the study contains Structural MRI scans from people from the ADNI dataset at various cognitive stages, including Cognitive Normal, Mild Cognitive Impairment, and AD. The MLP classifier performs multi-level classification. They achieved 96.66% as classification accuracy. The study demonstrates that the suggested technique properly identifies disease severity levels and aids in the diagnosis of the condition at an earlier phase.”

2.3 Deep Learning Models

2.3.1 Convolutional Neural Network

It is a deep neural network model that is extensively used for image and video recognition, classification, and processing. In order to extract characteristics from the input data, the network employs a hierarchical layer structure. Each model layer learns to detect more complex traits in the data it receives. Its utility is divided into two parts:

The first part is termed Features Extraction (FE) operation, and the second part is called classification procedure. However, the FE stage includes extracting the most informative characteristics from input photos, but the "classification" step, following a learning phase, uses an MLP model to give a label for every test data sample according to its class belonging[17]. Talking about the architecture of CNN in extracting features part: This model architecture is composed of different types of layers that execute operations on the input data. The first layer represents a convolutional layer that applies a series of adjustable filters to the input picture, resulting in a set of feature maps that highlight various features of the image. The second layer is often, a pooling max or avg layer. This layer has the role of reducing the dimensions of its input features map or an activation layer that applies non-linearity to the model by applying an activation function (such as ReLU) to the output of the preceding layer. Next, we have the flattening layer employed to turn the preceding layer's multidimensional output, which is often a convolutional layer, into a one-dimensional vector. This lets the flattened features be processed by the next fully linked layers. The last layers of a CNN are generally full layers that employ the information learned by the convolutional layers to produce a prediction about the received data. The figure 10 represents an example of CNN architecture:

"Fu'adah.Y, Wijayanto.I, and Al,(2021) [17], utilized an MRI dataset that was classified into 4 classes : [No demented, Mild demented, Very mild demented, and Moderate demented]. This dataset represents AD stages and named AD(4 stages). This study created an automated AD classification to categorize the 4 mentioned classes. They used CNN approach with AlexNet architecture for features extraction and a MLP for classification. They utilized 75% of the data as training data and the

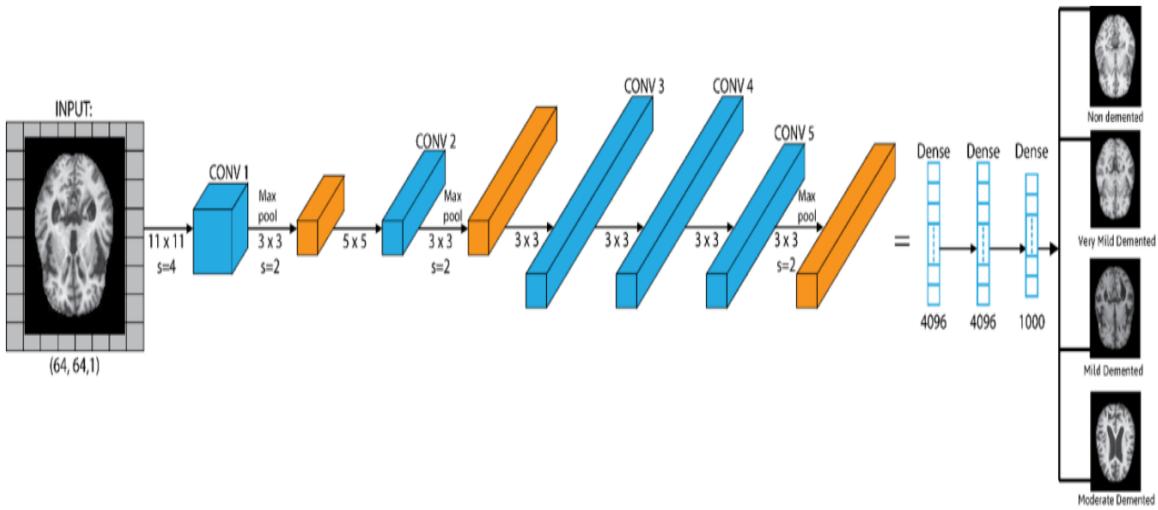


Figure 10. Example of CNN Architecture [18]

remaining 25% as validation data. A total of 498 MRI pictures were used as training data and 166 photos were put to use for validation. MRI images are trained using the AlexNet architecture with the Adam optimizer. They achieved the greatest accuracy of 95%.”

”Zaabi.M, Smaoui.N, and Al,(2020) [19], suggested a deep-based technique for AD by categorizing brain pictures as normal or AD brain. They did an experience using AlexNet for extracting features and MLP for classification. The researchers also utilized the Open Access Series of Imaging Studies dataset to evaluate the Transfer Learning technique, and the findings demonstrated a classification accuracy of 92.86%.”

2.3.2 Auto Encoder

The Auto Encoder (AE) is one of the common models used in the ML field for unsupervised learning missions. It’s an architecture of neural networks that learns to encode and decode data using an encoder and decoder network, with a bottleneck or latent space layer in the middle that creates a compressed representation of the input data. Based on the nature of the input data and the intended output, the encoder and decoder may be built using multiple kinds of neural network layers, like fully connected layers or convolutional ones. To reduce the reconstruction error among the input as well as the output, Auto-Encoders (AEs) are commonly trained via Back-Propagation(BP). An

AE's purpose is to learn a compressed representation of the input data which represents the most significant characteristics while reducing reconstruction mistakes among the input and output. It is used for complex tasks such as the extraction of features. It has been intensively investigated as a DL architecture for the diagnosis of AD. The use of AE for AD diagnosis was inspired by the need for reliable and automated approaches for the disease's early identification and prognosis. Several studies have employed AEs in the context of AD diagnosis to extract characteristics derived from imaging modalities such as MRI and PET and clinical data. The compressed representation of the input data from the bottleneck of AE is then fed into several ML approaches for AD identification, including as SVMs and MLPs. The figure 11 represents an AE architecture:

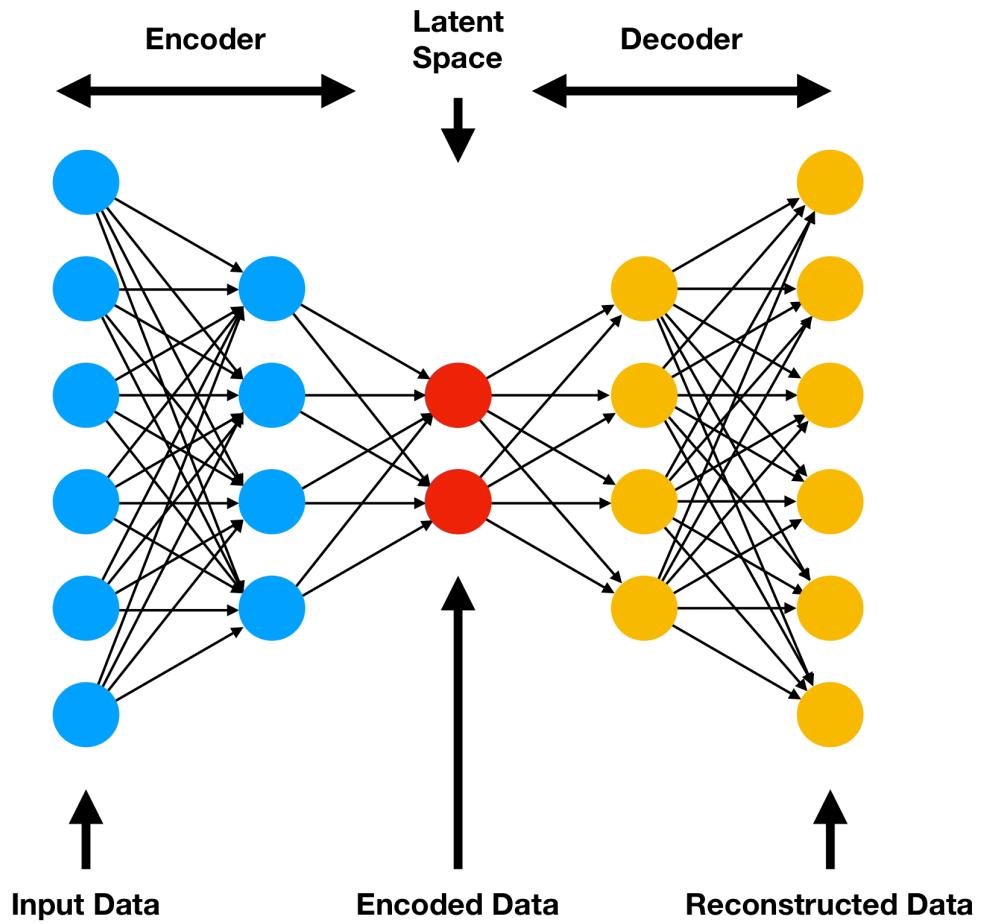


Figure 11. Autoencoder Architecture[20]

”Hedayati.R, Khedmati.M and Al, (2021)[21], proposed a two-step method for the diagnosis of AD using ML techniques. In the first step, an ensemble of convolutional auto encoders was used for feature extraction in order to generate image features from the input images. In the second step, they employed a convolutional neural network for features extraction, and MLP for classification, distinguishing between AD and Normal Condition (NC), AD and Mild Cognitive Impairment (MCI), and MCI and NC. The results demonstrate high accuracy rates of 95% for AD/NC, 90% for AD/MCI, and 92.5% for MCI/NC, indicating the effectiveness of the proposed method. This study was done using the ADNI dataset. It also highlights the method’s reliability in early-stage AD diagnosis and its ability to minimize errors in detecting the normal condition.”

”Tuan.P, Phan.T and Al, (2022) [22], utilized the ADNI dataset. The images include PET scans from Normal Control and AD brains. For the FE approach, this article is based on mapping the PET brain images into Regions of Interest (ROI). To extract features from the ROIs, they utilized many AEs. The connection weights learned from AEs are used to rank ROIs based on their network contribution. The top-ranked ROIs were sent into the SVM classifier as input features. The highest accuracy they achieved was 93.53%”.

2.3.3 Deep Belief Network

Deep Belief Networks(DBNs) are a form of the ANNs made up of numerous layers of linked neurons that are especially effective at learning hierarchical representations of input data that may be employed to extract high-level characteristics important for a variety of uses. They’ve performed well in a wide range of applications, including computer vision and voice recognition, as well as medical picture analysis, such as AD identification and classification.

Restricted Boltzmann Machines (RBMs) are neural networks with a relatively shallow architecture compared to DNNs. They play a crucial role in DBNs. RBMs consist of two layers: the visible layer, also known as the input layer, and the hidden layer. Each neuron-like unit or node in the RBM is represented by a circular shape. The connections between nodes exist between layers but not within the same layer. Many inputs from the visible layer are merged at each hidden node by multiplying

each input by its appropriate weight and summing the results. This sum is then added to the bias term of the node, and the result is then transmitted via the activation function to create the node's output and it is repeated several times.

The node's output is compared with the input data to calculate the loss. The weights and biases are then updated to reduce the error and ameliorate his RBM's ability to model the input data. An RBM's weights and biases are trained with contrastive divergence, a training technique that updates the weights to minimize the difference between what the model expects and the actual input data, they are trained layer by layer to extract high-level features from the input data. Each layer of a DBN is an RBM that is taught unsupervised using a training procedure called contrastive divergence. The Initial layer RBM receives the input data and teaches a set of features that are transmitted onto the following layer. The first layer's output is next fed into the next layer of RBM, which learns a collection of higher-level characteristics determined by the first layer's input. This procedure is repeated until the output of its final layer is fed into an algorithm with supervised learning, including a SoftMax classifier. DBNs are successful in extracting features from MRI data and may be used to extract relevant data from MRI data for a variety of applications, including AD diagnosis and classification. They are capable of learning complex representations of MRI data, such as the shape and intensity of brain structures, which can be used to identify small changes in AD. Among the advantages of using them for FE from MRI data is their ability to learn hierarchical representations of the information that is entered.

The figure 12 shows the DBNs Architecture :

” Faturrahman.M, Wasito.I, and Al, (2017) [24], proposed a classification method for AD based on Open Access Series Of Imaging Studies dataset using DBN for extracting features and SVM for classification. The proposed model achieved an accuracy of 92% in detecting AD using the MRI data”.

”In this study, Shen.T, Jiang.J and Al, (2019) [25] selected the data for this article from the freely accessible Alzheimer's Disease Neuroimaging Images dataset. To extract information from brain pictures, the researchers utilized DBN. They chose SVM for classification and they tested their model by classification accuracy and training cost. They discovered that increasing the number of network epochs resulted in improved accuracy and reduced training costs and when the number of epochs

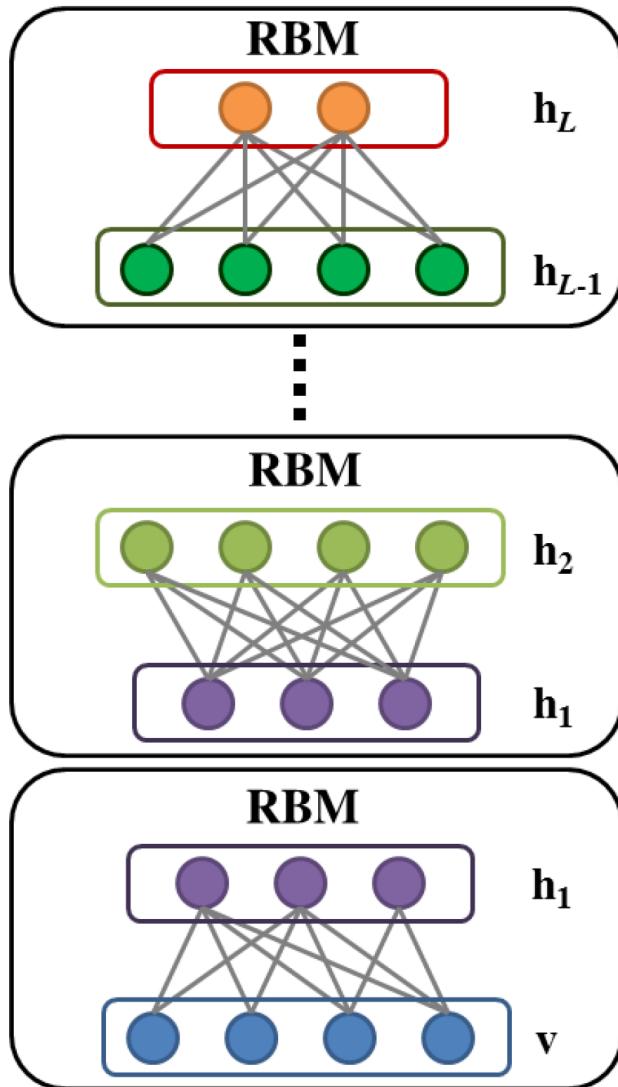


Figure 12. Deep Belief Network Architecture[23]

reached 90, stability was obtained, so, they picked that value for their tests. They achieved 86% accuracy in predicting AD from MCI.”

2.4 Conclusion

Following an examination of the related work on Multi Layer Perceptron, Support Vector Machines. It is possible to conclude that they are all strong ML algorithms that have been widely applied in a variety of situations. DL techniques such as Convolutional Neural Networks, Auto-Encoders, and

Deep Belief networks have produced impressive results in the past few years as well as are now commonly utilized in a variety of situations.

Proposed Model

3.1 *Introduction*

AD is an illness that affects the brain and produces memory and thinking problems. Early illness detection is critical, and ML is a technique that can assist with this. ML analyzes images of the brain, such as MRI scans, to identify patterns that suggest Alzheimer's disease. ML can detect the disease rapidly, even in its early stages. Abnormalities or changes in brain structure can be identified by employing MI analysis techniques by extracting data using a CNN and classifying with an MLP algorithm. In this work, our objective is to develop an efficient model that can aid in the early detection of this disease. To achieve this, we will commence by presenting the system architecture, describing the database utilized, and explaining the pre-processing techniques employed. Then, we will represent the Features Extraction phase, which allowed us to extract the essential characteristics, followed by the classification phase, which identifies the class of the input image. Finally, we will show the examination results.

3.2 *System Architecture*

The objective of this research is to create a system capable of classifying individuals as "Mild Demented," "Moderate Demented," "Non Demented," or "Very Mild Demented" based on images. The system consists of two stages. In the first stage, a CNN with the InceptionV3 architecture is employed to extract relevant features from the images. The subsequent stage involves using the MLP to classify the images. Figure 13 illustrates the architecture of the system utilized in our research for image classification.

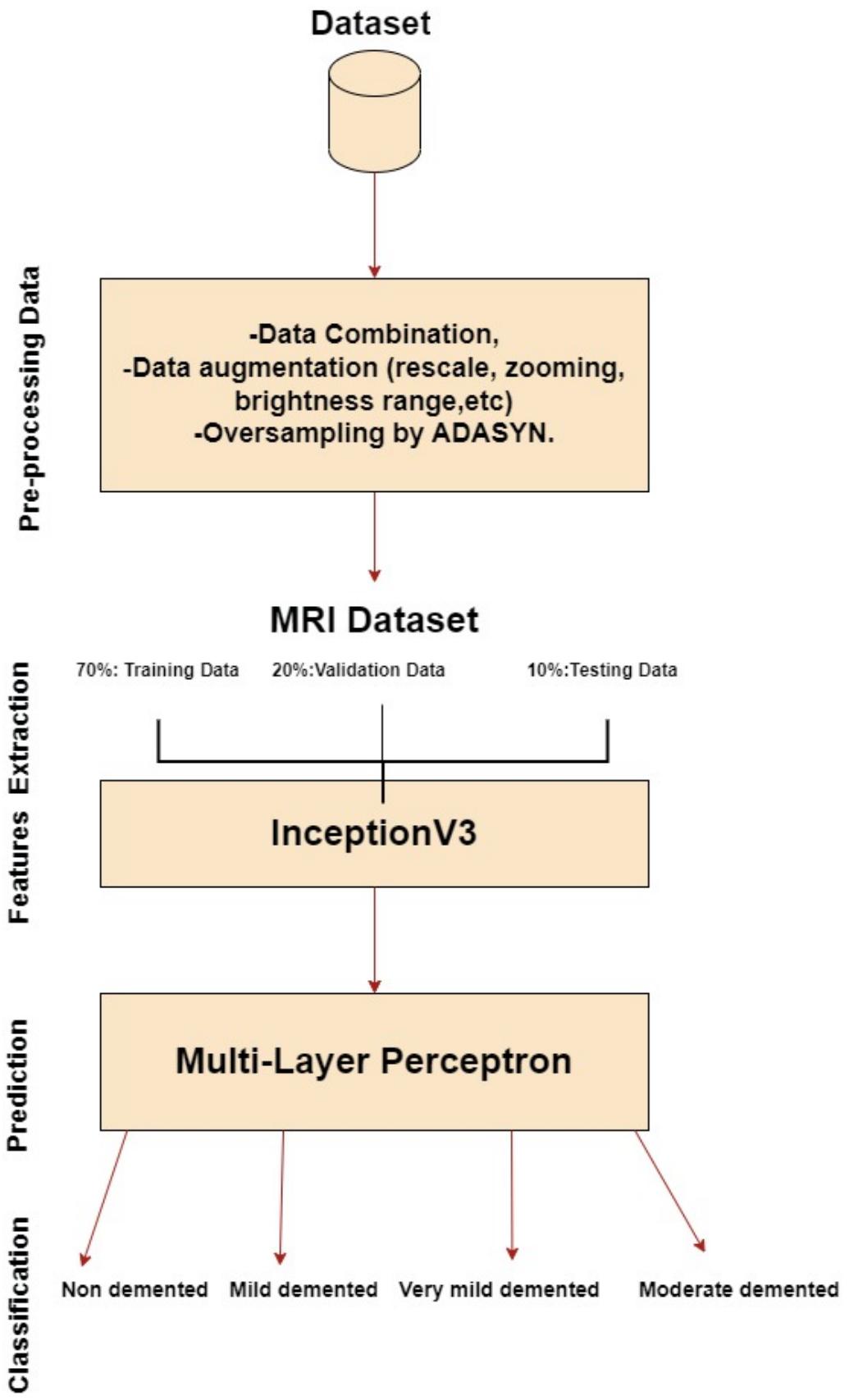


Figure 13. Architecture of Proposed Model

3.3 Data Acquisition

3.3.1 Database Description

3.3.1.1 Databases used in Alzheimer's Disease field

Many databases utilized in the field of AD including the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset [26], Open Access Series of Imaging Studies (OASIS) dataset [27], Australian Imaging Biomarkers and Lifestyle Flagship Study of Ageing (AIBL) dataset [28] and Dementia Bank dataset [29].

In this study, I've chosen a dataset containing 4 classes of images named "Alzheimer's Dataset (4 class of Images)" representing AD stages [30]. This dataset is collected by Sarvesh Dubey [31].

The shape of the images is a size of 176x208 pixels, and the image's mode is "L". "L" indicates "Luminance" and this signifies that the images are grayscale, and each pixel value reflects the level of brightness of the picture's and each pixel in the image is represented by 8 bits. The dataset contains two main subfolders: train and test folders. Within each subfolder, there are 4 other subfolders named 'Non-Demented', 'Very Mild Demented', 'Mild Demented', and 'Moderate Demented'. The dataset contains 6400 files. However, the training folder contains 5121 image files and the test folder contains 1279 images. The figure 14 shows an example of each class.

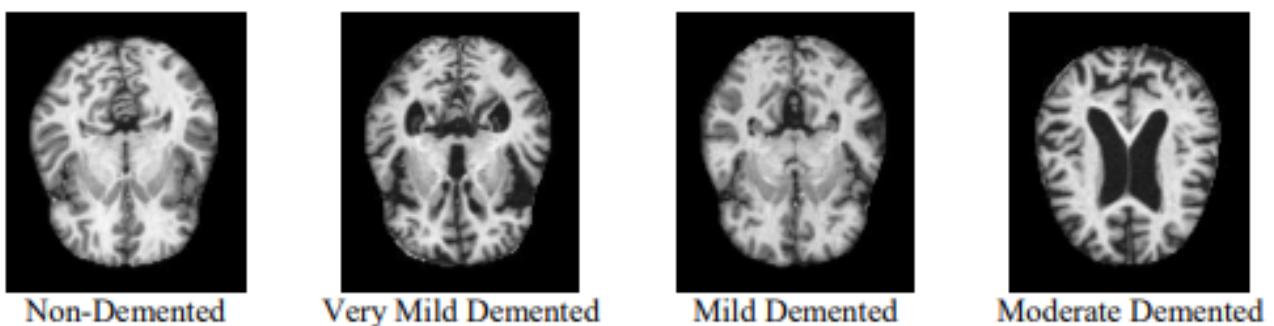


Figure 14. Images from the utilized Dataset[32]

The four classes in the dataset are described as follows:

- Nondemented:** The MRI of the brain typically shows a non-enlarged, symmetrical ventricles and a non-shrinking size of the cerebral cortex.

- Very Mild Demented:** The MRI of the brain shows a slightly bigger ventricles, and a small decrease in the size of the cerebral cortex.

- Mild Demented:** The MRI of the brain shows a slightly enlarged or asymmetrical ventricles and a mild shrinkage in the size of the cerebral cortex.

- Moderate Demented:** The MRI of the brain reveals a noticeably enlarged or asymmetrical ventricles, along with a significant reduction in the size of the cerebral cortex.

Each folder holds images that have been divided into classes, the distribution of those is shown in the following Table 1.

	Non Demented	Mild Demented	Very Mild Demented	Moderate Demented	Total
Train	2560	717	1792	52	5121
Test	640	179	448	12	1279
Total	3200	896	2240	64	6400

Table 1. *Original Dataset Images Distribution*

3.3.2 Image preprocessing

3.3.2.1 Data Combination

First of all, in order to enhance the training process and improve the system's generalization performance, we've created a new dataset named "New dataset". This involved merging the contents of the original train and test folders into a single folder, which included all four classes. By consolidating the data, the training dataset became larger, allowing the system to learn from a more extensive range of examples and variations. Finally, we presented the content of my "New dataset". The table 2 describes the new distribution of images in each class:

The bar chart shown in Figure 15 displays the distribution of pictures throughout the dataset's subfolders. From this bar chart visualization, we noticed that our dataset is imbalanced.

	Non-Demented	Mild Demented	Very Demented	Mild Demented	Moderate Demented	Total
Files Number	3200	896	2240	64		6400

Table 2. New Dataset Images Distribution

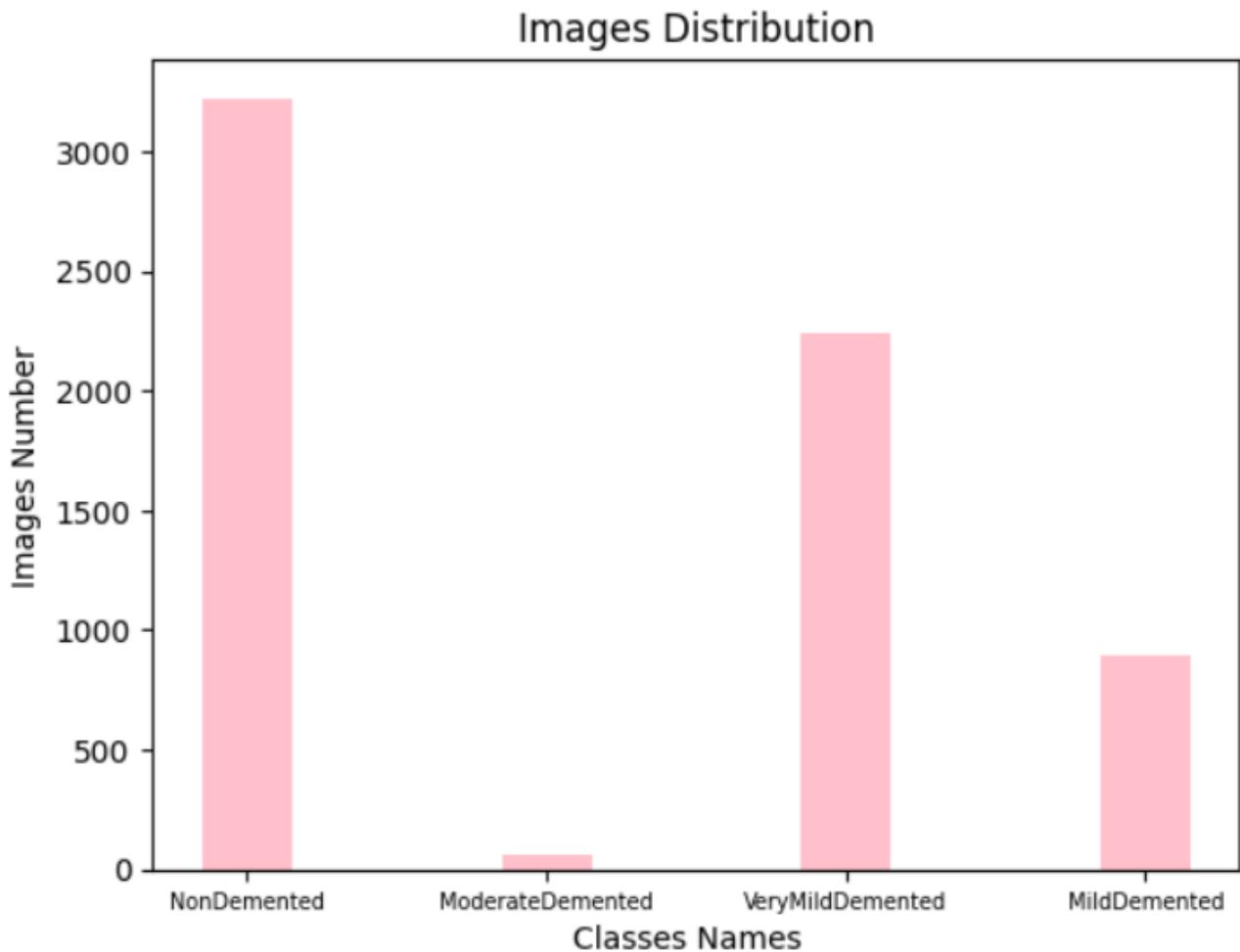


Figure 15. Image Distribution of New Dataset: Bar Chart visualization

3.3.2.2 Data Augmentation

In this part, we did the Data Augmentation (DA) to create more data samples. DA is a technique used in ML and DL to improve the amount and variety of a training dataset by modifying or transforming existing data samples. We set the size of the image to 160 by 160 pixels, and various transformations such as rescaling, zooming, brightness adjustment, data format, horizontal flipping using the Image Data Generator class from the Keras library. The zoom range parameter specifies the extent of zooming that can be applied to the images. It allows the images to be zoomed in or out within a

defined range, based on a multiplier of their original size. Also, the brightness adjustment parameter sets the range of brightness adjustments to be applied to the images. It allows the brightness to be varied within the range defined by the user. However, we defined the filling mode parameter for any newly created pixels during image transformations. In this case, we used "constant", meaning that the new pixels will be filled with a constant value. Additionally, we enabled the horizontal flipping of the images parameter. When set to True, the images can be flipped horizontally. Finally, the data format parameter defines the format of the input image data. In this case, we used "channels last", indicating that the input shape of the image data is expected to be in the format (batch size, height, width, channels). Our goal from this technique is to increase model performance and generalization by exposing it to a broader variety of variations and characteristics.

3.3.2.3 Oversampling

We applied the ADASYN algorithm to the augmented data and corresponding labels to balance the class distribution. This algorithm generates synthetic samples for the minority class. Then, we reshaped the resampled data to (160,160,3) to ensure that all the images have the same dimensions after oversampling and ready to be fed to the input layer of our features extraction model. Finally, these are the number of oversampled data instances and the corresponding label numbers:

- Number of samples: 12394
- Height of each image: 160
- Width of each image: 160
- Number of color channels: 3
- Number of labels: 4

3.3.2.4 Data Splitting

In this part, we split the data into three groups: training, validation, and testing data. We used the 'scikit-learn' library's 'train test split' function twice. First, we split the data into 90% for the train set

and 10% for the test set. Subsequently, we split the train set into 80% for the train set and 20% for the validation set. So, we allocated 70% of the data for training, 20% of the data for validation, and 10% of the data for testing. The figure 16 represents a pie chart created using Python and the matplotlib library to visualize the percentage of data that was split into the training, validation, and testing sets.

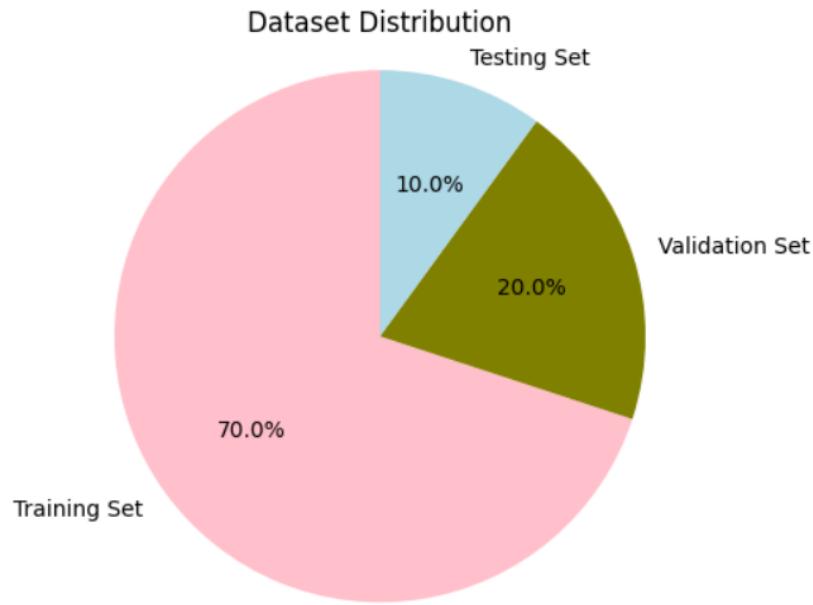


Figure 16. Distribution of the Split Dataset

The figure 17 represents a graphic representation of this operation:

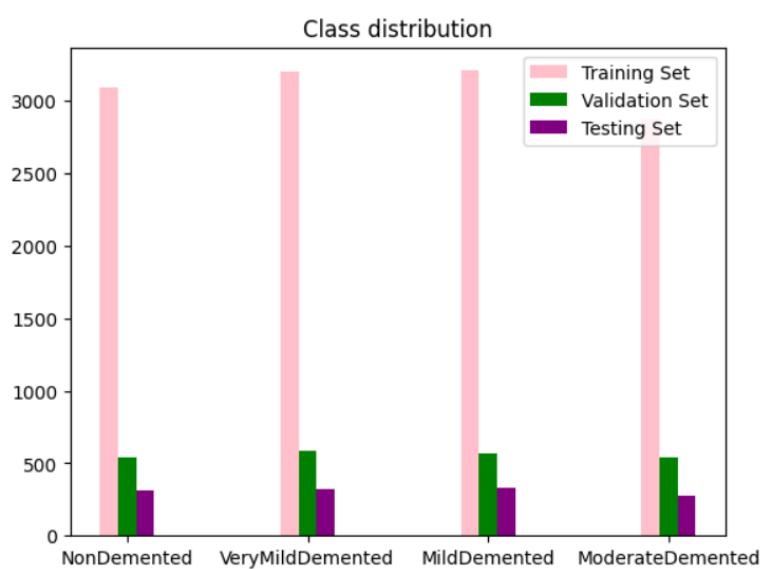


Figure 17. Bar chart Representation of the Images for each Class

The dataset looks to be balanced according to the class distribution, with relatively equivalent amounts of instances in all classes throughout the training, validation, and testing sets.

3.4 *Features extraction*

During this stage, we employed CNN with InceptionV3 architecture [33]. We loaded the InceptionV3 model structure through TensorFlow Keras applications module [34] and we created our model instance. We used the "input shape=(160, 160, 3)", "include top=False", and "weights=imageNet" [35] to set up the structure of the model. This implies that the model's input shape will be defined by size, the top fully-connected layers will be eliminated, and the model will be started with ImageNet pre-trained weights. We employed a pre-trained model to help me in preventing overfitting by employing it as an initial base for developing a fresh model. However, we took advantage of Transfer Learning by using the pre-trained weights and architecture of the InceptionV3 model. In Transfer Learning, a machine exploits the knowledge gained from a previous task to improve generalization about another[36]. Inception-v3 is an extended network of the popular GoogleNet [37]. It was developed by Google in 2015 [38]. It is an image recognition model that has been shown to attain greater than 78.1% accuracy on the ImageNet dataset[39]. The model is the culmination of many ideas developed by multiple researchers over the years [40]. It is an improved version of the Inception v1 and Inception v2 networks, with numerous architectural changes. Its architecture has a module known as the "Inception module", allowing the network to simultaneously learn and integrate many filters of varied sizes. This model is predefined with an input layer size of 299x299x3. It is composed of multiple stacked modules, each having a specific arrangement of stacked sub-modules. The sub-modules in Inception V3 are designed to capture information at different scales. Inception A sub-module consists of parallel branches with 1x1, 3x3, and 5x5 convolutions. The outputs of these branches are concatenated along the depth dimension to capture features from multiple scales. The concatenated feature maps are then fed into a grid size reduction module, which typically includes a 1x1 convolutional layer and a max or average pooling layer. This helps reduce spatial dimensions and increase depth. Inception B also follows a similar structure, but with different kernel sizes. It utilizes 1x1, 3x3, and 7x7

convolutions to capture details at different levels. The module C, primarily uses 1x1 convolutions for dimensionality reduction, along with 3x3 convolutions for capturing local details. This model employs a technique called factorized convolutions . It uses two separate convolutional layers, where the input is convolved first with a 7x1 filter to capture vertical features, and then with a 1x7 filter to analyze horizontal features. It contains two auxiliary classifiers placed at specific points within the network. These classifiers help in the training process by comparing their predictions to the actual labels and updating the network's parameters accordingly. The final predictions are made using the main classifier of the network. The following figure 18 shows the proposed architecture of the model.

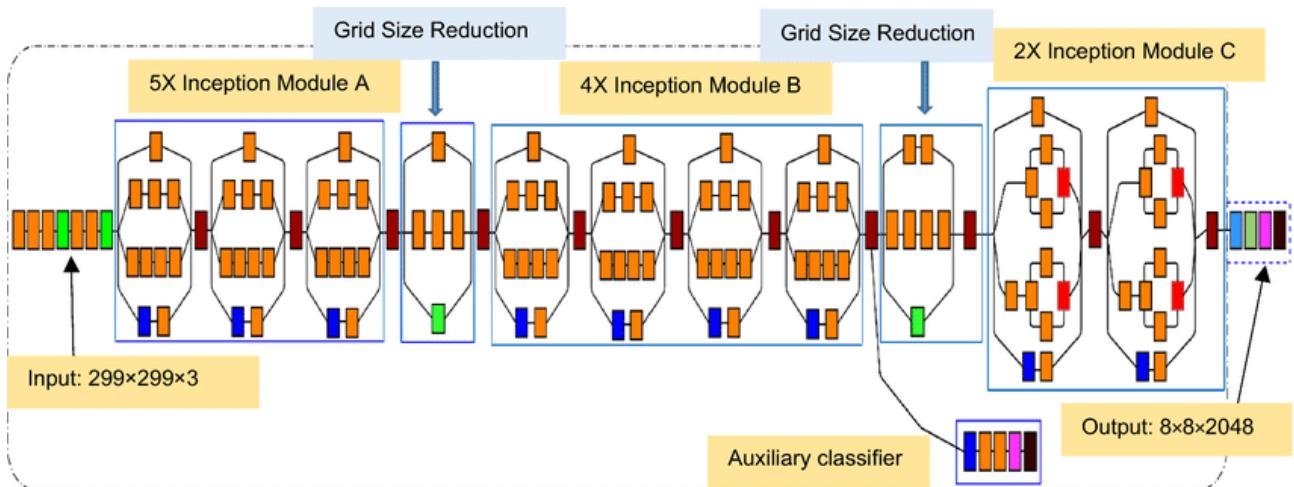


Figure 18. A Basic Representation of Pre-trained InceptionV3 Architecture [41]

The following table 3 shows the components of the Inception-V3 Model.

As reported in [42], the Inception V3 architecture contains 42 layers in total.

3.5 Multi Layer Perceptron for Classification

In the late 1950s, Marvin Minsky and Seymour Papert invented this form of neural network named the Multi layer Perceptron(MLP) [43]. In the area of classification, MLP is frequently employed as the last layers of a neural network, in order to transfer the results of the preceding ones to determine percentages. These layers are made up of nodes (Each node has a collection of inputs, a weight, as

Type	Patch / Stride Size	Input Size
Conv	$3 \times 3/2$	$299 \times 299 \times 3$
Conv	$3 \times 3/1$	$149 \times 149 \times 32$
Conv padded	$3 \times 3/1$	$147 \times 147 \times 32$
Pool	$3 \times 3/2$	$147 \times 147 \times 64$
Conv	$3 \times 3/1$	$73 \times 73 \times 64$
Conv	$3 \times 3/2$	$71 \times 71 \times 80$
Conv	$3 \times 3/1$	$35 \times 35 \times 192$
$3 \times$ Inception	Module 1	$35 \times 35 \times 288$
$5 \times$ Inception	Module 2	$17 \times 17 \times 768$
$2 \times$ Inception	Module 3	$8 \times 8 \times 1280$
Pool	8×8	$8 \times 8 \times 2048$
Linear	Logits	$1 \times 1 \times 2048$
Softmax	Classifier	$1 \times 1 \times 1000$

Table 3. Basic InceptionV3 Architecture [41]

well as a bias parameter) where each of the nodes in the layer links to all the nodes of the layer that came before it due to its perception learning algorithm. The perceptron learning algorithm works by changing the weights (The values included within a kernel that is multiplied by the appropriate pixel value) of the connections among the input characteristics and the output neurons based on the difference between the expected and real output. This weight adjustment is an essential principle of neural networks, which is still employed in current neural networks. To be more specific, all the information is received by the input layer and passed on through the hidden layers, where nodes are used to execute calculations on the given inputs using the learned weights as well as biases. The bias measures how distant predictions are compared to their expected value.

3.5.1 MLP Architecture

The following figure 19 shows the MLP architecture:

The figure shows that x_1, x_2, x_3, x_4 , and x_5 represent the input vectors, while 0.2, 0.5, 0.6, 0.1, and 0.7 represent the weight vectors, and the bias value is set to 2. In general, the mathematical function for the weighted sum with bias is: $Z = w_1x_1 + w_2x_2 + \dots + w_nx_n + \text{bias}$. Then, the hidden layer activation functions introduce non-linearity into the output of a neuron by mapping the weighted sum

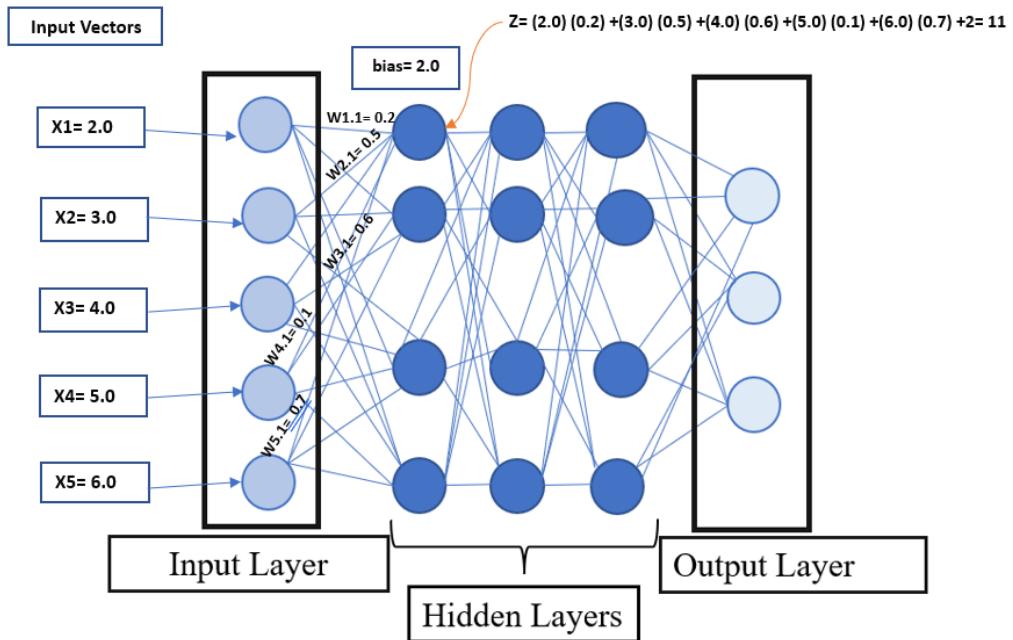


Figure 19. MLP Network Architecture with a SoftMax output layer

of the inputs to a new output value, helping the model to learn complicated correlations between inputs and outputs. These are some of the commonly used activation functions:

1. **The sigmoid function:** It is often utilized in issues that involve binary classification in the output layer. It converts every value entered to a number that ranges from 0 to 1. The sigmoid function is mathematically defined as follows:

$$f(x) = \frac{1}{1 + e^{-x}}$$

The following figure 20 represents the Sigmoid Function Graph.

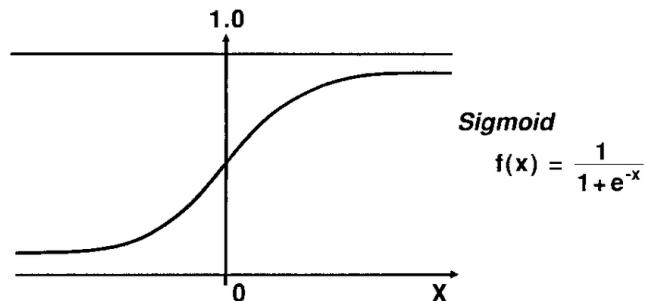


Figure 20. Sigmoid Function Graph[44]

2. **The ReLU function:** The Rectified Linear Unit maps any negative input value to 0 and every other positive input value is mapped to itself and this is how it is defined:

$$f(x) = \max(0, x)$$

This function is often employed in neural network hidden layers and has been successfully demonstrated to work excellently in deep networks. The following figure 21 represents the ReLU Function Graph.

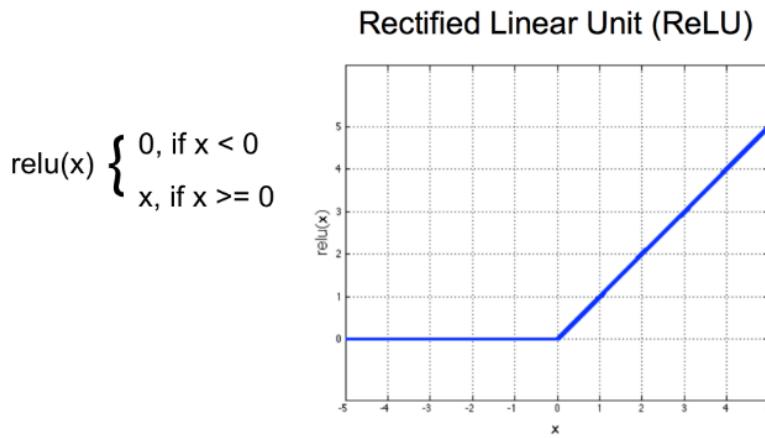


Figure 21. ReLU Function Graph[45]

3. **The Softmax function:** It is a very known activation function in neural networks. It works on multi-class classification issues and we find it in a neural network's output layer. This function changes a vector of real numbers into a probability distribution that adds to one, with each member of the output vector representing the probability of the associated class. This is how it is defined:

$$\text{Softmax}(x_i) = \frac{e^{x_i}}{\sum_{j=1}^n e^{x_j}}$$

The following figure 22 shows the probability distribution over K classes using the SoftMax

function:

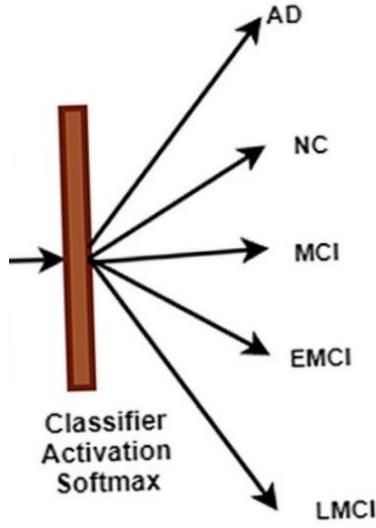


Figure 22. SoftMax K Classes Probabilities

Among the advantages of MLP:

1. **Nonlinear modeling:** MLPs can determine complicated nonlinear communication between input and output variables, making them applicable to tasks involving nonlinearities.
2. **Generalization:** If correctly trained, MLP may generalize strongly to new, previously unknown data, which renders them useful for tasks that the data distribution that may vary with time.
3. **Availability:** MLP is a very known neural network architecture that contains a lot of tools and libraries available for implementation.
4. **Scalability:** By raising the number of neurons as well as layers in the network, MLP is capable of managing big datasets with high-dimensional data.

For the classification architecture, three dropouts, three batch normalization, and three dense layers and a flatten layer sat before the first dense layers. These dense layers consist of an input layer, one

hidden layer, and an output layer. The first two dense layers have ReLU activation function. The final layer has a SoftMax as a non-linear activation function.

3.6 Evaluation metrics

The confusion matrix is essentially a summary of the predicted results for a certain classification issue. It compares real data for a variable target to predictions from a model. Correct and incorrect predictions are shown and grouped by class, allowing them to be evaluated against defined values. The following figure 23 shows the confusion matrix:

Confusion Matrix

		Actually Positive (1)	Actually Negative (0)
		True Positives (TPs)	False Positives (FPs)
Predicted Positive (1)	True Positives (TPs)	False Positives (FPs)	
Predicted Negative (0)	False Negatives (FNs)	True Negatives (TNs)	

Figure 23. The Confusion Matrix[46]

- **True Positive (TP):** Observations that have been classified as positive and are actually positive.
- **False Positive (FP):** Observations that have been classified positive and are actually negatives.
- **True Negative (TN):** Observations that have been classified as negative and are actually negative.

- **False Negative (FN):** Observations that have been classified negative and are actually positive.

This matrix makes it possible to deduce the following parameters:

- **Accuracy:** It is the number of correctly predicted data points out of all the data points [47]. It is calculated using the following formula:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$$

- **Precision:** it is the number of positive predictions divided by the total number of positive class values predicted[48]. It is calculated using the following formula:

$$Precision = \frac{TP}{TP+FP}$$

- **Recall:** It is the number of True Positives divided by the number of True Positives and the number of False Negatives[49]. It is calculated using the following formula:

$$Recall = \frac{TP}{TP+FN}$$

- **F1 score:** It is the harmonic mean of accuracy and recall[50]. It is calculated using the following formula:

$$F1score = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

3.7 Experiments and Evaluation

In this study, we used a SAMSUNG brand PC, which belongs to the 11th generation of Intel Core processors. It has a multi-core processor with I7.2.8 GHz as frequency clocks and 16GB as RAM. For the programming language, we used Python, which is an interpreted, dynamic, portable, and easy-to-learn language. We used TensorFlow as an ML library. TensorFlow is a free and open-source

software library for ML and AI. It can be used across a range of tasks but has a particular focus on training and inference of deep neural networks [51]. Also, we used Keras as a TensorFlow interface. "Keras" is an open-source software library that provides a Python interface for ANNs. "Keras" acts as an interface for the TensorFlow library, Keras contains numerous implementations of commonly used neural-network building blocks such as layers, objectives, activation functions, optimizers, and a host of tools to make working with image and text data easier to simplify the coding necessary for writing deep neural network code [52]. In addition, we used as a work environment "Google Colab", Colab allows us to write and execute Python code in a browser with no configuration required, free access to GPUs, and with easy sharing, it's a particularly important environment Suitable for ML and data analysis.

3.7.1 Results and Discussions

After seeing the architecture of our system. We will present and discuss the series of experiments by changing the parameters (Dropout, epochs, etc). As a beginning, we've fixed 30 as the epochs number, 0.5 as dropout, 0.0001 as the learning rate for the ADAM optimizer, and 4 as the number of neurons of the output layer. Then, we tried to work with an input layer and an output layer only.

3.7.1.1 Zero hidden layer

The following table 4 represents the system's performance for classification using MLP with an input and an output layers only , knowing that the output .

Input Layer Neurons	Accuracy	Precision	Recall	F1-score
18432	77.25%	85%	77%	80.8%

Table 4. Evaluation Metrics of our Neural Network

3.7.1.2 One hidden layer

Our goal is to create a performant system, so we decided to try another option to achieve better results. In this case, we added the first hidden layer with a different number of neurons and observed which one performed better than the others. As shown in Table 5, increasing the number of neurons in the

Hidden Layer Neurons	Accuracy	Precision	Recall	F1-score
400	96.18%	96%	96%	96%
500	97.44%	98%	97%	97%
650	96.31%	96%	96%	96%
800	96.22%	96%	96%	96%

Table 5. Performance Metrics for Different Numbers of Neurons of Hidden layer

MLP model can lead to a decrease in accuracy and other performance metrics. Therefore, we will fix the number of neurons of the first hidden layer at 500. Then, we are going to try adding another hidden layer with a lower number of neurons. The result is shown in Table .

3.7.1.3 Two hidden layers

In order to make better results, we added the second hidden layer with a different number of neurons and see which one is better than the others.

Hidden Layer Neurons	Accuracy	Precision	Recall	F1-score
50	88.41%	92%	88%	88%
100	95.32%	95%	95%	95%
200	92.25%	94%	92%	92%
300	94.75%	95%	95%	95%
500	94.84%	95%	95%	95%

Table 6. Model Performance Metrics

This variation didn't show a better result for this classification as shown in the table 6, for this reason, we fixed the model on an input layer, a hidden layer with 500 neurons, and an output layer. We tried to change the epochs number of the model 10, 30, 50, 80, and 100 and track its work in the table 7.

Epochs	Accuracy	Precision	Recall	F1-Score
10	91.80%	92%	92%	92%
30	97.44%	98%	97%	97%
50	92.72%	93%	93%	93%
80	95.70%	95%	95%	95%
100	91.74%	93%	91%	92%

Table 7. Accuracy, Precision, Recall, and F1-Score for Different Epochs

The table 7 shows that 30 as epochs number released the best result. So, we fixed the system on 30 epochs number. Now, we will test the learning rate with different values as shown in the table.

Learning Rate	Accuracy	Precision	Recall	F1-Score
0.00001	91.74%	93%	91%	92%
0.0001	97.44%	98%	97%	97%
0.001	90.87%	91%	91%	91%
0.01	62.51%	65%	62%	63%

Table 8. Accuracy, Precision, Recall, and F1-Score for Different Learning Rates

From these results, We kept 0.0001 as the learning rate. Trying to make the system give its best performance, we decided to test a variety of dropouts in order to make better results. The following table 9 illustrates our findings.

Dropout	Accuracy	Precision	Recall	F1-Score
0.2	87.19%	90%	87%	87%
0.5	97.44%	98%	97%	97%
0.7	93.50%	94%	93%	93%

Table 9. Results of the Dropout Experiments

We found that using a dropout rate of 0.5 resulted in the best performance for our model. The figure 24 shows our final results. To evaluate our model, we compared it with other papers, including our chosen reference: 'Automated Classification of Alzheimer's Disease Based on MRI Image Processing using Convolutional Neural Network (CNN) with AlexNet Architecture'.

```

Training Accuracy: 99.88%
Validation Accuracy: 97.20%
Testing Accuracy: 97.44%
40/40 [=====] - 3s 39ms/s

Classification Report
precision    recall    f1-score
NonDemented      0.98      1.00      0.99
VeryMildDemented 1.00      1.00      1.00
MildDemented     0.94      0.98      0.96
ModerateDemented 0.99      0.92      0.95

accuracy          0.97
macro avg         0.98      0.97      0.97
weighted avg      0.97      0.97      0.97

```

Figure 24. Final Results

We created the table 10 to display the classification accuracy results of numerous AD research that used different FE as well as classification algorithms. Our suggested model, which used a combination of CNN with InceptionV3 architecture for FE and MLP for classification on the AD dataset with four classes, achieved the highest accuracy of 97.44%. Previous research employing the same dataset, CNN with MLP for classification achieved an accuracy of 95% which is lower than our result.

3.8 Creating the graphical user interface

To make it easier for doctors to evaluate our system, we built a graphical interface that allows them to select an MRI image for testing it. The interface is made up of a total of two interfaces: The first one is for authentication, and the second one is for image testing. This part of this chapter will introduce the interface.

3.8.1 Definition of a graphical user interface

A GUI is a digital interface in which a user interacts with graphical components such as icons, buttons, and menus.[53]. Smartphones, PCs, and Ipads all include a graphic element called a GUI. In terms of interaction between humans and machines, it is a valuable component of software application programming, changing text-based commands with user-friendly actions. Its purpose is to provide the consumer with options that are simple to locate, comprehend, and apply. In this context, the goal of this graphical interface is to allow each user to test a new MRI. We utilized Gradio as Library. Gradio allows you to quickly create customizable UI components around your TensorFlow or PyTorch models or even arbitrary Python functions[54].

3.8.2 Authentication

This is an authentication screen shown in Figure 25. Users must have an account to access the test page and are required to enter their username and password.

Alzheimer's Disease Early Detection - Login

The login interface features a 'Username' field containing 'ABIR' and a 'Password' field containing '123'. Below the fields are 'Clear' and 'Submit' buttons. To the right, a message reads 'Welcome to the Alzheimer's Disease Early Detection Interface' above a 'Flag' button.

Figure 25. Login Graphical User Interface

3.8.3 Downloading the Image in the Interface

The doctor selects an image and puts it to the test on the model that was created by pressing on "Click to Upload". This is shown in the figure 26.

The prediction interface includes an 'image' input field, a 'Drop Image Here' area, and a 'Click to Upload' button. Below these are 'Clear' and 'Submit' buttons. To the right, there is an 'output' field containing '{...}' and a 'Flag' button.

Figure 26. Prediction Graphical User Interface

A window opens to allow you to select as shown in figure 27.

3.8.4 Classification Result

After selecting the required picture and clicking the 'Submit' button, the image will be processed by the model that we have created, and the result will be displayed on our page within a few seconds. Here is the figure 28 showing this operation.

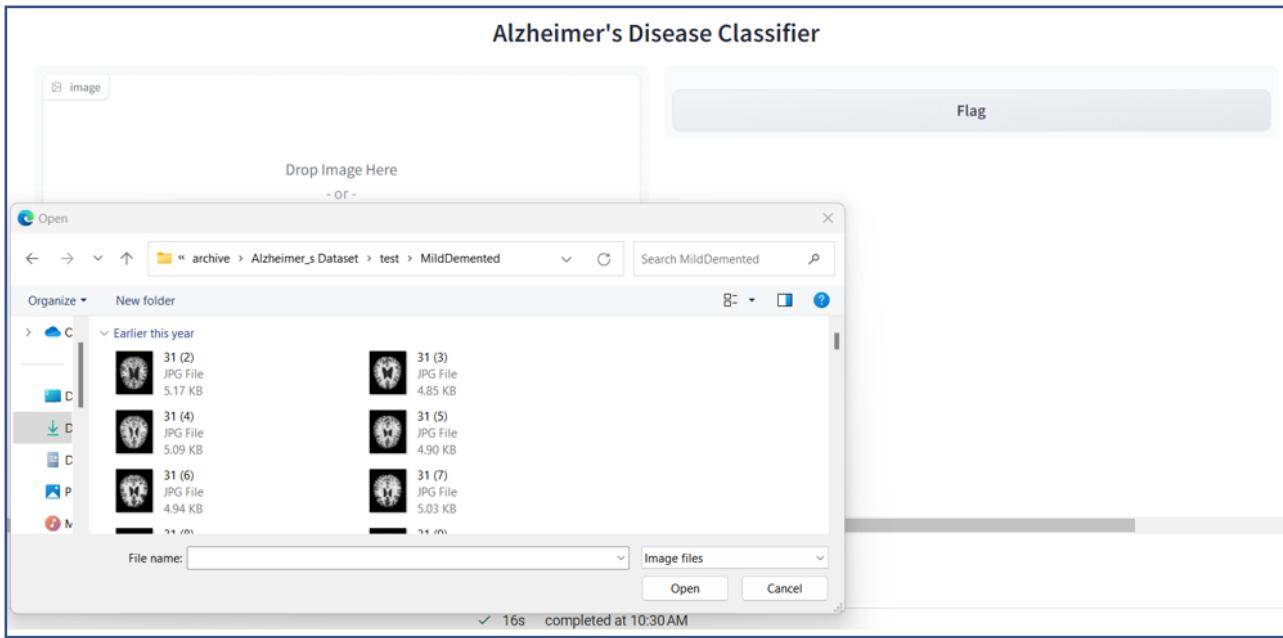


Figure 27. *Image Selection*

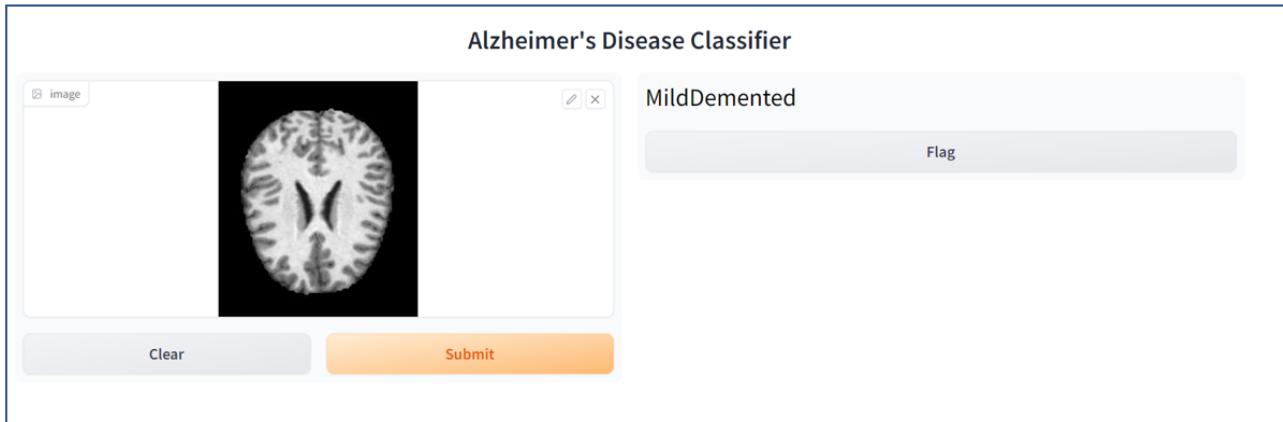


Figure 28. *Classification Result*

3.8.5 Conclusion

In that chapter, we described the model architecture and the evaluation metrics. Then, we showcased the best results obtained during our training. We earned the best result in the table by using the InceptionV3 feature extraction model and the MLP classification method. We reached a very high accuracy of 97.44%, demonstrating the promise of DL models for AD diagnosis. InceptionV3 is a very effective deep CNN capable of extracting highly useful features from medical photos. MLP is a form of ANNs capable of modeling complicated non-linear interactions between variables that serve as inputs and outputs. Our study shows that DL models might become a significant tool for the

early recognition and characterization of AD. Then, We presented a GUI to test images. It presents a GUI for interacting with the proposed model. The interface makes it simple to choose a picture and evaluate the model's capacity to distinguish items within it. Users may input a picture of their choosing, and the model will process it by employing its trained algorithms for establishing the things inside it. The GUI enables consumers to see what the model has learned and gives a simple yet efficient method for exploring the DNN algorithm's ability.

Reference	Year	Dataset	Features Extraction Model	Classification Model	Accuracy (%)
Faturahman.M, Wasito.I and Al	2017	Open Access Series of Imaging Studies	Deep Belief Network	Support Vector Machines	92
Shen.T, Jiang.J, and Al	2019	Alzheimer's Disease Neuroimaging Images	Deep Belief Network	Support Vector Machines	86
Zaabbi.M, Smaoui,N and Al	2020	Open Access Series of Imaging Studies	Convolutional Neural Network	Multi-layer Perceptron	92.86
Bansal.D, Khama.K, and Al	2020	Alzheimer's Disease Neuroimaging Images	Bag of features	Support Vector Machines	86
Liu.M, Li.F, and Al	2020	Alzheimer's Disease Neuroimaging Images	Convolutional Neural Network	Multi-layer Perceptron	92.5 (AD/NC)
					77.5 (MCI/NC)
Tian.J, Smith.G and Al	2021	UK Biobank	Convolutional Neural Network	Support Vector Machines	82.44
Raju.M, Gopi.V and Al	2021	Alzheimer's Disease Neuroimaging Images	Convolutional Neural Network	Multi-layer Perceptron	96.66
Fu'adah.Y, Wijayanto.I, and Al	2021	AD (4 classes)	Convolutional Neural Network	Multi-layer Perceptron	95
Hedayati.R, Khedmati.M, and Al	2021	Alzheimer's Disease Neuroimaging Images	Ensemble of Auto Encoders and a Convolutional Neural Network	Multi-layer Perceptron	95 (AD/NC)
					90 (AD/MCI)
					92.5 (MCI/NC)
Tuan.P, Phan.T and Al	2022	Alzheimer's Disease Neuroimaging Images	Auto Encoders	Support Vector Machines	93.53
Proposed Model	2023	Alzheimer's Dataset (4 class of Images)	Convolutional Neural Network (InceptionV3)	Multi-layer Perceptron	97.44

Table 10. Classification Models and Accuracy

General Conclusion

AD is a serious and very common disease that has a global prevalence. It is a severe neurological illness affecting millions of individuals throughout the world. The condition is defined by the buildup of aberrant proteins in the brain, resulting in the destruction of brain cells with a gradual decline in cognitive function. It still has no treatment, despite the age of the study. However, plenty of progress had been produced to comprehend the illness and devising medications to limit its course. The lifestyle factors such as bad diet, lack of exercise, and isolation from social engagement, also, play an interesting role in the progression of AD. To summarize the scientific part of this disease, while much remains to be known about AD, enormous progress has been achieved toward comprehending the condition and creating medicines that can assist to limit its course. Ongoing studies and the development of novel medicines will be vital in the hunt for an effective therapy for this serious illness. ML techniques, such as DL, showed potential in predicting AD at early stages by analyzing MRI and PET images. These algorithms can recognize and discriminate small changes in the brain, which may indicate the presence of AD during the normal aging process. In the first chapter, titled 'Alzheimer's Disease,' we discussed the factors contributing to AD, the rising cases, and the economic impact, as well as research and domains axes, and methods of screening for AD. In the second chapter, named "Related Work", we discussed five different models: "Support vector machine", "Multi-Layer Perception", "Convolutional Neural Network", "Auto-Encoder", and "Deep Belief Network". For each model, we referenced some old researches that had been done using the defined model. The third chapter, titled "Proposed Model," provides a comprehensive overview of various components including system architecture, data acquisition, feature extraction, classification, evaluation metrics, experiments, and evaluations. In addition, a comparison of our results with those of other related works is presented, highlighting the performance of our model. Furthermore, we have developed two GUIs to facilitate the usage of the system and we finished with a general conclusion. The main goal of the proposed model is to develop an effective system for the early detection of Alzheimer's Disease using MRI images. We achieved our goal with a very high accuracy rate of 97.44% by using InceptionV3 as the Features Extraction Model and MLP as the Classification Model. As the

next step, we plan to further validate and enhance our system by testing it on additional Alzheimer databases, which will help us assess its performance. Additionally, we aim to explore the potential of our system by testing its interface with other types of medical images for the detection and diagnosis of various diseases. We hope to contribute to the development of innovative tools that can aid in the early identification and treatment of a wide range of medical conditions.

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Alzheimer's Disease Recognition Using Machine Learning

Abir HADRICH

الخلاصة: ركزت هذه الأطروحة، التي تحمل عنوان "التعرف على مرض الزهايمير بالتعلم الآلي" على التعرف والتصنيف للصور الطبية لتشخيص مرض الزهايمير. في هذا العمل، يتم اقتراح نموذج لكشف الرنين المغناطيسي لمرض الزهايمير يتم عرض نموذج CNN-MLP ، ويتم تحقيق معدل تصنیف بنسبة حوالي 97.44%

Résumé : Cette mémoire, intitulée "Reconnaissance de la maladie d'Alzheimer à l'aide de l'apprentissage automatique", se concentre sur la reconnaissance et la classification d'images médicales pour le diagnostic de la maladie d'Alzheimer. Dans ce travail, un modèle est proposé pour la détection de la maladie d'Alzheimer à partir d'images par résonance magnétique. Un modèle CNN-MLP est proposé et le taux de classification atteint est environ 97.44%.

Abstract: This project, entitled "Alzheimer's Disease Recognition Using Machine Learning," focuses on the recognition and classification of medical images for the diagnosis of Alzheimer's disease. In this work, a model is proposed for magnetic resonance imaging detection of Alzheimer's disease. A CNN-MLP model is proposed, and the classification rate achieved is about 97.44%.

المفاتيح: التعلم العميق، التعلم الآلي، مرض الزهايمير، الشبكات العصبية التلقائية، صور الرنين المغناطيسي، التصوير متعدد الطبقات.

Mots clés : Apprentissage profond, Apprentissage automatique, Maladie d'Alzheimer, Réseaux de neurones convolutifs, Images de résonance magnétique, Perception multicouche.

Key-words: Deep Learning, Machine Learning, Alzheimer's disease, Convolutional Neural Network, Magnetic Resonance images, Multi-Layer Perception.

