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Theme

Efficient Image Classification for Early Prediction of Alzheimer's Disease

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Dedication

This work is specifically intended:

To my beloved parents
My mother Dalila, may God be pleased with her I love you very much.
My late father Nasreddin, may he rest in peace, who will be in my heart and prayers forever.

They Always encouraged, supported, and guided me to work hard to achieve success for my country
To my grandfather's pure soul,
May God have mercy on him who died of Alzheimer's disease, which was the reason for choosing this theme.

To my sisters Ikram, Icharak, Asma, Amina, Bachira, Sara for their support and positive feedback.

To my brothers Ali and Taher who stood by me until the last moment.

To my supportive partner Kaouthar; Thanks for this wonderful Coincidence that made me know you closely.It was a pleasure to work with you.

My cat Oreo, and my best friend Ilham, my cousin Malak, and my friends Radia, Lina, and Basma.

To my friends Saddam,Salah and Adoun.

To my great self who struggled and strived

To all of my university friends and colleagues who have encouraged me during my work.

HABITA Atidel

I dedicated this thesis **To my father,**

Who accompanied me and still encouraged me along my academic journey, may God make you a crown above our heads

To my mother

who gave birth to me, my nanny, and my teacher

May God bless you with health and longevity. May God grant you success in your academic journey.

What I am today, thanks to your sacrifices and prayers. May God protect you and your health. I love you so much.

To my sisters

Asma, Soundous, Salsabil, and Isra

I wish you all the best, I wish you success in your studies and reach what you intend to achieve.

To my brothers

Mohemmed El Amine, Yahia

I wish you success and access to the highest ranks. I love you all.

To my nephews

Ahmed Mouanis, Abd El Hia, and our next guest soon

may God protect you and grow you in good health, you are the sweetness of the family

To the pure soul of my grandfather,

may God have mercy on him

To my partner,

Atidel

I appreciate your effort and struggle with me in order to write this thesis, may God bless you, it was great working with you.

To myself, who struggled and strived

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HABITA Atidel, BENDEHIBA Kaouthar

Abstract

Alzheimer’s disease is a type of brain disease. It is a progressive disease which means it gets worse with time there is no cure and his diagnosis is a medical challenge. Therefore, early diagnosis is crucial and can help to improve symptoms significantly. As technology advances, deep learning techniques have recently achieved great success in medical image analysis. This project aims to develop a method of Alzheimer's disease diagnosis using MRI images, which can distinguish medical images of the brain to help doctors to classify and predict Alzheimer's disease. This is based on deep learning with convolutional neural networks (CNN) used to predict Alzheimer from the Kaggle dataset. Experiments results have given encouraging prediction and accuracy in comparison with other work cited in related works.

Keywords: *Alzheimer’s Disease, Brain, Deep learning, Medical Image, MRI, CNN, Dataset, Prediction.*

الملخص

مرض الزهايمر هو نوع من أمراض الدماغ. فهو مرض تقدمي ، مما يعني أنه يزداد سوءًا بمرور الوقت ، ولا يوجد علاج له ، ويشكل تشخيصه تحديًا طبيًا. لذلك ، فإن التشخيص المبكر أمر بالغ الأهمية ويمكن أن يساعد في تحسين الأعراض بشكل كبير. مع تقدم التكنولوجيا ، حققت تقنيات التعلم العميق مؤخرًا نجاحًا كبيرًا في تحليل الصور الطبية. يهدف هذا المشروع إلى تطوير طريقة لتشخيص مرض الزهايمر باستخدام صور التصوير بالرنين المغناطيسي ، والتي يمكنها تمييز الصور الطبية للدماغ لمساعدة الأطباء على تصنيف مرض الزهايمر والتنبؤ به. يعتمد هذا على التعلم العميق باستخدام الشبكات العصبية التلافيفية (CNN) المستخدمة للتنبؤ بمرض الزهايمر من مجموعة بيانات Kaggle. أعطت نتائج التجارب تنبؤًا ودقة مشجعة مقارنة بالأعمال الأخرى المذكور في جزء الاعمال ذات صلة.

الكلمات المفتاحية: *مرض الزهايمر ، الدماغ ، التشخيص ، التعلم العميق ، الصورة الطبية ، التصوير بالرنين المغناطيسي ، CNN، مجموعة البيانات ، التنبؤ.*

Résumé

La maladie d'Alzheimer est un type de maladie du cerveau. C'est une maladie évolutive, ce qui signifie qu'elle s'aggrave avec le temps, qu'il n'y a pas de remède et que son diagnostic est un défi médical. Par conséquent, un diagnostic précoce est crucial et peut aider à améliorer considérablement les symptômes. À mesure que la technologie progresse, les techniques d'apprentissage en profondeur ont récemment remporté un grand succès dans l'analyse d'images médicales. Ce projet vise à développer une méthode de diagnostic de la maladie d'Alzheimer à l'aide d'images IRM, qui peut distinguer des images médicales du cerveau pour aider les médecins à classer et à prédire la maladie d'Alzheimer. Ceci est basé sur l'apprentissage en profondeur avec des réseaux de neurones convolutifs (CNN) utilisés pour prédire la maladie d'Alzheimer à partir de l'ensemble de données Kaggle. Les résultats des expériences ont donné des prédictions et une précision encourageantes en comparaison avec d'autres travaux cités dans les travaux connexes.

Mots clés : *Maladie d'Alzheimer, Diagnostic, Deep Learning, Image médicale, IRM, CNN, Data Set, Prédiction.*

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List of acronyms

CNS The Central Nervous System.

ADAS-Cog13 Assessment Scale-Cognitive Subscale.

RAVLT REY Auditory Verbal Learning Test.

FAQ Functional Assessment Questionnaire.

MMS Mini-Mental State Examination.

EHRs Electronic Health Records.

CNN Convolutional Neural Networks.

PNS Peripheral Nervous System.

MRI Magnetic Resonance Imaging.

FMRIF Functional Magnetic Resonance Imaging.

PET Positron Emission Tomography.

MEG Magnetoencephalography.

CT Computerized Tomography.

AD Alzheimer's Disease.

MCI Mild Cognitive Impairment.

SPECT Single-Photon Emission Computed Tomography.

AI Artificial Intelligence.

ML Machine Learning.

NN Neural Network.

DL Deep Learning.

NL Natural Language.

EHR Electronic Health Records.

CNN Convolutional Neural Networks.

GPUS Graphics Processing Units.

GANS Generative Adversarial Networks.

NICT New Information And Communication Technologies.

DNN Deep Neural Network.

DLN Deep Learning Networks.

ANN Artificial Neural Networks.

RNN Recurrent Neural Networks.

DRL Deep Reinforcement Learning.

LSTM Long-Term and Short-Term Neural Networks.

RBFN Radial Basis Function Network.

GAN Generative Adversarial Network.

KNN K-Nearest Neighbors.

CLI Command Line Interface.

FC Fully Connected Layer.

CDR Clinical Dementia Assessment.

PIL Python Pillow.

TPR True Positive Rate.

FPR False Positive Rate.

ROC Receiver Operating Characteristic Curve.

General Introduction

Introduction

Alzheimer's disease (AD) is a progressive neurological disorder that causes short-term memory loss, paranoia, and delusions that are mistaken for the effects of stress or aging. AD does not have adequate health care. Ongoing medication is necessary to control AD. AD is chronic, so it can last for years or the rest of your life. Therefore, it is extremely important to prescribe the drug at the right time to avoid huge brain damage. Early detection of this disease is a long and expensive process because most of the time we collect a lot of data and use sophisticated tools to make predictions and involve experienced doctors. Such as magnetic resonance imaging (MRI) and positron emission tomography (PET), and others, have been developed and used to identify activated, and molecular biomarkers linked to Alzheimer's disease.

According to the Centers for Disease Control and Prevention **[1]**, in 2020, approximately 5.8 million Americans have Alzheimer's disease. Figures suggest that the number will rise to 14 million by 2060.

Nowadays, artificial intelligence, (machine learning, and deep learning) are used, it is possible to analyze data on a large scale and with different algorithms, detecting patterns in very not much time.

In this way, there is a significant improvement in diagnostic methods using techniques that are even imperceptible to human experience and reasoning. Moreover, nowadays, the world of machine learning is more advanced than ever, thanks to new deep neural networks. Simply put, deep neural networks allow the creation of systems powerful enough to represent any finite deterministic mapping between a given set of inputs and a set of corresponding outputs. These techniques enable powerful data processing, allowing us to analyze processes as complex as image identification or natural language processing.

Background & Motivations

Alzheimer's Disease (AD) is one of the most common forms of dementia, which could cause cognitive damage, memory disorders, memory loss, and difficulties in decision-making, verbal communication, concentration, thinking, and judgment. The AD symptoms progress slowly over time to undermine patients' living ability to perform daily tasks. So far, there is no complete cure for AD, and all treatments are to slow AD-related symptoms worsening based on patients' symptoms. However, these treatments add an endless financial burden on patients, their families, and the government health care system. Thus, it is essential to achieve a reliable and efficient method to detect AD as early as possible. Patients could then have immediate treatments to slow down the symptom progress early, avoiding the worst dementia effects.

Magnetic Resonance Imaging (MRI), including structural MRI (sMRI) and functional MRI (fMRI), is the primary medical imaging tool to help understand and evaluate the anatomical changes of sensitive regions related to AD. Therefore, MRI is the most significant source for medicine, and it is also an essential data source in AD detection research. contribute to diagnosing AD in the early stage. this type of data typically has a time -length of 6 to 12 months. It is made of various medical examinations and measures, such as Assessment Scale-Cognitive Subscale (ADAS-Cog13), REY Auditory Verbal Learning Test (RAVLT), Functional Assessment Questionnaire (FAQ), and Mini-Mental State Examination (MMS). This type of data includes Electronic Health Records (EHRs) and clinical recordings **[2].**

Multi-modality images help improve AD diagnosis, including MRI and Positron Emission Tomography (PET). As discussed above, to provide the information provided information related to anatomical structures across all brain regions. A PET scan can indicate the brain's metabolism.

Research Problem

According to the latest survey report in 2023, in the world is diagnosed with dementia every three seconds. In the United States of America alone, 6.7 million people live with Alzheimer's disease **[3],** and Algeria has approximately 500,000 patients **[4]**. While recent advances in treating early-stage Alzheimer's disease offer hope to millions of people suffering from memory loss and early cognitive decline **[3].**

AD prediction is to classify different stages of dementia progress so the early prediction becomes a classification problem. Many modeling techniques, such as statistical models and machine learning algorithms, have been explored with handcrafted features to improve the model's capability to understand more extensive health conditions. However, recent research mostly focuses on applying deep-learning algorithms to predict AD fundamentally and more precisely. The most difficult challenge to such a problem is, accuracy must be so high as to be almost ideal because any misclassification of one person may cause an error in the diagnosis.

The objective of the project is to efficient Image Classification for the early Prediction of Alzheimer's Disease, in order to address this goal, questions have been elaborated. Answer these questions will enable us to arrive to goal:

- What is Alzheimer's disease?
- How can Alzheimer's disease be diagnosed?
- How early prediction of Alzheimer's disease is done through pictures or how are these classified?
- Is it possible, through deep learning, to classify and distinguish images using specific dataset, and thus help in the diagnosis of Alzheimer's patients?
- What is the framework that can be followed to implement and test the chosen model?
- What is the level of accuracy that can be reached?

Research Objectives

The current research aims to build a system capable of classifying MRI images for early detection of Alzheimer's disease, using deep learning techniques, in order to make a practical contribution to the field of medicine. In other words, studying CNN deep learning classification technology, which can help Doctors in early diagnosis in general, but in particular, aims are working on a CNN model, to classify MRI images for early detection of Alzheimer's disease, and this through evaluating the model and achieving high accuracy to previous works using parameters group, and in the end creating an interface to present this work. The goals to achieve this are as follows:

1. Evaluate the performance of identified deep learning techniques for Alzheimer's disease detection against benchmark datasets at an early stage.

2. Given the identification of a promising deep learning technique, the following recommendations are made: Improving the performance of detecting Alzheimer's disease.

3. Validation of the proposed improved method for Alzheimer's disease detection comparison with representation techniques in machines /deep Learning with Kaggle Datasets.

Thesis Layout

The rest of the work is structured as follows:

- ✓ Chapter **I** presents an introduction to the Anatomy of the human brain, it, and the role of different imaging techniques. It also highlights learning about Alzheimer's and diagnosis the early detection.
- ✓ Chapter **Ⅱ** presents an updated review of Presenting a technical case implemented to detect or, classify Alzheimer's disease using deep learning. Learn about the role of artificial intelligence, feature extraction, transformation, and an overview of deep learning.
- ✓ Chapter **Ⅲ** Discussion of the proposed framework that works on the effective classification of Alzheimer's disease, the proposed algorithm was explained, and the work of the proposed framework was described by describing its stages and the functions of each stage. for early detection of Alzheimer's disease using patients' MRI data.
- ✓ Chapter **Ⅳ** provides the details of the experimental setup, results, and discussion. After introducing the tools, we used and the dataset and performance metrics used in this work.

Chapter I

Brain Imaging and Alzheimer's Diagnoses

I.1 Introduction

During this first chapter, we'll review the medical background needed to understand this work. We open this section with a detailed description of the anatomy of the human brain and then proceed with a description of brain imaging available for its evaluation as well as any technique allowing in vivo visualization of the central nervous system (CNS). It may relate to the definition and definitive diagnosis of Alzheimer's disease with some tests to diagnose it.

I.2 The Anatomy of the Human Brain

The nervous system is a complex network of nerves and cells that carry information to the brain and spinal cord, and from there to different parts of the body. The proper functioning of these nerves ensures that all organ systems (such as the cardiovascular, gastrointestinal, and immune systems) can properly communicate with each other.

The nervous system includes the central nervous system (CNS) and peripheral nervous system (PNS). The CNS consists of the brain and spinal cord, while the PNS consists of the somatic and autonomic nervous systems [**6**].

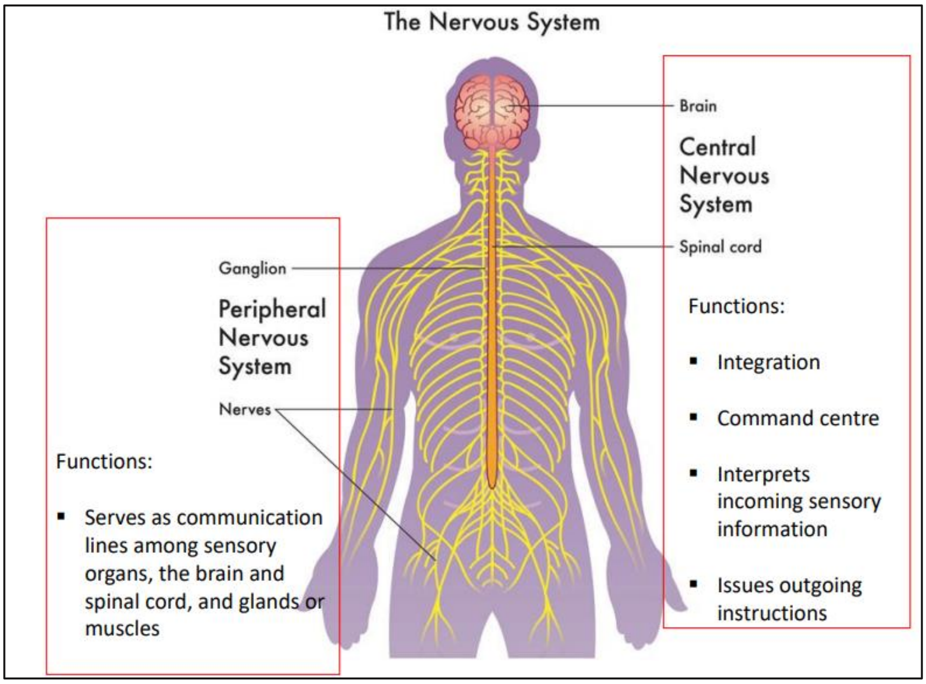

Figure I.1: Divisions of the nervous system **[5]**

The brain is like a central computer that controls all bodily functions. It is responsible for what we think and feel, learn and remember, and act and speak. It also controls things we don't quite understand. The brain sends information back and forth with the body. These messages travel through the spinal cord.

The main parts of the brain are the cerebrum, the brainstem, and the cerebellum.

I.2.1 The Cerebrum

The brain is divided into two hemispheres, which are also the largest in the human brain –

the two hemispheres account for 85% of the total brain mass. The cerebrum forms the upper part of the brain, covering and covering the diencephalon and brainstem like a mushroom cap that covers the top of its stem.

Raised crests of tissue called gyri, separated by shallow grooves called sulci, mark nearly the entire surface of the brain hemispheres. Deeper forests, called clefts, are large areas of the brain.

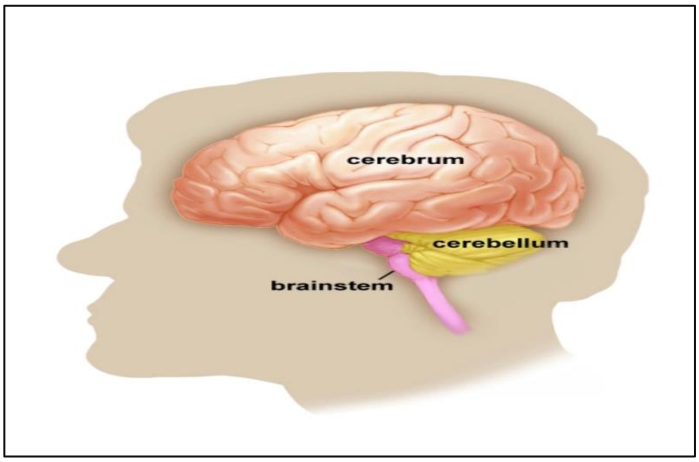

Figure I .2 Regions of The Brain**.**

Most of the brain is involved in processing somatosensory and motor information, conscious thought, and intellectual function. The outer cortex is composed of gray matter. Billions of neuronal cell bodies and unmyelinated axons are arranged in six discrete layers. Although only 2 – 4 mm this region accounts for approximately 40% of the total brain mass. The inner region consists of white matter - the tunnels for myelinated axons. Deep in the white matter of the brain is the third fundamental area of the brain, a group of subcortical gray matter called the basal ganglia. These nuclei, caudate nucleus, putamen, and globus pallidum, Is an important regulators of skeletal muscle movement.

I.2.2 The Brain Stem

The brainstem begins below the thalamus and is approximately 7 cm long before merging into the spine cable. Brainstem centers generate the tightly programmed automatic behaviors necessary for survival.

The brainstem, located between the brain and spinal cord, also provides access to the fiber pathways that Operate between higher and lower brain centers.

I.2.3 The Cerebellum

Located on the lower dorsal aspect of the brain, the cerebellum accounts for ~ 11% of the total brain mass. Like the cerebrum, the cerebellum has two major hemispheres with an outer cortex made up of gray matter with an inner region of white matter. The cerebellum is located dorsal to the pons and medulla and it protrudes under the occipital lobes of the cerebral hemispheres, from which it is separated by the transverse fissure. By processing inputs received from the cerebral motor cortex, various brain stem nuclei, and sensory receptors, the cerebellum provides the precise timing and appropriate patterns of skeletal muscle contraction for smooth, coordinated movements and agility needed for our daily lives (e.g., driving). Cerebellar activity occurs subconsciously, we have no awareness of it.

I.3 Brain Imaging

At the birth of neuroscience, it was difficult to understand how the brain worked because, at the time, those studying it did not have the technology to analyze and measure brain activity in real time. thankfully, we have come a long way since the first dissections of the human brain, and we can use a multitude of wonderful technology devices that enable the study of the brain and its inner workings **[6][8].**

Figure I .3 Brain Imaging Data.

Brain imaging, the use of quantitative techniques to study the structure and function of the central nervous system, and is an objective method of scientifically studying the healthy human brain in a non-invasive manner. It is also increasingly used in quantitative studies of brain disorders and psychiatric disorders. Neuroimaging is a very multidisciplinary field of study rather than a medical specialty.

Brain imaging techniques provide the ability to noninvasively map the structure and functions of the brain. This is achieved either by directly measuring the currents and magnetic fields produced by neural activity, by injecting radioisotope agents to outline regions through emitted radiation, or by measuring tissue-specific responses to an externally applied energy source such as a magnetic field. The obtained signals provide identifying information about the structures and physiological activities of the brain lending answers to questions about structural integrity, relevant particularly in clinical applications, as well as relating brain function to human cognition and behavior **[7].**

Neuroimaging differs from neuroradiology which is a medical specialty and uses brain imaging in a clinical setting. Neuroradiology is practiced by radiologists who are medical practitioners. Neuroradiology primarily focuses on identifying brain lesions, such as vascular disease, strokes, tumors and inflammatory disease. In contrast to neuroimaging, neuroradiology is qualitative (based on subjective impressions and extensive clinical training) but sometimes uses basic quantitative methods. Functional brain imaging techniques, such as functional magnetic resonance imaging (fMRI), are common in neuroimaging but rarely used in neuroradiology **[8].**

Neuroimaging falls into two broad categories:

1. Structural imaging This technique deals with the structure of the nervous system and the diagnosis of gross (large scale) intracranial disease (such as a tumor) and injury.

2. Functional imaging This imaging technique is used to diagnose metabolic diseases, and lesions on a finer scale, do neurological and cognitive psychology research and build brain-computer interfaces. Functional imaging enables the processing of information by centers in the brain visualized directly. Therefore, such processing causes the area of the brain involved to increase its metabolism and to "light up" on a scan. The main types of neuroimaging include **[9]:**

I.3. 1 Magnetic Resonance imaging (MRI)

This imaging method is a painless, non-invasive imaging technology that produces 3D detailed anatomical images of our brain, as well as our body. An MRI scanner consists of an outsized doughnut-shaped magnet that always encompasses a tunnel within the center. Patients are placed on a table that slides into a tunnel where brain and body scans occur. During the examination, the scanner uses magnetic fields that emit radio waves to manipulate the magnetic position of the hydrogen protons in the body. The rotation and energy release of the protons are detected by a powerful antenna that sends the information to a computer. The computer analyzes the information, and through complex mathematical calculations, creates a clear, cross-sectional black-and-white image of the body. These images can be converted into **[10]**.

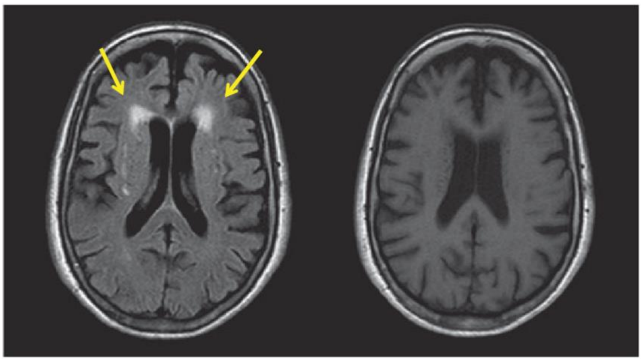

Figure I .4: Brain MRI images of patient showing frontal atrophy and anterior periventricular white matter abnormalities (arrows).

I.3.2 Functional Magnetic Resonance Imaging (FMRI)

Functional magnetic resonance imaging (fMRI) is one of the most common and widely used brain imaging techniques. This technology uses a powerful magnetic field and radio waves to capture detailed images of brain activity, allowing researchers to track how different neural regions interact and change over time.

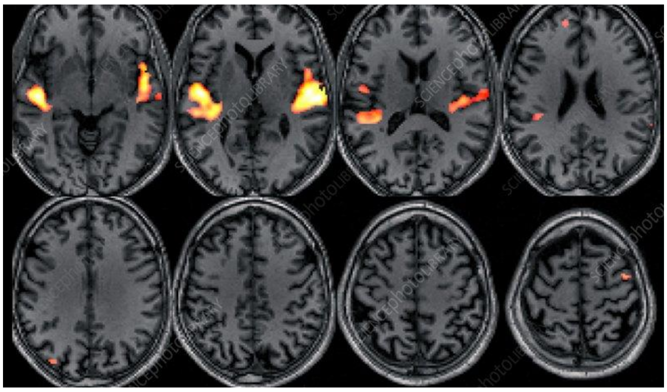

Figure I .5 : Exemple Brain FMRI images scan

Can detect changes in blood flow and oxygen levels that result from your brain's activity. It uses the magnetic field of the scanner to affect the magnetic nuclei of hydrogen atoms, so they can be measured and converted into images.

FMRIs have many uses, such as:

- Assessing brain activity
- Finding brain abnormalities
- Creating pre-surgical brain maps.

I.3.3 Positron emission tomography (PET)

A Positron emission tomography (PET) scan uses a radioactive tracer that attaches to the glucose in your bloodstream. Since your brain uses glucose as its primary fuel source, the tracer accumulates in areas of higher brain activity.

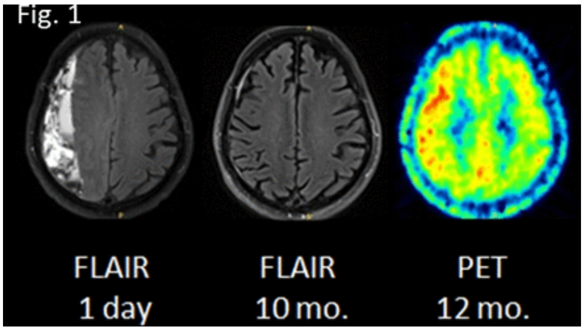

Figure I .6: PET imaging of translocator protein detects

A PET scan can see these tracers and observe how they move and accumulate in your brain. This allows doctors to see trouble spots where glucose isn't moving correctly. PET scans can evaluate:

- Alzheimer's.
- Tumors.
- Seizures.

I.3.4 Magnetoencephalography (MEG)

Magnetoencephalography (MEG) measures the magnetic field from neuron electrical activity. This type of scan can locate and identify malfunctioning neurons in your brain. Doctors use MEG to evaluate both spontaneous brain activity, as well as neuronal responses triggered by stimuli. MEG allows doctors to assess areas such as:

- Epilepsy sources.
- Motor areas.

- Sensory areas.

Figure I .7: MEG Brain scan.

I.3.5 Computerized Tomography (CT scan)

Computerized Tomography of the brain is nothing but an X-ray of the head taken repeatedly and constructed by a computer to give two-dimensional images of the head. Hence, there is a risk of radiation exposure as it happens in the case of taking a chest X-ray. It is less costly, less

Figure I .8: Brain Image by CT.

time-consuming, and available in most cities when compared to an MRI brain. This helps in identifying trauma to skull bones that cover the brain **[11].**

I .4 Alzheimer’s Disease

Alzheimer's disease is an irreversible progressive brain disease that slowly destroys Memory and thinking skills, and the ability to perform the simplest tasks. Exist most Alzheimer's patients experience their first symptoms in their 60s. However, estimates vary experts estimate that more than 5 million Americans may be living with Alzheimer's. Alzheimer's disease is now the sixth leading cause of death in the U.S. states, but recent estimates suggest the disease may rank third after heart disease and cancer are the leading cause of death in older adults. Alzheimer's disease is the most common cause of dementia in older adults. Dementia Loss of cognitive function (thinking, memory, and reasoning) and behavioral ability to the extent that it interferes with a person's daily life and activities **[12].** The beginning stages of dementia can vary from mild to severe. When a person becomes fully reliant, they have entered the most critical stage of their functioning. Daily life activities can be done for someone else. Brain change type determines various causes of dementia. Dementia with Lewy bodies and frontotemporal lobe disease are other types of dementia that may arise spontaneously.

Dementia comes in various forms and combinations, including vascular and mixed dementia. The latter is when one experiences a blend of cognitive impairments simultaneously. Dementia is often accompanied by one or more diseases, as observed in individuals. vascular dementia and Alzheimer's can both have a significant impact.

Dr. Alois Alzheimer’s is the eponym for a neurodegenerative illness known as Alzheimer's disease, which he first described in 1906. Changes in brain tissue were discovered in a deceased woman who suffered from an atypical psychological disorder. Unpredictable behavior, speech problems, and memory loss are all indications of symptoms. Return She died and he examined her brain and found numerous abnormal masses (now called amyloid plaques) and tangled bundles of fibers (now called neurofibrillary tangles or tau tangles). These plaques and tangles in the brain are still considered some of the main features of the brain Alzheimer's disease. Another characteristic is the loss of connections between nerve cells (neurons) in the brain. Neurons carry information between different parts of the brain, From the brain to the muscles and organs of the body **[13].**

Scientists continue to decipher complex brain changes associated with disease onset and onset Progression of Alzheimer's disease. Brain damage seems likely to start ten or more years before memory and other cognitive problems appear. Simultaneously seemingly asymptomatic people in the preclinical stages of Alzheimer's disease are toxic changes happening in the brain. Abnormal protein deposits forming amyloid plaques and tau tangles were found throughout the brain. Once healthy neurons stop functioning and if they lose their connection to other

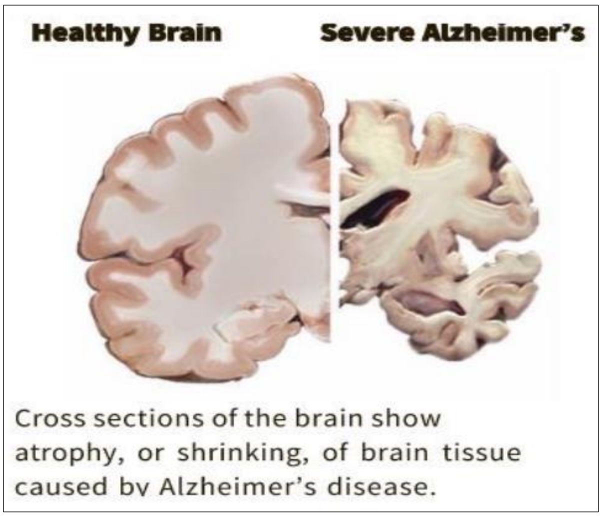

Figure I .9: The Difference Between a Healthy Brain and Severe Alzheimer's **[12].**

neurons,they die. The damage first appeared in the hippocampus; part of the brain essential for memory formation. The more neurons die, the more parts of the brain die affected, and they begin to shrink. Damage occurs in the late stages of Alzheimer's disease mainly; the brain volume was significantly reduced **[14].**

I. 5 Diagnosis of Alzheimer's Disease

Before the early 2000s, the only sure way to know whether a person had Alzheimer's disease was through autopsy, a procedure that is performed after death. by dint of advances in research, laboratories, and imaging tests are now available to help a doctor or researcher see biological signs of the disease, or biomarkers, in a living person **[15].** Doctors now use a variety of methods and tools to determine whether people with thinking or memory problems have Alzheimer's disease or not. Diagnosing Alzheimer's disease may involve the following tests:

I.5.1 General questions

Asking the person experiencing symptoms, as well as a family member or friend, questions about overall health, use of prescription and over-the-counter medicines, diet, past medical problems, ability to carry out daily activities, and changes in behavior and personality.

I.5.2 Physical and neurological exam

A healthcare provider will perform a physical exam. A neurological exam may include **[16]:**

- Reflexes.
- Muscle tone and strength.
- Ability to get up from a chair and walk across the room.
- Coordination.
- Sense of sight and hearing.
- Balance.

I.5.3 Laboratory tests

Blood and urine tests may help rule out other potential causes of memory loss and confusion, such as a thyroid disorder or vitamin levels that are too low. Blood tests also can measure levels of beta-amyloid protein and tau protein, but these tests aren't widely available and coverage may be limited.

I.5.4 Mental Status and neuropsychological testing

Your provider may give you a brief mental status test to assess memory and other thinking skills, like problem-solving test attention, counting, and language. Longer forms of this type of test may provide more details about a mental function that can be compared with people of a similar age and education level. These tests can help establish a diagnosis and serve as a starting point to track symptoms in the future **[16].**

I.5.5 brain imaging exams

Commonly used brain imaging techniques are:

- **Computerized Tomography (CT)** imaging of the head is the first step in understanding Alzheimer's disease**,** head CT scans give a detailed look inside the brain., the scan helps your doctor rule out conditions that mimic Alzheimer’s disease. CT scans also help detect the loss of brain mass linked to Alzheimer’s disease. In an affected brain, there are typically abnormal levels of a protein called amyloid, which causes amyloid plaques to form. Along with plaques in the brain, Alzheimer’s disease destroys important neurons, causing the brain to shrink. Your doctor will notice shrinkage on a CT scan **[17].**

- **MRI of the head** Magnetic resonance imaging (MRI) uses a powerful magnetic field, radio frequency pulses, and a computer to produce detailed pictures of organs, soft tissues, bones, and virtually all other internal body structures. MRI can detect brain abnormalities associated with mild cognitive impairment (MCI) and can be used to predict. In later stages, MRI may show a decrease in the size of different areas of the brain (mainly affecting the temporal and parietal lobes) **[18].**
- **PET and PET/CT of the head** A positron emission tomography (PET) scan is a diagnostic examination that uses small amounts of radioactive material (called a radiotracer) to diagnose and determine the severity of a variety of diseases. A PET/CT scan can help differentiate Alzheimer's disease from other types of dementia. Another nuclear medicine test called a single-photon emission computed tomography (SPECT) scan is also used for this purpose.

I. 6 Conclusion

Alzheimer’s disease (AD) is the most common neurodegenerative disease. AD symptomology, which includes neuronal decay and brain atrophy, causes a significant decline in cognitive functions over time such as memory, recall, behavior, and language. When a patient presents with symptoms of AD, image and clinical data are collected to diagnose the patient and monitor the progression of the disease.

Given the developments and technology that we have reached from techniques and devices such as IRM.FIRM.PET ..., the brain can be photographed, and dissected on it closely through them, and thus possible to analyze, monitor and discover various diseases and abnormalities such as Alzheimer's disease, as we discussed it in this research.

In this chapter, information and explanations were presented about the brain in general and Alzheimer's disease in particular. We also talked about the different stages of its diagnosis and monitoring using techniques and devices for early detection of it. In the next chapter, we will also discuss the interests and reviews of developers of artificial intelligence and what they did for the early diagnosis of Alzheimer.

Chapter II

Literature Review

II.1 Introduction

The aging of the world population leads to an increase in the number of people with dementia. Recent studies show that 55 million people suffer from dementia, of which 60-70% suffer from Alzheimer's disease (AD). AD may be called one of the most common neurodegenerative diseases Causes severe cognitive impairment and behavioral problems. As AD progresses, brain structure and metabolism change. Demonstration The disease involves atrophy of the cerebral cortex and hippocampus, Ventricular enlargement, and changes in regional glucose uptake. These changes can be quantified, especially using medical imaging methods Using Magnetic Resonance Imaging (MRI).

In this chapter, we will present a case of art implemented for detecting or classifying Alzheimer's disease using deep learning. Before this, we will look to know the role of artificial intelligence, feature extraction, and transformation, and a general look at deep learning.

II.2 The Role of Artificial Intelligence

II.2.1 What's The AI

Artificial intelligence (AI) is a field of computer science concerned with the creation of intelligent machines that can perform tasks that normally require human intelligence **[18],** such as B. learning, reasoning, problem-solving, cognition, and natural language processing. Artificial intelligence aims to create machines that can think and act like humans and enable them to perform tasks that would otherwise require human intervention.

Artificial intelligence technology uses a variety of techniques, including machine learning (ML), neural network (NN), deep learning (DL), natural language processing (NL), and robotics, to allow machines to learn and improve from experience, thereby changing their behavior over time. These technologies enable machines to process large amounts of data, recognize patterns, make predictions, and act on that data.

The concept of artificial intelligence (AI) dates back to ancient times when Greek mythology depicted humanoid machines like the bronze automaton Talos and the idea of self-moving objects that mimic humans. However, the development of artificial intelligence as a field of study began in the 1950s with the aim of creating machines that could mimic human intelligence.

In 1956, a group of researchers organized the Dartmouth Conference, where they coined the term "artificial intelligence" and set out the goal of creating machines that "can do things that humans need intelligence to do." The conference marked the birth of artificial intelligence as a formal field of research.

Early on, AI researchers focused on developing programs that could solve problems by sifting through vast amounts of data and applying logical rules. However, these early efforts proved limited, and progress in AI research has been slow.

In the 1960s, AI research turned to the development of expert systems, programs that mimic the decision-making abilities of human experts in a given domain. Expert systems are widely used in fields such as medicine and finance but are limited by their inability to learn and adapt to new situations.

In the 1980s and 1990s, AI research made major advances in the field of machine learning and neural networks, which allow machines to learn from experience and improve their performance over time. These developments have led to the creation of intelligent systems that can recognize patterns, make predictions, and even understand natural language.

In the 21st century, artificial intelligence continues to advance rapidly, driven by breakthroughs in deep learning, natural language processing, and robotics. Today, artificial intelligence is being used in a variety of applications, from self-driving cars to medical diagnostics to virtual assistants, and its impact on society is rapidly expanding **[19].**

Artificial intelligence in medicine is an umbrella term used to describe the application of machine learning (ML) algorithms and other cognitive technologies in medicine. Simply put, artificial intelligence is the ability of computers and other machines to mimic human perception to learn, think, make decisions, and act. Thus, artificial intelligence in healthcare is the use of machines to analyze and manipulate medical data, often with the aim of predicting specific outcomes. A key use case of AI in healthcare is the use of ML and other cognitive domains for medical diagnostic purposes. AI can use patient data and other information to help doctors and healthcare providers make more accurate diagnoses and treatment plans. AI can also help improve predictive and preventive medicine by analyzing big data to provide patients with better prevention recommendations **[19].**

II.2.2 Applications and Goal In AI

Medical AI technology has many applications, including:

- **Medical Image Analysis**: Medical AI technologies can analyze medical images such as X-rays, CT scans, and MRI scans to detect abnormalities and help diagnose conditions. For example, AI can help detect cancer by identifying patterns in medical images that are difficult for the human eye to discern. AI algorithms can also be trained to analyze large volumes of medical images to identify patterns and trends that human radiologists might miss, potentially leading to earlier, more accurate diagnoses.
- **Drug discovery**: AI medical technology can help researchers identify potential new drugs and speed up the drug discovery process **[20].** For example, AI can analyze large volumes of scientific literature and identify new drug targets based on genetic and molecular data. AI can also simulate drug interactions and predict the effectiveness of potential treatments, reducing the need for costly and time-consuming laboratory experiments.
- **Electronic Health Records (EHR)**: AI healthcare technologies can analyze patient data stored in EHRs to improve clinical decision-making, identify high-risk patients, and adjust treatment options. For example, AI can analyze patient data to identify patterns in disease progression, drug use, and treatment outcomes. This can help healthcare providers make more informed decisions about patient care and improve patient outcomes.
- **Virtual Healthcare Assistant**: Medical AI technologies can assist healthcare providers with administrative tasks such as scheduling appointments, managing patient records, and answering patient questions. For example, virtual medical assistants can help patients schedule appointments, obtain medical information, and receive reminders about medications and treatments. This helps improve patient retention and reduces the workload for healthcare provider

II.3 Deep Learning

II.3.1 Definition of Deep Learning

Is a set of learner techniques and automatic sage which has enabled significant advances in artificial intelligence in the last years. In machine learning, a program analyzes a set of data in order to derive rules that will allow conclusions to be drawn about new data. Deep learning is based on what has been called, by analogy, "Artificial neural networks", composed of thousands of units (the "neurons") each of which performs small, simple operations. The results of a first layer of "neurons" serve as input to the calculations of a second layer and so on.

Deep learning enables computational models with multiple layers of processing to learn multiple degrees of abstraction for representations of data. These techniques have considerably improved the state of the art in voice recognition, visual object recognition, object detection **[21],** and various other areas such as drug development and genomics deep learning.

II.3.2 History Deep Learning

The history of deep learning can be traced back to the 1940s **[22]** when Warren McCulloch and Walter Pitts proposed a mathematical model of artificial neurons, which serves as the neural network used in deep learning today. The basis of network models. However, researchers did not begin to develop deep learning (DL) algorithms and architectures until the 1980s and 1990s.

In the 80s, researchers such as Yann LeCun, Geoffrey Hinton, and Yoshua Bengio made significant contributions to the development of deep learning algorithms such as convolutional neural networks (CNN) **[23]** and backpropagation, helping to solve some of the challenges in training deep neural networks.

In the 2000s, the availability of large datasets and advances in computer processing power pushed deep learning research further. In particular, the advent of graphics processing units (GPUs) has made it possible to train deep neural networks faster and more efficiently.

Since then, deep learning has become increasingly prevalent in a wide range of applications, including image recognition, natural language processing, and robotics. The development of deep learning has also led to breakthroughs in fields such as healthcare, finance, and transportation.

In recent years, researchers have continued to refine and expand the capabilities of deep learning algorithms, including the development of more advanced architectures such as generative adversarial networks (GANs) and attention mechanisms. As a result, deep learning is expected to continue to play a significant role in the development of artificial intelligence technologies in the years to come.

II.3.3 field of application of deep learning

The fields of application of DL techniques are diverse. Indeed, these techniques develop in the field of computer science applied to NTIC, robotics, recognition or comparison of shapes, safety, health, assisted learning by computer science, and more generally artificial intelligence.

Deep learning allows a deformable computer to analyze emotions revealed by a photographed or filmed face, or analyze the movements and position of fingers of one hand, which can be useful for translating sign language, improving the automatic positioning of a camera, etc.

They are used for certain forms of aid to medical diagnosis (e.g., automatic recognition of cancer in medical imaging), or for forecasting or prediction (e.g., prediction of the properties of soil filmed by a robot or the prediction of diseases).

II.3.4 Deep Learning Techniques

II.3.4.1 Convolutional Neural Network (CNN)

The first neural network is said to have been developed by Yann LeCun in *1988* Networks operated by image processing and object recognition. CNN is a neural network type specialized for topological data processing like a grid. in different areas such as Image and video recognition and classification. it is used to identify Human faces, objects, traffic signs, and self-driving cars. recent. In ML, a convolutional network is a type of feed-forward neural network Inspired by biological processes. Five (5) main actions are shown In CNN that is:

- Convolutional layers.
- the layer of rectified linear units.
- pooling layer.
- fully connected layers.
- Loss layer.

II.3.4.2 Recurrent Neural Network (RNN)

The layers in an RNN form an upright cycle, in other words, it Uses the output of a layer as a new input in a new layer. These current neural networks are often created to annotate images, machine translate, or process natural language when they aid in the interpretation of Time or sequence information. RNN for automatic detection of sleep apnea and automatic language processing.

II.3.4.3 Long-Term and Short-Term Neural Networks (LSTM)

LSTM is a type of RNN capable of learning and memorizing dependencies in the long run, the RNN remembers the outputs of these networks to use them as-is new entries. There are also explanations for networks like RNNs' long-term and short-term memory for music composition, Approval, or development of new drugs.

II.3.4.4 Radial Basis Function Network (RBFN)

The full name of RBFN is Radial Basis Function Network, which is an artificial neural network for pattern recognition and function approximation. It has three layers - input, hidden, and output - and uses radial basis functions to transform input data into a higher-dimensional space. The network's learning algorithm involves a learning phase and a testing phase, during which the weights are adjusted to minimize the error between the actual output and the desired output. RBFNs have been applied to various applications such as image recognition, speech processing, and financial forecasting.

II.3.4.5 Generative Adversarial Network (GAN)

This is a deep learning algorithm using GAN, we can create new Instances of data similar to the data that compose them. The GAN consists of a generator and a discriminator against the network, the generation consists in synthesizing the respiratory movement through a contradictory network dual condition generation in 4D CT imaging. They are used to also for super-resolution reconstruction and segmentation in MRI.

II.3.4.6 K-Nearest Neighbors (KNN)

ANN stands for k-Nearest Neighbors, a nonparametric machine learning algorithm for classification and regression. It involves finding the k closest data points in the training set to a given input and making a prediction based on the majority class or mean of these k neighbors. The value of k is usually chosen based on cross-validation or other performance metrics. ANN is a simple and intuitive algorithm that can be applied in different domains but can be computationally intensive for large datasets and high-dimensional feature spaces.

II.3.4.7 Artificial Neural Network (ANN)

ANN stands for Artificial Neural Network, a machine-learning model inspired by the structure and function of the human brain. It consists of an input layer, one or more hidden layers, and an output layer consisting of interconnected nodes that process and transmit information. During training, the network learns to adjust link weights and biases to minimize the error between predicted and actual outputs. Artificial neural networks can be used for tasks such as classification, and regression, and have been applied in different fields such as image recognition, natural language processing, and robotics. Artificial neural networks are powerful models, but they can be complex and require careful tuning of parameters for optimal performance.

II.3.5 Fundamental principle of deep learning

Deep learning is based on the structure and function of the human brain, specifically the way neural networks process information. The key idea is to use deep neural networks with multiple layers to learn and represent complex patterns and relationships in data.

During training, the network adjusts the weights and biases of the connections between nodes to minimize the difference between the predicted and actual outputs. This is done using a process called backpropagation, which involves propagating the error in the network's predictions back through the layers to adjust the weights and biases of the connections.

Deep learning algorithms use nonlinear activation functions to enable the network to model complex, nonlinear relationships between inputs and outputs. These activation functions are applied at each node in the network to determine the output based on the input and weights of the connections. By using multiple layers of nonlinear transformations, deep neural networks can learn hierarchical representations of data, where each layer extracts increasingly abstract and complex features of the data. This allows the network to learn complex patterns and relationships that would be difficult or impossible to capture using traditional machine-learning methods.

II.3.6 Deep Learning in the detection and prediction of diseases

Today modern medicine cannot be practiced without the use of images, whether in dermatology, radiology, cardiology, urology, or gastroenterology. . .etc. Precision medicine is a new approach to clinical research and patient care that emphasizes understanding and treating disease by integrating a person's multimodal or multi-omics data to take patient-specific decisions. With the large and complex datasets generated using precision medicine diagnostic approaches, new techniques of processing and understanding these complex data were necessary. At the same time, computing has advanced rapidly to develop techniques that allow the storage, processing, ng, and analysis of these complex data sets, a feat that traditional statistics and early computer technologies could not accomplish.

Machine learning, a branch of artificial intelligence, is a computational methodology that aims to identify complex patterns in data that can be used to make predictions or classifications about new invisible data or for advanced exploratory data analysis. Machine learning analysis of multimodal medical data accuracy allows large datasets to be analyzed and ultimately better understand human health and disease. This review focuses on the use of machine learning for the "big data" of precision medicine, in the context of genetics, genomics, and beyond.

II.4 Related Works

II.4.1 Work by Soliman and IA

In this study **[24],** the authors proposed to predict AD with a neural network deep 3D convolutional (3D-CNN) As shown in Figure II.1, which can learn generic features capturing AD biomarkers. The authors succeeded in classifying the MRI data of the Alzheimer's subjects from normal controls using a dataset using 3013 scans where the accuracy of the training data reached 96.5% and that of the test data reached 80.6%. A summary of the experimental results is given in Table 2.1, After that, there are two 3D (3x3x3) convolution layers with a size of 324 core, max pooling (2x2x2), and 3D convulsion layer (3x3x3) with a core size of 512 and a max pooling size (2x2x2).

Table II.1: Performance of the proposed model on the ADNI dataset

Class	Precision	Recall	Fl-score	Accuracy	Support
CN	0.78	0.92	0.84	0.92	159
MCI	0.76	0.80	0.78	0.80	157

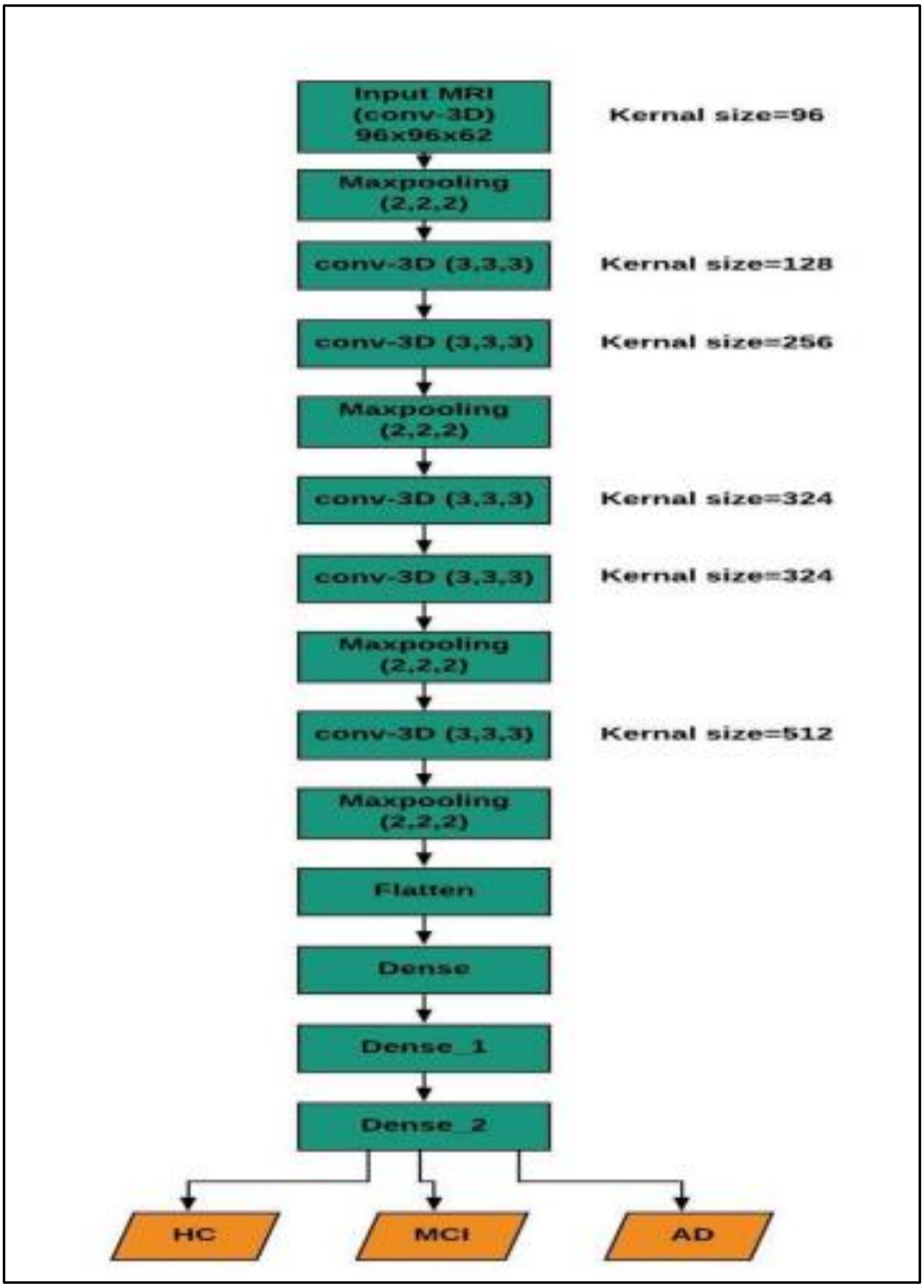

Figure II.1: Block diagram of proposed Alzheimer's disease diagnosis framework **[24].**

II.4 .2 Work by Dhinagar and IA

In this study, Dhinagar and la. **[25]** proposed a deep-learning approach to classify Alzheimer's disease using T1-weighted 3D brain MRI images. They have also implemented a random forest classifier as a reference model in extracting key radiomic features from the same weighted MRI images T1. Their random forest classifier is shown in Figure II.2.

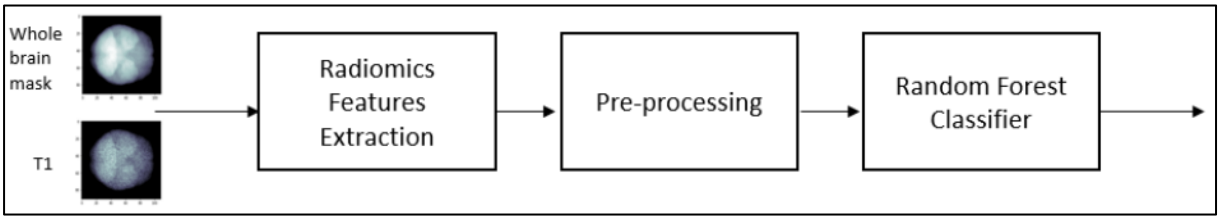

Figure II.2: Machine Learning Pipeline for Neurodegenerative Disease Prediction **[25]**

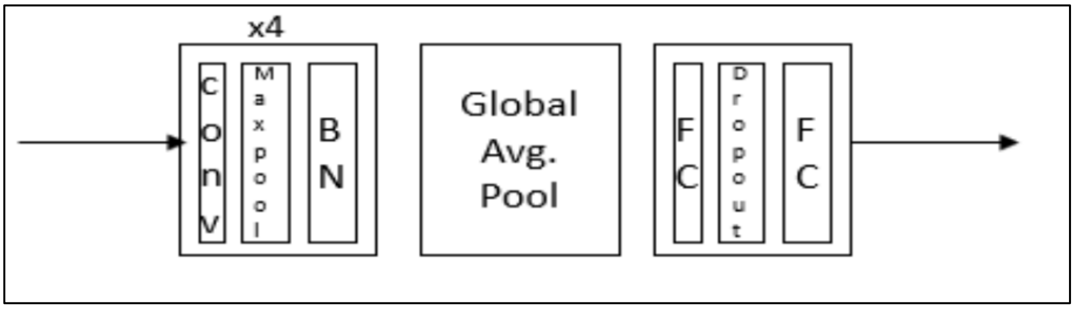

Figure II.3: The architecture of the 3D Convolutional Neural Network (CNN) **[25].**

The architecture of their 3D CNN model is shown in Figure II.3. The entry for this model is 91x109x91. The CNN consists of 4 modules consisting of 3 layers: Convolutional (conv), Max-Pooling (max pool), and Batch Normalization (BN) to extract features from the convolutional layers have 64, 64, 128, and 256 filters respectively. The feature extraction block is connected via a global mean layer to a fully connected layer (FC) with 512 neurons, a reject layer, and a layer fully connected with a sigmoid activation function for binary problem classification. The binary cross-entropy function is used as the loss function for CNN.

Table II.2 Performance of the random forest classifier and 3D CNN for AD classification [25].

Metric	OASIS	
	Random	CNN 3D
ROC-AUC	0.558(0.038)	0.789(0.038)
PR AUC	0.556(0.048)	0.795(0.042)
Accuracy	0.571(0.018)	0.742(0.036)
Precision	0.575(0.041)	0.724(0.055)
Recall	0.603(0.105)	0.793(0.039)
F1-score	0.580(0.037)	0.755(0.029)

The performance of the 3D-CNN and random forest classifier in the OASIS database on various parameters is summarized in Table II.2. The results show that the proposed 3D-CNN outperforms the random forest classifier for AD classification.

II.4.3 Work by Martin and IA

The model proposed in **[26]** is a new deep-learning architecture based on a set of random blocks created by a sequence of 2D convolutional layers, batch normalization, and pooling. A major challenge in this work was to avoid overfitting because the number of features was very large (25,755) compared to the number of samples (132 patients). To solve this problem, the model uses a set of identical sub-models, each with the same weights, with a final pass taking an average of through the submodels. To facilitate the exploration of the feature space, each sub-model receives a random permutation of features. Characteristics correspond to magnetic signals reflecting neural activity and are arranged in a matrix structure, which is interpreted as a 2D image processing by convolutional networks 2D.

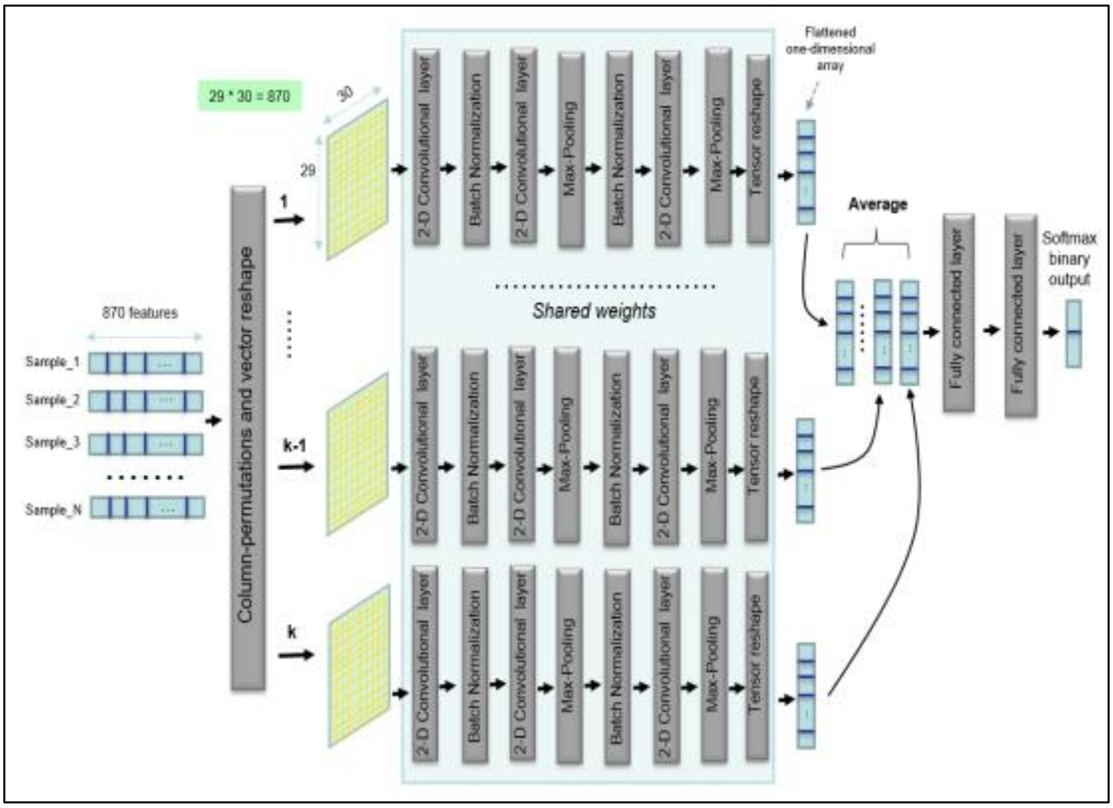

Figure II.4: Randomized 2D CNN model **[26].**

The proposed detection model is a binary classifier (disease/non-disease) which has the highest classification scores compared to other deep learning architectures and classical machine learning classifiers, such as Random Forest and Vector Machine of Support achieved an average F1 Rating of 0.92. A rigorous validation procedure is proposed to carry out the comparison, allowing an in-depth analysis of the results.

II.4.4 Work by Jalindre and IA

The main purpose of the work of Jalindre and la, **[27]** is to build a deep model of Powerful learning for early AD detection and medical image classification for different stages of AD. The author relies on the CNN model Pretrained transfer learning models such as VGG 16 (Fig. II.5) and ResNet 50 (Fig. II.6) and a personalized CNN. Four classification metrics are used: Mild dementia, very mild dementia, moderate dementia, and non-dementia. to make it more the author has created a web application for this purpose, which is useful for both patients' and doctors' AD remote analysis verification. It also determines the AD-stage Patients on the AD spectrum. Actual results show that VGG16 and ResNet 50 were improved to achieve 95% and 84% accuracy respectively. The authors also built a custom model that showed 93% accuracy in the Classification of AD stages (Figure II.7 and Table II.3).

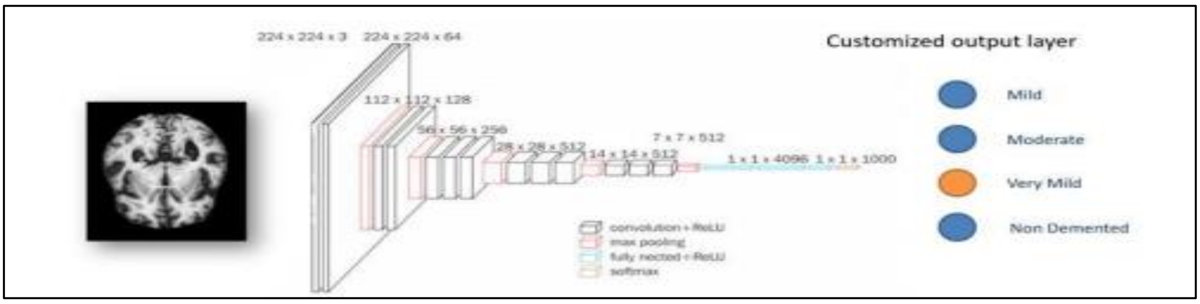

Figure II.5: Approach to the use of VGG **[27]**

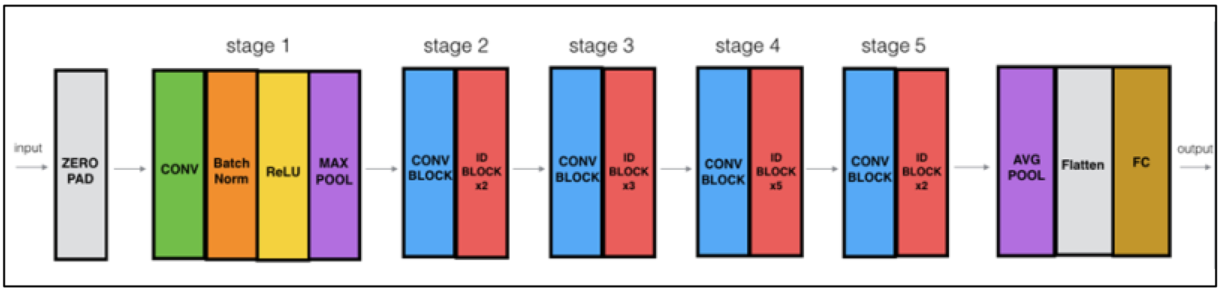

Figure II .6: ResNet50 architecture **[27]**

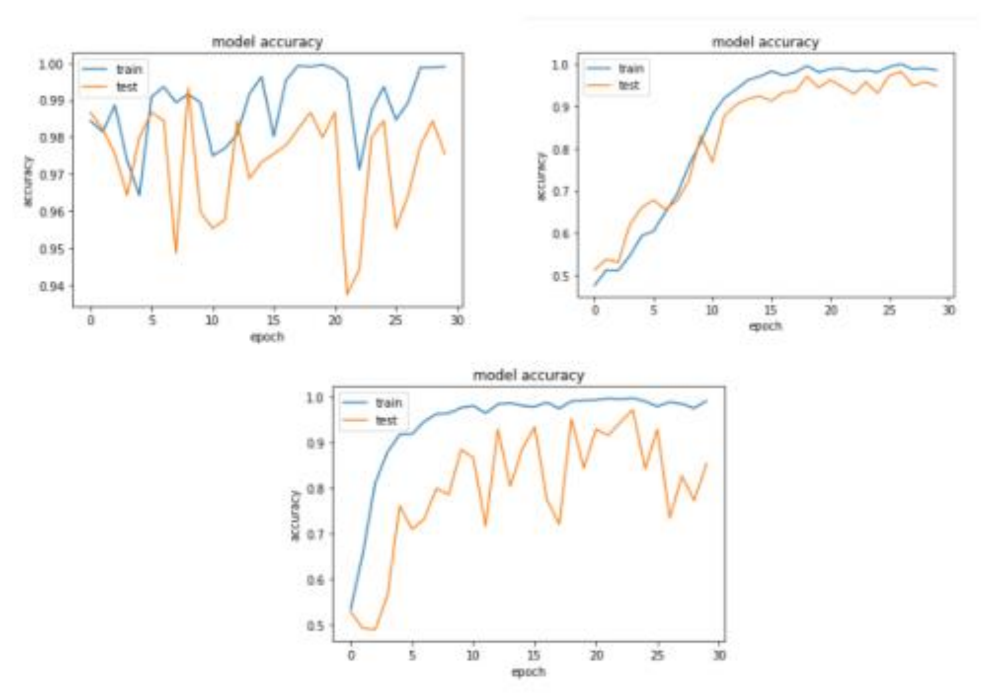

Figure II.7: Accuracy of training and validation of CNN, VGG 16 and Resnet 50 **[27].**

Table II.3: Comparison of performance metrics of the three proposed models (Custom CNN, VGG16, ResNet50) **[27].**

Models	Precision	Recall	F1 Score
Custom CNN Model	93%	93%	93%
VGG16	95%	95%	95%
ResNET 50	87%	84%	83%

II.5 Conclusion

Deep Learning is a vast field that is developing and opening up every day Explore and respond to many human needs and issues, including Classification and segmentation, which play an important role in facilitating care healthy. Alzheimer's disease (AD) is one of the most common dementias It is the only treatment for people for whom there is no cure or effective treatment is early detection, a lot of research has been done to detect them and manage the disease with magnetic resonance imaging. We saw Some of the works in this chapter that use convolutional neural networks to detect the disease. and in the next chapter, we will explain the proposed methods and techniques that help effectively detect this

Chapter III

The proposed approach for early diagnosis of Alzheimer's disease

III.1 Introduction

A timely diagnosis of the disease is useful in organizing healthcare plans, early intervention, right symptoms management, affordable interventions, and provision of safety measures. This is confirmed by the researchers the importance of early diagnosis of Alzheimer's disease **[9].** Recently, several methods and techniques have been proposed for the detection of Alzheimer's disease from brain images. Machine learning and deep learning techniques enable the accurate classification of Alzheimer's disease subjects **[28].**

In this chapter, we will discuss the framework proposed that works on effective classification in Alzheimer's disease, the algorithm that was proposed was explained, and the work of the proposed framework was described by describing its stages and the functions of each stage. where suggested to use deep learning (DL) models to perform multimodal data fusion and convolutional neural networks (CNNs) for early detection of Alzheimer's disease using patients' MRI imaging data.

III.2 Data proposed

In this research work, we have chosen weighted MRI scans of the brain because it provides good contrast of grey and white matter. Our study is based on MRI scans from a publicly available database Kaggle which 36 Mo brain scans images were downloaded and collected from OASIS This data contains images of the brain of Infected, non-infected, and moderately infected persons divided into four categories (Very Mild Demented, Nondemented, Mild Demented, Moderate Demented).

III.3 Algorithm Applied

III.3.1 Deep learning

Deep learning originates from artificial neural network theory. With reference to the human brain, the information is graded and processed, and neural networks of different levels are established. Deep learning obtains key feature information from data such as images and texts by simulating the human brain and effectively extracts multi-level feature information **[29].**

Deep learning mainly describes the attributes of specific objects through hierarchical processing based on a large amount of edge feature information. It is a process from low-level feature extraction to high-level feature combination **[30].** As an important method of machine learning, deep learning is an effective way to use neural network models to process large amounts of data and obtain abstract features. A deep neural network model consists of many layers, and each layer contains a large number of neurons. The neural network model can not only realize the abstract expression of data but also has a strong learning function. We can generalize the deep learning workflow into three processing steps data understanding and preprocessing, deep learning model creation and training, and validation and interpretation **[31].** So, we conclude that there are two main reasons that lead us to choose deep learning over traditional machine learning methods for image classification:

- **Ability to learn complex features:** Deep learning models are able to learn complex and abstract features from images that may be difficult or impossible to extract using traditional machine learning methods. This is particularly useful in medical imaging.
- **Better performance on large datasets:** Deep learning models are typically able to outperform traditional machine learning methods when large amounts of labeled data are available and can often achieve higher accuracy.

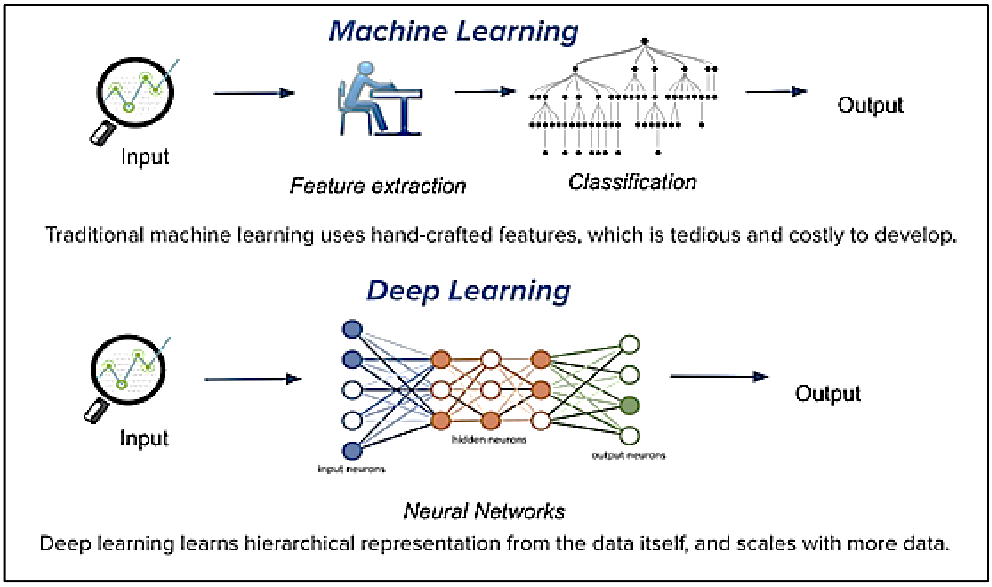

Figure III. 1: The Difference Between Deep Learning and Machine Learning

III.3.2 Processing steps deep learning

Classification methods differ from one method to another according to what suits your purpose and what you suggest. For example, in machine learning, will go through three basic stages: extracting features, reducing features, and classifying, while in deep learning, these stages are collected simultaneously using CNN so there is no need to manually extract the features, its layers work on that. (Explanation of learning layers in the next title).

Deep learning algorithms are made by connecting layers between them the first step is the input layer followed by the hidden layer(s) and at the end the output layer. We proposed in our research for finding a result the following steps.

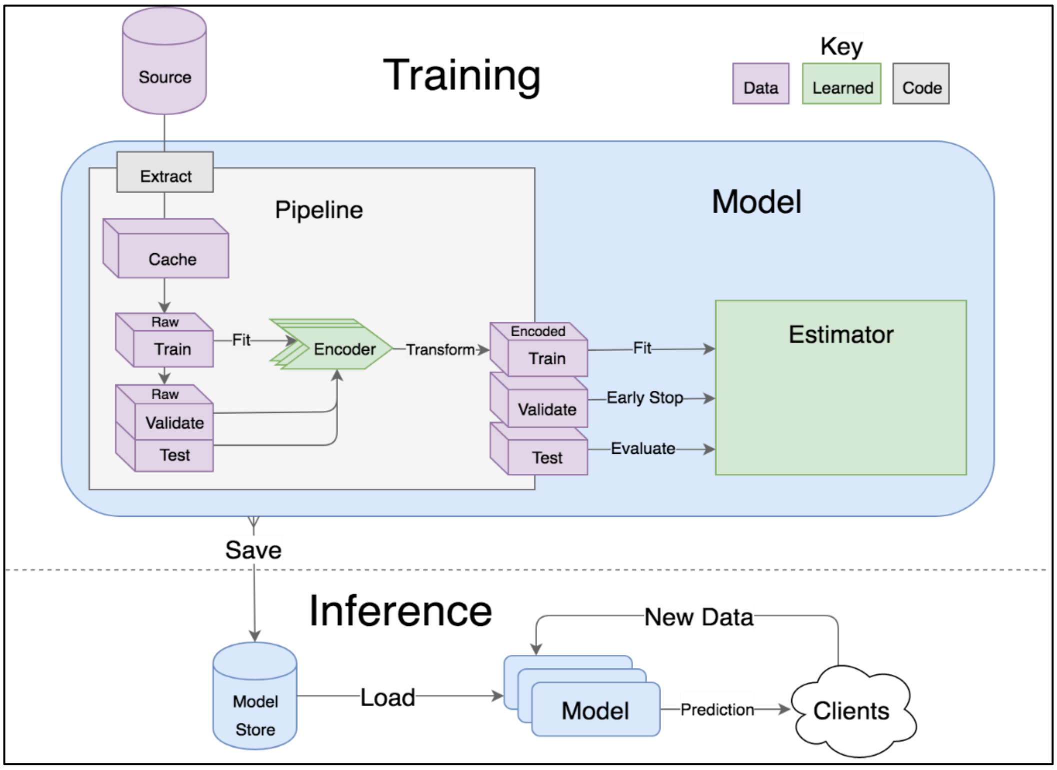

Figure III.2: Diagram of the proposed approach in the deep learning model.

1. **Collect and Preprocessing Step:**

after understanding the goal of the model, the type of data you need, and the problem constraints.is collecting the data and preprocessing it this includes cleaning and preprocessing the data to remove noise, missing values, or inconsistencies. The data should also be split into training, validation, and testing sets. we choose an appropriate architecture that will work for our problem. This can include selecting the number of convolutional layers, pooling layers, types of activation functions, and other hyperparameters that affect the model's performance **[32].**

2. Compiling the Model step

The requirement of the compilation step in deep learning is to configure the model for the fitting/training process to be successfully completed. It is during the compile step that some of the critical components or parameters of the training procedure are defined for the evaluation procedure. as, we have the loss, optimizer, metrics, and others. The kind of loss is determined by the type of problem we are encountering and what we need to solve. The optimizers are usually Adam, RMSprop, or similar optimizers for computations, and the metrics can be accuracy or any other user-defined metrics for analysis.

3. The Fit and Train Model step

The subsequent logical step is to bind the model to the training dataset. The fitting function directs the model to a specified number of epochs (iterations over the dataset). This data is broken down into small parts (called batches) and fed individually into neural networks. The batch size is the total number of training samples in the batch. To generalize the model, we use more than one epoch in most deep-learning models. The higher the number of epochs, the more parameters are changed, resulting in a more efficient model **[32].**

With this function, important parameters such as the number of training epochs, input and output data, validation data, and many more are determined. It is used to calculate and compute these basis functions. The aptitude phase must be continuously evaluated throughout the training process. It is important to ensure that the trained model performs well, improving accuracy and reducing overall losses. By an optimization algorithm by determining the loss function and choosing the appropriate learning rate. It is also important to remember that the model is by no means overly complicated. To do this, you need to use a continuous assessment with a tool like Tensor board to analyze the different charts and find out if these patterns are overtrained **[33].**

4. Evaluation step

After training the model, evaluation and predictions one main step of the deep learning model, so the model must be tested with variable data and random tests to see its effectiveness on un-trained data and if its efficiency of performance matches the required and if the performance is satisfactory or not **[33].**

III.4 Deep learning architecture proposed

III.4.1 Convolution neural network (CNN)

Yann LeCun is a director of Facebook's AI Research Group. He is widely known as the pioneer of convolutional neural networks (ConvNets), which are a type of deep learning model that is specifically designed to deal with 2D shapes like images. LeCun built the first ConvNet, known as LeNet, in 1988. This neural network was primarily used for character recognition tasks, such as reading zip codes and digits. The success of LeNet demonstrated the potential of ConvNets in computer vision tasks and paved the way for the development of more advanced deep learning models **[34].** ConvNets are unique in that they can learn directly from the input data without the need for human feature extraction. This means that the network can automatically discover essential features from the input, making it more powerful and efficient than traditional machine learning models. ConvNets have been widely employed in various fields, including visual recognition, medical image analysis, image segmentation, natural language processing, and many more **[35][36].**

In summary, Yann LeCun's contribution to the development of ConvNets has revolutionized the field of computer vision and deep learning. His pioneering work has opened up new possibilities for solving complex real-world problems using artificial intelligence. Among them, the convolution layer completes the feature extraction task, and the pooling layer is used for feature mapping. the full connection layer is similar to the general neural **[31].**

The first layer of a CNN is the convolutional layer. This is the main building block of CNN where most calculations occur. It requires fewer components, such as input data, feature maps, and filters **[35].**

1. Convolutional layer

This is the first stage used to extract various features from the input image. In this layer, the mathematical operation of convolution between the input image and a filter of a given size M x M is performed. Dragging a filter over the input image creates a bitmap product between the filter and the portion of the input image that affects the filter size (M x M) **[37].** The output is called a feature map, which gives us information about the image such as Corners and edges. This feature map is then passed to other layers to learn many other features of the input image.

CNNs can also contain additional convolutional layers **[38].** This makes the CNN architecture hierarchical, with subsequent layers seeing pixels in the receptive field of previous layers. The convolutional layers then convert the mapped image into numerical values, allowing the network to understand and extract the value patterns **[39].**

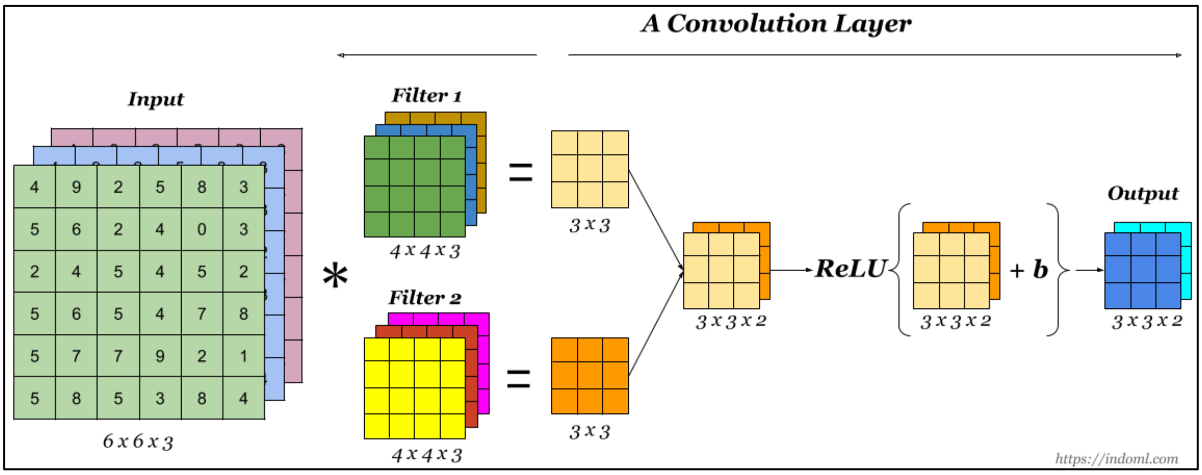

Figure III. 3: Example explain first layer in CNN "Convolution neural network".

2. Layer pooling

Grouping levels are used to reduce dimensionality, known as downsampling. It reduces the parameters used in the input. This is done by reducing connections between layers and working independently on each feature map. Pooling operates like a convolutional layer in that it shifts a filter across the input, but without weights **[39].** This filter applies an associative function to the values in the sink field to populate the resulting array.

Pooling layers usually act as a bridge between convolutional layers and FC layers. This CNN model generalizes the features extracted by the convolutional layers and helps the network identify features independently. With its help, the calculations in the network are also reduced **[37].** There are two types of layer pooling: average pooling and max pooling.

- Average Pooling: in the receiver field calculated the average value of the filters scanning the input to pass to the output network.
- Maximum pooling: It chooses the value pixel the biggest one and when the filter sweeps the input sends it to the output array. In general, it uses Maximum pooling is used more than average pooling.

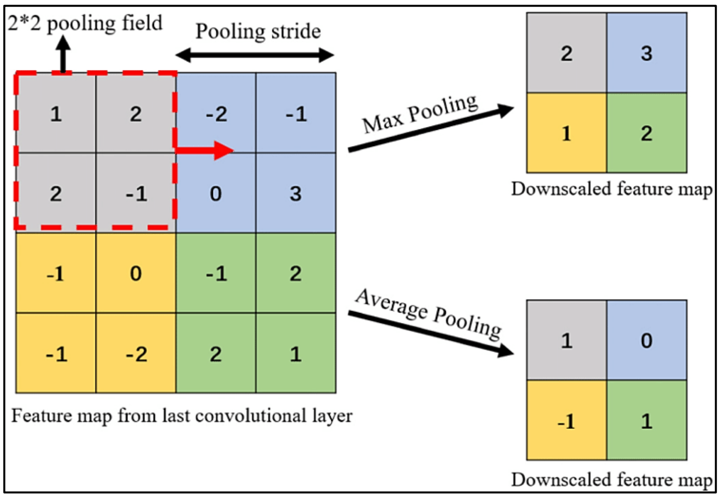

Figure III. 4: Examples for Max and Average Pooling Layer.

Although pooling loses important data, it still provides CNNs with many advantages. It helps reduce the risk of overfitting and complexity while increasing efficiency. It also improves the stability of CNN.

3. Fully Connected Layer (FC)

The Fully Connected Layer (FC) is a type of layer in a Convolutional Neural Network (CNN) where all nodes in the output layer are directly connected to the nodes in the previous layer. Its function is to classify images based on features extracted from previous layers with their respective filters **[38].** To achieve this, the input image from the previous layers is flattened and fed into the FC layer, where mathematical operations usually take place across several layers. Two fully connected layers are often used as they perform better than a single connected layer, thereby reducing human supervision in the CNN **[39].** Unlike ReLu functions used in pooling and convolution layers, FC layers typically use a SoftMax activation function to correctly classify inputs, producing a probability of 0 or 1.

The SoftMax Activation Function can be mathematically expressed as:

$$f_i(x) = \frac{e(x_i)}{\Sigma_j e(x_j)}$$

And ReLu function is expressed as:

$$f_{(x)=\max(0,x)} \quad (1)$$

According to Equation 1, the output of ReLu is the maximum value between 0 and the input value. The output is 0 when the input is negative and the input when the input is positive. We can then rewrite Equation 1 as follows:

$$f(x) = \begin{cases} 0, if\ x < 0 \\ x, if\ x \geq 0 \end{cases}$$

III.4. 2 Models of CNN Architecture

Moving on to the discussion on CNN models, this section covers various architectures, their uses, and their evolution. Pre-trained models are also available, which can be easily adapted for use cases and model requirements. Below are some of the popular and widely used CNN architectures:

1. LeNet: LeNet, which was introduced in 1998, is the first and most widely used Convolutional Neural Network (CNN) architecture. It was created to tackle the challenge of recognizing handwritten digits. The architecture of LeNet includes several convolutional and

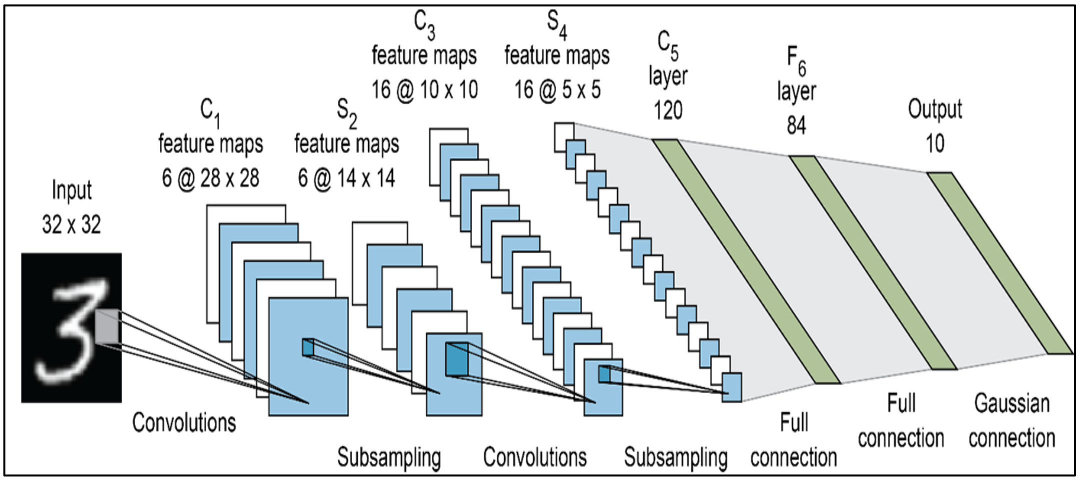

Figure III.5: The pre-trained LeNet network architecture.

pooling layers, followed by a fully connected layer. The model comprises five convolutional layers and two fully connected layers **[41].** LeNet represents the inception of CNNs for computer vision tasks. However, the model encounters a vanishing gradient issue, resulting in ineffective training. To overcome this problem, a max pooling layer with a shortcut connection is utilized between the convolutional layers to down sample the image's spatial dimensions. This technique aids in avoiding overfitting and enhancing the CNN's training efficiency **[40].**

2. AlexNet: AlexNet is the deep learning architecture that made CNN popular. Developed by Alex Krizhevsky and his friends. AlexNet is similar to the LeNet architecture, but it is deeper, larger, and contains convolutional layers stacked on top of each other **[41].** AlexNet won the ImageNet Large Scale Visual Recognition Competition (ILSVRC) in 2012. It was developed for use with large image datasets. Alex Net consists of 10 layers divided into 5 convolutional layers and a set of max pooling layers, 3 fully connected layers and 2 drop layers. Relu is the activation function used at all levels. SoftMax is the activation function used by the output layer. The total number of parameters in the scheme is about 60 million **[40].**

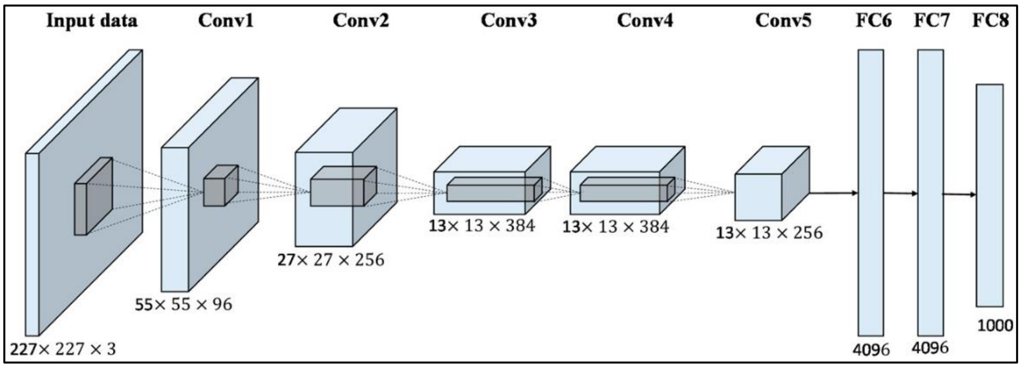

Figure III. 6: The AlexNet architecture.

3. ZF Net: ZF Net is a CNN architecture that uses a combination of fully connected layers and CNN. ZF Net is developed by Matthew Zeiler and Rob Fergus. The network has relatively fewer parameters than Alex Net. It was an improvement over Alex Net by adjusting the hyperparameters of the architecture, increasing the size of the intermediate convolutional layers, and decreasing the step size and filter on the first layer **[41].** The ZF Net CNN architecture consists of a total of seven layers: the convolutional layer, the maximal (minimization) pooling layer, the serialization layer, the convolutional layer with linear and first-step activation function, and drop-in for regularization purposes applied before the fully connected output **[41].** The goal of the generated ZFNet is to visualize network performance statistically to track CNN performance by analyzing neuronal activation.

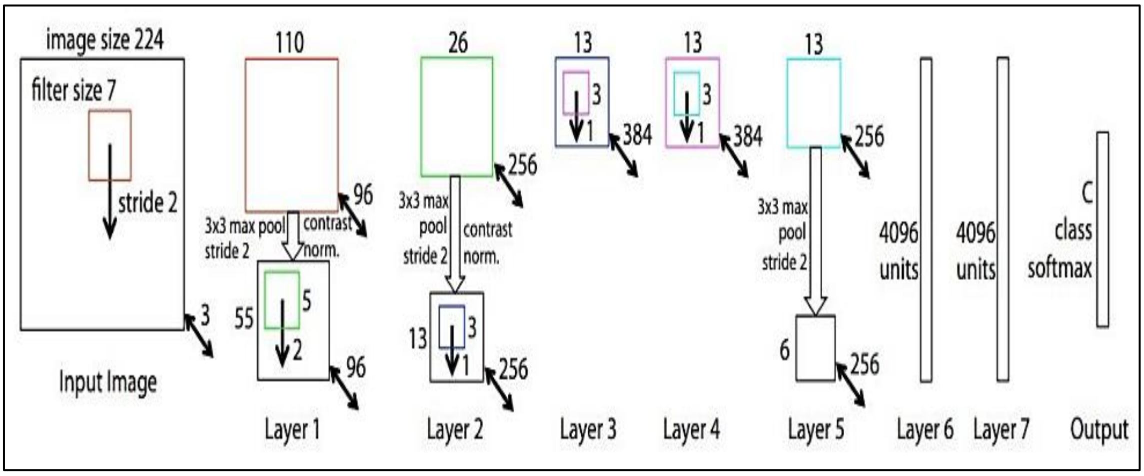

Figure III. 7: The Structure Of The ZF Net Model.

4. GoogleNet: GoogLeNet is the CNN architecture that Google used to win the ILSVRC classification task in 2014. The error rate in the top 5 was 6.67%, which was almost as good as human performance **[38].** It achieves a deeper structure using a number of distinct techniques, including 1×1 convolution and global mean pooling. The GoogleNet CNN architecture is a computationally expensive deep convolutional neural network. It is now being used in a variety of computer vision applications, such as face detection and identification, adversarial training, and so on **[41].** It uses heavy deconvolution layers on top of CNNs to remove spatial redundancy during training and to reduce the parameters that need to be learned, and it also provides shortcut connections between the first two convolutional layers and consists of 22 conv layers**.** Relu is the activation function utilized at all levels. and SoftMax is the activation function used in the output layer. The total number of parameters in this architecture is around 60 million **[38].**

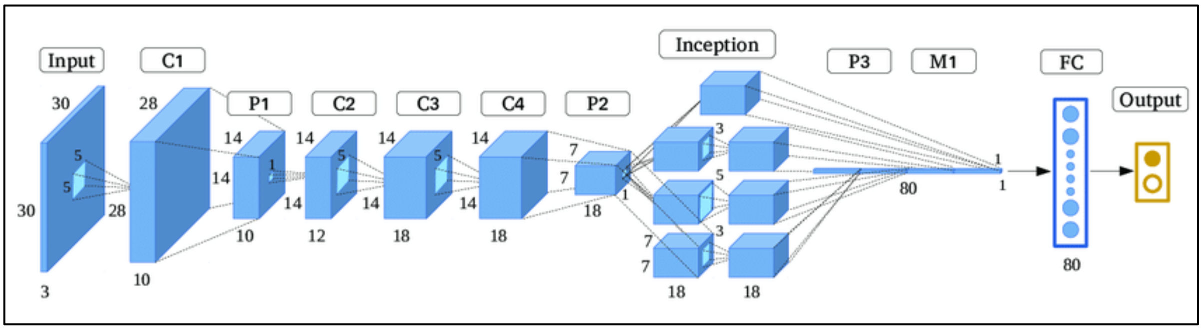

Figure III. 8: GoogleNet architecture.

5. VGGNet: VGGNet is a CNN architecture developed by Karen Simonyan and Andrew Zisserman et al. at the University of Oxford. VGGNet is a 16-layer CNN with up to 95 million parameters and is trained on more than 1 billion images **[31].** It can capture large input images of 224 x 224 pixels which contain 4096 convolutional features. CNNs with large filters are expensive to train and data-intensive, which is the main reason why CNN architectures such as GoogLeNet (AlexNet architecture) perform better than VGGNet for most image classification tasks where the size of the input images is between 100 x 100 pixels and 350 x 350 pixels **[38].** The VGG CNN model is computationally efficient and serves as a solid foundation for many computer vision applications due to its applicability to many tasks **[37].**

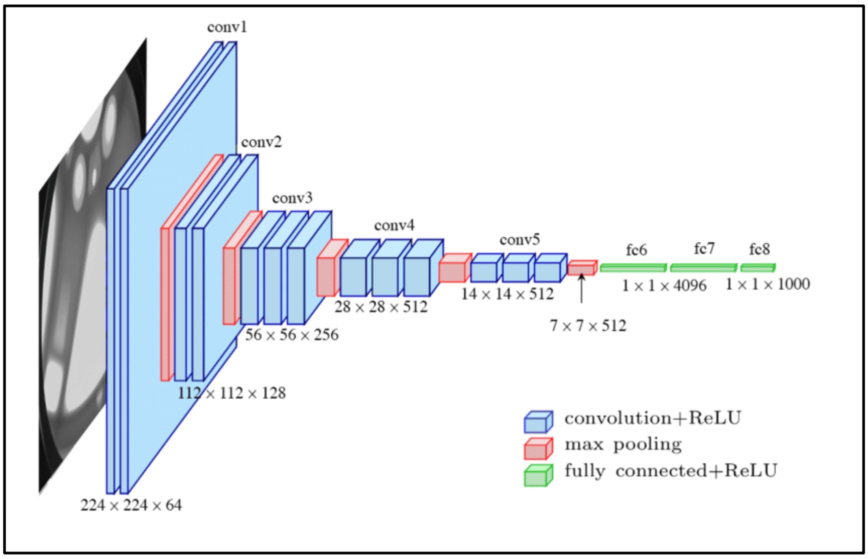

Figure III. 9: The standard VGG-16 network architecture.

6. ResNet: ResNet is a CNN architecture developed by Kaiming He et al. For winning the 2015 ILSVRC ranking task with a top-five error of just 15.43% **[38].** ResNet is one of the most widely used and effective deep learning models today. The network contains 152 layers and over a million parameters. CNNs are mainly used for image classification tasks with 1000 categories, but ResNet proves that CNNs can also be used successfully to solve natural language processing problems such as sentence completion or machine understanding. The CNN ResNet architecture is computationally efficient and can be scaled up or down to match the computing power of the GPUs **[38].**

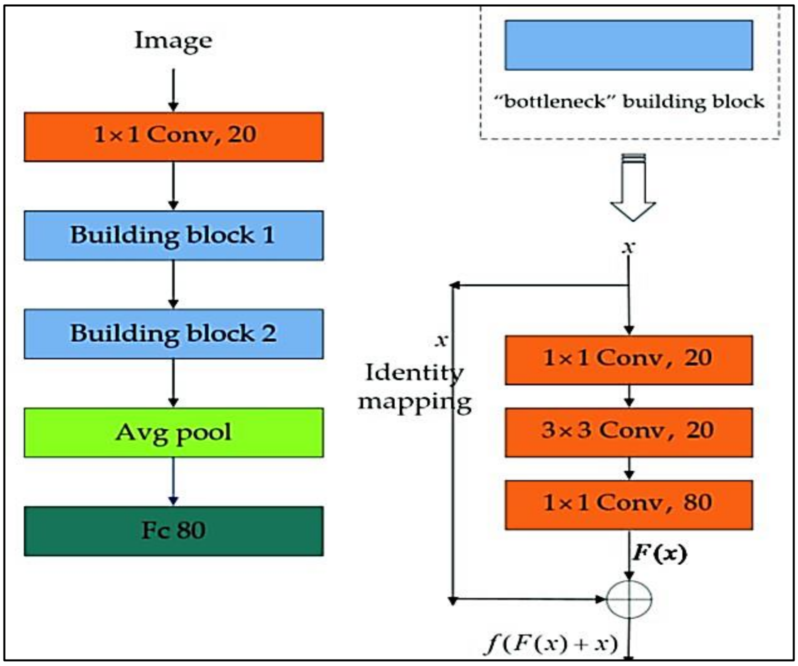

Figure III. 10: A Residual Network for Shortcut Connection.

7. **MobileNets:** MobileNets are CNNs that can be installed on a mobile device for image classification or object detection with low latency. Developed by Andrew G Trillion and others, MobileNets are very small CNN structures, making it easy to run in real-time using embedded devices such as smartphones and drones **[38].** The architecture is also very flexible, so it has been tested on CNNs with 100 to 300 layers and still performs better than other architectures like VGG Net. Real-world examples of the Mobile Nets CNN architecture include CNNs built into Android phones to run Google's Mobile Vision API, which can automatically identify tags for common objects in images **[41].**

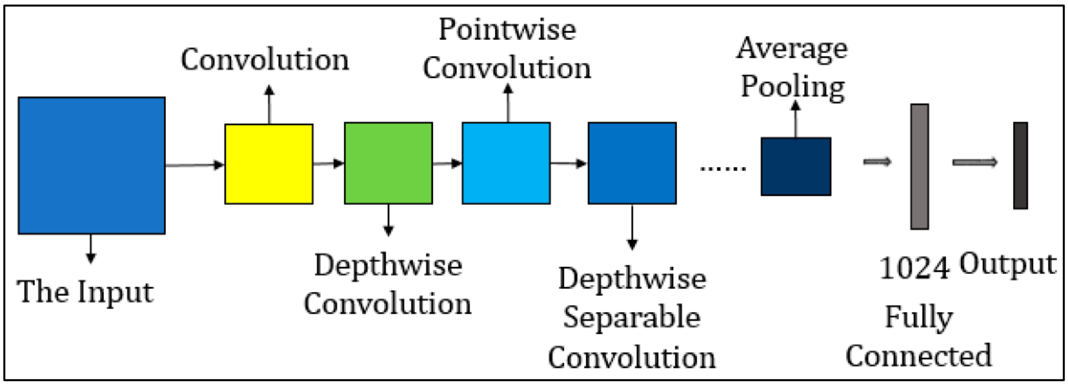

Figure III. 11: The Structure of The Mobile net V1 Network.

III.4.3 Other CNN tools

Convolutional neural networks (CNNs) have several tools that can be used during training to improve performance. Some of the most important tools are:

❖ **Padding**

Convolution and pooling operations can make the input matrix smaller and this may cause image information to disappear. Padding is used to top and solves this problem; it simply consists of adding zeros all around a matrix to increase image size **[35].** (Padding is a related term for convolutional neural networks as it refers to the number of pixels added to an image as it is processed by the CNN core **[43].** as shown in Figure Ⅲ.11.

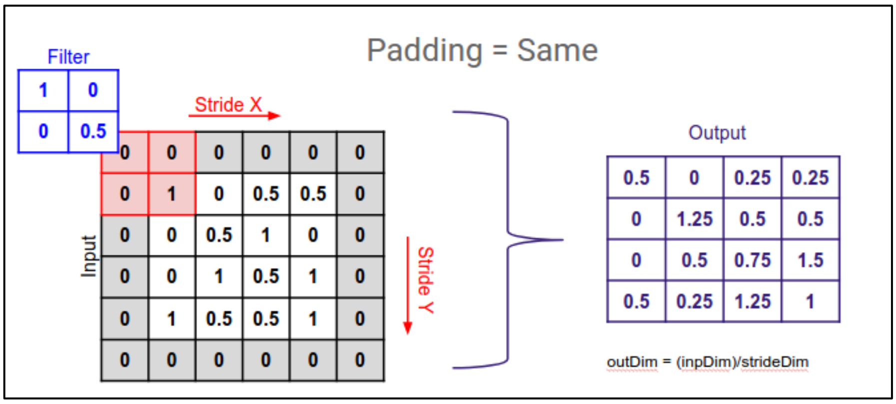

Figure III. 12: Padding Example of Type Same.

❖ **Activation function**

An activation function is a mathematical function used on a signal. It reproduces the activation potential found in the field of human brain biology**.** It allows the passage of information if the stimulation threshold is reached. Concretely, its role is to decide whether or not to activate a neuron response and it maps the resulting values between 0 and 1 or -1 to 1, etc. depending on function: Sigmoid, ReLU, Softmax…**[42].**

❖ **Error function**

The error function also called the loss function or cost function specifies how the network training penalizes the deviation between the expected signal and the real. It calculates the error between the desired or known output and the output produced by the network. Various error functions suitable for different tasks can be used **[44].** When the SoftMax function is used to predict a single class among K classes mutually exclusive. The Euclidean error function is generally used to regress to real values. In the case of classification into two classes, the most used error function is the binary cross-entropy**.**

- **Overfitting**

The overfitting problem is generally caused when certain neurons are too interrelated and too dependent as learning progresses. Thus, the dropout makes it possible to avoid the problem of over-learning by the random deletion of certain dependent links, by specifying each time mainly a very important parameter which is the "rate"**[45].**

The parameter rate: is a value between 0 and 1 and which implies the probability of deletion of an inter-neuronal link. In practice, it is generally between 0.2 and 0.75**.**

- **Batch normalization**

Batch normalization is a technique that improves the speed and final performance of an artificial neural network**.**

It is used to normalize and scale the data at the input of the neural network by adjusting all the values of the input layer, this allows to regularize of the neural model and avoids certain very high data dominating others. This also makes it possible to take advantage of the smallest data which can be very important to the functioning of the neural network **[35].**

- **Early stopping**

Early stopping is a method of regularization that involves interrupting the training of a learning model when the loss of a validation data set begins to increase and the performance of the training model begins to increase **[46].**

- **Data augmentation**

Data augmentation in data analysis is a technique used to increase the amount of data by adding slightly modified copies of already existing data or newly created synthetic data from existing data. It acts as a regulator and helps reduce overfitting when training a machine learning model. It is closely related to oversampling in data analysis **[47].**

- **Optimization**

We explain in this section two optimization methods widely used in
CNNs:

- RMSprop method: This is an optimization method developed by Professor Geoffrey Hinton. Instead of letting all gradients accumulate for Momentum, it only accumulates gradients in a fixed window.

RMSprop also tries to dampen oscillations, but in a different way than impulse. RMSprop also avoids having to adjust the pace of learning, and does it automatically. Additionally, RMSprop chooses a different learning rate for each parameter. In RMSprop, each update is performed according to specific equations **[48][35].**

- Adam method: Adam is the abbreviation of "Adaptive Moment Estimation", it is the most used optimization method in deep learning. It offers another way to use past gradients to calculate current gradients. Adam also uses the concept of adaptive momentum by adding fractions of previous gradients to the current gradient. This optimization method has become quite widespread and is practically accepted for use in training neural networks. It's easy to get lost in the complexity of some of these new optimizers. Adam is generally considered to be quite robust in selecting hyperparameters, although sometimes the learning speed needs to be tweaked from the suggested default **[48][35].**

III.5 Conclusion

Several techniques have been proposed by researchers for helped them to diagnose different disease special neural diseases such as Alzheimer's disease. Various ways are suggested to show her efficiency by using AI machine learning or deep learning.

In this chapter, we introduced the proposed work in our project showing data which we worked in deep learning by using the convolution neural network algorithm and the essential steps for creating a deep learning model then, we go about explaining the CNN algorithm and how to work it and with some parameters and function uses in CNN model. In the next chapter, we will discuss how we implement our work and the final result.

Chapter IV

Experiments, Results, and Discussion

IV.1 Introduction

After addressing the theoretical aspect of our project and deep learning in the previous chapters, this chapter is dedicated to the implementation of our model detection and classification of Alzheimer's disease. Explains and present the tools we used in this work and the results obtained. In addition, at the end will be analyzed and discussed the final result.

IV.2 Development Tools

In this section, we will present the hardware and software, and libraries then the data used in our work.

IV.2.1 Material Tools

In order to implement this project, we used a range of materials and her features as flowing:

- Lenovo t440s ThinkPad laptop
  - ✓ Processor: Intel (R) Core (TM) i7-4600U CPU @ 2.10GHz 2.69GHz
  - ✓ Memory (RAM, random memory in phones and computers): 8,00 GB
  - ✓ Operating System: Windows 11 Pro(64-bit).

IV.2.2 Logical Tools

1. **Python programming language**

Python was developed in 1991 in the Netherlands, designed by Guido van Rossum. It was mainly inspired by the ABC programming language and C language. Python is a so-called high-level language, that is to say, that it moves away from machine language easier to read and write, and closer to human language. Python is also a portable language that can be executed in the same way on a Windows, Mac OS, or GNU/Linux computer, as well as on mobile OS like Android or IOS **[49].**

Figure IV 1: Python logo.

2. Google Colab

Google Colaboratory, or "Colab", is a cloud-based Jupyter Notebook environment. It runs in your web browser. You can write and run Python code, share your code while editing it with other team members, and document everything by combining rich text, diagrams, images, HTML, and LaTeX in a single notebook **[50].**

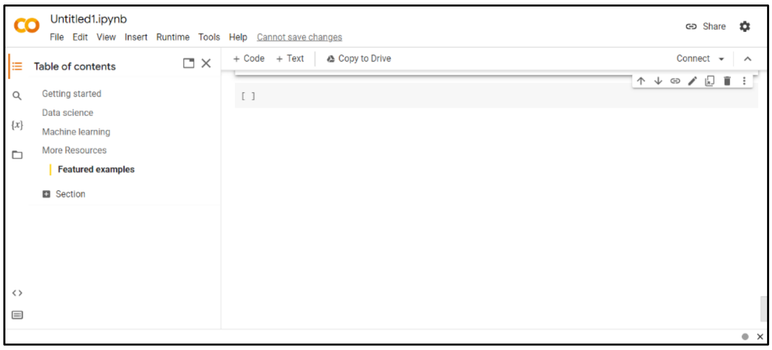

Figure IV.2: Interface of Google Colab.

3. Navigator Anaconda

Anaconda Navigator is a desktop graphical user interface (GUI) included with the Anaconda Distribution that allows you to launch applications and manage conda packages, environments, and channels without using command line interface (CLI) commands. Available for Windows, macOS, and Linux **[51].**

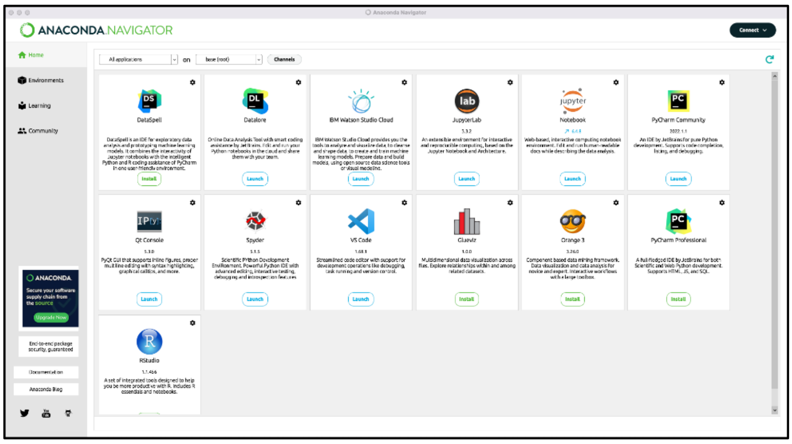

Figure IV.3: Navigator Anaconda

4. Jupyter Notebook

Jupyter Notebook is an open-source web application that can be used to create and share content documents containing live code, equations, visualizations, and text narration. **[52].**

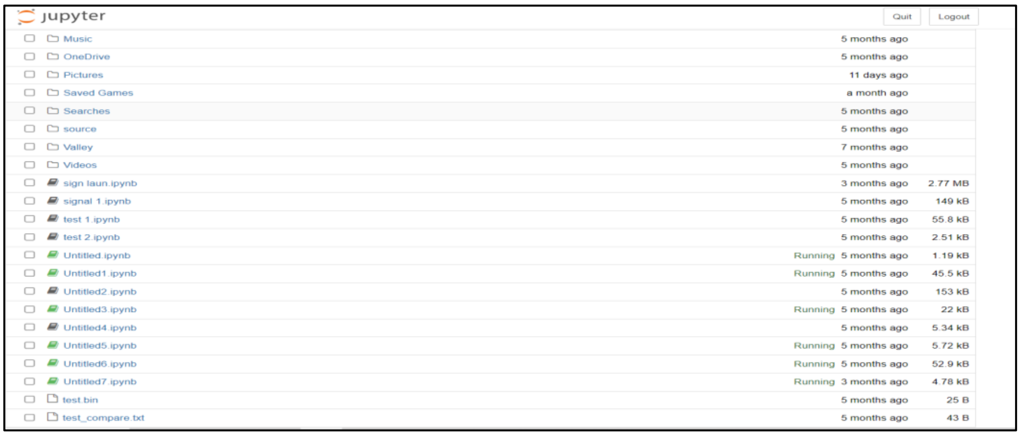

Figure IV.4: Jupyter Notebook.

IV.2.3 Library

1. TensorFlow

TensorFlow is an open-source machine learning tool developed by Google. It is based on the Disbelief framework for machine learning, deep learning, and statistical and predictive analytics.

Figure IV.5: TensorFlow logo.

2. Pandas

Pand Pandas is a Python programming language library specifically for data science. Developed in 1991, it is the most popular programming language for data analysis and machine learning. Pandas is designed for data manipulation and analysis **[53]**.

Figure IV.6: Pandas logo.

3. Matplotlib

Matpl Matplotlib is a plotting library available for the Python programming language as a component of NumPy, a resource for numerical big data processing. Matplotlib uses an object-oriented API to embed charts in Python applications **[54]**.

Figure IV.7: Matplotlib logo.

4. PIL

Python Pillow is an open-source library, a Python imaging library that enhances the image processing capabilities of our Python interpreter. The library supports several functions such as opening, editing and saving images in different formats **[55]**.

Figure IV.8: PIL logo.

5. NumPy

NumPy is a Python library for manipulating arrays. It also has functions for working with linear algebra, Fourier transforms, and matrices. This is an open-source project and you can use it for free. NumPy stands for Numerical Python **[56]**.

Figure IV.9: NumPy logo.

6. Scikit-learn

Scikit-learn is a key library for the Python programming language. Scikit-learn focuses on machine learning tools, including the mathematical, statistical, and general-purpose algorithms that form the basis of many machine learning techniques **[57]**.

Figure IV.10: Scikit-learn logo.

IV.2.4 Alzheimer's Disease Dataset

In our research, we used a dataset from the site of the Kaggle dataset **[58]**. Data was collected manually from various websites, and each label is verified. We have 6400 (5121 for training, 1279 for testing) images from the Kaggle Alzheimer's Dataset. Data were divided into four categories according to the scores (Table IV.1), data preprocessing is the main part of extracting efficient and accurate results for these algorithms based on the CNN model. The image size of Kaggle Alzheimer's Dataset Images of MRI is 176×208. For a good understanding of the classification, we explained the classes of data as following:

- **Mild demented:** individuals who experience noticeable cognitive decline, at this stage perform daily activities with assistance.
- **Moderate demented:** characterized by more significant cognitive decline they often require more assistance.
- **Very mild demented:** is an early stage of dementia where cognitive decline is minimal and may not be readily noticeable. They can function independently .
- **Nondemented:** refers to individuals who do not exhibit any signs or symptoms of dementia. They have a normal cognitive function.

Table IV.1: Number of images used in the dataset.

Alzheimer's Disease Dataset			
Train 80%		Test 20%	
Very Mild Demented	1792	Very Mild Demented	448
Non-Demented	2560	Non-Demented	640
Mild Demented	717	Mild Demented	179
Moderate Demented	52	Moderate Demented	12
Totals	5121	Totals	1279
Totals Dataset		6400	

IV.3 Experiment and Result

IV.3.1 Data loading

We used Kaggle Alzheimer's Dataset for our project as we mentioned earlier. So, load images in directory a condition the data be structured in file directory format.

```
Found 5121 files belonging to 4 classes.
Using 4097 files for training.
Found 5121 files belonging to 4 classes.
Using 1024 files for validation.
```

Figure IV.11: Preprocessing image datasets loaded for training and validation.

IV.3.2 Visualize the data

The visualization data help us to understand what is being used as input for our model and also to see if our images have been loaded in correctly or not.

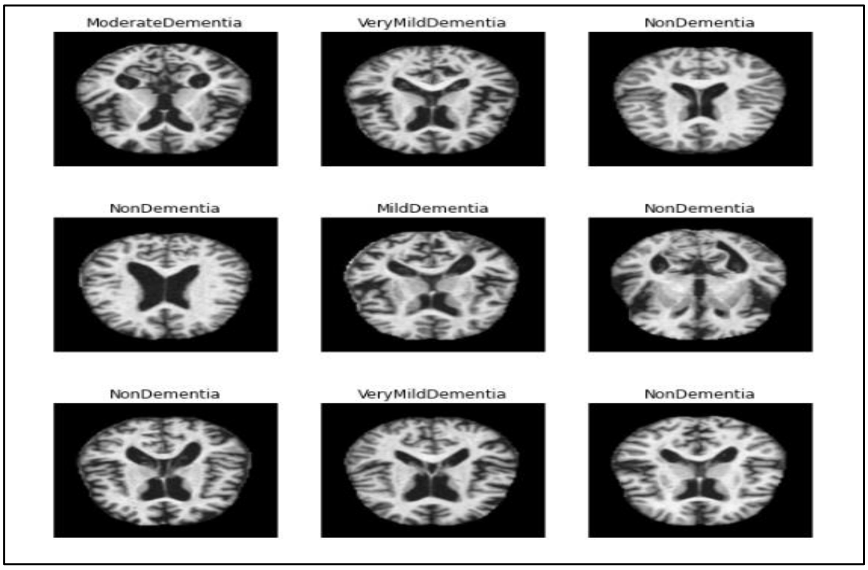

Figure IV.12: Images loaded from our dataset.

IV.3.3 Build the model

For building up the layered we used CNN architecture her main components are convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply filters to the input data, capturing local patterns and detecting features such as edges, corners, or textures. A convolutional block typically consists of several layers. Pooling layers

```
[ ]  model.summary()

     Model: "sequential_7"
     _________________________________________________________________
      Layer (type)                Output Shape              Param #
     =================================================================
      conv2d (Conv2D)             (None, 176, 208, 16)      448

      conv2d_1 (Conv2D)           (None, 176, 208, 16)      2320

      max_pooling2d (MaxPooling2D  (None, 88, 104, 16)      0
      )

      sequential (Sequential)     (None, 44, 52, 32)        2160

      sequential_1 (Sequential)   (None, 22, 26, 64)        7392

      sequential_2 (Sequential)   (None, 11, 13, 128)       27072

      dropout (Dropout)           (None, 11, 13, 128)       0

      sequential_3 (Sequential)   (None, 5, 6, 256)         103296

      dropout_1 (Dropout)         (None, 5, 6, 256)         0

      flatten (Flatten)           (None, 7680)              0

      sequential_4 (Sequential)   (None, 512)               3934720

      sequential_5 (Sequential)   (None, 128)               66176

      sequential_6 (Sequential)   (None, 64)                8512

      dense_3 (Dense)             (None, 4)                 260

     =================================================================
     Total params: 4,152,356
     Trainable params: 4,149,988
     Non-trainable params: 2,368
     _________________________________________________________________
```

Figure IV.13: Summary of our model architecture (CNN).

downsample the feature maps, reducing spatial dimensions and focusing on the most salient information. Fully connected layers follow the convolutional and pooling layers, learn global patterns, and make predictions based on the extracted features. The type of model architecture.

The figure IV.13 provides an overview of the model's architecture of CNN by listing the names of the layers used and their order within the network and the parameters of each layer described are detailed.

IV.3 .4 Training the model

After creating and compiling the model, it comes training step using the fitting method. For that, we use callbacks to adjust our learning rate and stop the model once it converges. The figure IV.14 and IV.15 are representing the beginning and ending the training of the Model.

```
Epoch 1/100
257/257 [==============================] - 21s 44ms/step - loss: 1.1212 - auc: 0.7782 - accuracy: 0.7782 - val_loss: 1.6902 -
val_auc: 0.6371 - val_accuracy: 0.6371 - lr: 0.0100
Epoch 2/100
257/257 [==============================] - 11s 41ms/step - loss: 0.9717 - auc: 0.8160 - accuracy: 0.8160 - val_loss: 1.9972 -
val_auc: 0.6243 - val_accuracy: 0.6243 - lr: 0.0089
Epoch 3/100
257/257 [==============================] - 11s 41ms/step - loss: 0.9487 - auc: 0.8236 - accuracy: 0.8236 - val_loss: 100.7968
- val_auc: 0.6634 - val_accuracy: 0.6634 - lr: 0.0079
```

Figure IV.14: First iterations of model training.

```
Epoch 61/100
257/257 [==============================] - 11s 42ms/step - loss: 0.2005 - auc: 0.9925 - accuracy: 0.9925 - val_loss: 0.2793 -
val_auc: 0.9850 - val_accuracy: 0.9850 - lr: 1.0000e-05
Epoch 62/100
257/257 [==============================] - 11s 42ms/step - loss: 0.1974 - auc: 0.9925 - accuracy: 0.9925 - val_loss: 0.2793 -
val_auc: 0.9851 - val_accuracy: 0.9851 - lr: 8.9125e-06
Epoch 63/100
257/257 [==============================] - 11s 42ms/step - loss: 0.2026 - auc: 0.9920 - accuracy: 0.9920 - val_loss: 0.2794 -
val_auc: 0.9851 - val_accuracy: 0.9851 - lr: 7.9433e-06
```

Figure IV.15: Last iterations of model training.

IV.3.5 Evaluation of the Model

That evaluation is crucial to assess the generalization ability of the trained model on unseen data. It helps in determining the model's effectiveness and its potential for deployment in real-world scenarios. We used the following metrics for assessing our model:

❖ **Accuracy:** Accuracy is a commonly used metric to evaluate the performance of a classification model, including CNNs, accuracy is calculated by comparing the predicted class labels with the true class labels for each sample in the evaluation dataset. If the predicted class

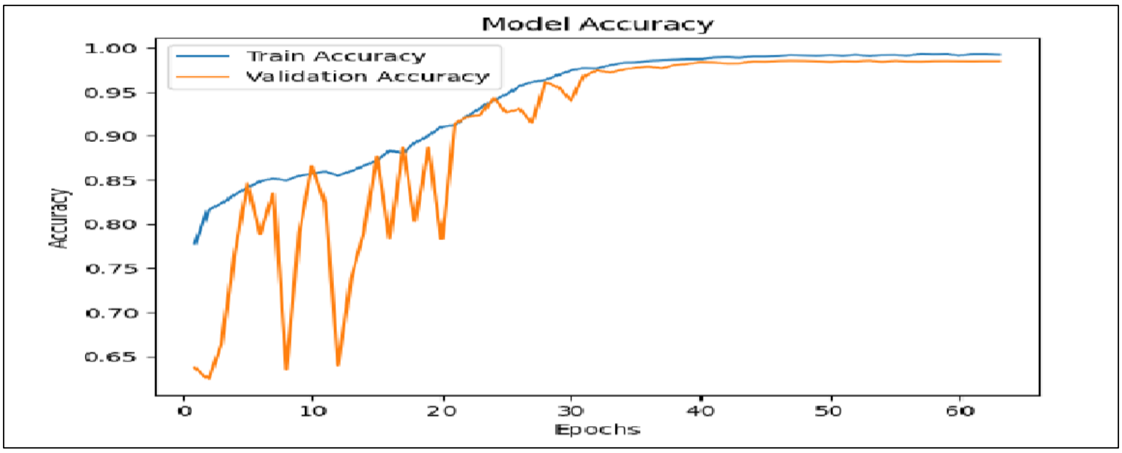

Figure IV.16: Accuracy curve with respect to the number of epochs in the validation and training dataset.

label matches the true class label, it is considered a correct prediction. The accuracy is then calculated as the ratio of correct predictions to the total number of predictions. The figure represents our accuracy values in train data and validation data.

❖ **AUC:** The Area Under the Curve (AUC) is a widely used evaluation metric for binary classification problems, including those tackled by CNNs. It measures the performance of the model in terms of the trade-off between the true positive rate (sensitivity or recall) and the false positive rate. This is what was obtained through the train the model.

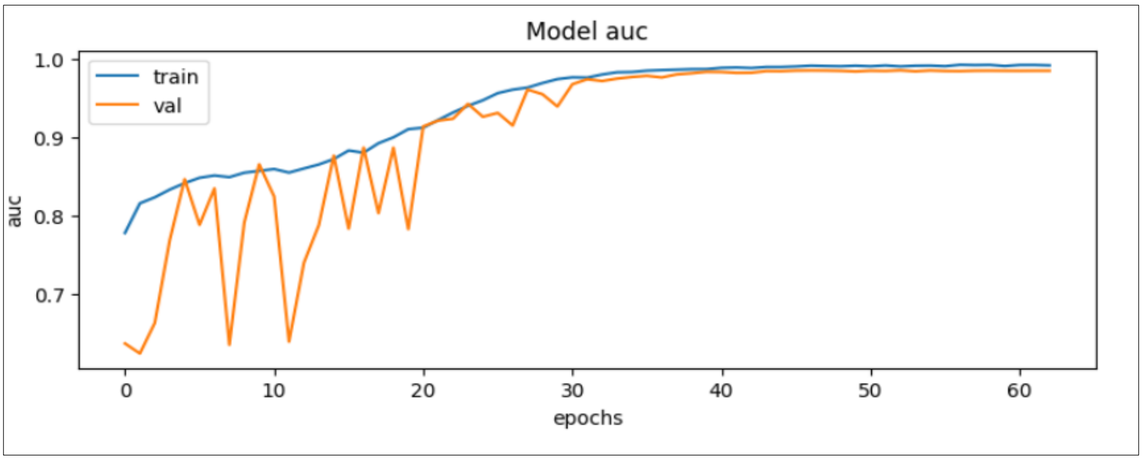

Figure IV.17: Auc curve with respect to the number of epochs in the validation and training dataset.

❖ **Loss:** During the training process, the model aims to minimize the loss by adjusting its parameters (weights and biases) through optimization algorithms such as gradient descent because the model with the lowest error is considered the best.

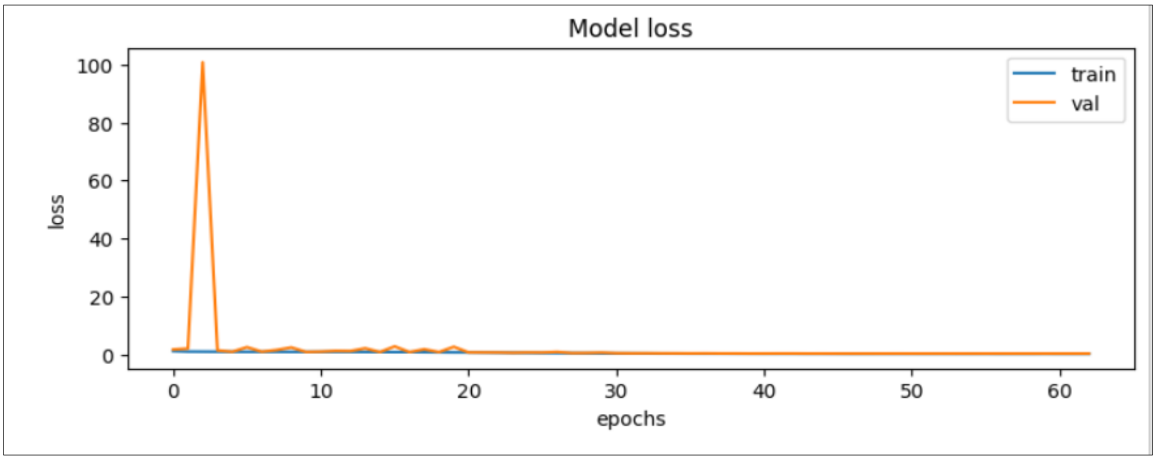

Figure IV.18: Loss curve with respect to the number of epochs in the validation and training dataset.

❖ **Precision:** Precision measures the proportion of correctly predicted positive instances out of all instances predicted as positive. It focuses on the quality of positive predictions and is calculated using the formula:

$$\textbf{Precision} = \textbf{True Positives} / (\textbf{True Positives} + \textbf{False Positives})$$

Note: A high precision indicates a low rate of false positives, meaning that the model is effective in correctly identifying positive instances.

❖ **Recall:** also known as sensitivity or true positive rate, measures the proportion of correctly predicted positive instances out of all actual positive instances. It focuses on capturing as many positive instances as possible and is calculated using the formula:

$$\textbf{Recall} = \textbf{True Positives} / (\textbf{True Positives} + \textbf{False Negatives})$$

Note: A high recall indicates a low rate of false negatives, meaning that the model is effective in capturing most of the positive instances.

❖ **F1 Score:** The F1 score is the harmonic mean of precision and recall. It provides a single metric that balances both precision and recall. The F1 score is calculated using the formula:

$$\textbf{F1 Score} = \textbf{2} * (\textbf{Precision} * \textbf{Recall}) / (\textbf{Precision} + \textbf{Recall})$$

Note: The F1 score ranges between 0 and 1, where a value of 1 indicates perfect precision and recall.

Note: Precision, recall, and F1 score are commonly used evaluation metrics, particularly for binary classification tasks, but they can also be extended to multi-class classification problems by considering macro-averaging or micro-averaging techniques. Figure shown the result of our performance of model.

```
print(precision,recall,f1)

0.8333330182752394 0.833984375 0.833086107742408
```

Figure IV.19: Precision, recall, and F1 score values in our model.

❖ **ROC:** The Receiver Operating Characteristic curve is a graphical representation of the performance of a binary classification model. It illustrates the trade-off between the true positive rate and the false positive rate.

The ROC curve is created by plotting the true positive rate (TPR) on the y-axis against the false positive rate (FPR) on the x-axis at various threshold settings. The TPR is the proportion

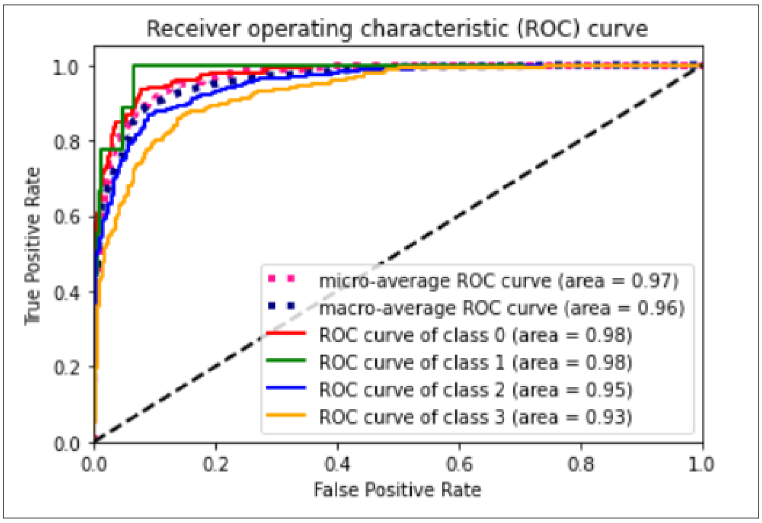

Figure IV.20: Receiver operating characteristic curve (ROC) graph.

of positive instances correctly classified as positive, and the FPR is the proportion of negative instances incorrectly classified as positive.

The ROC curve was plotted using sklearn. metrics library, as shown in Figure IV.22. The roc_curve and auc functions from this library were utilized to obtain the essential values required to construct the graph.

❖ **Classification report**: A classification report is a way to evaluate the performance of a classification model. It provides a summary of various metrics that help assess the model's accuracy, precision, recall, F1-score, and support for each class in a classification task. Additionally, a classification report includes the following metrics: micro avg, weighted and samples avg.

```
80/80 [==============================] - 1s 12ms/step
Classification Report:
              precision    recall  f1-score   support

           0       0.50      0.32      0.39       179
           1       0.00      0.00      0.00        12
           2       0.69      0.84      0.76       640
           3       0.62      0.53      0.57       448

   micro avg       0.65      0.65      0.65      1279
   macro avg       0.45      0.42      0.43      1279
weighted avg       0.63      0.65      0.63      1279
 samples avg       0.65      0.65      0.65      1279
```

Figure IV.21: Classification report for each class in testing data

❖ **Confusion matrix:** A confusion matrix is a matrix that summarizes the performance of a machine learning model on a set of test data. displays the number of correct and incorrect predictions made by a classification mode. It consists of rows representing the instances of the actual class and columns representing the instances of the predicted class. In essence, a confusion matrix comprises four fundamental components **[59]**:

1. True Positives (TP): Represents the number of patients correctly classified as having Alzheimer's disease.

2. True Negatives (TN): Represents the number of patients correctly classified as not having Alzheimer's disease.

3. **False Positives (FP):** Represents the number of patients misclassified as having Alzheimer's but actually not having Alzheimer's.

4. **False Negatives (FN):** Represents the number of patients misclassified as not having Alzheimer's but actually having Alzheimer's.

The figure (Figure 22) below displays the confusion matrix of our model. We note that the model was able to classify three categories (mild dementia, non-dementia, very mild dementia) relatively correctly, and the remaining one (moderate dementia) was not able to classify them clearly and accurately.

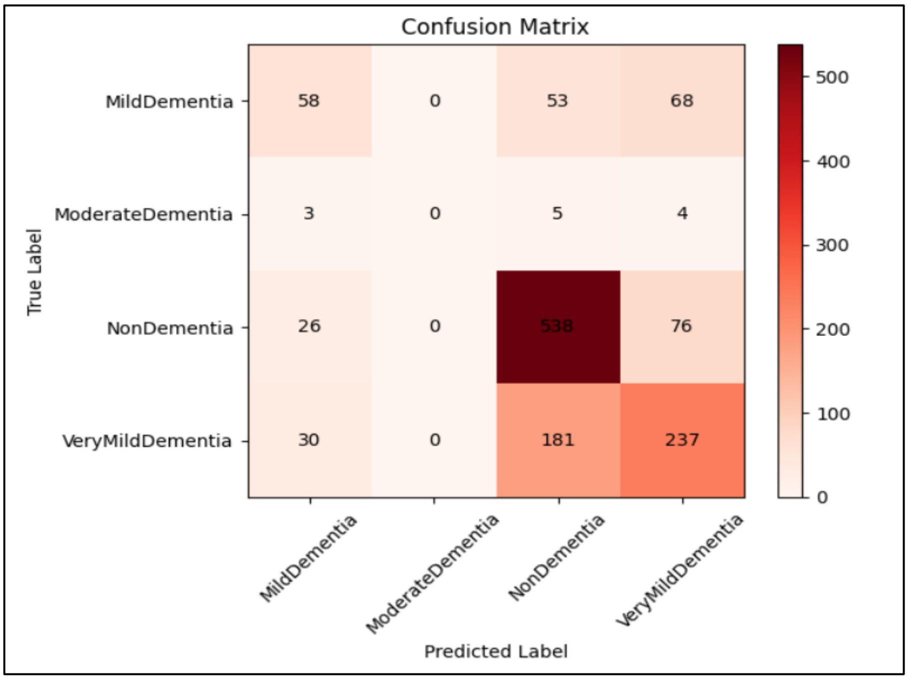

Figure IV.22 Confusion Matrix of the model CNN.

IV.4 Discussion

The study of brain magnetic resonance images for accurate and early prediction of Alzheimer's disease has attracted great interest as a result of the increasing number of cases of Alzheimer's disease. In our work, using CNN, we can point out that there are systems that help in the early prediction of Alzheimer's disease, and thus the possibility of prevention, or control of it. We used an ensemble of parameters and functions such as SoftMax, categorical cross entropy, early stopping, and accuracy matric, with optimizer Adam for building CNN architecture which consists of layers of conv2D and max pooling and dropout followed by flatten for the transition from convolution layer to fully connected layer and is again followed by the dens layer, in the last we get around four million trainable parameters to total 4 million and 152356 Also, the model was trained for 100 epochs several times and each time we enhanced the value until we reached an acceptable result which had a loss of 0,20 and an accuracy of 0,99 in just 63 epochs. After training, we need now to evaluate the performance of the classification model for generalization, for that, we used various metrics such as accuracy, loss, precision, F1 score, Recall …and confusion matrix which applied on test data to displays the number of correct and incorrect predictions where we get that most of the prediction was correct (1267 right ones out of 1279 of data test. So, we can tell that the classification perform is nearly perfect.

we summarize the results obtained which define the metrics performance of our model with data train and data testing. In the end, we achieved the desired, which is the prediction and early detection of Alzheimer's disease with an accuracy of 99%, but the work remains in development due to the instability of MRI dataset. our CNN model can play an effective role in classifying and predicting Alzheimer's patients by processing captured MRI images.

Table IV.2: Metrices evaluations values.

Metrics Evaluations	Values
Loss	0,2026
Auc	0,9920
Accuracy	0,9920
Precision	0,83333
Recall	0,83398
F1	0,83308

IV.5 Conclusion

In this chapter, we have presented the different tools used and steps we have taken to achieve the best performance for our project of Alzheimer early prediction. We have shown and discuss results in terms of precision and error and performance. and our deep learning approach generated the accuracy with value 99%.

General Conclusion

Conclusion

Due to the success achieved in the medical field through the use of artificial intelligence in various medical fields, we have been working on using medical images with different properties and linking them to the field of artificial intelligence. Deep learning is an effective means to provide promising solutions based on datasets to help humans cope with Alzheimer's disease. it is an active area of research.

The objective of our work is to classify images for early prediction of Alzheimer's disease. we used the MRI image for early diagnosis and to identify the stages or cases of AD for that we adopted the CNN method as the binary classification method and the Kaggle dataset for Alzheimer's we got inspired by some previous works [24, 25, 26, 27] which have worked on the same problem This thesis started with a general introduction and ends with a general conclusion was composed of four chapters (three are theoretical and one is an application). In the end, from our results and from the previous works we conclude that it is possible to classify the images MRI for early detect Alzheimer's disease. where we obtained an accuracy of 99% satisfying results using deep learning (CNN) And therefore it is possible to early detection Alzheimer's disease. It's important to note also that while significant progress has been made and has high accuracy, early prediction of Alzheimer's disease is still a complex and evolving field, and more research is needed to improve a great accuracy and reliability of identifying individuals at risk.

Finally, future work will be Extending the work to test the proposed technique on large and realistic data. This step will provide valuable insights into the scalability and generalizability of the technique. After that Presenting the project at hospitals would be a significant step in showcasing its potential for real-world implementation. And also, we can integrate the system to detect other neurodegenerative diseases. And in this, we have contributed forward-thinking to advancing the field and why not making a positive impact in healthcare.

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Abstract

Alzheimer’s disease is a type of brain disease. It is a progressive disease which means it gets worse with time there is no cure and his diagnosis is a medical challenge. Therefore, early diagnosis is crucial and can help to improve symptoms significantly. As technology advances, deep learning techniques have recently achieved great success in medical image analysis. This project aims to develop a method of Alzheimer's disease diagnosis using MRI images, which can distinguish medical images of the brain to help doctors to classify and predict Alzheimer's disease. This is based on deep learning with convolutional neural networks (CNN) used to predict Alzheimer from the Kaggle dataset. Experiments results have given encouraging prediction and accuracy in comparison with other work cited in related works.

Keywords: *Alzheimer’s Disease, Brain, Deep learning, Medical Image, MRI, CNN, Dataset, Prediction.*

الملخص

مرض الزهايمر هو نوع من أمراض الدماغ. فهو مرض تقدمي ، مما يعني أنه يزداد سوءًا بمرور الوقت ، ولا يوجد علاج له ، ويشكل تشخيصه تحديًا طبيًا. لذلك ، فإن التشخيص المبكر أمر بالغ الأهمية ويمكن أن يساعد في تحسين الأعراض بشكل كبير. مع تقدم التكنولوجيا ، حققت تقنيات التعلم العميق مؤخرًا نجاحًا كبيرًا في تحليل الصور الطبية. يهدف هذا المشروع إلى تطوير طريقة لتشخيص مرض الزهايمر باستخدام صور التصوير بالرنين المغناطيسي ، والتي يمكنها تمييز الصور الطبية للدماغ لمساعدة الأطباء على تصنيف مرض الزهايمر والتنبؤ به. يعتمد هذا على التعلم العميق باستخدام الشبكات العصبية التلافيفية (CNN) المستخدمة للتنبؤ بمرض الزهايمر من مجموعة بيانات Kaggle. أعطت نتائج التجارب تنبؤًا ودقة مشجعة مقارنة بالأعمال الأخرى المذكور في جزء الاعمال ذات صلة.

الكلمات المفتاحية: *مرض الزهايمر ، الدماغ ، التشخيص ، التعلم العميق ، الصورة الطبية ، التصوير بالرنين المغناطيسي ، CNN، مجموعة البيانات ، التنبؤ.*

Résumé

La maladie d'Alzheimer est un type de maladie du cerveau. C'est une maladie évolutive, ce qui signifie qu'elle s'aggrave avec le temps, qu'il n'y a pas de remède et que son diagnostic est un défi médical. Par conséquent, un diagnostic précoce est crucial et peut aider à améliorer considérablement les symptômes. À mesure que la technologie progresse, les techniques d'apprentissage en profondeur ont récemment remporté un grand succès dans l'analyse d'images médicales. Ce projet vise à développer une méthode de diagnostic de la maladie d'Alzheimer à l'aide d'images IRM, qui peut distinguer des images médicales du cerveau pour aider les médecins à classer et à prédire la maladie d'Alzheimer. Ceci est basé sur l'apprentissage en profondeur avec des réseaux de neurones convolutifs (CNN) utilisés pour prédire la maladie d'Alzheimer à partir de l'ensemble de données Kaggle. Les résultats des expériences ont donné des prédictions et une précision encourageantes en comparaison avec d'autres travaux cités dans les travaux connexes.

Mots clés : *Maladie d'Alzheimer, Diagnostic, Deep Learning, Image médicale, IRM, CNN, Data Set, Prédiction.*