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Brain Tumor Detection Using Deep Learning : Design of Neural Architectures and Deployment of a Graphical Interface

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Thank you

We thank ALLAH the Almighty for giving us the courage and will to complete this work as part of our master's thesis.

The work was carried out at the Faculty of Technology, Electrical Engineering Department, Belhadj Bouchaib University - Ain Temouchent, under the direction of **Dr. BENGANA Abdelfatih**, who is gratefully acknowledged for his dynamism and willingness to help us carry out this study.

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Finally, we would like to thank all those who have contributed in any way to the Completion of this memoir.

Dedication

I dedicate this modest work to the people who are dear to me and who have supported me throughout the ordeals that have given light to this work.

I quote in particular:

- *Father, I'd like to thank you for your love, your generosity, your understanding... Your support has been a beacon throughout my life. No dedication can express the love, esteem and respect I've always had for you.*

- *My mother, in you I see the perfect mother, I thank you for your support, your sacrifices and your precious advice, for all your assistance and your presence in my life, I receive through this work, however modest it may be, the expression of my feelings and my eternal gratitude.*

- *My little brother Adem: for his moral support and for always being there for me.*
- *To my partner Hadil, with whom I spent one of the best years of my university career.*

Slimane Ostmane Nesrine

It is with all my feelings of respect, with the experience of my gratitude, that I dedicate my graduation and my joy.

- *To the apple of my eye, the source of my joy and happiness, my better half,*

  Mom.

- *To the man who made me a woman, to my support who was always by my side to back me up,*

  To my prince, Dad.

- *To my sister Intissar for the love she reserves for me.*
- *To all the members of my family. My aunts and cousins.*
- *As a token of the friendship that unites us and the memories of all the times we spent together, I dedicate this work to my partner Nesrine.*
- To all who have contributed to my success and to all who love me

<u>Habib hadil farida</u>

Abstract

Early detection of brain tumors is essential to improve patients' chances of survival. To this end, automatic detection methods are continually being developed. Diagnosis of this serious disease can be lengthy and vary between doctors. Deep learning, using convolutional neural networks, can identify brain tumors from MRI images, offering a promising approach to improving the accuracy and speed of diagnosis.

This work presents the identification of brain tumors using convolutional neural networks “CNN”. Thus, our system relies on database augmentation, image pre-processing and extracted features using the CNN criée model and other implemented models such as VGG16,VGG19 and the NasNet exploiting the transfer learning method.

Key words :Brain tumor, CNN, VGG, NasNet, Deep Learning, learning transfer, MRI, Detection.

ملخص

يُعد الكشف المبكر عن أورام الدماغ ضرورياً لتحسين فرص نجاة المرضى. ولتحقيق ذلك، يتم تطوير طرق الكشف التلقائي باستمرار. يمكن أن يستغرق تشخيص هذا المرض الخطير وقتاً طويلاً ويتفاوت بين الأطباء. يمكن للتعلّم العميق، باستخدام الشبكات العصبية التلافيفية، تحديد أورام الدماغ من صور التصوير بالرنين المغناطيسي IRM، مما يوفر نهجًا واعدًا لتحسين دقة وسرعة التشخيص.

يعرض هذا العمل تحديد أورام الدماغ باستخدام الشبكات العصبية التلافيفية .(CNNs) وبالتالي، يعتمد نظامنا على زيادة قاعدة البيانات، والمعالجة المسبقة للصور واستخراج الميزات باستخدام نموذج CNN ونماذج أخرى مطبقة مثل VGG16 و VGG19 و NasNet من خلال استغلال طريقة التعلم التحوّلي.

الكلمات المفتاحية: الورم الدماغي، CNN، VGG، NesNet، التعلم العميق، نقل التعلم، والتصوير بالرنين المغناطيسي،

Réumé

La détection précoce des tumeurs cérébrales est essentielle pour améliorer les chances de survie des patients. Pour cela, des méthodes de détection automatique sont continuellement développées. Le diagnostic de cette maladie grave peut être long et varier entre les médecins. Le deep learning, utilisant des réseaux de neurones convolutions, permet de repérer les tumeurs cérébrales à partir d'images IRM, offrant ainsi une approche prometteuse pour améliorer la précision et la rapidité des diagnostics.

Ce travail présente l'identification des tumeurs cérébrales en utilisant les réseaux de neurones convolutifs "CNN". Ainsi, notre système repose sur augmentation de la base de données , prétraitement d'images et caractéristiques extraites en utilisant le modèle CNN criée et d’autre modèle implémenté tel que VGG16,VGG19 et le NasNet en exploitant la méthode de transfert d'apprentissage.

Mots clés : Tumeur cérébrale, CNN, VGG, NasNet,Deep Learning, transfert d'apprentissage, IRM, Détection.

Liste of figure:

General introduction

GENERAL INTRODUCTION

A brain tumor is a cell growth in the brain, which can be benign (non-cancerous) or malignant (cancerous) in nature.

Brain tumors represent a category of neurological diseases that require early detection and accurate diagnosis to optimize patient outcomes.
Radiologists have traditionally relied on imaging methods such as MRI and CT scans to detect and evaluate brain tumors.

The field of computer science known as artificial intelligence (AI) strives to develop machines capable of mimicking specific cognitive functions.
including learning, reasoning and problem solving
The use of artificial intelligence (AI) can make a major contribution to the rapid and accurate detection of cancer. Using advanced deep learning algorithms, AI has the ability to discern complex patterns in medical images such as X-rays, MRIs or CT scans, patterns that may escape human perception. This comprehensive analysis capability enables tumors to be identified in their earliest stages, increasing the chances of successful treatment.

Deep learning, an area of artificial intelligence (AI) based on artificial neural networks, has made significant inroads into the analysis of healthcare images. Convolutional neural networks (CNNs) are proving especially adept at examining medical images, thanks to their ability to autonomously identify discriminating features directly from the initial data. These models tend to outperform conventional image processing approaches, offering greater accuracy and reliability.

This work will then describe a program whose main objective is to build a highly accurate brain tumor detection model using deep learning.

We began by creating a convolutional neural network (CNN), We then implemented models such as VGG16, NesNet and ResNet50, whose main aim is to improve program performance and speed up development using the learning transfer technique.

All on the "google colab" platform, with "python" as the programming language

Chapter I:

Brain tumor and medical imaging

I Introduction:

Brain cancer, a complex and devastating disease, remains one of the world's most pressing health issues, and a leading cause of increased mortality in both children and adults.

Brain tumours are abnormal cell masses that can develop at the expense of intra- or extra-cerebral tissue structures..

Brain tumors are classified according to their histological appearance and topography, thus forming a wide histological variety with variable prognosis and evolution.This introduction will explore the different types of brain tumours, their potential causes such as genetic factors; as well as the symptoms that can alert to their presence. We'll also look at diagnostic methods, from advanced medical imaging to biopsies.

I.1 *Brain cancer:*

Are abnormal clusters of cells that develop at the expense of tissue structures inside or outside the brain . Although they are relatively rare, they remain a public health problem due to the mortality and morbidity associated with them.

Brain cancer is a form of tumor that remains in the brain or central nervous system.

Brain tumors are classified into different types according to their nature, origin, growth rate and stage of progression. They can be benign or malignant, and are classified into two types according to their origin: primary brain tumors and secondary brain tumors.

A primary tumor originates directly from the brain. If the tumor emerges in the brain due to an existing cancer in other organs of the body, such as the lungs, stomach, etc., then it is known as a secondary brain tumor or metastasis. **[1]**

I.2 *Brain anatomy:*

Fundamentally located in the skull, the brain is responsible for managing and coordinating most of our actions: the body's internal functions (heartbeat, blood circulation, muscle contractions or digestion), the so-called higher functions (thought, emotions, personality, ability to communicate or learn) and finally, the five senses, which enable us to relate to the outside world: sight, hearing, touch, smell and taste.

Thanks to scientific progress, we know more and more about how the brain works. We now know that it functions thanks to billions of interconnected neurons. We also know that it is organized into different zones, each managing different functions **[3].**

The brain is divided into two hemispheres - right and left - which are linked by a structure called the corpus callosum. Each hemisphere controls the motor and sensory functioning of the opposite half of the body. Thus, the right hemisphere controls the left and vice versa. In addition, the area responsible for language is located on the left in a right-handed person , and on the right in a left-handed person. Several functional areas have been identified within the central nervous system, each involved in a specific function: language, consciousness, memory, emotions, behavior, movement... **[7]**

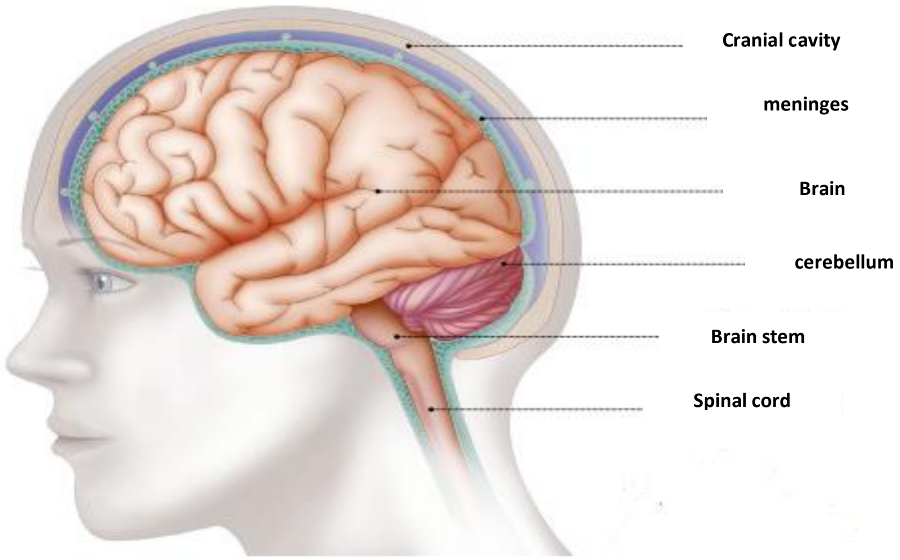


Figure I: Anatomy of the central nervous system (CNS) [4]

I.2.1 The different parts of the brain and their functions:

The brain is highly organized. It is made up of several parts, each of which has a specific role to play, while at the same time complementing each other.

- **The cerebral hemispheres :**

The cerebral hemispheres are the largest parts of the brain. There are two of them: a right hemisphere and a left hemisphere. We often speak of right brain and left brain. The

Hemispheres control all our higher mental functions: voluntary movement, thinking, learning, memory, etc.

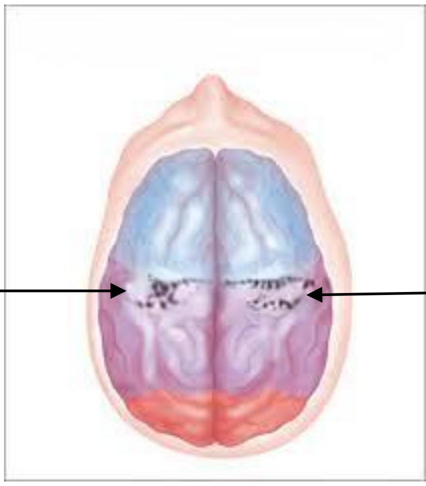


Figure II: The two cerebral hemispheres [3]

Each hemisphere is itself divided into four areas called lobes, in which these different functions are managed: the frontal lobe, the parietal lobe, the temporal lobe and the occipital lobe.

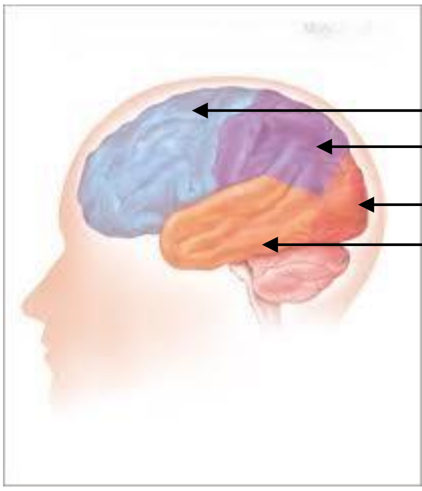


Figure III: The fourth lobes of the left hemisphere [3]

- ❖ **The brain stem :**

The brain stem connects the cerebral hemispheres to the spinal cord. It controls the body's vital functions: heartbeat, breathing, blood pressure. It also controls eye mobility, facial movements and swallowing.

- ❖ **The cerebellum :**

The cerebellum is located at the back of the brain stem, below the occipital lobes. It is responsible for our reflexes, movement coordination and balance.

❖ **Pituitary and hypothalamus :**

The pituitary gland and hypothalamus are nerve structures located at the base of the brain, in the middle of the skull.

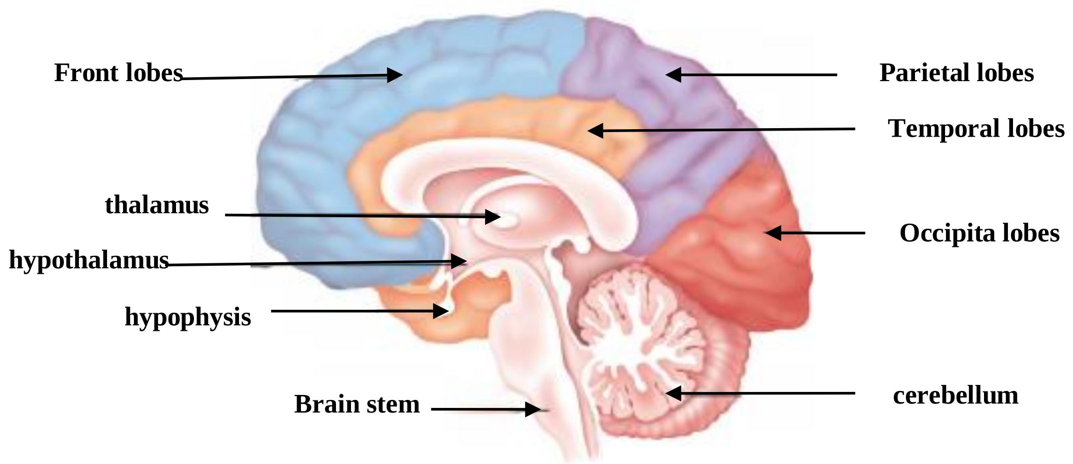


Figure IV: The brain (sagittal section) [3]

The size of a pea, the pituitary plays a fundamental role in hormone production. It controls numerous functions such as growth, production of breast milk, puberty and fertility.

The hypothalamus, located slightly above the pituitary, is in contact with all the other areas of the brain. It regulates hunger and thirst, body temperature, sleep, sexuality and heartbeat **[3].**

I.3 The various common brain tumors:

Tumors can affect the central nervous system. Histological knowledge has made it possible to classify tumors according to: **[6]**

1. Primary or secondary brain tumors.
2. Benign or malignant brain tumors (grading).
3. According to cellular origin (WHO histological classification).

I.3.1 Primary and secondary brain tumors:

- **Primary tumors:**

Originate in the brain. A distinction is made between benign tumors (two-thirds of primary tumors), composed of non-cancerous cells, and malignant tumors, made up of cancerous cells. Whether benign or malignant, primary tumors can cause serious symptoms, particularly when located in key functional areas of the brain. **[7]**

- **Secondary tumors:**

Are metastases of a pre-existing cancer. They arise when cells from an initial tumor outside the brain migrate via the bloodstream to brain tissue.

Certain advanced cancers are frequently associated with the development of brain metastases: lung, skin, kidney and breast cancers. **[7]**

I.3.2 Benign and malignant brain tumors:

Tumors can be classified as benign or malignant.

- **Benign non-cancerous tumors :**

If the cells are not cancerous, the tumor is considered benign.

Benign tumours can be surgically removed. They can become very large, sometimes weighing several kilograms.

They can be dangerous, for example when they appear in the brain and compress the normal structures in the limited space of the skull.

They can exert pressure on vital organs or block ducts.

- **Malignant cancerous tumors :**

Malignant means that the tumor is made up of cancerous cells and may invade neighboring tissues.

I.3.3 According to cellular origin (WHO histological classification):

The WHO (World Health Organization) distinguishes around 200 types of brain tumor [4], classified according to the cells in which they develop. **[4]**

The most common brain tumors are:

I.3.3.1 Gliomas:

About (58%) mainly astrocytomas, glioblastomas, oligodendroglia, ependymata

These tumors develop at the expense of the supporting structures of the nervous system, the glial cells. There are different types of glial cell from which different types of glioma can develop.

Astrocytic tumors develop from star-shaped glial cells (astrocytes). As these tumors can degenerate (benign to malignant transformation), regular follow-up is essential. They can develop in any region of the brain or spinal cord. The main astrocytic tumors are as follows:

- Pilocytic astrocytomas (grade I) Predominantly affect children and adolescents. Malignant transformation is extremely rare.
- Diffuse astrocytomas (grade II) These mainly affect young adults and have a high propensity for malignant transformation.
- Anaplastic astrocytomas (grade III) these mainly affect people aged 50 and over, and have a high propensity for malignant transformation into glioblastomas.
- Glioblastomas (grade IV astrocytomas) These malignant tumors are most common in adults, mainly between the ages of 45 and 70.

Oligodendrogliomas (grades II and III) are so named because they develop from oligodendrocytes, the glial cells responsible for forming the myelin that insulates nerve fibers.

Ependymomas develop in the cervical cavities, from the glial cells lining the cerebral ventricles. Their malignancy varies. Tumor growth can lead to obstruction of CSF circulation, resulting in hydrocephalus, and may require bypass surgery. These tumors mainly affect children and adolescents.

I.3.3.2 Meningiomas:

About (20%)Meningiomas develop at the expense of the meninges, in the cranium or along the spinal column. Most meningiomas are benign, but in isolated cases they can have an unfavorable evolution (benign to malignant).

I.3.3.3 Pituitary adenomas:

About (14%) Pituitary adenomas are benign tumors (grade I) in the vast majority of cases. A distinction is made between :

- Non-functional tumours: symptoms result from pressure exerted by the tumour on neighbouring brain regions. Given the proximity of the optic nerve, the first symptoms may be visual disturbances. A decrease in the secretion of pituitary hormones is also commonly observed.
- Functional tumors are made up of hormone-secreting cells. Their presence can manifest itself in hormonal problems such as menstrual disorders or growth problems.

I.3.3.4 Neurinomas:

About (7%) These benign tumors (grade I in most cases) develop at the expense of peripheral nerve sheaths, which are made up of cells different from those in the brain.

These tumors are not found in the brain, but in the cranial and peripheral nerves throughout the body. The nerve most frequently affected is the auditory nerve (acoustic neuroma); its compression can lead to hearing and balance problems.

I.3.3.5 Medulloblastomas :

These malignant tumors (grade IV) located in the cerebellum mainly affect children (80% of those affected are under 15).

I.3.3.6 Lymphomas:

A lymphoma is a tumor affecting the lymphatic system. Primary CNS lymphomas are relatively rare malignant tumors. Weakening of the immune system (e.g. post-transplant medication, AIDS) seems to favor their development.

Secondary CNS lymphoma usually manifests as invasion of the brain envelope in patients with lymphoma elsewhere in the body.

Metastases are not included in this list. They account for 30-40% of all intracranial tumors.

I.4 Risk factors:

It is very difficult to know why a brain tumor develops. Only exposure to radiation and immunosuppression are recognized as risk factors: they only concern certain tumors and a very small minority of patients. **[7]**

Scientists have little certainty about the factors that can increase the risk of brain cancer. Only two parameters have been formally identified as inducing an increased risk of brain tumors: [**7]**

- **Irradiation**: ionizing radiation received in varying doses in the head or neck region (X-rays, radiotherapy, etc.) slightly but significantly increases the risk of developing a radiation-induced brain tumor several years later.
- **Immunosuppression:** the body's defenses (immune system) may be weakened in certain hereditary diseases or chronic illnesses associated with immune deficiency (such as AIDS). These patients are at increased risk of developing brain lymphoma in the long term. Hereditary forms of brain tumors are very rare, but certain hereditary syndromes or diseases are thought to increase the risk of occurrence: tuberous sclerosis of Bourneville, von Hippel Lindau syndrome, and neurofibromatosis.
  It is estimated that 2% of primary brain tumors in children are linked to a familial genetic component, half of which are gliomas.

Researchers are investigating the role of other factors (hormone replacement therapy, electromagnetic waves, cell phone use, diet, pesticides, use of certain chemicals, etc.) in the occurrence of brain cancers. Current data do not allow us to conclude with any certainty as to their actual role.

I.5 Possible Symptoms:

The signs and symptoms described below are not necessarily indicative of a tumor; they may have many other causes.

The symptoms of a brain tumor are due to the pressure exerted on brain tissue. They depend much more on the tumor's location and rate of growth than on its nature. Analysis of the functional disturbances suffered will generally help to localize the tumor**[4].**

- Headaches occurring: often at night or in the early hours of the morning. Most of the time, these pains are new and different from headaches.
- Nausea and vomiting due to pressure in the cranium.
- loss of appetite.
- dizziness and balance disorders.
- Vision disorders: flickering, visual field disturbance or perception of double images.
- Visual, auditory or olfactory hallucinations.
- Slurred speech and difficulty finding words.
- Changes in mood, behavior and personality.
- learning and reasoning difficulties.
- epileptic seizures.

I.5.1 Spinal cord tumor :

Depending on the location of the tumour, the following symptoms may appear:

I.5.1.1 Pain:

- Chest pain for tumors located in the chest.
- Pain in the neck, arms, back or legs for tumors located in the neck or back.

I.5.1.2 Weakness of limbs or trunk:

- Numbness, tingling, inability to feel temperature variations.
- Muscle spasms.

- Loss of bowel or bladder control.
- Powerlessness.

I.6 Diagnostic steps:

Several steps are required to determine the origin of the symptoms described and to confirm or rule out the presence of a brain tumor. [4]

I.6.1 Complete physical examination:

If a brain tumor is suspected, your doctor will perform a complete physical examination. This helps to rule out or diagnose a whole range of other diseases that may be causing your symptoms.

Analysis of a blood sample will detect inflammation, changes in the blood count, chronic disease or organic disorders.

I.6.2 Neurological examination:

- The purpose of neurological examinations is to.
- Check that the nervous system is functioning properly.
- Determine your ability to react and coordinate.
- Analyze the reaction of different muscle groups to external stimuli. Particular attention is paid to eye mobility, field of vision and pupillary reflex. If the results of the neurological examinations reinforce the suspicion of a brain tumour, imaging tests will be carried out.

I.6.3 Imaging examinations:

They can be used to confirm or rule out the disease, and in the event of a positive result, to determine its spread and identify affected structures.

❖ **Computed tomography :**

The CT scanner or tomodensito-meter The CT scanner, better known as scanner or CTscan, is a device in which the patient is scanned by a beam of X-rays (as in a conventional X-ray). The emitter rotates around the patient, while the receivers measure the intensity of the rays as they pass through the body. The examination lasts just a few seconds.

The scanner provides a highly accurate view of intracranial structures and lesions.

Figure V: CT scan of the brain [3]

- **Magnetic resonance imaging (MRI)**

  MRI is based on the observation of tissue subjected to an intense magnetic field. It is more precise than CT, but can take up to an hour to complete. CT and MRI are used not only for diagnosis, but also for precise planning of surgery and stereotactic radiotherapy.

Figure VI: MRI of the brain [14]

- **fMRI or Functional Magnetic Resonance Imaging**

fMRI can be used to locate brain regions involved in specific functions, such as movement, language or memory. These brain areas are activated following specific instructions given to the patient during the examination.

❖ **Cerebral angiography or arteriography**

Radio logical examination of cerebral blood flow after injection of contrast medium into an artery (usually the femoral artery in the groin). It is performed under local anaesthetic. A probe (small tube) is inserted into the groin artery and then directed towards the arteries in the neck.

❖**Positron Emission Tomography (PET)**

PET, also known as p*ositron emission tomography,* isa so-called functional medical imaging method, i.e. it provides information on the function of organs, tissues or cells.

It is therefore complementary to so-called anatomical medical imaging techniques, such as radiography, ultrasonography, computed tomography (CT, generally referred to as "X-ray scanning"), or magnetic resonance imaging (MRI), which provide information on organ structure, shape, boundaries, and in some cases contents (bone structures, bladder stones, etc....).

❖ **General principle of PET imaging :**

Nuclear imaging, whether scintigraphy, single-photon emission computed tomography (SPECT) or PET, involves injecting a radiopharmaceutical (or radiotracer) into a patient, animal or test object (phantom). This drug is a coupling between a carrier molecule (single molecule, group of molecules, protein, antibody) also known as a tracer or vector, and a radioactive isotope (or radioisotope) known as a *marker.*

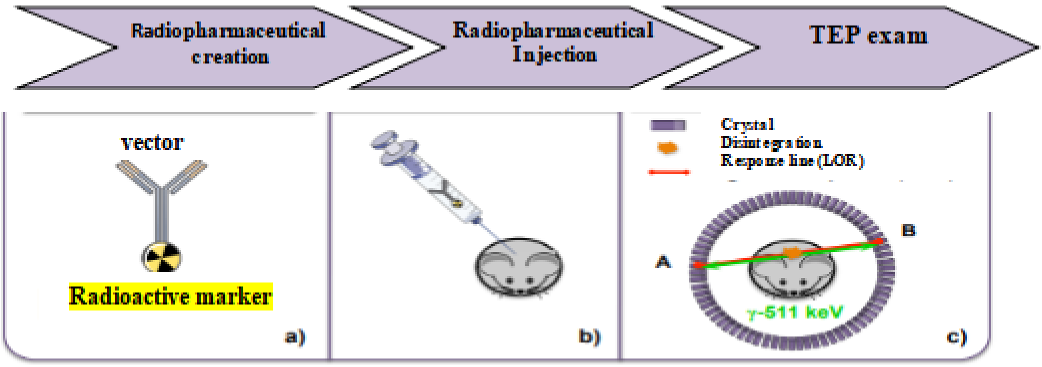


Figure VII: Schematic diagram showing the principal of a PET scan

a) Creation of the radio pharmaceutical; b) injection of the radiopharmaceutical; c) detection of the information on a PET ring.

I.6.4 Biopsy:

A biopsy is a tissue sample followed by microscopic analysis. Biopsy is essential for making a definitive diagnosis, and provides precise information on tumor type and grade, to guide treatment decisions.

There are two types of biopsy:

- Open biopsy which requires a craniotomy and general anesthesia.
- Stereotactic brain biopsy

Performed after trepanning (drilling a small hole) of the skull, by inserting a special needle into the tumor. The tumor is precisely localized using medical imaging techniques.

I.6.5 Lumbar puncture:

Procedure whereby a needle is inserted between the lumbar vertebrae to collect cerebrospinal fluid (CSF) . The CSF is analyzed to detect the presence of cancer cells.

I.7 Conclusion*:*

This chapter concludes with a look at the key aspects of this complex disease, from its origins and symptoms to diagnostic methods. We now turn to an exciting new chapter dedicated to Deep Learning, a revolutionary discipline of artificial intelligence that promises major advances in the fight against brain tumors.

Chapter II:

Deep learning

II Introduction:

This chapter is dedicated to a general presentation of neural networks and their architectures, as well as to the principle of Deep Learning, one of the main technologies of Machine Learning. There are several types of neural networks, including convolutional neural networks (CNNs), specialized in image processing. The chapter concludes with a comparative table of several research projects based on the same principle

II.1 General information on artificial neural networks:

Artificial neural networks (ANNs) are mathematical and computational models inspired by human nerve cells, known as formal neurons. This biological analogy has motivated researchers to develop functional equivalents between biological and formal neurons. Over the past three decades, significant advances have been made, with applications in diverse fields: finance (financial risk assessment), medicine (medical diagnostics), banking (credit card fraud detection), aeronautics (autopilot programming), weather forecasting, imaging, pattern recognition, and signal processing. [7]

II.1.1 Neural network definition:

Artificial neural networks are highly connected networks of elementary processors operating in parallel. Each elementary processor calculates a unique output based on the information it receives. Any hierarchical structure of networks is obviously a network. **[8]**

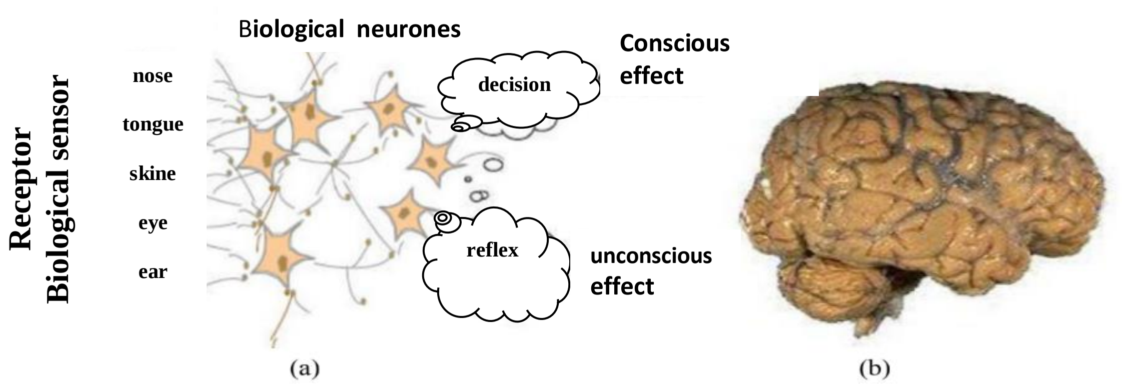


Figure VIII: Structure of a biological neural network and the human brain [10]

II.1.2 Biological neural networks biological neural networks:

The human brain contains around 100 billion neurons. These neurons enable you, among other things, to read this text while maintaining regular breathing to oxygenate your blood, activating your heart to ensure efficient circulation of this blood to nourish your cells, and so on. Each of these neurons is highly complex **[10].**

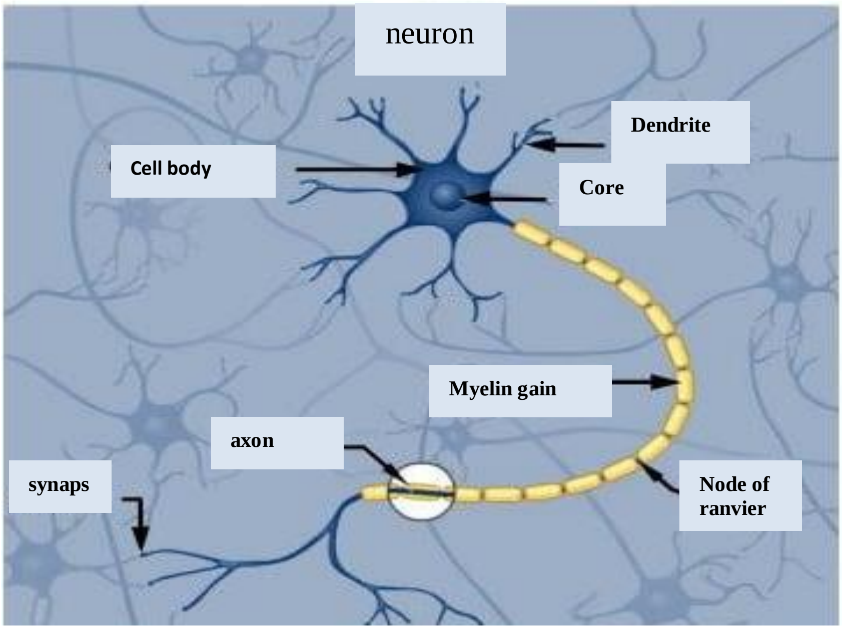


Figure IX: Model of a biological neuron [10]

II.1.3 Formal or artificial neural networks:

A "formal neuron" (or simply "neuron") is a non-linear, bounded algebraic function whose value depends on parameters called coefficients or weights. The variables of this function are usually called the neuron's "inputs", and the value of the function is called its "output".

A neuron is therefore first and foremost a mathematical operator, whose numerical value can be calculated with a few lines of software. We have become accustomed to graphically representing a neuron as shown in figure 2 **[10].**

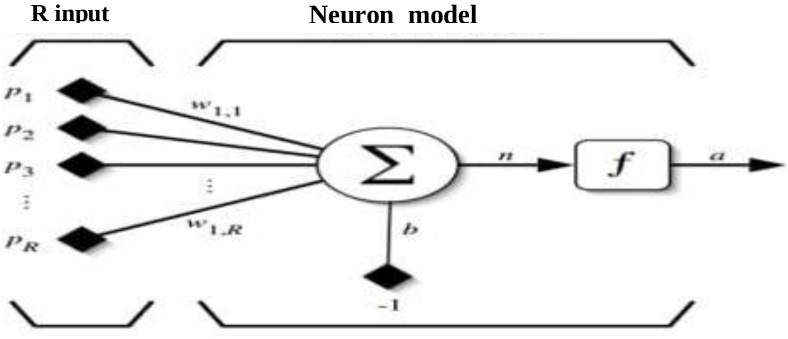


Figure X: Model of a formal (artificial) neuron

II.1.4 From the biological neuron to the formal neuron:

Historically, the inspiration for RNAs came from the desire to create intelligent artificial systems capable of performing operations similar to those routinely performed by the human brain. Diagram **03** and Table **04** show the analogy between the formal neuron and the biological neuron. [7]

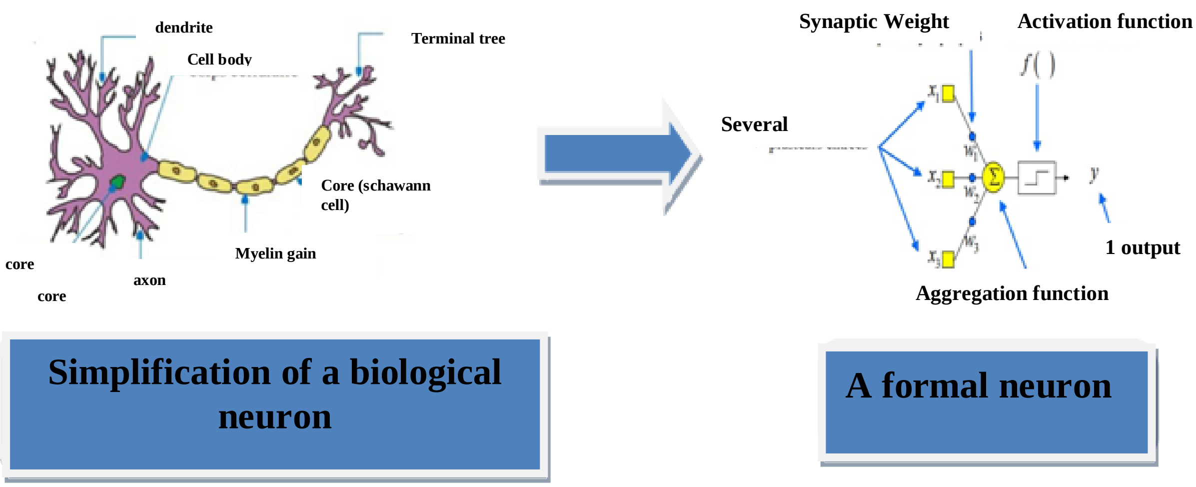


Figure XI; Analogy between biological and artificial neurons [8]

Tableau I: Analogy between biological and artificial neurons [7]

BIOLOGICAL NEURON	FORMAL NEURON
Synapsis	Connection weight
Axons	Output signal
Dendrites	Input signal
core or somma	Activation function

II.1.5 Neural network architecture:

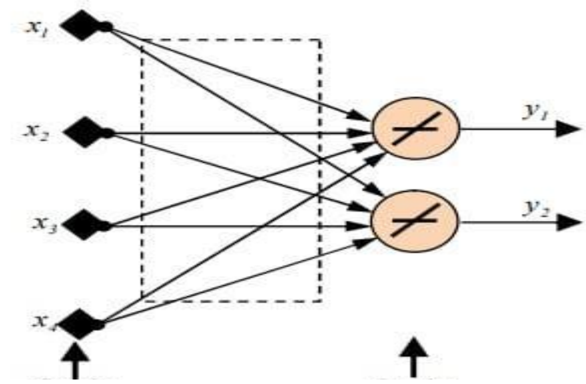
The architecture of a neural network is the organization of neurons within the network. It varies according to the task to be learned. Most neural networks use the same type of neuron. Although some rare architectures employ specialized neurons. A neural network is generally composed of several layers, from inputs to outputs. Two main types of architecture can be distinguished: non-looped neural networks and looped neural networks. **[10]**

II.1.6 Non-looped neural networks:

A non-looped neural network realizes one (or more) algebraic functions of its inputs, by composing the functions realized by each of its neurons. This type of network is graphically represented by a set of neurons "connected" to each other, with information flowing from inputs to outputs without "backtracking"; if we represent the network as a graph whose nodes are the neurons and edges the "connections" between them, the graph of a non-looped network is acyclic. The term "connections" is a metaphor: in the vast majority of applications, neural networks are algebraic formulas whose numerical values are calculated by computer programs, not physical objects (specialized electronic circuits). **[10**

II.1.6.1 Single-layer neural networks:

Modifiable of a single-layer network is such that organized input neurons are fully connected to other organized output neurons by a modifiable layer of weight **Figure XII.**



Input layer **output layer**

Figure XIII: Schematic diagram of a single - layer neural network [10]

II.1.6.2 Multilayer neural networks:

In a neural network, neurons are organized in layers. Neurons in one layer are not connected to each other, but only to neurons in subsequent layers. Usually, each neuron in a layer is connected to all the neurons in the next layer, and only the next layer. This allows us to introduce the notion of direction of information flow (activation) within a network, and thus define the concepts of input neuron, output neuron. By extension, we call the input layer the set of input neurons, and the output layer the set of output neurons. Intermediate layers that have no contact with the outside world are called hidden layers.

Figure XIV shows a non-looped neural network with a particular structure, which is very frequently used: it comprises inputs, two layers of hidden neurons and output neurons. The neurons in the hidden layer are not connected to each other. This structure is known as a multilayer perceptron

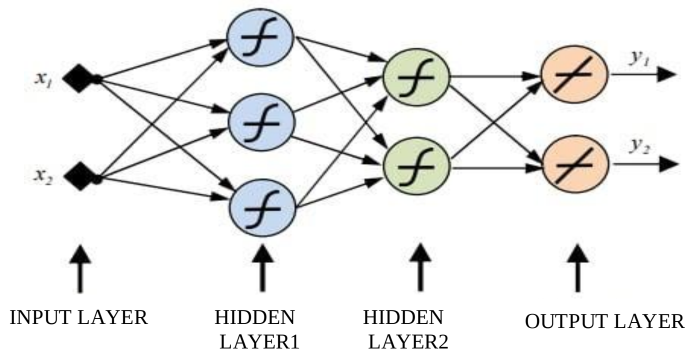


Figure XV: Diagram of a non - looped neural networks (multilayer perceptron)[10]

Multi-layer networks are also much more powerful than single-layer networks. By using two layers (a hidden layer and an Output layer), provided that a sigmoid activation function is used on the hidden layer, a network can be trained to approximate most functions to arbitrary precision (this may, however, require a large number of neurons on the hidden layer). Except in rare cases, artificial neural networks exploit two or three layers.

II.1.6.3 Networks of neurons with local connections:

This is a multi-layered structure, but like the retina, it retains a certain topology. Each neuron maintains relationships with a small, localized number of neurons in the downstream layer. Connections are therefore fewer than in a conventional multilayer network **Figure XVI**

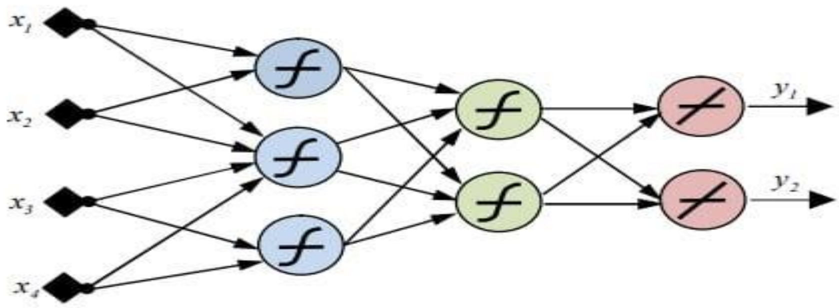


Figure XVII: Diagram of a neural network with local connection [10]

Non-looped neural networks are static objects: if the inputs are independent of time, so are the outputs. They are mainly used for nonlinear function approximation, classification or static nonlinear process modeling.

II.1.7 Looped neural networks:

Unlike non-looped neural networks, whose connection graph is acyclic, looped neural networks can have any connection topology, including loops that bring the value of one or more outputs back to the inputs. In order for such a system to be causal, it is obvious that there must be a delay at each loop: a looped neural network is therefore a dynamic system, governed by differential equations. Since most applications are carried out by computer programs, we place ourselves in the framework of discrete-time systems, where differential equations are replaced by difference equations. These are feedback or recurrent neural networks. **Figure XVIII**

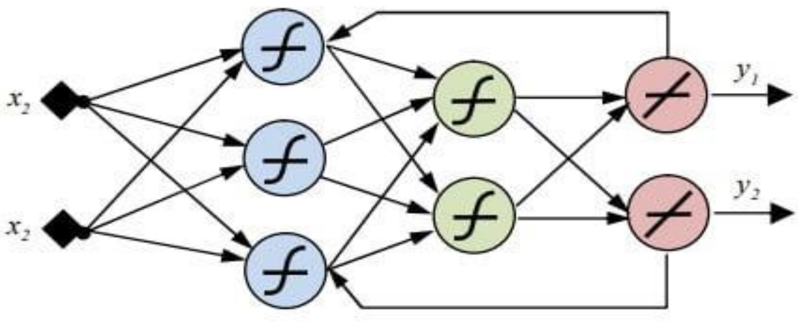


Figure XIX: Diagram of a looped neural network [10]

II.2 *History of deep learning:*

Tableau II: The major stages of deep learning [11]

Year	Contributor	Contribution
300 AC	Aristotle	introduction of associationism, beginning of the story of humans trying to understand the brain
1873	Alexander Bain	introduction of Neural Groupings as the first neural network models
1943	McCulloch and Pitts	introduction of the McCulloch-Pitts (MCP) model, considered to be the ancestor of artificial neural networks
1949	Donald Hebb	Considered the father of neural networks, he introduced Hebb's learning rule, which served as the foundation for modern neural networks.
1958	Frank Rosenblatt	introduction of the first perceptron
1974	Paul Werbos	introducing retro propagation
1980	Teuvo Kohonen	introduction of self-organizing cards
1980	Kunihiko Fukushima	introduction of the Neocognitron, which inspired convolutional neural networks
1982	John Hopfield	introduction of Hopfield networks
1985	Hilton and Sejnowski	introduction of Boltzmann machines
1986	Paul Smolensky	introduction of Harmonium, later known as restricted Boltzmann machines

1986	Michael I. Jordan	definition and introduction of recurrent neural networks
1990	Yann LeCun	introduction of LeNet and demonstrated the capabilities of deep neural networks
1997	Schuster and Paliwal	introduction of bidirectional recurrent neural networks
1997	Hochreiter and Schmidhuber	introduction of LSTM, which solved the vanishing gradient problem in recurrent neural networks
2006	Geoffrey Hinton	introduction of the Deep belief Network
2009	Salakhutdinov and Hinton	introduction of Deep Boltzmann Machines
2012	Alex Krizhevsky	introduction of AlexNet, winner of the ImageNet challenge

II.3 Definition of Deep Learning:

Deep Learning" is a set of machine learning techniques that has enabled major advances in artificial intelligence in recent years. In machine learning, a program analyzes a set of data in order to derive rules that will lead to conclusions about new data (**Figure II-16**). **[10]**

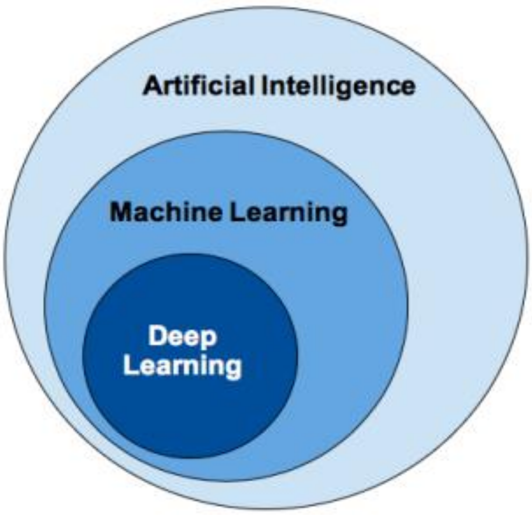


Figure XX: The relationship between artificial intelligence ML and Deep learning

Deep Learning is based on an artificial neural network inspired by the human brain. This network is made up of "layers" of neurons, the higher the number of layers, the "deeper" the network. Each layer receives and interprets information from the previous layer.

In machine learning, a program examines a set of data to establish rules that will enable conclusions to be drawn on new data, unlike traditional algorithms, which perform the feature extraction stage manually, making the task difficult and time-consuming, and requiring a specialist in the field. In Deep Learning, this step is performed automatically by the algorithm. For example, for visual recognition, the first layers of units identify lines, curves and angles. The other upper layers identify shapes, combinations of shapes, objects, contexts... etc. **Figure XXI**

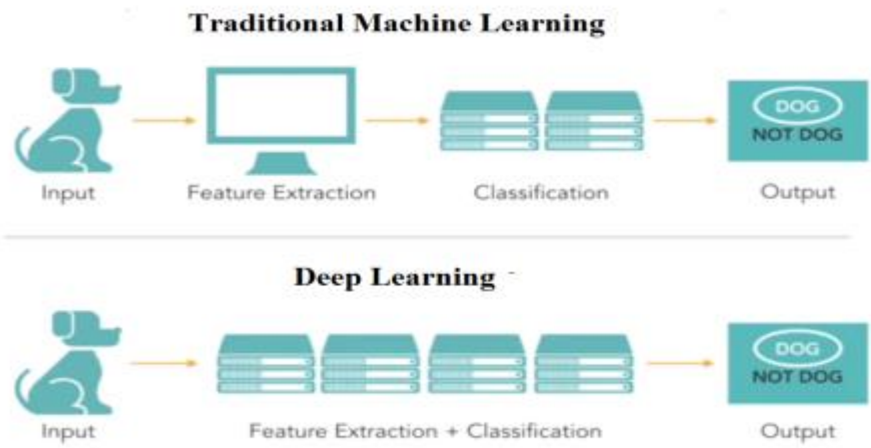


Figure XXII: The difference between deep learning and machine learning

II.4 How Deep Learning works:

Neural networks are layers of nodes, just as the human brain is made up of neurons. Nodes within individual layers are connected to adjacent layers. The deeper the network, the more layers it has. In an artificial neural network, signals travel between nodes and assign corresponding weights. A heavier weighted node will have a greater effect on the next layer of nodes. The final layer compiles the weighted inputs to produce an output. Deep learning systems require powerful hardware, as they process large amounts of data and involve many complex mathematical calculations. However, even with such advanced hardware, deep learning training calculations can take weeks.

Deep learning systems require large amounts of data to return accurate results; as a result, information is fed in the form of huge data sets. When processing the data, artificial neural networks are able to classify the data with the answers received from a series of true or false binary questions involving highly complex mathematical calculations. **[12]**

II.5 Depth learning principles:

Deep learning consists of a multitude of methods from the field of machine learning that exploit a set of nonlinear nodes located in several layers to extract and convert entity variable values from the input vector. The individual layers of such a system have as input the outputs of the preceding layers, with the exception of the initial input layer which receives signals or input vectors from the external environment.

In addition, unsupervised and supervised techniques can be applied to system training. This leads to the possible application of these models to supervised learning tasks such as classification, and to unsupervised tasks such as pattern analysis. Deep learning models also rely on the extraction of higher-level entities from lower-level entities in order to obtain a stratified representation of the input data via an unsupervised learning approach on the different entity levels. A classification of notions and theories is obtained by learning different layers of data representations representing different levels of data absorption

Deep learning is a branch of machine learning algorithms that:

- Uses multiple layers of non-linear processing nodes for entity extraction and transformation. Successive layers use the output of previous layers as input.
- Learn unsupervised (e.g. model analysis) and/or supervised (e.g. classification).
- Learn several levels of representation linked to different levels of abstraction. These levels represent a hierarchy of concepts **[13].**

II.6 Classification of deep learning :

Deep learning can be classified into three main classes according to the objectives for which they were designed [13]

II.6.1 Deep networks for unsupervised or generative learning:

Aim to capture the high-order correlation of unlabeled input data for pattern recognition or synthesis. When used to characterize common statistical distributions of observed data and their associated classes, networks have a generative mode and could be transformed into discriminative networks for further learning.

II.6.2 Deep supervised learning networks:

Supervised models are used when target label data is available, as they can directly provide discriminating power for classification purposes.

II.6.3 Hybrid deep networks:

Are the combination of the two types of networks mentioned above, so that unsupervised deep networks could provide an excellent initialization on the basis of which discrimination could be examined. **Figure XXIII**

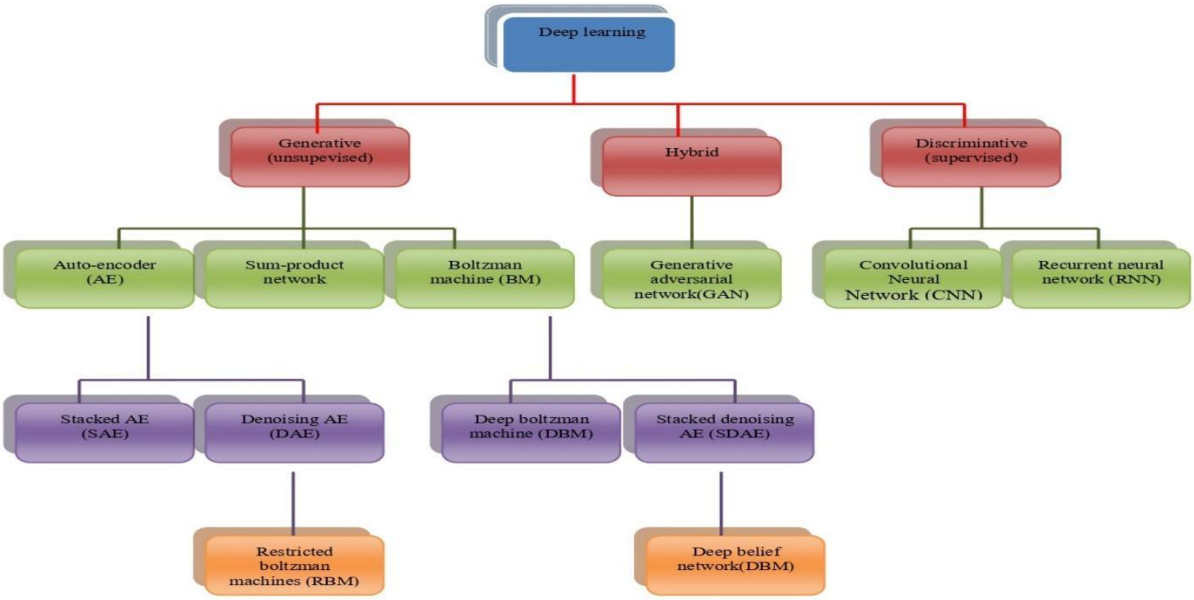


Figure XXIV: Classification of deep learning methods [13]

II.7 The importance of Deep Learning:

- Machine learning works only with structured and semi-structured data sets, while deep learning works with structured and unstructured data.

- Deep learning algorithms can efficiently perform complex operations, while machine learning algorithms cannot.

- Machine learning algorithms use labeled data samples to extract patterns, while deep learning accepts large volumes of input data and analyzes the input data to extract the characteristics of an object.

- The performance of machine learning algorithms decreases as the number of data increases; so to maintain model performance, we need deep learning. **[12]**

II.8 Fields of application for deep learning:

Deep Learning is used in particular to develop autonomous driving systems for automobiles, and is also responsible for the spectacular improvements seen in recent years in speech recognition, robotics, bioinformatics, imaging and language translation. Progress in deep learning has been made possible in particular by increased computer power and the development of large databases **[11] Figure XXV**

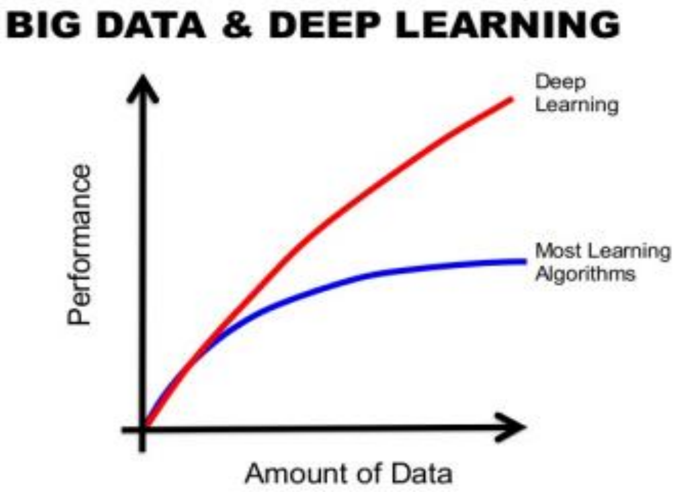


Figure XXVI: The difference in performance between DP and most ML algorithms as a function of the amount of data [11]

II.9 Architecture of deep neural networks:

There are many different types of deep architecture. Most of them are derived from certain original architectures. **[16]**

A convolutional neural network (CNN) is a type of artificial neural network that is highly effective in image classification, and is referred to by the acronym CNN or ConvNet (Convolutional Neural Networks). A CNN is simply a stack of several convolution, pooling and ReLU correction layers, in which each image received as input is filtered, reduced and corrected several times, to finally form a vector which, in the classification problem, contains the probabilities of class membership. The intermediate layers can be stacked in different ways, provided that the output of one layer has the same structure as the input of the next layer.

II.9.1 CNN processing layers :

CNN consists of a stack of independent processing layers:

II.9.1.1The convolution layer (CONV):

The convolution layer is the key component of convolutional neural networks, and always constitutes at least their first layer. In this layer, instead of applying a scalar product between the internal values and weights of each neuron, as in traditional neural networks, we apply a convolution product. This convolution product acts as a feature extractor for the input images. Characteristic convolution filtering involves "dragging" a window representing the characteristic over the image and calculating the convolution product between the characteristic and each portion of the scanned image. Three hyper-parameters are used to dimension the volume of the convolution layer (also known as the output volume): 'depth', 'pitch' and 'margin'.

- **Layer depth:** number of convolution kernels or neurons associated with a single receptive field.
- **Pitch:** Controls the overlap of receptive fields. The smaller the pitch, the more the receptive fields overlap, and the greater the output volume.
- **The 0 margin or zero pudding:** Sometimes it's convenient to place zeros at the boundary of the input volume. This allows you to control the spatial dimension of the output volume. In particular, it is sometimes desirable to maintain the same surface area as that of the input volume (Figure).

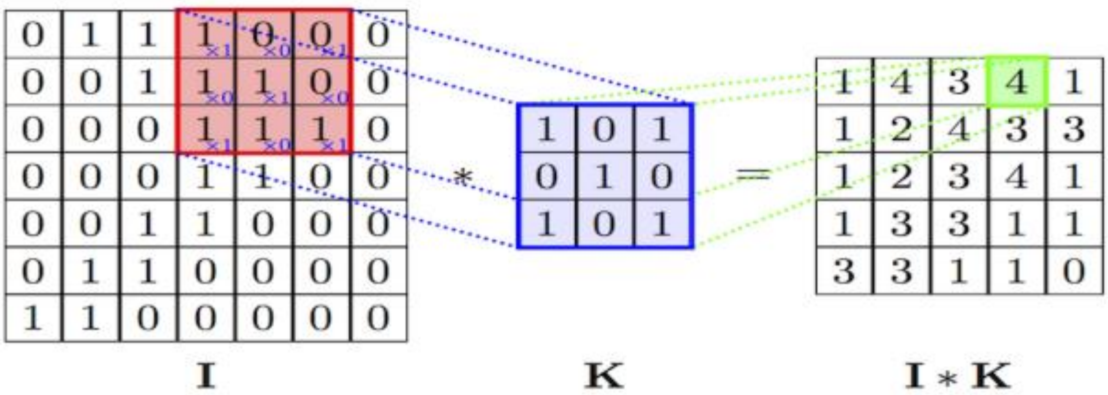


Figure XXVII: Illustration of convolution

II.9.1.2 Pooling layer (POOL):

The input image is cut without overlap into a series of NxN pixel rectangles. The pooling operation is applied to each of these. This type of layer is often placed between two convolution layers. The pooling operation consists in reducing the size of the images while preserving their important characteristics, thus reducing the amount of parameters and computation in the network. There are several types of pooling, such as MAX pooling (Max pooling returns the maximum element over a calculation window), AVG pooling (Average pooling returns the average element over a calculation window). The most commonly used method is "Max Pooling", in which a tile moves (like a filter) over the image surface. At each tile position, the highest value is extracted. This produces a new image with only the image's outstanding values. We'll have a featuremap of 9 by 9 pixels to start with, and we often use a tile of 2 or 3 pixels and a value of 2 pixels for the pitch. At the end, the output image is 7 by 7 pixels (7) (Figure).

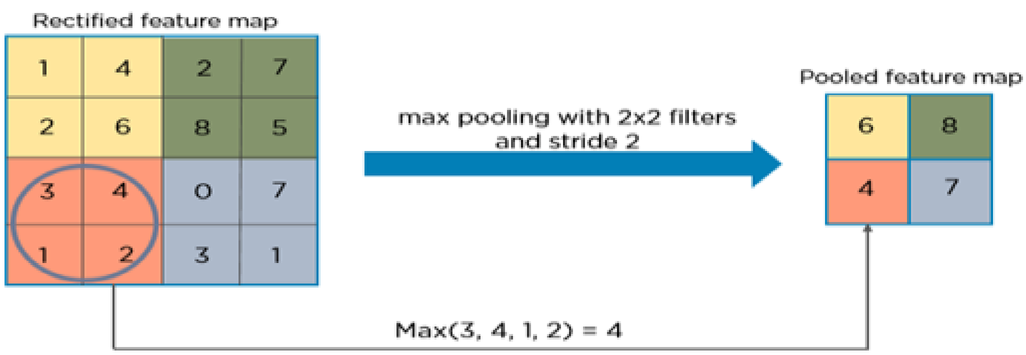


Figure XXVIII: Pooling with a 2x 2 filter and a step size of 2

II.9.1.3Correction layer (ReLU):

The rectified linear unit layer is an activation function. There are various activation functions that enable non-linearity in the various CNN layers. Some of the best-known are :

- ReLU correction (short for Rectified Linear Units): f(x)=max (0,x). This function enhances the non-linear properties of the decision function and the network as a whole, without affecting the receiving fields of the convolution layer.
- Hyperbolic tangent correction f(x)=tanh(x)
- The saturating hyperbolic tangent correction: f(x)=|tanh(x)|.
- Correction using the sigmoid function.

The Relu correction is preferable because it results in neural network formation several times faster without making a significant difference to accuracy generalization (Figure).

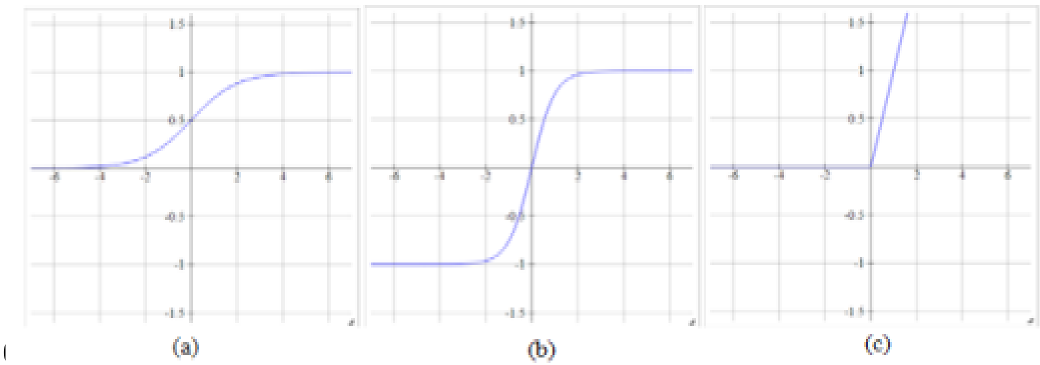


Figure XXIX: Three activation function

II.9.1.4 Fully connected layer (FC):

After several layers of convolution and max-pooling, high-level reasoning in the neural network takes place via fully connected layers. Neurons in a fully connected layer have connections to all outputs in the previous layer. Their activation functions can therefore be calculated with matrix multiplication followed by polarization shifting.

II.9.1.5 Loss layer (LOSS):

The loss layer specifies how the network drive penalizes the deviation between the expected and actual signal, and is normally the last layer in the network. Various loss functions adapted to different tasks can be used here. The (Soft max) function calculates the probability distribution over the output classes

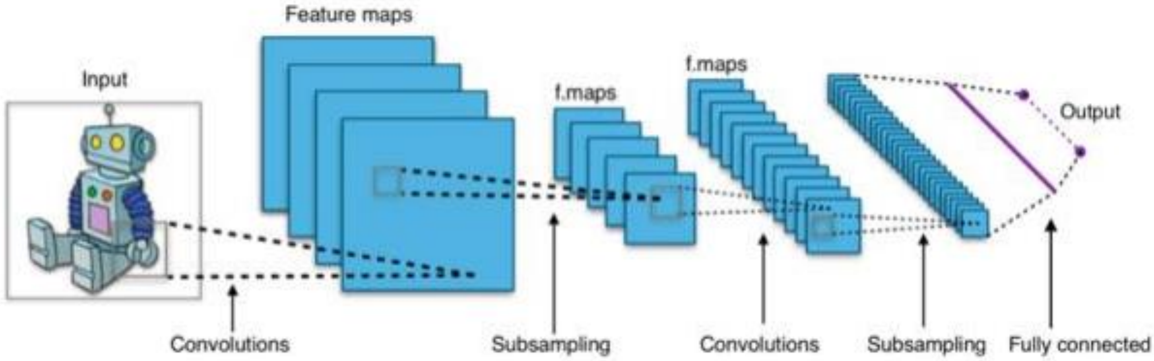


Figure XXX:Examples of CNN models

II.9.2 Architecture of a recurrent neuron (RNN):

The idea behind RNNs is to use sequential information. In a traditional neural network, we assume that all inputs (and outputs) are independent of each other. But for many tasks, this is a very bad idea. If we want to predict the next word in a sentence, we need to know the words that came before. RNNs are called recurrent, because they perform the same task for each element in a sequence, with the output dependent on previous calculations. **[11]** Another way of thinking about RNNs is that they have a "memory" that captures information about what has been calculated so far. In theory, RNNs can use information in arbitrarily long sequences, but in practice, they are limited to looking only a few steps back. It is used for :

- Language modeling and text generation.
- Machine translation.
- Voice recognition and image description.

As recurrent neural networks have many connections, simplified representations are often used, where a single arrow represents a complete W-weight matrix. The following figure shows a classical network, with a recurrent layer followed by a classical dance layer:

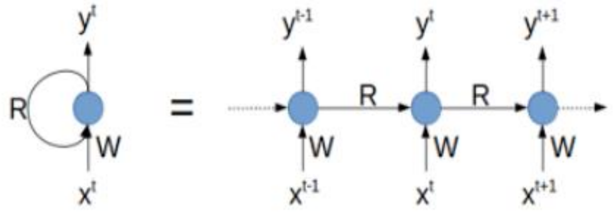


Figure XXXI: Simple RNN with a recurrent layer and a dense layer

II.10Transfer learning :

Transfer learning (TL) is a machine learning (ML) research problem that focuses on storing the knowledge gained from solving one problem and applying it to a different but related problem, such as the knowledge gained from learning to recognize cars could be applied when attempting to recognize trucks. This area of research has some connection with the long history of psychological literature on transfer of learning, although the practical links between the two fields are limited. From a practical point of view, the reuse or transfer of information from previously learned tasks for the learning of new tasks has the potential to significantly improve the sample effectiveness of a learning agent. Transfer learning is used when we don't have enough annotated data to train our model. When there is a pre-trained model that has been trained on similar data and tasks. **[11]**

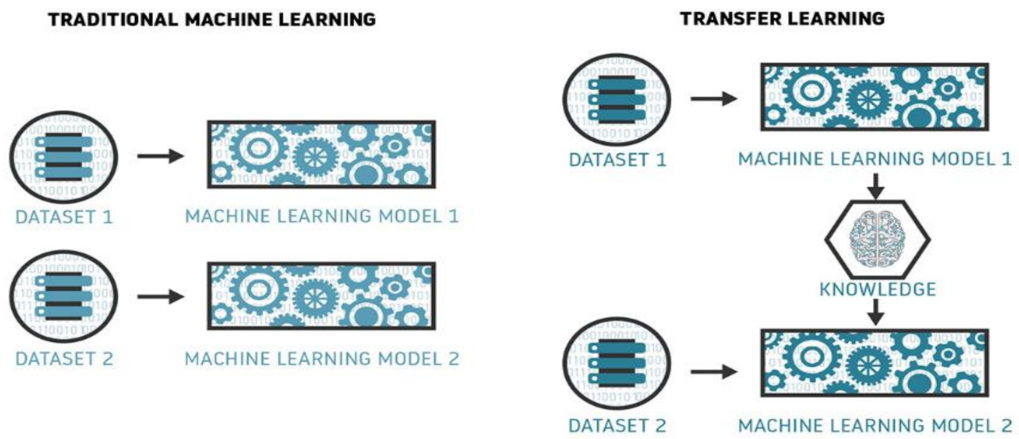


Figure XXXII: Machine learning and transfer learning [8]

II.11 Transfer Learning principal*:*

The feature-based approach, which does not modify the original model and allows new tasks to benefit from the complex features learned from previous tasks. However, these features are not specialized for the new task and can often be improved by fine-tuning.

Fine-tuning, which modifies the parameters of an existing model to form a new task. The original model is "unfrozen" and re-trained on new data, increasing performance for the new task **[17].**

In the field of computer vision, the intuition is that if a model is trained on a sufficiently large and general data set, it will effectively serve as a generic model of the visual world. Among the main pre-trained models used in computer vision for TL are the following:

- Visual Geometry Group (VGG) and all its variants such as the VGG16 model, which is a 16-layer CNN trained on a subset of the ImageNet dataset, a collection of over 14 million images belonging to 22,000 categories. Characterized by its simplicity, the VGG model was developed to increase the depth of these CNNs in order to enhance model performance. The VGG model is the basis of revolutionary object recognition models and has become one of the most popular architectures **[17].**

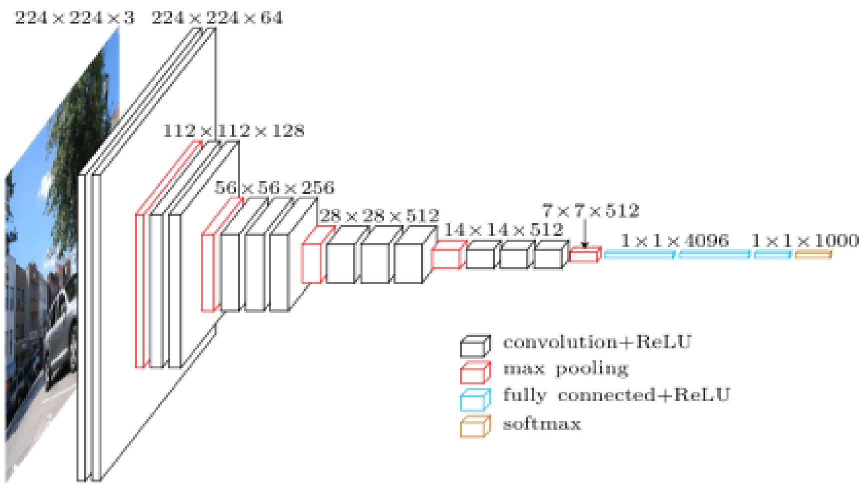


Figure XXXIII: VGG16 architecture

- NASNet Extended When designing NASetLarge, Neural Architecture Search (NAS) is used and also Starter Cells are used to build the model layer, as in the case of InceptionNet-V3. The design of NASNet uses two types of cells: the normal cell and the reduction cell**.[26]**

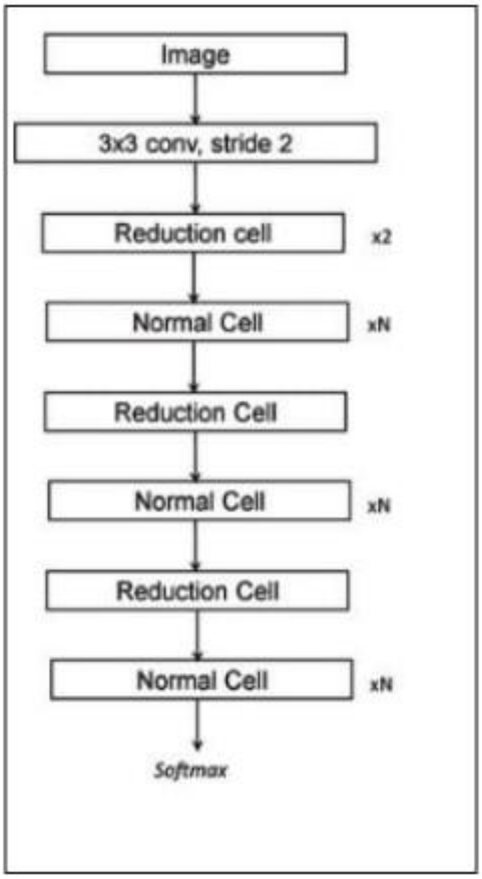


Figure XXXIV: Architecture of NASNetlarge [26]

- **Comparative table between several memories :**

Tableau III: Comparison of several memoires

	2019/2020 **Presented by :** **-KHERMAZA ELYES** **-BOUTIARA ABDELOUAHAB**	**2021/2022** **Presented by :** **-OTMANI CHAHINEZ**	**2022/2023** **-BEKKAR LATIFA** **-GOUCEM SAFA**
The network used	(Pre-trained) -VGG16 -ResNeT sequence -Inception -R-CNN mask	-CNN model	-CNN model -Pre-trained Mobile Net -Inception-ResNet-v2
The database	253 MRI images (before) 7313MRI images (after)	A total of 3264 MRI images of various shapes	394 MRI images

		and lengths	
Database augmentation technique	1-Rotation 2-Le resize 3-Vertical flip 4-Flip horizontal 5-Width offset 6-Height offset 7-Modifying brightness	1-Semitized axial 2-Rotation 3-Random cropping 4-Color change 5-Noise addition 6-Zoom 7-Contrast change	1-Data Increase
MRI image pre-processing	Data increase factor =21	(160 × 160× 3).	(200*200*3) (height/length/channel)
Download site	(Open source) Github	(Open source) KAGGLE	(Open source) KAGGLE
Results Obtained	- They found **VGG16 to be the** most accurate (highest percentage of successful detection) and fastest of the three. - they've proved that it's better to use a **GPU** graphics gas pedal, which is far more powerful than the **CPU,** so the TPU is best suited to the large number of calculations.	-A model that offers greater precision in terms of training and validation. - The model is not complicated. -The proposed CNN model can achieve a maximum accuracy of **98.861%**. **GPU-based**	-A predictive accuracy of **99%,** surpassing all previous studies in the literature. The 32-batch model gives a better result than a higher number of batches, and the ADAM optimizer would be better than the SGD optimizer.

II.12 Classification evaluation metric:

Various metrics can be used to evaluate the results of a classification model. We have opted for the confusion matrix to evaluate the performance of our program.

II.12.1 Confusion matrix:

The confusion matrix is a summary of the results of predictions on a classification problem, making it possible to carry out in-depth statistical analysis more quickly, and to facilitate the reading of results thanks to a clear visualization of the data.

True and false positives and negatives are plotted as a matrix as shown in the **Table IV**

Table V: Confusion matrix

	Predicted classes	
Real classes	**TP**	**FN**
	FP	**TN**

II.12.2 Definition of terms:

TP: The number of cases in which the model has correctly predicted a tumor and this prediction is correct.

FP: A false positive occurs when the model predicts a malignant tumor when there is none.

FN: A false negative occurs when the model predicts that there is no tumor when in fact there is.

TN: A true negative represents a case where the model correctly predicts that there is no malignant tumor.

II.12.3 Evaluation metrics:

There are several evaluation metrics that can be derived from the confusion matrix. Here are some of the most common metrics:

Accuracy: also called Positive Predictive Value, measures the proportion of positive observations that have been correctly identified, presented by the following formula:

$$\textbf{Accuracy} = \frac{TP}{TP+FP}$$

Sensitivity:(true positive rate) measures the ability of the model to correctly identify positive instances, Presented by the following formula:

$$\textbf{Sensitivity} = \frac{VP}{VP+FN}$$

Specificity: (rate of true negatives) measures the ability of a model to correctly identify negative instances, Presented by the following formula:

$$\textbf{Specificity} = \frac{VN}{VP+FN}$$

Classification rate: Often called accuracy, this metric measures the proportion of correct predictions in relation to the total number of predictions made by a classification model, and is an overall measure of model performance.
Present using the following formula:

$$\textbf{Classification rate} = \frac{TP+TN}{TP+TN+FP+FN}$$

Execution time: This is a key performance measure in computing and is often used to evaluate the efficiency and speed of a program. It is the total time required for a program or function to run from start to finish.

II.13 Conclusion:

Deep learning and transfer learning have revolutionized the way we approach complex problem solving. By exploiting pre-trained models on large amounts of data, these approaches make it possible to apply knowledge gained on one task to another. Now we turn our attention to an exciting new chapter, presenting the results of our experiments using DL and TL on our dataset. We'll start with a detailed analysis of the performance of the trained models.

Chapter III:

Implementation and results

III Introduction:

In this chapter, we will adopt several methods for early detection and prediction of brain tumors. To achieve this, we will use deep learning after a pre-processing step in which we resize the brain images followed by a data augmentation step.

At the end of this chapter, we'll make a comparison between the different methods mentioned. Use classification evaluation measures (classification rate, accuracy, sensitivity, specificity and confusion matrix).

III.1 Materials used:

Our approach to the procedure for carrying out this work requires a combination of hardware and software to facilitate implementation.

III.1.1 Hardware environment:

The hardware used for this work is a Lenovo Thinkpad E590 laptop with the following specifications:

- CPU: Intel(R) Core (TM) i7-8565U CPU @ 1.80GHz 2.00 GHz.

- RAM: 16 GB.

- Disk: 1TB.

- GPU: Intel HD graphics + AMD Radeon RX 550X.

- Microsoft WINDOWS.

III.1.2 Software environment:

III.1.2.1 The programming language used (Python)

The algorithmic programming edited for our work was under Python version 3.8, dedicated or numerical calculations, signal processing and image processing.

III.1.2.2 Kaggle

Kaggle, a subsidiary of Google LLC, is an online community of data scientists and machine learning practitioners. Kaggle enables users to search and publish datasets, explore and create models in a web-based data science environment, work with other data scientists and machine learning engineers, and enter competitions to solve data science challenges. Allows data scientists to share code and analysis in Python. **[20]**

III.1.2.3 Python libraries:

A library is a collection of functions and routines that can be easily reused. Python is an open source language offering a multitude of libraries, such as :

- **TensorFlow**

Is a library created by the Google Brain team in the form of a proprietary system dedicated to DL neural networks, enabling extremely complex problems to be solved and allowing neural networks **to** be trained and executed for number classification, recurrent neural networks, etc.

- **Keras**

Keras is a high-level deep learning library based on Theano and TensorFlow, offering a simple and practical solution for designing a variety of deep learning models, and enabling the rapid creation of neural networks.

- **Numpy**

NumPy is a library for the Python programming language, designed to manipulate matrices or multidimensional arrays and mathematical functions operating on these arrays. **[19]**

- **Matplotlib**

Matplotlib is a Python programming language library for plotting and visualizing data in graphical form. It can be combined with the NumPy and SciPy scientific computing libraries**. [19]**

III.1.2.4 GoogleColab :

Colaboratory, often shortened to "Colab", is a product of Google Research. Colab allows anyone to write and run Python code of their choice through the browser. It's an environment particularly suited to machine learning, data analysis and education. In more technical terms, Colab is a hosted service for Jupyter notebooks that requires no configuration and provides free access to computing resources, including GPUs.

We used Google Colab in our implementation, because this platform can be used to train Deep Learning models.

III.2 *Implementation and results:*

III.2.1 Drive parameters:

- **Epochs**

A learning epoch means that the learning algorithm has made one pass through the training dataset, where the examples have been separated into "batch size" groups. **[23]**

- **Loss function**

To evaluate the quality of a neural network model, i.e. to find the values w and b that correspond to our model minimizing the cost function. The aim is to make the model understand whether its prediction is satisfactory or not. **[24]**

- **Batch normalization**

It has long been known that network learning converges faster if its inputs are centered and reduced (mean = 0, variance = 1). As each layer observes inputs produced by layers above it, it would be advantageous to obtain centered and reduced inputs for each layer. Batch normalization is a component that sits between layers of the neural network and continuously takes the output of a particular layer and normalizes it before sending it to the next layer as input. **[12]**

- **Dropout**

Dropout consists in temporarily ignoring randomly selected neurons during learning. During this phase, when neurons are randomly removed from the network, the other neurons will have to intervene and manage the representation required to predict the missing neurons. One neuron is retained for each iteration with probability p, otherwise it is eliminated.

In the test phase, all neurons are kept, so we want the neurons' outputs at test time to be identical to their outputs at training time. **[25]**

- **Optimizer Adam**

The name Adam is derived from adaptive moment estimation. It is an algorithm for first-order gradient optimization of objective functions, based on adaptive lower-order moment estimates**. [23]**

III.2.2 Database:

To carry out this brain tumor detection project, it was necessary to build a database containing MRI images.

Hospitals and medical imaging centers were not helpful, as they classify the nature of our database as "sensitive" and among "confidential patient information".

The solution was publicly accessible open source platforms, so our database was obtained from 'Kaggle'.

```
[4] from google.colab import drive
    drive.mount('/content/gdrive')

    Mounted at /content/gdrive
```

Figure XXXV : Database import code from google Drive

Our database is composed of approximately 253 MRI images presenting the two 2 classes of files:

- **Class 01:** Presence of the tumor named "Yes" with 155 images.
- **Class 02:** Absence of the tumor named "No" with 98 images.

- **Data base preparation:**

The images will be divided into 2 important sets:

1. Train sets: 80% of the data will be used in the training phase.
2. Test sets: 20% of the data will be used in the test phase.

Table VI: Data base preparation

Dataset	**Number of images**
Train sets	2687
Test sets	671
Total	3357

- **Database augmentation:**

As this number of images is insufficient to train our neural networks, we have resorted to "data augmentation", an extremely practical solution to this problem that artificially increases the amount of data used by Deep Learning tools. The various techniques used to achieve this are :

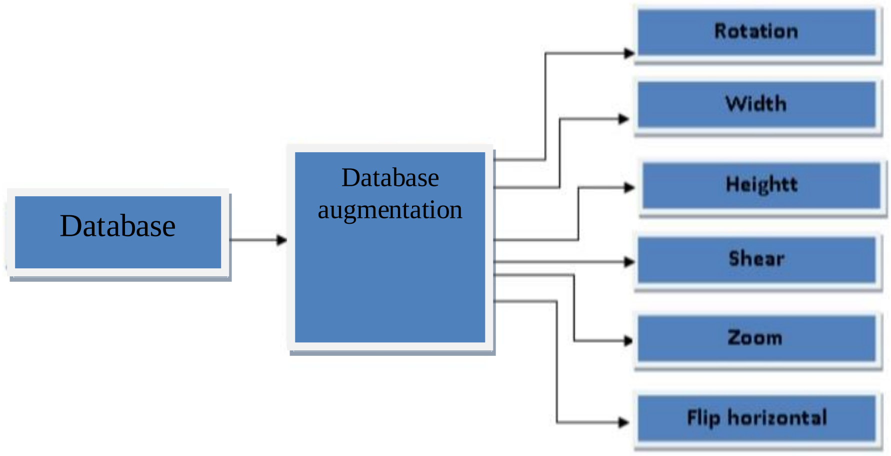


Figure XXXVI: Diagram of database augmentation techniques

After applying data augmentation to our database, the total number of MRI images increased to 3357. **Figure XXXVII**

```
# Chemins vers les répertoires de données
train_dir = '/content/gdrive/MyDrive/brain_tumor_dataset'
output_dir = 'dataset/augmented_train'

# Créer le répertoire de sortie s'il n'existe pas
os.makedirs(output_dir, exist_ok=True)

# Initialiser le générateur d'augmentation d'images
datagen = ImageDataGenerator(
    rotation_range=40,
    width_shift_range=0.5,
    height_shift_range=0.5,
shear_range=0.5,
    zoom_range=0.5,
    horizontal_flip=True,
    fill_mode='nearest'
)

# Parcourir chaque catégorie (yes/no)
categories = ['yes', 'no']
for category in categories:
    input_dir = os.path.join(train_dir, category)
    category_output_dir = os.path.join(output_dir, category)
    os.makedirs(category_output_dir, exist_ok=True)
```

```
Found 3357 images belonging to 2 classes.
Found 3357 images belonging to 2 classes.
```

Figure XXXVIII: Database augmentation implementation code

III.2.3 Methods of development:

We will present the steps of our algorithm:

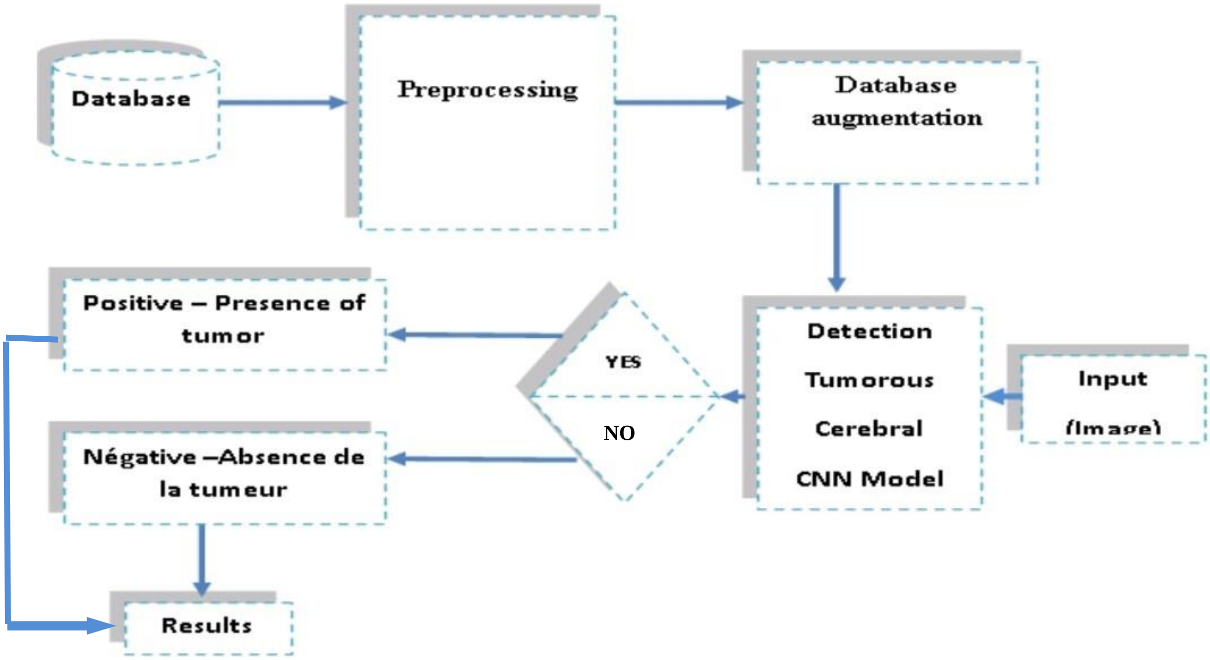


Figure XXXIX: Overiew of our system

III.2.4 Data pre-processing:

In the pre-processing section, we will perform pre-processing of the training and validation data to train the CNN network more efficiently. These pre-processings are performed by applying the following operations:

- Resize all MRI images to the same size (160x160x3).

- Mix all MRI images randomly.

- Divide the database into two sets, the first 80% for training and the second 20% for testing, at random.

III.2.5 Deep learning:

In this section, we'll create simple and modified CNN architectures, with the aim of carrying out a comparative study to extract the essential factors of Deep Learning.

III.2.5.1 CNN1 model:

We began by creating a classical convolutional neural network. The architecture of this network is formed by two convolution layers: **Figure XL**

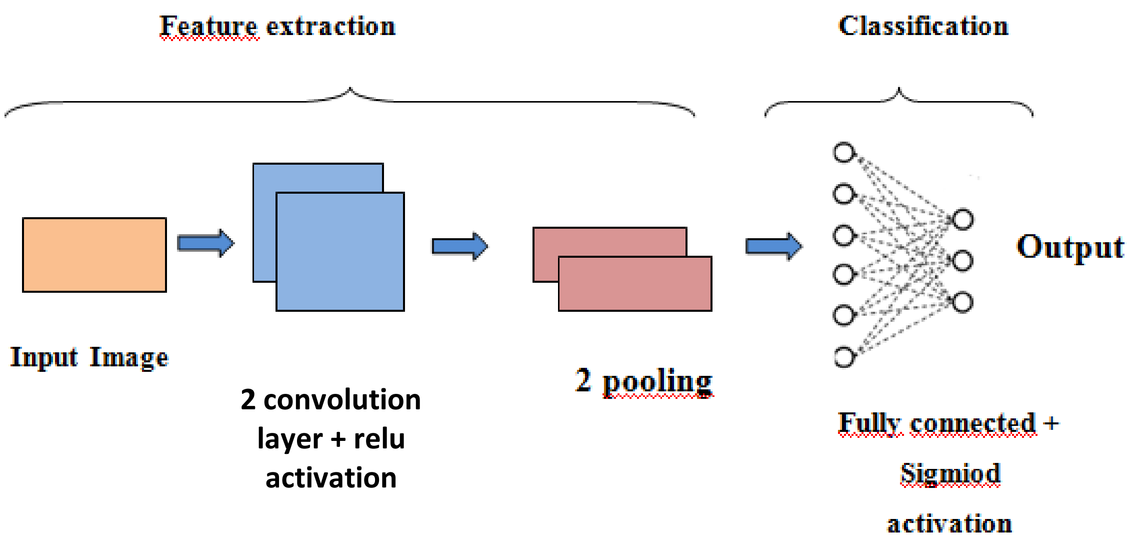


Figure XLI: CNN1 convolutional neural network structure

- **Creation of the CNN model :**

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 62, 62, 32)        896

 max_pooling2d (MaxPooling2  (None, 31, 31, 32)        0
 D)

 conv2d_1 (Conv2D)           (None, 29, 29, 64)        18496

 max_pooling2d_1 (MaxPoolin  (None, 14, 14, 64)        0
 g2D)

 flatten (Flatten)           (None, 12544)             0

 dense (Dense)               (None, 128)               1605760

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 1)                 129

=================================================================
Total params: 1625281 (6.20 MB)
Trainable params: 1625281 (6.20 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Figure XLII: Creating the CNN model

III.2.5.2 Modified CNN2 model:

In this section, an additional regularization layer (L2) has been added to reduce overfitting.

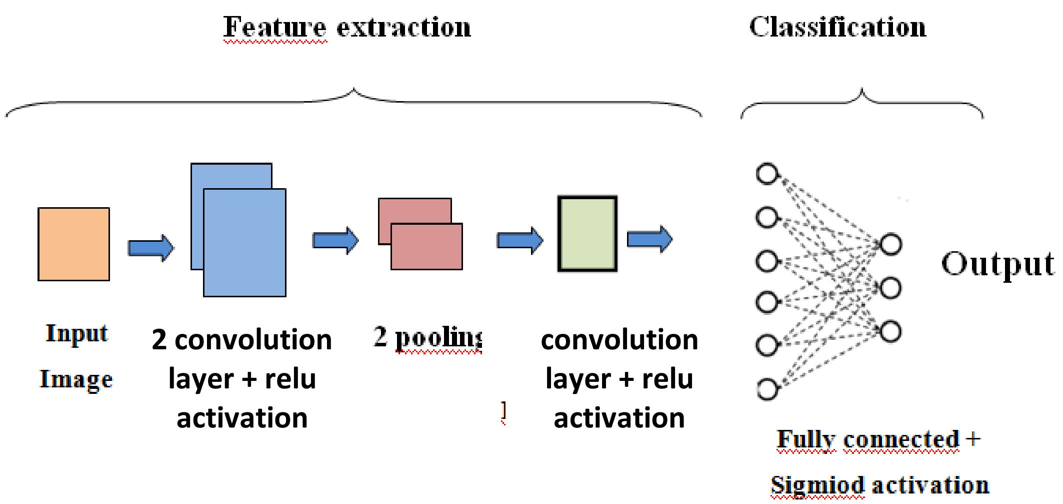


Figure XLIII: Structure of CNN2 convolutional neural network

- **Creation of the modified CNN2 model :**

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_14 (Conv2D)          (None, 62, 62, 32)        896

 max_pooling2d_14 (MaxPooli  (None, 31, 31, 32)        0
 ng2D)

 conv2d_15 (Conv2D)          (None, 29, 29, 64)        18496

 max_pooling2d_15 (MaxPooli  (None, 14, 14, 64)        0
 ng2D)

 flatten_7 (Flatten)         (None, 12544)             0

 dense_14 (Dense)            (None, 128)               1605760

 dropout_7 (Dropout)         (None, 128)               0

 dense_15 (Dense)            (None, 1)                 129

=================================================================
Total params: 1625281 (6.20 MB)
Trainable params: 1625281 (6.20 MB)
Non-trainable params: 0 (0.00 Byte)
```

Figure XLIV: Creation of the modified CNN2 model with the L2 regularization layer

III.2.5.3 Modified VGG-16 model:

To improve the performance and efficiency of the model, the VGG-16 model was chosen.

This is the architecture we used:

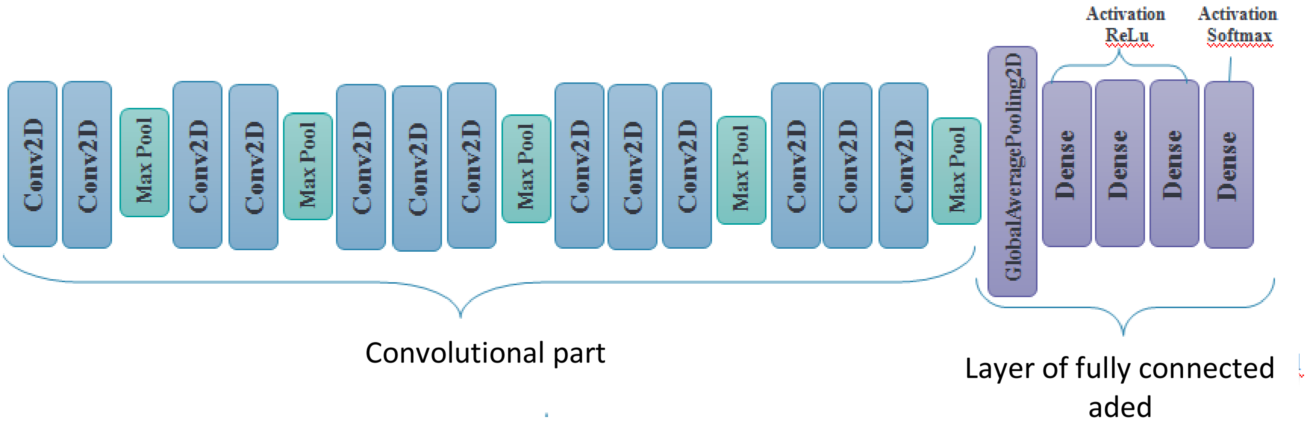


Figure XLV: VGG-16 architecture

III.2.5.4 Modified VGG-19model:

Then we worked with the model VGG-19, here is the architecture used :

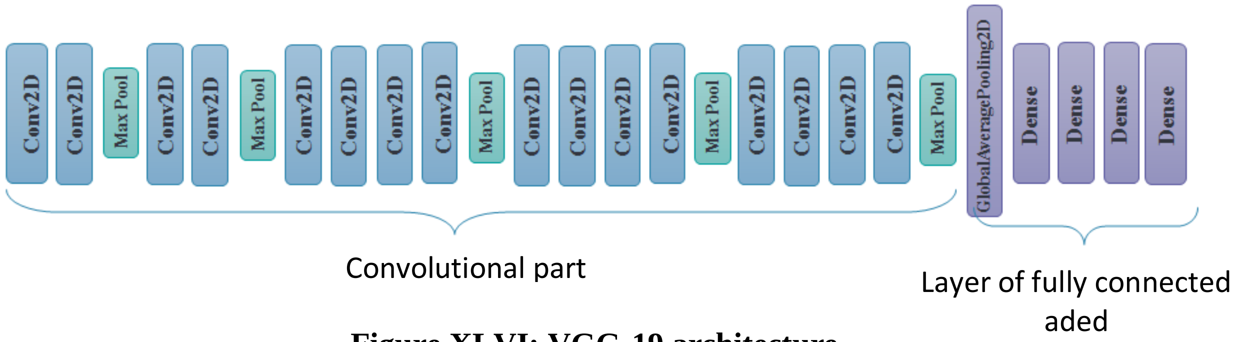


Figure XLVI: VGG-19 architecture

III.2.5.5 NasNet large model:

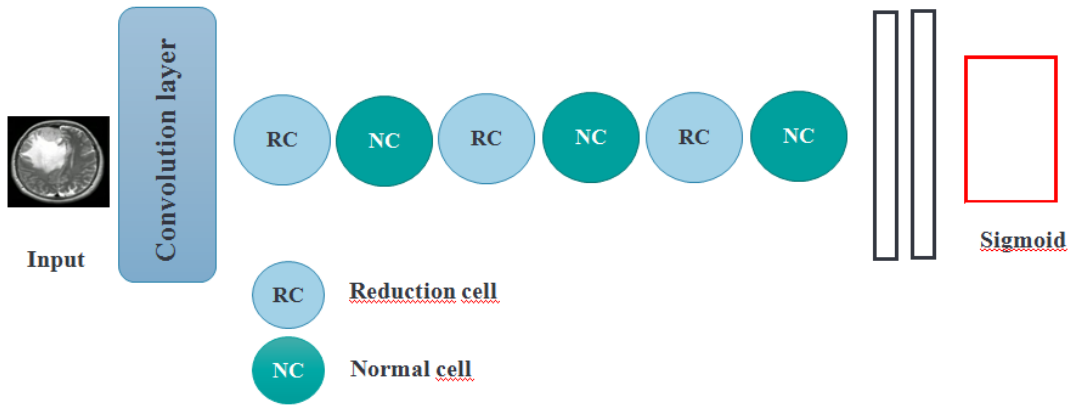
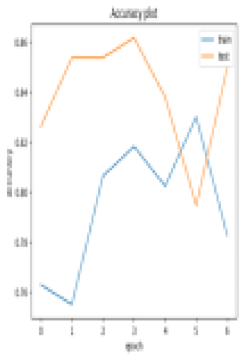
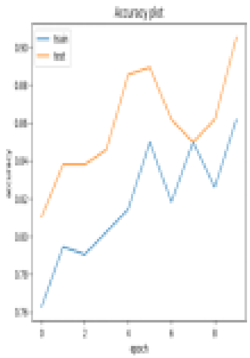
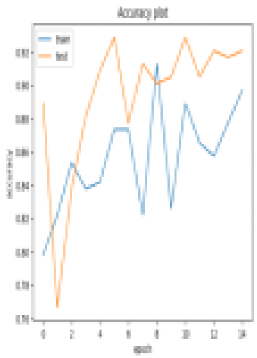
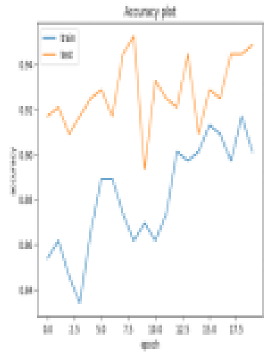
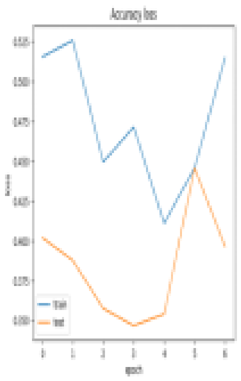
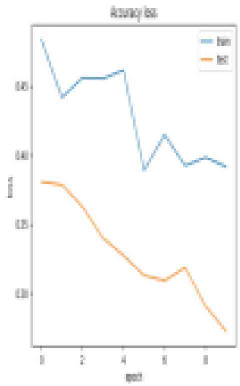
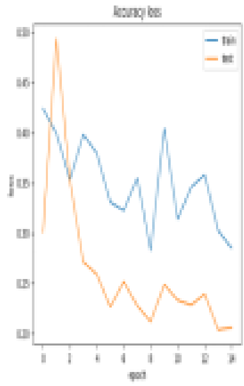
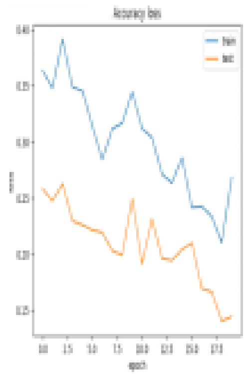


Figure XLVII: Nasnet large model

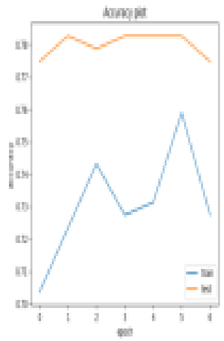
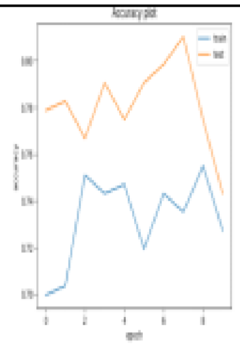
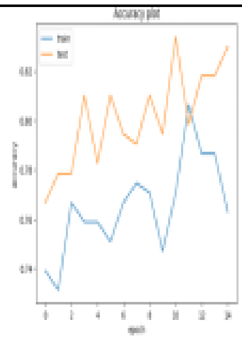
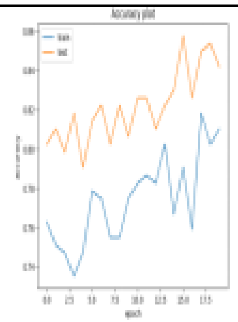
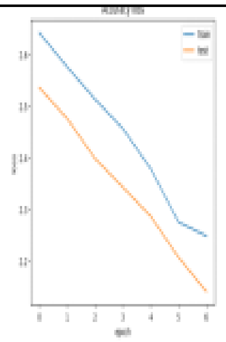
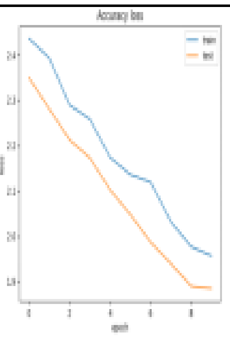
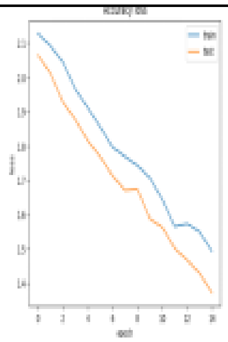
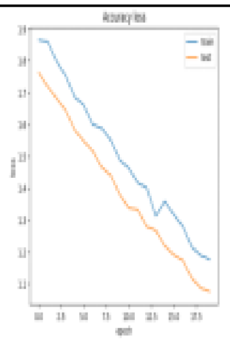
- **Model results without database augmentation :**
  - **CNN:**

Table VII: Results of the CNN model without database augmentation

	Epoch=7	Epoch=10	Epoch=15	Epoch=20
Accuracy				
Loss				
Precision	64%	61%	61%	62%

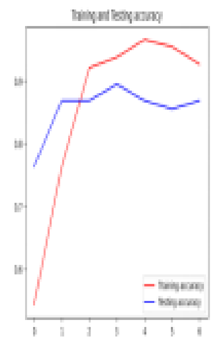
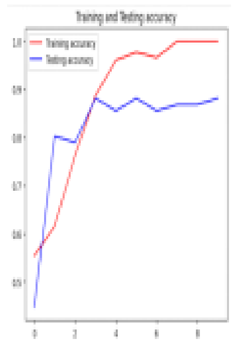
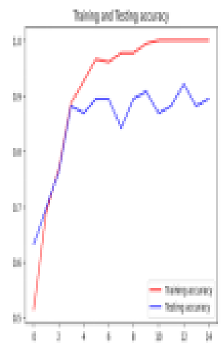
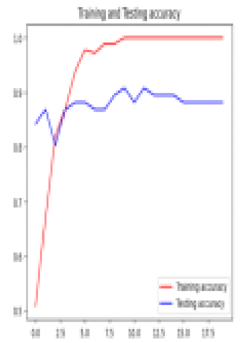
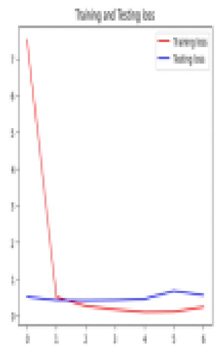
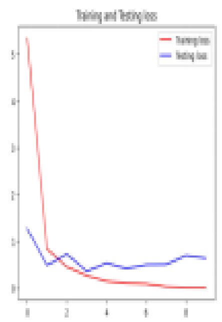
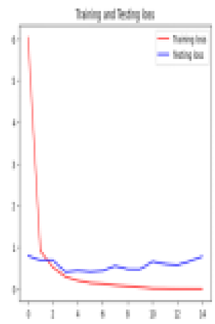
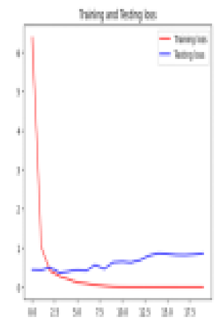
➢ **CNN2:**

Table VIII: Results of the CNN2 model without database augmentation

	Epoch=7	Epoch=10	Epoch=15	Epoch=20
Accuracy				
Loss				
Precision	60%	61%	60%	61%

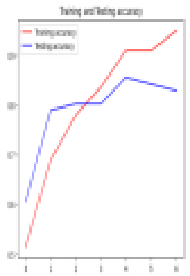
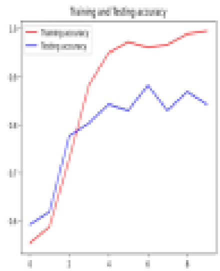
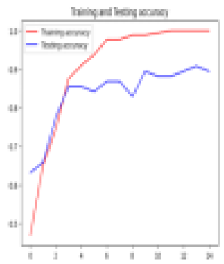
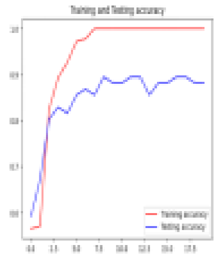
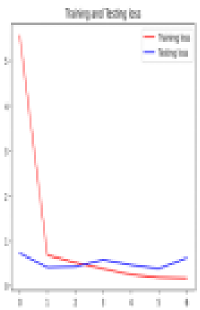
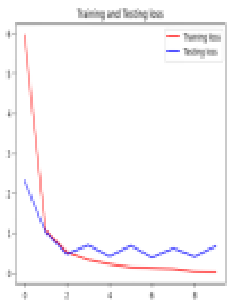
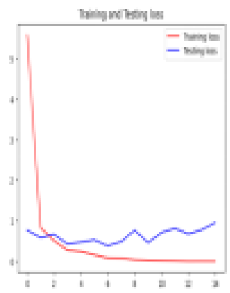
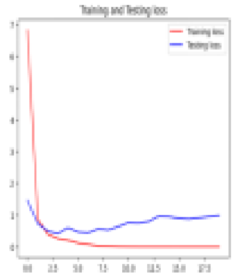
- **VGG16 :**

Table IX: Results of VGG16mdel wihout database augmentation

	Epoch=7	Epoch=10	Epoch=15	Epoch=20
Accuracy				
Loss				
Precision	89%	86%	90%	88%

➢ **VGG19:**

Table X: Results of the VGG 19 model without database augmentation

	Epoch=7	Epoch=10	Epoch=15	Epoch=20
Accuracy				
Loss				
Précision	**83%**	**87%**	**90%**	**88%**

➢ Results obtained:

1. CNN Basic:

Accuracy Average: About 60%

Observations: Basic CNN networks, without additional layers of regularization or database augmentation, can often have difficulty generalizing, especially if the database is limited in size or variety. This can result in lower average performance compared to more complex models

2. CNN with Regularization Layer:

Average accuracy: Close to basic CNN (~60%)

Observations: Adding an L2 regularization layer can help prevent overfitting, but if accuracy remains around 60%, this suggests that other limiting factors, such as model complexity or database size, play a more important role.

3. **VGG16 and VGG19** :

Accuracy: About 90%

Observations: The VGG16 and VGG19 architectures, which are deep and pre-trained models on large databases like ImageNet, have a much greater ability to extract discriminating characteristics from images. Their depth and the richness of their convolution layers allow a better generalization and a much higher precision.

III.2.5: Model evaluation before augmentation:

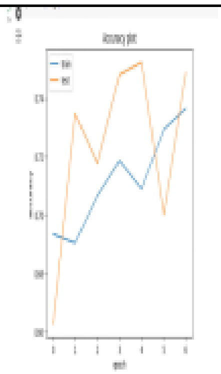
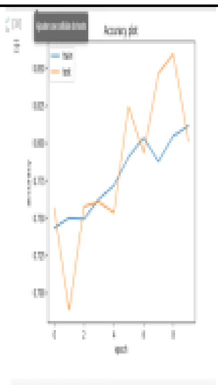
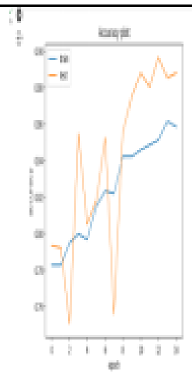
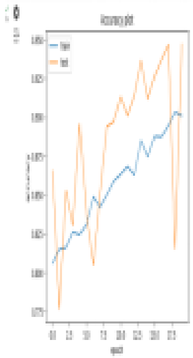
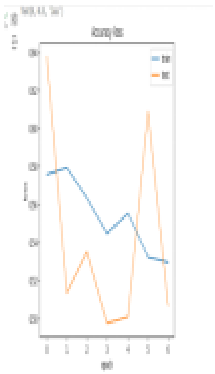
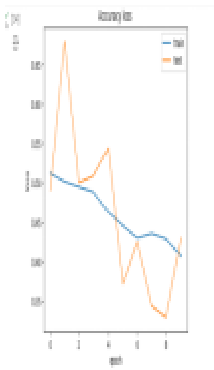
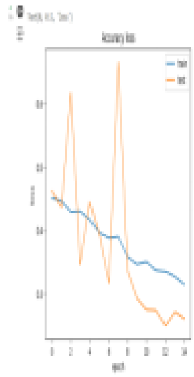
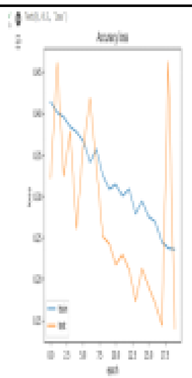
Table XI: Test results according to the dataset of 2 classes

Classe	The model	Accuracy	Précision	Sensibilité
	CNN	52.56%	59.06%	73.54%
	CNN2 modifie	54.54%	60.63%	73.54%
	VGG-16 modifie	88.15%	88.57%	88.15%
	VGG-19modifie	90.78%	90.77%	90.78%

- **Model results after database augmentation :**

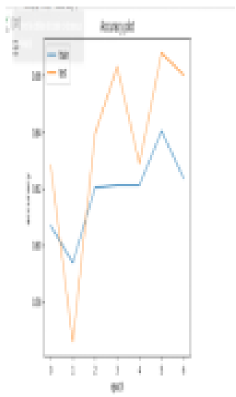
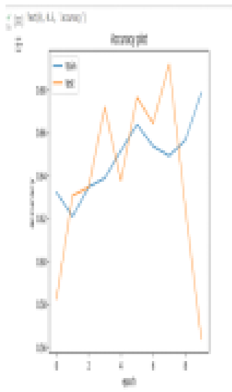
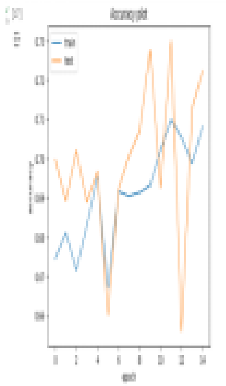
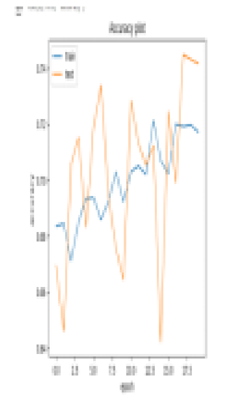
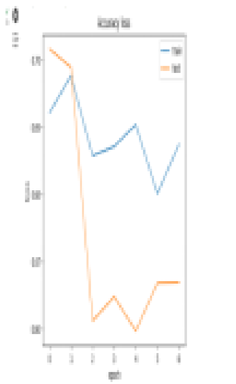
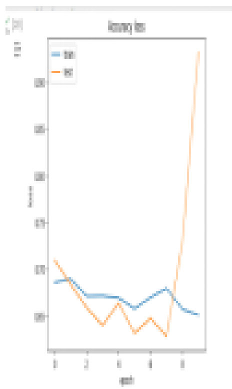
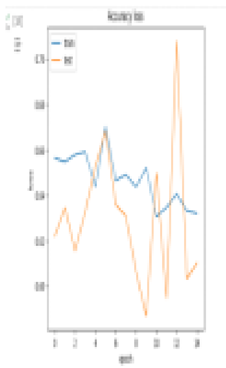
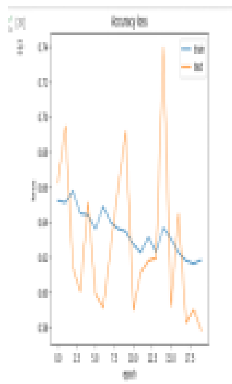
  - **CNN:1**

Table XII: Results of the CNN model after database augmentation

	Epoch =7	Epoch=10	Epoch=15	Epoch=20
Accuracy				
Loss				
Précision	50,89 %	50,13 %	50,10%	50,06%

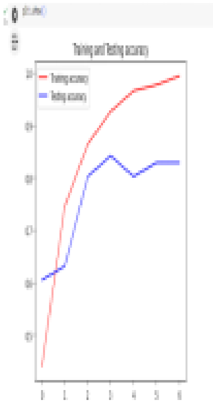
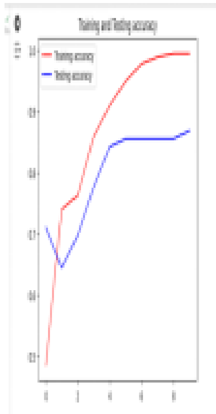
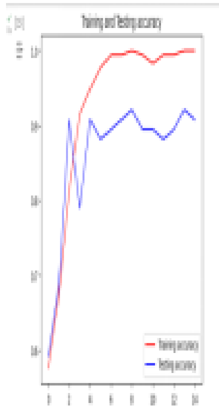
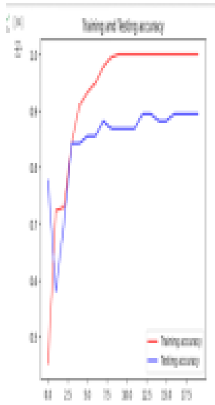
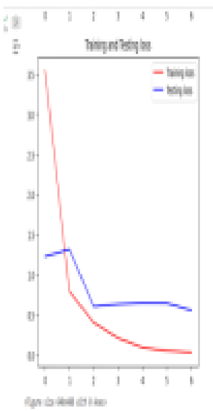
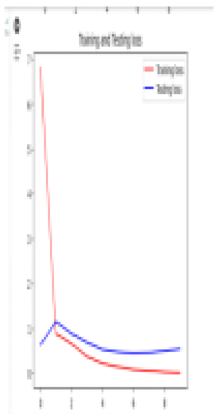
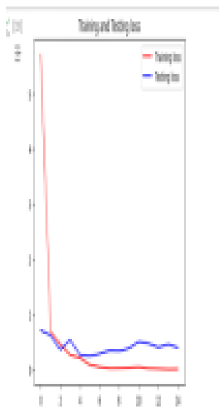
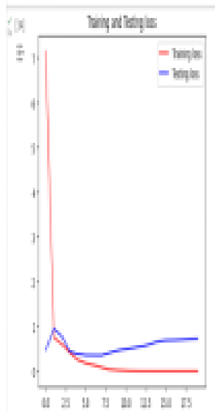
- **CNN 2**

Tableau XIII: Results of the CNN2 model after database augmentation

	Epoch=7	Epoch=10	Epoch=15	Epoch=20
Accuracy				
Loss				
Precision	50,86%	50,10%	52,45%	49,36%

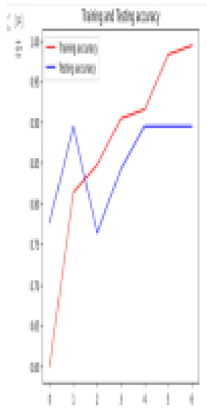
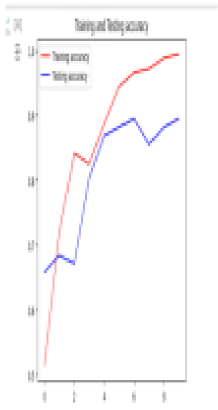
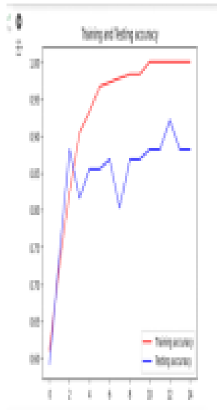
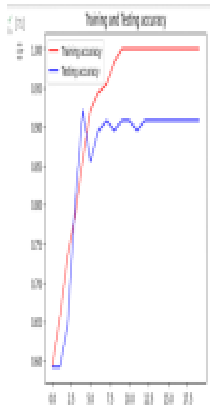
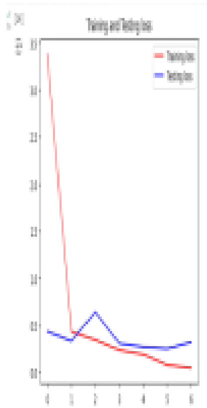
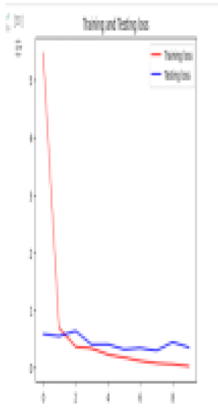
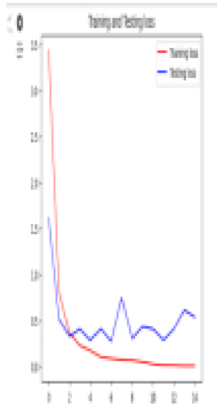
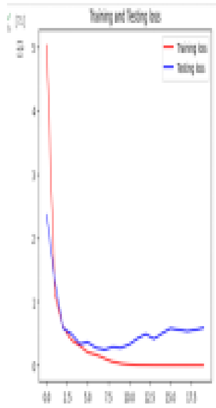
- **VGG 16**

Tableau XIV: Results of the VGG16 model after data base augmentation

	Epoch=7	Epoch=10	Epoch=15	Epoch=20
Accuracy				
Loss				
Precision	83%	86,84%	90,86%	89,48%

- **VGG19**

Tableau XV: Results of the VGG19 model after database augmentation

	Epoch=7	Epoch=10	Epoch=15	Epoch=20
Accuracy				
Loss				
Precision	**91,06%**	**90,24%**	**90,13%**	**91,32%**

- **Results obtained:**

1. **Basic and CNN with regularisation**

Accuracy Average:

CNN simple: 50%

CNN with regularisation: 52%

Observations: The learning capacity of simple CNN models, or with regularisation techniques such as Dropout or L2 regularisation, is limited. As a result, their accuracy is significantly lower (50% and 52%).

Even if the data increases, the improvement is limited for these models. This demonstrates that, in order to obtain significant benefits, it is essential to have a more complex architecture.

III.2.6 Model proposed with transfer leaning:

After presenting the dataset used and the pretreatment carried out in our work, we then focus on the extraction part of the characteristics and the classification according to the model used. The pre-trained models we will apply in our solution are:

1. VGG16 architecture
2. VGG19 Architecture

1. **Model 1 "VGG16" modified:**We explained well in the second chapter, we kept the convolutionelle part which contains 18 layers, afterwards we added 4 dense layers to adapt it to the classification of tumours.

New layers added:

GlobalAveragePooling2D

Dense : activation 'relu'

Dense : activation 'relu'

Dense : activation 'relu'

Dense : activation 'softmax'

2. **Model 2 "VGG19" modified:** This model applies the same layers as the VGG 16 model, except that it contains 21 layers, subsequently the same previous dense layers were added.

Accuracy Average:

- **VGG16 : 89%**
- **VGG19 : 91%**

Observations: The deep architectures of the VGG16 and VGG19 models offer a wide variety of parameters, enabling them to acquire complex features and generalise them efficiently to test data.

As the data grows, these models can improve their ability to detect variations in images, resulting in high accuracies (89% and 91% respectively).

III.2.7 Model evaluation after augmentation:

Tableau XVI: Test results according to the detaser of 2 classes

Classes	The model	Accuracy	Precision	Sensitivity
	CNN	68.26%	50.10%	44.08%
	CNN2 modifie	72.82%	52.45%	40.54%
	VGG-16 modifie	89.47%	89.48%	89.47%
	VGG-19 modifie	92%	94.32%	90.17%
	NasNet modifie	96%	95.7%	95.4%

- **Discussion of the Results:**

1. Model Complexity and Depth:

VGG16 and VGG19 architectures are much deeper than basic CNN networks. This depth allows capturing more complex and abstract characteristics of the input data, which greatly improves accuracy.

2. Pre-training on Large Databases:

VGG16 and VGG19 models are often pre-trained on large databases like ImageNet. This pre-workout allows the model to start with weights already optimized for a wide range of image recognition tasks, which can be very beneficial when refined (fine tuning) on a new database.

3. No Database Increase:

Database augmentation is an important technique to improve model generalization by creating modified versions of drive images (for example, by rotation, cropping, etc.). The absence of this technique in your experiments may explain why basic CNN models have not achieved higher levels of accuracy.

4. **Adjustment**:

Although regularization is important to prevent over-learning, its effect is limited if the basic model is not complex enough or if the database is insufficient. In your case, it seems that regularization alone was not sufficient to significantly improve the accuracy of basic NDCs.

III.3 Comparison with other works in the literature:

Tableau XVII: comparison of our model with other existing state of the art works found in the literature

	Accuracy	**Epochs**	**Execution time**
Our work	96%	26	3min
Existing work[19]	96.82%	30	5min

Various machine learning methods and techniques have been developed by many researchers using publicly available datasets to detect brain MRI images. The table shows an evaluation of our model against other state-of-the-art work under study. According to this table , we propose an architecture that has higher prediction performance for brain tumour identification than other methods reported in the literature, even though we use a relatively smaller database.

III.4 Application interface:

We have chosen to integrate our pre-trained convolutional neural network into a graphical interface so that the results of our network can be visualised

We have chosen to integrate our pre-trained convolutional neural network into a graphical interface so that the results of our network can be visualised.

To create and host our Streamlit application on Google Colab using Ngrok, we need two essential tools: Streamlit and Pyngrok.

Streamlit: Streamlit is a powerful and easy-to-use tool for creating interactive web applications in Python, particularly useful for data science and machine learning projects. It allows developers to quickly transform their data analyses and machine learning models into interactive web applications without requiring extensive web development knowledge.

Ngrok: Ngrok allows you to create secure tunnels from your local machine to the internet. It supports HTTP, HTTPS, and TCP protocols and is a powerful and easy-to-use tool for exposing local applications to the internet. Ngrok is particularly useful for developers who need to share their in-progress applications quickly and securely for testing, demos, or feedback.By combining these steps, you can develop and host a Streamlit application in a Google Colab environment. Using Ngrok creates a secure tunnel, making your application accessible online via a public URL generated by Ngrok. This method is particularly useful for sharing prototypes and demonstration applications with colleagues or clients without needing to deploy the application on a remote server.Click on this URL to access your Streamlit application hosted on Google Colab.

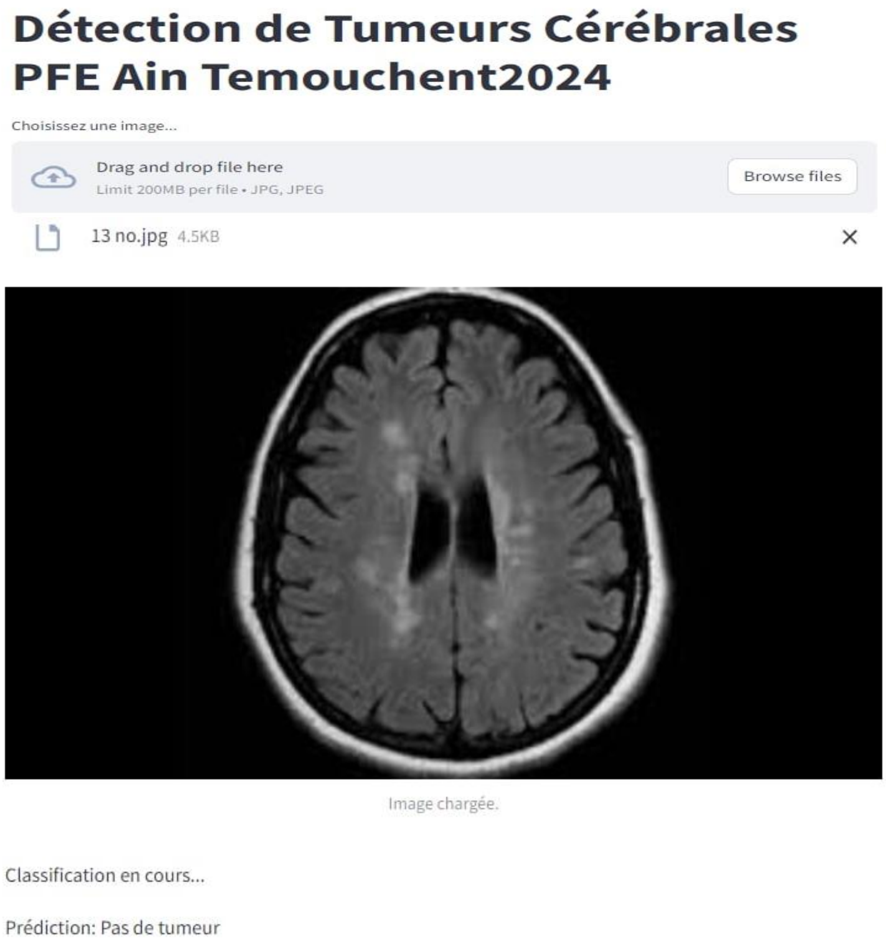


Figure XLVIII : application interface

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III.5 Conclusion:

In this chapter, we implemented the CNN, VGG16 , VGG19 and Nasnet models with the aim of classifying brain MRI images as yes/no tumours. We examined the steps involved in image pre-processing, model construction and compilation, and the application of transfer learning. As well as model analysis. Finally, we made a comparison between the four models and concluded that the Nasnet model can classify our data with 96% accuracy.

General conclusion & Perspective

This thesis explored the detection of brain tumours using deep learning techniques applied to MRI images. The main objective was to compare the effectiveness of different convolutional neural network (CNN) architectures in the precise and rapid identification of brain tumours, a critical area for improving medical diagnosis and increasing the chances of treatment and recovery of patients.

The CNN, VGG16, VGG19 and NaSNet architectures were implemented and evaluated in terms of accuracy, sensitivity, specificity and processing time. Each model has demonstrated its own advantages and disadvantages in the context of brain tumour detection.

- **CNN template:**

The basic CNN model has been shown to be effective in capturing fundamental features of MRI images. Its simpler structure compared to deeper architectures allowed for faster formation, but with slightly lower accuracy.

- **VGG16 ,VGG19 and Nasnet :**

The VGG16 , VGG19 and Nasnet models, with their increased depth, showed improved ability to detect complex patterns associated with brain tumours. VGG16, with its 16 layers, offers a good compromise between performance and computational cost. VGG19, with its 19 layers without forgetting the Nasnet model , how provides superior accuracy

- **Perspective:**

With regard to future work, we intend to extend this work to experiment with larger datasets and other types of orders to classify 4 classes and use other techniques such as models DenseNet+SVM and Cross Validation.

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