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THÈME

Brain Tumour Classification Using Deep Learning

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Abbreviation and Notation

WHO: World Health Organisation

NS: Nervous System

CNS: Central Nervous System

BT: Brain Tumour

MRI: Magnetic Resonance Imaging

MRS: Magnetic Resonance Spectroscopy

CT: Computed Tomography

SS-SS: Single Sample with a Single Spoon

GBM: Glioblastoma Multiform

AI: Artificial Intelligence

CAD: Computer-Aided Detection

DNNs: Deep Neural Networks

DL: Deep Learning

GAN: Generative Adversarial Network

AE: Auto-Encoder

SOM: Self-Organizing Map

RBM: Restricted Boltzmann Machine

DBN: Deep Belief Network

MLP: Multi-layer Perceptron

ANN: Artificial Neural Network

RNN: Recurrent Neural Network

CNN: Convolutional Neural Network

ILSVRC: ImageNet Large Scale Visual Recognition Challenge

RESNET: Residual Network

GPU: graphics processing units

CUDA :(Compute Unified Device Architecture

CUDNN: CUDA® Deep Neural Network library

API: Application programming interface

PDE: Partial differential equation

TP: True positive

TN: True negative

FP: False positive

FN: False negative

RGB: Red Green Blue

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General Introduction

General Introduction

In 2020, there were 308.102 new diagnosed cases with brain tumours worldwide. Oppositely, there were 251.329 death cases with brain tumours (cancer) and nervous system all over the world too, which means 81% at least of people lose their lives. In addition, according to the National Brain Tumour Society, Approximately 88,970 more will be diagnosed with brain tumours in 2022 in the US only. These numbers do increase year by year influencing the general life of people, also brain tumour has the twelfth rate of death among all the known cancers.

Brain tumours are aggressive diseases that attack children and adults with no mercy, even in medical science it's hard to deal with it especially since the brain is the most important and complicated organ in the human body**.** Tumours are caused by the abnormal growth of cells. Brain tumours can be benign or malignant (noncancerous tumours) or (cancerous). They might also be classified as primary or secondary tumour the last World Health Organization (WHO) classification mentioned that there are more than 120 types of Brain tumours.

Primary tumours are the ones that start in the brain or the central nervous systems (CNS) while the secondary tumours start in other body parts and are spared in the brain.
The WHO classified the brain tumours into four grades depending on the degree of growth and abnormality of brain tissue, the dangerous tumours with 3 and 4 grades are the ones with the high possibility of becoming cancer, other tumours with 1 and 2 grades are less dangerous. The most spared types of brain tumours are gliomas with their sub-types that can be primary or secondary tumours depending on their grade, the pituitary tumours are the ones that grow in the glands of the pituitary, and meningioma represent 36.1% of all the primary tumours.

Early detection of brain tumour is so important as a first step and its classification is the second important step for the doctors and the patient to get the great planning treatment By Research The MR imagining is the best way to do these important steps because of the high technology and great results avoiding the Biopsy that may cause a diagnostic error for its danger

Since there are so many datasets of brain tumour MRI available for which can be paid to use or free, there is a necessity to develop a system for the early detection and classification of brain tumours MRI images.

Machine Learning and Deep learning techniques have made a whole change in the medical world and helped many doctors to solve huge health problems. Moreover, we can find some researchers and data scientists create and developed some programs that trait images.

With transfer learning technique, we can implement the available pre-trained models that will reduce a lot of work, and by saying the available there is a plenty of models to choose from.

For our study, we choose four models: VGG16, VGG19, ResNet152V2, and ResNet50. Using three different datasets obtained from Kaggle. The transfer learning technique let you retrain the last layer of the model which contain the classes of the classification in our case brain tumours

Furthermore, we developed our own Convolutional Neural Network (CNN) model with four different architectures, every time we try to rise the performance of the model by changing some of the parameters like number of layers, optimizers, filters size … etc. We manage to achieve some impressive result with the final model. After that, we did a brief comparison with the state of the art methods.

The first chapter contain the medical side of this study, starting with the brain tumour and its types, symptoms and causes, and speaking about how brain tumour is diagnosed using different types of technology equipment then finally giving some recent statistics about the disease.

In the second chapter, we started with artificial intelligence and its branches like machine learning and deep learning, and then we talked about the relation and the importance of AI in the medical field giving some examples about that. We ended up with the different deep learning techniques that we going to use in the study.

In the last chapter, we defined our system architecture and gives a brief description of the used datasets, preprocessing techniques and some evaluation metrics used to measure the performance of the created CNN model. Finally, we ranked our model with the transfer learning technique models and some state of the art methods.

CHAPTER I

Brain Tumour

Introduction

The brain is the most complicated organ (structure) in human's body, which it is the primarily responsible for distinguishing us as human beings. We get to think about our most important choices, our believes, our actions, from moving the smallest finger to driving tracks...etc. It's all by the brain is surrounded by the skull, so accessing it and exposing it to danger is very difficult, but there is a little mass that can probably destroy it which called tumour so in this chapter we will specifically make a total study about the brain tumour how it start, the most common causes and symptoms types and explain more about the most important once from over 100 sub-type of tumour, it's how can the patient get the diagnosis also show numbers of the World Health Organization.

So it has to be protected, the skull bones of the head contained the brain and protect it from any extraction problems and shocks. In the last decade the brain tumour, grow highly specially Pituitary, meningioma, and glioma tumours.

Mainly in this chapter we will try to know more about the brain tumours by studying it basic causes showing the commune symptoms, other types ,how the brain tumour can be diagnosed and how it influence peoples life around the world.

The brain Tumour is a composed word of two parts brain & tumour we are going to define each part itself.

1.1 Brain Tumour

The growth of abnormal cells in the tissues of the brain. Brain tumours can be benign (not cancer) or malignant (cancer) [1].
Brain cancer is a malignant growth of abnormal brain cells in the brain. A grouping of abnormal cells is called a tumour. Some tumours are benign and some are malignant. There are several different types of tumours that occur in the brain and spinal cord. Different cells in the brain and spinal cord give rise to various kinds of tumours. Spinal cord tumours and brain tumours may grow quickly or slowly [2].

- **Brain**

We can find so many definitions for the brain some of them are:
The organ inside the head that controls all body functions of a human being. Made up of billions of nerve cells, the brain is protected by the cranium (the bones that form the head) [1].

The brain integrates sensory information and directs motor responses; in higher vertebrates, it is also the centre of learning. The human brain weighs approximately 1.4 kg (3 pounds) and is made up of billions of cells called neurons [3].

It is made up of three major parts: the cerebrum, the cerebellum, and the brain stem. The cerebrum is the largest part of the brain and controls thinking, learning, problem solving, emotions, memory, speech, reading, writing, and voluntary movement. The cerebellum controls fine motor movement, balance, and posture. The brain stem controls breathing, heart rate, and the nerves and muscles used to see, hear, walk, talk, and eat [1].

- **Tumour**

An abnormal mass of tissue that forms when cells grow and divide more than they should or do not die when they should. Tumours may be benign (not cancer) or malignant (cancer). Benign tumours may grow large but do not spread into, or invade, nearby tissues or other parts of the body. Malignant tumours can spread into, or invade, nearby tissues. They can also spread to other parts of the body through the blood and lymph systems. Also called neoplasm [1].

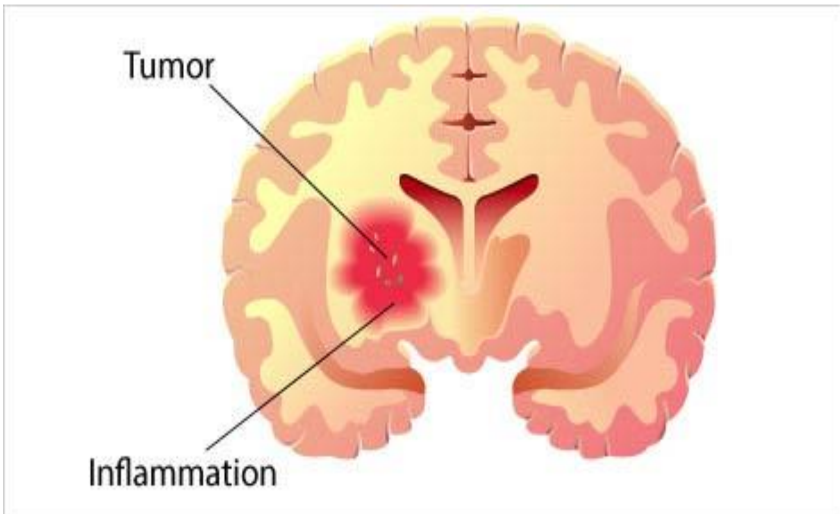


Figure 1. Brain tumour [4].

1.2 Brain Tumour Causes

Doctors are not sure what causes most the tumours. The only known environmental cause of brain tumours is having exposure to large amounts of radiation from X-rays or previous cancer treatment. Some brain tumours occur when hereditary conditions are passed down among family members [5].

Mutations (changes) or defects in genes may cause cells in the brain to grow uncontrollably, causing a tumour.

More causes that are possible are:

- Family history of cancer.
- Genetic mutation that causes abnormal cell growth.
- Long-term of treatment for other cancers.
- Exposure to certain chemicals (possible cause) [5].

1.3 Brain Tumour Symptoms

According to the doctors community there are a bunch of symptoms depends on specific terms like type, size, and shape, rate of growth and location of the tumours.

The first and clear symptom is Headaches are a common symptom of a brain tumour:

- are worse in the morning when waking up
- occur while you're sleeping
- Are made worse by coughing, sneezing, or exercise [6].

More symptoms:

- Unexplained nausea or vomiting
- Vision problems, such as blurred vision, double vision or loss of peripheral vision
- Gradual loss of sensation or movement in an arm or a leg
- Difficulty with balance
- Speech difficulties
- Feeling very tired
- Difficulty making decisions
- Inability to follow simple commands
- Personality or behaviour changes
- Seizures, especially in someone who doesn't have a history of seizures
- Hearing problems [7].

Other common symptoms include:

- eye problems, such as drooping eyelids and unequal pupils
- uncontrollable movements
- hand tremors
- loss of balance
- loss of bladder or bowel control
- numbness or tingling on one side of the body
- trouble speaking or understanding what others are saying
- changes in mood, personality, emotions, and behaviour
- Difficulty walking [6].

1.4 Brain Tumour Diagnoses

Looking for the ways we can diagnose the brain tumour we find six kinds, we divided it to two types:

1.4.1 First type: technology equipment

1.4.1.1 Magnetic Resonance Imaging (MRI)

An MRI scan uses a large magnet, radio waves, and a computer to create a detailed, cross-sectional image of internal organs and structures [8].

Gadolinium-enhanced MR imaging remains the standard of care for brain tumour diagnosis, treatment planning, and post treatment response assessment. Current criteria for therapeutic response assessment rely on anatomic MR imaging with integration of clinical assessments, although future updates integrating advanced MR imaging or PET information are likely forthcoming [9].

The following are examples in which an MRI scanner would be used:

- anomalies of the brain and spinal cord
- breast cancer screening for women who face a high risk of breast cancer
- injuries or abnormalities of the joints, such as the back and knee
- certain types of heart problems
- diseases of the liver and other abdominal organs
- the evaluation of pelvic pain in women, with causes including fibroids and endometriosis
- Suspected uterine anomalies in women undergoing evaluation for infertility [8].

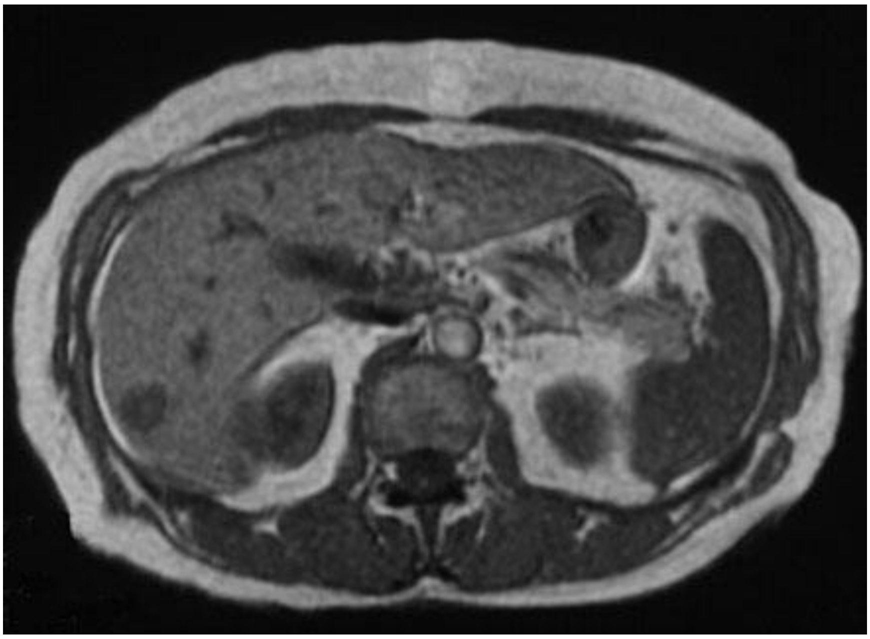


Figure 2. MRI scan without contrast showing possible tumour in the liver. (Bottom) MRI scan of the same patient using contrast. Images courtesy of Dc. Peter Choyke, Clinical Centre, NIH [1].

1.4.1.2 Magnetic resonance spectroscopy (MRS)

MRS is a non-invasive technique that can be used to measure the concentrations of different chemical components within tissues. The technique is based on the same physical principles as magnetic resonance imaging (MRI) and the detection of energy exchange between external magnetic fields and specific nuclei within atoms [10].

1.4.1.3 Computed tomography (CT)

Computed tomography (CT) is a diagnostic imaging test used to create detailed images of internal organs, bones, soft tissue and blood vessels. The cross-sectional images generated during a CT scan can be reformatted in multiple planes, and can even generate three-dimensional images which can be viewed on a computer monitor, printed on film or transferred to electronic media. CT scanning is often the best method for detecting many different cancers since the images allow your doctor to confirm the presence of a **tumour** and determine its size and location. CT is fast, painless, **non-invasive** and accurate. In emergency cases, it can reveal internal injuries and bleeding quickly enough to help save **lives** [11]. **Both** CT and MRI have some advantages over each other. CT takes less time for imaging and offers high spatial resolution compared to MRI. This property of CT makes it ideal for chest and bone-related diagnosis. However, the contrast of CT for soft tissue imaging is not high compared to MRI. Therefore, MRI is the most popular because of its high-resolution imaging capability [12].

1.4.2 Second Type: Medical test

1.4.2.1 Biopsy

A biopsy needle is a tool employed to fetch a portion of tissue at a point in the volume of diseased tissue, i.e., a Single Sample with a Single Spoon (SS-SS). Using this tool, the pathological status of the unhealthy tissue is generally represented by that of the specimen [13]. A biopsy also helps your care provider determine how aggressive your cancer is [7]. Patients perform a biopsy to assess the tumour's form and classification following early detection of abnormality using brain MRI. In this respect, the biopsy findings for detecting brain tumours are regarded as an absolute test [14].

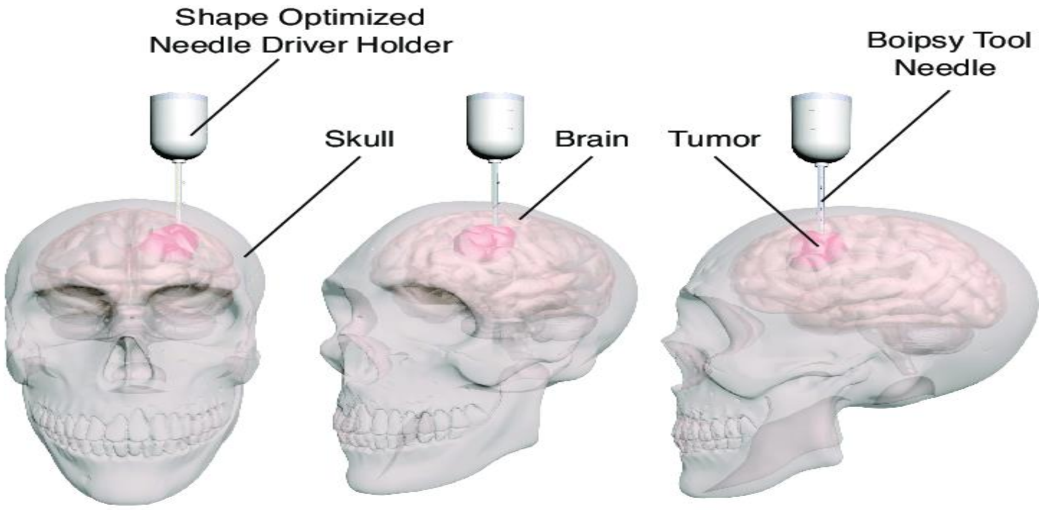


Figure 3. Biopsy of brain tumour [13].

1.4.2.2 Neurological examination

A neurological examination is the assessment of sensory neuron and motor responses, especially reflexes, to determine whether the nervous system is impaired. This typically includes a physical examination and a review of the patient's medical history, but not deeper investigation such as neuroimaging [15].

1.4.2.3 Physical Exam

Is the process of evaluating objective anatomic findings through the use of observation, palpation, percussion, and auscultation [16].

1.5 Types of brain tumour

Coming to the brain tumour types there is more than 120 type, the most know and essential once are down below with details:

Brain tumours can be benign (noncancerous tumours) or malignant (cancerous). They are also classified as primary and secondary. Primary tumours start in the brain or Central Nervous Systems whereas the secondary tumours spread from other body parts into the brain. Depending on the degree of abnormality of brain tissue, the tumours are type cast into four grading levels. Tumours with 1 and 2 are low grades which are less dangerous. 3 and 4 grade tumours are high-grade tumours that are highly susceptible to cancer [17].

1.5.1 Primary tumours

A brain tumour that first develops in the brain is called primary brain cancer [18].

Many different types of primary brain tumours exist. Each gets its name from the type of cells involved [18].

Examples include:

- Pituitary tumours are often diagnosed because they frequently lead to symptoms of endocrine dysfunction via the overproduction or underproduction of hormones. Symptoms of endocrine dysfunction may include agalactorrhea, infertility, and/or signs of classical endocrine-related syndromes, such as hyperprolactinemia, acromegaly, and Cushing disease. Some tumours may also cause clinically significant nonendocrine signs and symptoms, depending on their location and size, such as visual impairment; however, tumours are also sometimes found incidentally on radiographs in asymptomatic patients. Therapy for pituitary tumours depends on the specific type of tumour and may include transsphenoidal surgery, pituitary-directed medications (e.g., somatostatin receptor ligands, dopamine agonists), and/or radiation [19].

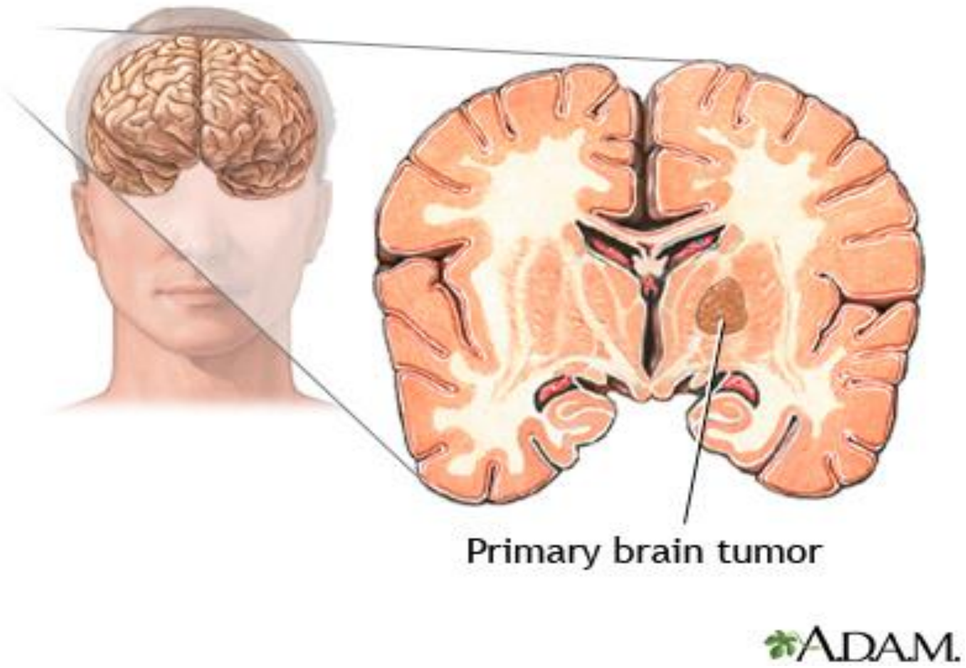


Figure 4. Primary brain tumour [20].

- Gliomas are a subset of neuroepithelial tumours that have histologic features similar to normal glial cells (astrocytes, oligodendrocytes, and ependymal cells). It is important to note that, although pilocytic astrocytoma is reported as malignant in population-based cancer registry data according to historical convention, it is categorized as non-malignant by the WHO and considered as such in clinical practice [19].

1.5.2 Secondary tumours (Malignant)

Secondary brain tumours are tumours that result from cancer that starts elsewhere in your body and then spreads (metastasizes) to your brain. Secondary brain tumours most often occur in people who have a history of cancer. Rarely, a metastatic brain tumour may be the first sign of cancer that began elsewhere in your body [18]. Metastases may occur anywhere along the neuroaxis, and require complex multidisciplinary care with neurosurgery, radiation oncology, and medical oncology [21]. Any cancer can spread to the brain, but common types include Breast cancer, Colon cancer, Kidney cancer, Lung cancer and Melanoma [7].

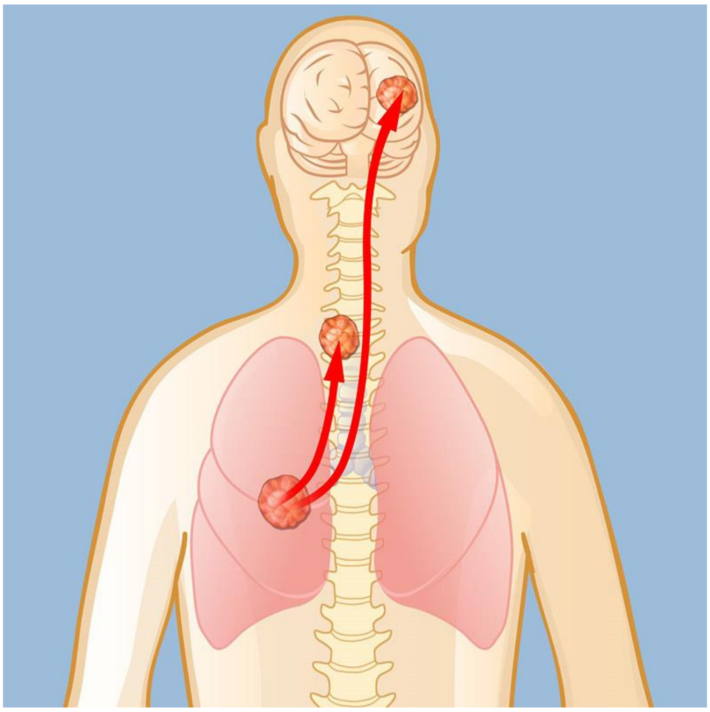


Figure 5. Malignant cells from a tumour in the lungs can move into the bloodstream; once there the tumour can metastasize to the brain and/or the spine [22].

Can grow rapidly, they are considered life threatening because they may spread within the brain and spinal cord, or come back after treatment. A malignant brain tumour may be called brain cancer. Unlike malignant tumours in other parts of the body, malignant brain tumours usually do not spread outside the brain and spinal cord [5]. Therefore, in clinical practice, malignant gliomas refer to glioblastoma and other aggressive diffuse gliomas (e.g. grade 3 anaplastic astrocytoma and oligodendroglia) [[19]. 45% of primary brain tumours are gliomas, of which glioblastoma multiform (GBM) is the most common and aggressive with a median survival rate of 14 months [23]. With an incidence of 3.2 per 100,000 and a median age at diagnosis of 64 years [21].

1.6 Statistics

This year, an estimated 25,050 adults (14,170 men and 10,880 women) in the United States will be diagnosed with primary cancerous **tumour**s of the brain and spinal cord. A person’s likelihood of developing this type of **tumour** in their lifetime is less than 1%. Brain **tumour**s account for 85% to 90% of all primary central nervous system (CNS) **tumour**s. Worldwide, an estimated 308,102 people were diagnosed with a primary brain or spinal cord **tumour** in 2020 [24].

Malignant brain and other CNS tumours account for a small proportion (approximately 1%) of all invasive cancer cases in the United States, but are the most commonly diagnosed solid tumour in children and adolescents and the leading cause of cancer death among males aged <40 years and females aged <20 years. In 2021, an estimated 83,570 individuals will be diagnosed with brain and other CNS tumours in the United States (24,530 malignant tumours and 59,040 non-malignant tumours), and 18,600 people will die from the disease. Malignant tumours account for less than one-third of all brain and other CNS tumours diagnosed in the United States but the majority of deaths from the disease [19].

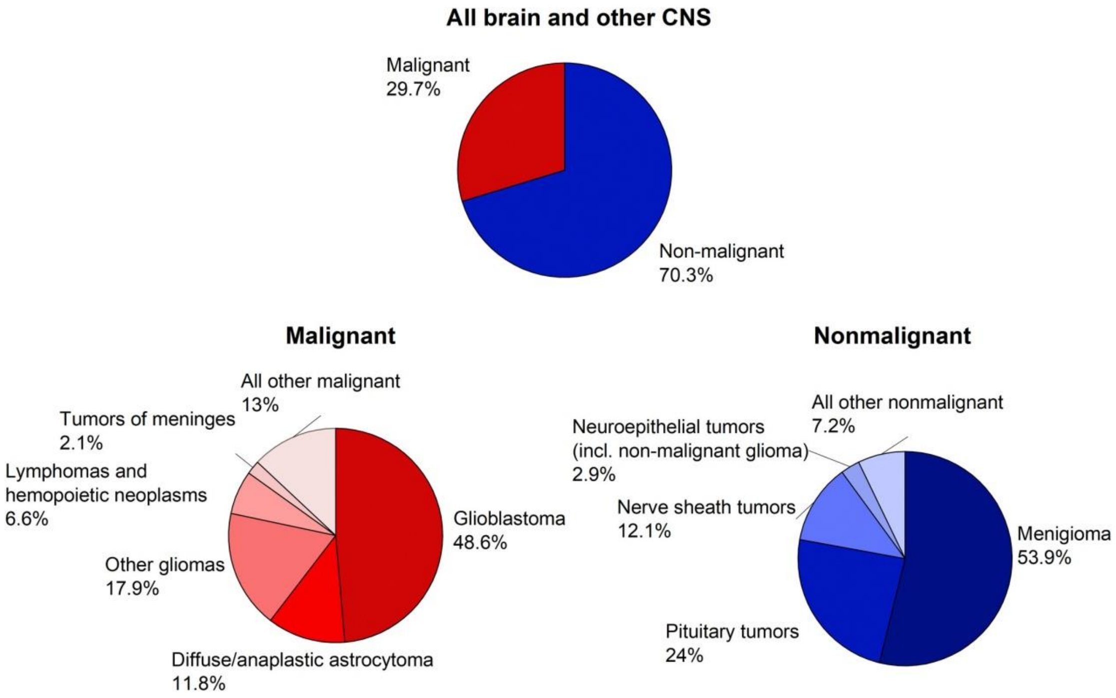


Figure 6. All brain and CNS tumour percentage in malignant and non-malignant [25].

1.7 The five-year survival rate

The 5-year survival rate tells you what percent of people live at least 5 years after the tumour is found. Percent means how many out of 100. The 5-year survival rate for people in the United States with a cancerous brain or CNS tumour is almost 36%. The 10-year survival rate is almost 31%, Age is a factor in general survival rates after a cancerous brain or CNS tumour is diagnosed. The 5-year survival rate for people younger than age 15 is about 75%. For people age 15 to 39, the 5-year survival rate nears 72%. The 5-year survival rate for people age 40 and over is 21%. However, survival rates vary widely and depend on several factors, including the type of brain or spinal cord tumour. Talk with your doctor about what to expect with your diagnosis [24].

The American Cancer Society's estimates for brain and spinal cord tumours in the United States for 2022 include both adults and children.

- About 25,050 malignant tumours of the brain or spinal cord (14,170 in males and 10,880 in females) will be diagnosed. These numbers would be much higher if benign (non-cancer) tumours were also included.
- About 18,280 people (10,710 males and 7,570 females) will die from brain and spinal cord tumours [24].

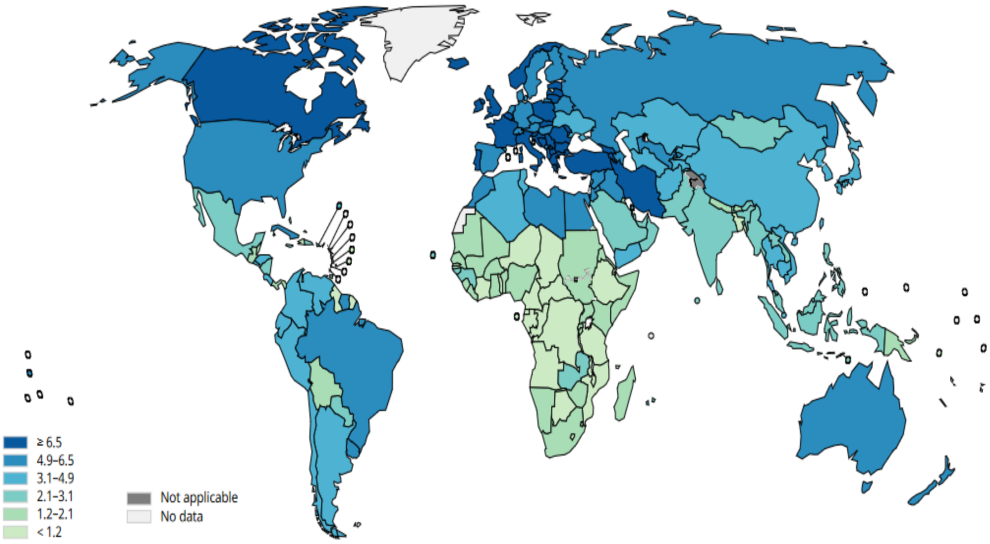


Figure 7. Age standardized (World) incidence rates, brain, central nervous system, males, and all ages [26].

Conclusion

In this chapter, we get knowledge about the brain tumours that effect people around the world and how it is diagnosed by MRI. Using That MRI, we can create a data base that will help much people for early detection and classification using AI technologies which we are going to be detailed it in the next chapter

CHAPTER II

Deep Learning Techniques

Introduction

Artificial intelligence (AI) is sometimes defined as the art of building machines that are able to perform tasks which, if performed by humans, would require intelligence [27].

Machine Learning (ML) is a subset of AI techniques and refers to a computer program that can *learn* how to produce behaviour not explicitly programmed by the program's author [28].

This behaviour is learned based on the data given, by minimizing the error between the current action and the ideal one, and a feedback mechanism (the famous "error backpropagation") that uses it to lead the machine to self-recognize, and internally improve its performances [28].

Deep Learning (DL) is a subset of machine learning, which uses multilayer neural networks to solve complex problems. They exploit the processing of contextual data. Deep learning techniques are, therefore, more suitable for learning unstructured data [28].

The revolution in Artificial Intelligence in Medicine has surprised us, fascinated us, sometimes frightened us, and mostly benefitted us [29]. It eventually became incorporated into the field of medicine, reaching the point where there is now a scientific discipline of "artificial intelligence in medicine". Virtually all medical imaging and medical image analysis conferences (such as RSNA, ECR, and MICCAI) are now dominated by deep learning applications and papers, and new start-ups announce themselves every day [30]

This chapter gives a compact overview of the basic principles of AI in Medicine, specifically on deep neural networks. A section talking about deferent types of DL techniques and their functionalities

2.1 Artificial Intelligence

Artificial intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions. The term may also be applied to any machine that exhibits traits associated with a human mind such as learning and problem solving.

The ideal characteristic of artificial intelligence is its ability to rationalize and take actions that have the best chance of achieving a specific goal. A subset of artificial intelligence is machine learning, which refers to the concept that computer programs can automatically learn from and adapt to new data without being assisted by humans. Deep learning techniques enable this automatic learning through the absorption of huge amounts of unstructured data such as text, images, or video.

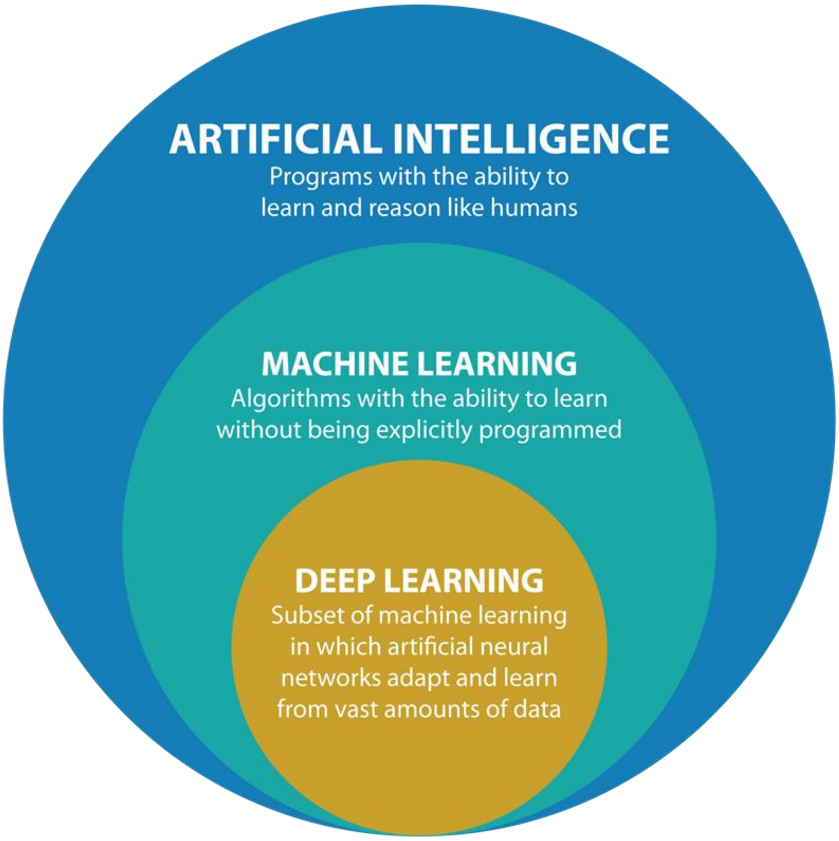


Figure 8 Deep Learning, Machine learning, AI.

The applications for artificial intelligence are endless. The technology can be applied to many different sectors and industries. AI is being tested and used in the healthcare industry for dosing drugs and different treatment in patients, and for surgical procedures in the operating room [31].

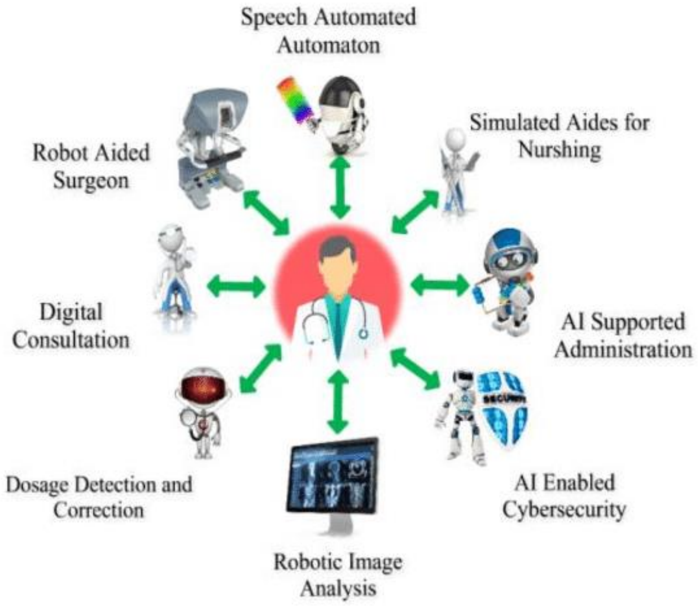


Figure 9. Application Areas of AI in Healthcare.

2.2 Machine learning

In healthcare, the most common application of traditional machine learning is precision medicine – predicting what treatment protocols are likely to succeed on a patient based on various patient attributes and the treatment context. The great majority of machine learning and precision medicine applications require a training dataset for which the outcome variable (e.g. onset of disease) is known; this is called supervised learning.

The most complex forms of machine learning involve deep learning, or neural network models with many levels of features or variables that predict outcomes. There may be thousands of hidden features in such models, which are uncovered by the faster processing of today's graphics processing units and cloud architectures. A common application of deep learning in healthcare is recognition of potentially cancerous lesions in radiology images. Deep learning is increasingly being applied to radionics, or the detection of clinically relevant features in imaging data beyond what can be perceived by the human eye. Both radionics and deep learning are most commonly found in oncology-oriented image analysis. Their combination appears to promise greater accuracy in diagnosis than the previous generation of automated tools for image analysis, known as computer-aided detection or CAD [32].

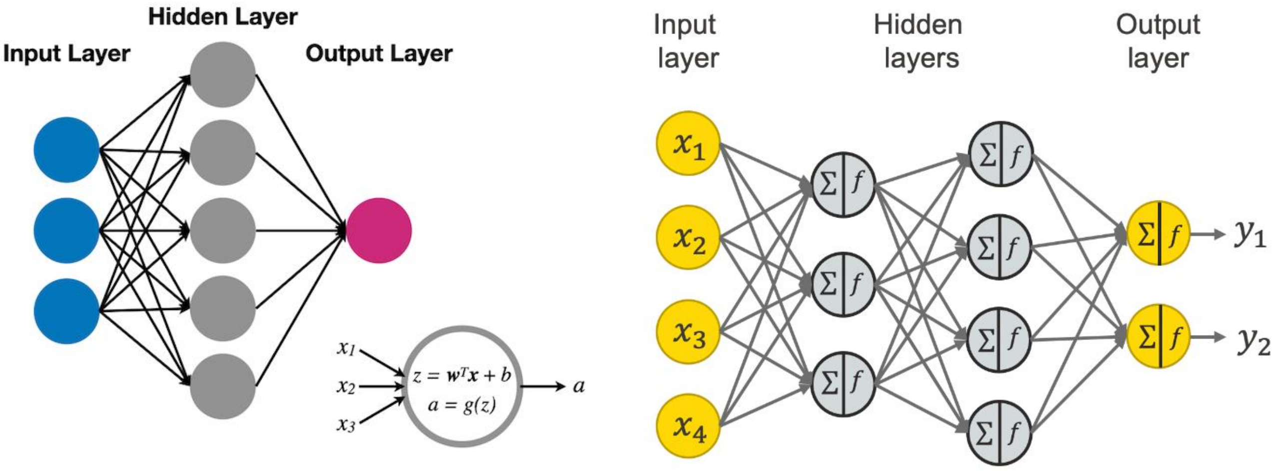
2.3 Deep learning

Deep learning can be considered as a subset of machine learning. It is a field that is based on learning and improving on its own by examining computer algorithms. While machine learning uses simpler concepts, deep learning works with artificial neural networks, which are designed to imitate how humans think and learn. Until recently, neural networks were limited by computing power and thus were limited in complexity. However, advancements in Big Data analytics have permitted larger, sophisticated neural networks, allowing computers to observe, learn, and react to complex situations faster than humans. Deep learning has aided image classification, language translation, speech recognition. It can be used to solve any pattern recognition problem and without human intervention.

Artificial neural networks, comprising many layers, drive deep learning. Deep Neural Networks (DNNs) are such types of networks where each layer can perform complex operations such as representation and abstraction that make sense of images, sound, and text. Considered the fastest-growing field in machine learning, deep learning represents a truly disruptive digital technology, and it is being used by increasingly more companies to create new business models [33].

2.4 Deep learning techniques

A typical deep neural network contains multiple hidden layers including input and output layers. Figure 11 shows a general structure of a deep neural network comparing with a shallow network [34].



Shallow Network **Deep Neural Network**

Figure 10. A general architecture of a shallow network and a deep neural network.

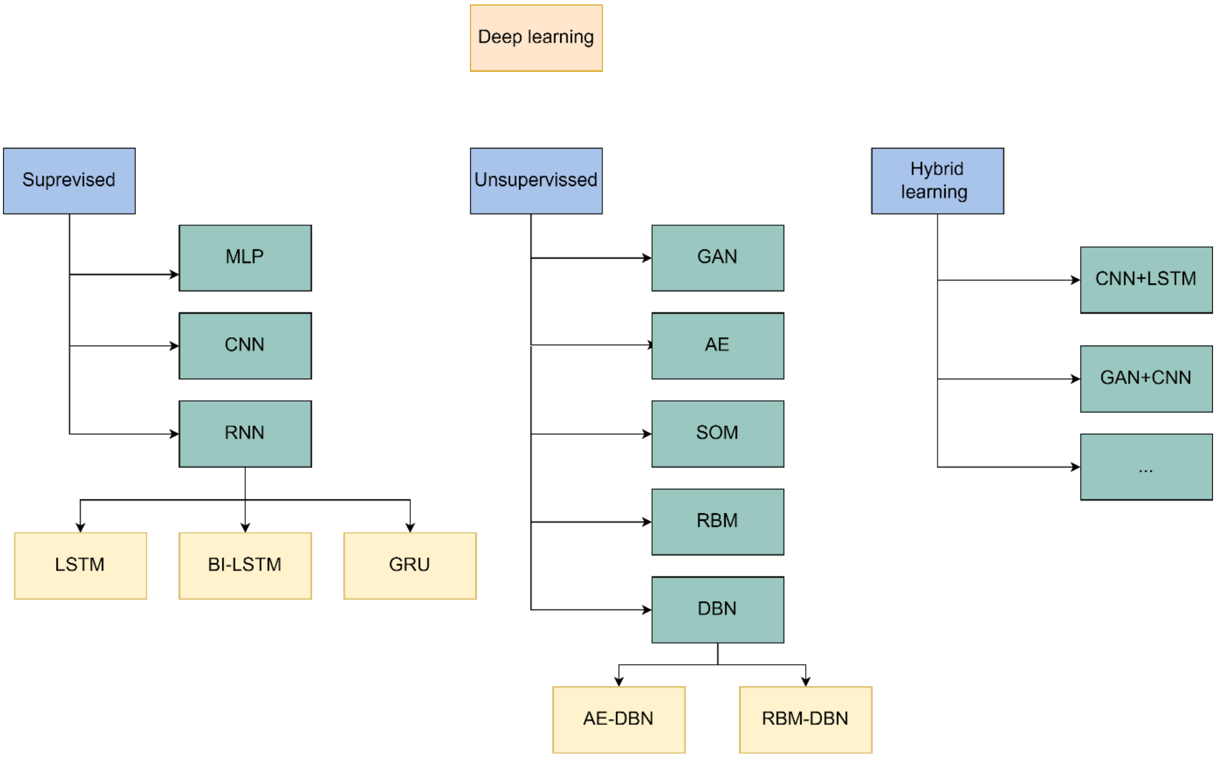


Figure 11. DL techniques, broadly divided into three major categories, deep networks for supervised or discriminative learning, deep networks for unsupervised or generative learning and deep networks for hybrid learning.

2.4.1 Deep Networks for Unsupervised Learning

This category of DL techniques is typically used to characterize the high-order correlation properties or features for pattern analysis or synthesis, as well as the joint statistical distributions of the visible data and their associated classes [35]. The key idea of generative deep architectures is that during the learning process, precise supervisory information such as target class labels is not of concern. As a result, the methods under this category are essentially applied for unsupervised learning as the methods are typically used for feature learning or data generating and representation [36].

2.4.1.1 Generative Adversarial Network (GAN)

A Generative Adversarial Network (GAN), designed by Ian Goodfellow, is a type of neural network architecture for generative modelling to create new plausible samples on demand. It involves automatically discovering and learning regularities or patterns in input data so that the model may be used to generate or output new examples from the original dataset.

2.4.1.2 Auto-Encoder (AE) and Its Variants

An auto-encoder (AE) is a popular unsupervised learning technique in which neural networks are used to learn representations. Typically, auto-encoders are used to work with highdimensional data, and dimensionality reduction explains how a set of data is represented. Encoder, code, and decoder are the three parts of an auto encoder.

2.4.1.3 Kohonen Map or Self-Organizing Map (SOM)

A Self-Organizing Map (SOM) or Kohonen Map[37] is another form of unsupervised learning technique for creating a low-dimensional (usually two-dimensional) representation of a higher-dimensional data set while maintaining the topological structure of the data. SOM is also known as a neural network-based dimensionality reduction algorithm that is commonly used for clustering [38].

2.4.1.4 Restricted Boltzmann Machine (RBM)

A Restricted Boltzmann Machine (RBM) [39] is also a generative stochastic neural network capable of learning a probability distribution across its inputs. Boltzmann machines typically consist of visible and hidden nodes and each node is connected to every other node, which helps us understand irregularities by learning how the system works in normal circumstances.

2.4.1.5 Deep Belief Network (DBN)

A Deep Belief Network (DBN) [40] is a multi-layer generative graphical model of stacking several individual unsupervised networks such as AEs or RBMs that use each network's hidden layer as the input for the next layer, i.e. connected sequentially.

2.4.2 Deep Networks for Supervised Learning

This category of DL techniques is utilized to provide a discriminative function in supervised or classification applications. Discriminative deep architectures are typically designed to give discriminative power for pattern classification by describing the posterior distributions of classes conditioned on visible data [35].

2.4.2.1 Multi-layer Perceptron (MLP)

Multi-layer Perceptron (MLP), a supervised learning approach, is a type of feedforward artificial neural network (ANN). It is also known as the foundation architecture of deep neural networks (DNN) or deep learning. A typical MLP is a fully connected network that consists of an input layer that receives input data, an output layer that makes a decision or prediction about the input signal, and one or more hidden layers between these two that are considered as the network's computational engine [36].

The output of an MLP network is determined using a variety of activation functions, also known as transfer functions, such as ReLu (Rectified Linear Unit), Tanh, Sigmoid, and Softmax.

2.4.2.2 Recurrent Neural Network (RNN) and its Variants

A Recurrent Neural Network (RNN) is another popular neural network, which employs sequential or time-series data and feeds the output from the previous step as input to the current stage [41]. Like feedforward and CNN, recurrent networks learn from training input, however, distinguish by their “memory”, which allows them to impact current input and output through using information from previous inputs. Unlike typical DNN, which assumes that inputs and outputs are independent of one another, the output of RNN is reliant on prior elements within the sequence. However, standard recurrent networks have the issue of vanishing gradients, which makes learning long data sequences challenging [36].

2.4.2.3 Convolutional Neural Network (CNN or ConvNet)

The Convolutional Neural Network (CNN or ConvNet) is a popular discriminative deep learning architecture that learns directly from the input without the need for human feature extraction. Figure 13 shows an example of a CNN including multiple convolutions and pooling layers. As a result, the CNN enhances the design of traditional ANN like regularized MLP networks. Each layer in CNN takes into account optimum parameters for a meaningful output as well as reduces model complexity. CNN also uses a ‘dropout’ that can deal with the problem of over-fitting, which may occur in a traditional network [36].

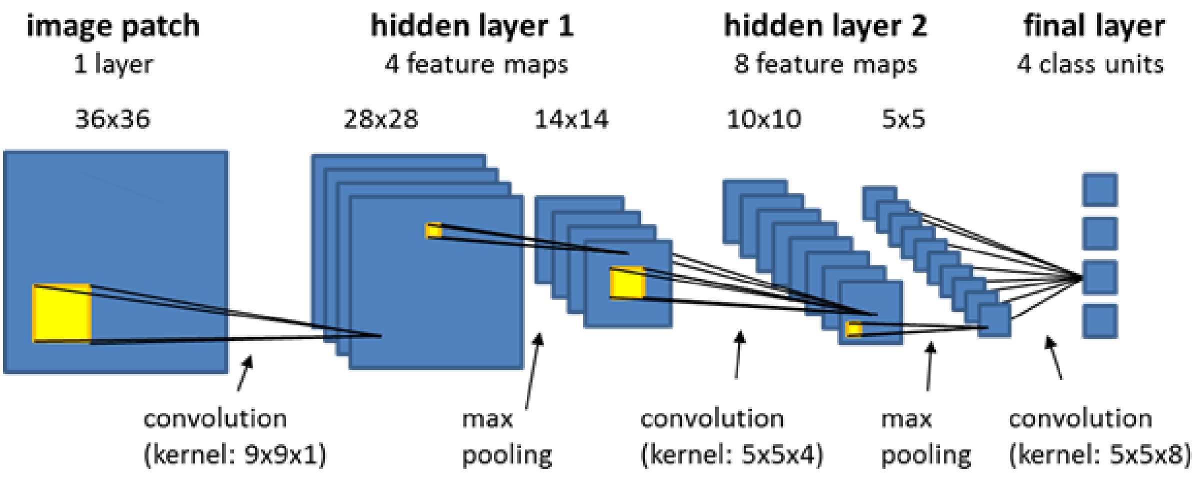


Figure 12. An example of a Convolutional Neural Network.

2.4.3 Hybrid Deep Neural Networks

Generative models are adaptable, with the capacity to learn from both labelled and unlabelled data. Discriminative models, on the other hand, are unable to learn from unlabelled data yet outperform their generative counterparts in supervised tasks. A framework for training both deep generative and discriminative models simultaneously can enjoy the benefits of both models, which motivates hybrid networks [36].

Hybrid deep learning models are typically composed of multiple (two or more) deep basic learning models, where the basic model is a discriminative or generative deep learning model

2.4.4 Transfer Learning

Transfer learning for machine learning is when existing models are reused to solve a new challenge or problem. Transfer learning is not a distinct type of machine learning algorithm, instead it is a technique or method used whilst training models. The knowledge developed from previous training is recycled to help perform a new task. The new task will be related in some way to the previously trained task, which could be to categorise objects in a specific file type. The original trained model usually requires a high level of generalisation to adapt to the new unseen data [42].

Transfer learning means that training won't need to be restarted from scratch for every new task. Training new machine learning models can be resource-intensive, so transfer learning saves both resources and time. The accurate labelling of large datasets also takes a huge amount of time. The majority of data encountered by organisations can often be unlabelled, especially with the extensive datasets required to train a machine learning algorithm. With transfer learning, a model can be trained on an available labelled dataset, and then be applied to a similar task that may involve unlabelled data [42].

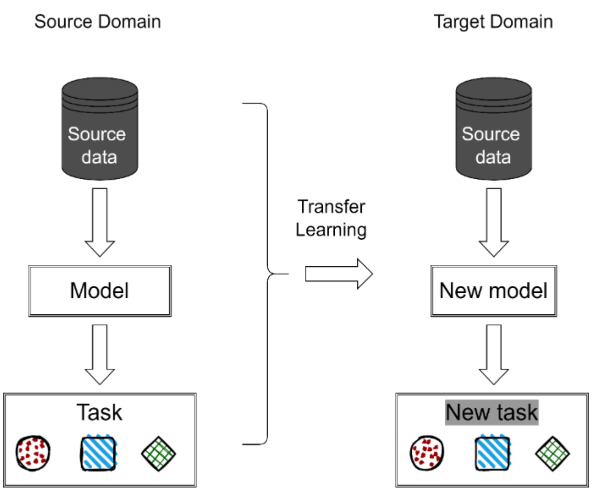


Figure 13. An illustration of a transfer learning process.

We used four pre-trained CNN models in our work, we choose these models based on their parameters and popularity so we can make comparison with previous studies. Those models can be found in the Keras application site.

2.4.4.1 VGG16 model

VGG16 is a simple and widely used Convolutional Neural Network (CNN) Architecture used for ImageNet, a large visual database project used in visual object recognition software research. The VGG16 Architecture was developed and introduced by Karen Simonyan and Andrew Zisserman from the University of Oxford, in the year 2014, through their article “Very Deep Convolutional Networks for Large-Scale Image Recognition.” ‘VGG’ is the abbreviation for Visual Geometry Group, which is a group of researchers at the University of Oxford who developed this architecture, and ‘16’ implies that this architecture has 16 layers (explained later) [43].

The VGG16 model achieved 92.7% top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes. It was one of the famous models submitted to ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in the year 2014. It made improvements over AlexNet architecture by replacing large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple three × three kernel-sized filters one after another. VGG16 was trained for weeks using NVIDIA Titan Black GPUs.

VGG16 is used in many deep learning image classification techniques and is popular due to its ease of implementation. VGG16 is extensively used in learning applications due to the advantage that it has.

VGG16 is a CNN Architecture, which was used to win the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2014. It is still one of the best vision architecture to date [43].

VGG16 is composed of 13 convolutional layers, 5 max-pooling layers, and 3 fully connected layers. Therefore, the number of layers having tunable parameters is 16 (13 convolutional layers and 3 fully connected layers). That is the reason why the model name is VGG16. The number of filters in the first block is 64, then this number is doubled in the later blocks until it reaches 512. This model is finished by two fully connected hidden layers and one output layer. The two fully connected layers have the same neuron numbers which are 4096. The output layer consists of 1000 neurons corresponding to the number of categories of the ImageNet dataset. In the next section, we are going to implement this architecture on Keras [44].

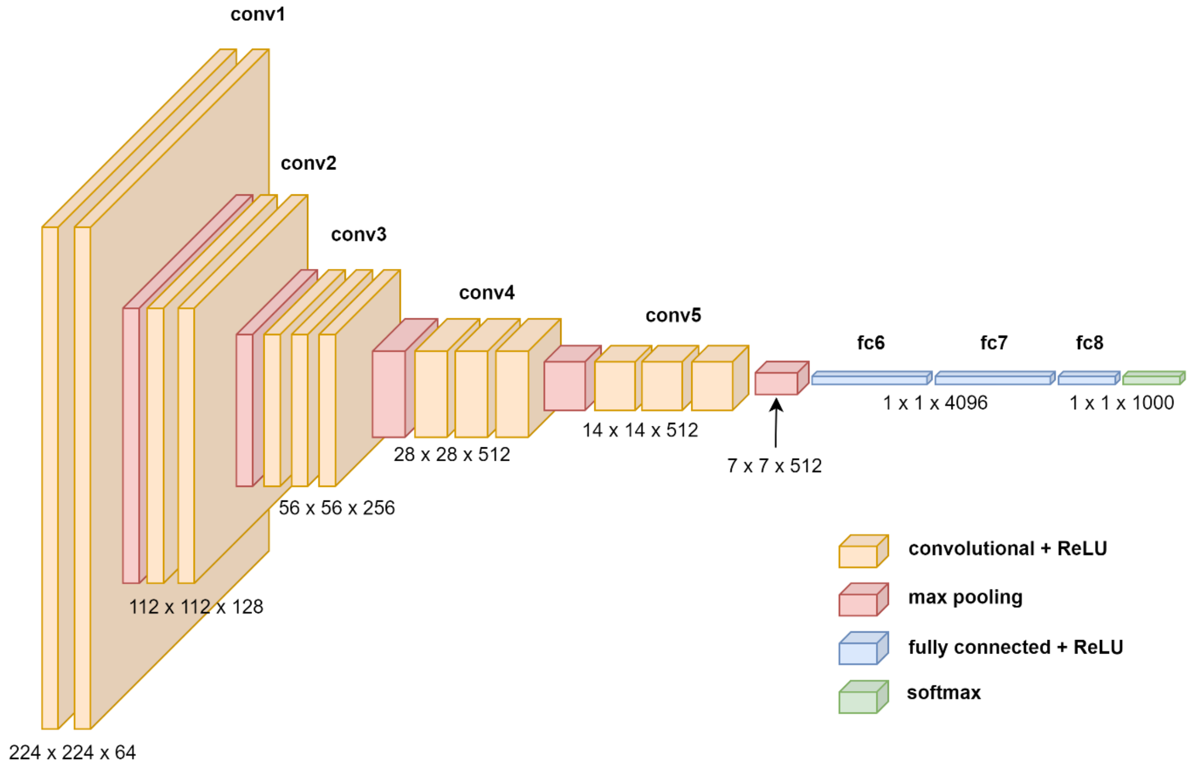


Figure 14. VGG16 Architecture.

2.4.4.2 VGG19 model

The concept of the VGG19 model (also VGGNet-19) is the same as the VGG16 except that it supports 19 layers. The "16" and "19" stand for the number of weight layers in the model (convolutional layers). This means that VGG19 has three more convolutional layers than VGG16. We'll discuss more on the characteristics of VGG16 and VGG19 networks in the latter part of this article [45].

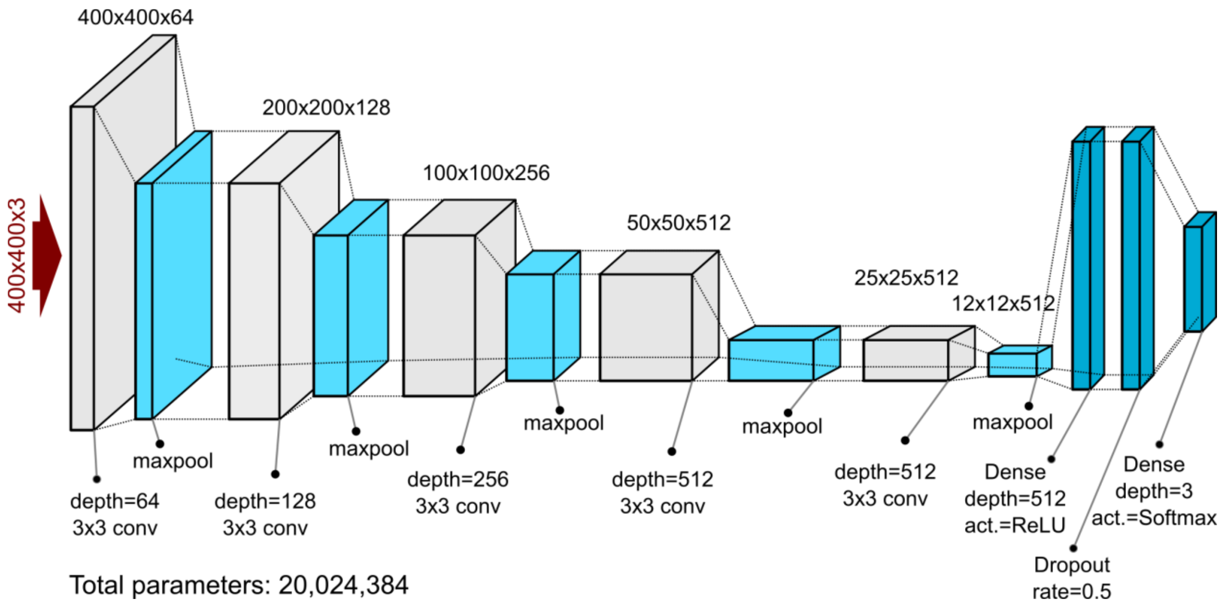


Figure 15. VGG19 Architecture.

As we can see the above diagram accurately depicts the VGG-19 architecture. This architecture is basically composed of 3 types of layers i.e. Convolution layer to extract the feature from the image by employing different number and types of filters, Max-pooling layer to decrease the image size and to extract the feature from the feature map obtained from these filters present in the Convolution layer , Flatten layer to turn the batches of feature maps into 1D tensor and finally 3 Fully-Connected where first two has a dense unit of 4096 layer final classification layer has 1000-way ILSVRC classification and thus contains 1000 channels (one for each class). The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks. For the final classification layer which has softmax activation for the predicting the probabilities of each class [46].

2.4.4.3 ResNet50 and ResNet152V2 models

ResNet stands for Residual Network. It is an innovative neural network that was first introduced by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their 2015 computer vision research paper titled 'Deep Residual Learning for Image Recognition' [47].

Deep Residual Network is almost similar to the networks which have convolution, pooling, activation and fully connected layers stacked one over the other. The only construction to the simple network to make it a residual network is the ***identity connection*** between the layers [48].

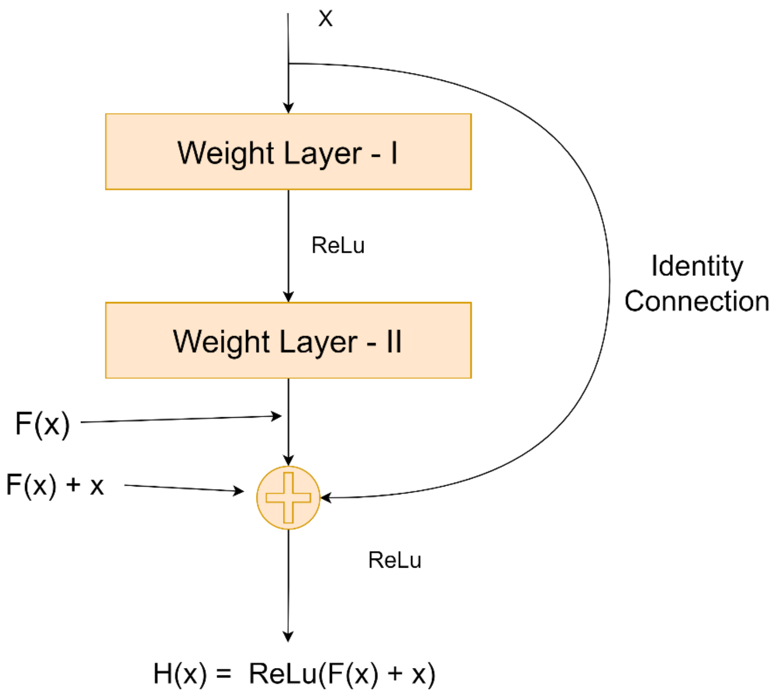


Figure 16. A Residual Block of Deep Residual Network.

This model was immensely successful, as can be ascertained from the fact that its ensemble won the top position at the ILSVRC 2015 classification competition with an error of only 3.57%. Additionally, it also came first in the ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation in the ILSVRC & COCO competitions of 2015.

ResNet has many variants that run on the same concept but have different numbers of layers. Resnet50 is used to denote the variant that can work with 50 neural network layers [47].

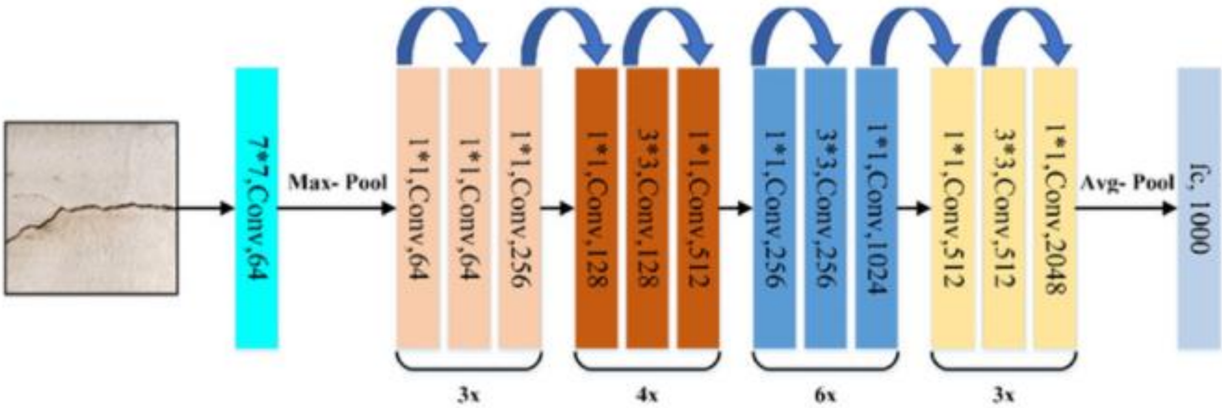


Figure 17. The architecture of ResNet-50 model.

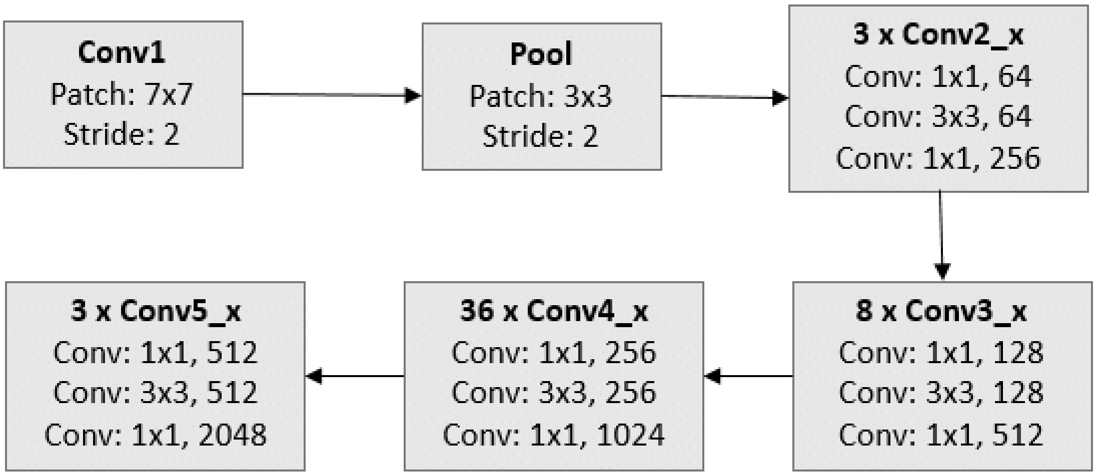


Figure 18. The architecture of ResNet-152V2 model.

2.5 AI in Healthcare field

The use of artificial intelligence in healthcare has the potential to assist healthcare providers in many aspects of patient care and administrative processes, helping them improve upon existing solutions and overcome challenges faster. Most AI and healthcare technologies have strong relevance to the healthcare field, but the tactics they support can vary significantly between hospitals and other healthcare organizations. And while some articles on artificial intelligence in healthcare suggest that the use of artificial intelligence in healthcare can perform just as well or better than humans at certain procedures, such as diagnosing disease, it will be a significant number of years before AI in healthcare replaces humans for a broad range of medical tasks [49].

Artificial intelligence is not one technology, but rather a collection of them. Most of these technologies have immediate relevance to the healthcare field, but the specific processes and tasks they support vary widely. Some particular AI technologies, these are some particular AI technologies of high importance to healthcare

- Natural language processing
- Rule-based expert systems
- Physical robots
- Robotic process automation
- Machine learning – neural network and deep learning

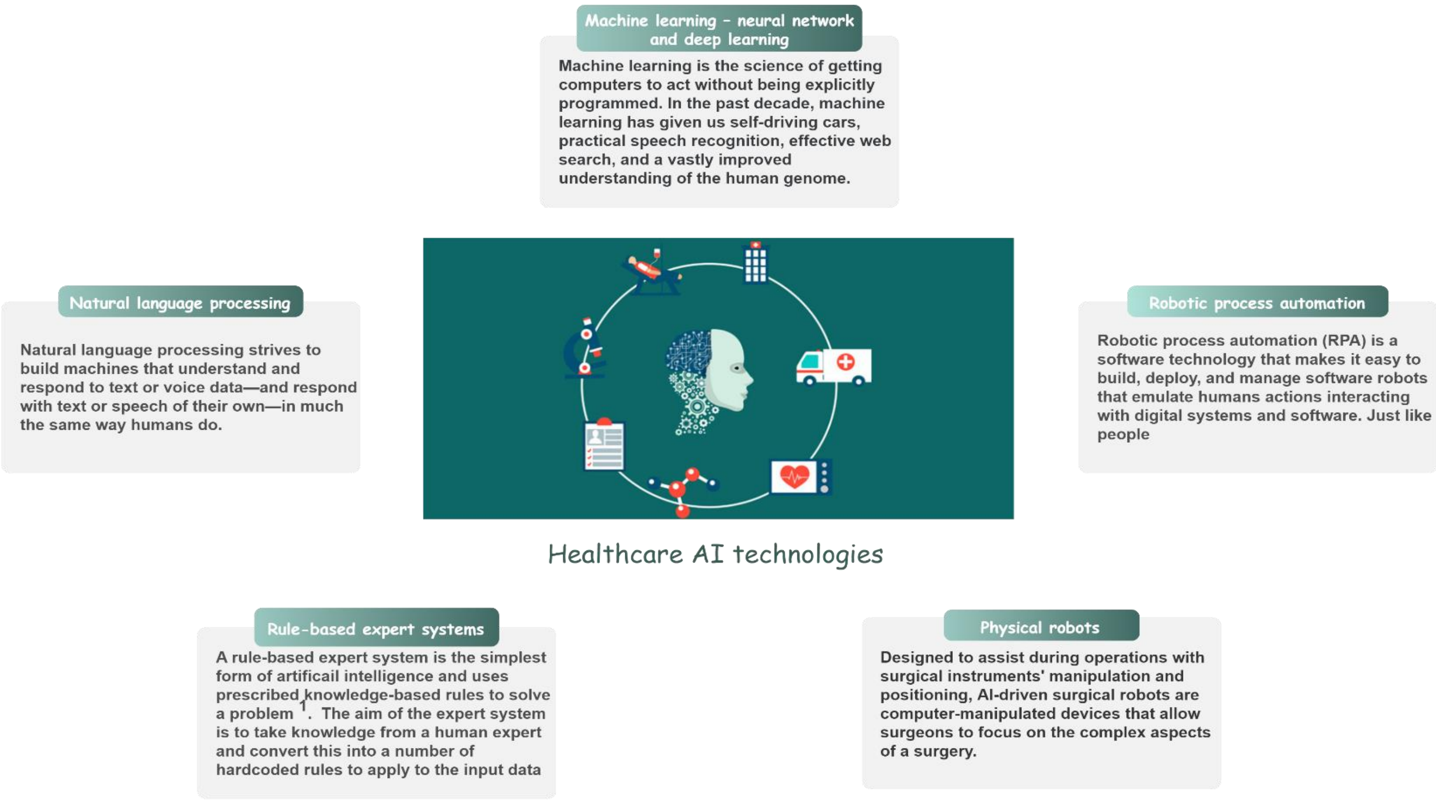


Figure 19. Healthcare AI technologies.

Conclusion

This chapter talks about AI, Machine learning and deep learning. Their cases of use and importance in health care field.

We mentioned most if not all existing techniques, explaining how they function and how can we put them in use. Giving examples specifically on some transfer learning pre-trained models and how we can improve them to perform certain tasks (in our case brain tumour classification based on MRI).

In the next chapter, we are going to create a CNN model that fits our purpose. We are going to compare the result of this model with the pre-trained models mentioned previously. Then we are going to lift the performance of this model by tuning some of its parameters.

CHAPTER III

Application development

Introduction

We introduce in this chapter an integrated system for Brain Tumour Classification based on MRI's. We started with explaining the system architecture from the collecting of the dataset to the preprocessing techniques done to the data, to the final step of prediction.

The dataset is collected from KAGGLE dataset site and verified by medical professionals for the safety of the use. It contains around 11k MRI sample of different classes of brain tumour (Glioma, Meningioma, Pituitary Tumour and no tumour). The dataset size is someway important in the training phase; it makes some remarkable difference in the performance.

After that, we did some basic image augmentation to our data so the finale model is much more robust and efficient. A brief section speaking about the used Hardwar and Software materiel.

Going to the prediction methods, in this study we relied on two approach. Starting with Transfer learning, we chose several model based on their popularity and performance so we can make a comparison with the next approach CNN model.

In the second approach, we created a various CNN models and every time we try to lift up the performance of that model taking in consideration the parameter and speed of the prediction

Finally, we make a comparison with the state of the art methods used on the same dataset type (Brain Tumour MRI's) to get an idea on how our model ranks in this field.

3.1 System Architecture

The Figure 20 present the architecture of the Image classification system dedicated to classify brain tumour images. It consists of a labelled dataset input obtained from health organizations, used to train a classification model.

Our system is used to predict newly taken images of brain tumour, by passing them through the previously trained model, to make the diagnostic process much easier, faster and most importantly accurate.

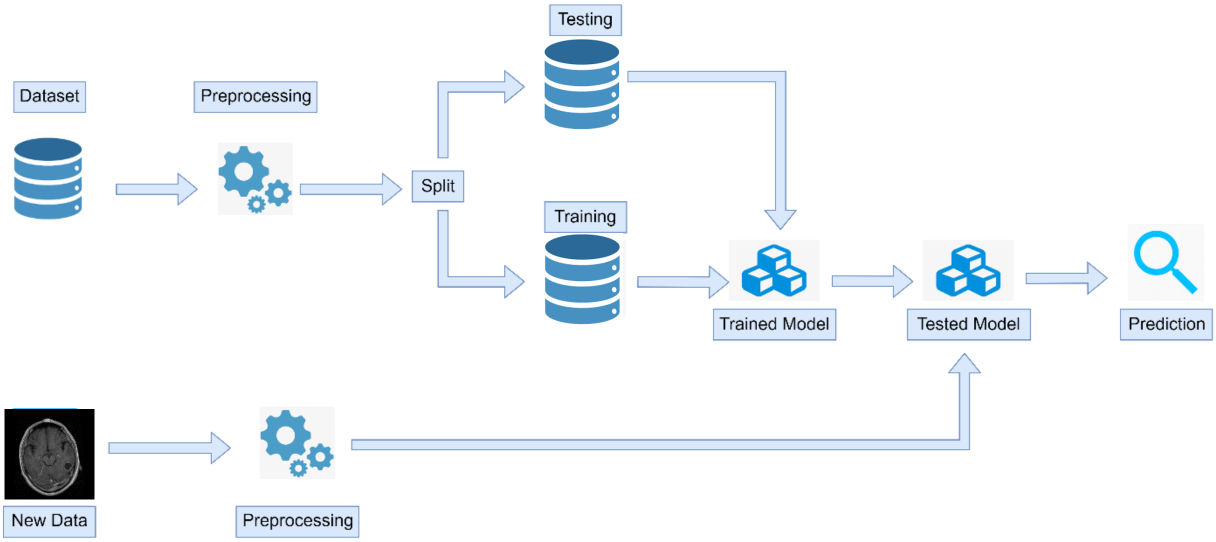


Figure 20. Brain Tumour Image Classification System.

3.2 Dataset description

To evaluate the performance of this work, we used three different datasets all of them provided by kaggle Datasets [50]–[52]. The scope of the data set was for college project only. However, the data have been cleaned and correctly represented. The data may need second validation by professionals before used in real-life applications

This latter contains (3264, 7022, 11100) respectively containing four classes (Glioma, Meningioma, Pituitary, No tumour) for each one. More Information can be found in the Table1 bellow.

	Glioma	Meningioma	Pituitary	No tumour	Total
Dataset 1	962	937	901	500	3264
Dataset 2	1621	1645	1757	2000	7022
Dataset 3	2772	2774	2873	2700	11119

Table 1. Dataset description.

3.3 Pre-processing

Data pre-processing is a crucial stage that transforms the data into a usable and efficient format, so that it can fit as an input to the deep learning. Pre-processing refers to all the transformations on the raw data before it is fed to the machine learning or deep learning algorithm. For instance, training a convolutional neural network on raw images will probably lead to bad classification performances [53]. The pre-processing is also important to speed up training (for instance, centring and scaling techniques) [54].

Image data augmentation is perhaps the most well known type of data augmentation and involves creating transformed versions of images in the training dataset that belong to the same class as the original image.

Transforms include a range of operations from the field of image manipulation, such as shifts, flips, zooms, and much more.

In our system, we used four types of augmentation technics.

- Rescale is a value by which we will multiply the data before any other processing. Our original images consist in RGB coefficients in the 0-255, but such values would be too high for our models to process (given a typical learning rate), so we target values between 0 and 1 instead by scaling with a 1/255 factor.
- shear range is for randomly applying shearing transformations
- zoom range is for randomly zooming inside pictures
- Horizontal flip is for randomly flipping half of the images horizontally --relevant when there are no assumptions of horizontal asymmetry [55].

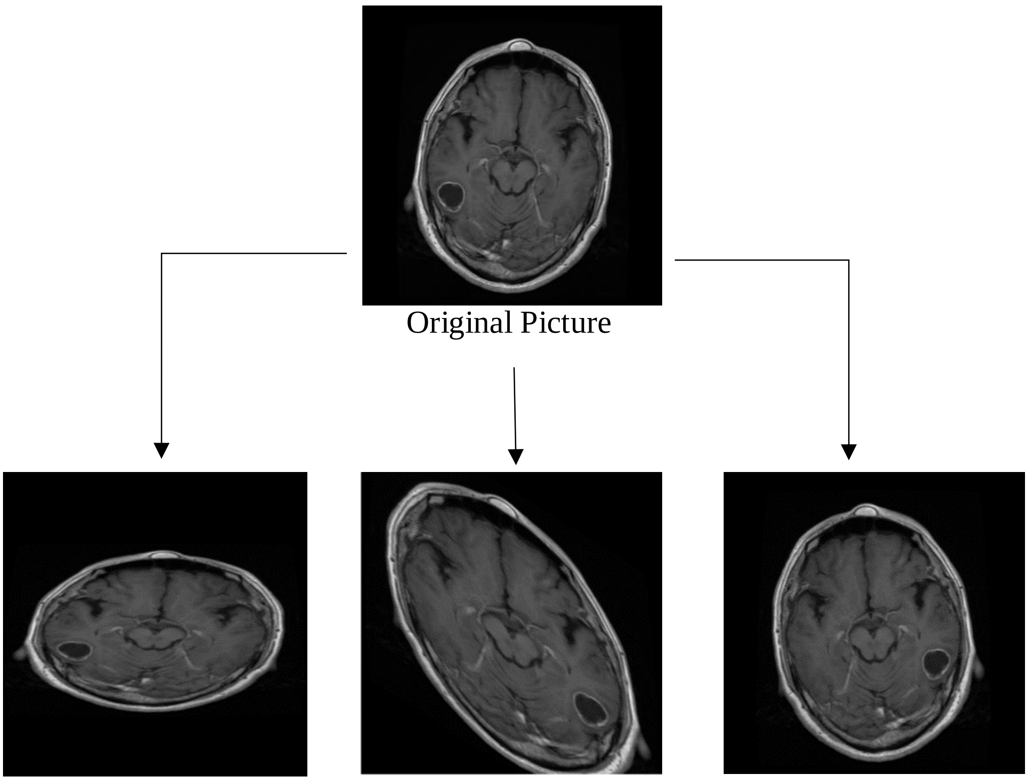


Figure 21. Image augmentation samples.

3.4 Metrics

The confusion matrix is a cross table that records the number of occurrences between two rates, the true/actual classification and the predicted classification,

3.4.1 Classification report

It is one of the performance evaluation metrics of a classification-based machine-learning model. It displays your model's precision, recall, F1 score and support. It provides a better understanding of the overall performance of our trained model [56].

3.4.1.1 Accuracy

In general, the accuracy metric measures the ratio of correct predictions over the total number of instances evaluated.

$$\boldsymbol{Accuracy} = \frac{Tp+Tn}{Tp+Fp+Tn+Fn} \qquad (1)$$

3.4.1.2 Precision

Precision is the ratio of true positives to the sum of true and false positives.

$$\boldsymbol{Precision} = \frac{Tp}{Tp+Fp} \qquad (2)$$

3.4.1.3 Recall

Recall is the ratio of true positives to the sum of true positives and false negatives.

$$\boldsymbol{Recall} = \frac{Tp}{Tp+Fn} \qquad (3)$$

3.4.1.4 F1 Score

The F1 is the weighted harmonic mean of precision and recall. The closer the value of the F1 score is to 1.0, the better the expected performance of the model is.

$$\boldsymbol{F1\ Score} = 2.\frac{Precision\ x\ Recall}{Precision+\ Recall} \qquad (4)$$

3.4.1.5 Support

Support is the number of actual occurrences of the class in the dataset. It does not vary between models; it just diagnoses the performance evaluation process.

3.4.2 Confusion Matrix

A confusion matrix presents a table layout of the different outcomes of the prediction and results of a classification problem and helps visualize its outcomes.

3.5 Hardwar Environment

In our work, we used a desktop computer with the following specification:

- AMD Ryzen™ 3 3100 3.9Ghz processor
- 16 Gb DDR4 RAM
- NVIDIA GeForce GTX 1050 with 6.1 compute capability (2Gb VRAM)
- Window 10 OS

3.6 Software Environment

Our CNN models developed in the Anaconda Environment, We used Jupyter Notebook as an editor for our python program, Also CUDA (Compute Unified Device Architecture) and cuDNN (CUDA® Deep Neural Network library) are necessary for the work to get done [57].

3.6.1 Tensorflow

Created by the Google Brain team, TensorFlow is an open source library for numerical computation and large-scale machine learning. TensorFlow bundles together a slew of machine learning and deep learning models and algorithms and makes them useful by way of a common metaphor. It uses Python to provide a convenient front-end API for building applications with the framework, while executing those applications in high-performance C++.

TensorFlow can train and run deep neural networks for handwritten digit classification, image recognition, word embedding, recurrent neural networks, sequence-to-sequence models for machine translation, natural language processing, and PDE (partial differential equation) based simulations. Best of all, TensorFlow supports production prediction at scale, with the same models used for training [58].

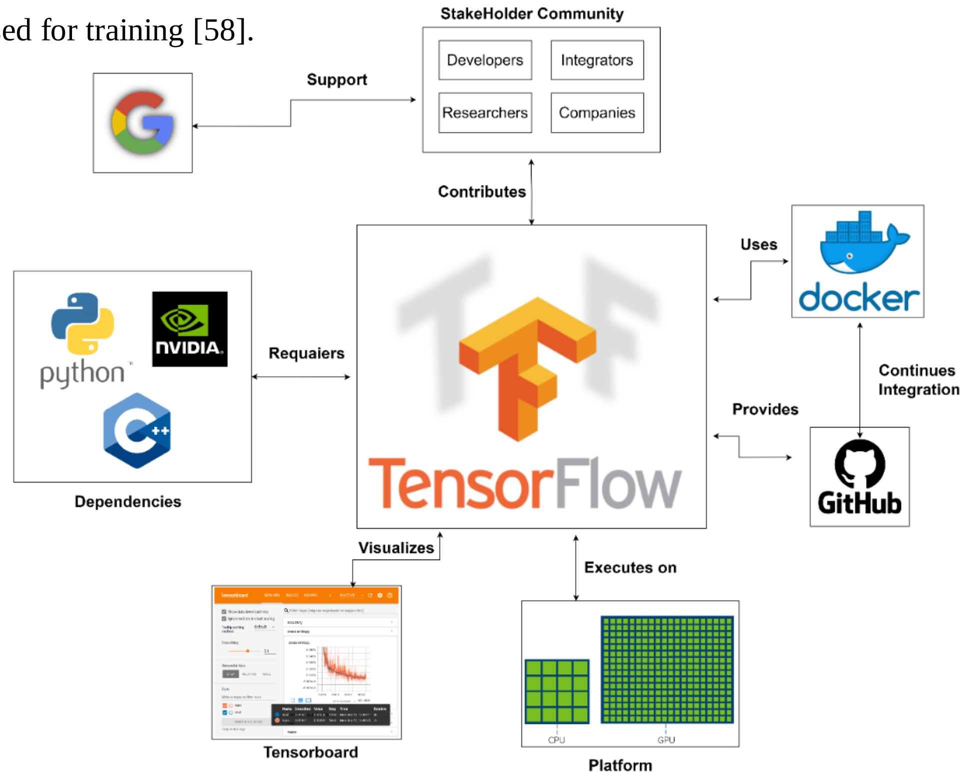


Figure 22. Tensorflow Ecosystem.

3.6.2 Keras

Keras is a high-level, deep learning API developed by Google for implementing neural networks. It is written in Python and is used to make the implementation of neural networks easy. It also supports multiple backend neural network computation.

Keras is relatively easy to learn and work with because it provides a python frontend with a high level of abstraction while having the option of multiple back-ends for computation purposes. This makes Keras slower than other deep learning frameworks, but extremely beginner-friendly [59].

Keras allows you to switch between different back ends. The frameworks supported by Keras are:

- Tensorflow
- Theano
- PlaidML
- MXNet
- CNTK (Microsoft Cognitive Toolkit)

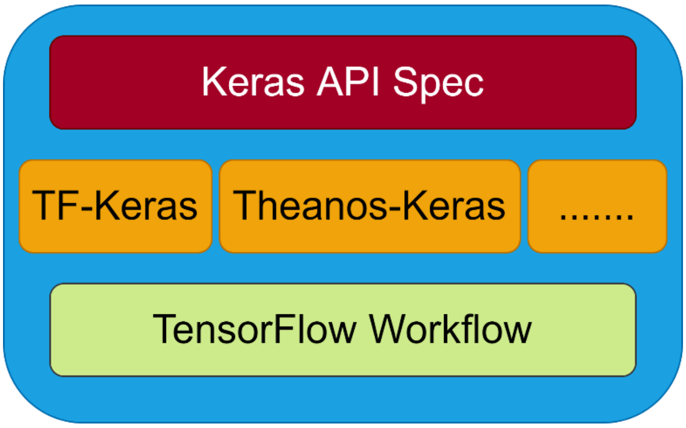


Figure 23. Keras Backend.

Those are the principle packages that we used in our work, Also we used other secondary packages (Matplotlib, Seaborn, Numpy, Pandas …etc.) to import our data, do image augmentation, plotting the results…etc.

3.7 Prediction Methods

We took two approach in our work:

We start with Transfer learning using already trained models and by making changes to the last few layers of them so they can predict what we fed them with in this case Brain Tumour MRI (our data set).

In the second approach, we create our own CNN model; by creating one specifically for our dataset, we can achieve a high performance model (precision, accuracy and low prediction time).

3.7.1 Transfer learning approach

In this part, we used four of the most popular models out there and retrain them with our dataset to see the results. Also in this approach, we used three different datasets (small to large), so we can get an idea on how the dataset size affect our deep learning process.

			Training		**Testing**	
		Epoch	Accuracy (%)	Loss	Accuracy (%)	Loss
Dataset 1	**VGG16**	15	89.45	0.294	74.37	1.810
		30	**96.52**	**0.1377**	88.11	**1.214**
	VGG19	15	90.25	0.1585	75.39	1.764
		30	94.18	0.1478	**89.36**	2.578
	ResNet50	15	68.54	0.8368	47.72	5.096
		30	77.02	0.9584	56.67	2.680
	ResNet152V2	15	91.28	0.7336	73.35	12.578
		30	95.71	0.7529	86.89	4.259
Dataset 2	**VGG16**	15	91.72	0.0603	91.29	0.1665
		30	**97.95**	**0.0582**	**95.04**	**0.1057**
	VGG19	15	91.08	0.0986	91.54	0.1628
		30	96.20	0.07958	93.75	0.1236
	ResNet50	15	74.58	0.7618	70.11	1.2945
		30	75.12	0.7920	72.57	0.8472
	ResNet152V2	15	91.88	0.5126	88.58	0.6716
		30	97.39	0.2354	94.03	0.1498

Dataset 3	**VGG16**	15	94.17	0.0591	93.24	0.4625
		30	**98.07**	**0.0465**	95.26	0.6068
	VGG19	15	94.26	0.0986	92.33	0.2140
		30	97.03	0.0859	95.49	**0.1077**
	ResNet50	15	77.18	0.8597	73.54	1.5873
		30	78.57	0.6309	75.95	2.1414
	ResNet152V2	15	95.08	0.8369	92.11	4.3268
		30	97.61	0.5297	**97.58**	6.5757

Table 2. Transfer learning models performance.

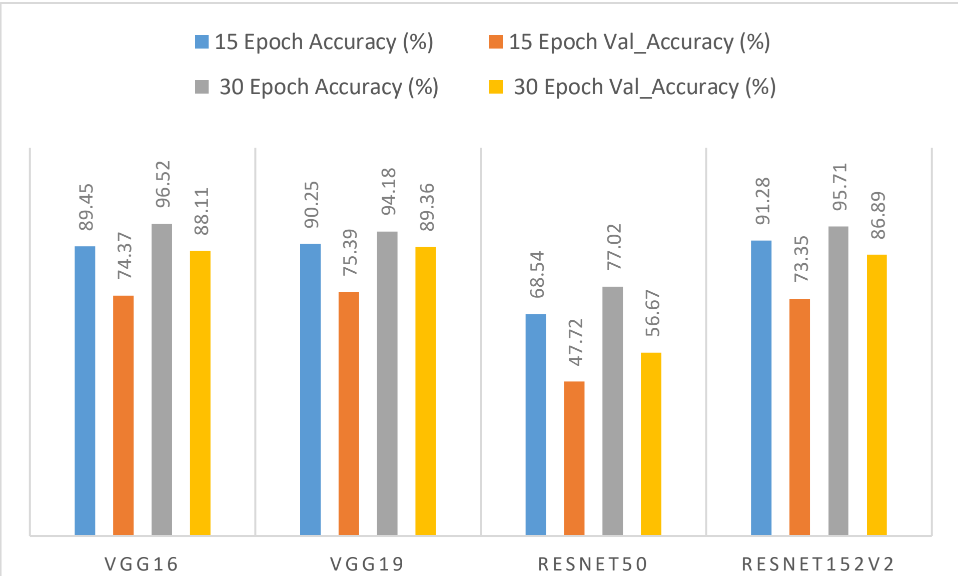


Figure 24. Accuracy evaluation Dataset 1.

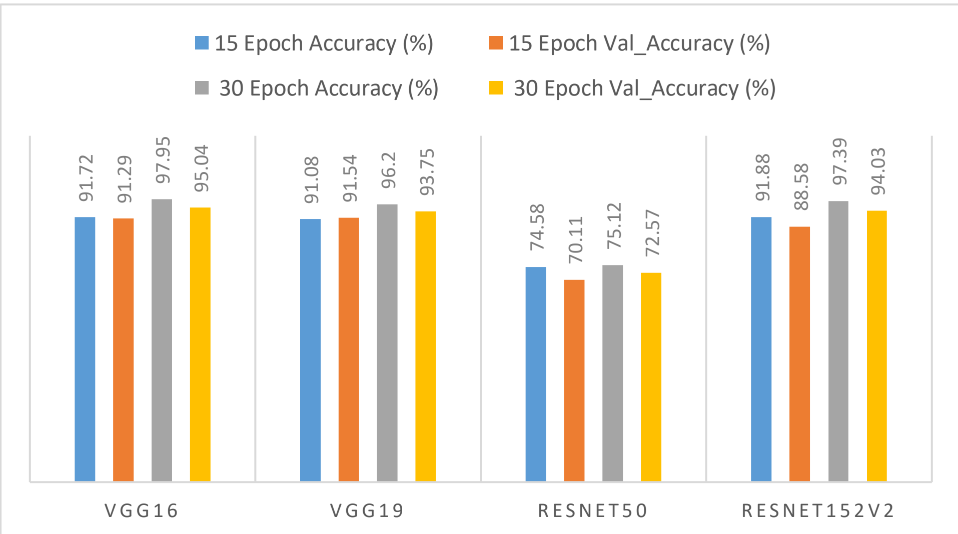


Figure 25. Accuracy evaluation Dataset 2.

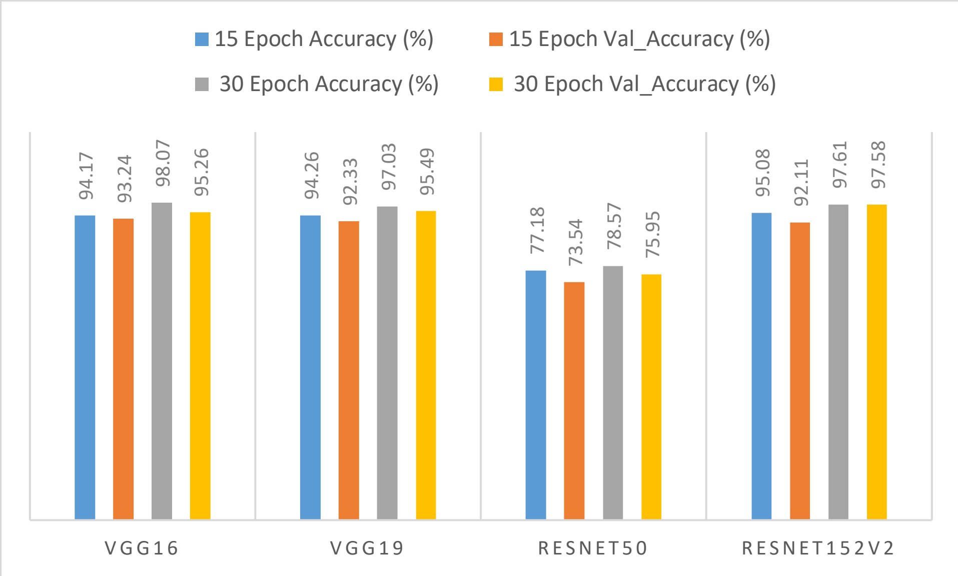


Figure 26. Accuracy evaluation Dataset 3.

After doing these training with different datasets we can conclude that the larger the training data, the better the classification performance. However, when the number of training data is insufficient, sometimes better classification results can be obtained. Therefore, when you do classification experiments, if you cannot get a large data set, you can do more experiments and choose the best results [60].

3.7.2 CNN model approach

We try to find the best model that fit our application, in our case its Brain tumour MRI, we did some researches on how the different layers of the CNN treat images and we came up with four different architectures that contain different parameters and layers number. The following Table 3 represent the proposed architectures.

		Conv layer		**Max pooling layer**		**Activation**
		N.kernel	Kernel size	Pool size	strid	
Model 1	Conv1	16	3x3	2x2	2	softmax
		16	3x3			
Model 2	Conv1	8	2x2	2x2	2	softmax
		8	2x2			
		8	2x2			
		8	2x2			
Model 3	Conv 1	16	3x3	2x2	2	softmax
	Conv 2	32	3x3	2x2	2	
		32	3x3			

	Conv 3	64	3x3	2x2	2	
		64	3x3			
		64	3x3			
	Conv4	128	3x3	2x2	2	
		128	3x3			
Model 4	Conv 1	16	3x3	2x2	2	softmax
	Conv 2	32	3x3	2x2	2	
		32	3x3			
	Conv 3	64	3x3	2x2	2	
		64	3x3			
		64	3x3			
	Conv4	128	3x3	2x2	2	
		128	3x3			
	Conv5	256	3x3			
		256	3x3			

Table 3. Architecture of the proposed models.

3.7.2.1 First Architecture

A simple two Convolutional (Conv2D(16x(2x2))) layers followed by a MaxPooling (2x2) layer and then the flattened layer + Activation function (softmax), each Conv Block layer is paired with a (‘relu’) activation function and last is the dense layer containing 4 nodes to represent our four classes.

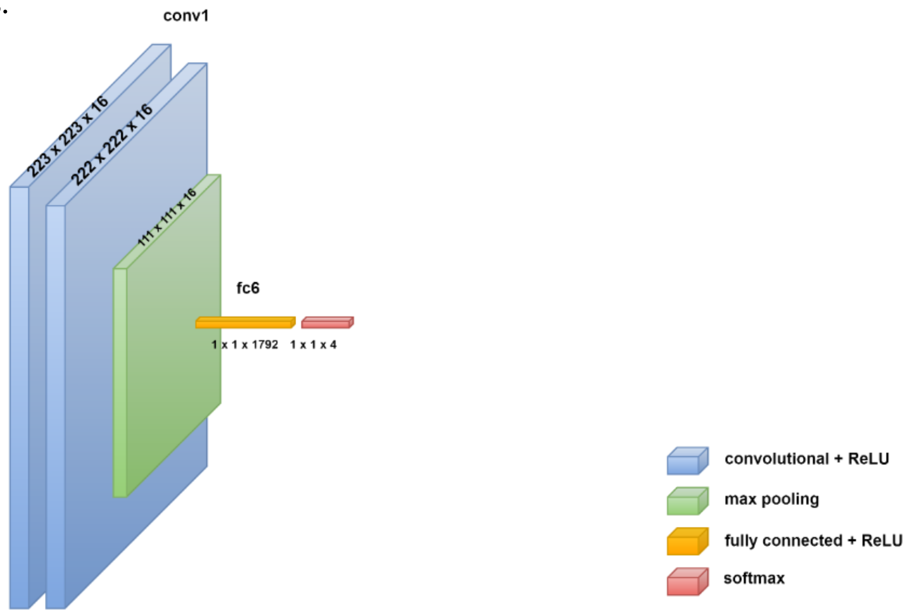


Figure 27. First Architecture.

3.7.2.2 Second Architecture

In the second architecture we divided the two (16x(2x2)) Conv layer into four (8x(2x2)) Conv layers followed by (2x2) MaxPoling layer and the rest is the same

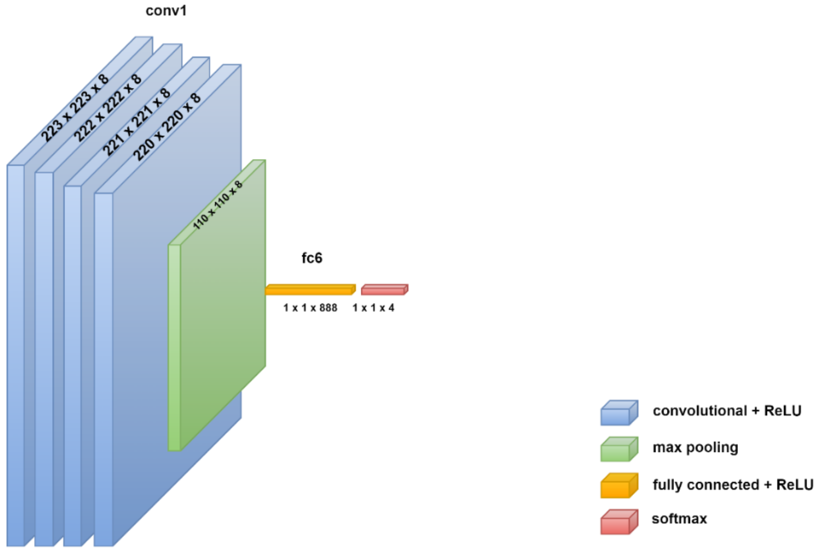


Figure 28. Second Architecture.

3.7.2.3 Third Architecture

This time we increased the number of the hidden layers furthermore and also increased the filter shape to be (3x3), we have eight Convolutional layer. A single (16x(3x3)) Conv layer, two (32x(3x3)), three (64x(3x3)) and then two (128x(3x3)), every Conv block is followed by a MaxPolling layer and all the Conv layers are also followed by a ('relu') activation function

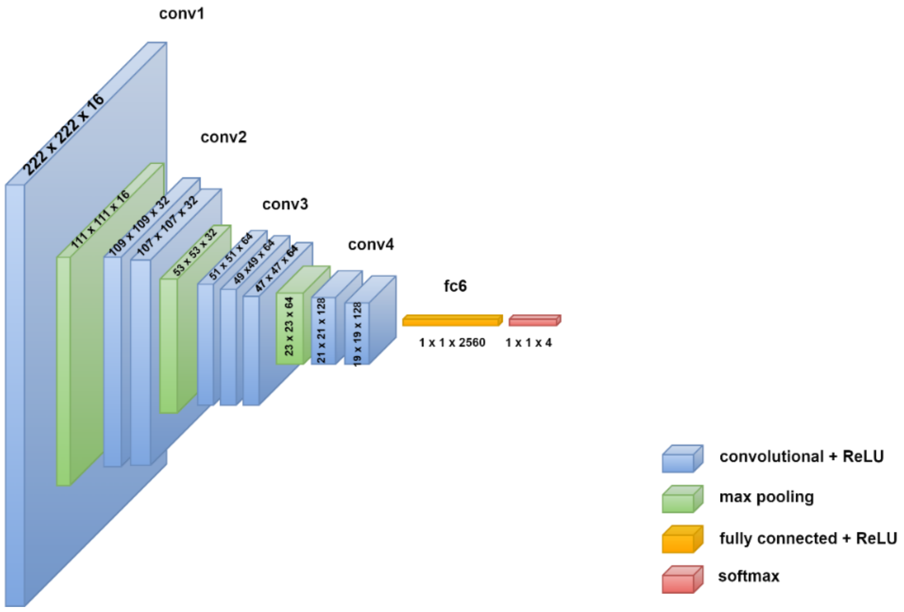


Figure 29. Third Architecture.

3.7.2.4 Fourth Architecture

In this last model we try to make a small modification to the previous model because we got a very good results, we added two more (256x(3x3)) Conv layers to the architecture by doing this we could raise the testing accuracy a little more, we ended up with the following results.

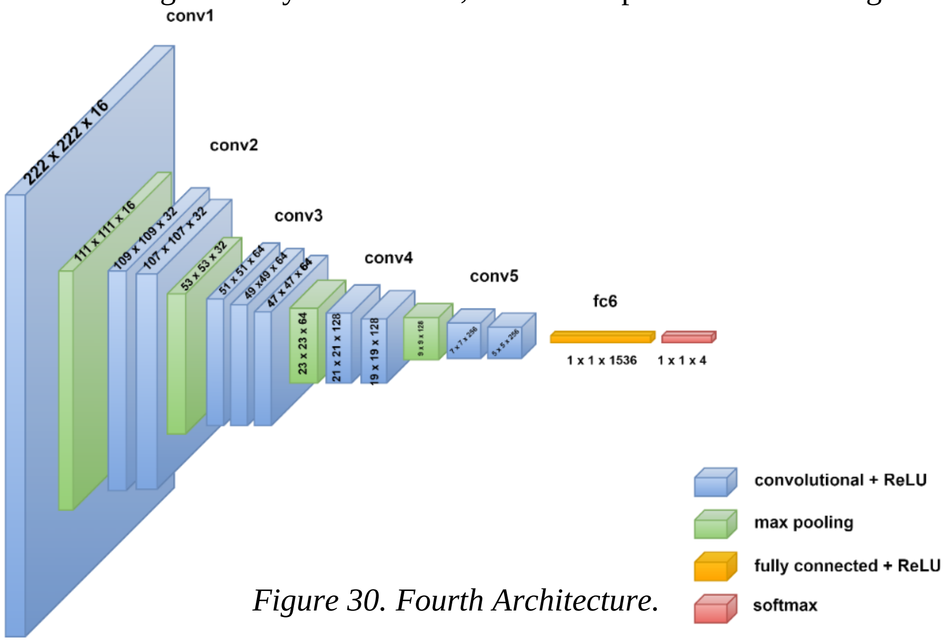


Figure 30. Fourth Architecture.

			Training		**Testing**	
	Trainable parameters	Epoch	Accuracy (%)	Loss	Accuracy (%)	Loss
Model 1	789,796	15	88.97	0.3100	83.28	1.0174
		30	**90.01**	**0.3440**	**89**	**0.6857**
Model 2	388,100	15	88.37	0.03154	91.35	0.2405
		30	**93.36**	**0.1249**	**92.55**	**0.0369**
Model 3	512,964	15	97.92	0.0809	99.04	0.0363
		30	**99.65**	**0.0399**	**99.52**	**0.0106**
Model 4	1,238,980	15	98.46	0.0349	99.40	0.0110
		30	**99.87**	**0.0478**	**99.76**	**0.0109**

Table 4. Models Performance and evaluation (Data Set 3).

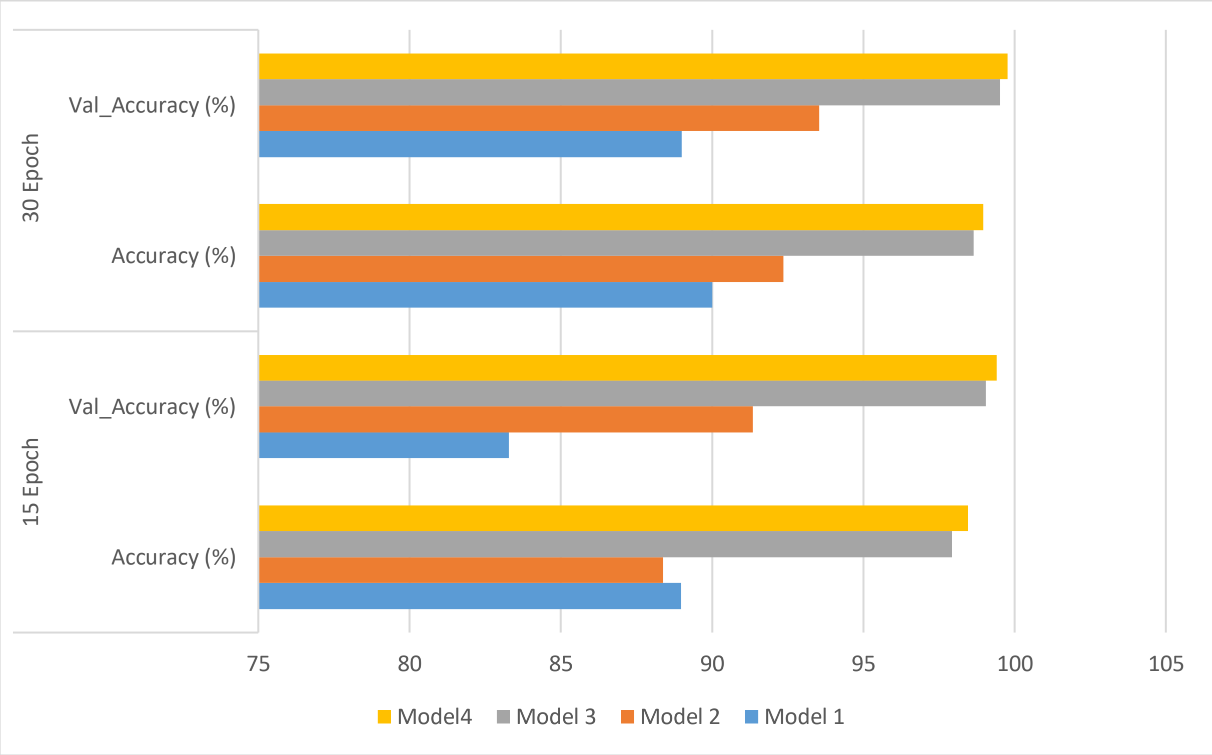


Figure 31. Models Accuracy Comparison.

3.8 Performance evaluation

For results analysis, several performance metrics (precision, recall, f1-score, support and accuracy) are evaluated. Accuracy is the most common way to determine the performance of a classification model. The fourth model paired with the third dataset gives us the following results

	precision	Recall	F1-Score	Support
Glioma	0.99	0.82	0.90	400
Meningioma	0.89	0.99	0.94	421
No_Tumour	0.94	1.00	0.97	510
pituitary	0.97	0.97	0.97	374
Accuracy			**0.95**	**1705**
Macro Avg	0.95	0.94	0.94	1705
Weighted Avg	0.95	0.95	0.95	1705

Table 5. Classification report.

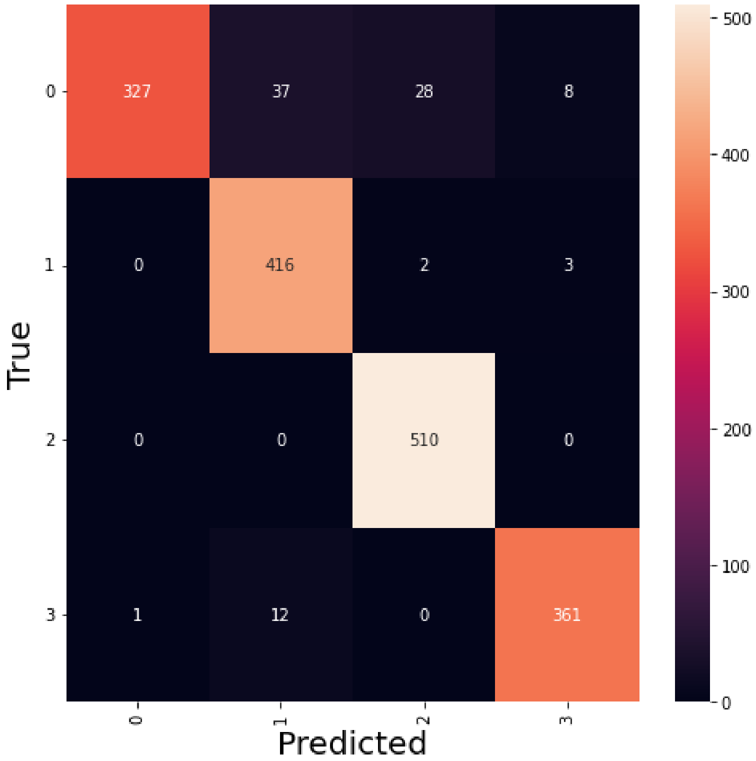


Figure 32. Confusion matrix.

3.9 Comparison with the stat of the art

In order to give an idea on where our brain tumour prediction system ranks performance-wise, we compare it with works that used the same performance measures. Table 6 provides a broad comparison based on classification accuracy as a metric. The comparison shows that our method outperforms all the state-of-the-art methods.

	Techniques	Type of classification	Dataset	Accuracy (%)
M. A. Ansari et al. 2020 [61]	DWT+PCA+GLCM+ SVM	Binary	T1-weighed CE-MRI, 140 tumour affected, 60 normal	98.91
P. Afshar et al. 2019 [62]	CNN	Multi	T1-weighed CE-MRI, 708 meningioma's, 1426 gliomas, and 930 pituitary tumours	90.89
Hossam H. Sultan et al. 2019 [63]	CNN	Multi	T1-weighed CE-MRI, 708 meningioma's, 1426 gliomas, and 930 pituitary tumours	96.13

Amin Kabir A et al. 2019[64]	CNN	Binary	TCIA (REMBRANDT)	94.2
S. Deepak et al. 2019 [65]	CNN (Google Net), KNN, SVM	Multi	Figshar	98
Proposed Model	CNN	Multi	T1-weighed CE-MRI, 2774 meningioma's, 2772 gliomas, and 2874 pituitary tumours, 2700 no tumour	**99.7**

Table 6. Comparison with the stat of the art.

Conclusion

The CNN technique is a great way to make predictions based on images. We try some pretrained models using transfer learning method to make a brain tumour classification system. The dataset used had some basic preprocessing before it enters the network; it make the model more robust and accurate by giving different version of the same image to the neural network, this is one to the training data only.

The best results achieved by the transfer learning technique is 97.58% on accuracy by the ResNet architecture. We need to mention too that both VGG models did pretty well with a 95.49% accuracy. Our model in the other hand got a whopping 99.76% accuracy. We manage to achieve this result by testing four different architecture that we create, by tuning some of the parameters of the convolutional neural network. In the end we did a small comparison with the stat of the art methods

General Conclusion

General Conclusion

Our study aims to propose a program from deep learning, which works on the early detection and classification of brain tumours to assist doctors in the medical field

This study is divided into two major parts, in the first one we used a pre-trained transfer learning models Like VGG16, VGG19, ResNet50, and ResNet152V2, the second part we proposed CNN models with four different architectures

Firstly, the pre-trained models were trained with three different datasets with four classes, and each one gives a different result, starting with the dataset 1; VGG16, VGG19, and ResNet152V2 gives close results for testing accuracy(88.11%, 89.36%, 86.89%), ResNet50 ranked last with an accuracy of 56.67% for testing.

The second dataset has more elements than the first. Technically, it took more time to be processed, and all the results changed in a better way the highest training (97.95 %) and testing (95.04 %) accuracy goes to VGG16 model. We can notice that VGG16 perform very well with small data in fact it is one of the strength point of the VGG architecture working with smaller data.

The last dataset gave us the best result overall, obviously it has the bigger number of samples around 11119 divided into four different classes of brain tumour. ResNet152V2 comes first with 97.58 % testing and 97.61 % training, the performance of the rest are very close except for ResNet50 seems to struggle more with bigger datasets. We can also notice that ResNet152V2 benefits a lot from the large number of imagers and that’s where VGG does not work well with.

On The second part, we proposed a CNN model with four different architectures. We used the last dataset, which is the largest for the sake of a better result. These architectures differs in the number of hidden layers that compose the model and the kernel size of each layer. Each architecture has more layers in it but not necessarily more parameters; we did this on purpose to show that the number of parameters does not affect the performance of the model directly as the results describe.

As mentioned in the table 4 chapter 3, the first two models achieved a 89% and 93.55% accuracy respectively. Then the third and fourth model manage to achieve a 99.52% and 99.76% accuracy respectively, there is no big difference in the architecture of these last models and so the result, but still the slight percentage difference in accuracy can make a big change in the decision making process

In comparison with other published works. This model ranks pretty well; actually, it is the best overall model in term of accuracy. The highest stat of the art method got an accuracy of

98.91% [62] with this model (DWT+PCA+GLCM+SVM). We need to mention that the dataset used in our work is not the same as the stat of the art methods, so the comparison might not be accurate.

Even if the developed system showed great and high accuracy for the classification, it is still recommended to get a confirmation from a medical expert because of the error probability.

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Abstract

A brain tumour is a fatal disease affects children and adults the disease might be detected using physical exam, neurological exam but for the classification, it is done with biopsy. That last one is concerned with brain surgery, which is so hard and complicated itself. Nowadays it is so important for the early detection because of the five-year rate of survival.

The early detection and classification could help to choose the perfect plan for treatment. With the big development and change in technology and AI techniques could help in diagnosis and classification without any huge risks, Using the available data of MRI images that are studied from the radiologist.

In our study, we took two approaches, the first including four transfer learning models and the second including a CNN model, to both classify different types of brain tumour. Using three different datasets available at kaggle

With the CNN approach, we manage to achieve an accuracy of 99.76 %. The Experimental Results shows that our proposed Convolution Neural Network model (CNN) gives the best accuracy as compared to other transfer learning techniques. At last, we make a small comparison with the state of the art methods.

ملخص

ورم المخ هو مرض قاتل يصيب الأطفال والبالغين ويمكن اكتشاف المرض بالفحص الجسدي والفحص العصبي ولكن بالنسبة للتصنيف يتم إجراء الخزعة. يتعلق الأمر الأخير بجراحة الدماغ ، والتي هي نفسها صعبة ومعقدة. في الوقت الحاضر ، من المهم جدًا الكشف المبكر بسبب معدل البقاء على قيد الحياة لمدة خمس سنوات.

يمكن أن يساعد الاكتشاف المبكر والتصنيف في اختيار الخطة المثالية للعلاج. مع التطور الكبير والتغيير في التكنولوجيا وتقنيات الذكاء الاصطناعي يمكن أن تساعد في التشخيص والتصنيف دون أي مخاطر كبيرة ، وذلك باستخدام البيانات المتاحة لصور التصوير بالرنين المغناطيسي التي تمت دراستها من أخصائي الأشعة.

في دراستنا ، اتخذنا طريقتين ، الأول يشتمل على أربعة نماذج تعلم نقل والثاني يتضمن نموذج CNN ، لتصنيف أنواع مختلفة من أورام المخ. استخدام ثلاث مجموعات بيانات مختلفة متاحة في kaggle

من خلال نهج CNN ، تمكنا من تحقيق دقة تصل إلى 99.76٪. تظهر النتائج التجريبية أن نموذجنا المقترح للشبكة العصبية الالتفافية (CNN) يعطي أفضل دقة مقارنة بتقنيات تعلم النقل الأخرى. أخيرًا ، نجري مقارنة صغيرة مع أحدث الأساليب.