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GENERAL INTRODUCTION

Brain cancer is a serious disease that touchs millions of people in the whole world. Early detection plays a crutial role in improving treatment and patient survival rates. In recent years, advancements in medical imaging, specifically Magnetic Resonance Imaging (MRI), combined with the power of image processing techniques and deep learning algorithms, have revolutionized the field of brain cancer detection.

MRI provides detailed structural and functional information about the brain, making it a valuable tool for identifying abnormalities associated with brain tumors. However, manually analyzing large volumes of MRI data to detect cancerous regions can be time consuming, subjective, and exposed to human error. To overcome these limitations, researchers and medical professionals have turned to image processing and deep learning approaches to develop automated and accurate brain cancer detection systems.

Image processing techniques involve applying various filters, feature extraction methods, and segmentation algorithms to enhance the MRI images and identify regions of interest. These techniques help in highlighting tumor boundaries, differentiating between healthy and abnormal tissues, and providing quantitative measurements of tumor characteristics such as size, shape, and texture.

Deep learning, a subfield of artificial intelligence, has gained significant attention in medical imaging due to its ability to gain knowledge of compound patterns and features directly and exclusively from the data. Convolutional Neural Networks (CNNs), the popular deep learning architecture, have demonstrated exceptional performance in analyzing medical images, including MRI scans. By training CNNs on large datasets of labeled MRI images, these networks can learn to distinguish between normal and cancerous brain tissue, enabling automated tumor detection with high accuracy and efficiency.

The integration of image processing techniques and deep learning algorithms has led to remarkable advancements in brain cancer detection. These methods have the potential to assist radiologists and clinicians in the early identification of tumors, allowing for timely intervention and personalized treatment plans. Moreover, automated detection systems can help reduce the burden on medical professionals, enhance diagnosis accuracy, and improve patient outcomes.

In conclusion, the combination of image processing and deep learning techniques has opened up new possibilities for brain cancer detection in MRI images. With continuous research and development, these approaches are capable to revolutionize the field of oncology, enabling early diagnosis and improving the overall management of brain cancer patients.

The following report is organized in three Chapters:

• the first chapter contains a state of the art study of the medical procedure. First we detailed the structure of the brain and tumors, their role and possible affections. Then we detailed the MRI imaging technique and highlighted its importance for brain cancer detection.

• the second chapter presents artificial intelligence algorithms, and explains deep neural networks in particular as a powerful architecture for intelligent task automation. It's also dedicated to the working strategy development, where we detailed the methods used for image processing, customized model development and parameter optimization.

• the final chapter is for model evaluation and performance testing using chosen parameters, a comparative study is also conducted to validate the performance of our strategy.

1 CHAPTER1 : STATE OF THE ART

1.1 Introduction

MRI imaging plays a critical role in deep learning for brain cancer detection. Its ability to lay out high resolution images with good soft tissue contrast allows for accurate identification and characterization of brain tumors. The complex and diverse information captured by MRI scans serves as valuable training data for deep learning algorithms, enabling them to learn intricate tumor patterns and features. By harnessing the power of MRI imaging, deep learning techniques have the potential to revolutionize early detection, precise tumor segmentation, and treatment planning for brain cancer, ultimately leading to improved patient outcomes.

1.2 Understanding Brain Tumors

A tumor is an uncontrolled cell proliferation. The basic units of the body are the cells, which form the tissues and the biological structure. The body continuously produces new cells to support our growth, restore damaged tissue, and repair wounds.

Cells typically divide and expire in an organized manner, with each recently developed cell replacing a deceased one. Cells can, on sometimes, develop abnormalities and continue to grow. A tumor is a growth or lump formed by aberrant cells in solid tumors such a brain tumor. [1]

1.2.1 tumors classification

It's common to categorize brain tumors as benign or malignant. Other body parts' tumors are likewise referred to by these names. The distinction is less obvious when it comes to brain tumors. [2]

Benign tumors

Normal benign brain tumor growth is modest, and they seldom metastasize. The growth of a benign tumor may alter the way the brain functions. This may be deadly and requires immediate medical attention. A benign tumor may occasionally develop a malignant mutation over time.

Malignant tumors

Brain cancer is another name for a malignant brain tumor. While some malignant brain tumors advance slowly, others do so quickly. Because of their potential to enlarge, spread to the brain or spinal cord, or recur after therapy, they are regarded as potentially fatal.

Primary cancer

Primary brain cancer is the name for a cancer that begins in the brain. It might extend to other nervous system regions. Primary brain malignancies often do not reach outside the brain, unlike other malignant tumors that may do so throughout the body.

Secondary cancer

Sometimes cancer spreads to the brain via the circulation after beginning in another area of the body. This is referred to as a metastasis or secondary cancer. Melanoma, lung, breast, kidney, and bowel cancers are the ones that are most likely to spread to the brain. The name of the primary cancer is retained by a metastasis. For instance, even though the patient may be experiencing symptoms as a result of the disease being in the brain.

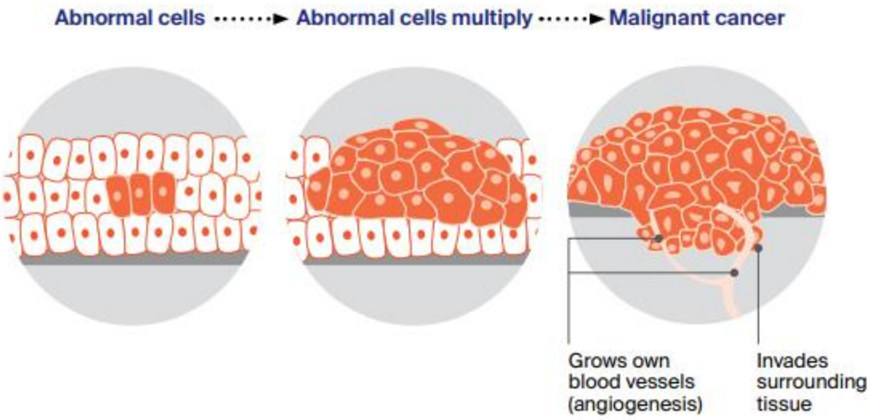

figure 1 : How cancer starts

1.2.2 The brain and spinal cord

The central-nervous-system (CNS) contains of the brain and spinal cord. The many CNS regions work in concert to regulate how the mind and body function.

The brain

The sense body parts that command taste, smell, touch, sight, and hearing send nerve signals to the brain, which the brain receives and interprets. The muscles and organs also receive messages from it via the nerves. Memory, personality, and behavior are all controlled by the brain. The cerebellum, brain stem, and cerebrum make up the majority of the brain.

Spinal cord

From the brain flow to the lower back, the spinal cord runs. It is composed of nerve tissue that forms the peripheral nervous system, a web of nerves that attachs the brain to every region of the body. The spinal column, which is made up of a number of vertebrae, protects the spinal cord as it travels through the spinal canal.

Meninges

The brain and spinal cord are both covered by these flimsy membrane-like layers of defense.

Cerebrospinal fluid (CSF)

CSF, which can be be present inside the cranium and spinal column, encircle and shields the brain and spinal cord from harm.

Pituitary gland

This is around the size of a bean and is found at the base of the brain. Hormones are made by the pituitary gland and released into the blood stream. These hormones adjust a variety of bodily processes, including as development, metabolism, and growth.

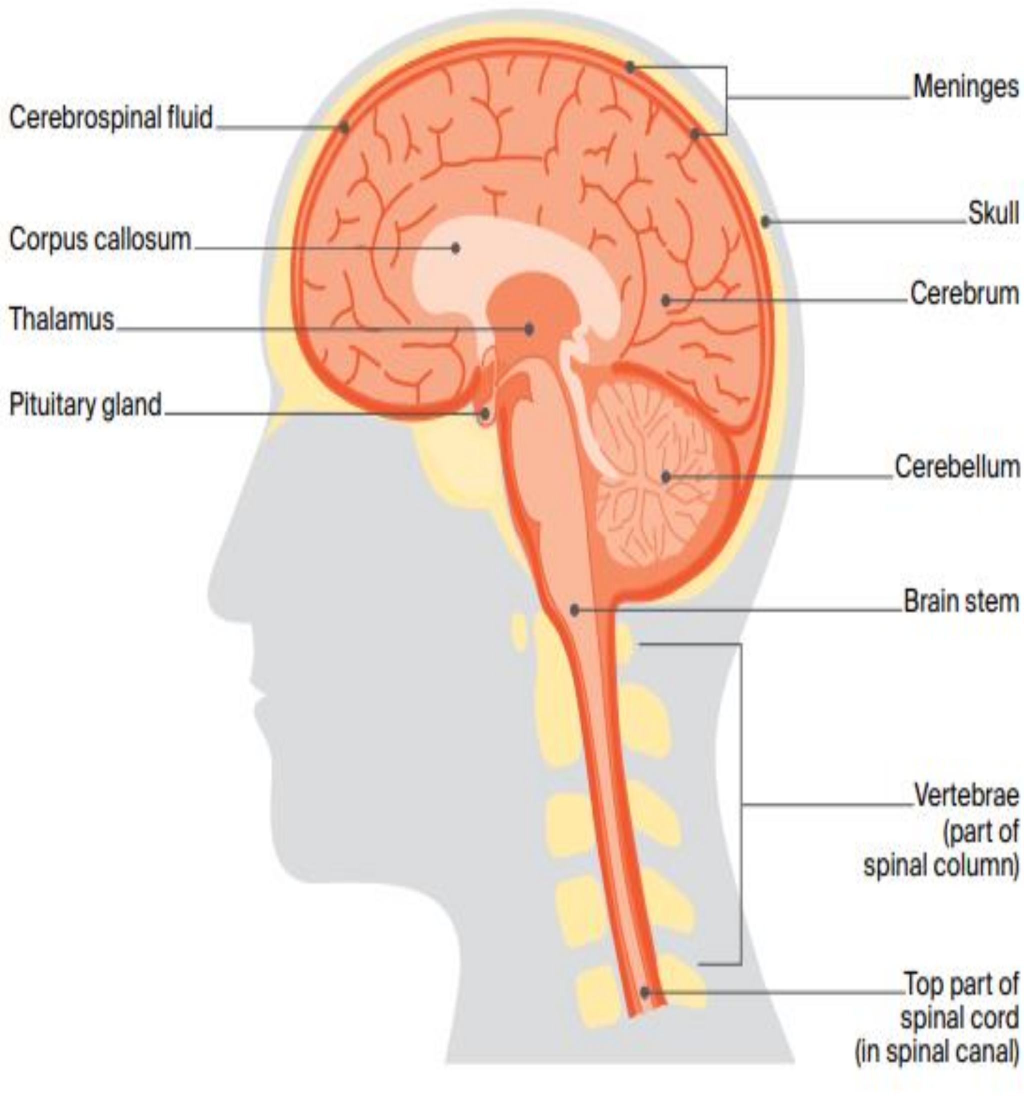

figure 2 : The central nervous system.

1.2.3 The parts of the brain

The cerebrum is the biggest component of the brain. Hemispheres are the names given to its two parts. The parietal, frontal, occipital, and temporal lobes are the four primary regions that each hemisphere is separated into.

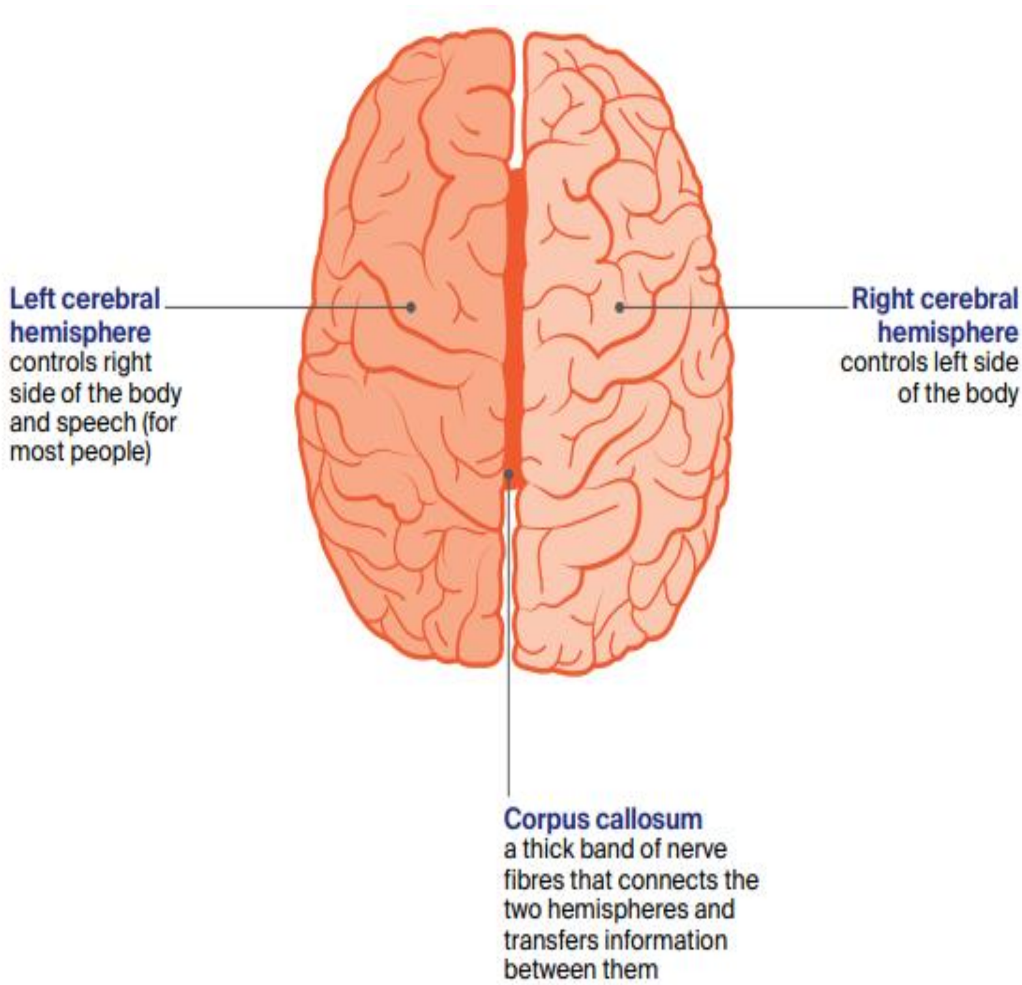

figure 3 : Top view

The cerebellum and the brain stem are the two other major components of the brain. At the rear of the head is where the cerebellum is positioned. The brain stem joins the spinal cord to the brain. Distinct biological functions are managed by distinct brain regions.

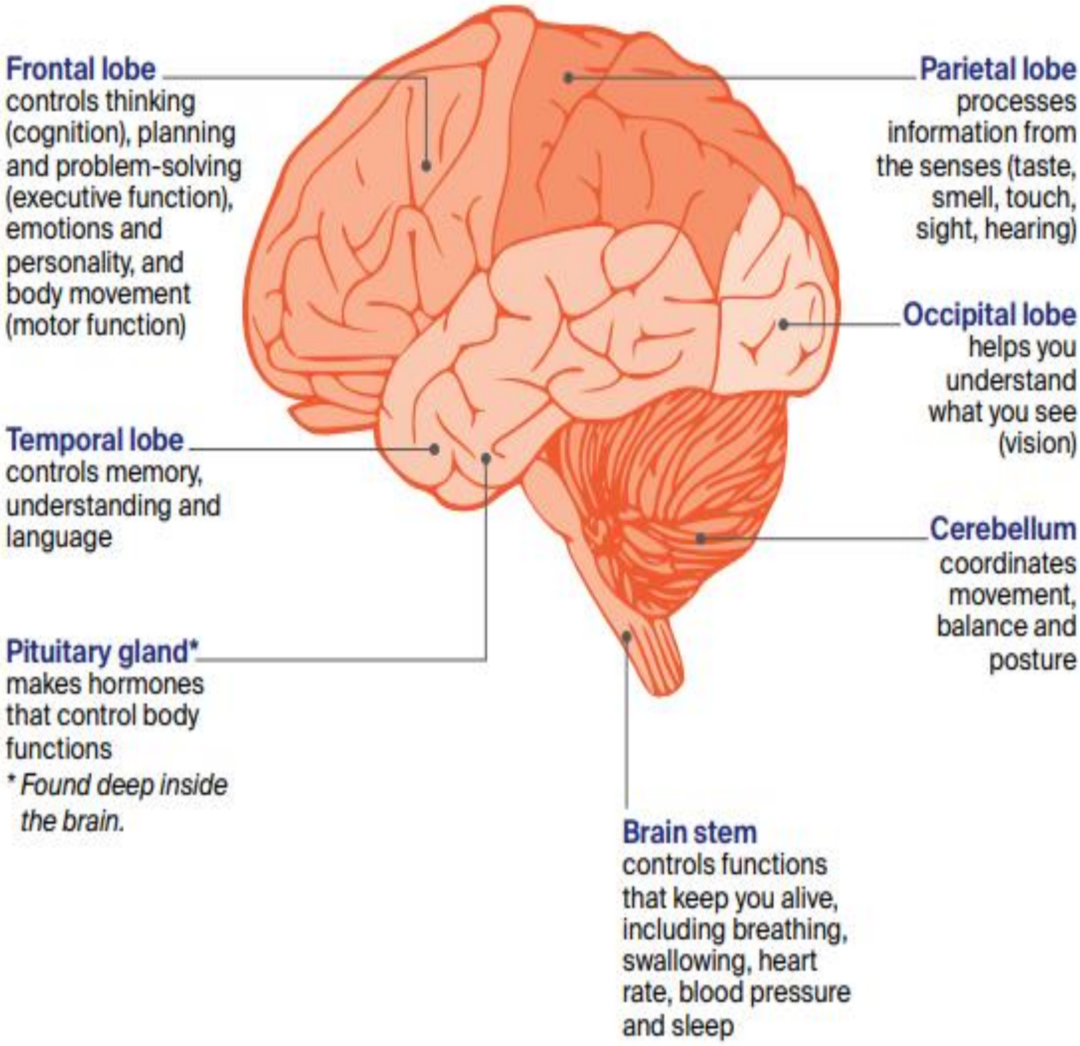

figure 4 : Side view

1.2.4 Types of tumors

Different tissues and cells that make up the brain can differentiate into several tumor kinds. Brain and spinal cord Primary tumors come in more than 40 different varieties. They may begin anywhere along the spinal cord or in the brain. Based on the kind of cell they originate from and the way the cells are expected to act, tumors are categorized. Almost all typical kind of malignant brain tumors are gliomas. [3]

Common types of primary brain tumours are :

- **Glioma tumors** These tumors kick off in the glial (neuroglia) cells of the brain.

Astrocytoma

• begins in glial cells referred to as astrocytes.

• could be benign or malignant

Glioblastoma (GBM)

• kind of malignant astrocytoma

• may arise from an astrocytoma that is slowly expanding

• more than half of all gliomas are composed of

• prevalent in both adults and kids

Ependymoma

• begins in ependymal cells, which are glial cells

• more typical in kids than in adults

• either benign or cancerous

Oligodendroglioma

• begins in oligodendrocytes, which are glial cells

• more typical among teens

• cancerous; may grow slowly or quickly

- **Non-glioma tumors** These tumors originate from different types of brain cells..

Medulloblastoma

• cancerous tumor that originates in the cerebellum

• Children experience it more often than adults do

Meningioma

• begins in the meninges, the membranes that envelop the brain and spinal cord

• main brain tumor most frequently found, typically benign and slow developing

pituitary tumor

• pituitary gland is where it begins.

• frequently benign

Schwannoma

• begins in the nerve-surrounded Schwann cells of the brain and spinal cord.

• typically benign

• contains acoustic neuromas and vestibular schwannomas

1.2.5 The risk factors

Most brain and spinal cord tumors have unrevealed causes, however certain factors are known to raise a person's risk, such as:

Family history

Even though it is uncommon for CNS tumors to circuit in the family tree, some individuals receive a genetic code alteration from their parents that raises the danger of getting a brain tumor. As an illustration, some individuals have a hereditary disorder called neurofibromatosis, which can result in largely non cancerious tumors of the CNS.

Radiation therapy

A modest increase in the risk of developing a brain tumor, particularly meningioma, is possible in patients those who undergone radiation therapy to the skull, espacially to treat pediatric leukemia.

Chemical exposure

Brain tumors have been associated to exposure to pesticides, vinyl chloride, employment in the rubber industry, and petroleum refining.

1.2.6 Brain cancer symptoms

The location of the brain tumor and its rate of growth both influence the symptoms. Symptoms may appear quickly or over the course of time gradually.

General symptoms

Intracranial pressure, often known as brain tumor pressure, can grow. Because the tumor occupies a lot of space, causes brain lump, or obstructs the passage of cerebrospinal fluid around the brain, leading to pressure increase.

Symptoms of increased pressure inside the skull include:

• headaches: Usually stronger in the morning

• Vomiting and nausea are frequently worse in the morning or after shifting positions (from sitting to standing).

• perplexity and annoyance

• double or blurry vision

• seizures (fits): can cause hands, arms, or legs to jerk or twitch, or they can impact the entire body.

• sleepiness

• weakness in several bodily areas

• a lack of cooperation

• consciousness is lost

• having trouble speaking or coming up with the correct phrases

Symptoms and position

The symptoms experienced will depend on the place of the tumor is in CNS.

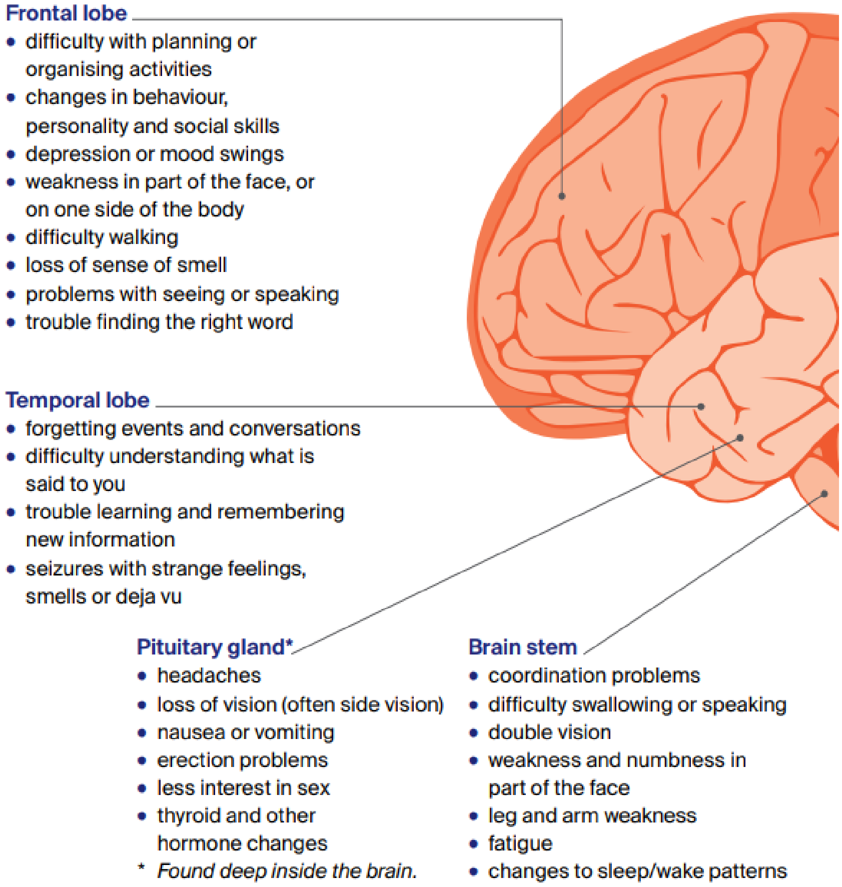

figure 5 : the position of the tumor and it 'effect

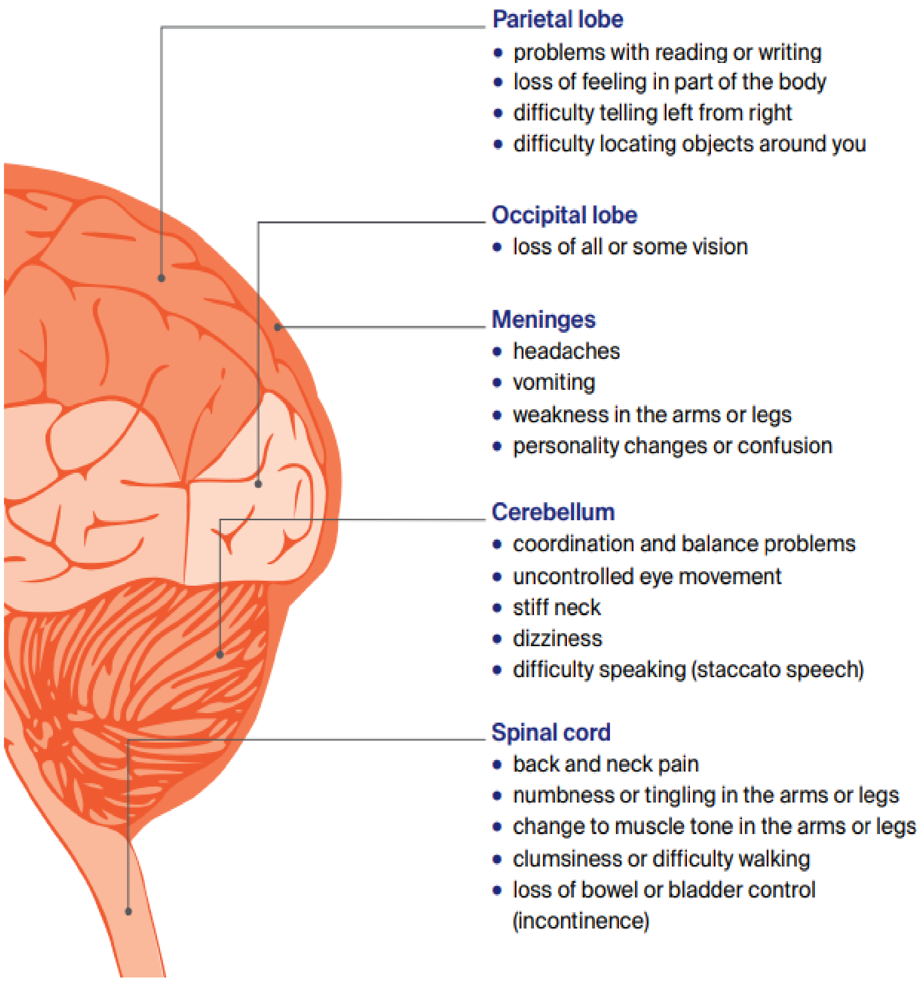

figure 6 : the position of the tumor and it'effect_2

1.2.7 Diagnosis

Many people who've been diagnosed with a brain or spinal cord tumor visit the doctor first cause they are feeling sick. On occasion, a brain tumor is discovered while an eye exam or while a scan for an unrelated condition, like a skull injury. When experiencing unexpected symptoms (such a strong headache, a seizure, or losing consciousness), some people travel directly to the emergency room of a hospital. The symptoms and medical history will be discussed with the doctor, who will also perform a physical examination. [4]

Physical examination

The doctor will examine the neurological system to see how well the speech, hearing, vision, and movement, among other bodily functions, are functioning. A neurological examination includes the following steps:

• testing the reaction time (knee jerks)

• evaluating the power of arm and leg muscles

• demonstrate balance and coordination by walking

• testing sense of touch or sensitivity to pinpricks

• Brain workouts like simple math problems or memory tests

Additionally, the physician could use an ophthalmoscope to examine eyes and test pupil and eye movements. The optic nerve, the one transmitting data from the eyes to the brain, may be seen by the doctor. An early indicator of increased pressure to the brain may be a bulge of the optic nerve.

Blood tests

Blood tests may be performed to evaluate general health. Additionally, blood tests may be done to determine if the tumor is releasing unusually high levels of hormones, It can be a sign that the pituitary gland is damaged.

CT scan

If an MRI is not an option, the physician may opt for a CT (computerized tomography) scan instead. This scan produces finely detailed images of the inside of the body using x-rays and a computer. Prior to the scan, a dye (contrast) may be injected into a vein to aid in improving the clarity of the images.The patient might feel warm and have an acrid in his mouth as a result of the contrast. Additionally, he can get the urge to urinate. Usually, these sensations subside within a few minutes.

MRI scan

An MRI (magnetic resonance imaging) is typically advised by the physician may opt fo to look for brain tumors and to assist in treatment planning. A strong magnet and a computer are used in an MRI scan to create detailed images of the body. If the patient has any metallic device in his body (such as surgical clips from heart or bowel surgery an MRI scan is not possible. Some pacemakers may be affected by the magnet, however more recent pacemakers frequently work with MRIs.

The MRI scan technologist administers an injection of a dye to highlight any oddity in the brain during an MRI. The next step will involve having the patient lie down on a table within a huge metal tube that is open on both ends. [5]

Compared to images from a CT scan, images from an MRI scan are typically more detailed.

1.2.8 Grading tumors

Based on how the tumor's cells seem in comparison to healthy cells, the tumor will be graded. The grade indicates the potential rate of growth of the malignancy. The World Health Organization's classification system is most frequently applied to brain tumors. Typically, tumors of the brain and spinal cord are graded from 1 to 4.

To relate the degree of other cancer kinds in the body, a stage is assigned. Since most primary brain and spinal cord tumors don't spread to other body parts, they are not staged in this manner.

Grades of CNS tumors

- **grade 1:** These tumors are low grade, slow developping and benign.
- **grade 2:** These tumors are low grade and normally grow slowly. They are more likely to come back after therapy and can develop into a higher grade malignancy.
- **grades 3 and 4:** These tumors are high grade, quicker growing and malignant. They can spread to other sections of the brain and tend to come back following treatment.

1.2.9 Prognosis

The prognosis refers to the anticipated course of an illness. No one can accurately anticipate how the disease will progress.

Several variables may influence the prognosis, such as:

• the tumour kind, the spot, severity and biology

• Current age, overall well-being and ancestral background

• if a tumor has affected adjacent normal tissue in the brain

• how well a tumor reacts to therapy.

Either high grade and low grade cancers can substantially damage the functioning of the brain and represent a danger to life, but the prognosis could be improved if the tumor is low-grade or if a doctor can remove the whole tumor without concern.

Certain tumors in the cerebral cortex or spinal column, particularly gliomas, could continue to form or return. Additionally, they might evolve into a higher-grade malignancy. In this circumstance, therapies including surgery, radiation therapy, or chemotherapy may be performed to reduce signs, slow the development of the tumor as much as possible, and maintain the quality of life.

1.3 MRI Imaging and Brain Cancer Detection

In order to provide precise images of the inside body structures, magnetic resonance imaging, also known as MRI, employs strong magnetic fields and radio waves. MRI is particularly well-suited for imaging the brain because it offers high soft tissue contrast. It is a useful tool for identifying and tracking brain cancer because it enables imaging of the structure and anomalies of the brain. [5]

1.3.1 MRI Modalities for Brain Cancer Imaging

To capture various characteristics of brain tissue and aid in the detection of brain cancer, multiple MRI modalities are used [6]. There are three modalities in our dataset:

- **T1-weighted Imaging**

High-resolution anatomical images with good contrast between various brain tissues are produced by T1-weighted imaging. It is helpful for determining the tumor's position in respect to neighboring structures and for visualizing the tumor's form.

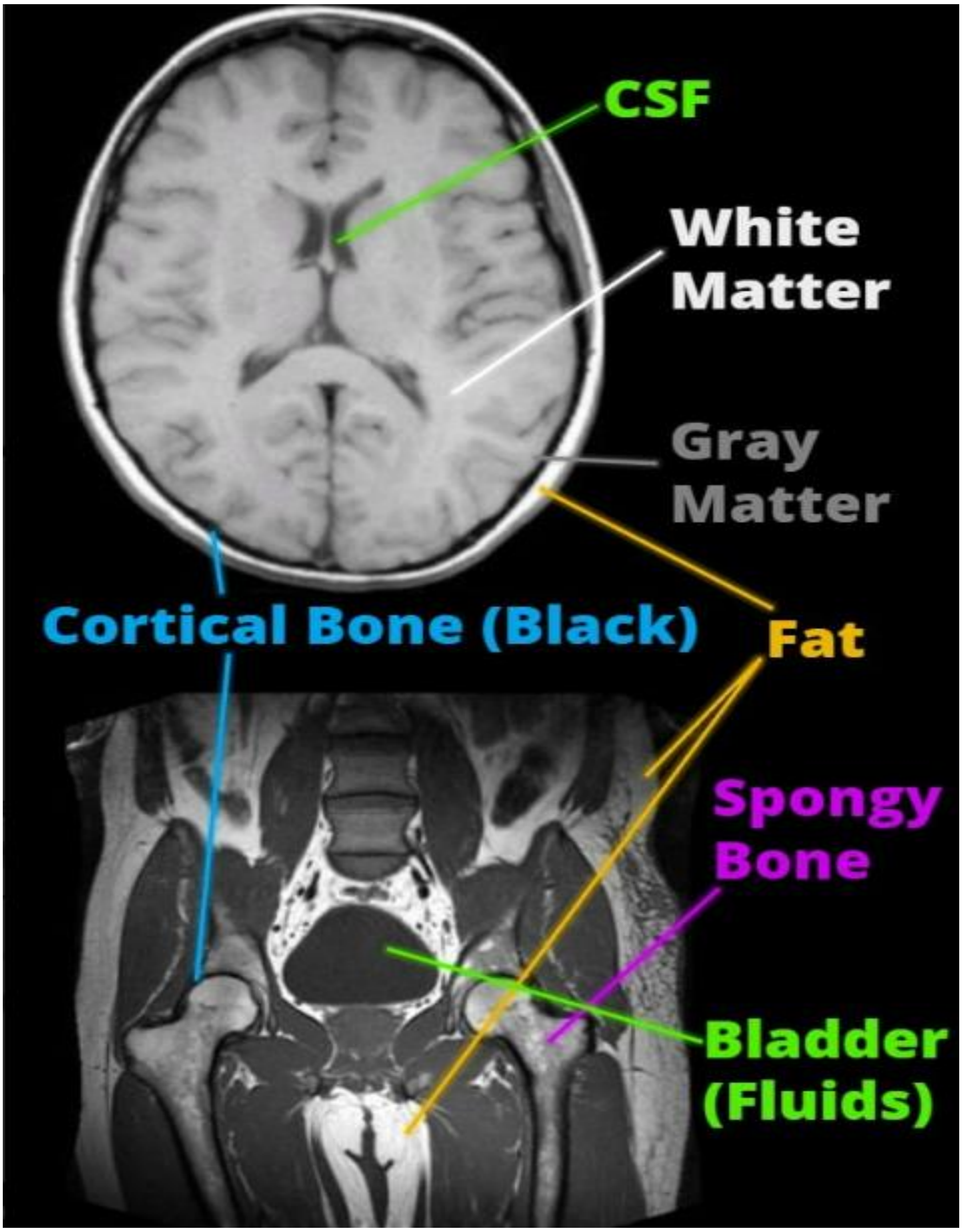

figure 7 : T1-weighted MRI

- **T2-weighted Imaging**

T2-weighted imaging reveals variations in water content, reveals tissue edema, and reveals aberrant signal intensities. On T2-weighted images, tumors frequently show distinctive signal characteristics that help with the identification and characterisation of the tumor.

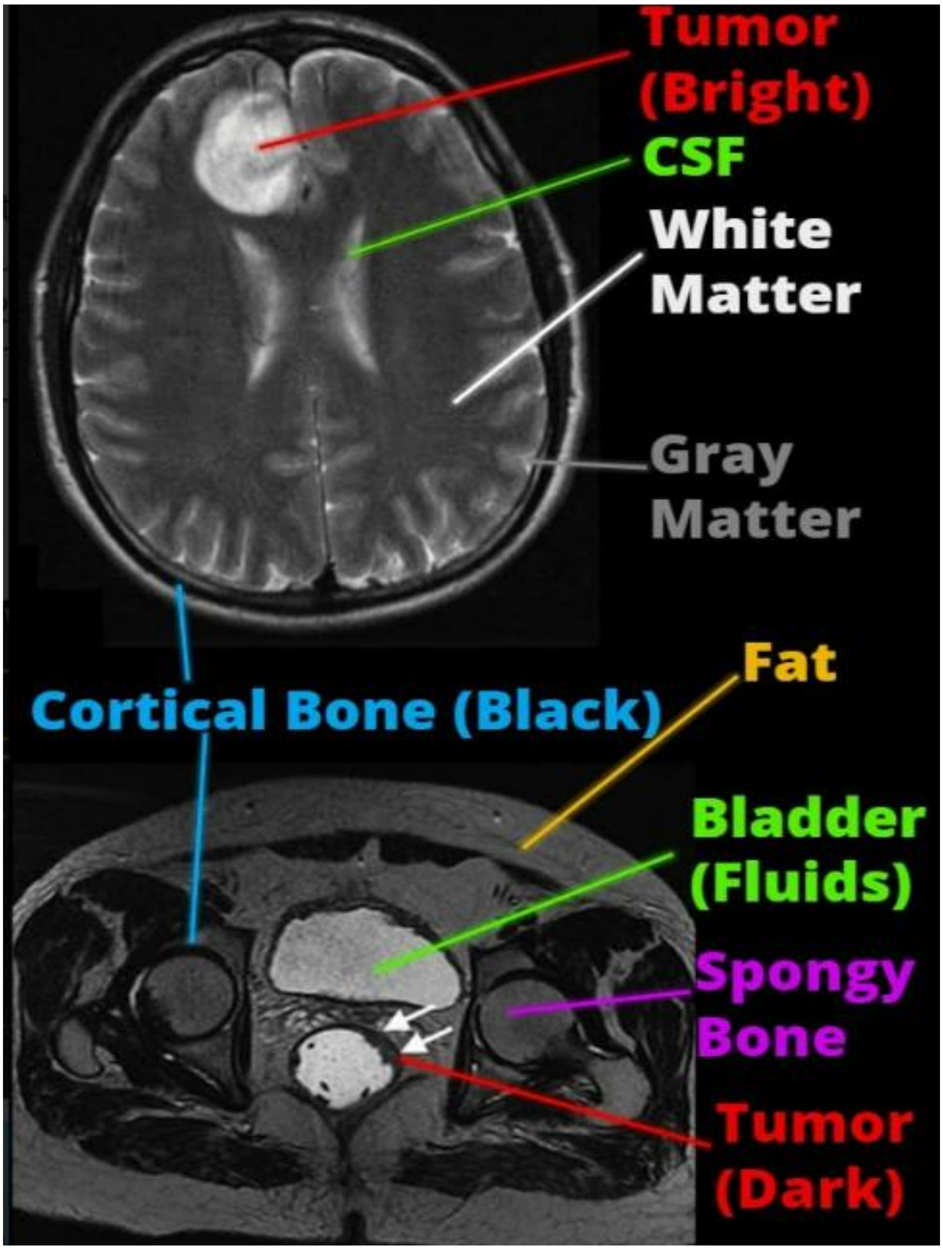

figure 8 : T2-weighted MRI

- **Fluid Attenuated Inversion Recovery (FLAIR)**

The most typical application of FLAIR is to reduce cerebrospinal fluid (CSF), which can obscure structural information in T2 weighted brain images. FLAIR is quite useful for identifying cerebral edema. This is due to the fact that cerebral edema is bright in both FLAIR and T2 weighted scans, but FLAIR suppresses CSF, making detection simpler.

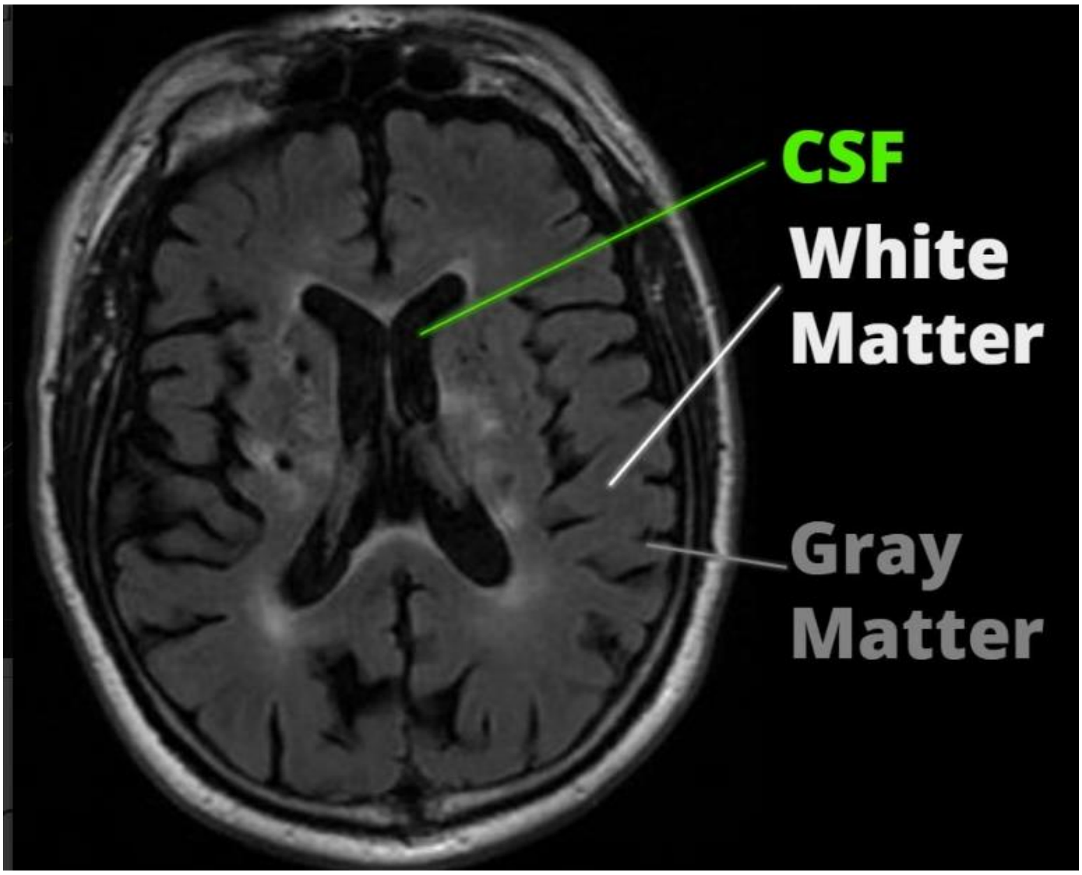

figure 9 : FLAIR MRI

1.3.2 Deep Learning Approaches for brain cancer detection

During the past decades, a wide range of machine learning and deep learning models for detecting brain tumors have been proposed. In this section, a summary of such models is presented.

1.3.2.1 Brain tumor detection with segmentation based machine learning technique

As a large volume of medical MRI imaging data is gathered through image acquisition, the researchers are now proposing different machine learning methods to identify brain tumors. These methods are based on feature extraction, feature selection, dimensionality reduction, and classification techniques. Most of those suggested machine learning models are focused on the binary identification of brain tumors. For example, ***Kharrat et al***. proposed a binary classification of brain images using a support vector machine (SVM) and a genetic algorithm (GA) [7]. In this study, the features are extracted using Spatial Gray Level Dependency (SGLDM) method. In a different study, ***Bahadure et al***., used Berkeley wavelet transformation (BWT) and SVM to segment and categorize normal and abnormal brain tissues [8]. They were able to achieve **96.5%** prediction accuracy on 135 images. In a related study, ***Rehman et al.***, used a Random Forest (RF) classifier to the 2012 BRATS dataset [9]. They compared their model to other classifiers and found that the RF classifier achieve better results in terms of precision and specificity.

Later, for the purpose of identifying brain tumors, ***Chaplot et al***. used a discrete wavelet transform (DWT) as a feature extractor and SVM as a classifier [10]. On 52 images, they achieved ***98%*** prediction accuracy. The K-nearest neighbor (KNN) classifier was then applied by ***El-Dahshan et al***. to 70 images, and the results showed ***98.6%*** prediction accuracy [11]. For feature extraction and feature reduction, they employed DWT and the principle component analysis (PCA), respectively. They also used Particle Swarm Optimization (PSO) and SVM to select and classify textural features. To detect different grading of glioma tumors***, Chen et al***., used a 3D convolution network to segment the tumor region [12]. The segmented tumors are then classified using the SVM classifier. They also used the recursive function exclusion (RFE) method to extract features with significant discriminatory information. More recently, ***Ranjan et al***., proposed a new model using 2D Stationary Wavelet Transform (SWT) as a feature extractor, and AdaBoost and SVM classifiers to detect brain abnormalities.

Although those techniques significantly enhanced brain tumor detection accuracy, they still have several limitations, including:

- Since all these methods are based on binary classification (normal and abnormal), it is not sufficient for the radiologist to decide the patient's treatment concerning tumor grading.

- Those methods are based on different hand-crafted feature extraction techniques, which are time-consuming, complex, and in many cases not effective.

- Techniques that were used in those studies performed well with a small amount of data. However, working with a large volume of data required advanced classifiers

1.3.2.2 Brain tumor detection using convolution neural networks (CNN)

CNN presents a segmentation-free method that eliminates the need for hand-crafted feature extractor techniques. For this reason, different CNN architectures have been proposed by several researchers. Most of the CNN models reported multiclass brain tumor detection, including a vast number of image data. For example, ***Sultan et al***., suggested a CNN model with 16 layers [13]. The CNN model tested on two publicly available datasets. One dataset identified tumors as meningioma, glioma, and pituitary tumors, and the other dataset differentiated between the three grades of glioma tumors, including Grade II, Grade III, and Grade IV. They achieved **96.1%** and **98.7%** prediction accuracies on datasets with 3064 and 516 images, respectively. ***Hossain et al***., used the Fuzzy C-Means clustering technique to extract the tumor area from the MRI images [14]. They proposed a new CNN-basedmodel and compared it to six other machine learning models. The reported ***97.9%*** prediction accuracy outperforms prior models.

A novel hybrid CNN model was created by ***Ertosun et al***. in a different study to find multiclass glioma tumors [15]. For Grade II, Grade III, and Grade IV glioma tumors, they achieved classification accuracy of ***96.0%, 71.0%,*** and ***71.0%,*** respectively. In a similar study, ***Anaraki et al.***, identified glioma tumors with ***90.9%*** prediction accuracy using CNN and GA [16]. They obtained ***94.2%*** prediction accuracy for the diagnosis of pituitary, meningioma, and glioma tumors. More recently, ***Özyurt et al***., suggested a combined Neutrosophy and CNN model. In this model , the Neutrosophy technique is used to segment the tumor zone, the segmented portion is extracted using the CNN model and then classified using SVM and KNN classifiers [17]. In a different study, ***Iqbal et al***., introduced a 10-layer CNN model to tackle this problem [18]. They carried out their experiment on the BRATS 2015 dataset and achieved promising results. As it is discussed here, CNN appears to be doing well for a large image dataset. However, it also suffers from two main limitations as follows:

- CNN model required a vast number of images for training, which is often difficult to obtain in the medical imaging field.

- Convolutional Neural Networks (CNN) perform remarkably well at classifying images that are quite similar to the dataset. CNNs, on the other hand, struggle to classify images that have a slight tilt or rotation. This can be fixed by utilizing data augmentation to continuously introduce new variants to the image during training. To address this problem in our research, we employed the data augmentation technique

1.3.2.3 Brain tumor detection through transfer learning

Transfer learning does well when the volume of data is limited since such a model is previously trained on a large dataset (e.g., the ImageNet database), containing millions of images. In this approach, the pre-trained model with adjusted weights is adopted for the classification tasks. Another benefit is that it does not require a massive amount of computational resources since only the model's fully connected layers need to be trained. Due to such advantages, different transfer learning models have been used for diagnosing brain tumors. For instance, ***Talo et al***., used a pretrained ResNet34 model to detect normal and abnormal brain MRI images. A large-scale of data augmentation is also carried out to reach high prediction accuracy [19]. Furthermore, for detecting multiclass brain tumors, ***Swati et al***., proposed a fine-tuned VGG19 model [20]. Later on ***Lu et al***., suggested a fine-tuned AlexNet structure to diagnose brain abnormalities [21]. In this study, just 291 images were used. In a similar study, ***Sajjad et al***., used a fine-tuned VGG19 model for multiclass brain tumor detection and conducted it on 121 images [22]. They achieved an overall prediction accuracy of ***87.4%*** before the data augmentation. Finally, by applying the data augmentation technique, they increased the accuracy to ***90.7%.*** Despite all the benefits, there are several shortcomings associated with transfer learning which are listed below:

- Pre-trained models fail to obtain satisfactory results when training on imbalance datasets. They are more biased towards classes with a larger number of samples [23].

- Proper fine-tuning is required in pre-trained models. Otherwise, the model will fail to achieve satisfactory results .

Although previous studies achieved significant improvement in brain tumor diagnosis, there is still room for improvement. This research mainly concentrated on overcoming those shortcomings by fine-tuning the deep learning models and improving forecast accuracy.

1.4 Conclusion

Magnetic Resonance Imaging (MRI) has transformed the way brain cancer detection is done. With the help of image processing techniques and deep learning, the potential for tumor identification, segmentation, and characterization has greatly increased. These techniques provide automated and precise methods for detecting and characterizing brain tumors which can bring huge benefits to patients. As research on these techniques continues, they hold.

2 CHAPTER 2 : IMPLEMENTING A DEEP LEARNING MODEL FOR BRAIN CANCER DETECTION IN MRI IMAGES

2.1 Introduction

This chapter will put together some of our new understanding about neural networks into a robust conceptual structure, emphasising the need of precise assessment of models and balancing between Learning and generalisation.

2.2 Deep learning

Deep learning is a special branch of artificial intelligence that stresses the development of successive layers of progressively relevant representations. Deep learning is a revolutionary way to acquire representations through data. The "deep" in "deep learning" refers to several layers of representations rather than any type of greater comprehension that can be gained by the approach. The depth of the model refers to the amount of layers that go into a data model.

Layered patterns learning or hierarchical representations learning could have been better titles for the study. Today's deep learning approaches usually involve hundreds, if not thousands, of representational levels that are learned dynamically via exposure to input data. Other machine learning techniques, referred to as shallow learning techniques, prefer instead to focus on learning just one or two layers of data representations.

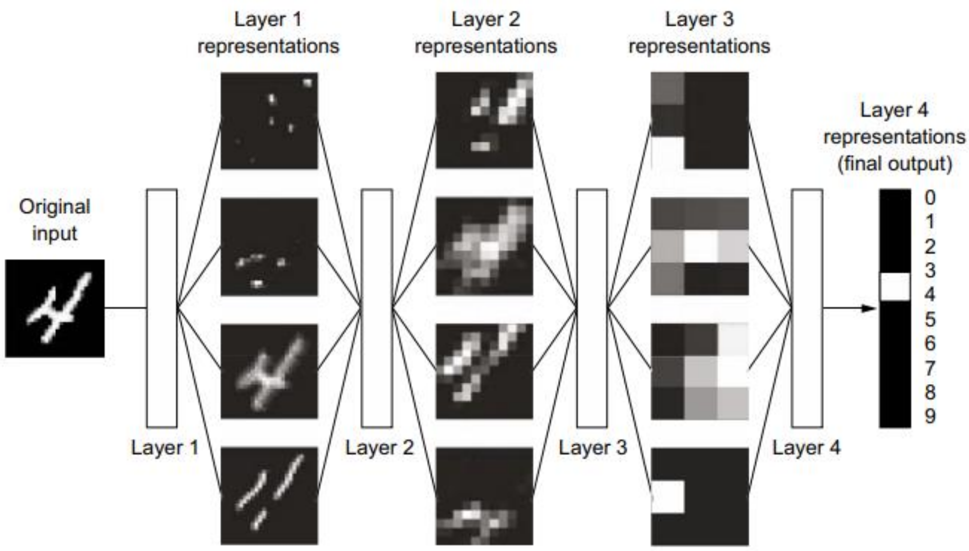

figure 10 : Data representations

On a technical level, a multiple-stage approach of acquiring information interpretations is what deep learning actually is. It's an easy notion, however it turns out that when correctly scaled, even quite basic systems can finish up appearing miraculous. [24]

2.2.1 Understanding how deep learning works

The neuron is the building block of every deep learning method, but in order to harvest its capacity, it must be used in multiple stacks that are called layers, we define this as a neural network. A network of neurons is composed of:

• An input layer: this is the first layer of every neural network, it holds the data that is to be processed,

• A hidden layer (at least): responsible for performing mathematical operations on the values provided by the previous layer. A network with one or two middle layers is called a shallow network, a network with at least 3 middle layers is a deep neural network.

• An output layer: it displays the result of all previous operations. The number of output neurons is equal to the number of desired classes of results.

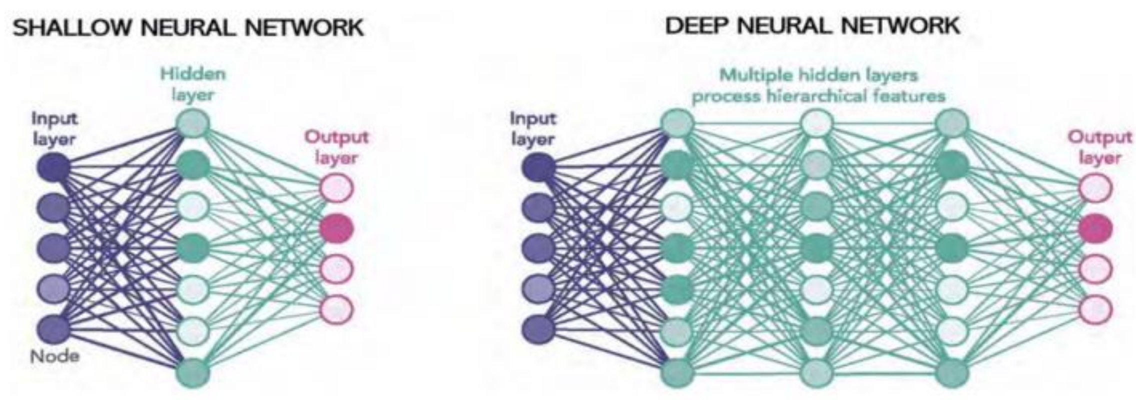

figure 11: Shallow and Deep neural networks

At each neuron, the input signals are multiplied by weights. The neuron calculates the scalar product of input signals and corresponding weights, and adds a bias to the result. Let X = x_1, x_2, ..., x_n an input vector, W = w_1, w_2, ..., wn a weights vector, and b a bias, the neuron calculates the scalar product as follows:

$$S=\sum_{i=1}^{i=n} x_i w_i + b = x_1 w_1 + x_2 w_2 + \cdots + x_n w_n + b \qquad (2\text{-}1)$$

The result is subjected to an activation function, which helps standardize the value. An activation function is a nonlinear mathematical operation that decides whether the neuron gets activated or not. Some commonly used functions are:

• Sigmoid: also called logistic function [25], is defined as:

$$S(x) = \frac{1}{1+e^{-x}} \qquad (2\text{-}2)$$

• ReLU: for Rectified Linear Unit [25], defined as f(x) = max(0, x):

$$f(x) = \begin{cases} 0 & < 0 \\ x & \geq 0 \end{cases} \qquad (2\text{-}3)$$

• Softmax: calculates the probability distribution of an event over n events, probabilities are used to determine the class of the input [26]. The softmax formula is as follows:

$$f(x_i) = \frac{e^{x_i}}{\sum_j^k e^{x_i}} \qquad (2\text{-}4)$$

After training the network on data (called training data), a model is obtained containing the weights of neural connections. A portion of the training data is used to validate the model, by comparing the output of the network to the correct data labels, this set is called validation data. To test the accuracy of the model, another set of data is used, called testing data, the new set contains data samples that the model has not seen before, and serve to assess the performance of the model. The conventional train/test data split is 80%-20% [26].

A deep learning model is not a first time success, it is an iterative process that must be improved by changing its parameters, we call them hyperparameters

2.2.2 Hyperparameters tuning

The learning process of a neural network can be controlled and optimized by configuring hyperparameters to optimal values. A hyperparameter is a variable that defines the structure and performance of a network. The following are the most common hyperparameters for deep learning models:

Number of hidden layers

Hidden layers define the depth of a neural network, they are important for feature learning [26]. In general purpose neural networks, the more hidden layers there are, the better the performance gets. Yet, a potential problem of designing very deep networks is the saturation of performance, which consumes computation resources and execution time.

Activation function

Activation functions are used to determine the output of the network's layers, they are used to add a nonlinearity aspect to the network, as the model tends to adapt better to different sets of data using nonlinear functions rather than linear functions. The choice of an activation function affects the output of the network, sigmoid and tanh are better suitable for binary classification, softmax is more used for multiclass classification, ReLU helps for cases of multiclass classification with interactive effects (the effect of a variable depends on other variables) [27].

Loss function

A loss function calculates the error between the actual class of a sample and the predicted value by the model. The mean values of loss function over the entire sample database is called cost function. Loss function is extremely important for evaluating and optimizing deep neural networks.

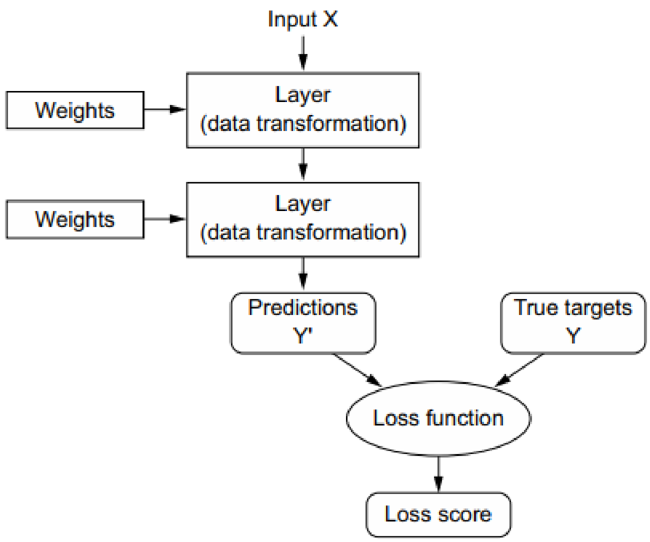

Figure12 : A loss function measures the quality of the network's output

Optimization algorithm

This hyperparameter tries to find a set of intrinsic parameters that perform well with performance metrics (mean quadratic error, log error, etc ..), using gradient descent calculus. An optimization algorithm is an iterative process, it uses parameters to make predictions on data samples, compare the predicted result to the actual data class, calculate the prediction error and update the parameters

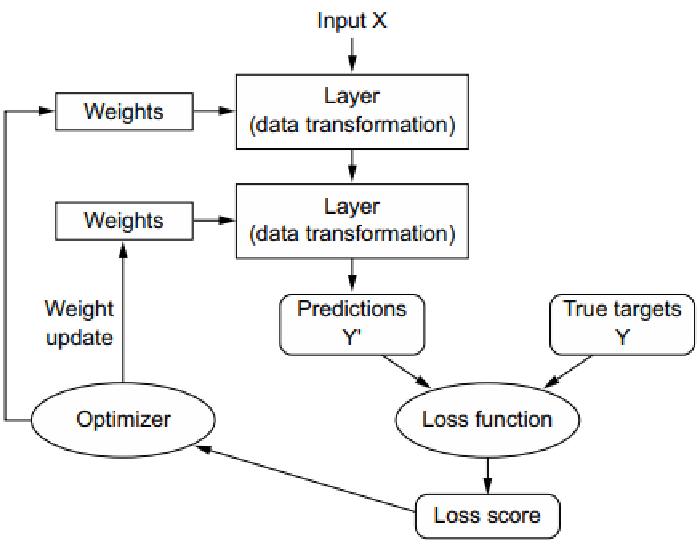

Figure13: The loss score is used as a feedback signal to adjust the weights.

A model with an extremely small loss on its data used for training, and a low misfit among predictions : y_pred, and projected targets : y_true, will ultimately be developed. The model had "learned" how to relate the right outputs to the right inputs. It may look to be magical from afar, but when reduced down into its most fundamental parts, it is actually pretty basic. [24]

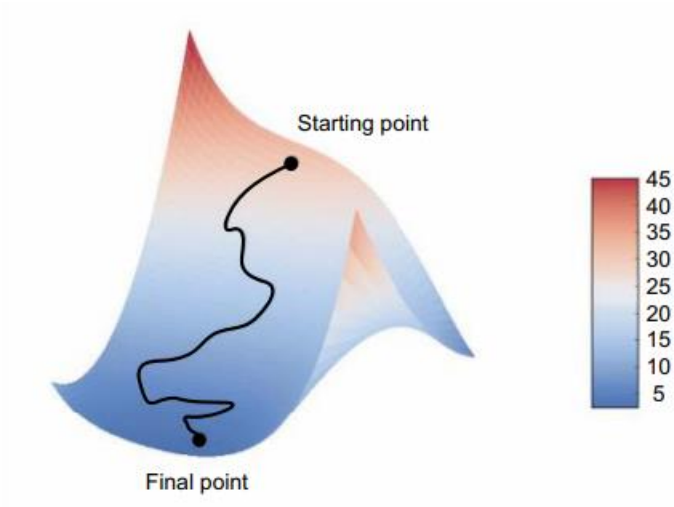

figure 14 : Gradient descent

It exists various SGD variations that differ by computing the subsequent weight update based on prior weight updates as opposed to only considering the gradients' current value. Adagrad, RMSprop, SGD with momentum, and a number of additional programs come to mind. These variations are referred to be optimizers or optimization strategies. We should pay close attention to the idea of momentum, which is present in many of these variations. Momentum handles two SGD problems: local minima and convergence speed. [28]

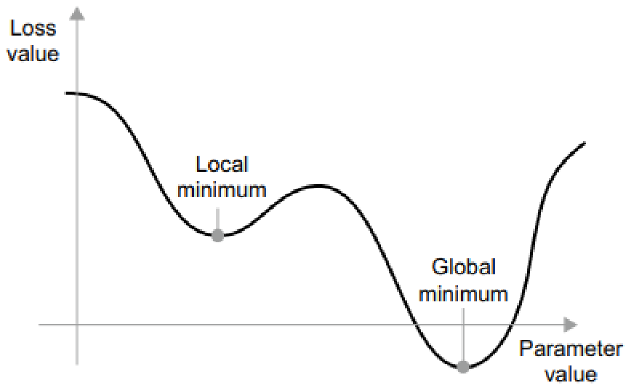

figure 15 : A local minimum and a global minimum

Learning rate

Learning rate defines the speed of convergence of the optimization algorithm towards the optimal minimum of the loss function. A high number gets the algorithm to converge faster but is less precise; a low number means a slower convergence rate, but a better guarantee for global minima searching.

Number of epochs

This hyperparameter defines the number of times that the learning algorithm circles around the input data.

Batch size

It is the number of samples that are processed every time the model is updated. The batch size should be between one and the number of samples in the database.

2.2.3 Generalization: The goal of machine learning

Generalization, as compared to optimization, means how well a model that has been trained works on data it hadn't seen before. Optimization relates to the act of altering a model to get the maximum performance feasible on the training data (the learning in machine learning). obviously the goal of the game is to achieve effective generalization, but we have no influence over generalization; what we are able to do is adjust the model to its training set of information. Overfitting sets in and generalization suffers when we do that too efficiently. (12)

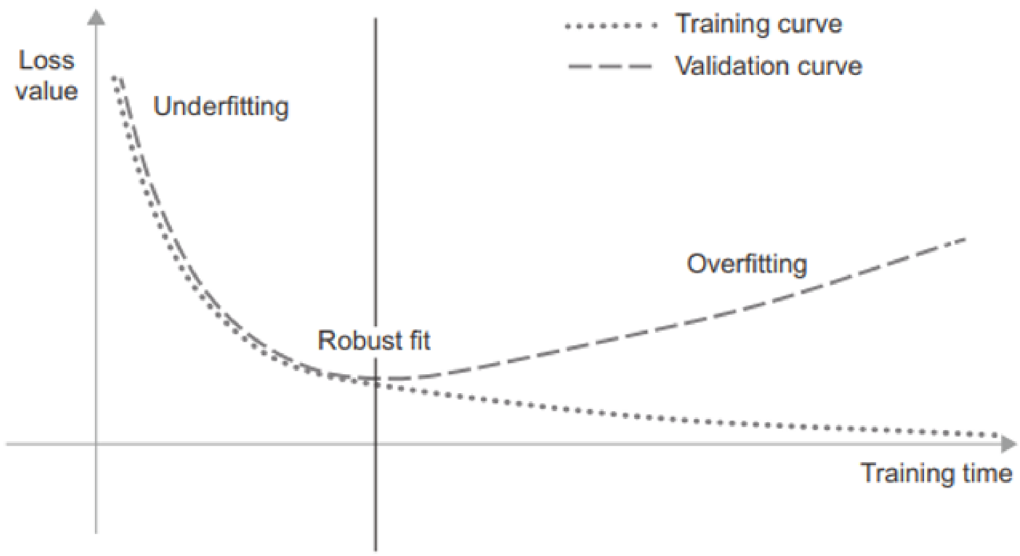

figure 16 : Canonical overfitting behavor

Overfitting is especially prone to take place whenever the information we have is noisy, if it includes unpredictability, or if it includes unusual traits.

Improving generalization

It's time to shift our attention to optimizing generalization once our model has demonstrated some generalization power and the ability to overfit.

- **Early stopping**

Arguably the best approaches to boost generalization is to find the particular training point where we have achieved the highest adaptable fit, the precise split in an underfit curve and an overfit curve.

- **Regularization**

With the goal to enhance the accuracy of the model during validation, regularization techniques are a collection of recommended practices that deliberately impede the ability of the model to match the training data perfectly.

REDUCING THE NETWORK

There is no hidden formula that can tell exactly the number of layers to use or how big every single one should be. To establish the appropriate model size for our data, we must test a range of possible designs (on our validation set, not our test set, of course). Beginning with relatively few layers and parameters and increasing the size of the layers or adding new layers until we see decreased results with regard to validation loss is the traditional technique for obtaining a suitable model size.

WEIGHT REGULARIZATION

In this case, a simple model is one having fewer variables or one having a lower entropy in the parameter variable distribution. Thus, restricting an algorithm's complexity by requiring that its weights only take minuscule values leads to a more regular distribution of weight values, which minimizes the chance of overfitting. This procedure, known as weight regularization, requires adding a cost for having large weights in the model's loss coefficient. There are actually two kinds of this cost:

- L1 regularization : The expense imposed is related to the absolute value of the weight coefficient (the L1 norm of the weights).

- L2 regularization : The expense imposed is related to the square of the value of the weight coefficients (the L2 norm of the weights). L2 regularization is frequently referred to as weight decay in the setting of neural networks.

- **Dropout**

Serves as one of the most efficient and extensively used regularization algorithms for neural networks. When dropout is added to a layer, some of the layer's output attributes are at random eliminated (set to zero) during training.

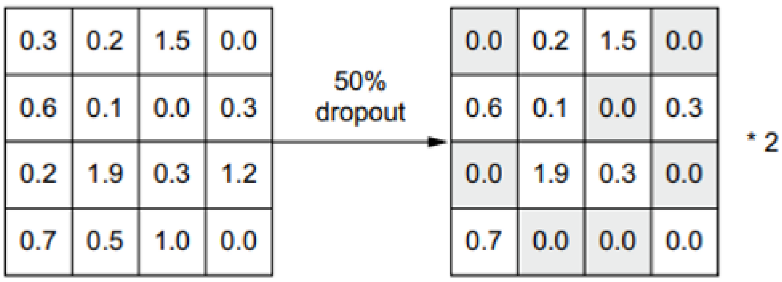

figure 17 : applying dropout

2.2.4 Convolution Neural Network

The oldest and greatest success story of deep learning is computer vision. Google Photos, Google image search, YouTube, video filters in camera apps, OCR software, and many other services let us engage with deep vision models on a daily basis. Additionally, these models serve as the foundation for cutting-edge research in robotics, AI-assisted medical diagnosis, self-operating retail checkout systems, and even autonomous farming.

The issue space that sparked the initial growth of deep learning between 2011 and 2015 was computer vision. Convolutional neural networks, a subset of deep learning models, began to perform extremely well in image classification contests around that time [24].

A CNN is composed of two parts [29]:

• a convolution network: it is a succession of filters that are applied to the input image, resulting in new images called feature maps, the goal is to extract features from input images. At the end of the convolutional network, feature maps are concatenated to obtain a feature vector,

• a classification network: comprizing fully connected layers to classify images, based on the feature vector provided by the previous network.

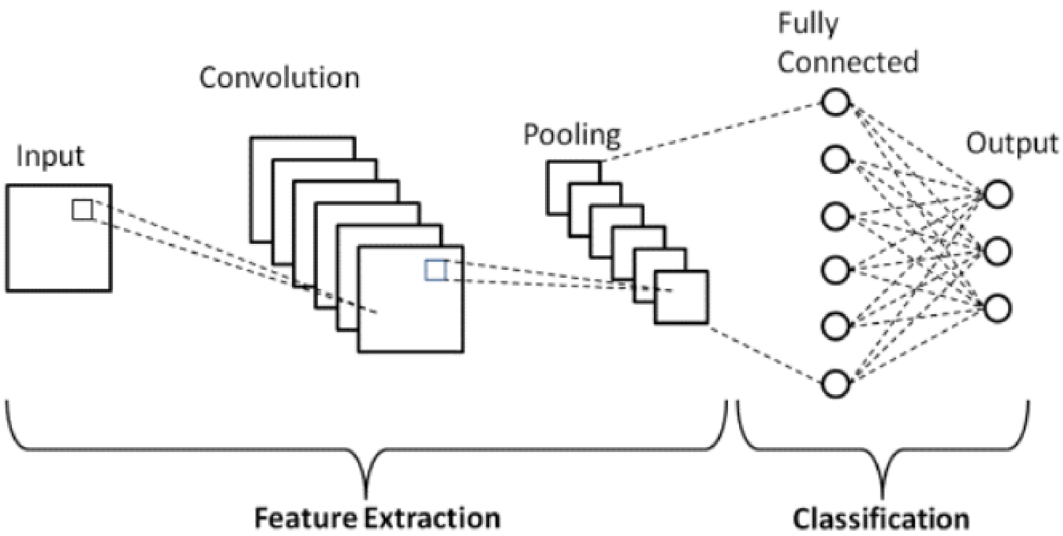

figure 18: Convolutional neural network architecture[29]

CNNs are architectured as follows [29]:

• Input layer: images are formatted to tensors and used as an input to the CNN.

• Convolution layer: it detects features and locates them on the image using convolutional filters. The user chooses a filter that will be applied to the image, the filter slides on the image matrix following a parameter called stride (number of steps along one direction), and preforms a convolution calculus. The output is a feature map that contains extracted information.

A dense layer learns global patterns in its input feature space, whereas a convolution layer learns local patterns. This is the key distinction between a dense layer and a convolution layer.

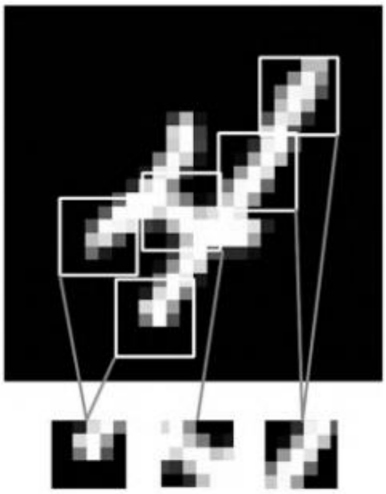

figure 19 : Images can be broken into local patterns such as edges, textures [24]

• Pooling layer: responsible for reducing the dimensions of feature maps while retaining their relevance. Max pooling and average pooling are the most used techniques, while max pooling retains the maximum value of each window of the feature map, average pooling calculates the mean value of each window. This layer helps reduce model parameters and computational resources.

• Fully connected layer: this layer is responsible for the classification, each neuron is connected to all previous and following neurons. The number of output neurons is equal to the number of classes, each neuron outputs the class probability of the input image.

2.2.5 Modern convnet architecture

The model architecture typically determines whether it succeeds or fails. If we adopt an incorrect architecture, our model may be compelled to use less-than-ideal measurements, which no quantity of training data can cure. A robust model architecture, on the other hand, will accelerate learning and allow our model to make the most of the available training data, reducing the need for large datasets. An effective model design makes it easier to find an excellent feature in the search space or else reduces the size of the search space. Like feature engineering and data curation, the purpose of model design is to reduce the issue so that gradient descent may address it.

In addition, most convnets have pyramid-like architectures (feature hierarchies).The total amount of filters increases with layer depth, whereas the dimension of the feature maps decreases.

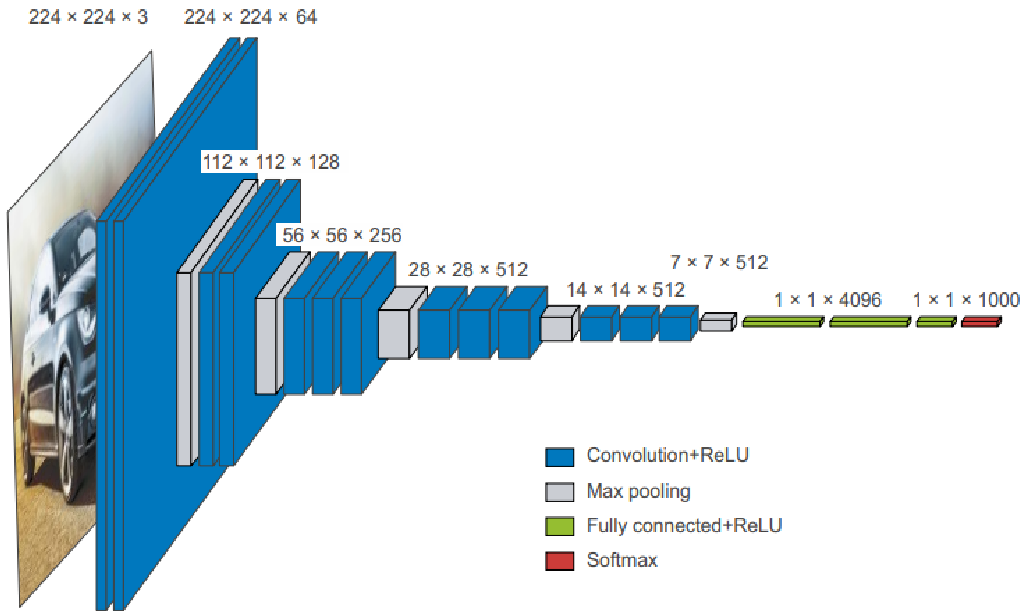

figure 20 : The VGG16 architecture

Deeper hierarchies are beneficial since they encourage reuse of information and, as a result, abstraction.Generally a large stack of thin layers surpasses a narrow stack of thick layers . Nevertheless, the issue of vanishing gradients limits the number of layers that can be stacked. An essential model architecture pattern called resudial connections is introduced to solve this problem. [30]

Residual connections

The residual connection acts as an information tunnel across noisy or disruptive blocks (such as blocks containing relu activations or dropout layers) to allow gradient information from early layers to transit noiselessly through a deep network. This method was first used by the ResNet family of models in 2015..

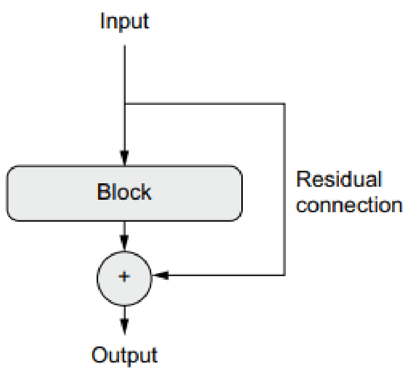

figure 21 : A residual connection around a processing block

2.3 Implementation

For our problem and based on our dataset and literature review we will be interested in implimenting an image classification model.

2.3.1 Environment

For our classification, we proposed a deep convolutional neural network (CNN), since CNNs are best suitable for image recognition, detection and classification, and are known for their high performance and flexibility. The CNN model was developed using Python 3.7, and trained on the Kaggle platform, an online Python editor for machine learning. Python provides users with a diverse set of libraries for machine learning, of which we took advantage for this work. Tensorflow and Keras were used because they offer a direct access to neural network tools, as well as an important set of predefined functions for optimization and performance monitoring.

2.3.1.1 What's TensorFlow?

Google is the main developer of TensorFlow, a Python-based, open-source machine learning framework. TensorFlow's main goal is to give engineers and researchers the ability to work with mathematical expressions over numerical tensors, much like NumPy does. However, TensorFlow significantly outperforms NumPy in the following ways:

- It is capable of calculating the gradient associated with any differentiable expression automatically, thus rendering it ideal for machine learning.
- It is capable of running not just on CPUs, but additionally on GPUs and TPUs, which are extremely parallel hardware accelerators.
- TensorFlow computations can be conveniently dispersed across multiple machines.
- TensorFlow applications can be transferred to different runtimes, like as C++, JavaScript (for browser-based apps), or TensorFlow Lite (for smartphones or embedded devices), among others. TensorFlow solutions are thus simple to deploy in real-world situations.

very crucial to note how TensorFlow is made up of many separate packages. In actuality, it's a platform that supports a diverse ecosystem of elements, some developed by Google and others by third-party developers. TensorFlow Serving, for example, is used for production deployment; TF-Agents is used for reinforcement-learning research; TFX is used for industry-strength machine learning workflow management; and the TensorFlow Hub is a library of pretrained algorithms. When these parts are coupled, they can be used for a wide range of applications, from innovative studies to mass production. [31]

2.3.1.2 What's Keras?

Any deep learning model can be easily defined and trained using the deep learning Python API, which is built on top of TensorFlow. In the beginning, Keras was created for research with the intention of facilitating quick deep learning experiments. TensorFlow enables Keras to run on a variety of hardware platforms.

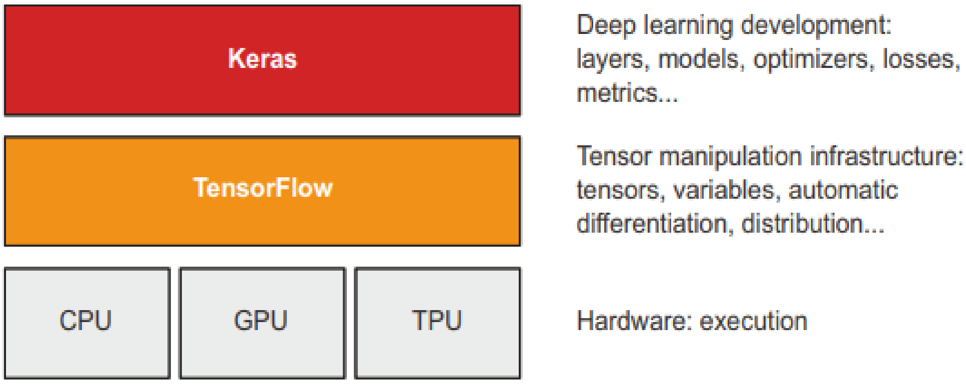

figure 22 : Keras and TensorFlow

Keras is well-known for prioritizing the programmer's experience. It's an API for humans, not machines. It follows standards for reducing cognitive load by offering simple workflows, reducing the number of tasks required for typical applications, and delivering clear, useful information in the case of user error. As a result, Keras is simple to learn for newcomers and extremely effective for a professional to use.

2.3.2 Downloading the data

The information we'll work with will typically come into one of these categories.:

- • Vector data: Rank-2 structure tensors (samples, features), with every one of the samples including a vector of quantitative properties ("features").
- • Sequence data or timeseries data: Rank-3 structure tensors (samples, timesteps, features), whereas every sample is an ordered set of vectors of features
- • Images: Shape Rank-4 tensors (samples, height, width, channels), with each sample is a 2D grid of pixels corresponding to a vector of data ("channels").
- • Video: Rank-5 structure tensors (samples, frames, height, width, channels), in which each sample represents an image sequence (of length frames).

2.3.2.1 Image data

Height, width, and color depth are the three dimensions that most images have. Although rank-2 tensors might be used to store grayscale images because they only have one color channel, by convention image tensors are always rank-3, even if grayscale photos only have a single color channel. Thus, a tensor of shape (128, 256, 256, 1) could hold a batch of 128 256 256 grayscale images, whereas a tensor of shape (128, 256, 256, 3) could hold a batch of 128 256 256 color photos.

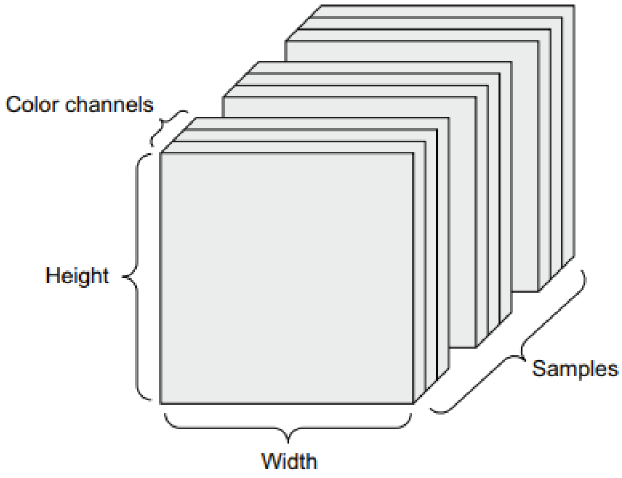

figure 23 : A rank-4 image data tensor

2.3.2.2 Our data

Our work aims to classify MRIs into two classes, making it a two-class problem. The data for our Neural Networks is in digital format (.jpg).

This data is collected from Kaggle. The folder contains 3264 MRI images. These images were split in the ratio of 7:3 for the Training and Testing phases, accordingly

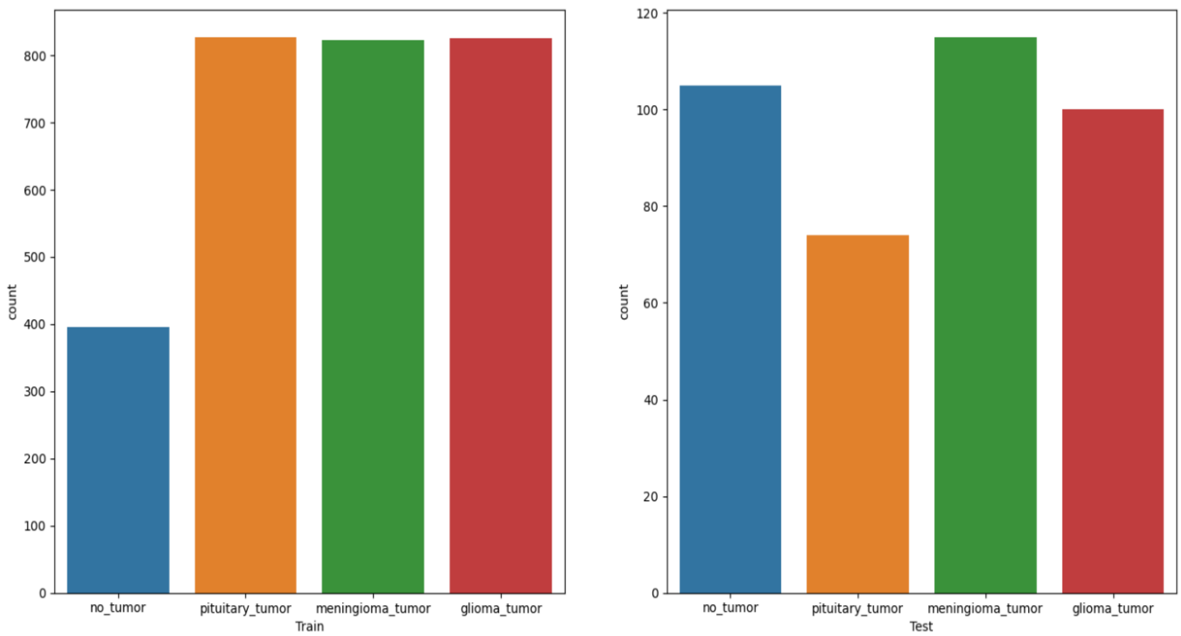

figure 24 : data explorer

I gathered then the tumor classes to a single folder yes_tumor to get at the end a trainning data of 395 image of no_tumor and 2475 image of yes_tumor and a testing data of 105 image of no_tumor and 289 of yes_tumor.

Hence, we will classify based on a Brain MRI image whether a patient has Brain Tumor or not.

2.3.3 Building the model

A graph of layers represents a deep learning model. That is the Model class in Keras. We are employing the sequential models, which are straightforward stacks of layers that transfer a single input to a single output. However, the range of network topologies is significantly greater. Here are a few typical examples:

- Two-branch networks
- Multihead networks
- Residual connections

When the model architecture is specified, we must select three further items:

- Loss function: The amount that will be reduced during training. It provides a metric for achievement for the current task.
- Optimizer: Establishes how to revise the network based on the loss function. It employs a form of stochastic gradient descent (SGD).
- Metrics: Success indicators that we want to track throughout training and validation, such as classification accuracy. Training, unlike loss, will not explicitly optimize for these variables. As a result, measurements aren't required to be differentiable.

Keras has a plethora of standard features that include everything we require:

Optimizers:

- SGD (with or without momentum)
- RMSprop
- Adam
- Adagrad

Losses:

- CategoricalCrossentropy
- SparseCategoricalCrossentropy
- BinaryCrossentropy
- MeanSquaredError
- KLDivergence
- CosineSimilarity

Metrics:

- CategoricalAccuracy
- SparseCategoricalAccuracy
- BinaryAccuracy
- AUC
- Precision
- Recall

Problem type	Last-layer activation	Loss function
Binary classification	sigmoid	binary_crossentropy
Multiclass, single-label classification	softmax	categorical_crossentropy
Multiclass, multilabel classification	sigmoid	binary_crossentropy

Table 1 : last activation and loss function

2.3.4 Data preprocessing

Based on the literature review of the work that have been done and on some experimental search using the OpenCV library we chose to use the following techniques.

2.3.4.1 Cropping

A dark background surrounds the central image of the brain in the MRIs. This black background is useless for learning about the tumor and would be wasted if fed to neural networks. As a result, trimming the photographs around the primary contour might be beneficial.

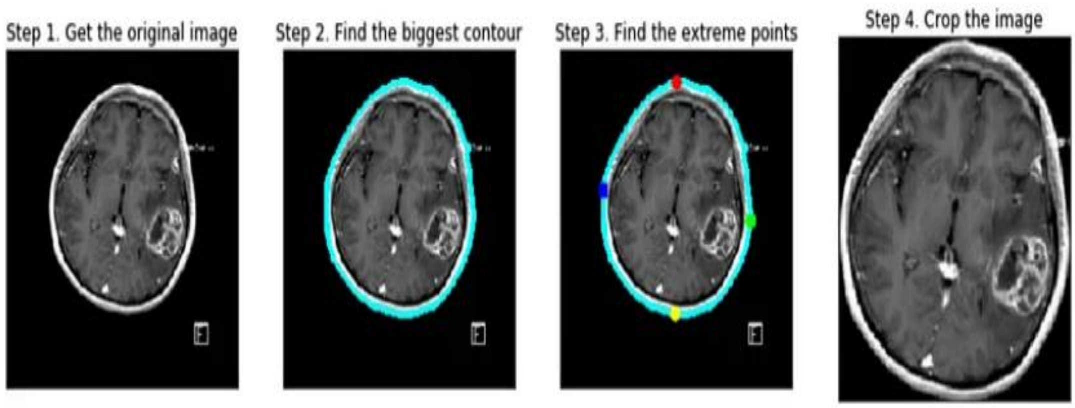

figure 25 : image cropping

2.3.4.2 Nlm : Non-Local Means Denoising

The approach works on a simple principle: replace a pixel's color with a median of the colors of comparable pixels. However, the most comparable pixels to that particular pixel have no need to be that close. It is thus permissible to scan a large section of the image in trying to find all the pixels that closely match the pixel to be denoised. [32]

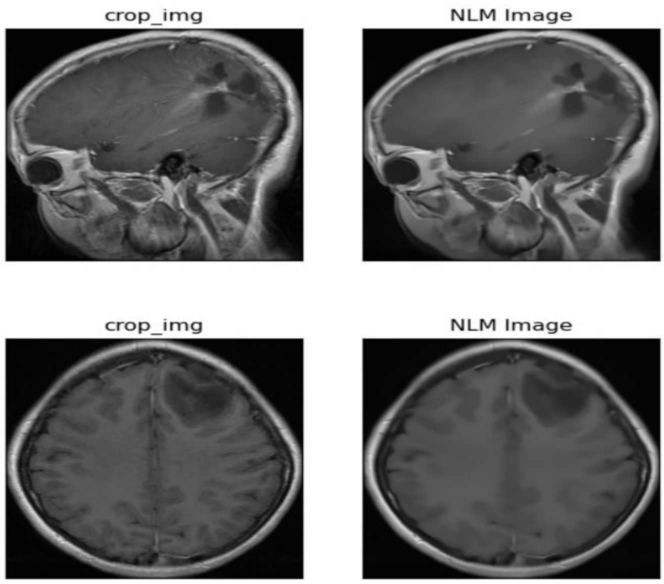

figure 26 : applying an NLM filter on MRI images

2.3.4.3 Histogram equalisation

Histogram equalization is a contrast correction approach in image processing that makes use of the image's histogram. The best method for image enhancement is histogram equalization. It improves the quality of images without sacrificing information.

This method typically raises the global contrast of numerous photos, particularly when the image's useable data is represented by close contrast values. The intensities on the histogram can be better spread with this change. This permits areas with poor local contrast to gain contrast. This is accomplished using histogram equalization, which effectively spreads out the most common intensity values. [33]

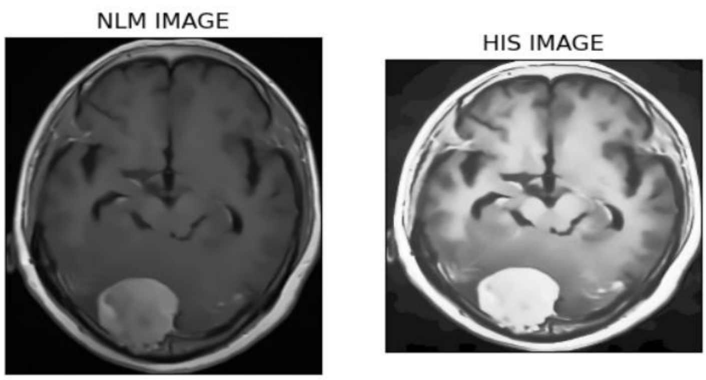

figure 27 : applying histogram equalization on MRI

2.3.5 Using data augmentation

The amount of data collected was insufficient, which could cause the models to under-fit. As a result, we would employ a clever Data Augmentation strategy to expand the amount of data. To create similar photos, this approach employs rotations, flips, changes in exposure, and so on. Using this strategy, we can greatly enhance the size of data.

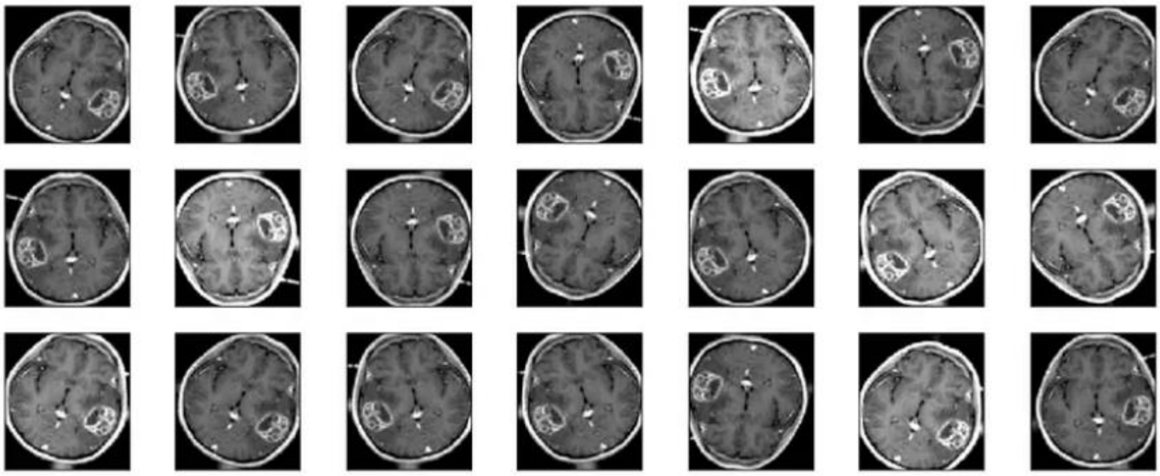

figure 28 : augmented images

2.3.6 Leveraging a pretrained model

The training process for deep convolutional neural network models on very big datasets might take days or even weeks.

Reusing the model weights from pre-trained models that were created for common computer vision benchmark datasets, including the ImageNet image recognition tasks, is a way to speed up this procedure. The best models can be downloaded and used immediately, or they can be included in a new model to solve our own computer vision issues. [34]

2.3.6.1 Feature extraction with a pretrained model

The process of extracting interesting features from fresh samples involves exploiting the representations that a model that has already been trained has learned. Then, a fresh classifier that was trained from start is fed these features.

Convnets used for image classification include two main components: a densely connected classifier at the end and a sequence of pooling and convolution layers at the beginning. The model's convolutional base is the initial component. Using a previously trained network's convolutional base, fresh data is sent through it, and a new classifier is then trained using the results. This is how feature extraction works with convnets.

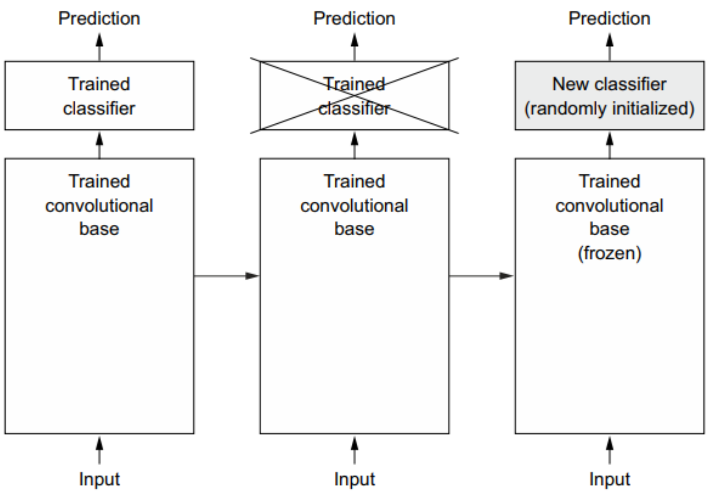

figure 29 : Swapping classifiers

2.3.6.2 Fine-tuning a pretrained model

Fine-tuning entails jointly training the model's newly included component and unfreezing certain of the top layers of a frozen model base for the purpose of feature extraction. Fine-tuning implies the process of making incremental changes to more abstract model representations with the goal to make them more appropriate to the current issue. [24]

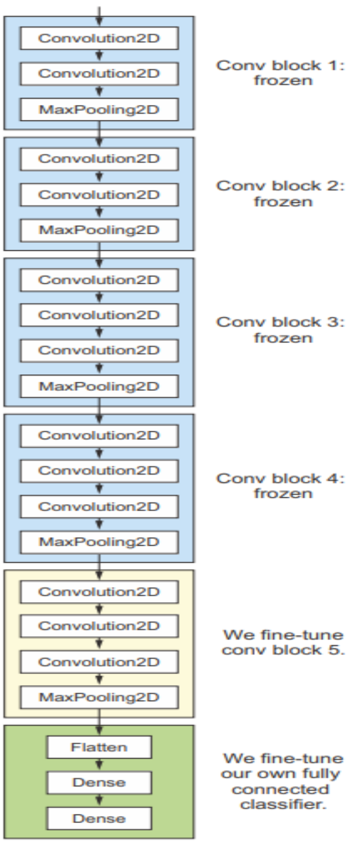

figure 30 : Fine-tuning the VGG16 network

2.4 Conclusion

In this chapter, we proposed a method for processing images, based on cropping, filtering, histogram equqlization and augmentation, therefore allowing a better edge definition and noise removal, and proposed a customized and fine-tuned CNN model for the purpose of brain MRI images binary classification. In the following chapter, we will experiment with the model and study the effect of preprocessing on the accuracy of classification.

3 Chapter 3: results and discussion

3.1 Introduction

This chapter is dedicated to model deployment and performance assessment. We proceeded to experiment with the effect of preprocessing techniques on the efficiency of the CNN model, along with the analysis and interpretation of the results

3.2 Evaluation metrics

To assess the performance of a neural network, we use a set of indicators:

3.2.1 Confusion matrix

The confusion matrix is an important metric that describes the complete performance of the model . For the example of a binary classification task, it provides 4 values:

- True Positives (TP): positive prediction, positive class
- True Negative (TN): negative prediction, negative class
- False Positive (FP): positive prediction, negative class
- False Negative (FN): negative prediction, positive class [35]

3.2.2 Accuracy

The rate of correct predictions of all performed predictions

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FN} \qquad (3\text{-}1)$$

3.2.3 Precision (Positive Predictive Value)

It is the rate of correct positive prediction of all positive predictions

$$Precision = \frac{TP}{TP+FP} \qquad (3\text{-}2)$$

3.2.4 Recall (Sensitivity)

Also called true prediction rate (TPR), it is the rate of correct positive predictions of all correct predictions

$$Rcall = \frac{TP}{TP+FN} \qquad (3\text{-}3)$$

3.2.5 F1 score

Harmonic mean between precision and recall values, ranging between 0 and 1

$$F1_{score} = 2 * \frac{1}{\frac{1}{pecision}+\frac{1}{recall}} \qquad (3\text{-}4)$$

3.3 Results

We gonna start by altering the architechture of the model and choosing the one with the best results and then apply the image processing techniques and data augmentation to refine our results and finally compare it to the results obtained after training on a pretrained model and fine tuning it.

3.3.1 Architecture effect

The architecture with the best result was a sequential model with:

- an input layer that uses 3-channels images with size (250*250)
- five convolution blocks containing a conv2d layer with increesing number of filter going from 32 to 512 of 3*3 size, a RELU activation fuction and a same padding. Followed by a MaxPooling layer, Dropout layer and a BatchNormalization Layer.
- A classifier head containing a flatten layer followed with a dense layer with 512 units and a relu activation followed by a dropout layer and a batchnormalization layer
- An output layer : dense layer with 2 units and a sigmoid activation

For validation loss= 0.347 and validation accuracy= 0.913 we have

Diagnosis	Value	number of samples	Precision	Recall	F1-score
No_tumor	0	105	0.81	0.89	0.85
Yes_tumor	1	289	0.96	0.92	0.94

table 2 : Evaluation metrics - Original database

TP=93	FP=12
FN=22	TN=267

table 3 : Confusion matrix - Original database

3.3.2 Image processing effect

While applying our our processing techniques we measured the results on our data dor each process and for the combination of ones with the best results.

3.3.2.1 Cropping effect

For validation loss= 0.318 and validation accuracy= 0.921 we have

Diagnosis	Value	number of samples	Precision	Recall	F1-score
No_tumor	0	105	0.78	0.98	0.85
Yes_tumor	1	289	0.99	0.88	0.93

table 4 : Evaluation metrics – Cropped database

TP=103	FP=02
FN=29	TN=260

table 5 : Confusion matrix - Cropped database

3.3.2.2 Histogram equalisation effect

For validation loss= 0.38 and validation accuracy= 0.88 we have

Diagnosis	Value	number of samples	Precision	Recall	F1-score
No_tumor	0	105	0.78	0.76	0.77
Yes_tumor	1	289	0.91	0.92	0.92

table 6 : Evaluation metrics – database with histogram equalization

TP=80	FP=25
FN=22	TN=267

table 7 : Confusion matrix - database with histogram equalization

Despite the good result showen by applying the histogram equalisation on the datasets in the literature review, we had bad result because by passing from the 3 channel images to greyscale , we lost features.

3.3.2.3 Non-Local Means Denoising

For validation loss= 0.311 and validation accuracy= 0.934 we have

Diagnosis	Value	number of samples	Precision	Recall	F1-score
No_tumor	0	105	0.81	0.99	0.89
Yes_tumor	1	289	1.00	0.91	0.95

table 8 : Evaluation metrics – database with NLM filtering

TP=104	FP=01
FN=25	TN=264

table 9 : Confusion matrix– database with NLM filtering

3.3.2.4 Cropping and NLM effect

For all the combination between the image processing techniques the Cropping with NLM denoising gives the best results but almost as the NLM effect alone.

For validation loss= 0.308 and validation accuracy= 0.936 we have

Diagnosis	Value	number of samples	Precision	Recall	F1-score
No_tumor	0	105	0.81	0.99	0.89
Yes_tumor	1	289	1.00	0.92	0.95

table 10 : Evaluation metrics – cropped database with NLM filtering

TP=104	FP=01
FN=24	TN=265

table 11 : Confusion matrix– cropped database with NLM filtering

3.3.3 Data augmentation effect

After adding a data augmentation block using flipping, rotation and brightness and increasing the number of epochs we managed to refine our results.

For validation loss= 0.301 and validation accuracy= 0.944 we have

Diagnosis	Value	number of samples	Precision	Recall	F1-score
No_tumor	0	105	0.83	0.99	0.90
Yes_tumor	1	289	1.00	0.91	0.95

table 12 : Evaluation metrics – augmented database

TP=104	FP=01
FN=21	TN=268

table 13 : Confusion matrix– augmented database

3.3.4 Levereging and fine tuning a pretrained model effect

After training multiple versions of pretrained models(InceptionResnet V2,VGG16…), the **EfficientNetB0** model (already exist as Keras application) which have a total of 237 layers organized in 7 blocks, gave the best results using transfer learning with the weights from the **ImageNet** dataset. The fine tuning of the seventh block does not improve the results.

For validation loss= 0.078 and validation accuracy= 0.972 we have

Diagnosis	Value	number of samples	Precision	Recall	F1-score
No_tumor	0	105	0.96	0.99	0.97
Yes_tumor	1	289	1.00	0.91	0.99

table 14 : Evaluation metrics – database with pretrained model

TP=105	FP=00
FN=11	TN=278

table 15 : Confusion matrix– database with pretrained model

3.4 Discussion

The experiments that were conducted on the proposed model focused on the characteristics of the image, and helped study the effect of preprocessing on the accuracy and loss of convolutional neural networks in this particular case. After analyzing the results, we can deduce the following:

- Cropping: after finding the brain contour, cropping helped reduce the size of the images, removed unnecessary information, diminished the model execution time by reducing the number of pixels. In terms of performance, cropping increased the accuracy compared to the unprocessed image database.
- Filtering: dark and light pixel adjustment using Non-Local Means Filter helped reduce the speckle noise present in the image, resulting in an overall neater image with less unnecessary parameters to retain. This filter allowed better accuracy and less error than the previous results, proving that noise has the most devastating effect on CNN performance.
- Data augmentation: By creating fresh and varied instances to train datasets, data augmentation helped us enhance the performance and results of our models.
- Pretrainrd Model: Instead of starting from scratch, we used the weights and features learned by the pre-trained model as a starting point so we can leverage the knowledge and experience of the pre-trained model to avoid overfitting issues. With this transfer learning we managed to obtain even better resuls and increase the accuracy in less time.

3.5 Conclusion

The comparative study conducted on our work showed that our strategy gave reliable results. The accuracy rate and performance metrics were satisfying, proving that the proposed model can serve as an aiding tool for decision making.

SUMMARY

In this research project, we delved into the complex task of addressing the classification problem of MRI brain cancer images using a deep neural network architecture. Our primary aim was to develop a robust system and evaluate its performance in accurately classifying these images. To lay a solid foundation for our study, we conducted an extensive anatomical exploration of the brain, delving into its intricate structure and functionality, while also gaining insights into how tumors affect various regions and functions.

The overarching objective of our study was to create an automated assessment tool capable of distinguishing between cancerous and non-cancerous cases in MRI images, employing the power of machine learning algorithms. For this purpose, we proposed the utilization of a deep neural network architecture, specifically opting for convolutional neural networks (CNNs) due to their proven track record in image classification and object detection tasks. CNNs excel at capturing intricate patterns and features in images, making them an ideal choice for our application.

With meticulous care, we designed a CNN architecture specifically tailored for binary classification of MRI brain cancer images. To optimize its performance, we fine-tuned various hyperparameters, ensuring an optimal convergence to achieve the best possible results. By carefully adjusting parameters such as the number of layers, the size of filters, and the learning rate, we aimed to strike a balance between model complexity and performance.

However, our research did not stop at the development of the customized CNN architecture. We recognized the crucial role of image preprocessing in enhancing the quality and interpretability of the input data. Hence, we conducted an in-depth investigation into various preprocessing techniques. Through our experimental protocol, we explored the effects of cropping, filtering, and augmentation on the MRI images. These techniques aimed to eliminate unnecessary information, reduce noise, and augment the dataset to create a more diverse and representative training set. By integrating these preprocessing steps into our workflow, we sought to further enhance the performance and robustness of our classification system.

Additionally, we explored the application of transfer learning to our dataset. By leveraging a pretraining model, we aimed to benefit from the wealth of knowledge and feature representations learned from a model trained on a large-scale dataset. Transfer learning allowed us to accelerate the training process, improve the generalizability of our model, and potentially overcome limitations associated with a relatively small dataset. By adapting and fine-tuning the pretraining model to our specific task, we aimed to boost the performance of our deep neural network architecture even further.

Through our proposed strategy, encompassing the customized CNN architecture, carefully designed preprocessing techniques, and the incorporation of transfer learning, we observed significant improvements in terms of class accuracy. Moreover, the implementation of these techniques led to a reduction in false negatives and false positives, which are critical factors in medical image analysis. The promising results obtained in this work highlight the potential of deep neural networks as valuable aiding tools in the general assessment of MRI brain cancer cases.

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Abstract

This report is part of the final dissertation for the research master's degree in Information System Techniques (IST).

Our research focuses on developing a binary classification system for MRI Brain Cancer images. This system is based on convolutional neural networks (CNN).

Preprocessing, learning and performance evaluation were carried out, and prediction results reached 97.2%.

Key words: MRI, image classification, Tumors, Brain Cancer, deep neural network, CNN.