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A Deep Learning Web Application for MRI Brain Tumor Images Analysis

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Jury

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Thinks

Above all, we would like to thank GOD for granting us health, the possibility and the will to start and continue our studies.

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Dedicate

I dedicate this memoir to:

My dearest mother for all her love and devotion, to my father who has always been there for me and who gave me a magnificent model of hard work and perseverance.

My dear brother Abde Samad for his unfailing encouragement.

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My Angel Mohammed Adam

All the people of my big family.

My dear binomial " FETTAH Abir " and all her family.

To all my friends of promotion and especially : DJEZZAR Meryem, and to my close friends: TOUMI Fatima Zahraa, ATIA Ibtissem, HAKOUM Khawla Nor El houda and AMARI Aycha.

I hope that they will find in this work all my gratitude and love.

To myself.
Bouchra

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To all the people I love and who love me

To myself.
Abir

Abstract

The scope for improved disease detection and treatment planning is accompanied by accurate and fully automatic algorithms for brain tumor classification and segmentation from volumetric 3D magnetic resonance imaging (MRI). Glioma, is one of the most common types of primary brain tumors and is divided into two grades according to the World Health Organization (WHO). While the human interpretation of the large amount of MRI image data is not only irreproducible but also depends on expertise, time consuming and efforts.

In this work, we try to address this problem by developing a web application to classify brain tumors into two classes: High-Grade Glioma (HGG) and Low-Grade Glioma (LGG). The proposed solution includes two parts. First, applying a pretrained Convolutional Neural Network based model using VGG-16, ResNet-50 and Inception V3 for transfer learning to four datasets one for each MRI modality (T1, T1ce, T2 and FLAIR) to select which modality presents more specific features and information, passing by image pre-processing and data augmentation. To further improve tumor classification, non-tumorous slices were removed from the HGG class of the selected dataset and then was separately used to train the three models. Secondly, we present our web application Med3csEG that is one of the support system decisions by mentioning all the steps of the modeling and realization of every functionality which are introduced in home page, login and registration pages and the main page for completing the brain tumors classification task.

Evaluations on BraTS 2019, attest that T1 presents the most discriminative features to distinguish between LG and HG gliomas with 0.9513, 0.907 and 0.9487 for the accuracy, sensitivity and specificity respectively. The Inception V3 model trained on T1 dataset outperforms the other models with 0.9975, 0.9894 and 1 for the accuracy, sensitivity and specificity respectively.

Experimental results demonstrate that using Inception V3 model with T1 MRI modality has the potential to achieve good results in brain tumor classification.

Keywords

Deep learning, CNN, transfer learning, classification, segmentation, BraTS 2019 dataset, HGG, LGG, MRI, MED3csEG, web application.

Résumé

La possibilité d'améliorer la détection des maladies et la planification des traitements s'accompagne d'algorithmes précis et entièrement automatiques de classification et de segmentation des tumeurs cérébrales à partir de l'imagerie volumétrique 3D par résonance magnétique (IRM). Le gliome est l'un des types les plus courants des tumeurs cérébrales primaires et est divisé en deux grades selon l'Organisation mondiale de la santé (OMS). L'interprétation humaine de la grande quantité de données d'images IRM est non seulement non reproductible mais dépend également de l'expertise, du temps et des efforts.

Dans ce travail, nous essayons de résoudre ce problème en développant une application web pour classer les tumeurs cérébrales en deux classes : Gliome de haut grade (GHG) et Gliome de bas grade (GBG). La solution proposée comprend deux parties. Tout d'abord, l'application d'un modèle pré-entraîné basé sur un réseau de neurones convolutif utilisant VGG-16, ResNet-50 et Inception V3 pour transférer les connaissances acquises à quatre ensembles de données, un pour chaque modalité d'IRM (T1, T1ce, T2 et FLAIR), afin de sélectionner la modalité qui présente des caractéristiques et des informations plus spécifiques, en passant par le prétraitement des images ainsi l'augmentation des données. Pour améliorer encore la classification des tumeurs, les coupes non tumorales ont été supprimées de la classe HGG de l'ensemble de données sélectionné, puis ont été utilisées séparément pour entraîner les trois modèles. Deuxièmement, nous présentons notre application web Med3csEG qui est l'une des systèmes d'aide à la décision en mentionnant toutes les étapes de la modélisation et de la réalisation de chaque fonctionnalité qui sont introduites dans la page d'accueil, les pages d'authentification et d'enregistrement et la page principale pour compléter la tâche de classification des tumeurs cérébrales.

Les évaluations sur BraTS 2019, attestent que la modalité T1 présente les caractéristiques les plus discriminantes pour distinguer les gliomes LG et HG avec 0,9513, 0,907 et 0,9487 pour la précision, la sensibilité et la spécificité respectivement. Le modèle Inception V3 entraîné sur l'ensemble de données T1 surpasse les autres modèles avec 0,9975, 0,9894 et 1 pour la précision, la sensibilité et la spécificité respectivement.

Les résultats expérimentaux montrent que l'utilisation du modèle Inception V3 avec la modalité IRM T1 peut permettre d'obtenir de bons résultats dans la classification des tumeurs cérébrales.

Mots clés

Apprentissage profond, CNN, apprentissage par transfert, classification, segmentation, base de données BraTS 2019, GHG, GBG, IRM, MED3csEG, application web.

الملخص:

يرافق تحسين نطاق اكتشاف المرض وتخطيط العلاج خوارزميات دقيقة وتلقائية بالكامل لتصنيف ورم الدماغ وتجزئة من التصوير بالرنين المغناطيسي ثلاثي الأبعاد (MRI). الورم الدبقي ، هو أحد أكثر أنواع أورام الدماغ الأولية شيوعًا وينقسم إلى درجتين وفقًا لمنظمة الصحة العالمية (WHO) ، في حين أن الترجمة و التحليل البشري لكمية كبيرة من بيانات الصور الناتجة عن التصوير بالرنين المغناطيسي ليس فقط غير قابل للتكرار ولكنه يعتمد أيضًا على الخبرة والجهد والوقت.

في هذا العمل ، نحاول معالجة هذه المشكلة من خلال تطوير تطبيق ويب لتصنيف أورام الدماغ إلى فئتين: الورم الدبقي عالي الدرجة (ودع د) والورم الدبقي منخفض الدرجة (ودم د). الحل المقترح يشمل جزئين : أولاً ، تطبيق نموذج قائم مسبقًا على الشبكة العصبية التلافيفية باستخدام نموذج VGG-16 و ResNet-50 و Inception V3 لنقل التعلم إلى أربع مجموعات من البيانات واحدة لكل طريقة تصوير بالرنين المغناطيسي (T1 و T1ce و T2 و FLAIR) لتحديد الطريقة التي تقدم ميزات أكثر دقة و المعلومات اوفر ، مروراً بالمعالجة المسبقة للصور وزيادة البيانات. لزيادة تحسين تصنيف الورم ، تمت إزالة الشرائح غير الورمية من فئة ودع د لمجموعة البيانات المحددة ثم تم استخدامها بشكل منفصل لتدريب النماذج الثلاثة. ثانيًا ، نقدم تطبيق الويب الخاص بنا Med3csEG وهو أحد أنظمة دعم القرارات من خلال ذكر جميع خطوات النمذجة وتحقيق كل وظيفة يتم تقديمها في الصفحة الرئيسية وصفحات تدوين الدخول والتسجيل والصفحة الرئيسية لاستكمال مهمة تصنيف أورام الدماغ. ثانيًا ، تطوير تطبيق الويب الخاص بنا الذي يحتوي على الصفحة الرئيسية وصفحات تدوين الدخول والتسجيل والصفحة الرئيسية لتصنيف أورام المخ.

تشهد التقييمات التي أجريت على BraTS 2019 أن المجموعة T1 تقدم أكثر الميزات دقة للتمييز بين الورم الدبقي ع د و م د مع 0.9513 و 0.907 و 0.9487 من أجل الدقة والحساسية والنوعية على التوالي. يتفوق النموذج Inception V3 المدرب على مجموعة البيانات T1 على النماذج الأخرى بـ 0.9975 و 0.9894 و 1 من حيث الدقة والحساسية والنوعية على التوالي.

تظهر النتائج التجريبية أن استخدام نموذج Inception V3 مع مجموعة البيانات T1 المتحصل عليها عن طريق التصوير بالرنين المغناطيسي انه لديه القدرة على تحقيق نتائج جيدة في تصنيف هذا النوع من أورام المخ.

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Glossary

MRI : Magnetic Resonance Imaging

DL: Deep Learning

AI : Artificial Intelligence

DBNs : Deep Belief Networks

GANs : Generative Adversarial Networks

CNN : Convolution Neural Network

ResNet : Residual Network

RNNs : Recurrent Neural Networks

Convo: Convolution.

FC: Fully connected

BraTS : Brain Tumor Segmentation Challenge

HGG: High-Grade Glioma

LGG: Low-Grade Glioma

ReLU: Rectified Linear Unit

VGG : Visual Geometry Group

UML: Unified Modeling Language

DB : Database

TP: true positives

TN: true negatives

FP: false positives

FN: false negatives

Web-App: Web Application

MED3csEG: Medical 3D Classification & Segmentation web application

Introduction

Brain is one in all the foremost complex organs within the human body that works with billions of cells. Sometimes these cells can be exposed to an uncontrolled division of cells and formed an abnormal group of cells around or inside the brain that's what we called brain tumors.

This kind of tumors can affect the traditional functionality of the brain activity and cause many problems. Cerebral tumors are classed to benign tumors or low-grade (grade I and II) and malignant tumors or high-grade (grade III and IV). Some of the benign brain tumors are Gliomas (low-grade Gliomas LGG), and the majority of malignant brain tumors are Gliomas (high-grade Gliomas HGG).

Due to the considerable progress in medical image acquisition devices comprises different modalities and processes, including Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), among others, the medical data is quite voluminous.

Magnetic resonance imaging (MRI), a typical non-invasive imaging technique that produces efficient, secure and high quality brain images. With the provision of comprehensive information and the support of multimodal brain images, doctors can perform quantitative analyses of brain tumors such as the diameter, volume and maximum amount of brain lesions, which allows the development of a diagnosis and optimal treatment plan for patients.

This manual brain tumors diagnosis is often painstaking and requires significant and tedious efforts on the part of the medical expert that can be highly subjective, evaluations and prognoses can be slow. This puts focus on two solutions: firstly the advanced deep learning algorithms that can play a pivotal role in supporting clinicians detecting different forms of tumors. A commonly used deep learning method for image segmentation and classification is to train a Convolutional Neural Networks (CNN).

Secondly the use of medical and healthcare web applications that have become very popular and getting improved day by day in order to minimize the effort and the time for the users and make the whole process easy in one click.

In this thesis we'll present our work in three chapters, for the first one it's an overview about medical context of human brain and brain tumors; secondly State-of-the-art related to classification and segmentation of brain tumors with a

summary of Methods used in both classification and segmentation of these tumors. Finally the most important part of our work is the conception and realization of our web application that presents a Decision Support System in the aim of helping doctors to make decisions for the classification of brain tumors because it has the potential to enable earlier and faster diagnosis with more accurate and objective diagnostic results, also the results of the classification task using three metrics sensitivity, specificity and accuracy.

Chapter 1

Medical Context

Introduction

The brain allows human beings to think, learn, and innovate. However, scientists are far from discovering everything the brain can do. This unique organ controls all aspects of our body, from the heartbeat to emotions, learning, and memory. The brain's ability to perform this set of functions makes the human being what he is.

Medical and neuroscientific research to understand this organ is increasing as dozens of diseases of the brain and nervous system are responsible, in most cases, for the hospitalization and death of patients.

Revolutionary imaging techniques, including Magnetic Resonance Imaging (MRI), have made possible exploring the human body to examine different parts of the brain to assist experts in advanced diagnosis.

In this chapter, we first introduce the anatomy of the brain, then present the different lesions, tumors and their diagnosis finally conclude with the techniques and new treatments used.

1 Anatomy of the human brain

1.1 Humain brain

In our nervous system, the command center is the brain. This three-pound organ (approximately 1.4 kg) is made up of billions of cells called neurons, the junctions between them known as synapses.

They enable electrical and chemical messages to be transmitted from one neuron to the next in the brain, a process that underlies basic sensory functions and that is critical to learning, memory and thought formation, and other cognitive activities. [14] [15] [16]

1.2 The components of the human brain & their functions

The human brain is composed of Cerebrum, Cerebellum and Brainstem (Figure 1.1).

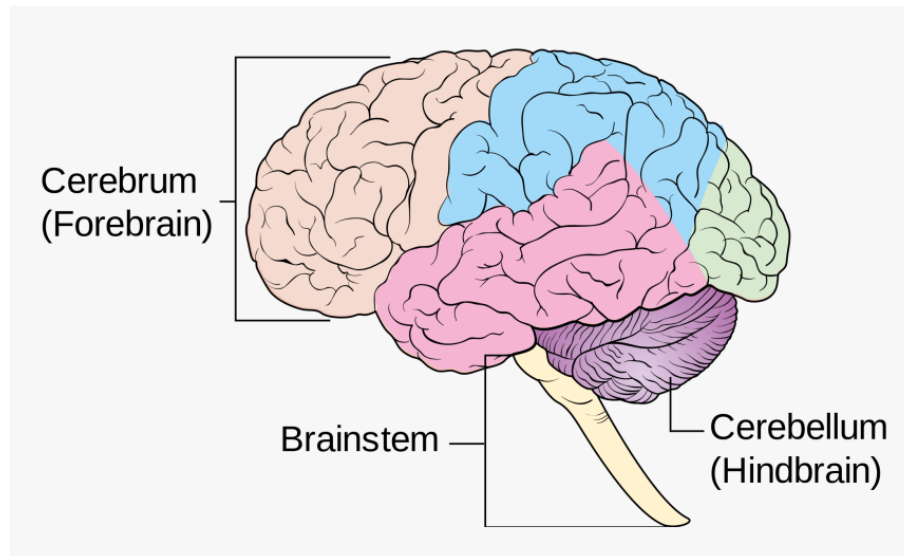


Figure 1.1 – Brain components [1].

1. Cerebrum: or the cerebral cortex is the largest part of the brain which consists of four lobes: the frontal, parietal, temporal and occipital. The Cerebral cortex comprises the right and left hemispheres. It's the source of intellectual activities and considered the seat of complex thoughts. [14]
2. Cerebellum: or little brain situated under the cerebrum. Its function is to coordinate muscle movements, posture, balance and cardiac centers... [17]
3. Brainstem: is the lower prolongation of the brain, it is responsible for controlling reflexes and vital life functions such as heart rate, breathing, and blood pressure. Act as a link to connect the cerebrum and cerebellum to the spinal cord. [18]

1.3 Brain protection

The brain is one of the sensitive organs so it needs to be more protected; this protection is provided by the hard bone of the skull and three layers of tissue called meninges, is also cushioned and secured by the cerebrospinal fluid (CSF). [18]

1.4 What is a tumor?

It is an abnormal mass or growth of cells, arises when they reproduce too quickly or do not die when they should. [19] [20]

Generally, there are three types of tumors:

- Benign: These tumors cannot multiply or grow, and sometimes they do it very slowly, they are noncancerous.
- Pre-malignant: they are benign but they have the potential to become cancerous. [20]
- Malignant: are made of cancers cells and developed quickly, they have the possibility to invade nearby tissues. Cancer can emerge anywhere in the body. [19]

1.5 Cerebral tumors

A cerebral tumor is a collection of abnormal cells in the brain. Cerebral tumors are classified into two categories: primary which begins in the brain and secondary which spread from another organ to the brain (metastatic). [21]

Grades and types of brain tumors

Many different types of primary brain tumors exist, and they are classified and named according to the type of cell develop from, their position in the brain and how fast they grow and spread.

Primary brain tumors:

They can originate from Brain cells, Meninges, nerve cells, glands. The most common ones are:

- Gliomas (that develop from glial cells).
- Meningioma (grows from the middle layer of meninges) .
- Schwannoma (neuroma).
- Pituitary adenoma.

Secondary brain tumors:

They begin elsewhere and metastasize to the brain thus they are malignant in all cases. The following cancers can spread to the brain:

- Lung cancer.
- Breast cancer .
- Kidney cancer.
- Skin cancer.

Grade:

Is an indication of aggressiveness that describes how similar or abnormal the tumor cells appear compared to a normal cell under a microscope and their rate

of growth also the likelihood of growing back after treatment.

Brain tumors are graded from I to IV, as grouped by the World Health Organization (WHO) Cells from low-grade tumors (grades I and II) look more normal and generally grow more slowly than cells from high-grade tumors (grades III and IV).

Grade	Description
Grade I tumor	<ul style="list-style-type: none"> • Benign = non-cancerous. • Slow growing. • Cells look almost normal under a microscope • Usually associated with long-term survival. • Rare in adults.
Grade II tumor	<ul style="list-style-type: none"> • Relatively slow growing. • Sometimes spreads to nearby normal tissue and comes back (recurs). • Cells look slightly abnormal under a microscope. • Sometimes comes back as a higher grade tumor.
Grade III tumor	<ul style="list-style-type: none"> • Malignant = cancerous. • Actively reproduces abnormal cells. • Tumor spreads into nearby normal parts of the brain. • Cells look abnormal under a microscope. • Tends to come back, often as a higher grade tumor.
Grade IV tumor	<ul style="list-style-type: none"> • Most malignant. • Grows fast. • Easily spreads into nearby normal parts of the brain. • Actively reproduces abnormal cells. • Cells look very abnormal under a microscope. • Tumor forms new blood vessels to maintain rapid growth. • Tumors have areas of dead cells in their center (called necrosis).

1.6 Causes of brain tumors

Until now the causes of most brain tumors are not fully understood, but there are a few factors that can increase the risk of cerebral tumors.

- Radiation exposure: most often from radiation therapy to the head.
- Family history: Gene changes can raise the risk of developing a brain tumor. [22]

1.7 What are the symptoms?

Brain tumor symptoms rely to tumor size, type and location. The most common include:

- Headaches.
- Nausea.
- Vomiting .
- Seizures.
- Behavior changes.
- Memory loss.
- Vision or hearing problems. [23]

1.8 How is a brain tumor diagnosed and evaluated?

Diagnosis of a cerebral tumor starts by asking a set of questions about symptoms and family health history then physical exam including the neurologic exam. Other tests may be requested to confirm this diagnosis:

- CT scan (CAT scan): computed tomography is a procedure that makes a series of detailed pictures of areas inside the body, taken from different angles. This can be done with contrast to show up organs or tissues more clearly.
- PET scan (Positron Emission Tomography scan): A way to locate malignant tumor cells in the body by using a small amount of radioactive glucose, which is injected into a vein that shows up malignant tumor cells brighter in the picture.
- MRI (Magnetic Resonance Imaging): is a medical imaging technique that uses magnet and radio waves to create detailed images of the organs and tissues within the body. This procedure creates more detailed pictures than CT scan that can detect abnormalities such as tumors and infection; that's

why we'll use it in our final project (graduation project).

There are many types of advanced MRI:

- Functional MRI (fMRI).
 - Diffusion tensor imaging (DTI).
 - Magnetic resonance spectroscopy (MRS)..
 - Perfusion MRI..
 - Hemosiderin Imaging.
- Angiogram: It's an invasive test uses x-rays and a contrast material to create images of blood vessels in the brain. [24]
 - Biopsy: Is the remove of very small piece of the tumor tissue, to look for cancer cells under a microscope and determine the exact type of the tumor.

1.9 Treatments for Brain Tumors

Various therapies are recommended to treat brain tumors. They depend on the size, type and the location of the tumor, its growth rate and the overall health of the patient.

- Surgery: Generally used as first step in treatment to remove as much of the tumor as possible without damaging surrounding tissues.
- Radiation therapy: Called also radiotherapy uses x-rays, gamma rays, neutrons, protons, and other sources to kill cancer cells and reduce tumors by damaging their DNA.
- Chemotherapy: Called also anticancer medications used to slow down or kill fast-dividing cells by using chemical compounds (or drugs). It is prescribed when surgery and/or radiation are not enough to remove a tumor. [25]
- Targeted biological therapy: Called also biotherapy or immunotherapy. This treatment targets the tumor's specific genes, proteins, or the tissue. Biotherapy can attack tumor cells specifically resulting less damage to normal cells. [26]

Conclusion

In this chapter we presented first the anatomy of the brain. Then, we gave an overview of tumors and their types especially brain tumors. In the end, we focused on the diagnosis and the techniques used mainly the detailed information generated by medical imaging in particular magnetic resonance imaging (MRI), which has an important role in the exploration of the human body and the brain imaging.

Due to the large scale of the medical image data, complex image processing and deep learning have emerged as a major player in the healthcare field to assist doctors in their interpretation and decision making.

In order to facilitate the complexity for them we are going to present one of the common deep learning methods for image classification and segmentation and related works in the next chapter.

Chapter 2

State-of-the-art related to classification and segmentation of brain tumors and Methods

1 Introduction

In human's life routine the brain functions work continued through a billions of interconnected neurons; this is the power of the human brain, and the reason to imitate its general idea of working in processing data, detecting objects, recognizing speech, translating languages, making decisions, and segmenting images to build a network of interconnected artificial neurons.

Some kind of these neural networks are built with a large number of parameters and layers (more than five layers) that mean we're talking about deep learning which is the best solution for dealing with large volume of data, because of its networks that are modeled on similar networks of the human brain.

In this chapter, firstly, we'll define deep learning and its architectures, and then we provide a review on some of the recent state-of-the-art works related to the classification and segmentation of brain tumors and the used methods in both tasks.

2 Deep learning

2.1 Definition:

Deep learning (DL) is a subfield of machine learning (ML) and artificial intelligence (AI) concerned with algorithms driven by the structure of the brain and mimic the way humans analyzing, collecting, and interpreting knowledge. Its networks capable of learning with and without human supervision (learn from labeled and unlabeled data).

One of the important elements of data science is Deep learning which makes processing data and creating patterns for use in decision making faster and easier. [27] [28]

2.2 Major Architectures of Deep Networks:

Machine learning and deep learning models are categorized in three main families, supervised methods, unsupervised methods, and reinforcement methods.

Unsupervised methods:

Unsupervised method is the process when the target is to make groups of knowledge samples (clusters) supported some quite similarity measure between the elements of dataset.

The difference between supervised methods and clustering is that clustering is applied in an unsupervised manner, so no class labels are provided, and sometimes even the quantity of clusters isn't known a-priori. [29]

We'll mention some unsupervised neural networks:

1. Autoencoders: Autoencoders are an unsupervised learning technique in which we leverage neural networks for the task of representation learning. An autoencoder is a type of artificial neural network used to learn efficient data coding in an unsupervised manner. The aim of an autoencoder is to learn a representation (encoding) for a set of data. It is a data compression algorithm where the compression and decompression functions are:

- Data-specific: If you trained it on pictures of faces it'll compress pictures of trees in wrong way.
- Lossy: Every output will be degraded compared to the original input.
- Learned automatically: it need just appropriate training data to learn.

Nowadays; there are two important applications of autoencoders: data denoising and dimensionality reduction for data visualization.

The architecture of autoencoders is presented in the figure 2.1:

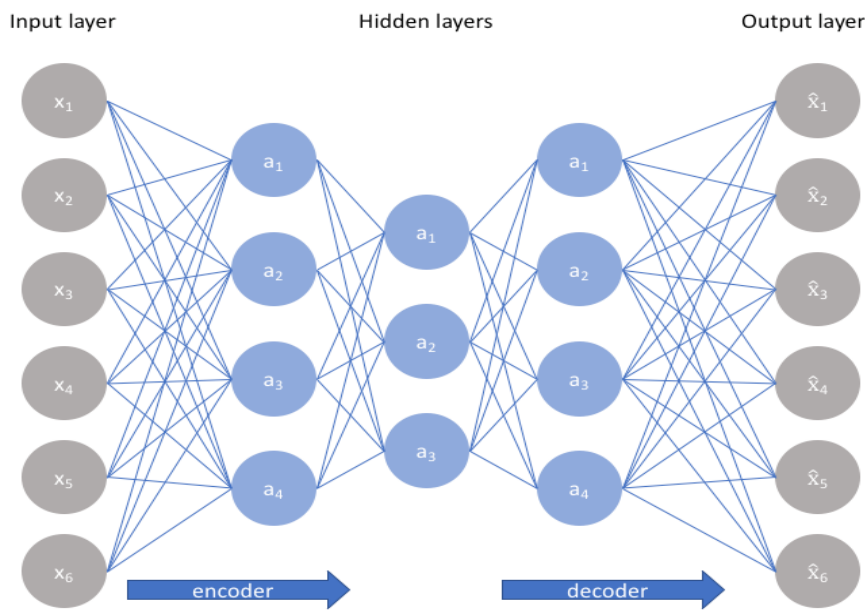


Figure 2.1 – Architecture of autoencoders [2]

2. Deep Belief Networks (DBNs):

Deep belief network is unsupervised network architecture with a unique training algorithm. This network made up with multiple hidden layers in which each pair of connected layer composed of layer of restricted Boltzmann machine (RBM). As is presented in the figure 2.2

The training of the algorithm pass on two phases: unsupervised pretraining using unlabeled samples, then supervised fine-tuning with labeled samples.

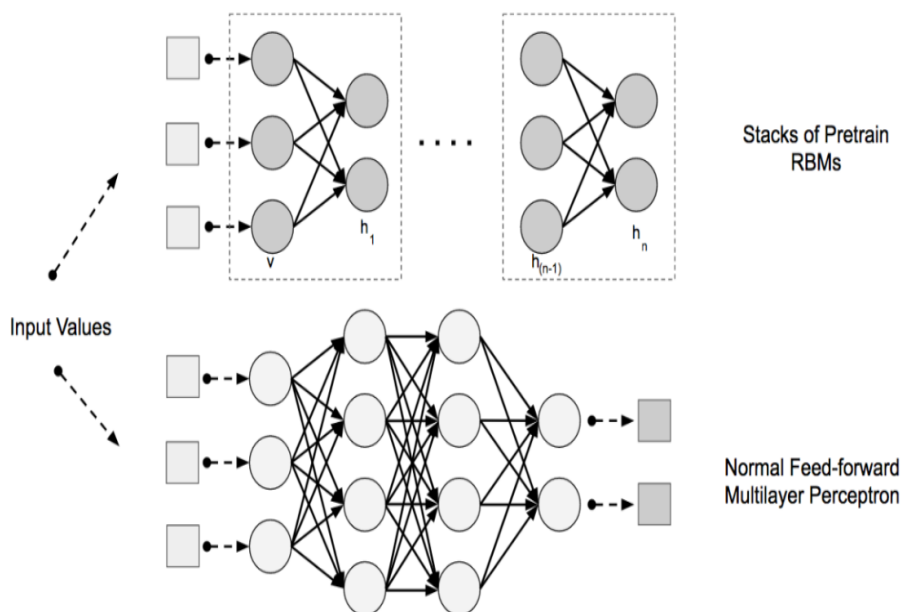


Figure 2.2 – The network architecture of a DBN [3]

3. Generative Adversarial Networks (GANs): It is an architecture that uses

two neural networks, in order to generate realistic instances of data; one called the generator, generates new instances, and the other, the discriminator, evaluates them and decides if this instance of data is one of the training dataset or not. As is presented in the figure 2.3.

It is used in many domains such as image generation, video generation and voice generation [4].

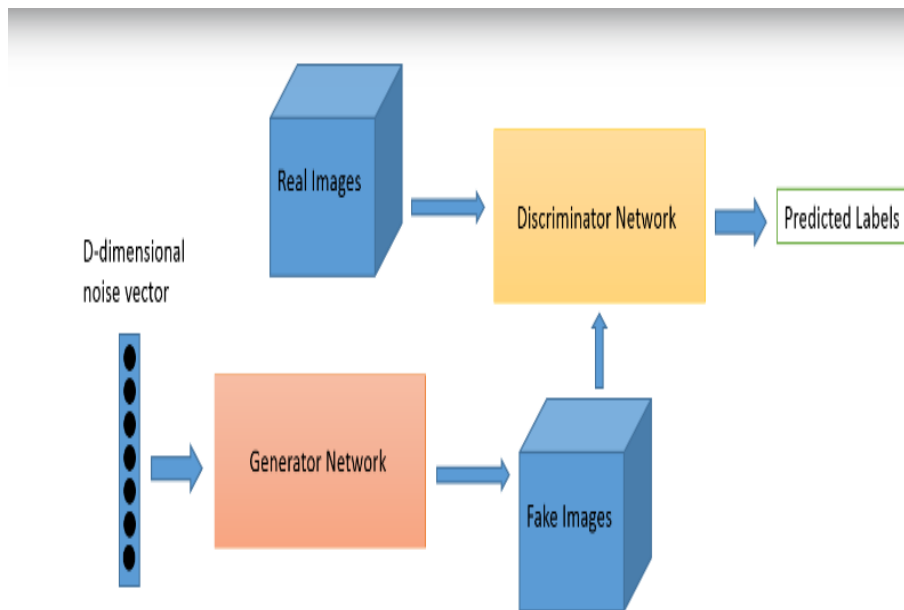


Figure 2.3 – GAN architecture [4]

Supervised learning:

For supervised learning tasks, deep learning methods eliminate feature engineering, by translating the data into compact intermediate representations akin to principal components and derive layered structures that remove redundancy in representation. The best-known architectures in supervised learning are the Convolution Neural Network (CNN).

1. Convolution Neural Network:

This type of neural networks is trained by using big data and owns the capability of extracting features from data via convolutions without manual extraction of features.

It is composed by several kinds of layers: an input layer, output layer, and hidden layers. The hidden layers consist of convolutional layers, ReLU layers, pooling layers, and fully connected layers as is presented in the figure 2.4

Convolution neural network is one of the most popular deep learning architectures used for classification and recognition of image, text, and sound. [3] [30]

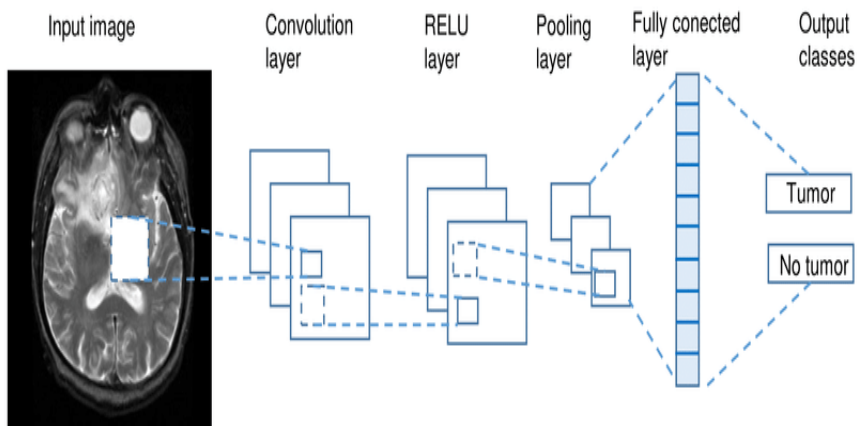


Figure 2.4 – High-level general CNN architecture [3]

There is a list of some of the more popular architectures of CNNs, the most known are (ordered by year of publication):

- LeNet-5 (1998) :
Is a very simple network consists of two convolutional layers, and three fully-connected layers; in addition to input and output layers and sub-sampling layers. [31]
- AlexNet (2012) :
AlexNet contains 5 Convolutional Layers and 3 Fully Connected Layers as well Overlapping Max Pooling layers. [32]
- GoogLeNet(2014):
It is a convolutional neural network that contains 22 layers; the basic convolutional block in GoogLeNet is named an Inception block. [33]
- VGG-16 (2014):
It has 13 convolutional with 3 fully-connected layers, in addition the ReLU and max-pooling layers. VGG-19 is a deeper variant of VGG16. [34]
- Inception-v3 (2015):
(the 3rd version of inception networks) is a convolutional neural network that composes of 48 layers deep and adds batch normalization. [35]

- ResNet-50 (2015):
Deep Residual Network is one of the deeper architecture of CNNs that based on the convolutional and identity blocks; contains up to 152 layers. [35]
- Xception (2016):
It represent an adaptation from Inception network; they involve depth-wise separable convolutions layers in place of the Inception modules. It uses 36 convolutional layers. [36]
- ResNeXt-50 (2017): Based on ResNet-50 and add parallel branches or paths within each module. [35]

Other families of supervised algorithms are Recurrent Neural Network (RNNs).

2. Recurrent Neural Network:

They are the most powerful and well-known subset used to recognize patterns in sequences of data and suited to processing time-series data and other sequential data; they add the concept of recurrent connections.

The Recurrent neural networks take as input the current input, and add time and sequence into account, we can say that they got a new dimension "temporal dimension".

It is a good solution for many problems like text processing, speech recognition, Language modeling and DNA sequences...

One of the most used algorithms of Recurrent Neural Networks is the Long Short-Term Memory Units (LSTMs) which known by providing: [37] [38]

- Better backpropagation.
- Better update equations.

The architecture of recurrent neural network is presented in the figure 2.5 below:

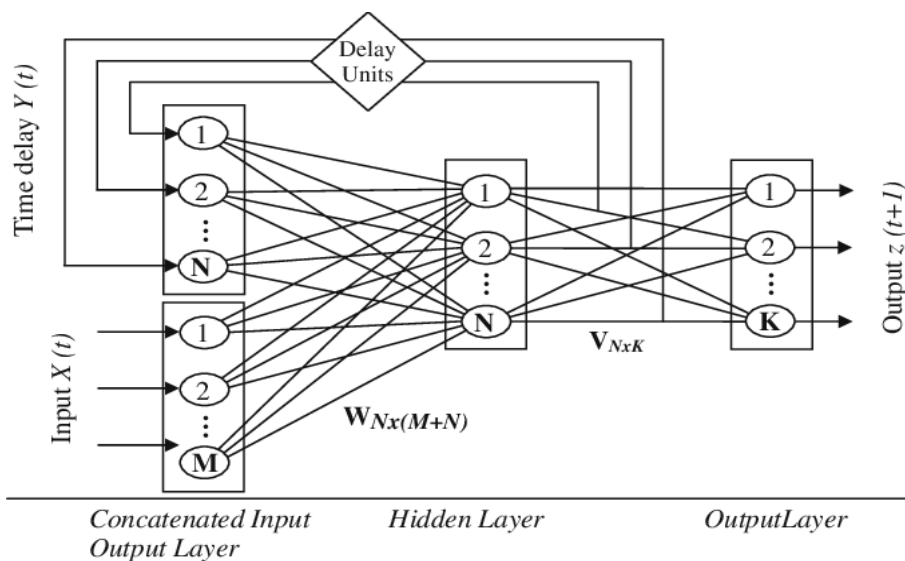


Figure 2.5 – A typical architecture of recurrent neural network [5]

Reinforcement learning:

Is the 3rd family of machine learning and deep learning; in this type of learning there is no supervisor but the reinforcement agent decides what to do to perform the given task and take a decision to solve the problem.

The processes of reinforcement learning is about making decisions sequentially and the output is usually depends on the state of the input. [39]

We can find this type of learning in Various Practical applications like:

- Robotics for industrial automation.
- Create training systems that provide custom instruction and materials according to the requirement of students.

3 State-of-the-art related to classification and segmentation of brain tumors

Nowadays brain tumors are one of the most dangerous, rapidly growing types of cancer, and deadliest diseases.

Specialists try to use different technics for detecting these tumors and localizing them (manually) and its performance depends on pathologists' experience, and this did not help so much due to long time consumption and human errors.

Based on that, researchers take attention on deep learning and its great performance in image classification and segmentation; due to their self-learning and generalization ability using large amounts of data.

3.1 Brain Tumor Dataset:

Over the last ten years, many researchers have focused on the segmentation and classification of tumors on MRI images of the brain, particularly with the availability of data through the Brain Tumor Segmentation (BraTS) Challenge.

BraTS utilizes multi-institutional pre-operative MRI scans and primarily focuses on the segmentation (Task 1) of intrinsically heterogeneous (in appearance, shape, and histology) brain tumors, namely gliomas. Furthermore, to pinpoint the clinical relevance of this segmentation task, BraTS also focuses on the prediction of patient overall survival (Task 2) and intends to evaluate the algorithmic uncertainty in tumor segmentations (Task 3).

All BraTS multimodal scans are available as NIfTI files (.nii.gz) and describe a) native (T1) and b) post-contrast T1-weighted (T1Gd), c) T2-weighted (T2), and d) T2 Fluid Attenuated Inversion Recovery (T2-FLAIR) volumes, and were acquired with different clinical protocols and various scanners from multiple institutions. All the imaging datasets have been segmented manually, by one to four raters, following the same annotation protocol, and their annotations were approved by experienced neuro-radiologists. [40]

3.2 Related works:

Since the appearance of this database in 2012, many researchers have contributed to the segmentation and classification of the different versions of this database. The most promising work uses deep learning models. The methods and results of the most recent work are summarized in the following table (Classification :C / Segmentation: S / Computational Precision Medicine: Radiology-Pathology Challenge (CPM: Rad-Path) :

AUTHOR AND YEAR	TITLE	TASKS	DATASET	METHODS	RESULTS
Hiba Mzoughi, et al. 2020 [41]	Deep Multi-Scale 3D Convolutional Neural Network (CNN) for MRI Gliomas Brain Tumor Classification	C	Brats 2018	Preprocessing: technique based on intensity normalization and adaptive contrast enhancement of MRI data. Classification: Used data augmentation and fully automatic deep multi-scale 3D CNN network architecture to classify glioma tumors into HGG and LGG.	The proposed method offers promising results outperforming the recently supervised and unsupervised state of art approaches by achieving an overall accuracy of 96.49% using the validation dataset.
Jianxin Zhang, et al. March 2020 [42]	Attention Gate ResU-Net for Automatic MRI Brain Tumor Segmentation	S	Brats 2017 2018 2019	They integrate attention gates and residual modules into U-Net architecture to produce Attention Gate ResU-Net (AGResU-Net) model	This method obtains dice similarity coefficient(DSC) of 0.876, 0.772 and 0.720 on the whole tumor, core tumor and enhancing tumor segmentation, respectively

<p>Linmin Pei, et al. 2019 [43]</p>	<p>Brain Tumor Classification Using 3D Convolutional Neural Network</p>	<p>C and S</p>	<p>CPM: Rad-Path on Brain Tumor Classification 2019</p>	<p>Use a 3D deep NN composed of two parts: The first part is brain tumor segmentation on the multimodal magnetic resonance image, and the second part performs tumor classification using tumor segmentation results.</p>	<p>The result offers 0.749 for dice score and 0.764 for F1 score for validation data, while 0.596 for dice score and of 0.603 for F1 score for testing data, respectively</p>
<p>Fatemeh Bashir Gonbadi, Hassan Khotanlou et al. 2019 [44]</p>	<p>Glioma Brain Tumors Diagnosis and Classification in MR Images based on Convolutional Neural Networks</p>	<p>C</p>	<p>IXI dataset and BraTS-2017</p>	<p>Preprocessing: Extracting the brain from the skull using Brain Extraction Tool (BET). Classification: Use CNN built by gathering several layers (Convolution, Max-pooling, Up-sampling, Dense) extract high level and low-level features from input images and finally classify the extracted feature maps.</p>	<p>It classifies the MRI images into three categories: Normal Brain, HGG, and LGG with a desirable accuracy of 99.18%</p>

Rupal R. Agravat, et al. 2019 [45]	Brain Tumor Segmentation and Survival Prediction	S and Survival Prediction	Brats 2019	Fully convolutional neural network with Three-layer deep encoder-decoder architecture is used along with dense connection at the encoder part.	They obtained as a dice Similarity of training dataset with focal loss implementation for whole tumor, tumor core, and enhancing tumor is 0.92, 0.90, and 0.79, respectively. For the validation dataset on the leaderboard with 58.6% accuracy and for test set of BraTS 2019 with 57.9% accuracy
S. Alqazaz, and al. 2019 [46]	Automated brain tumor segmentation on multi-modal MR image using SegNet.	S	Brats 2017 with four MRI modalities (Flair, T1, T1ce, and T2)	SegNet models with 3D MRI datasets and integrating the four maximum feature maps with pixel intensity values of the original MRI modalities.	Experimental results demonstrate that this method has potential to perform well on brain tumor segmentation and F-measure scores give 0.85, 0.81, and 0.79 for whole tumor, tumor core, and enhancing tumor, respectively.

<p>Feifan Wang et al.2020 [47]</p>	<p>3D U-Net Based Brain Tumor Segmentation and Survival Days Prediction.</p>	<p>S and Survival day's prediction.</p>	<p>BraTS 2019</p>	<p>Segmentation task proposed : 3D U-net based deep learning with normalization for each modality and two patching strategies based on the cuboid boundary of the brain. Survival days prediction task: select of seven numerical features such as the ratio of tumour size to brain size and tumour surface area from The predicted tumor images.</p>	<p>In segmentation: Dice coefficients for enhancing tumor, tumor core, and the whole tumor are 0.737, 0.807 and 0.894 respectively on the validation dataset, on the test dataset: 0.778, 0.798 and 0.852 4 respectively on the test dataset. -For the overall survival days prediction task: The accuracy 0.551 on the final test dataset. -Only one $4 \times 128 \times 128 \times 128$ image could be fed as input on single GPU platform, which likely restricts the capacity of the model.</p>
<p>Jonas Wacker, et al. 2019 [48]</p>	<p>Transfer Learning for Brain Tumor Segmentation</p>	<p>S</p>	<p>BraTS 2017 2018 in training data. BraTS 2018 in validation data Clinical dataset of the Syrian-Lebanese hospital in Brasilia (Brazil)</p>	<p>Preprocessing using normalization and Data Augmentation Prediction: use a ResNet34 encoder that results in the AlbuNet variant of TernausNet fully convolutional networks (FCNs) with pretrained convolutional encoders.</p>	<p>For the final result the dice score is about 10% higher for the AlbuNet3D and about 17% higher for the AlbuNet2D version with pretraining compared to the one without.</p>

<p>Lele Chen and all.2018 [49]</p>	<p>MRI Tumor Segmentation with Densely Connected 3D CNN.</p>	<p>S</p>	<p>Brats 2017</p>	<p>preprocessing :normalization for each MRI sequence Proposed a 3D Convolutional Neural Network (3D CNN) based model in which utilizes a hierarchical architecture to consider different types of brain tumors and Two-Stage Densely Connected 3D CNN. Using preprocessing: normalization for each MRI sequence</p>	<p>Dice scores: 0.72, 0.83 and 0.81 for the complete tumor, tumor core and enhancing tumor, respectively. This method gives better results in terms of compactness, temporal and spatial efficiency compared to the reported state-of-the-art results.</p>
<p>Guotai Wang, et al. February 2017 [50]</p>	<p>Automatic Brain Tumor Segmentation using Cascaded Anisotropic Convolutional Neural Networks.</p>	<p>S</p>	<p>BraTS 2017 for the validation and testing.</p>	<p>Use a cascade of fully CNN consists of multiple layers of anisotropic and dilated convolution filters, and they are combined with multi-view fusion to reduce false positives.Residual connections and multi-scale predictions are employed in these networks to boost the segmentation performance.</p>	<p>The experimental results show the utility of this approach, and it achieved average Dice scores of 0.7859, 0.9050, 0.8378 for enhancing tumor core, whole tumor and tumor core, respectively in validation set. Using testing set they got 0.7831, 0.8739, and 0.7748, respectively.</p>

<p>Fabian Isensee, et al. February 2017 [51]</p>	<p>Brain Tumor Segmentation and Radiomics Survival Prediction: Contribution to the BRATS 2017 Challenge</p>	<p>S and survival prediction</p>	<p>BraTS 2017</p>	<p>A robust segmentation algorithm in the form of a CNN. The network architecture was inspired by U-Net and has been carefully modified to maximize brain tumor segmentation performance. They use a dice loss function to cope with class imbalances and use extensive data augmentation to successfully prevent overfitting.</p>	<p>On the test set they obtained mean dice scores of 0.858 for whole tumor, 0.775 for tumor core and 0.647 for the contrast enhancing tumor and in validation set 0.896, 0.797 and 0.732 for whole tumor, tumor core and enhancing tumor, respectively. This approach achieves 52.6% accuracy, a Spearman correlation coefficient of 0.496 and a mean square error of 209607 on the test set.</p>
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These results show the value of using deep learning in the segmentation and classification of MRI images. It is moreover the conclusions of these researchers that led us to propose a web platform for the segmentation and classification of brain tumors.

4 Used methods in classification and segmentation of brain tumors

Driven by the increasing use and broad development of different medical imaging processes and modalities (especially MRI), advanced medical image-processing algorithms has become on the rise in the health care.

The accurate classification, segmentation and three-dimensional reconstruction brain tumors play an essential role in aiding clinical care and treatment.

A common deep learning method for computer vision tasks, such as object detection, image segmentation, image classification, among others is to train a Convolutional Neural Networks (CNN).

4.1 Classification:

In this order the proposed approach for classifying Glioma tumors in brain MRI images into High-Grade (HGG) or Low-Grade Glioma(LGG) tumor is a pretrained

convolutional neural network using Inception v3 as architecture.

Definition:

Classification is a supervised learning approach in which the machine learning algorithms learns from the input data and then uses this learning to classify new observations. It can be either a binary classification problem or a multi-class problem too. [52]

Image classification is the process of assigning one or more label to images according to predefined categories. Based on a set of images within a specific category, the algorithm teaches which class the test images belong to.

[53]

Convolutional Neural Network:

As we saw in the precedent section Convolutional Neural Network is a powerful neural network. Designed for working with two-dimensional image data, although they can be used with one-dimensional and three-dimensional data. It uses filters to extract features.

1. layers in CNN: [54]

There are five different layers in CNN:

- Input layer.
- Conv layer (Convo + ReLU).
- Pooling layer.
- Fully connected (FC) layer.
- Output layer.

- Input layer:

It contains image data that has the following dimensions: [width x height x depth]. It is a matrix of pixel values.

- Convolution Layer (Convo + ReLU):

Called also feature extractor layer. The convolution of an image with different filters can carry out operations such as edge detection, blur... etc by using filters.

- Calculate the dot product between receptive field (local region of the input image that has the same size as that of filter) and the filter, it results in a single integer which is the output volume (feature map).

- Slide the filter over the next receptive field of the same input image by a Stride (number of pixels shifts over the input matrix) and compute again the dot products between the new receptive field and the same kernel.

- Repeat this procedure until going over the entire input image, the output will be the input for the next layer.

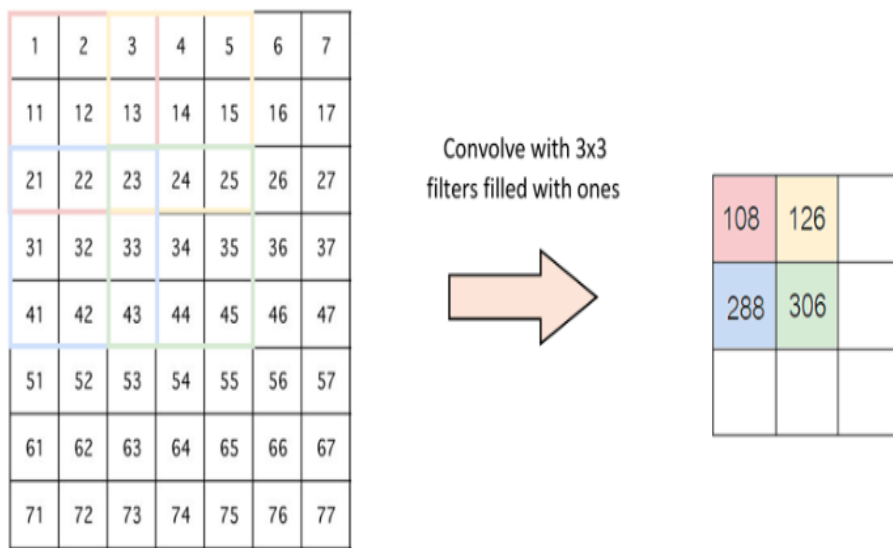


Figure 2.6 – Convolutional layer

[55]

Non Linearity (ReLU) : Rectified Linear Unit for a non-linear operation; applies an elementwise activation function $\max(0,x)$, to make all negative values to zeros (thresholding at zero).

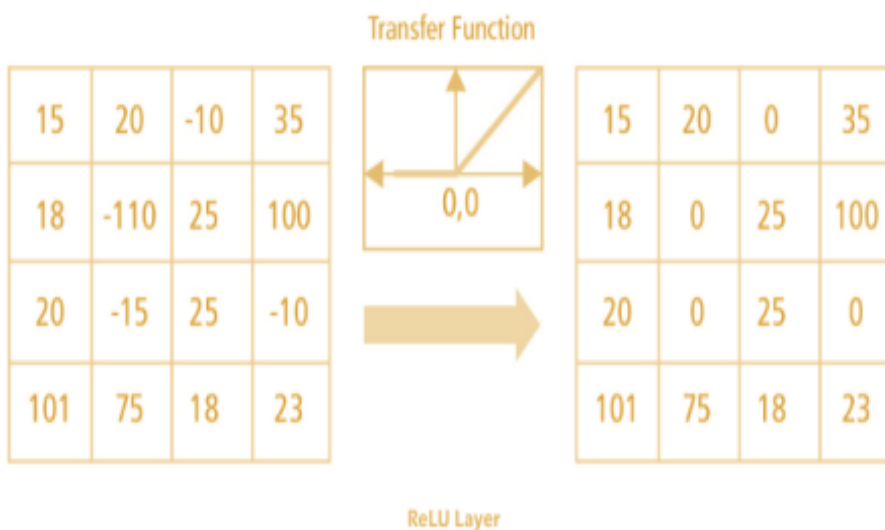


Figure 2.7 – RELU layer

[55]

- Pooling layer: Carry out a downsampling operation along the spatial dimensions(width, height).It can be of different types:
 - Max Pooling: takes the largest element from the rectified feature map.

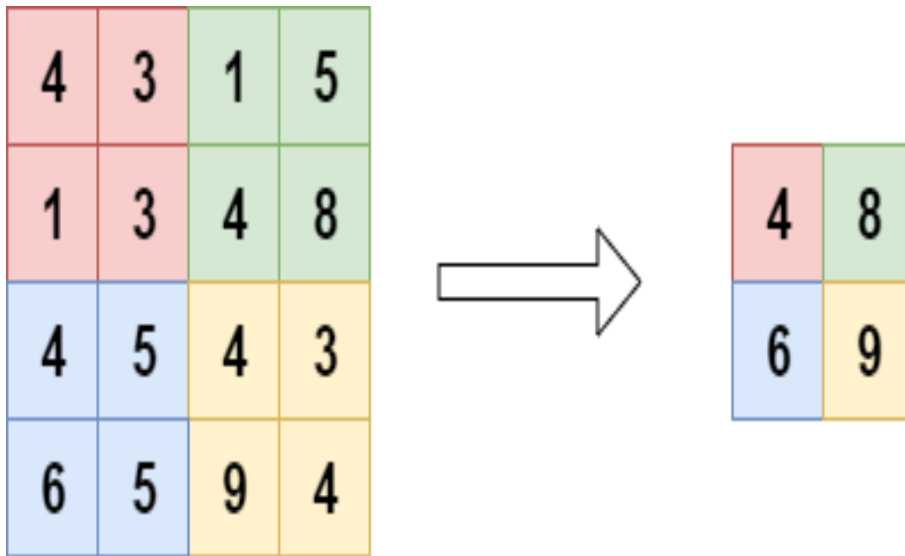


Figure 2.8 – Max Pooling

[6]

- Average Pooling: calculating the average for each patch of the feature map.

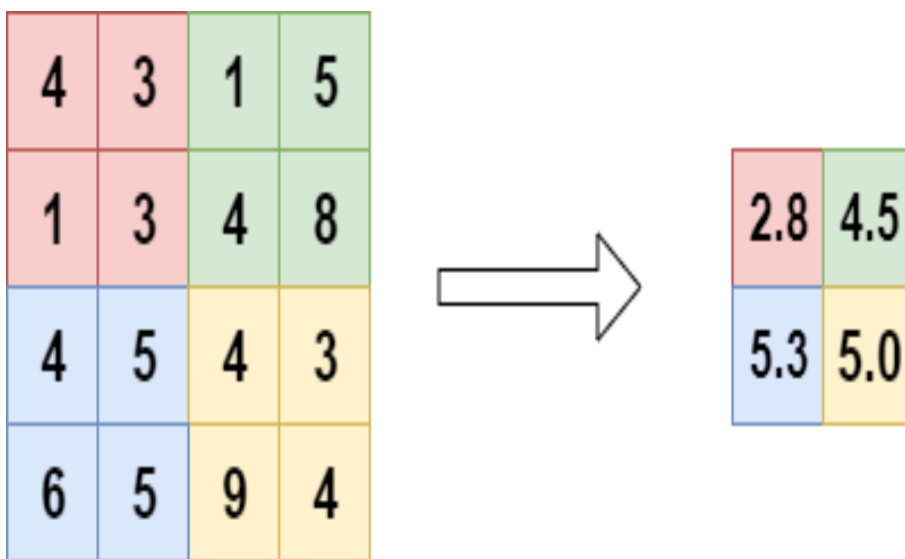


Figure 2.9 – Average Pooling

[6]

- Sum Pooling: Sum of all elements in the feature map.

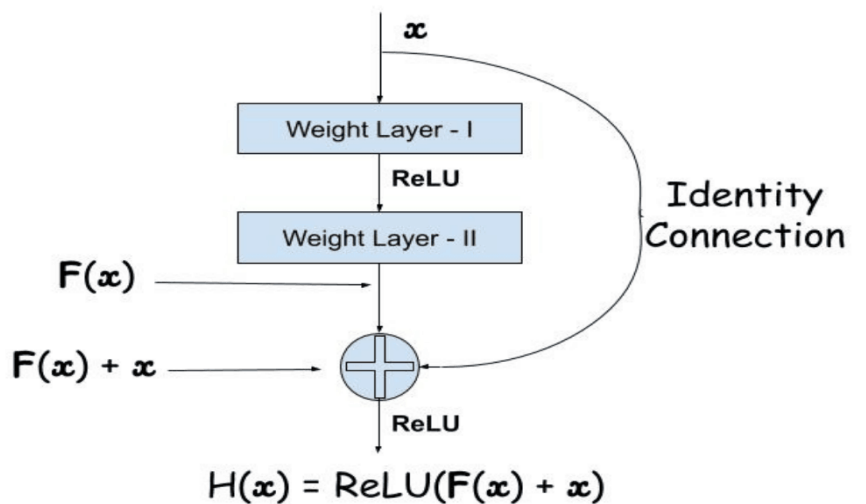
- Fully Connected Layer: Compute the class scores, by flattening the matrix into vector that can be an input for a fully connected layers which are same as Artificial Neural Networks and carry out the same mathematical operations.

- Output layer: The last fully-connected layer uses an activation function such as sigmoid or softmax to get probabilities of the outputs.

ResNet:

Deeper networks can provide more complex features, increasing the robustness and performance of the model. However adding more layers to the network does not work by simply stacking layers together. Deeper neural networks are difficult to train because of vanishing and exploding gradient types of problems. ResNet which is one of the common architectures of CNN allowed us to train extremely deep neural networks.

1. Definition: Residual Networks 'ResNets' are nearly similar to networks that have layers of convolution, pooling, activation and fully-connected layers. The basic building block for ResNets is the convolutional and identity blocks, which connect the output of one layer with the input of an earlier layer (skip connection). Below is the residual block in figure 2.10:



cv-tricks.com

Figure 2.10 – Residual block [6]

There are many alternatives of the ResNet architecture; the same idea but with a different number of layers: ResNet-50, ResNet-101, ResNet-110, ResNet-152...

2. Residual block: The support for training deeper networks that perform well or at least be identical to shallower networks will be provided by adding identity mapping addition to the residual output.
 - Learning the adding identity mapping (Input equal to output) from an input x to an output y : $H(x) = y$

- Instead of learning a direct mapping, the residual function uses the difference between a mapping applied to x and the original input:

$F(x) = H(x) - x$, which can be reframed into $H(x) = F(x) + x$, where $F(x)$ and x represents residual function and the identity function respectively (figure 2.11)

It is easier to optimize this residual function $F(x)$ compared to the original mapping $H(x)$ figure

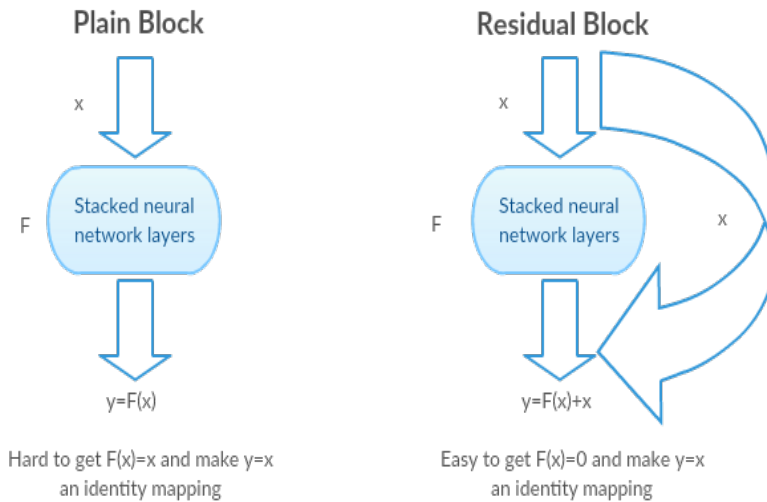


Figure 2.11 – Plain Block Vs Residual Block [7]

3. Types of residual blocks: There are two main types of blocks:
 - Identity Block: corresponds to the case where the input and output are of the same dimensions so the identity shortcuts (x) can be directly used. Below is an example of identity block where the upper path is the “shortcut path” and the lower path is the “main path”(figure 2.12):

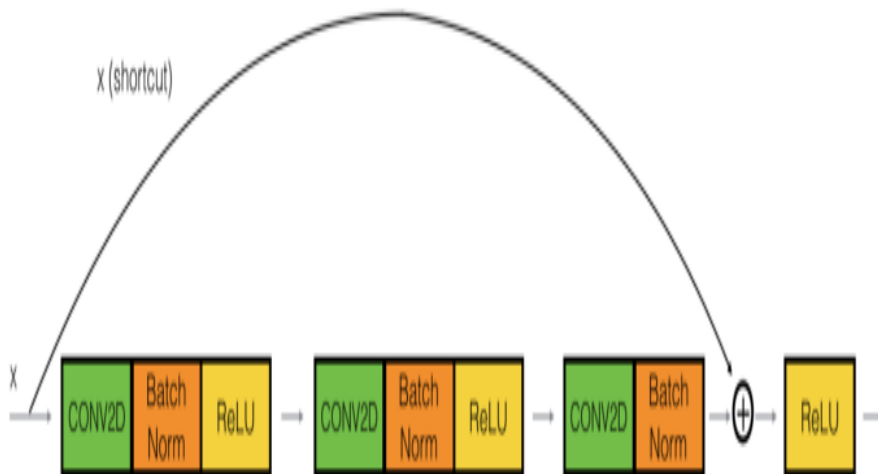


Figure 2.12 – Identity Block [8]

- Convolutional Block: Where dimensions don't match up, in this case a convolutional layer is added to the shortcut path, as is presented in the figure 2.13

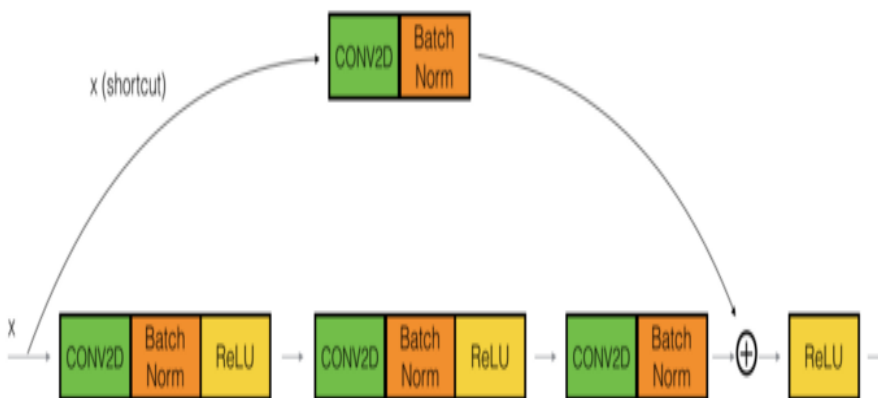


Figure 2.13 – Convolutional Block [8]

4. Architecture of ResNet-50: Consists of 5 stages. Every ResNet architecture carries out the initial convolution and max-pooling using 7×7 and 3×3 kernel sizes respectively. Each convolution block has 3 convolution layers and each identity block also has 3 convolution layers. The network has also an Average Pooling layer and then a fully connected layer with 1000 neurons (ImageNet class output). [56] [8]

The figure 2.14 presents the architecture of ResNet-50

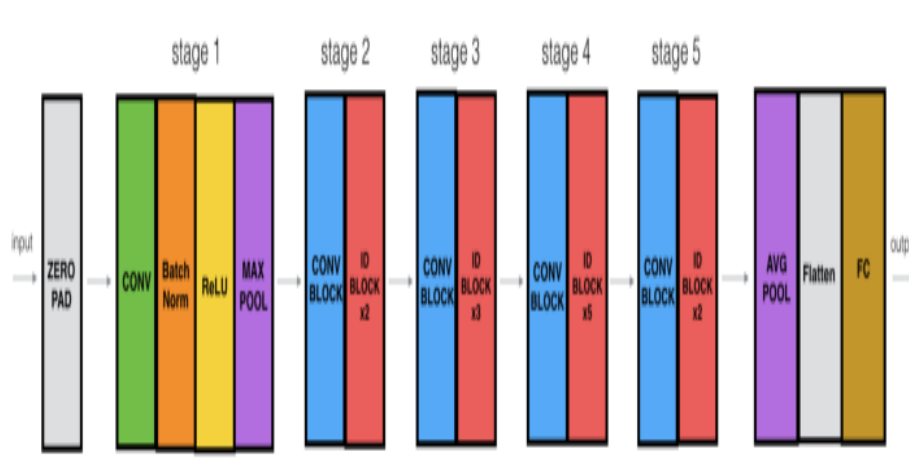


Figure 2.14 – Architecture of ResNet-50 [8]

VGG Net:

1. Definition:

Is invented by Visual Geometry Group (by Oxford University), VGG is a Convolutional Neural Network architecture based off of AlexNet. There are two architectures of VGG: VGG16 & VGG19.

2. Architecture:

- Input: VGG used RGB image in a 224x224 pixel.
- Convolutional Layers: In VGG, the convolutional layers use a very small receptive field 3x3. There are also 1x1 convolution filters which can be seen as a linear transformation of the input channels, followed by a ReLU layer. The convolution stride is fixed to 1 pixel.
- Max Pooling: is performed over a 2x2 pixel window.
- Fully-Connected Layers. VGG contained 3 fully-connected layers.
- Hidden Layers: All hidden layers are equipped with the non-linearity layer (ReLU). It is also noted that not all of networks contain Local Response Normalisation (LRN) due to their consumption of memory and time and does not improve the performance. [57]

3. VGG16:

VGGNet-16 contained 16 layers (13 convolutional layers + 3 Fully connected layers); it is very used due to its very uniform Architecture. In the community of extracting features from images VGG16 is one of the most preferred networks. [9]

The figure 2.15 presents the architecture VGG16

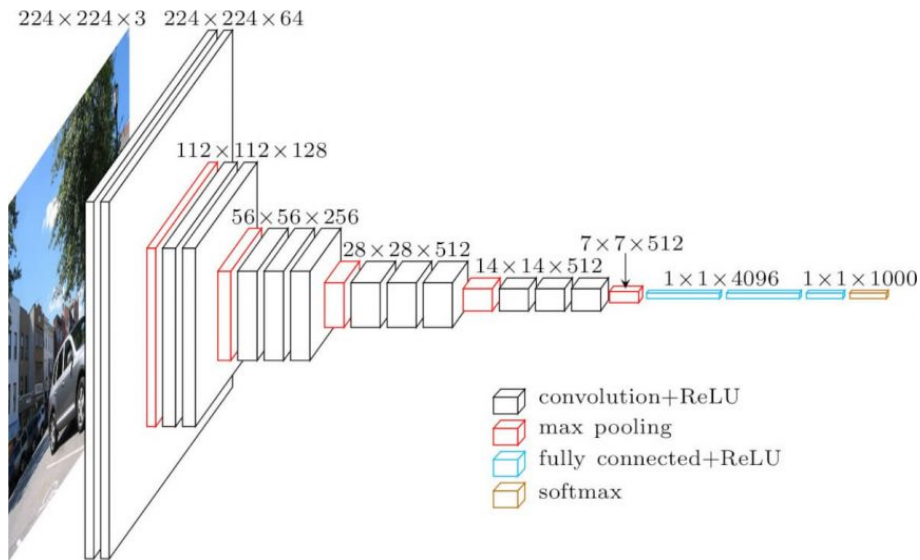


Figure 2.15 – VGG16 architecture [9]

Inception network:

1. Definition:

It is basically a convolutional neural network (CNN) but it's characterized -in addition to its common layers- by its unique module "Inception module" which was designed to solve the problem of computational expense, as well as overfitting, among other issues. In general Inception network is one of the possible solutions for computer vision problems. [10]

The popular versions of inception networks are as follows:

- Inception v1 or GoogLeNet
- Inception v2 and Inception v3.
- Inception v4 and Inception-ResNet.

2. Inception module:

Is a combination of convolution layers with different filter sizes (5X5, 3X3, 1X1) and max pooling, also it has a bottleneck layer(1X1 convolutions) which used for dimensionality reduction; then concatenate all of their output into a single output vector to form the input of the next layer. As is presented in the figure 2.16

The object from the convolutions of different sizes is to capture details at varied scales. [58]

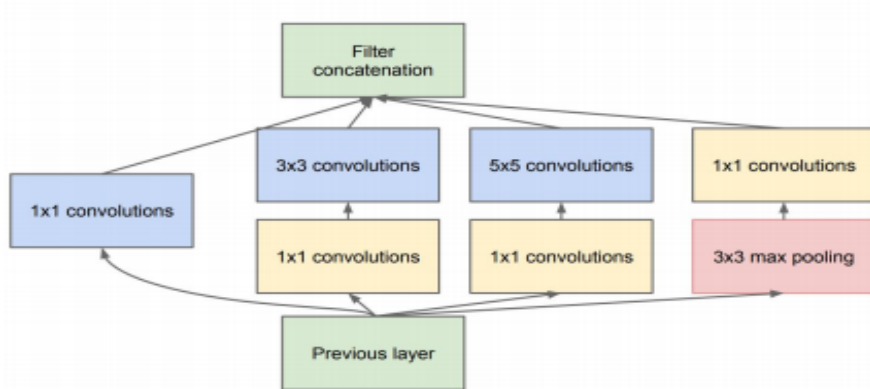


Figure 2.16 – Inception module with dimension reduction [10]

3. Inception v3:

Inception V3 is the 3rd version of inception architectures characterized by the additional of factorization ideas.

Inception V3 is widely-used as image recognition model; this model is made up of multiple blocks, including convolutions, average pooling, max pooling, concatenations, dropouts, and fully connected layers and using the Batch norm to activate inputs also the Softmax to compute the Loss. [11] [59]

Factorized Convolutions: It used to reduce the number of parameters and maintains a check on the network efficiency.

The diagram of the inception v3 model is shown below in figure 2.17:

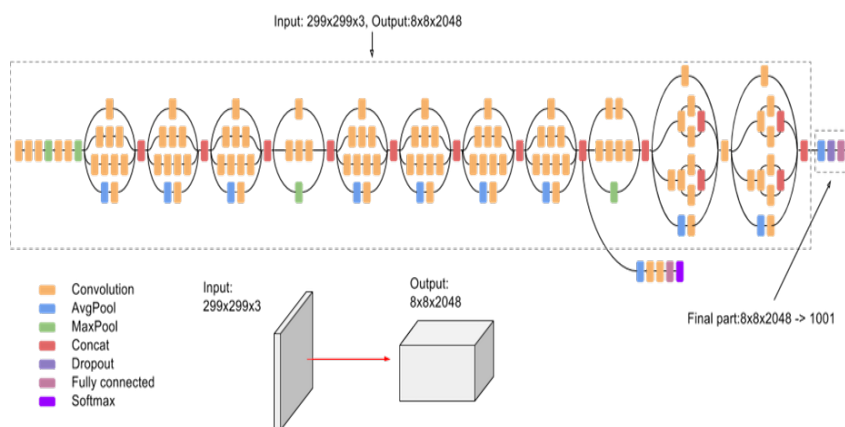


Figure 2.17 – Architecture of inception v3 model [11]

The architecture of Inception V3 network is built as explained below:

- **Factorization Into Smaller Convolutions** : This step helps to fast the training by replacing bigger convolutions with smaller convolutions: two 3×3 filters replaces one 5×5 convolution.
Result: Number of parameters is reduced by 28%.
- **Asymmetric convolutions**: In this level it replaces one 3×3 convolution by one 3×1 convolution followed by one 1×3 convolution.
Result: Number of parameters is reduced by 33%.
- **Auxiliary classifier**: Is a small CNN added between layers during training, and the calculated loss is grouped with the main network loss. It was already proposed in Inception-v1 but in this version it has some modifications used on the top of the last 17×17 layer; the Auxiliary classifier is applied as regularizer.
- **Grid size reduction**: It's about concatenating the features map of both convolution with stride 2 and of max pooling with stride 2 that's give a less expensive network but in same time still efficient. [60] [61]

Transfer learning:

In deep learning, this is a technique for reusing the weights from a pre-trained network model in a new related model.

In deep learning, most models that deal with complex problems require a large amount of data. However, the clinical implementation of supervised models can be really tough, including expert labeling, time and effort it takes to label data.

Instead of training our deep CNN architecture from scratch, from random initialization, we are going to use transfer learning to sort of transfer knowledge from ImageNet one of very large public data sets to our own classification task. [62]

Strategies for Deep Transfer Learning:

There are pre-trained deep neural networks that are now widely used for transfer learning.

In our classification task we are going to use VGG-16, Inception V3 and ResNet-50.

- Use the pre-trained model as feature extractors (figure 2.18):

- Delete the last prediction layer of the pre-trained model and replace it with our own prediction layers.
- Here weights of these pre-trained models are utilized as a feature extractor.
- Weights of the pre-trained model are frozen thus, are not updated during the training.

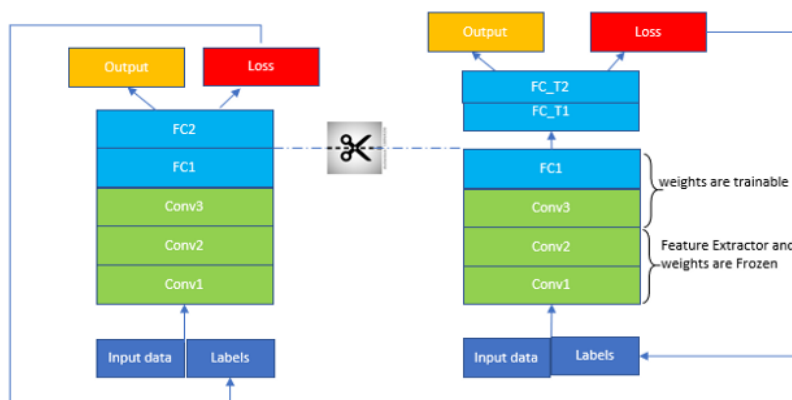


Figure 2.18 – Pre-trained model as feature extractors [12]

- Fine-tune the pre-trained models (figure 2.19):
 - Delete the last prediction layer of the pre-trained model and replace it with our own prediction layers.
 - Initial lower layers (very generic features) weights of pre-trained models frozen thus, they are not updated during the training.
 - Higher layers (specific features) of pre-trained models are trainable or fine-tuned.

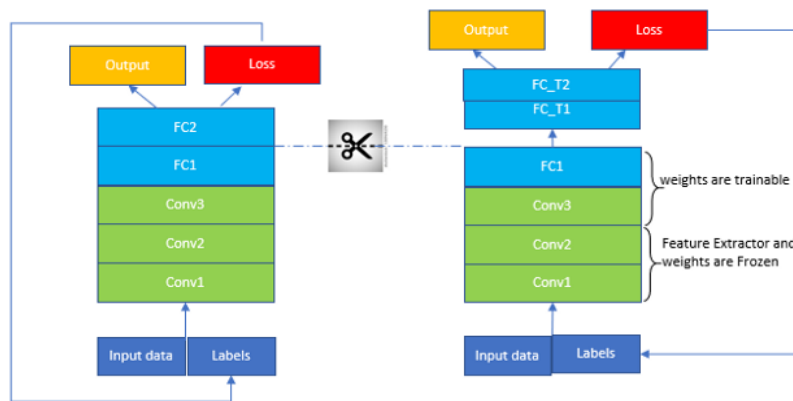


Figure 2.19 – Fine-tune the pre-trained model [12]

4.2 Segmentation using 3D U-Net architecture:

The proposed approach for segmentation of the whole brain tumor, tumor core and the enhancing tumor core is the 3D U-Net model.

Semantic segmentation:

Assigning a label to each pixel of an image with the corresponding class thus reaches fine-grained inference.

U-Net architecture:

U-Net is one of the most popular architectures for segmentation. It comprises of two paths: a contracting path, and an expanding path.

- The contracting path (encoder) is a typical convolutional network as used in image classification. It is based on repeated application of convolution and pooling operations, which gives us feature maps spatially smaller to classify better.

- The symmetric expanding path (decoder) takes the small feature maps through a series of up-sampling and up-convolution steps to return to the original image size.

To segment/localize better it also uses skip connections by concatenating the up-sample representations at each step with the corresponding feature maps at the contraction pathway. [63]

Below is the architecture of U-Net from the original paper (figure 2.20):

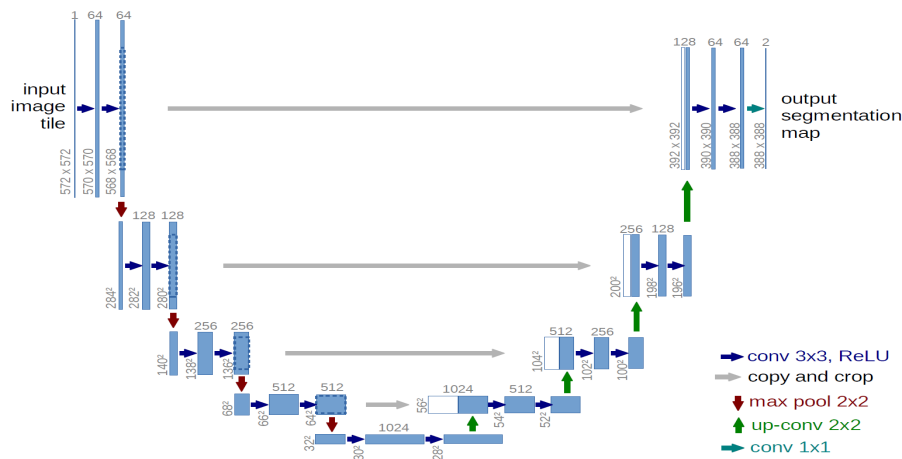


Figure 2.20 – The architecture of U-Net [13]

4.3 Soft Dice Loss:

Aside from the architecture, Soft Dice Loss is a most common loss function for segmentation tasks.

$$\mathcal{L}_{Dice}(P, G) = 1 - \frac{2 \times \sum_{i,j} p_{ij} g_{ij} + \epsilon}{\left(\sum_{i,j} p_{ij}^2\right) + \left(\sum_{i,j} g_{ij}^2\right) + \epsilon}$$

Soft Dice Loss will measure the error between our prediction map P, and our ground truth map G.

- p is our predictions.
- g is the ground truth.
- In practice each g_i will either be 0 or 1.
- ϵ is a small number that is added to avoid division by zero.

The soft Dice loss ranges between

- 0: perfectly matching the ground truth distribution g.
- 1: complete mismatch with the ground truth.

3D U-Net:

An extension to the U-Net called the 3D U-Net, is when we can feed any 3D sub volume into a segmentation architecture, thus replacing all of the 2D operations with their 3D analogues. In other words the 2D convolutions become 3D convolutions, and the 2D pooling layers become 3D pooling layers.

Conclusion

In this chapter, we've got presented a summary of deep learning and its architectures and therefore the State-of-the-art related to this work, and the most typical network architectures and methods of DL in both classification and segmentation of brain tumors.

We found that the selection of the strategy plays an awfully important role within the process and particularly to possess performance leads to a brief time.

Chapter 3

Conception and realization

Introduction

A web application is an application software running on a distant server interacting with user agents like an internet browser. Generally it performs many functions for the user. [64]

Nowadays; the healthcare industry goes through numerous changes with the advancement of technology and adopts the latest trend of converting everything into web applications; for this reason it made the life of anyone related to this domain easier whether he was a doctor or a patient. These types of applications are helping people a lot with their flexible strategies and saving time and effort; just click and you solve your problem.

In this chapter we'll present our web application and all the steps taken to achieve the desired result, from the conception to the obtained results.

1 Conception and modeling

The creation of Web application usually needs a combination of programming languages: Python, HTML, CSS, UML, and PHP...

In our case we'll start the process by the conception (design) after the first step, which is the formation of the application idea, and then we will start the design through an analyzing of functionalities, can be done rapidly and saves time later on.

As we know the design, development and maintenance of large, complex Web applications is becoming difficult and complex; to abstract and model them is the only way to manage this complexity.

We proposed one of the popular and most used methods of modeling Web application architecture UML short for Unified Modeling Language.

1.1 Unified Modeling Language(UML)

It is a graphical modeling language used for the designing and visual representation of all sorts of computer systems. It's born from the fusion of three object modeling languages (Booch, OMT, OOSE) that revolutionized modeling in the 90s.

UML is called a universal language because it is independent of programming languages. UML consist of 13 diagrams grouped 2 Diagram Structure: [65]

1. structural diagrams:

- Class Diagram.
- Component Diagram.
- Deployment Diagram.
- Object Diagram.
- Package Diagram.
- Composite Structure Diagram.
- Profile Diagram

2. behavioral diagrams:

- Use Case Diagram.
- Activity Diagram.
- State Machine Diagram.
- Sequence Diagram.
- Communication Diagram.
- Interaction Overview Diagram.

In this work we're going to focus on just 3 diagrams: Sequence Diagram, Use Case Diagram and Class Diagram.

1.2 Use Case Diagram:

The Use case diagram is composed of: Actors (human person or robot) that use the system and Use Cases (the functionalities proposed by the system).

Below is the use case diagram "Admin"

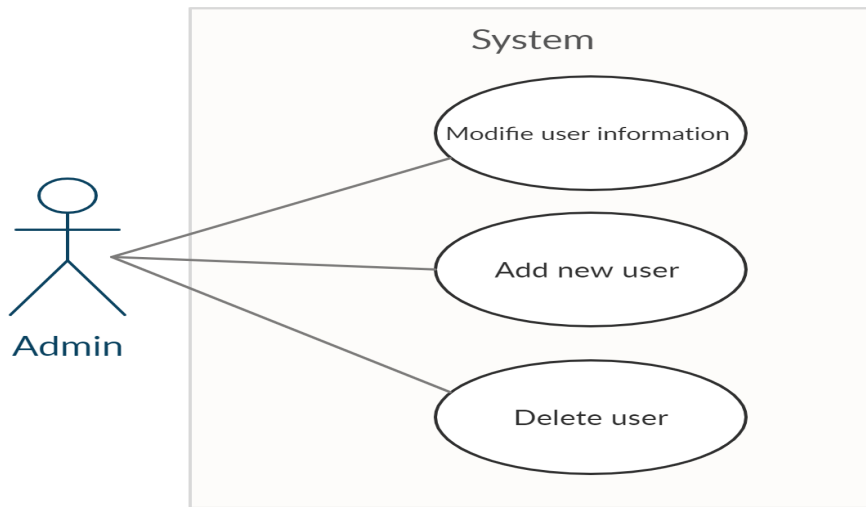


Figure 3.1 – Use case diagram "Admin"

An "Admin" actor is an administrator who can either add, modify or delete an user.

Below is the use case diagram "Doctor"

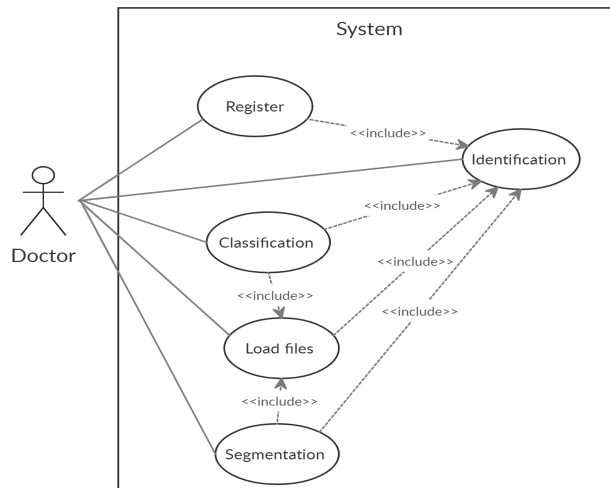


Figure 3.2 – Use case diagram for "Doctor"

"Doctor" is an actor of the medical profession who can use the application, after its authentication, for medical purposes such as the loading, classification or segmentation of a volume.

1.3 Class Diagram:

It represents the conceptual architecture of the system; it describes the classes that the system uses and their links.

Below is the class diagram for the system:

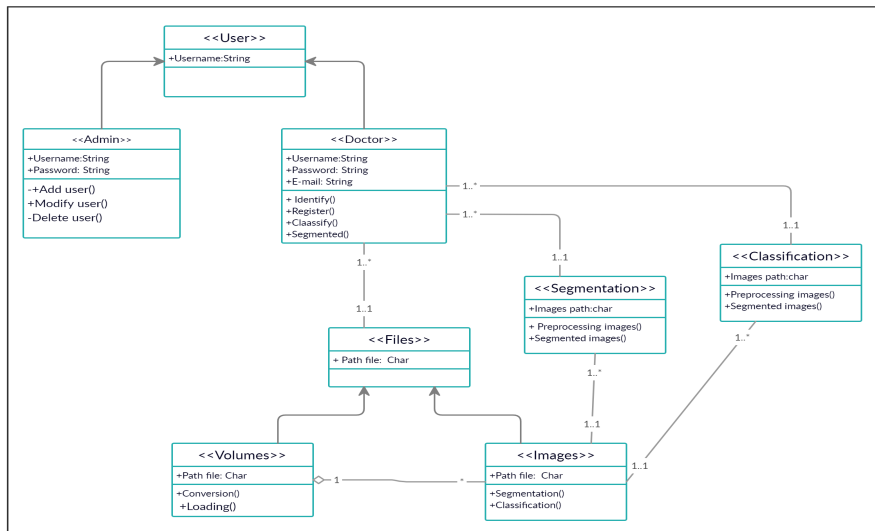


Figure 3.3 – Class diagram

1.4 Sequence Diagram:

This diagram presents the manner how the users interact with others in a particular scenario of a use case.

Below is the authentication and registration sequence Diagram :

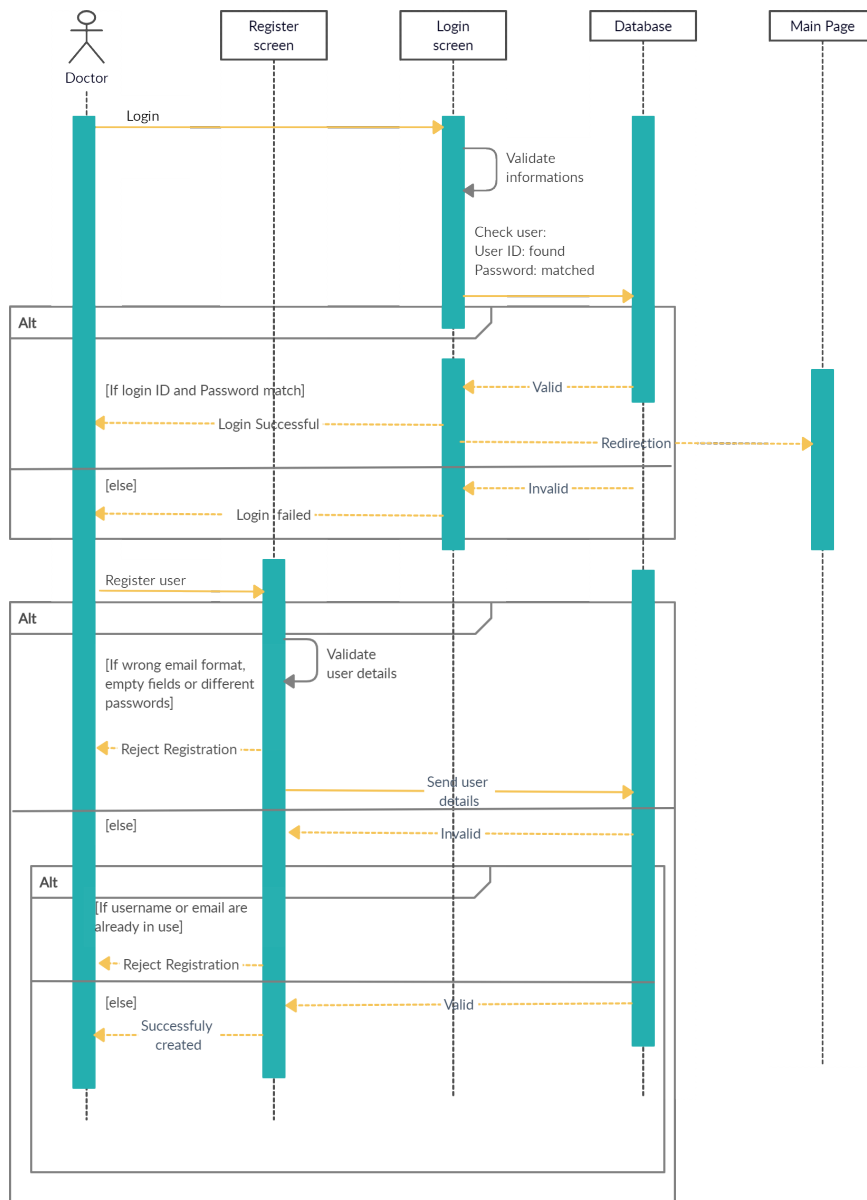


Figure 3.4 – Sequence Diagram "Authentication and registration".

An actor of type "doctor" must first login to the application, a data check is done on the database, if the username and password are correct the user will be transferred to the main page, otherwise he will be transferred to the registration page to create his account, in this step if all the entered information are valid the account will be added in the database or the registration will be rejected.

Below is the classification and segmentation sequence Diagram.:

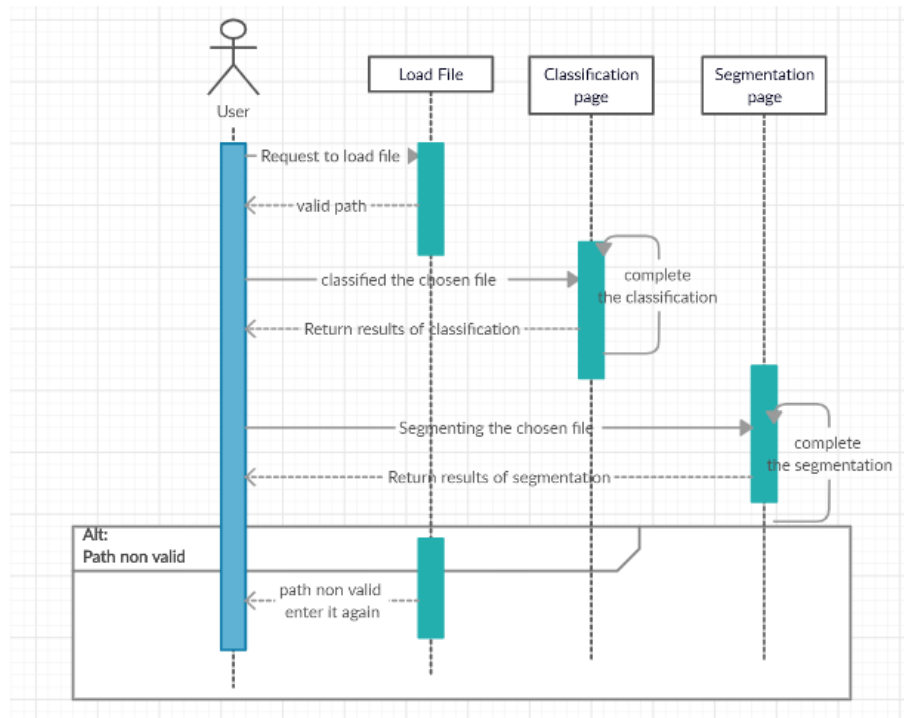


Figure 3.5 – Sequence Diagram "classification and segmentation".

For this part of the application the user could do three tasks, firstly he could load the NIFTI files by using path if it's valid he could pass to the next tasks classification or segmentation and he will get the results that he needs; otherwise he needs to re-enter it.

2 Used tools :

2.1 Python 3.6.9 :

Python is a high-level programming language, characterized by its simplicity, Ease of use and learns syntax emphasizes legibility also lets you work quickly. it is free to use(open source), even for commercial applications.

In this work we used Python 3.8.0.it is the newest major version of the Python, and offers many new features and optimizations. [66]

2.2 Jupyter notebook:

It is an open-source web application that enables you to form and share documents with codes, equations...

This browser-based tool gives the possibility to edit and execute code from the

browser, with the results of computations. [67]

2.3 Tensorflow-gpu 2.0.0:

TensorFlow is an open source Python library for large-scale machine learning. it is one of machine learning frameworks released by Google Brain team used to design, build, and train deep learning models. [68]

2.4 Keras2.3.1:

Keras is a high-level open-source library of neural network modules written in Python. It is the most used deep learning framework Because it is easy to extend, and to work with Python. [69]

2.5 Django 3.0.6:

Django is a high-level Python Web framework that allows rapid development and clean design of websites. It is free and open source. [70]

3 Experimental results and Discussion

3.1 Dataset:

In this work, we used the BraTS 2019 dataset for experiments, which contains images from 335 patients (259 HGG and 76 LGG), each patient was scanned with four sequences: T1, T1ce, T2 and FLAIR. We have selected a subset from the Brats dataset and divided it into four databases, one for each modality. Each modality from the previous four databases contains 155 slices for one patient; in this thesis we are going to work with these slices as PNG images. The used databases provided as a set of slices contain 2015 High-Grade Glioma (HGG) and 2015 Low-Grade Glioma (LGG) images from the T1, T1ce, T2 and FLAIR modalities respectively.

The examples of High and Low-Grade Glioma obtained by T1, T1ce, T2 and FLAIR modalities respectively are shown in Figure 3.6 and 3.7.

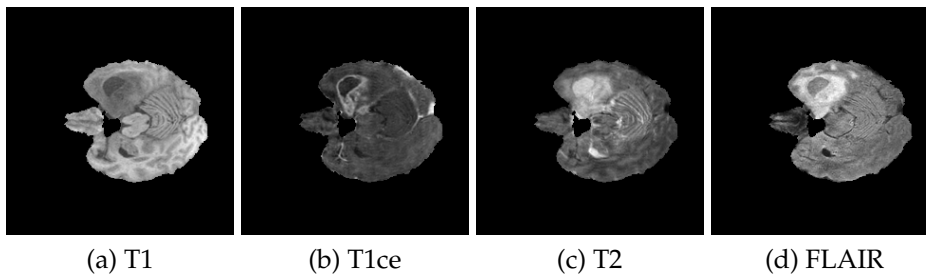


Figure 3.6 – HGG

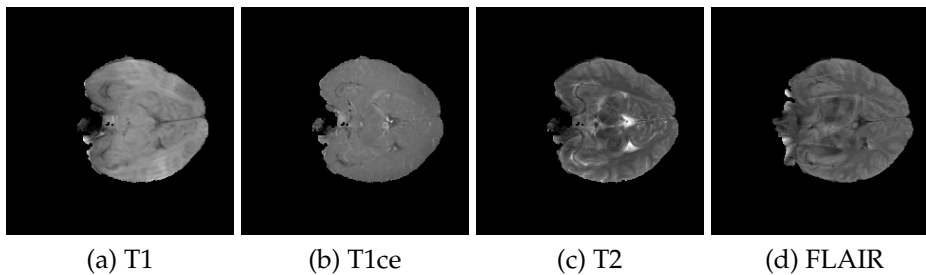


Figure 3.7 – LGG

3.2 Image Pre-Processing and Data Augmentation:

We have made a conversion for each NIfTI (nii) volume to PNG images, thus each volume gives us 155 PNG images. We have normalized and readjusted the size of all images to use them with the deep learning models (224*224 for VGG16 and Resnet50 and 299*299 for InceptionV3). One of the major challenges in PNG images is the existence of non-tumorous slices in both HGG and LGG classes. These slices can lead to false negatives in the predicted output results. Therefore, we need to remove all these slices from the HGG class, to ensure that all slices matches with the ground truth.

In order to augment the dataset, we transformed each image by rotation, shift and horizontal flip.

4 Experimental results and Discussion

Tumor classification was performed using a set of models of CNN developed in Jupyter Notebook on a local machine with a 4820k i7 processor, 56 GB RAM, an 8 GB GTX1070 GPU and Windows 10 operating system.

The Classification was achieved using three pre-trained models on ImageNet database: Resnet50, VGG16 and Inception v3; and BraTS 2019 database that was divided in to 4 databases one for each modality for the first stage as we mentioned before. Then the same models were applied on one pre-processed database (DB without the black slices in the HGG files) that allows the models to train well in order to find the ideal model for our case.

All the process of this work is presented in block diagram in Figure 3.8 and 3.9 and algorithm 1:

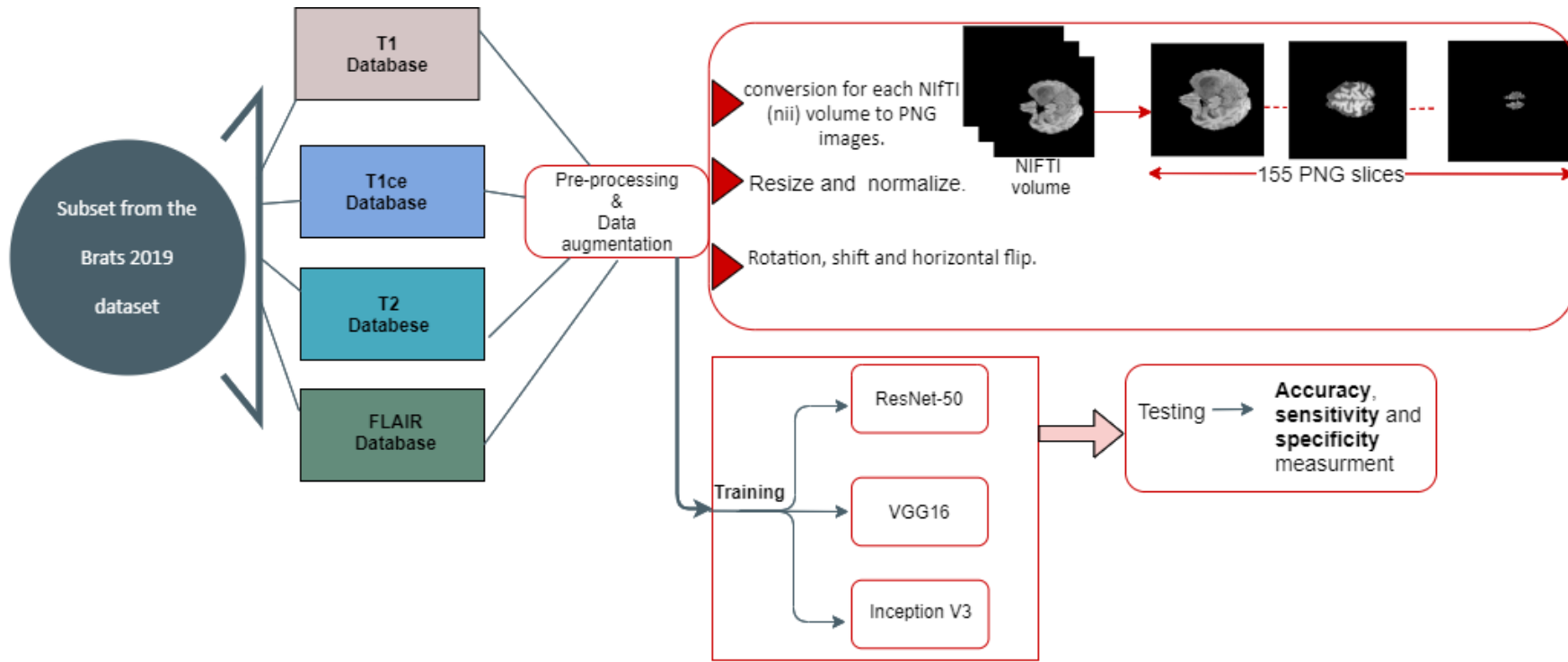


Figure 3.8 – Block diagram: the process of the selection of the database which allows the models to train well.

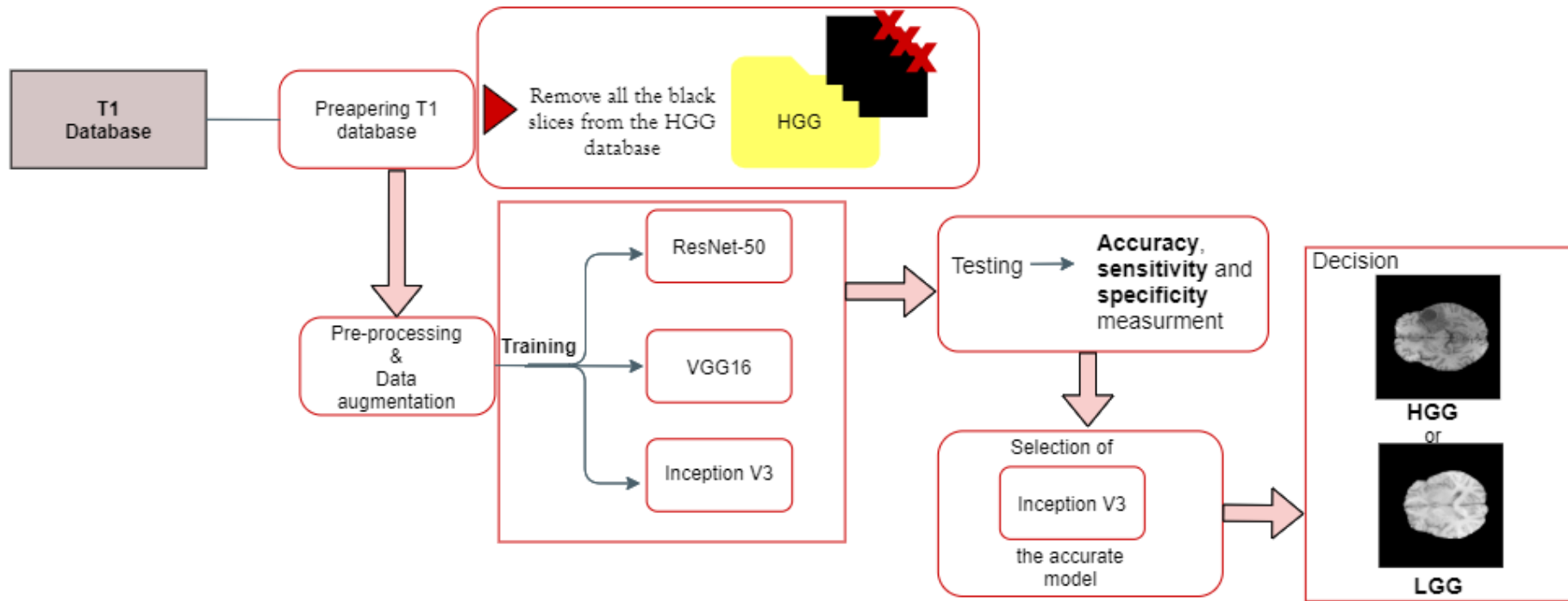


Figure 3.9 – Block diagram: the process of the selection of the best model for the T1 database.

The first block diagram presents the process of the selection of the database which allows the models to train well from the set of databases (T1, T2, T1ce and FLAIR) and the second block diagram presents the process of the selection of the best model for the database of modality T1.

Algorithm 1 Brain Tumor classification

Data: Brain MRI volume (T1 modality) **MRI**

Result: Decision (HGG or LGG) **D**

initialization: $i=0$ **IMG** = decomposition(**MRI**) **for each IMG do**

```

|    $cl = \text{classify}(\text{IMG})$  if  $cl == 'HGG'$  then
|   |    $i++$ 
|   end

```

end

if $i > 0$ **then**

```

|    $D = 'HGG'$ 

```

else

```

|    $D = 'LGG'$ 

```

end

The algorithm 1 above presents the process of classifying a total volume for one patient that used just one modality (T1 with conversion from nii volume to 155 slices PNG images) from the whole volume and the inception v3 model classified each image and in the same time a counter is increasing if the class was HGG, if it was not it won't be increased. At the end the counter will be tested if at least one image is classified as HGG class that means the patient has an HGG tumor if not (counter = 0) that means the patient has an LGG tumor.

All the models were trained for 50 epochs using batch size equal to 16 with SGD optimizer to minimize the loss function.

Firstly, we applied the chosen models on the first version of our databases (4 databases without pre-processing) for the purpose of finding which modality helped them to train well, the results of this training are shown in the Table 3.1 and in the Figure 3.10 the confusion matrices that summaries system's performance also the accuracy curve in Figure 3.11.

Where:

- Specificity = $(TN) / (TN + FP)$ = Probability of being test negative when disease absent.
- Sensitivity = $(TP) / (TP + FN)$ = Probability of being test positive when disease present.
- Accuracy = $(TN + TP) / (TP + FN + TN + FP)$.

With:

- True Positive (TP) is the number of positive predicted cases and they are actually positive.
- True Negative (TN) is the number of negative predicted cases and they are also actually negative.
- False Negative (FN) is the number of negative predicted cases while they are actually positive.

- False Positive (FP) is the number of positive predicted cases while they are actually negative.

Table 3.1 – The calculated performances of the three models applied in four databases.

Database	Model	Acc,	Sens,	Spec,
T1CE	Resnet50	0.9413	0.8894	0.9925
	VGG16	0.9438	0.8945	0.9925
	InceptionV3	0.9488	0.8995	0.9975
Flair	Resnet50	0.9437	0.8944	0.9925
	VGG16	0.9474	0.8969	0.9975
	InceptionV3	0.9487	0.8994	0.9975
T1	Resnet50	0.9513	0.907	0.9487
	VGG16	0.9413	0.8894	0.9925
	InceptionV3	0.95	0.9045	0.995
T2	Resnet50	0.9475	0.8969	0.9975
	VGG16	0.9424	0.8944	0.99
	InceptionV3	0.9463	0.8969	0.995

The table 3.1 resumed the results obtained by three models learned on four databases (T1, T2, Flair and T1CE without preprocessing) we had noticed that there is a difference in performance of models in terms of accuracy, sensitivity and specificity. In general; diagnostic support systems depend on a set of metrics to measure how well they predicts the outcomes; one of the important metrics is the sensitivity.

The higher value of sensitivity means lower value of false negative. In other words, patients who are actually unhealthy and got predicted as healthy. For that in Brain tumors classification, this metric is highly important and puts focus in it. On the basis of sensitivity values we can compare between the obtained results in training on each DB to find the one that will give the best generalization also the best performance with these models so this database is the T1 database. Secondly, we initiated learning with the preceding models on the T1 pre-processed database. We have noticed that the volume of HGG contains some black slices which are also found in LGG volumes. To avoid misclassification of these images, and since they do not contain any information, we have removed them from the HGG database. Such an action will allow us to consider all black slices as LGG and thus reduce the error rate. The obtained results with this pre-processing step are shown in the table 3.2 and Figure 3.12 and 3.13.

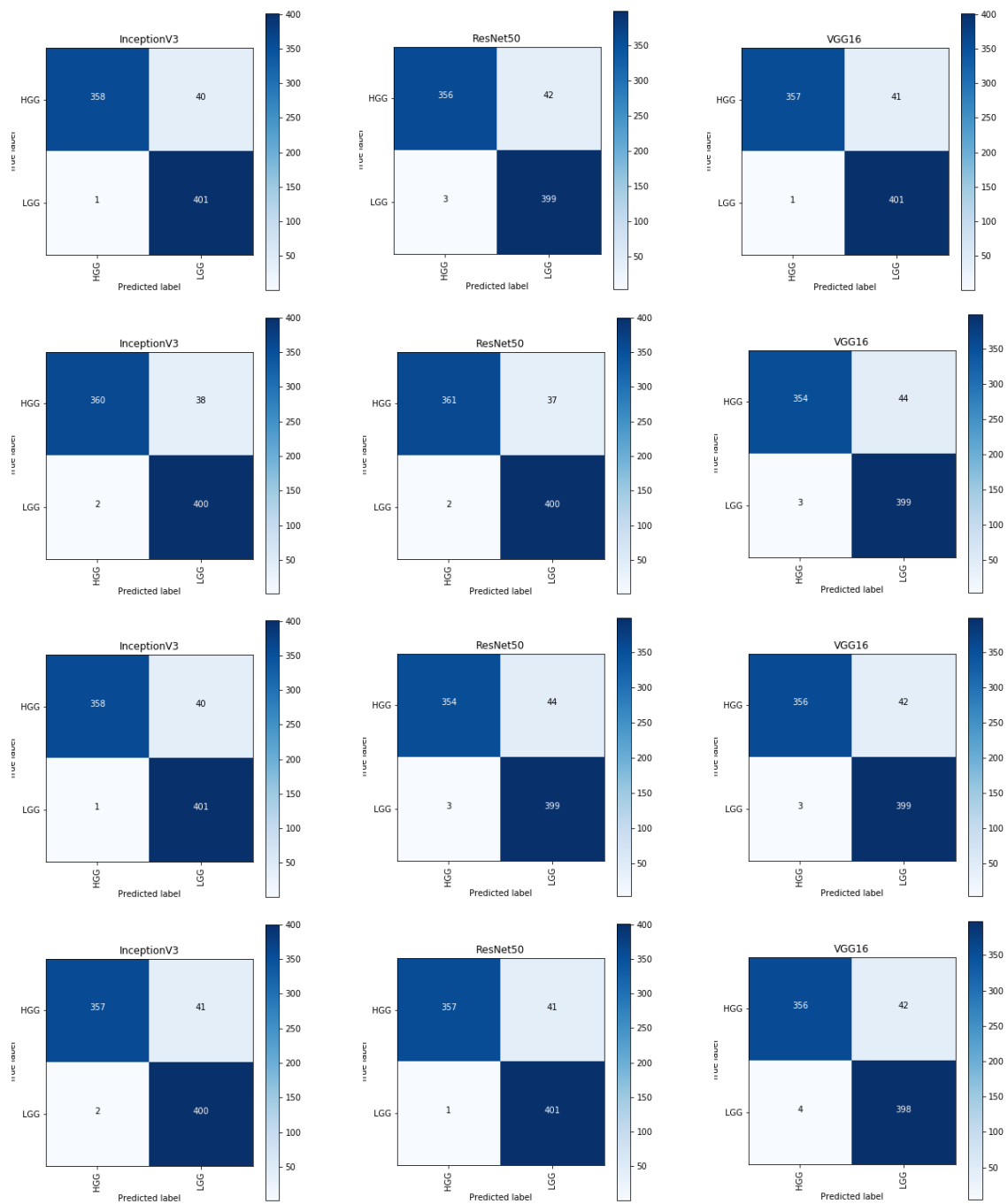


Figure 3.10 – Shows the confusion matrices for the four DBs(Flair, T1, T1CE and T2 respectively) with three models. With: High Grade Glioma (HGG): present images with tumor and Low Grade Glioma (LGG): present images without tumor.

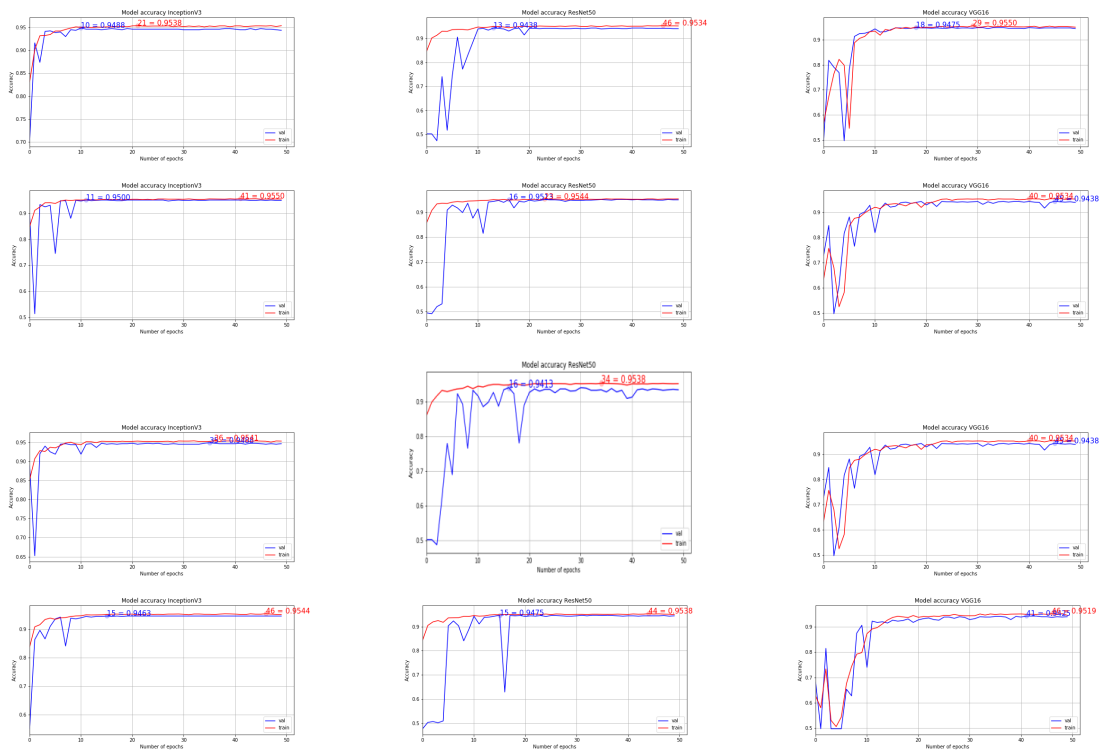


Figure 3.11 – shows the accuracy curve for the four DBs: Flair, T1, T1CE and T2 respectively; with three models Resnet 50, Inception v3 and VGG16 respectively, in the training and the test.

Table 3.2 – The obtained results of performances of training three models on T1 Database

Database	Model	Acc,	Sens,	Spec,
T1 preprocessed	Resnet50	0.9971	0.9876	0.9937
	VGG16	0.9954	0.9805	1
	InceptionV3	0.9975	0.9894	1

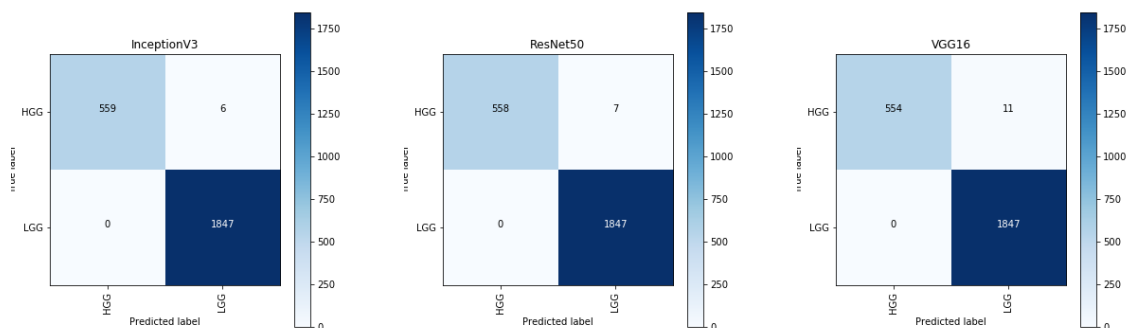


Figure 3.12 – Shows the confusion matrices for the pre-processed DB with VGG16, Inception v3 and Resnet50 models.

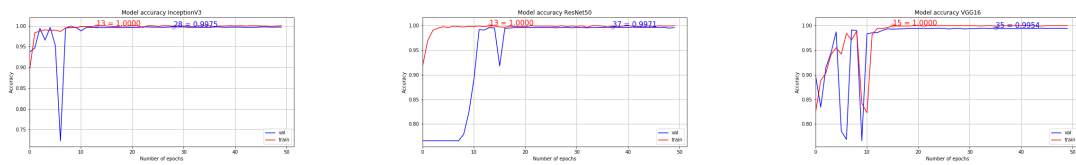


Figure 3.13 – Shows the accuracy curve for the T1 database; with three models Inception v3, Resnet 50 and VGG16 respectively, in the training and the test.

According to the found results and the ranking of models based on their performance Table 3.1, Inception v3 exceeds the others in regards to the highest values of precision, sensitivity and specificity.

Afterwards to classify the total volumes of one patient we used a loop where we utilized just one volume T1 and converted it to 155 PNG images; then the inception v3 model classified all the 155 PNG images and the result of this classification will be tested if at least one single slice from the 155 slices (images) is considered as HGG class so the whole volume is considered as HGG class and the patient will be classified as being sick.

If no slice is considered as HGG so the whole volume is considered as LGG class (all the 155 slices are LGG). algorithm 1.

5 Realization

Based on the design defined in this chapter with UML language; our MED3csEG web application was realized with python and django to develop and model each components and functions of this web application in order to give an integrated work to make all the process of analyzing the Gliomas brain tumors easy and elaborate with a high percentage of certainty also to ensure the integrity of the security for the data and information of patients.

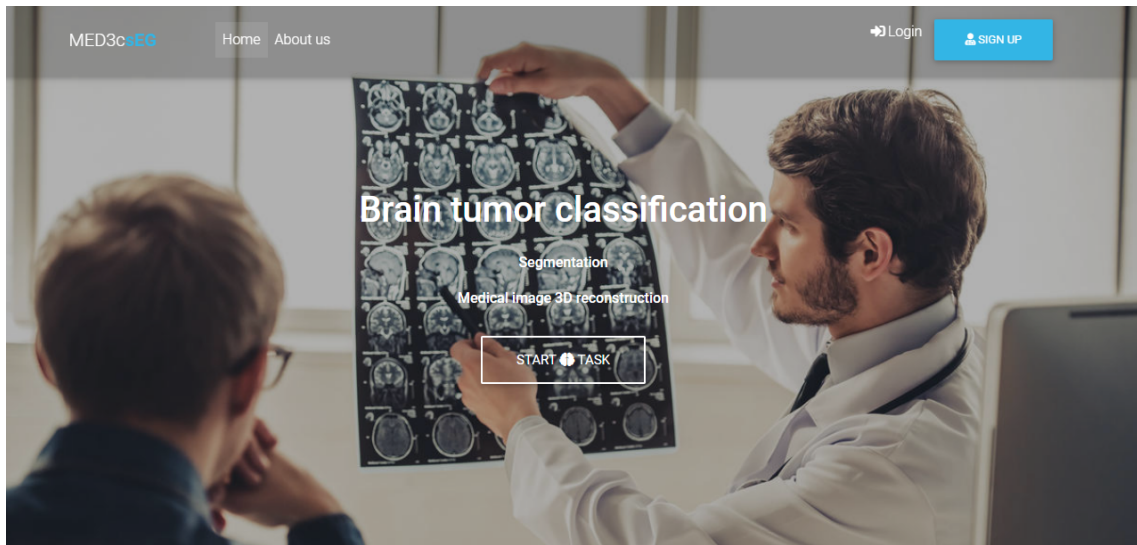
MED3csEG is the logo for our Web-App composed of: MED for medical, 3 for 3D reconstruction, C for classification and SEG for segmentation.

MED3csEG is one of the Multi-Page Applications; its functions can be mainly divided into the below several categories: Home page, Registration page, Login page, Classification page.

1. MED3csEG Home page:

Figure 3.14 is the home page of our web-app. Generally the home page offers a simple introduction and an initial idea of the whole App and its functionalities.

And this tour page mainly introduces: the presentation of the MED3csEG decision support system and an overview of all its functions also the access to the login and registration pages.



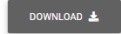
MED3csEG






Computer Aided Diagnosis System

MED3csEG is a Computer Aided Diagnosis System (CAD) for classifying Brain tumors in MRI images into High-Grade (HGG) or Low-Grade (LGG), Segmentation and 3D reconstruction.

Read details below to learn more about MED3csEG.







About MED3csEG

-  **Deep learning**
 Thanks to MED3csEG you can take advantage of all feature of image classification, segmentation and 3D reconstruction.
-  **Accurate results**
 To assist you in your interpretation and decision making.
-  **Lots of strictness**
 Because it is on high priority sector and people expect highest level of care and services. We care about the development of our Computer Aided Diagnosis System.





Watch our "2 min Quick Start" tutorial

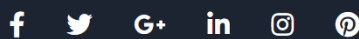


Not enough?

-  **Classification**
 -  classifying Glioma tumors in brain MRI images into High-Grade (HGG) or Low-Grade (LGG) tumor.
 -  Percentage of having HGG
 -  Percentage of having LGG



-  **Segmentation**
 -  Segmentation of the whole brain tumor
 -  Segmentation of the tumor core.
 -  segmentation of the enhancing tumor



2. MED3csEG Register page:

Figure 3.15 – Register page.

The above page is the page of registration that's one of the trickiest parts of web-Apps; it's composed of few number of form fields: Username, Email, Password and conformation of password.

It presents what information is needed to be recorded into the database for the user accounts.

3. MED3csEG Login page:

Figure 3.16 – Login page.

In the login page, that is the most important user interface elements in this web-App; it is the door to the world of classification and segmentation of brain tumors it offers tow type of inputs username and password.

It used as a complete access to the main page of MED3csEG and used to limit the access just for the already registered users.

4. MED3csEG Classification page:

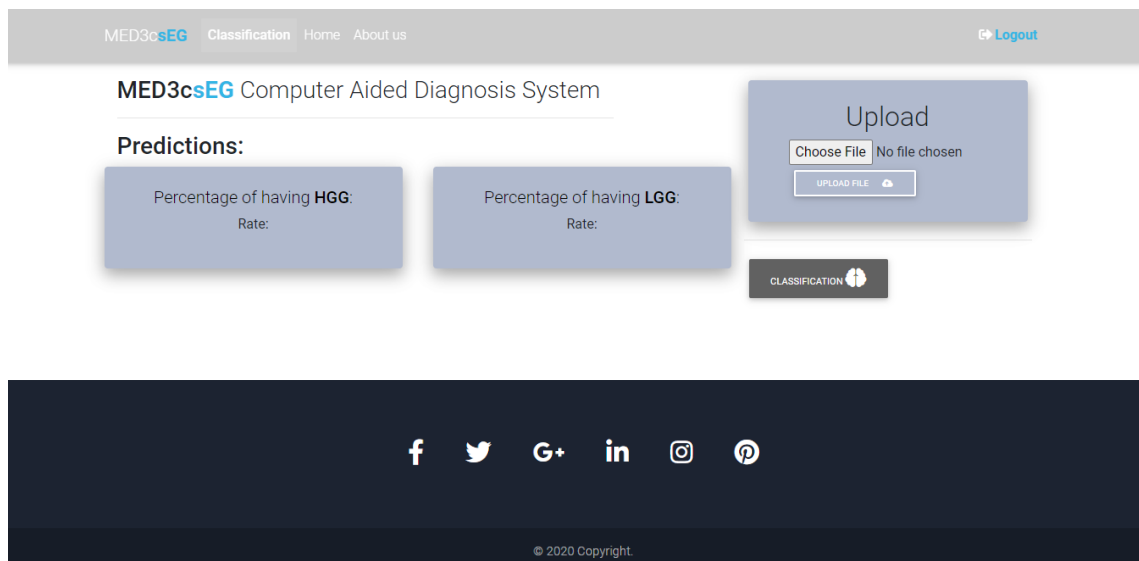


Figure 3.17 – Classification page.

The above figure illustrates the process of Classification. For the classification page there are two spaces of work one for loading volumes and the other to launch the classification and visualize the results.

The results in case of an HGG class: our model takes the 155 slices from the T1 volume of one patient and classified them, at the end it gives as the following result presented in the figure [3.18](#):

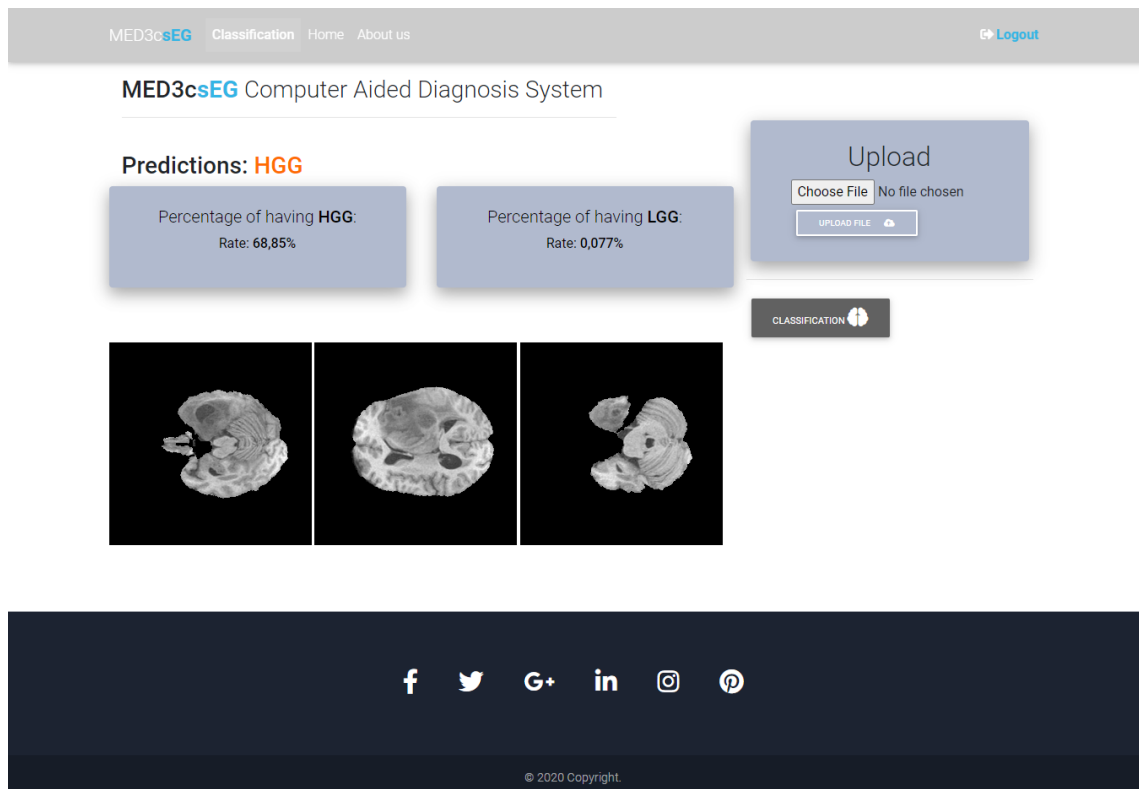


Figure 3.18 – Classification page.

Conclusion

In this chapter dedicated to conception and implementation we modeled our application by providing answers to our modeling and design questions. We were able to model it in the form of use case diagrams, class diagrams and then sequence diagrams.

Then we have presented the tools that helped us design and implement our application, the programming language and the framework, also the process of work and its steps without forgetting that we have chosen the T1 modality as our DB and the pre-trained Inception v3 as our classification model and its results after the training and test on T1 database.

At the end we have exposed the graphical representation of the global architecture of the application and the interfaces to illustrate the work that has been done.

General Conclusion & Perspectives

Brain tumors affect the human's life improperly, because of the abnormal growth of cells inside the brain. It may disturb brain function and be dangerous and life-threatening. Brain tumors are grouped into two categories benign tumors and malignant tumors. The first type is harmless compared to malignant tumors because malignant tumors grow rapidly and are harmful, while the former grow slowly.

One of the different types of medical imaging technologies based on a non-invasive approach is MRI that offers greater contrast images -especially of the brain- that provided different information about the shape or function of organs in the patient's body. Doctors base their decisions on this information but unfortunately, this kind of data is extremely difficult to exploit quantitatively and objectively. In this work our proposed approach is to create a web application to facilitate the classification of brain tumors.

Several technologies were necessary for the realization of our project like Python, UML, Django... ; and to get the object there is two ways to follow the first was the preparation of the database and to be more accurate the selection and preparation of which modality would be used; then the selection of the model of classification. Second way is the realization of the web App and all functionalities we need them on it.

The used modality from the set of modalities of MRI volumes (T1, T2, T1ce and Flair) was T1 modality that has undergone a number of preprocessing and data augmentations in addition to the elimination of dark slices from the HGG slices. About the chosen model it was the Inception v3 because of its optimal performances in comparison with Resnet50 and VGG16 applied on T1 modality; it gives 0.9975, 0.9894 and 1 for the accuracy, sensitivity and specificity respectively.

The final step as we mentioned before is the realization of our web application that contained Home page, login and registration pages and the main page for brain tumors classification.

This project has been an inspiring experience, very beneficial for us. Indeed, it allowed us to enrich our theoretical knowledge and skills in the field of design and programming. In addition, it was a great opportunity to carry out concrete work with clear and well-defined objectives.

For the moment the project is still in the implementation phase, we still have as a perspective the addition of the segmentation of brain tumors using the 3D U-Net architecture and the tumor reconstruction in 3D and put all these functionalities in our web App in order to make the decision easier for doctors.

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Abstract

The scope for improved disease detection and treatment planning is accompanied by accurate and fully automatic algorithms for brain tumor classification and segmentation from volumetric 3D magnetic resonance imaging (MRI). Glioma, is one of the most common types of primary brain tumors and is divided into two grades according to the World Health Organization (WHO). While the human interpretation of the large amount of MRI image data is not only irreproducible but also depends on expertise, time consuming and efforts.

In this work, we try to address this problem by developing a web application to classify brain tumors into two classes: High-Grade Glioma (HGG) and Low-Grade Glioma (LGG). The proposed solution includes two parts. First, applying a pretrained Convolutional Neural Network based model using VGG-16, ResNet-50 and Inception V3 for transfer learning to four datasets one for each MRI modality (T1, T1ce, T2 and FLAIR) to select which modality presents more specific features and information, passing by image pre-processing and data augmentation. To further improve tumor classification, non-tumorous slices were removed from the HGG class of the selected dataset and then was separately used to train the three models. Secondly, we present our web application Med3csEG that is one of the support system decisions by mentioning all the steps of the modeling and realization of every functionality which are introduced in home page, login and registration pages and the main page for completing the brain tumors classification task.

Evaluations on BraTS 2019, attest that T1 presents the most discriminative features to distinguish between LG and HG gliomas with 0.9513, 0.907 and 0.9487 for the accuracy, sensitivity and specificity respectively. The Inception V3 model trained on T1 dataset outperforms the other models with 0.9975, 0.9894 and 1 for the accuracy, sensitivity and specificity respectively.

Experimental results demonstrate that using Inception V3 model with T1 MRI modality has the potential to achieve good results in brain tumor classification.

Keywords

Deep learning, CNN, transfer learning, classification, segmentation, BraTS 2019 dataset, HGG, LGG, MRI, MED3csEG, web application.

Résumé

La possibilité d'améliorer la détection des maladies et la planification des traitements s'accompagne d'algorithmes précis et entièrement automatiques de classification et de segmentation des tumeurs cérébrales à partir de l'imagerie volumétrique 3D par résonance magnétique (IRM). Le gliome est l'un des types les plus courants des tumeurs cérébrales primaires et est divisé en deux grades selon l'Organisation mondiale de la santé (OMS). L'interprétation humaine de la grande quantité de données d'images IRM est non seulement non reproductible mais dépend également de l'expertise, du temps et des efforts.

Dans ce travail, nous essayons de résoudre ce problème en développant une application web pour classer les tumeurs cérébrales en deux classes : Gliome de haut grade (GHG) et Gliome de bas grade (GBG). La solution proposée comprend deux parties. Tout d'abord, l'application d'un modèle pré-entraîné basé sur un réseau de neurones convolutif utilisant VGG-16, ResNet-50 et Inception V3 pour transférer les connaissances acquises à quatre ensembles de données, un pour chaque modalité d'IRM (T1, T1ce, T2 et FLAIR), afin de sélectionner la modalité qui présente des caractéristiques et des informations plus spécifiques, en passant par le prétraitement des images ainsi que l'augmentation des données. Pour améliorer encore la classification des tumeurs, les coupes non tumorales ont été supprimées de la classe HGG de l'ensemble de données sélectionné, puis ont été utilisées séparément pour entraîner les trois modèles. Deuxièmement, nous présentons notre application web Med3csEG qui est l'une des systèmes d'aide à la décision en mentionnant toutes les étapes de la modélisation et de la réalisation de chaque fonctionnalité qui sont introduites dans la page d'accueil, les pages d'authentification et d'enregistrement et la page principale pour compléter la tâche de classification des tumeurs cérébrales.

Les évaluations sur BraTS 2019, attestent que la modalité T1 présente les caractéristiques les plus discriminantes pour distinguer les gliomes LG et HG avec 0,9513, 0,907 et 0,9487 pour la précision, la sensibilité et la spécificité respectivement. Le modèle Inception V3 entraîné sur l'ensemble de données T1 surpasse les autres modèles avec 0,9975, 0,9894 et 1 pour la précision, la sensibilité et la spécificité respectivement.

Les résultats expérimentaux montrent que l'utilisation du modèle Inception V3 avec la modalité IRM T1 peut permettre d'obtenir de bons résultats dans la classification des tumeurs cérébrales.

Mots clés

Apprentissage profond, CNN, apprentissage par transfert, classification, segmentation, base de données BraTS 2019, GHG, GBG, IRM, MED3csEG, application web.

الملخص:

يرافق تحسين نطاق اكتشاف المرض وتخطيط العلاج خوارزميات دقيقة وتلقائية بالكامل لتصنيف ورم الدماغ وتجزئة من التصوير بالرنين المغناطيسي ثلاثي الأبعاد (MRI). الورم الدبقي ، هو أحد أكثر أنواع أورام الدماغ الأولية شيوعًا وينقسم إلى درجتين وفقًا لمنظمة الصحة العالمية (WHO) ، في حين أن الترجمة و التحليل البشري لكمية كبيرة من بيانات الصور الناتجة عن التصوير بالرنين المغناطيسي ليس فقط غير قابل للتكرار ولكنه يعتمد أيضًا على الخبرة والجهد والوقت.

في هذا العمل ، نحاول معالجة هذه المشكلة من خلال تطوير تطبيق ويب لتصنيف أورام الدماغ إلى فئتين: الورم الدبقي عالي الدرجة (ودع د) والورم الدبقي منخفض الدرجة (ودم د). الحل المقترح يشمل جزئين : أولاً ، تطبيق نموذج قائم مسبقًا على الشبكة العصبية التلافيفية باستخدام نموذج VGG-16 و ResNet-50 و Inception V3 لنقل التعلم إلى أربع مجموعات من البيانات واحدة لكل طريقة تصوير بالرنين المغناطيسي (T1 و T1ce و T2 و FLAIR) لتحديد الطريقة التي تقدم ميزات أكثر دقة و المعلومات اوفر ، مروراً بالمعالجة المسبقة للصور وزيادة البيانات. لزيادة تحسين تصنيف الورم ، تمت إزالة الشرائح غير الورمية من فئة ودع د لمجموعة البيانات المحددة ثم تم استخدامها بشكل منفصل لتدريب النماذج الثلاثة. ثانيًا ، نقدم تطبيق الويب الخاص بنا Med3csEG وهو أحد أنظمة دعم القرارات من خلال ذكر جميع خطوات النمذجة وتحقيق كل وظيفة يتم تقديمها في الصفحة الرئيسية وصفحات تدوين الدخول والتسجيل والصفحة الرئيسية لاستكمال مهمة تصنيف أورام الدماغ. ثانيًا ، تطوير تطبيق الويب الخاص بنا الذي يحتوي على الصفحة الرئيسية وصفحات تدوين الدخول والتسجيل والصفحة الرئيسية لتصنيف أورام المخ.

تشهد التقييمات التي أجريت على BraTS 2019 أن المجموعة T1 تقدم أكثر الميزات دقة للتمييز بين الورم الدبقي ع د و م د مع 0.9513 و 0.907 و 0.9487 من أجل الدقة والحساسية والنوعية على التوالي. يتفوق النموذج Inception V3 المدرب على مجموعة البيانات T1 على النماذج الأخرى بـ 0.9975 و 0.9894 و 1 من حيث الدقة والحساسية والنوعية على التوالي.

تظهر النتائج التجريبية أن استخدام نموذج Inception V3 مع مجموعة البيانات T1 المتحصل عليها عن طريق التصوير بالرنين المغناطيسي انه لديه القدرة على تحقيق نتائج جيدة في تصنيف هذا النوع من أورام المخ.

الكلمات المفتاحية:

التعلم العميق ، الشبكة العصبية التلافيفية (ش ع ت) ، نقل التعلم ، التصنيف ، التجزئة ، مجموعة بيانات BraTS 2019 ، الورم الدبقي عالي الدرجة (و دع د) ، الورم الدبقي منخفض الدرجة (و دم د) ، التصوير بالرنين المغناطيسي ، تطبيق الويب ، MED3csEG