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Presented by:

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THEME

Brain Tumor Classification Using SVM Based on Deep Learning

In front of the committee composed of:

Dr. ……………………MCA President
Dr.…………………… MAA Examiner
Dr. KHOLLADI Nedjoua Houda MAA Supervisor

Academic year: 2019/2020

Dedications

Thanks to Allah first-then the efforts of my loved ones

who helped me a lot with their advice and efforts

when we were going to offer this job.

Dedicate this work to my dear mother,

To my Father.

To my all brothers and sisters

To all my best friends

To my Supervisor teacher **KHOLLADI** Nedjoua Houda

To all my colleagues.

Maamoun Mohammed Oussama

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Ladgham Seif Eddine

Acknowledge

Thanks to ALLAH Almighty who gave us

the strengts to complete this work.

Then thanks to our supervisor

Dr.« KHOLLADI Nedjoua Houda »

for his wonderful advice

and to follow up our work.

Thanks also to all the professors and friends

for their support and patience.

Abstract:

Images are the visual knowledge repositories that under these criteria act a serious role due to their variety in rendering and providing the information. Moreover, scientists utilized images as features to evolve new machines that can collect data and employ it for the amelioration of mankind.

In the field of medical imaging and computer-aided Diagnostic, almost all of the theories and concepts affiliated to image processing, machine learning, and optimization methods are discussed.

The key challenging task was the precision of the extraction of a brain tumor at earlier stages so that proper treatment can be adopted. As a result, the chances of survival of a tumor-infected patient can be increased significantly if the tumor is detected accurately in its early stage.

The most common primary brain tumors are:

- Gliomas (50.4%)
- Meningiomas (22.6%)
- Pituitary adenomas (18%)
- Nerve sheath tumors (9%)

Nowadays, CAD systems were typically utilized for an efficient and explicit recognition of brain anomalies. Computer-aided detection is systems that support doctors in the interpretation of the medical images, CAD is an interdisciplinary technology combining elements of AI and computer vision with image processing of radiological and pathology.

In this work the main focus is made on initially a Process which is relied on the Fusion of a variety of methods:

- Pre-processing Step: based on Enhancing Process which is relied on algorithms such as Histogram equalization and logarithmic transformation.

-Segmentation Process: The proposed system is designed on U-Net architecture that is a fully CNN(s), which have accomplished best in class execution for automatic medical image segmentation.

We did use U-net for extracting regions of interest that can extract lesion for discriminating symptoms of brain cancers different types of diseases.

- Features Extraction Step: are utilizing for obtaining the specific properties of the image by which a discriminant feature vector is provided and the images can be classified. It plays the role of a booster to the classifiers. Here in this work, we used two algorithms: GLCM: Gray Level Co-Occurrence Matrix (GLCM) proposed by Haralick et al. (1973), is one of the techniques widely employed as technique based texture, the main point of GLCM relies on the spatial relationship of the pixel (angle and distance) in the gray level images. We have merged this technique with other one based shape Moment Hue

- Classification Process: we used SVM algorithm to classifier all the extracted features and trying all the SVM kernels to chose the best one.

The main utility of this proposed model by using Imaging Techniques, it assists the doctors to observe and track the occurrence and growth of tumor-affected lesions at different stages so that they can detect prognostic diagnosis.

Through the proposed model it has performed an accuracy of 96.4, this means a good classification of the utilized dataset which holds Brain MRI images created by Jun Cheng in 2017.

Keywords: Image processing, Deep Learning, Convolutional Neural Network, Computer Aide Diagnostic, Brain tumor, Images Classification.

الملخص:

الصور هي مستودعات المعرفة المرئية والتي بموجب هذا التعريف تلعب دورًا جادًا في تقديم المعلومات وتحسينها. علاوة على ذلك ، يستخدم العلماء الصور كميزات لتطوير آلات جديدة يمكنها جمع البيانات وتوظيفها لتحسين الأداء البشري.

في مجال التصوير الطبي والتشخيص بمساعدة الكمبيوتر ، تتم مناقشة النظريات والمفاهيم المرتبطة بمعالجة الصور والتعلم الآلي وطرق التحسين حيث كانت المهمة الرئيسية الصعبة هي الدقة في استخراج ورم المخ في مراحل مبكرة حتى يمكن اعتماد العلاج المناسب. حيث فرص بقاء المريض المصاب بالورم على قيد الحياة يمكن أن تزداد بشكل كبير إذا تم اكتشاف الورم بدقة في مرحلته المبكرة.

أورام الدماغ الأولية الأكثر شيوعًا هي:

- الأورام الدبقية (50.4٪)
- الأورام السحائية (22.6٪)
- أورام الغدة النخامية (18٪)
- أورام غمد الأعصاب (9٪)

في الوقت الحاضر ، تُستخدم أنظمة CAD عادةً من أجل التعرف الفعال والصريح على تشوهات الدماغ. و هي بذلك تدعم الأطباء في تفسير الصور الطبية حيث تجمع بين عناصر الذكاء الاصطناعي ورؤية الكمبيوتر مع معالجة الصور الأشعة وعلم الأمراض .

في هذا العمل ينصب التركيز الرئيسي في البداية على عملية تعتمد على مجموعة متنوعة من الخطوات:

- ❖ خطوة ما قبل المعالجة: بناءً على عملية التحسين التي تعتمد على الخوارزميات مثل التدرج البياني للصورة وبعض العمليات الرياضية .
- ❖ عملية التجزئة: تم تصميم النظام المقترح على بنية U-Net وهي عبارة عن cnn (s) بالكامل ، والتي حققت أفضل تنفيذ في فئتها لتجزئة الصور الطبية تلقائيًا.

استخدمنا Unet لاستخراج منطقة الورم الدماغي والتي بدورها يتم استخراج الميزات والخصائص لتمييز أنواع مختلفة من سرطانات الدماغ.

- ❖ خطوة استخراج الميزات: تُستخدم للحصول على الخصائص المحددة للصورة التي يتم من خلالها يمكن تصنيف الصور بشكل فعال, في هذا العمل استخدمنا تقنيتين : مصفوفة التواجد المشترك ذات المستوى الرمادي (GLCM) التي اقترحها Haralick وآخرون. (1973) ، و هي إحدى التقنيات المستخدمة على نطاق واسع لاستخراج بعض الخصائص من نسيج الصورة ، وتعتمد النقطة الرئيسية لـ GLCM على العلاقة المكانية للبكسل (الزاوية والمسافة) في صور المستوى الرمادي. ثم دمجنا هذه التقنية مع تقنية آخر قائمة على **Moment** .
- ❖ عملية التصنيف: حيث استعملنا خورازمية **SVM** لتصنيف الميزات المستخرجة وتدريب النموذج.

من خلال تنفيذ النموذج المقترح . بلغت دقته 96.4 % وهذا يعني التصنيف الجيد لمجموعة البيانات المستخدمة التي تحتوي على صور الدماغ بالرنين المغناطيسي والتي تم جمعها سنة 2017 من قبل Jun Cheng.

<u>الكلمات المفتاحية :</u> معالجة الصور , التعليم العميق , التعلم الآلي , تصنيف الصور , الأورام الدماغية

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GLOSSARY

CAD: Computer Aided Diagnostic

AI: Artificial Intelligence.

ML: Machine Learning.

DL: Deep Learning.

CNN: Convolutional Neural Network.

GLCM: Gray Level Co-Occurrence Matrix.

LR: Logistic Regression.

NN: Neural Network.

MRI:Magnetic Resonance Imaging.

CT: Computerized Tomography.

CV: Computer Vision.

NN: Neural Network.

CNN: Convolusion Neural Network .

SVM: support vector machine.

KNN: K-Nearest Neighbor.

CSV: Comma-separated values

GENERAL INTRODUCTION

There is nothing specific about brain tumor symptoms which have made this research field an open key of challenges. Also, it is often conflicted about any other common disease. Ultimately, This issue can lead to a delay in the diagnosis which augments the risk factor. Once the affected-regions in MRI are well detected at an early stage is very crucial due to the process would follow either diagnosis or surgery. Several symptoms view nausea, vomiting, severe headache, speech problems, vision impairment, and hearing impairment, the problem in walking, and seizures.[43]

Analyzing and processing of MRI brain tumor images are the most challenging and upcoming field. To decide the accurate therapy for tumor-infected individually at the right stage, a very important technique is used: Magnetic resonance imaging (MRI), It is an advanced medical imaging method that can produce high-quality images of the human body. Magnetic resonance imaging (MRI) segmentation is a way operated in the domain of diagnosis and detection of lesions, tumors, or other abnormalities. It is also useful in the surgical evaluation and submit-surgical evaluation of the affected person.

The identification, classification, detection, and segmentation of infecting area in brain tumor of MRI images are a tedious and time-consuming task. To identify objects from images or videos an object recognition is one of the techniques used, to classify image we should select classification label classes based on some metrics as probability, loss, accuracy, etc. While object detection algorithms act as a combination of object localization and image classification, these algorithms can deal well with multi-class classification and localization with objects of multiple occurrences. In further extrusion is a segmentation technique in which we observe the presence of an object via a pixel-wise filter created for each object in the image. This technique determines the shape of each object which is more granular than the bounding box generated by object detection. Based on this information, the most suitable therapy, radiation, surgery, or chemotherapy can be decided. As a result, the chances of survival of a tumor-infected patient can be increased significantly if the tumor is detected accurately in its early stage.

In view, the past few years have witnessed a significant increase in the number of brain MRI scans related to brain tumors, that making it 10th most common form of tumor affecting children and adults alike.[15] Various research works have been carried out either to automatically detect lesions -ie. classification or segmentation of different masses in images using computer-aided detection systems or to provide a second opinion about the lesion detected through detection systems computer-assisted diagnosis. This has led to the detection of several brain MRI (s) diseases i.e. Alzheimer's disease, Parkinson's disorder, Dementias Glioma, Pituitary and Meningioma, and many more. all inspired by The American Association of Neurological Surgeon (AANS) have provided the list of classification of brain tumors for educational purposes.

This work, we will highlight some interesting proposed solutions from the literature review on the different techniques used for segmentation and classification of brain tumor from the Magnetic Resonance (MR) images. Among the two most trending techniques using conventional machine learning techniques, deep learning, and metaheuristic algorithms to enhance the classification accuracy. Initially, the main purpose of managing deep learning over conventional machine learning models is the development in neural networks, they acquire the high-level features from the images and excludes the expertise domain. When the dataset has a larger number of classes deep learning techniques outperform the classification. Also, the appearance of GPU-computing libraries causes the model to prepared multiple times quicker than on CPUs. Furthermore, the open-source programming bundles give productive GPU executions and freely accessible datasets, for example, ImageNet, can be utilized for training and testing variants of deep learning models.

Many models are proposed, but the optimal model is an open challenging task, each model has advantages and disadvantages. Moreover, each model is designed for a specific dataset and this last consider as an issue in this field, also others factors considered as criteria for the choice of the model, from our study case with researching for boosting the results via reading previous works done in this field lead us for the following motivations :

The objective of this dissertation is to propose an architecture of machine learning with employing different stages from preprocessing till classification passing through the features extraction that combined region of interests with edges of interests, also the use of segmentation algorithms, at the end of the proposed model we have implemented the classification to distinguish two classes from known diseases in Brain tumors to test MRI brain images. We are particularly interested in brain tumors. The question that arises is which algorithm will best preserve the original information while allowing the tumor to be extracted so that it can subsequently be characterized and possibly classified. Most of the algorithms use a pre-treatment phase which can for example reduce the irregularity of the tumor outline, which would distort its classification. We will not discuss the classification phase meanwhile we will provide the performance of the proposed model with the combination of algorithms used from preprocessing reaching the classification, the whole process works together to improve the evaluation phase of the different algorithms.

- Chapter 01: we have presented a brief overview of knowledge and information in machine learning, deep learning, classification algorithms, metric of evaluation the performance of classification algorithm.

- Chapter 02: we have highlighted of computer vision and image processing and the state of the art of the using algorithms from Preprocessing step till classification step, then we have detailed the related works that used classification based on SVM.

- Chapter 03: we have tackled our conception of the proposed architecture, with establishing for each phase its input and its outputs.

- Chapter 04: we have validated the execution of our model, the results out performed from the running of the proposed application, we have illustrated by computing statistical metrics that evaluate the performance of the model accuracy, precision, dice and recall, we have more showed it by the use of graphs.

CHAPTER 1

BACKGROUND AND STATE OF THE ART

1.1 Introduction

In the last few years. The use of Artificial Intelligence (AI) has become increasingly popular which is used nowadays, Deep Learning (DL) has the potential to change the future of healthcare.
Due to the artificial intelligence algorithms, Computer-aided-detection (CAD) becomes one of the most important systems to diagnose any diseases as soon as possible. In order to improve the diagnose of CAD, it requires using deep learning algorithms in the Image processing field. So, in this chapter, we present the basic concepts of machine learning, Deep Learning, Image Classification Techniques, Medical Imagining, and how to evaluate the efficacy of the system.

1.2 Neuronal Network and Deep Learning Algorithms

1.2.1 Machine learning

Machine learning is a field of study that uses the statistics and computer science principles, to create statistical models, used to perform major tasks like predictions and inference. These models are groups of mathematical relationships through the inputs and outputs of a given system. The learning procedure is the process of guessing the models parameters such that the model can achieve the stated task.[1]

1.2.1.1 Field of machine learning

machine learning is a common buzzword in Medical, E-commerce, Finance, Transportation and various sectors.

there are a lot of applications of these algorithms in different fields: [2]

Field	**Applications**
Computer vision	Face Recognition, Object Recognition, Robotics, Self-Driving cars, etc...
Medical	Drug Development, Biomedical Data Analysis, Neurosciences, etc.
Finance and E-commerce	Analytics, Insurance, Fraud detection, Financial Forecasting, Spam Email, etc.
Geography	Earthquake Detection, Weather Detection (google weather), etc.
Signal	language NLP, Speech Processing, etc.

Table 1.1: The Usage of Machine Learning

1.2.1.2 Types of machine learning Algorithms

There some variations of how to define the types of Machine Learning Algorithms but commonly they can be divided into categories according to their purpose and the main categories are the following: [1]

✓ **Supervised learning**

✓ **Unsupervised Learning**

✓ **Semi-supervised Learning**

✓ **Reinforcement Learning**

1.2.1.2.1 Supervised learning

The supervised machine learning algorithms are those algorithms which needs external assistance. The input dataset is divided into train and test dataset. The train dataset has output variable which needs to be predicted or classified. All algorithms learn some kind of patterns from the training dataset and apply them to the test dataset for prediction or classification. [3]

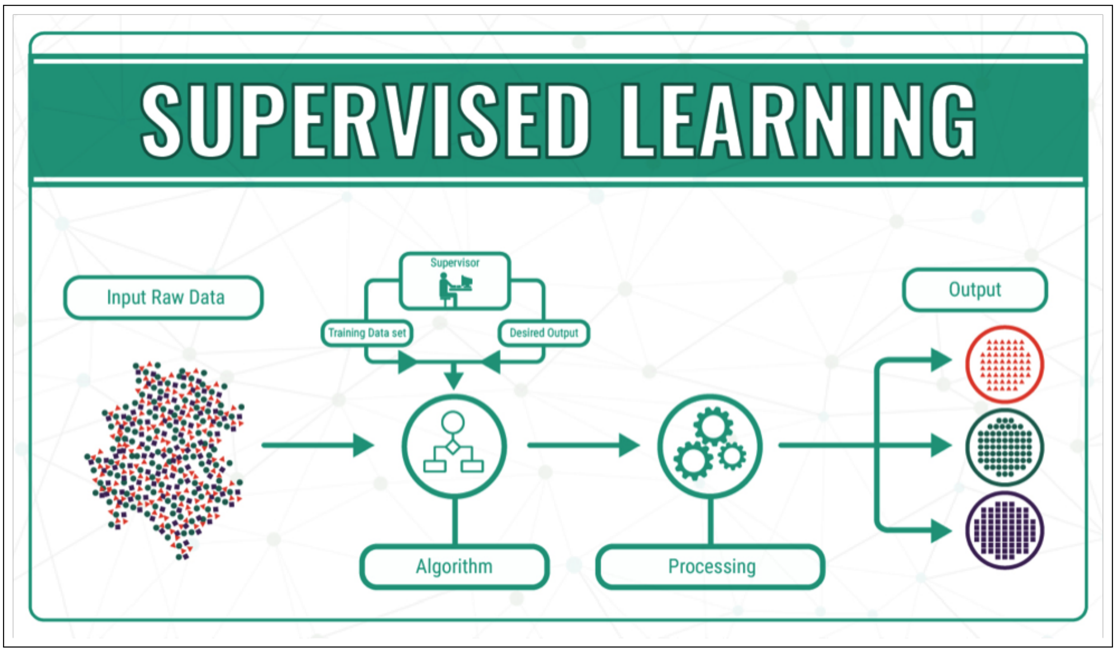

Figure 1.1: Example of supervised learning .

List of common algorithms

✓ Nearest Neighbor

✓ Naive Bayes

✓ Decision Trees

✓ Linear Regression

✓ Logistic Regression

✓ Support Vector Machines (SVM)

✓ Neural Networks

Logistic Regression

Logistic regression is a classification algorithm used to assign observations to a discrete set of classes. Some of the examples of classification problems are Email spam or not spam, Online transactions Fraud or not Fraud, Tumor Malignant or Benign.[5]

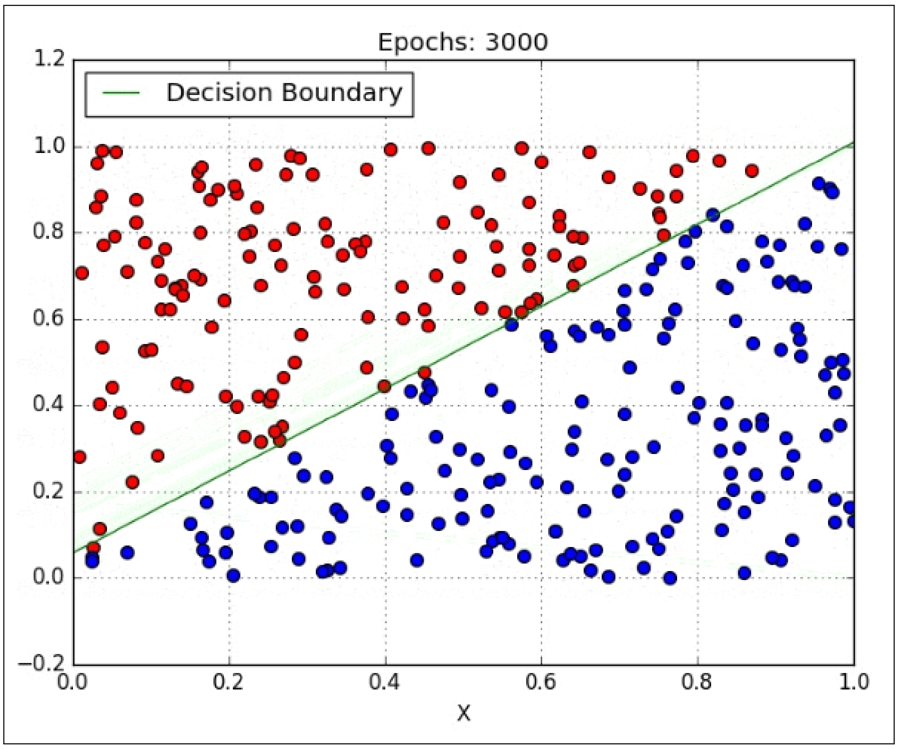

Figure 1.2: Logistic Regression Example.

1.2.1.2.2 Unsupervised Learning

The unsupervised learning algorithms learns few features from the data. When new data is presented, it uses the earlier learned features to identify the class of the data. It is mostly used for feature reduction and clustering. [3]

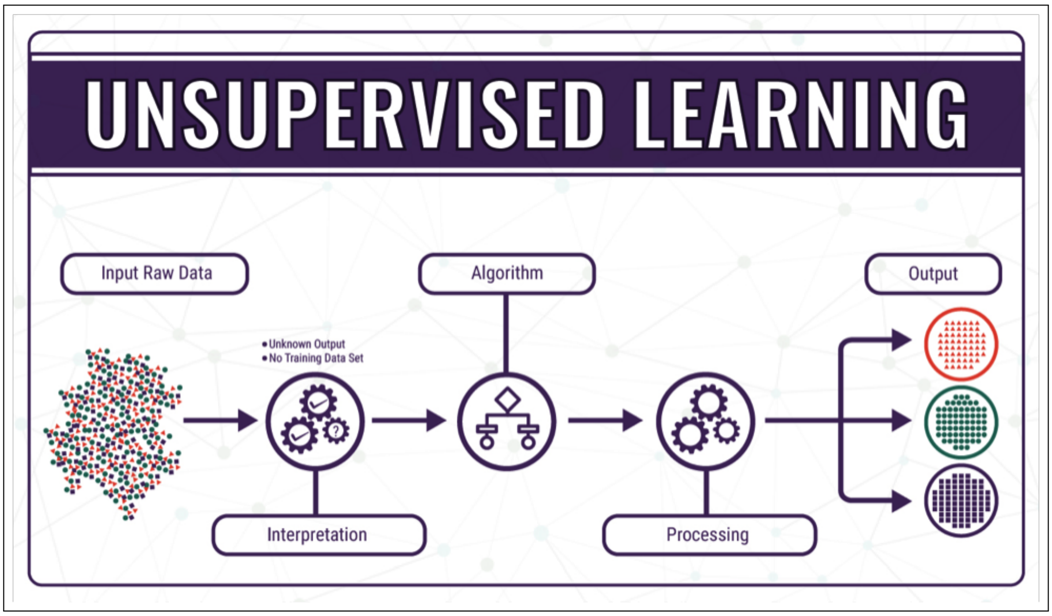

Figure 1.3: Unsupervised learning Architecture

Here are some of the most important unsupervised learning algorithms:

- Clustering
  - k-Means.
  - Hierarchical Cluster Analysis (HCA).
  - Expectation Maximization .
- Visualization and dimensionality reduction
  - Principal Component Analysis (PCA).
  - Kernel PCA.
  - Locally-Linear Embedding (LLE).
  - t-distributed Stochastic Neighbor Embedding (t-SNE). [6]
- Association rule learning
  - Apriori .
  - Eclat.

1.2.1.2.3 Semi-supervised Learning

Semi-supervised Learning algorithms is a technique which combines the power of both supervised and unsupervised learning. It can be fruit-full in those areas of machine learning and data mining where the unlabeled data is already present and getting the labeled data is a tedious process. [3]

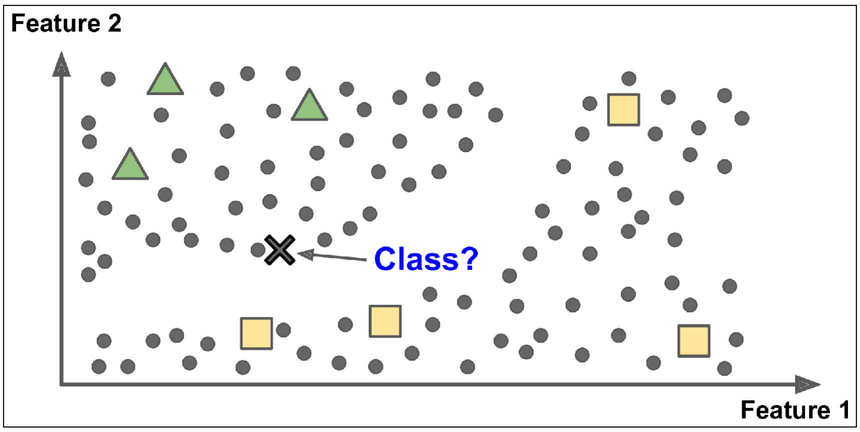

Figure 1.4: Example of Semi supervised learning

1.2.1.3 Big challenge in the machine learning process

✓ Insufficient Quantity of Training Data

✓ Nonrepresentative Training Data

✓ Poor-Quality Data

✓ Irrelevant Features

✓ Overfitting the Training Data

✓ Underfitting the Training Data [6]

1.2.2 Deep learning

Deep learning is a set of learning approaches trying to model data with multifaceted architectures uniting different non-linear transformations. The basic brick of deep learning is the neural network, that is combined to form the deep neural network. These techniques have allowed significant progress in the fields of image processing and sound, including facial recognition, computer vision, speech recognition, automated language processing, text classification (for example spam recognition). There exist some types of architectures for neural networks:

- The multilayer perceptrons, that are the oldest and simplest ones
- the Convolutional Neural Networks (CNN), particularly adapted for image processing
- The recurrent neural networks, used for sequential data such as text or times series. [7]

1.2.2.1 Artificial Neural Networks

An Artificial Neural network are very powerful brain-inspired computational models. Which have been active in several areas such as medicine, economics, engineering, computing and many others. [8]

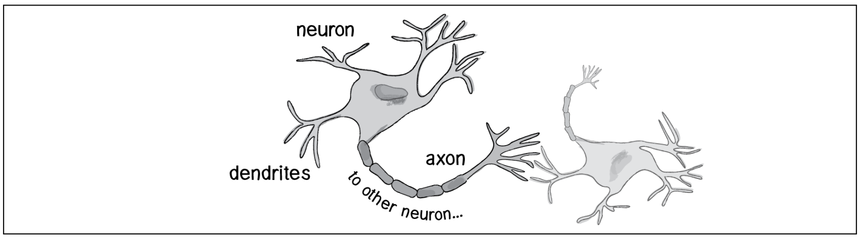

Figure 1.5: Natural neuron

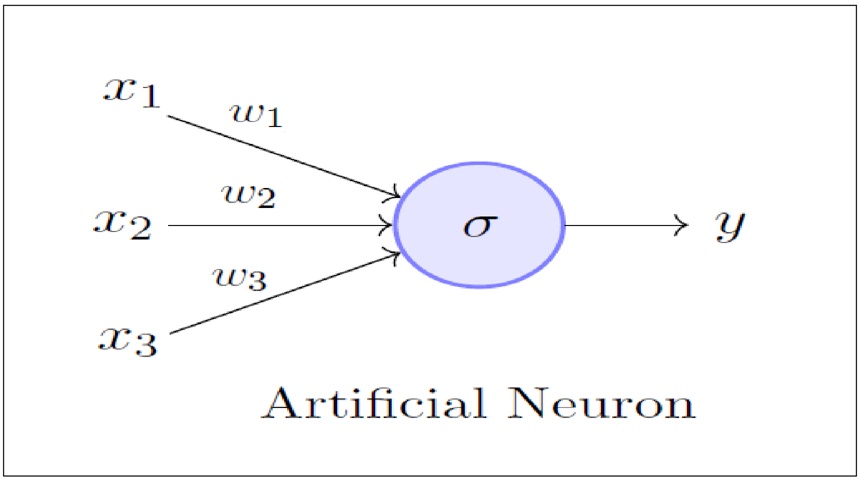

Figure 1.6: Artificial neuron

An artificial neural network is built on the optimization theory. It is a computational model inspired in the working of the human brain. It is consisting by a set of artificial neurons that are interconnected with other neuron these neurons rely on weights of the neural network. As The word network in Neural Network mentions to the interconnection between neurons present in several layers of a system. These weights represent the connections between the neurons which define the impact of one neuron on another.[8]

1.2.2.2 Convolutional Neural Network

Convolutional Neural Network (CNN) is a special case of the neural network described above. A CNN contains of one or more convolutional layers, often with a subsampling layer, which are followed by one or more fully connected layers as in a standard neural network.
The strategy of a CNN is interested by the discovery of a visual mechanism, the visual cortex, in the brain. The visual cortex covers a lot of cells that are responsible for detecting light in small, overlapping sub-regions of the visual field, which are called receptive fields. These cells work as local filters over the input space, and the more intricate cells have higher receptive fields. The convolution layer in a CNN do the function that is achieved by the cells in the visual cortex.
Each feature of a layer collects inputs from a set of features placed in a small neighborhood in the preceding layer called a local receptive field. With local receptive fields, features can extract elementary visual features, such as end-points, corners, oriented edges, etc., which are then combined by the higher layers.

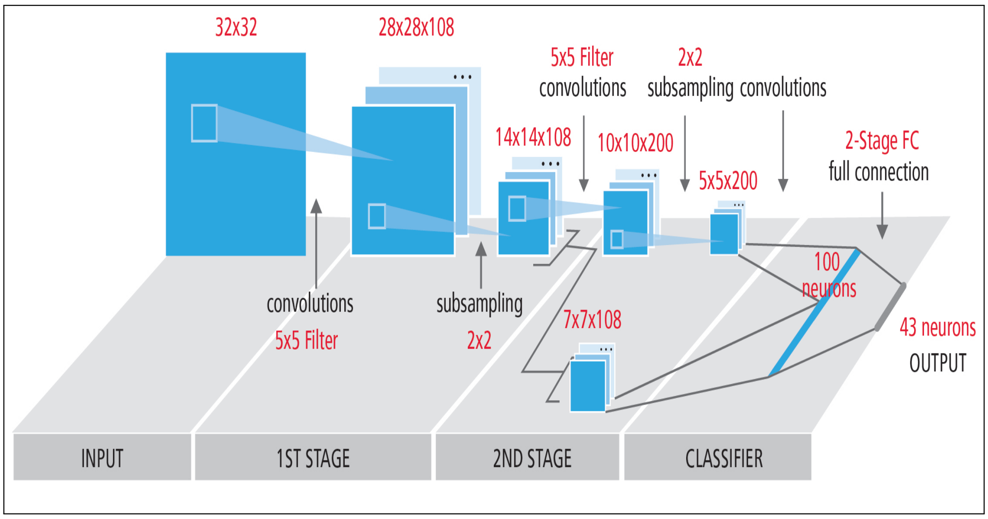

Figure 1.7: Typical block diagram of a CNN

1.2.2.2.1 Layers of CNNs

Convolution layers The convolution operation extracts various features of the input. The first convolution layer extracts low-level features like corners, edges, and lines. Higher-level layers extract higher-level features. Figure 8 illustrates the process of 3D convolution used in CNNs. The input is of size N x N x D and is convolved with H kernels, each of size k x k x D separately. Convolution of an input with one kernel produces one output feature, and with H kernels independently produces H features. [9]

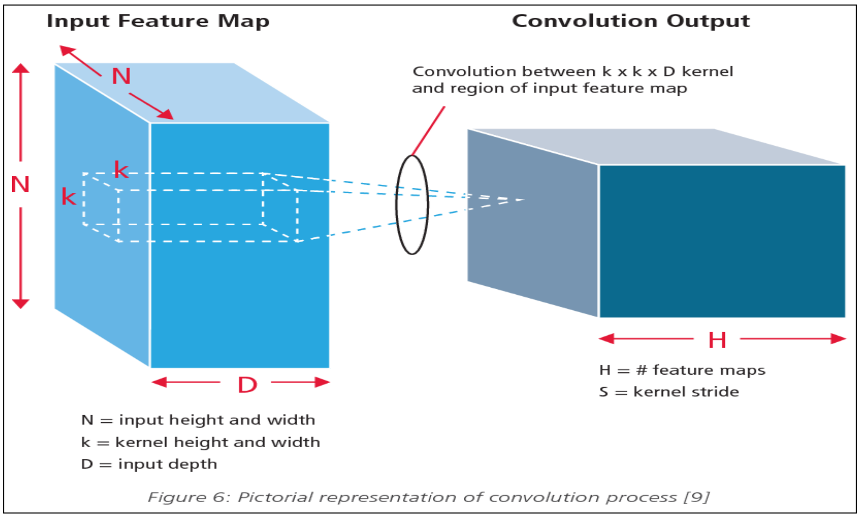

Figure 1.8: Pictorial representation of convolution process

Pooling/subsampling layers The pooling layer decreases the resolution of the features. It makes the features robust against distortion and noise. There are two ways to do pooling:

average pooling and max pooling. In both cases, the input is split into non-overlapping two-dimensional spaces.[9]

Fully connected layers Fully connected layers are oftentimes used as the final layers of a CNN. These layers mathematically sum a weighting of the previous layer of features, indicating the precise combination of "ingredients" to determine a certain target output result. In case of a fully connected layer, all the elements of all the features of the earlier layer get used in the calculation of each element of each output feature.[9]

1.2.2.2.2 Activation function

Activation functions are functions used in neural networks to calculates the weighted sum of input and biases, it is used to decide if a neuron can be released or not. It manipulates the presented data through some gradient processing usually gradient descent and afterwards produce an output for the neural network, that contains the parameters in the data. [1]

✓ **Sigmoid Function :** The Sigmoid AF is occasionally mentioned to as the logistic function or squashing function in several literature. The Sigmoid function research results have generated three variants of the sigmoid AF, which are used in deep learning applications. The Sigmoid is a non-linear AF used typically in feedforward neural networks. It is differentiable real function, specified for real input values, with some degree of smoothness and positive derivatives everywhere.[1]
✓ **Softmax Function :** The Softmax function is another kind of AF used in neural computing. It is used to calculate probability distribution from a vector of real numbers. The Softmax function produces an output which is a range of values between 1 and 0, with the total of the probabilities been equal to 1. [1]
The Softmax function is used in multi-class models where it returns probabilities of each class, with the target class having the maximum probability. The Softmax function generally appears in most all the output layers of the DL architecture.
✓ **Rectified Linear Unit (ReLU) Function :** The rectified linear unit (ReLU) activation function was proposed by Hinton and Nair 2010, and ever since, has been the most commonly used activation function for DL applications with state-of-the-art results to date. The ReLU represents a nearly linear function and therefore preserves the properties of linear models that made them easy to optimize, with gradient-descent method. The ReLU is a faster learning activation function, which has proved to be the most effective and widely used function. It

offers the perfect performance and generalization in DL compared to the Sigmoid and tanh AF. [1]

1.2.2.3 U-net

U-Net is a convolutional neural network that was developed for biomedical image segmentation at the Computer Science Department of the University of Freiburg, Germany.
The network is based on the fully convolutional network and its architecture was modified and extended to work with fewer training images and to yield more precise segmentation.
Segmentation of a 512 * 512 image takes less than a second on a modern GPU. The Architecture of the U-net[12]:

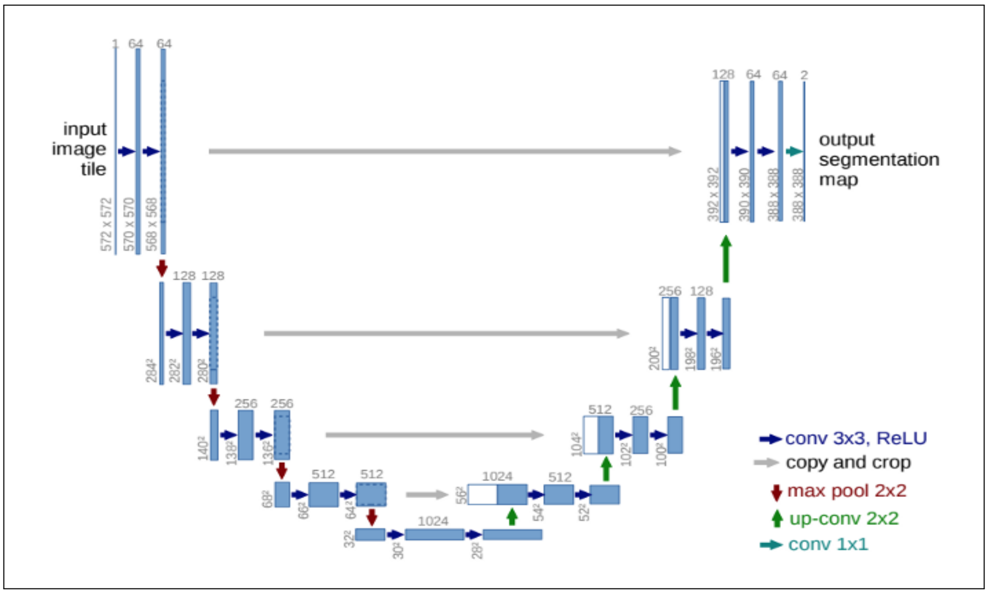

Figure 1.9: U-net Architecture

1.3 Image classification

Classification between the objects is simple mission for human but it is more difficult for machines. The increase of high-capacity computers, the availability of low-priced and high-quality video camera, and the growing need of automatic video analysis has created an attention in the object classification algorithms. A simple classification system contains of a fixed high camera above the concerned zone. Classification include image preprocessing, image sensors, object segmentation, object detection, object classification and feature extraction. Classification system contain of database that consists predefined patterns that likens with detected object to classify in to right category. Image classification is a challenging and important task in several application domains, including biometry, biomedical imaging, industrial visual inspection, robot navigation, video surveillance and vehicle navigation. Classification process consists of following steps:

- **Pre-processing:** atmospheric correction, noise removal, image transformation, main component analysis etc.
- **Detection and extraction of a object Detection:** includes detection of position and other characteristics of moving object image obtained from camera. And in extraction, from the detected object estimating the trajectory of the object in the image plane.
- **Training:** Selection of the particular attribute which best describes the pattern.
- **Classification of the object-Object:** classification step categorizes detected objects into predefined classes by using suitable method that compares the image patterns with the target patterns.[10]

1.3.1 Image classification methods

There is a lot of classification methods, we chose some of them:[10]

Classification method	**Description**	**Characteristics**
Artificial Neural network	ANN is a type of artificial intelligence that imitates some functions of the person mind. ANN has a normal tendency for storing experiential knowledge. An ANN consists of a sequence of layers, each layer consists of a set of neurons. All neurons of every layer are linked by weighted connections to all neurons on the preceding and succeeding layers	It uses Nonparametric approach. Performance and accuracy depends upon the network structure and number of inputs

Decision tree	DT calculates class membership by repeatedly partitioning a dataset into uniform subsets Hierarchical classifier permits the acceptations and rejection of class labels at each intermediary stage. This method consists of 3 parts: Partitioning the nodes, find the terminal nodes and allocation of class label to terminal nodes	DT are based on hierarchical rule based method and use Nonparametric approach.
Support Vector Machine	A support vector machine builds a hyper plane or set of hyper planes in a high- or infinite dimensional space, used for classification. Good separation is achieved by the hyper plane that has the largest distance to the nearest training data point of any class (functional margin), generally larger the margin lower the generalization error of the classifier.	SVM uses Nonparametric with binary classifier approach and can handle more input data very efficiently. Performance and accuracy depends upon the hyperplane selection and kernel parameter.
Fuzzy Measure	In Fuzzy classification, various stochastic associations are determined to describe characteristics of an image. The various types of stochastic are combined (set of properties) in which the members of this set of properties are fuzzy in nature. It provides the opportunity to describe different categories of stochastic characteristics in the similar form.	It uses Stochastic approach. Performance and accuracy depends upon the threshold selection and fuzzy integral.

Table 1.2: Image Classification Methods

the advantages and disadvantages of some classification methods [10]

Classification method	**Advantages**	**Disadvantages**
Artificial Neural network	• It is a non-parametric classifier. • It is an universal functional approximator with arbi trary accuracy. • capable to present functions such as OR, AND, NOT • It is a data driven self adaptive technique • efficiently handles noisy inputs • Computatio n rate is high	• It is semantically poor. • The training of ANN is time taking. • Problem of over fitting. •Difficult in choosing the type network architecture.
Decision tree	• Can handle nonparametric training data • Does not required an extensive design and training. • Provides hierarchical associations between input variables to forecast class membership and provides a set of rules n are easy to interpret. • Simple and computational efficiency is good.	• The usage of hyperplane decision boundaries parallel to the feature axes may restrict their use in which classes are clearly distinguishable. • Becomes complex calculation when various values are undecided and/or when various outcomes are correlated.

Support Vector Machine	• It gains flexibility in the choice of the form of the threshold. • Contains a nonlinear transformation. • It provides a good generalization capability. • The problem of over fitting is eliminated. • Reduction in computational complexity. • Simple to manage decision rule complexity and Error frequency.	• Result transparency is low. • Training is time consuming. • Structure of algorithm is difficult to understand • Determination of optimal parameters is not easy when there is non linearly separable training data.

Table 1.3: Advantages and Disadvantages of Different Classification

1.4 Big data and Medical Image

1.4.1 Big data

The term "Big Data" refers to the evolution and use of technologies that provide the right user at the right time with the right information from a mass of data that has been growing exponentially for a long time in our society. The challenge is not only to deal with rapidly increasing volumes of data but also the difficulty of managing increasingly heterogeneous formats as well as increasingly complex and interconnected data. [13]

1.4.1.1 Characteristics of Big Data

Big Data was defined by the “3Vs” but nowadays there is “5Vs” of Big Data which are also termed as the characteristics of Big Data as follows [13]:

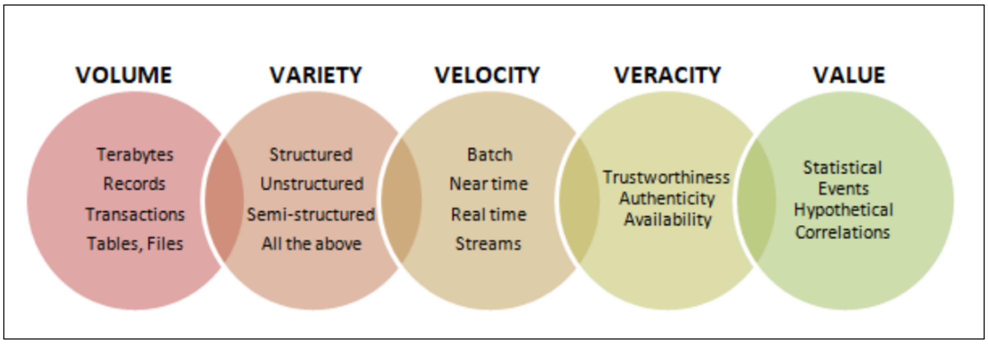

Figure 1.10: 5V Concept

1.4.2 Medical image

Medical imaging is the operation of producing visual images of inner structures of the body for medicinal and scientific study and treatment as well as a visible view of the function of interior tissues. This process creates data bank of regular structure and function of the organs to make it easy to recognize the anomalies. This process pursues the disorder identification and management. [14]

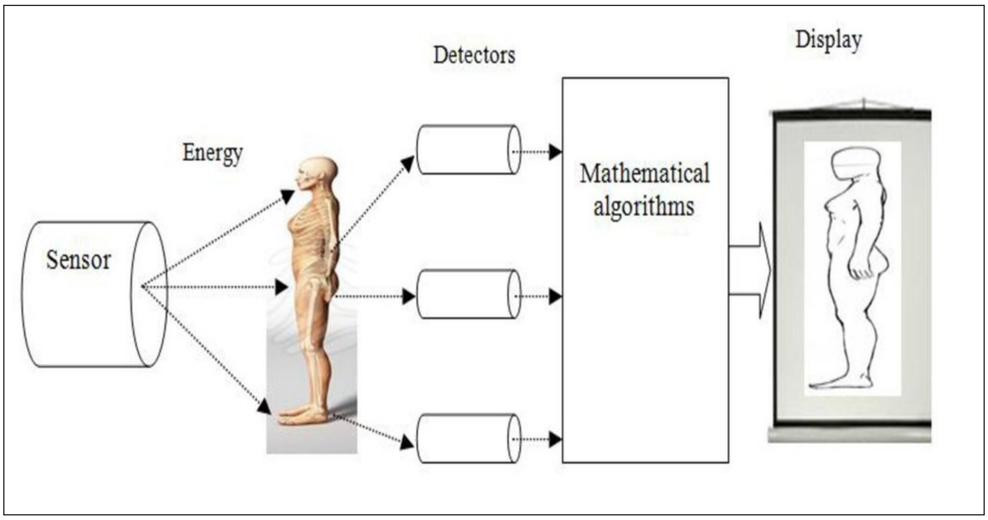

Figure 1.11: medical imaging

1.4.2.1 Medical image modalities

Some image modalities and the main characteristics: [16]

Modalities	**Main characteristics**	**Application**	**cost**	**Radiation source and type**
X-Rays	A photograph or image obtained through the use of x-rays.	Anatomical	Low cost	X-rays (ionizing)
CT	A method of examining body organs by scanning them with X rays and using a computer to construct a series of cross-sectional images	Anatomical Functional	Intermediate cost	X-rays (ionizing)
MRI	A method which uses magnetic signals to create image "slices" of the human body	Anatomical Functional	Intermediate cost	Electric and Magnetic fields (Non-ionizing)

Ultrasound	A method which use of high frequency sound to make image internal structures by signals from different densities tissues.	Anatomical Functional	Low cost	Sound waves (Non-ionizing)
PET	PET is a type of nuclear medicine technique in which tracers are used for diagnoses disease	Functional Metabolism	High cost	Positron (ionizing)
SPECT	A non-invasive technique for constructing cross-sectional images of radiotracer distribution inside the body	Functional	High cost	Photons (ionizing)

Table 1.4: Comparison between Medical Imaging Modalities

1.4.3 Big data and Medical imaging Challenge

In any industry in the world the method in which it leverages, analyze and manage can change. The most promising area in which big data use for making the big change is healthcare industry. Generally, to improve life quality, reduce costs of treatment avoid preventable diseases, predict outbreaks of epidemics, the medical analytics have the potential. In medicine and healthcare, the big data is referred as complex and large data, with suing of previous hardware or software they are difficult to analyze. Analysis, validation, data quality control, modeling, interpretation and integration of heterogeneous data cover by big data analytics. From the available large amount of data, it provides comprehensive knowledge discovering by big data analytics applications.

Big data is very useful for medical imaging. Which also finds its usages. In order to monitor, diagnose or treat medical conditions to see the human body the various technologies that are used indicated as medical imaging. To designate the techniques set that produce the image of internal part of body the medical imaging is often used. For clinical purposes like dysfunction, examine injury, seeking to reveal, pathology or diagnose to create the images processes and techniques are used. [17]

1.4.3.1 Diagnostic Medical Imaging with Big Data Characteristics

In diagnostic imaging in the configuration of big data the five main characteristics that should be respected are as follows:

1. **Value:** To analysis of their coherent referred as value of big data. For clinicians and patients it should be valuable.

2. **Variety:** Heterogeneity and Complexity of several dataset that can be unstructured, structured and semi-structured known as variety.

3. **Velocity:** To the frequency and speed of data analysis, creation and processing and motion of data referred as velocity. Velocity refers to data in motion as well as and to the speed and frequency of data creation, processing and analysis. Consistently, a large number of patients experience analytic imaging techniques, which comprise of a reasonable work process in which data is obtained through an imaging gadget, put away in a PACS (standard picture archiving and communication) framework, and along these lines outwardly assessed on DICOM (digital imaging and communications in medicine) or PACS watcher by a specialist, who delivers an unstructured or structured report agent of the clinical result of the assessment .

4. **Veracity:** Reliability, data quality, predictive value, uncertainty and relevance referred as veracity. Because decisions of death or life depend on the information reliability in healthcare data quality and Veracity are the fundamental issues.

5. **Volume:** In healthcare the quantity of big data referred as volume, which is assessed to drastically increment until the request for zettabytes (1021) by 2020. [17]

1.4.4 Brain image Datasets

A number of online neuroscience datasets are available which provide information regarding gene expression, neurons, macroscopic brain structure, and neurological or psychiatric disorders. Some datasets contain descriptive and numerical data, some to brain function, others offer access to 'raw' imaging data, such as postmortem brain sections or 3D MRI and fMRI images. Some focus on the human brain, others on non-human. [18]

Dataset	Diagnosis	N	Males %	Diseased
ABIDE I	Autism	1,095	85.2%	526
ADHD200	ADHD	965	61.8%	384
ADNI	Alzheimer's	1,682	55.0%	1,144
COBRE	Schizophrenia	146	74.7%	72
HBN	Psychiatric	689	59.7%	497
MCIC	Schizophrenia	194	71.6%	104
OASIS	Alzheimer's	415	38.6%	100

Table 1.5: Some of neuroscience datasets

1.4.5 Brain tumor

A brain tumor is an abnormal growth of tissue in the brain or central spine that can disrupt proper brain function. Doctors refer to a tumor based on where the tumor cells began, and whether they are cancerous (malignant) or not (benign).
All brain tumors can grow to damage areas of normal brain tissue if left untreated, which could be disabling and possibly fatal.
Brain and spinal cord tumors are different for everyone. They form in different areas, develop from different cell types, and may have different treatment options.[30]

brain tumors can be benign or malignant:

- **Benign Brain Tumor :** The least aggressive type of brain tumor is often called a benign brain tumor. They originate from cells within or surrounding the brain, do not contain cancer cells, grow slowly, and typically have clear borders that do not spread into other tissue. They may become quite large before causing any symptoms. If these tumors can be removed entirely, they tend not to return. Still, they can cause significant neurological symptoms depending on their size, and location near other structures in the brain. Some benign tumors can progress to become malignant.

- **Malignant Brain Tumor :** Malignant brain tumors contain cancer cells and often do not have clear borders. They are considered to be life-threatening because they grow rapidly and invade surrounding brain tissue. Although malignant brain tumors very rarely spread to other areas of the body, they can spread throughout the brain or to the spine.

These tumors can be treated with surgery, chemotherapy and radiation, but they may recur after treatment.[30]

1.4.5.1 Brain Tumor Type

With over 120 tumor types, it's challenging to diagnose and treat brain tumors. The most common primary tumor types found in adults are:

- **Gliomas :** Gliomas begin from glial cells found in the supportive tissue of the brain. There are several types of gliomas, categorized by where they are found, and where the tumor begins.
- **Meningimas :** Meningiomas are usually slow-growing, benign tumors that come from the outer coverings of the brain just under the skull. This type of tumor accounts for about one third of brain tumors in adults. They may exist for many years before being detected and are commonly found in the cerebral hemispheres just under the skull.
- **Pituitary Tumor :** The pituitary gland is located at the base of the brain and it produces hormones that control other glands in the body; specifically the thyroid, adrenal glands, ovaries and testes, glands for milk production in pregnant women, and the kidneys. Tumors in or around the pituitary gland can lead to problems with how these glands function. Also, patients may have vision problems. Pituitary tumors are frequently benign, and surgical removal is often the cure. Some are treated with medication to shrink or stop the tumor from growing.[30]

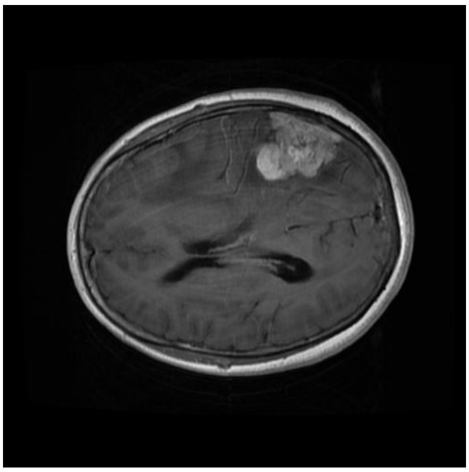

Figure 1.12: Meningimas tumor

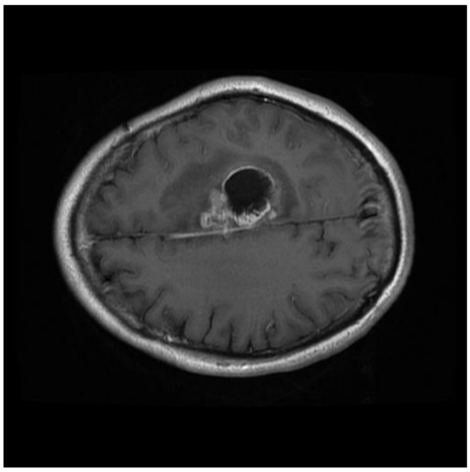

Figure 1.13: Gliomas Tumor

1.5 Classification Performance and Evaluation

After we implementing the model and getting some result in forms of a class or a probability, the next move is to detect how efficient is the model based on various metric using the test datasets. Some performance metrics are used to accurate various Machine Learning Algorithms. Choosing the right metric is very important because it affects performance of machine learning algorithm. [19]

1.5.1 Confusion Matrix

The Confusion matrix is the easiest and intuitive metrics used for finding the accuracy of the model. The main used is for Classification problem where the output can be of two or many types of classes.
CM is a table with two dimensions (“Predicted” and “Actual”), and groups of “classes” in both dimensions. Our Predicted ones are rows and Actual classifications are columns. CM in itself is not a performance measure as such, but almost all of the performance metrics are based on Confusion Matrix and the numbers inside it. [19]

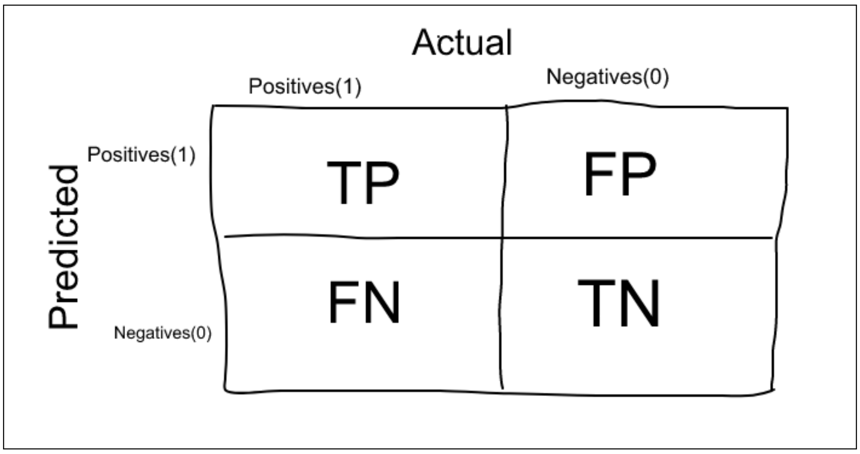

Figure 1.14: Confusion matrix

1.5.1.1 Confusion matrix Terms

- **False Negatives (FN):** False negatives are the cases when the actual class of the data point was 1 (True) and the predicted is 0 (False). False is because the model has predicted incorrectly and negative because the class predicted was a negative one (0).

- **True Positives (TP):** True positives are the cases when the actual class of the data point was 1 (True) and the predicted is also 1 (True)

- **False Positives (FP):** False positives are the cases when the actual class of the data point was 0 (False) and the predicted is 1 (True). False is because the model has predicted incorrectly and positive because the class predicted was a positive one (1)
- **True Negatives (TN):** True negatives are the cases when the actual class of the data point was 0 (False) and the predicted is also 0(False). [19]

1.5.2 Classifier Evaluation Metrics

1.5.2.1 Accuracy

Accuracy in classification problems is the number of correct predictions made by the model over all kinds predictions made.[19]

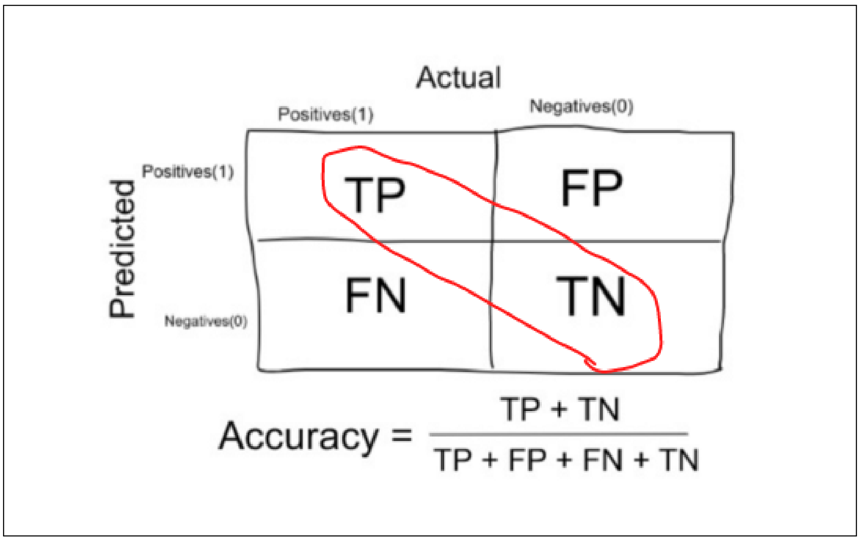

Figure 1.15: Accuracy Formula

When to use Accuracy?
Accuracy is a good measure when the target variable classes in the data are nearly balanced.
When NOT to use Accuracy
Accuracy should NEVER be used as a measure when the target variable classes in the data are a majority of one class. [19]

1.5.2.2 Precision

Precision is a measure based on CM that tells us what proportion of patients that we diagnosed as having cancer and actually had cancer. The predicted positives (People predicted as cancerous are TP and FP) and the people actually having a cancer are TP. [19]

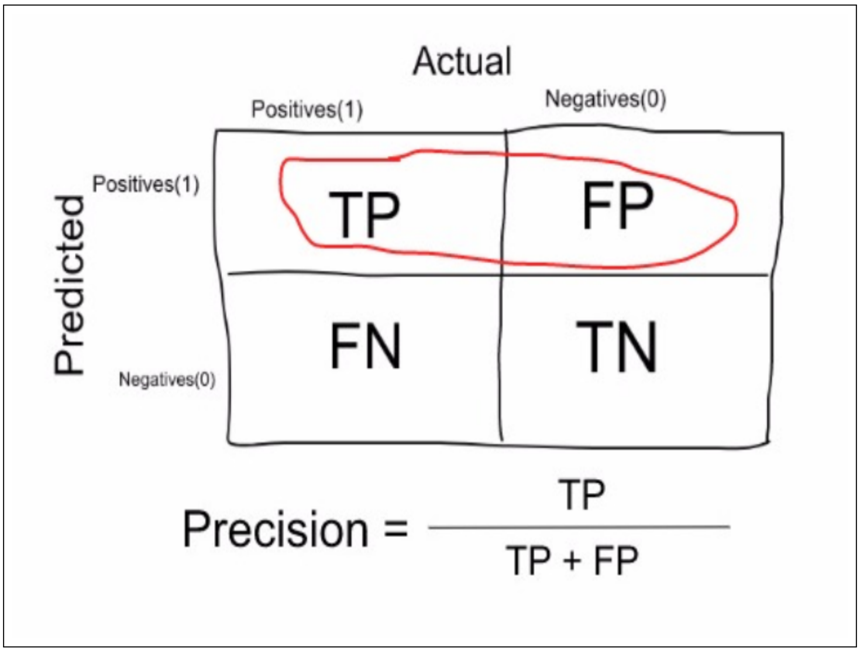

Figure 1.16: Precision Formula

1.5.2.3 Recall

Recall is a measure that tells us what proportion of patients that actually had cancer was diagnosed by the algorithm as having cancer. The actual positives (People having cancer are TP and FN) and the people diagnosed by the model having a cancer are TP. (Note: FN is included because the Person actually had a cancer even though the model predicted otherwise). [19]

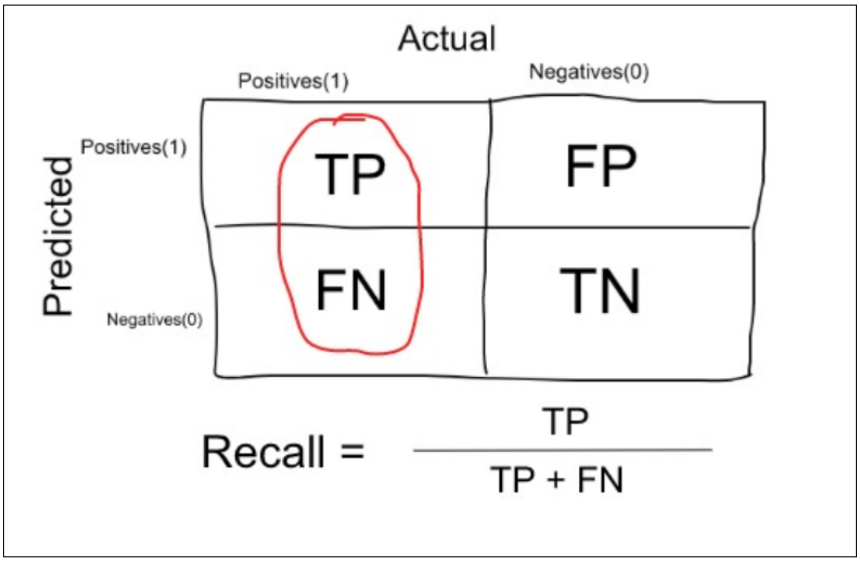

Figure 1.17: Recall Formula

1.5.2.4 Specificity

Specificity is a measure that tells us what proportion of patients that did NOT have cancer, were predicted by the model as non-cancerous. The actual negatives (People actually NOT having cancer are FP and TN) and the people diagnosed by us not having cancer are TN. (Note: FP is included because the Person did NOT actually have cancer even though the model predicted Specificity is the exact opposite of Recall. [19]

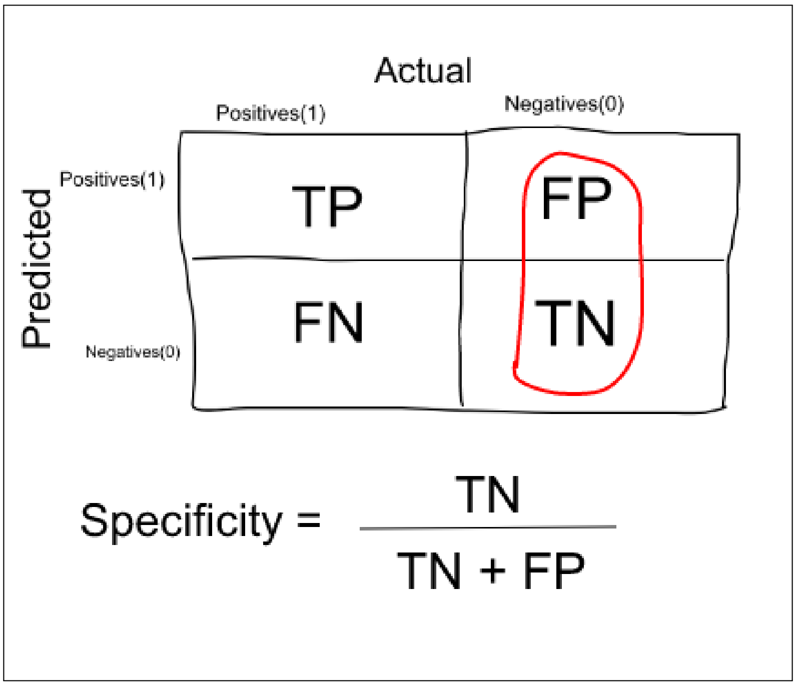

Figure 1.18: Specificity Formula

1.5.2.5 Dice score

The Dice similarity coefficient, also known as the Sorensen–Dice index or simply Dice coefficient, is a statistical tool which measures the similarity between two sets of data. This index has become arguably the most broadly used tool in the validation of image segmentation algorithms created with AI

$$Dice = \frac{2 \times TP}{(TP + FP) + (TP + FN)}$$

Figure 1.19: Dice Formula

1.5.2.6 The F1 score

The F1 Score is a number between 0 and 1 and is the harmonic mean of precision and recall. [20]

$$F_1 = 2 * \frac{precision * recall}{precision + recall}$$

Figure 1.20: F1 score Formula

1.6 Conclusion

Deep learning is an advanced technique of machine learning, which can solve many problems of classification, identification, segmentation ... etc. It is also an effective tool for dealing with large data. This technique is very similar to the human brain. Medical images have several types and variations in the devices they produce. They are an important way to diagnose diseases, so any error in reading and analysis will affect the results of medical diagnosis.
CAD and computer vision applications are the key to implement medical images. This is what led up to explain some related works in order to have more information about these types of technology.

CHAPTER 2

IMAGE PROCESSING

2.1 Introduction

Scientists found many problems in diagnosing medical images either because of many diagnostic requests or the difficulty of diagnosis itself. to do the right diagnostic we have to do some processing on images to improve the quality or to extract several features.
So, in this chapter, we present useful image processing techniques and feature extraction methods for the classification based on the used methods of the related works.

2.2 Computer Vision

Computer vision is the field of computer science that focuses on replicating parts of the complexity of the human vision system and enabling computers to identify and process objects in images and videos in the same way that humans do. Until recently, computer vision only worked in limited capacity.
Thanks to advances in artificial intelligence and innovations in deep learning and neural networks, the field has been able to take great leaps in recent years and has been able to surpass humans in some tasks related to detecting and labeling objects.
One of the driving factors behind the growth of computer vision is the amount of data we generate today that is then used to train and make computer vision better.[21]
Many popular computer vision applications involve trying to recognize things in photographs; for example:

- Object Classification: What broad category of object is in this photograph?
- Object Identification: Which type of a given object is in this photograph?
- Object Verification: Is the object in the photograph?
- Object Detection: Where are the objects in the photograph?
- Object Landmark Detection: What are the key points for the object in the photograph?
- Object Segmentation: What pixels belong to the object in the image?
- Object Recognition: What objects are in this photograph and where are they?

2.3 Computer-aided diagnosis (CAD)

CAD is a technology which includes multiple elements like concepts of artificial intelligence (AI), computer vision, and medical image processing. The main application of CAD system is finding abnormality in human body. Among all these, detection of tumor is the typical application because if it misses in basic screening, it leads to cancer.
The main goal of CAD systems is to identify abnormal signs at an earliest that a human professional fails to find. In mammography, identification of small lumps in dense tissue, finding architectural distortion and prediction of mass type as benign or malignant by its shape, size, etc. [22]

2.3.1 Applications of CAD system

CAD is used in the diagnosis of breast cancer, lung cancer, colon cancer, prostate cancer, bone metastases, coronary artery disease, congenital heart defect, pathological brain detection, Alzheimer's disease, and diabetic retinopathy

2.4 Image processing

Image processing is one of the methods for converting an image into digital form and performs some operations on it, to receive an enhanced image and to extract some useful information, like video frame or photograph and output could be an image or characteristics associated to that image. These methods will rapidly growing technologies today, by its applications for various aspects of a business, engineering, science and medical field.
Image processing basically includes the following three steps:

- Analyzing or manipulating for the image that includes data compression and image enhancement and spotting patterns which are not possible for viewing by human eyes like satellite photographs.
- Importing the image for optical scanner or digital photography
- Output is the last stage which result may be an altered image or report, based on image analysis. [23]

2.4.1 Image enhancement

Image enhancement is basically improving the interpretability or perception of information in images for human viewers and providing 'better' input for other automated image processing techniques. The principal objective of image enhancement is to modify attributes of an image to make it more suitable for a given task and a specific observer. During this process, one or more attributes of the image are modified. The choice of attributes and the way they are modified are specific to a given task. Moreover, observer-specific factors, such as the human visual system and the observer's experience, will introduce a great deal of subjectivity into the choice of image enhancement methods. There exist many techniques that can enhance a digital image without spoiling it.[41]

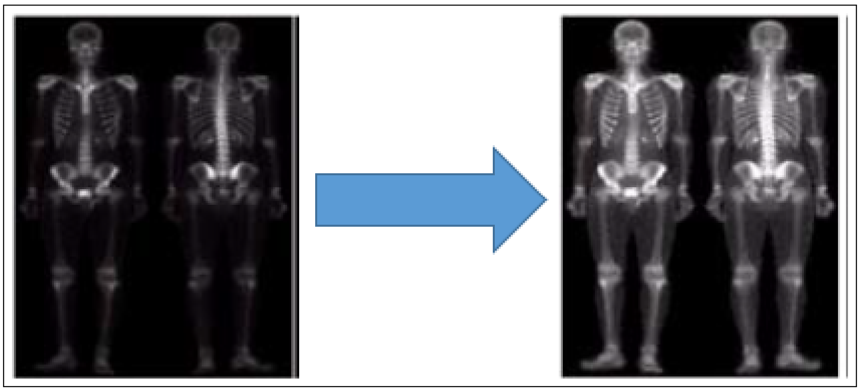

Figure 2.1: Image enhancement

The enhancement methods can broadly be divided in to the following two categories:

2.4.1.1 Spatial domain

spatial domain techniques directly deal with the image pixels. The pixel values are manipulated to achieve desired enhancement. [42]

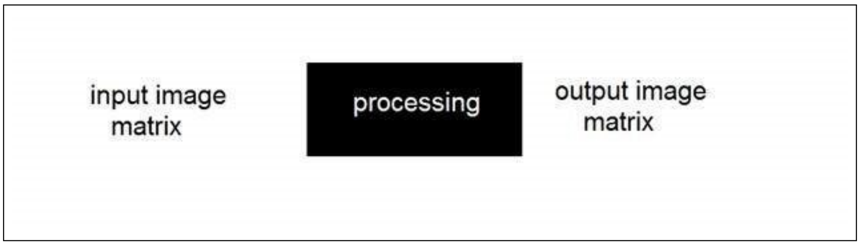

Figure 2.2: Spatial domain process

2.4.1.2 Frequency domain

the image is first transferred in to frequency domain. It means that, the Fourier Transform of the image is computed first. All the enhancement operations are performed on the Fourier transform of the image and then the Inverse Fourier transform is performed to get the resultant image. [42]

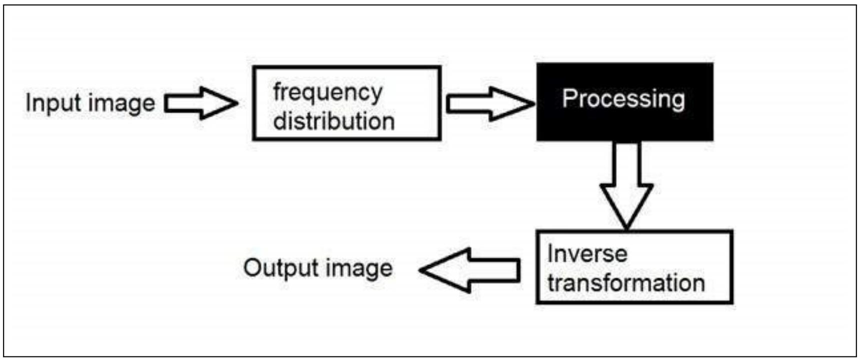

Figure 2.3: frequency domain process

2.4.1.3 Image Enhancement Techniques

2.4.1.3.1 Histogram equalization

Histogram equalization is a very common technique for enhancing the images. Suppose we have an image which is predominantly dark. Then its histogram would be skewed towards the lower end of the grey scale and all the image detail is compressed into the dark end of the histogram. If it could 'stretch out' the grey levels at the dark end to produce a more uniformly distributed histogram then the image would become much clearer. [42]

2.4.1.3.2 Contrast Stretching (CS)

To expand the range of brightness values in an image the contrast enhancement techniques are used, so that the image can be efficiently displayed in a manner desired by the analyst. The level of contrast in an image may vary due to poor illumination or improper setting in the acquisition sensor device. The idea is to modify the dynamic range of the grey-levels in the images. Linear Contrast Stretch is the simplest contrast stretch algorithm that stretches the pixel values of a low-contrast image or high contrast image by extending the dynamic range across the whole image spectrum. [42]

2.4.1.3.3 Thresholding

Histogram thresholding is used for segmenting on image; that is certain applied on pre-processing and post-processing techniques which requires to the threshold segmentation. Major Thresholding techniques proposed by the different researchers are Mean method, P-tile method, Histogram dependent technique, Edge Maximization technique, and visual technique. [24]

2.4.1.3.4 Logarithmic Transformations

Log transformation is one of the elementary image enhancement techniques of the spatial domain that can be effectively used for contrast enhancements of dark images. The log transform is essentially a grey level transform which means that the grey levels of image pixels are altered. The log transformation maps a narrow range of low input grey level values into a wider range of output values. [42]

2.4.1.3.5 Power law (Gamma) transformation

This transformation function is also called as Gamma Correction (GC). For various values of different levels of enhancements can be obtained. We know that different display monitors display images at different intensities and clarity. That means, every monitor has built-in Gamma correction in it with certain Gamma ranges and so a good monitor automatically corrects all the images displayed on it for the best contrast to give user the best experience. It also gives the overall increase or decrease outputs depending on the values of c and without contrast and sharpness control.[42]

2.4.1.3.6 Median Filter

The median filtering algorithm has good noise-reducing effects, it is a nonlinear signal processing technology based on statistics. The noisy value of the digital image or the sequence is replaced by the median value of the neighborhood (mask). The pixels of the mask are ranked in the order of their gray levels, and the median value of the group is stored to replace the noisy value.[?]

2.4.2 Segmentation

Segmentation of images is very important as large numbers of images are generated during the scan and it is unlikely for clinical experts to manually divide these images in a reasonable time. Image segmentation refers to segregation of given image into multiple non-overlapping regions. Segmentation represents the image into sets of pixels that are more significant and easier for analysis. It is applied to approximately locate the boundaries or objects in an image and the resulting segments collectively cover the complete image. The segmentation algorithms works on one of the two basic characteristics of image intensity; similarity and discontinuity. [24]

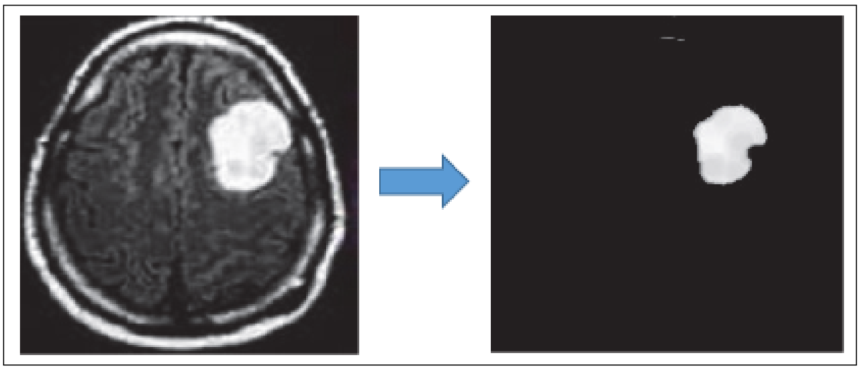

Figure 2.4: Segmentation process

2.4.2.1 Image Segmentation Techniques

Many image segmentation techniques are developed by researchers and scientists, which is most important and widely used on image segmentation techniques. [25]

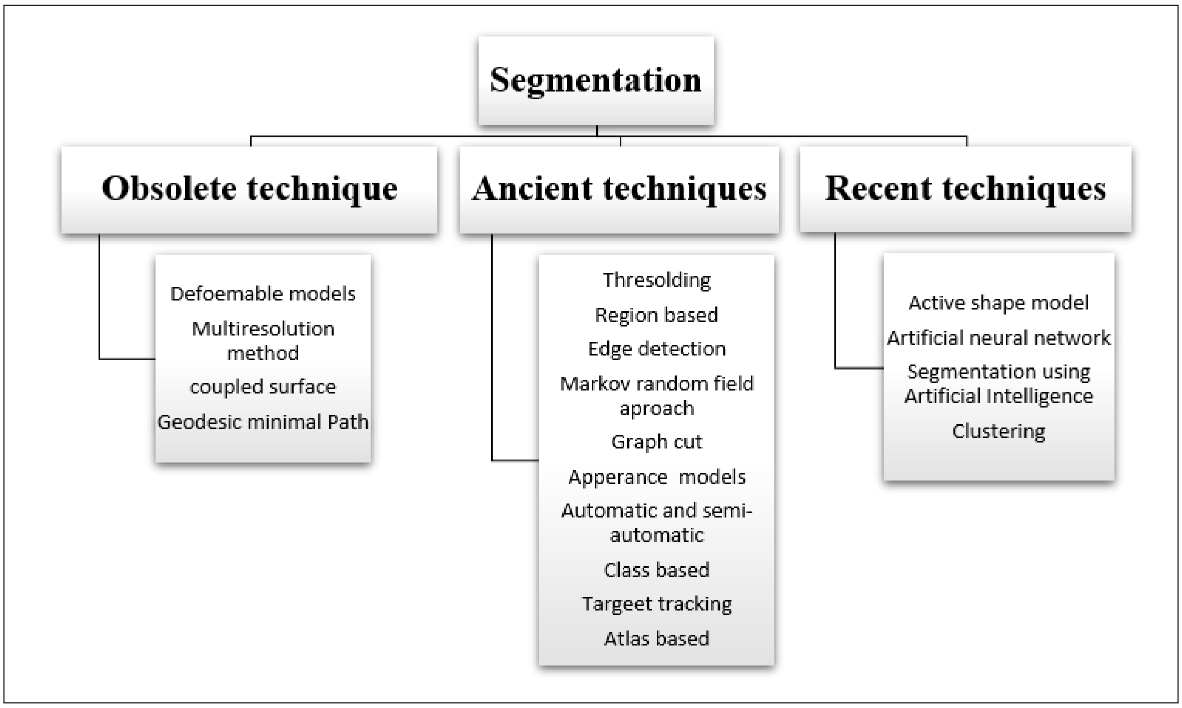

Figure 2.5: Segmentation Techniques

Obsolete techniques are very old and are not in use as of now. Ancient techniques are also old but are still in use in many applications. These techniques include thresholding, region based segmentation, edge detection, Markov random field approach, graph cut, appearance models, automatic and semi-automatic segmentation, class based segmentation, target tracking, and atlas based segmentation. [25]

2.4.2.1.1 Segmentation using Artificial Intelligence

In Artificial Neural Network, every neuron is corresponding to the pixel of an image. Image is mapped to the neural network. Image in the form of neural network is trained using training samples, and then connection between neurons, pixels is found. Then new images are segmented from the trained image.
Segmentation of image using neural network is performed in two steps, pixel classification and edge detection. [24]

2.4.3 Feature

Features are the numeric embodiment for raw data. There are countless ways to make raw data numeric. Features need to be extracted from available types of data. They are connected to the model, and so there is a reciprocal relationship of appropriateness between models and types of features. The appropriateness of features is based on task-relevancy and simplicity of process; and as such, its structure is based on these two aspects in respect to the task. [26]

2.4.4 Feature Type

2.4.4.1 Texture features

It is characterized by the spatial distribution of gray levels in a neighborhood. Since texture shows its characteristics both by pixel co-ordinates and pixel values. Image texture depends on the scale or resolution at which it's displayed. [26]

2.4.4.2 Shape features

Shape descriptors are a set of numbers that describe a given shape. Shape feature extraction techniques can be broadly classified into two groups, viz., contour based and region-based methods. The first technique calculates shape features only from the shape boundary, while the second method extracts features from the entire region. In addition, spatial relationship is also considered in image processing that tells object location within an image or the relationships between objects. It includes following two cases: absolute spatial location of regions and relative locations of regions. [28]

2.4.5 Feature Extraction

It is the process of collecting higher level information of an image such as shape, texture, color, and contrast. In fact, texture analysis is an important parameter of human visual perception and machine learning system. It is used effectively to improve the accuracy of diagnosis system by selecting prominent features. [26]

2.4.5.1 Feature Extraction Techniques

A summary of the survey of feature extraction techniques used in Brain tumor classification: [25]

Technique	**Extracted features**	**Remarks**
NSCT	Entropy, Contrast, Energy, Variance, Standard Deviation, Skewness, Kurtosis.	1. Outstanding features of NSCT like multiscale, multidirection, shift nvariance and better frequency selectivity and regularity than CT. 2. Ensure multiscale and Directionality features.
GLCM	Homogeneity(Angular Second Moment), Contrast, Entropy Correlation, Inverse Difference Moment, Variance, Sum Average, Sum Entropy, Difference Entropy, Inertia, Cluster shade and Cluster Prominence	1. The spatial relationship of the pixels are considered. 2. Extracted textural features. 3. Used to train the feed forward neural network.

DWT	Energy, Entopy, Homogenity, Dissimilarity And Contrast	1. Extract features from a MRI via successive excessive pass and occasional pass filtering ion various scales. 2. Provide localized frequency statistics approximately a function of a signal.
PCA	Extract the principal components that will explain largest amount of variation in the data. Covariance is a measure to find the relationship between the dimensions among the datasets.	1. Principal components can be identified by calculating the eigenvectors and eigen values of the data covariance matrix. 2. The main Advantage is that the patterns found in the data can be compressed by reducing the number of dimensions without loss of information.
GABOR	When a function is convolved with the Gabor wavelet, the frequency information near the center of the Gaussian is captured. Gabor wavelets are described by parameters that control orientation, frequency, phase, size, and aspect ratio and can take a variety of different forms.	1. Its main use is to extract the texture features. 2. The problem with these Gabor texture measures is the high computational cost consumed in the convolution calculation of the feature extraction process. 3. Only a small subset of the filters has important contributions to the identification process.

Table 2.1: feature extraction techniques

2.5 Classification problems

There are hardly many problems faced by the researchers and the developers in data analysis, especially in medical fields. Among these problems are those related to extracting features from images. There are several questions about what type of dataset to deal with and what type of medical imaging they have undergone, what characteristics should be chosen? Are these features really useful for the disease you are going to diagnose? Each disease has its own model, which is different from other diseases. Other problems related to identifying the important features. What is the effective way to identify important features? Especially with different features affecting training and learning for the model, as well as classification problems, what is the appropriate algorithm to be applied to give satisfactory, reliable and accurate results.

2.6 related work

Various theories and methodologies to extract information from images via computers have been explained and used by many researchers, academicians of different fields.

In the literature, there are many approaches and different modifications of the trained models that are implemented in mage analysis, classification, and segmentation. Different solutions have been tested on other medical databases, both on MRI images of brain tumors and on tumors from different parts of the human body [33]. These papers were not considered further, as the focus was on the papers using the same MRI image database or same tool of machine learning that we used.

The field of AI offers systems the strength to automatically apprentice and develop from experience by utilizing statistical methods without being explicitly programmed. It is a aggregation and conception of algorithms that can learn from and predict. Several methods or techniques of machine learning are known in this field as decision tree learning, associative rule learning, ANN, inductive logic programming, SVM, clustering, representation learning, sparse dictionary learning, etc. We handled our model by using SVM as supported tool from Machine Learning tools as proposed solution for Brain- Tumors Extraction.

Shankaragowda B.B. et Al. established the same architecture which held the following steps: preprocessing, segmentation, feature extraction and classification with some changes here and there. Their proposed classification of the MR image is binary classes:benign and malignant classes. The method is based on SVM classifier. The analysis return faster with this method and it avoids the necessity of biopsies.[32]

Ketan Machhale et Al . suggested a binary classification approach to sort from the brain MR images two classes as normal and abnormal. The model was defined in three steps, starting by pre processing to prepare the image followed by Feature extraction step to proceed training further way.They did three combination of machine learning techniques and they selected the best match, Support Vector Machine (SVM), K- Nearest Neighbor (KNN) and Hybrid Classifier (SVM-KNN) is used to classify 50 images. The high accuracy was improved from hybrid classifier (SVM –KNN). [34]

Nan Zhang et Al, adopted the multi kernel SVM classification along with the Merging process to extract brain tumor from multi sequence MR images. This approach lies on two phases. At first phase multi-kernel SVM for classifying the tumor lesion, this consists multi-image sources and produce multi-outputs. The second phase improves the edge of the tumor-affected area with utilizing distance and maximum likelihood measures.[35]

AlexNet and SqueezeNet. Then they have utilized the three combination of SVM, Knn and ELM in this orderto classify brain tumor t. They acquired accuracy rate 95.62% with SVM and 98.33 with ELM in their studies respectively.[33]

Vijay Wasule et Al designed an architecture based on SVM-KNN classifier to distinguish four classes into malignant or benign and low grade or high grade of the brain MR image. In feature extraction stage a GLCM technique was elaborated for obtaining features then stored as feature vectors. Entropy, energy, homogeneity, correlation and other features are computed. This technique reached an accuracy of 96% and 86% for SVM and KNN respectively. [31]

2.7 Conclusion

The image processing techniques and the features extraction methods are the key to how good a machine learning model is. If a set of inappropriate features are extracted, the model's predictions will be inaccurate and unreliable. So, we have to choose the best set of features that is compatible and correctly represent our dataset to provide accurate and reliable results. In the next chapter, we will present the proposed solution in our study and how to use the methods of extraction and classification.

CHAPTER 3

PROPOSED SOLUTION

3.1 introduction

the best classification is the result of many processes such as improving the quality of the image and extract the right features. All of these passes include many steps, as image enhancement and segmentation which are the two main steps in extracting the appropriate features that will strengthen the classification result.
In this chapter, we present our proposed solution, in which we will explain all the important steps in our study such as image enhancement, segmentation, feature extraction, and finally the classification.

3.2 General Architecture

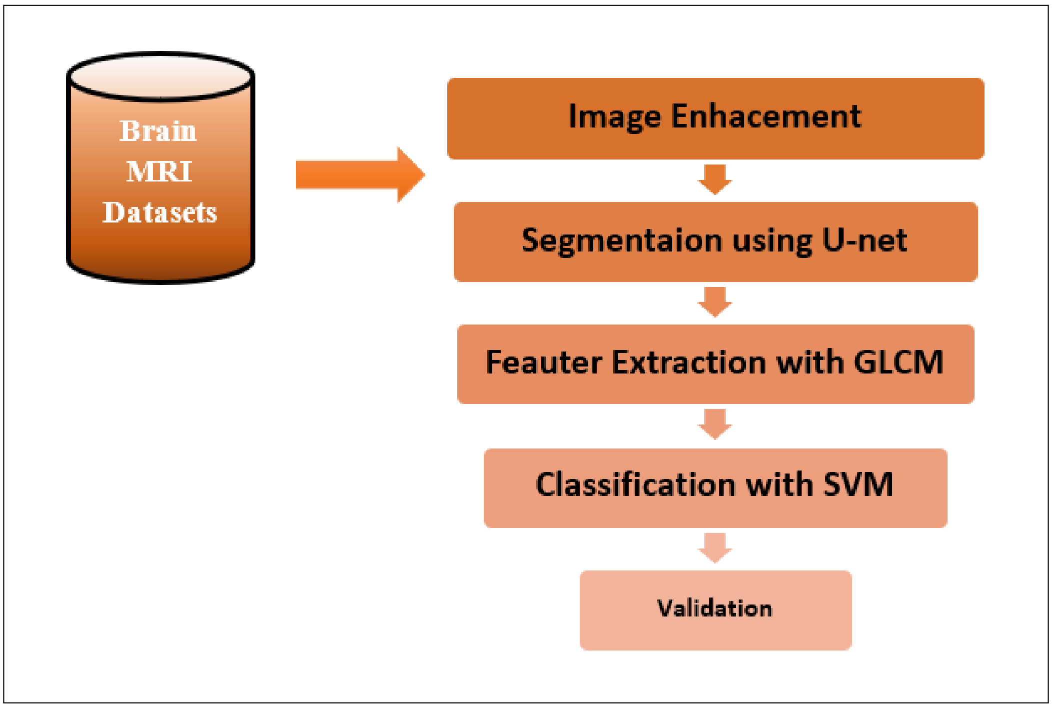

Figure 3.1: General Architecture

The general architecture describes the steps that make up the project and it is illustrated in Figure 3.1.
After we have received the images, we begin by preparing the input image for Enhancement as first step then move to segemnt it . and then we move to the stage of extracting features that are very important in images generally and medical images specifically. The phase of reduction features which is the most important phase for which we will do the normalization of our raw

data which have extracted to train our models and leads to more accurate classification.

3.3 Image enhancement process

This step used to improve the quality of brain images datasets to do best segmentation. We using different filters in OpenCV. It works better with gray-scale images.
The filters we used are median filter for removing noise from the image, and the histogram equalizer is used for contrast adjustment of the image and Gamma correction is also applied for preventing the image from darkening.

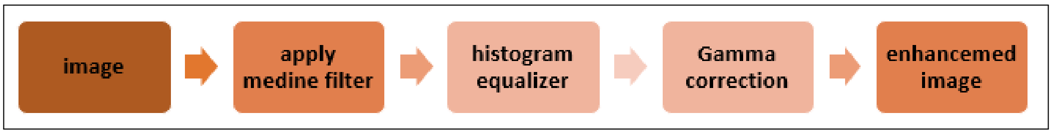

Figure 3.2: image enhancement steps

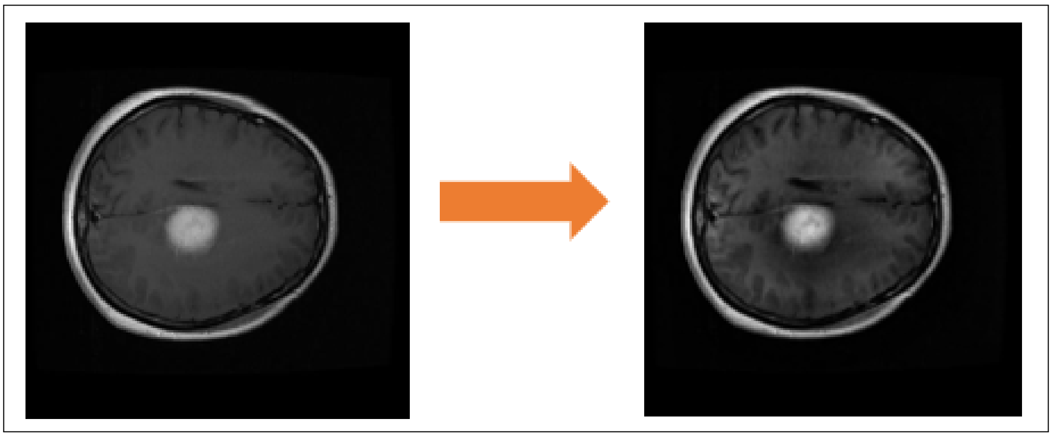

Figure 3.3: image enhancement example

3.4 Segmentation process

This phase is considered the most important phase in our project. It is a crucial phase for building a proper model. we present a model-based learning for brain tumor segmentation from multimodal MRI protocols. The model uses U-Net-based fully convolutional networks.

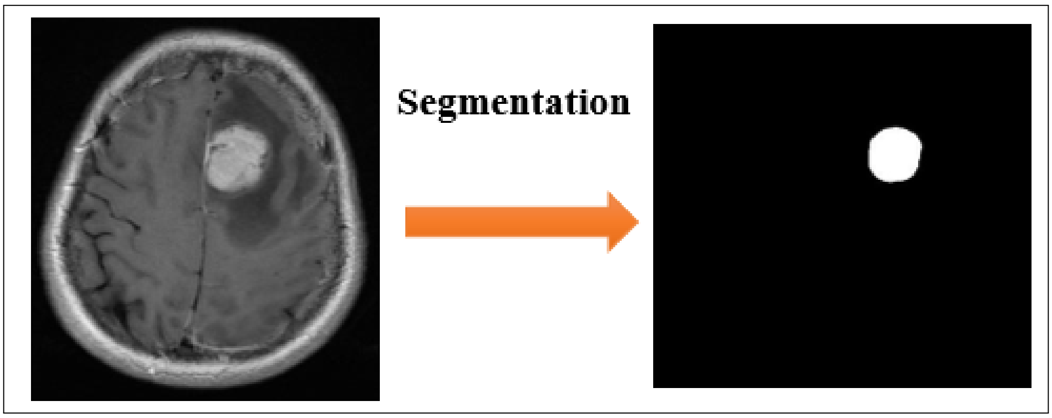

Figure 3.4: brain segmentation

3.4.1 U-net model Architecture

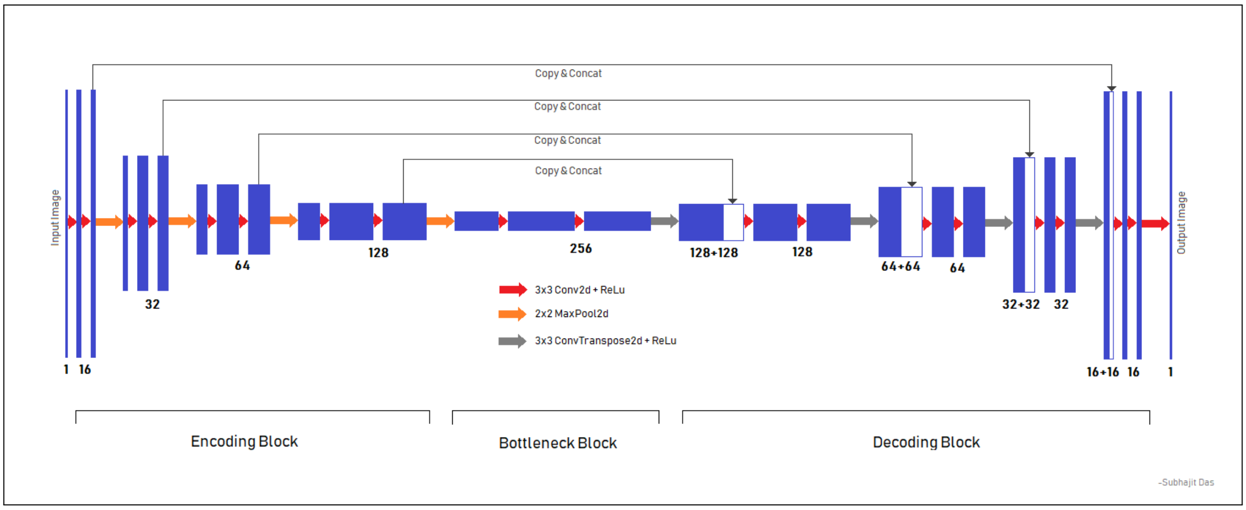

Figure 3.5: U-net model Architecture

3.5 Feature extraction process

At this phase, the input is raw medical images. Two fundamental types of features: texture features and shape features. For the first type we use GLCM features, and for the second type we use the moments features. The output is Numerical values of different dimensions. These features are the most common features in the analysis and recognition of patterns in medical images.

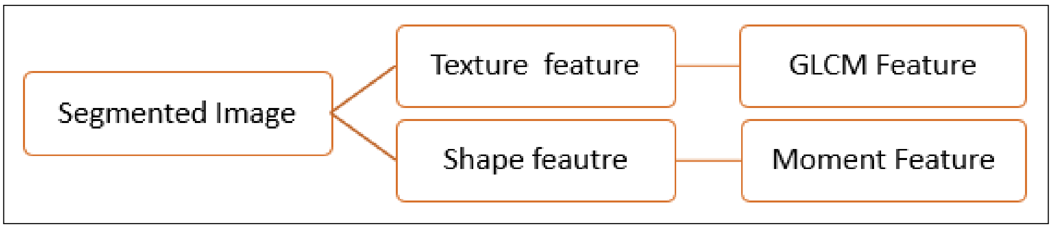

Figure 3.6: Feature extraction process

3.5.1 Texture feature Extraction

3.5.1.1 Gray-level co-occurrence matrix (GLCM)

GLCM is the statistical method of examining the textures that considers the spatial relationship of the pixels. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. [28]

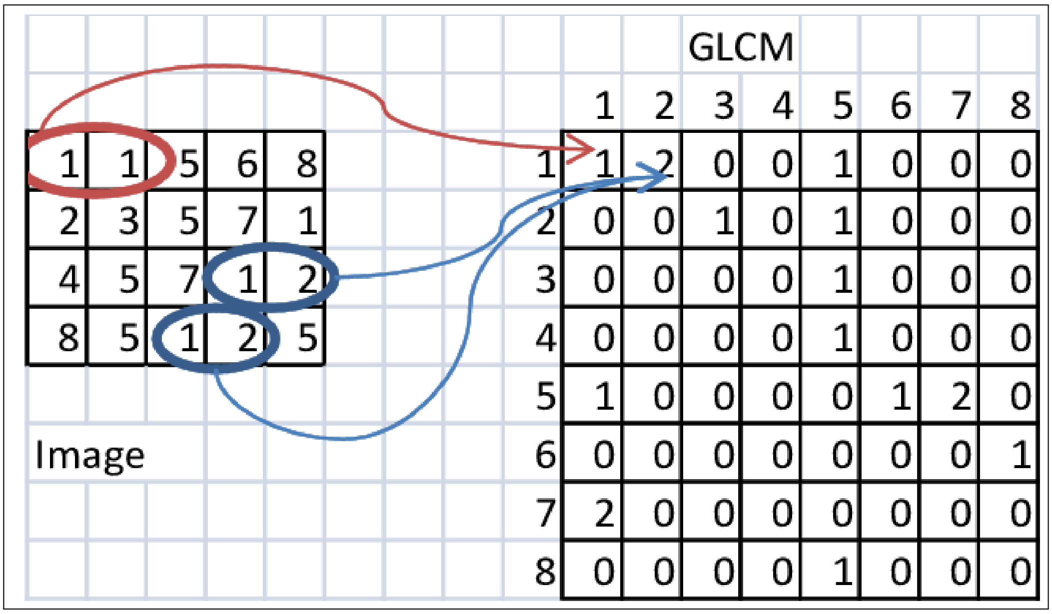

Figure 3.7: GLCM process

3.5.1.2 How to calculate GLCM matrix

1. Create framework matrix, if the original image has G Gray levels, then the dimension of the co-occurrence matrix is G*G.

2. Describe spatial relation between reference and neighbor pixels using two parameters (d, θ), which d is the distance between the pair of pixels and θ is the angle between them.

3. Count the occurrence and fill in framework matrix by checking all pixel pairs with distance d and direction θ assign value i to pixel 1 and value j to pixel 2.

Some Properties of gray-level co-occurrence matrix :

Name	Explanation	Formula
Energy	Measures how smooth the texture is. The value is 1 for a constant texture.	$\sum_{n=1}^{K}\sum_{m=1}^{K} p_{nm}^2$
Contrast	Measures the intensity difference between a pixel and its neighbour over the entire texture.	$\sum_{n=1}^{K}\sum_{m=1}^{K}(n-m)^2 p_{nm}$
Homogeneity	Measures the spatial closeness of the distribution of elements in the GLCM to the diagonal.	$\frac{\sum_{n=1}^{K}\sum_{m=1}^{K} p_{nm}}{1+\lvert n-j\rvert}$
Entropy	Measures the randomness of the GLCM	$-\sum_{n=1}^{K}\sum_{m=1}^{K} p_{nm}\log_2 p_{nm}.$
Correlation	Measures how correlated a pixel is to its neighbour over the image.	$\frac{\sum_{n=1}^{K}\sum_{m=1}^{K}(n-a_r)(m-a_c)}{\sigma_r^2\sigma_c^2}$

Figure 3.8: GLCM Properties

3.5.2 Shape features Extraction

Features describe the boundary of the image like area and centroid, help to extract specific information about the shape of the region. To calculate shape features we should know image moments, An Image moment is a number calculated using a certain formula, asset of moments computed from the digital image represented characteristics of image shape and give information about the geometric feature of the image.

In two-dimensional intensity distribution, the geometric function of pixels values with respect to spatial locations in the image can extract shape information such as image area and coordinates centroid. The first order moment will give the center of mass, where the mass of a pixel is its intensity; second order moment will give how this mass varies around the center of mass.

3.5.2.1 Moments

Image moments are used to describe objects and play an essential role in object recognition and shape analysis. Images moments may be employed for pattern recognition in images. Simple image properties derived via raw moments is area or sum of grey levels

3.5.2.1.1 Area

Calculate a number of pixels in the region. For Calculating area, we need to calculate its zeroes moment In a binary image, there are two possibilities 0 or 1, so in white pixel add 1 to moment to get all area.

3.5.2.1.2 Eccentricity

The ratio between the major axis and the minor axis in the region detected, when the ratio is 1, the region becomes a circle

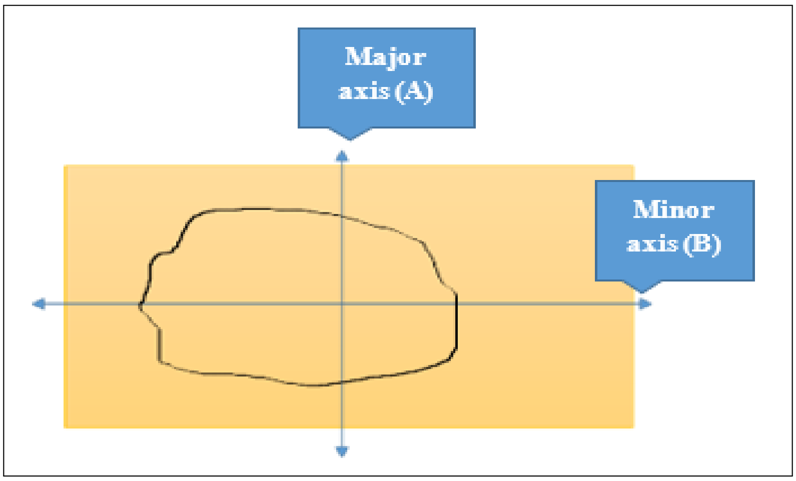

Figure 3.9: Eccentricity Property

Major axis (A): longest horizontal axis in region.
Minor axis (B): longest vertical axis in region.

3.5.2.1.3 Euler number

Describe relation between holes and connected region in our region. Let's say our image is all black color represented by variable S and have some holes represented by variable N. So our Euler number become:

$U = S - N$

This feature called as a logical invariant descriptor because its value doesn't change if image zoomed or oriented but also shouldn't increase the degree of zoom till holes disappear or become unrecognizing.

3.5.2.1.4 Convex area

To know convex hull we should first define a polygon.

- Polygon is a plane figure with at least three straight sides and angles.
- Convex polygon is defined as a polygon with all its interior angels less than 180.This means that all the vertices of the polygon will point outwards, away from the interior of the shape.
- Convex hull of set of point Q is the smallest convex polygon P for which each point in set Q is ether on the boundary of P or in its interior.

Let's see for example two regions S1, S2

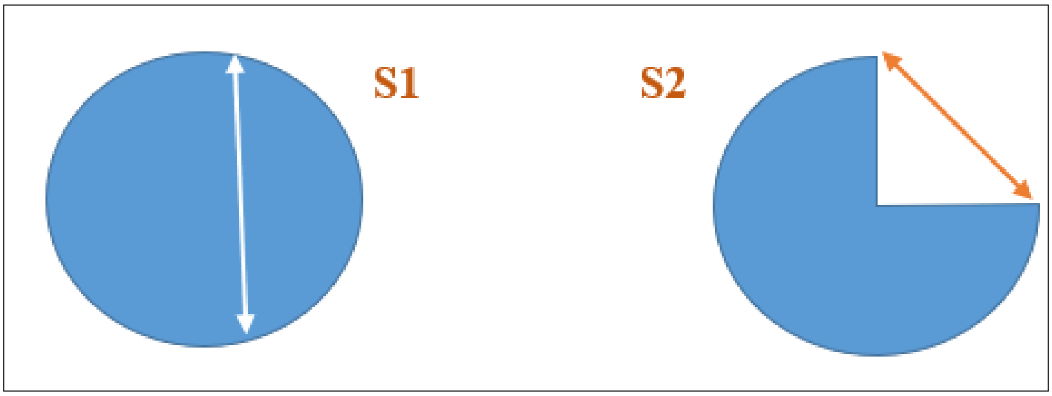

Figure 3.10: Convex area property

In case S1 region is convex. In case s2 region in not convex.

3.5.2.1.5 Solidity

Defined as the ratio of area over convex area

3.5.2.1.6 Orientation

The angle between the X-axis and the major axis of the ellipse that has the same second-moments as the region. Ranging from -pi/2 to pi/2 in counter-clockwise direction.

3.5.2.1.7 Extent

The proportion of the pixels in the bounding box that are also in the region. Computed as the area divided by the area of bounding box, where bounding box is the area of smallest rectangular that fit around region.

3.6 Feature normalization

we normalize the rest of features to make feature values Convergent as possible using Standard deviation and Mean And this done by compute mean of a group of one feature and subtract it from each sample in this feature group: Feature-group = Feature-group / std(feature-group)

3.7 Classification Using Support Vector Machine (SVM)

3.7.1 Description of algorithm

It distributes data items as points in n dimensional space where n is number of features, the data points is called the support vectors .Then the hyper plane is detected to separate points into two classes to made classification very well. The hyper plane is line used for splitting input data distribute in n dimensional space

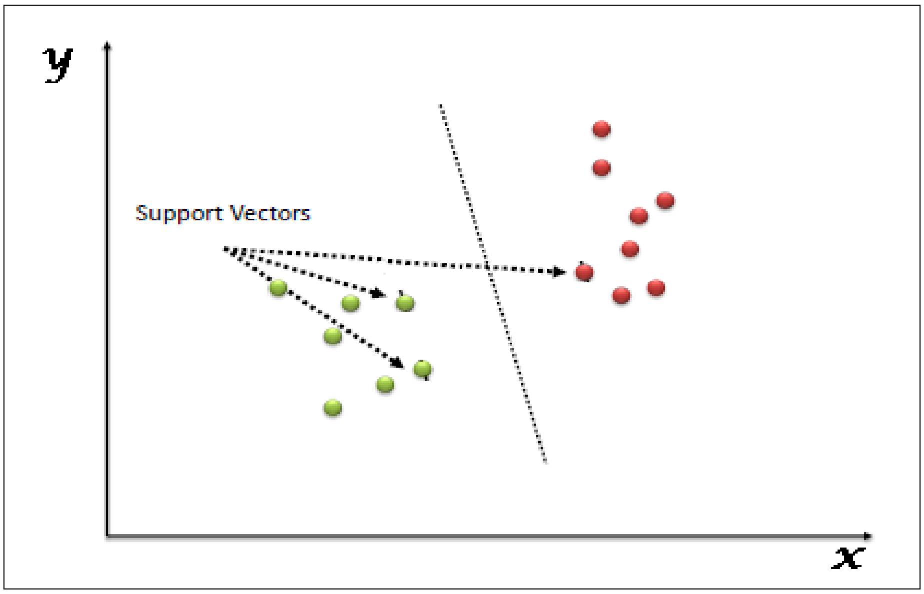

Figure 3.11: SVM classification

3.7.1.1 How to select the right hyper planes?

There are many scenarios to select the best hyper plane.

✓ Scenario (a): assume there are two classes (star and circle) The input data are distributed as two classes and there is three hyper planes detected as a figure (3-12). The right hyper plane is the line (C) because the hyper plane (c) is high margin compare to a hyper plane (a) and hyper plane (b).

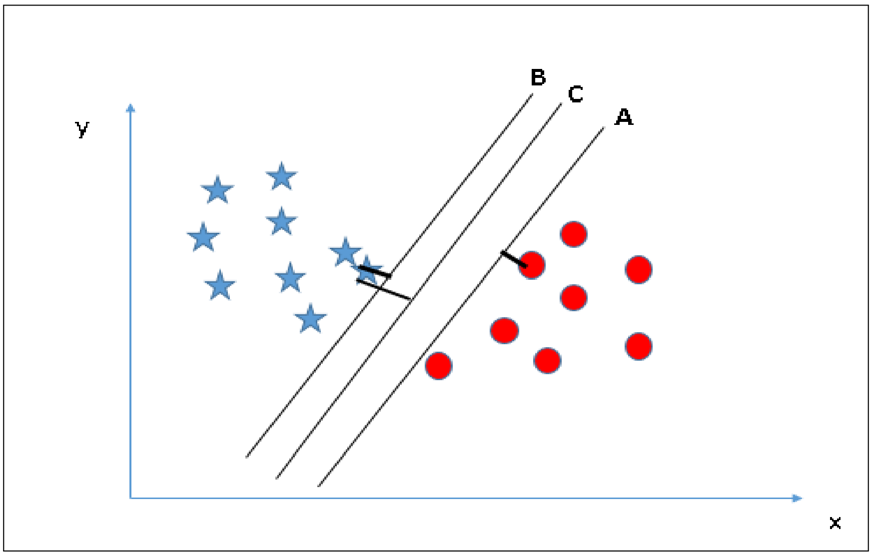

Figure 3.12: Scenario a classification

✓ Scenario (b): Data of one class distribute with the other class as fig (3-13). The hyper plane (a) is the correct because of it classified all class correctly.

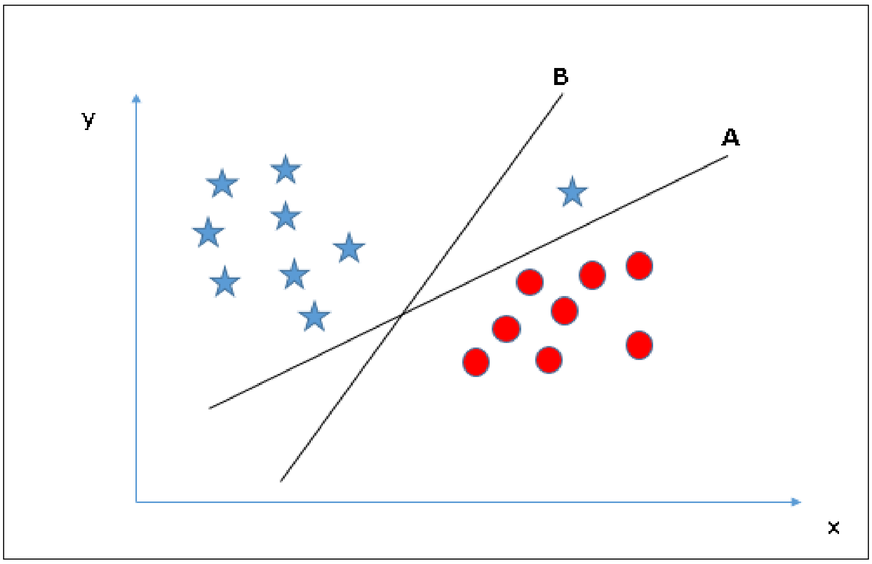

Figure 3.13: scenario b classification

✓ Scenario (c): Data of one class distribute with the other class and one of star class lies on outlier as fig (3-14).

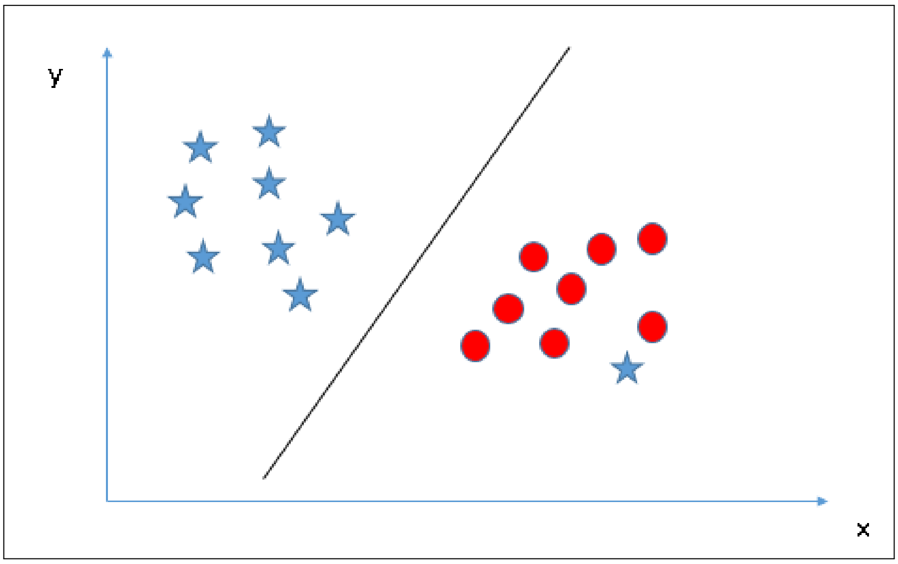

Figure 3.14: scenario c classification

After extracting all the features from the segmented image and storing it as csv file. the the SVM classifier began the training on two classes of tumor type (Glioma , Meningioma).

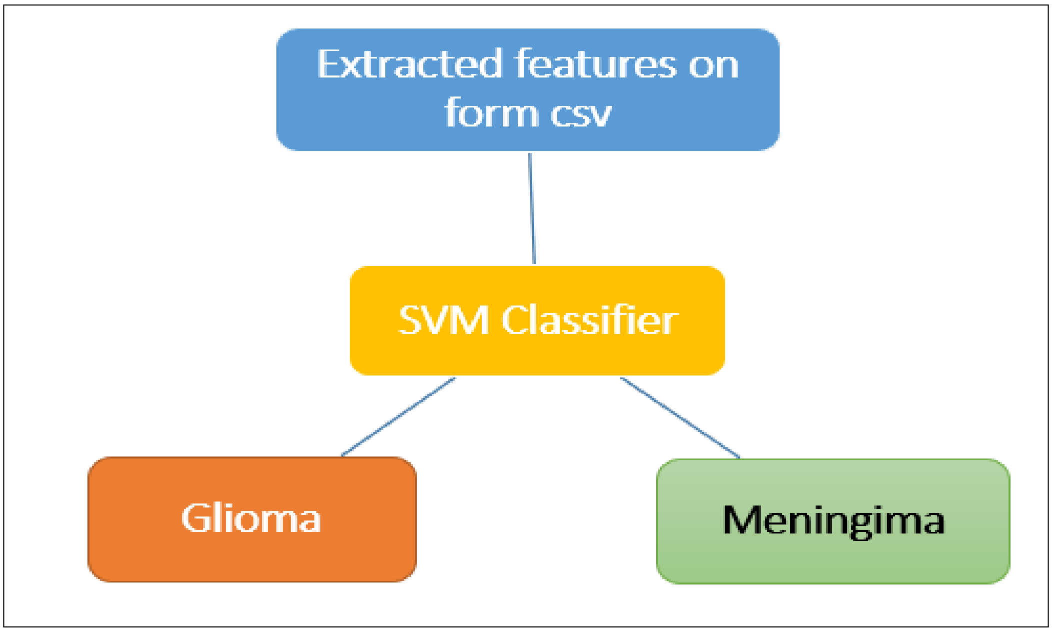

Figure 3.15: SVM model

3.8 conclusion

Previously we have presented the proposed solution, provided the overall structure of the solution organized in several phases, and presented each phase in detail. We will evaluate and discuss the obtained results by our proposed solution in the next chapter.

CHAPTER 4

VALIDATION

4.1 Introduction

As was explained in the previous chapter our model has five steps. Thus, in this chapter, we will explain the last one, explain the used tools and the programming code for each step. In the end, we will discuss the obtained results.

4.2 Dataset

In clinical settings, usually only a certain number of slices of brain CE-MRI with a large slice gap, not 3D volume, are acquired and available. A 3D model is difficult to construct with such sparse data. Hence, the proposed method is based on 2D slices. The brain T1-weighed CE-MRI dataset was acquired from Nanfang Hospital, Guangzhou, China, and General Hospital, Tianjin Medical University, China, from 2005 to 2010. We collected 3064 slices from 233 patients, containing 708 meningiomas, 1426 gliomas, and 930 pituitary tumors. The images have an in-plane resolution of 512*512 with pixel size 0.49*0.49 mm2. The slice thickness is 6 mm and the slice gap is 1 mm. The tumor border was manually delineated by three experienced radiologists. Four examples are illustrated in.

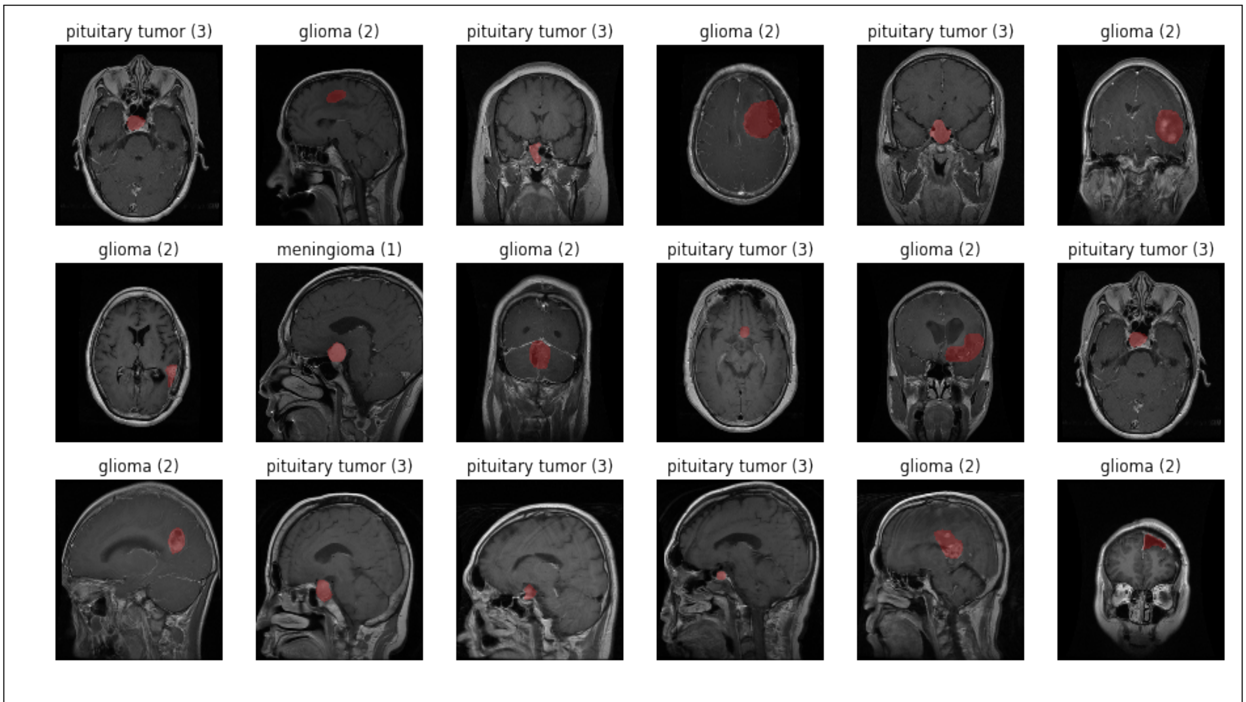

Figure 4.1: Dataset example

4.3 Tools

4.3.1 Python Language

Python is an interpreted high-level programming language and object-oriented programming, developed by Python Software Foundation. Its implementation began in December 1989. Python was created by Guido van Rossum. It is easily readable language. Python has several versions of Python 2.x or Python 3.x. We used the latest version of Python 3.6.7. [36]

‘

4.3.1.1 Why python

It's easy to work with and have access to high quality libraries. It is the most used in the field of artificial intelligence and Machine learning. Pandas, image-Net, pascal and mlxtend all support Python. Its interpreters are available for many operating systems. That is, the most famous libraries in the field of artificial intelligence are made by Python like cv2 and Scikit-learn. Scikit-learn guides to use Python language; although there are other programming languages use this libraries, but it's not as effective as Python. [36]

4.3.2 Google colab

Colaboratory is a free research tool for machine learning education and research. It's a Jupyter notebook environment that requires no setup to use, Colaboratory works with most major browsers, and is most thoroughly tested with latest versions of Chrome, Firefox and Safari. Jupyter is the open source project on which Colaboratory is based. Colaboratory allows you to use and share Jupyter notebooks with others without having to download, install, or run anything on your own computer other than a browser. [37]

4.3.3 TensorFlow

TensorFlow is an open-source library and a Python-friendly free for numerical computation and large-scale, Created by the Google Brain team that makes DL and ML faster and easier. TensorFlow can train and run deep neural networks for image recognition, recurrent neural networks, handwritten digit classification, natural language processing, word embeddings, sequence-to-sequence models for machine translation. . . ,and more. [40]

4.3.4 Numpy

NumPy is a library for the Python programming language that allows for more data storage with less memory. With a multidimensional array and other resources, NumPy allows Python programmers to store numbers efficiently.

4.3.5 Scikit-learn

Scikit-learn is a library in Python that provides many unsupervised and supervised learning algorithms. It's built upon some of the technology you might already be familiar with, like NumPy, pandas, and Matplotlib, also including SVM for Classification functionality. [38]

4.3.6 OpenCV

OpenCV (Open Source Computer Vision Library) is an open source computer vision and machine learning software library. OpenCV was built to provide a common infrastructure for computer vision applications and to accelerate the use of machine perception in the commercial products. Being a BSD-licensed product, OpenCV makes it easy for businesses to utilize and modify the code [39]

4.3.7 Configuration material

- GPU: 1xTesla T4, having 2496 CUDA cores, compute 3.7, RAM 16GB (Google Colab Pro)
- CPU: Intel (R) Core (TM) i5-6200U CPU @ 2.40GHz RAM 8GO (Our Labtop)

4.4 Code Explaining

Firstly, we started with the code of image enhancement to:

- Denoise a grayscale image with median filter
- Clahe is used for Histogram equalization of the image
- Enhances Sharpness and Contrast of images
- Gamma Correction for preventing darkening of images.

```
# Convert image to gray scale
gray_image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
# Non-Linear filter for noise removal
deNoised = ndimage.median_filter(gray_image, 3)
#Histogram Equalizer
#High pass filter for improving the contrast of the image
clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(8,8))
highPass = clahe.apply(deNoised)
#Gamma Transformation
#Prevent bleaching or darkening of images
gamma = highPass/255.0
gammaFilter = cv2.pow(gamma,1.5)
gammaFilter = gammaFilter * 255
```

Secondly, the code of our U-net model for segmentation:

```
def __init__(self, filters, input_channels=1, output_channels=1):
    super(DynamicUNet, self).__init__()
    if len(filters) != 5:
        raise Exception(f"Filter list size {len(filters)}, expected 5!")
    padding = 1, ks = 3
    #   Block 1
    self.conv1_1 = nn.Conv2d(input_channels, filters[0], kernel_size=ks, padding=padding)
    self.conv1_2 = nn.Conv2d(filters[0], filters[0], kernel_size=ks, padding=padding)
    self.maxpool1 = nn.MaxPool2d(2)
    #   Block 2
    self.conv2_1 = nn.Conv2d(filters[0], filters[1], kernel_size=ks, padding=padding)
    self.conv2_2 = nn.Conv2d(filters[1], filters[1], kernel_size=ks, padding=padding)
    self.maxpool2 = nn.MaxPool2d(2)
    #   Block 3
    self.conv3_1 = nn.Conv2d(filters[1], filters[2], kernel_size=ks, padding=padding)
    self.conv3_2 = nn.Conv2d(filters[2], filters[2], kernel_size=ks, padding=padding)
    self.maxpool3 = nn.MaxPool2d(2)
    #   Block 4
    self.conv4_1 = nn.Conv2d(filters[2], filters[3], kernel_size=ks, padding=padding)
    self.conv4_2 = nn.Conv2d(filters[3], filters[3], kernel_size=ks, padding=padding)
    self.maxpool4 = nn.MaxPool2d(2)
    # Bottleneck Part of Network.
    self.conv5_1 = nn.Conv2d(filters[3], filters[4], kernel_size=ks, padding=padding)
    self.conv5_2 = nn.Conv2d(filters[4], filters[4], kernel_size=ks, padding=padding)
    self.conv5_t = nn.ConvTranspose2d(filters[4], filters[3], 2, stride=2)
    # Decoding Part of Network.
    #   Block 4
    self.conv6_1 = nn.Conv2d(filters[4], filters[3], kernel_size=ks, padding=padding)
    self.conv6_2 = nn.Conv2d(filters[3], filters[3], kernel_size=ks, padding=padding)
    self.conv6_t = nn.ConvTranspose2d(filters[3], filters[2], 2, stride=2)
    #   Block 3
    self.conv7_1 = nn.Conv2d(filters[3], filters[2], kernel_size=ks, padding=padding)
    self.conv7_2 = nn.Conv2d(filters[2], filters[2], kernel_size=ks, padding=padding)
    self.conv7_t = nn.ConvTranspose2d(filters[2], filters[1], 2, stride=2)
    #   Block 2
    self.conv8_1 = nn.Conv2d(filters[2], filters[1], kernel_size=ks, padding=padding)
    self.conv8_2 = nn.Conv2d(filters[1], filters[1], kernel_size=ks, padding=padding)
    self.conv8_t = nn.ConvTranspose2d(filters[1], filters[0], 2, stride=2)
    #   Block 1
    self.conv9_1 = nn.Conv2d(filters[1], filters[0], kernel_size=ks, padding=padding)
    self.conv9_2 = nn.Conv2d(filters[0], filters[0], kernel_size=ks, padding=padding)
    # Output Part of Network.
    self.conv10 = nn.Conv2d(filters[0], output_channels, kernel_size=ks, padding=padding)
def forward(self, x):
```

After we segmented the image, we move to next step "extract feature".

```
#shape Feauter
m = skimage.measure.moments(im)
cr = m[0,1] /m[0,0]
cc = m[1,0] / m[0,0]

measure.moments_central(im,cr,cc)
label_img = label(im)
props = regionprops(label_img)

area.append(props[0].area)
extent.append(props[0].extent)
orientation.append(props[1].orientation)
convex_area.append(props[1].convex_area)
solidity.append(props[1].solidity)
eccentricity.append(props[1].eccentricity)
euler_number.append(props[2].euler_number)
```

```
# GLCM Texture Features
glcm = greycomatrix(t, [5], [0], symmetric=True, normed=True)
ds.append(greycoprops(glcm, 'dissimilarity')[0,0])
crr.append(greycoprops(glcm, 'correlation')[0,0])
cn.append(greycoprops(glcm, 'contrast')[0,0])
am.append(greycoprops(glcm, 'ASM')[0,0])
en.append(greycoprops(glcm, 'energy')[0,0])
ho.append(greycoprops(glcm, 'homogeneity')[0,0])
```

The next step is to save all the features as csv file:

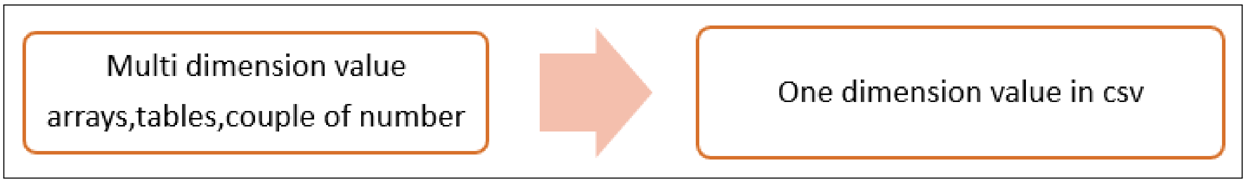

Figure 4.2: Features to CSV process

The result of our shape and texture feature code:

	area	orientatio	convex_ar	dissimilar	correlatio	contrast	ASM	energy	homogen	kurtosis	skew	Standard_	Mean	class
0	1	0.785398	1	0.3705	0.814922	88.35432	0.988076	0.99402	0.996569	-0.45527	0.386883	15.37441	0.943306	0
1	1	0.785398	2	0.486802	0.897712	116.1752	0.976404	0.988131	0.995311	5.984494	0.892902	23.71468	2.243156	0
2	1	0.785398	1	1.006996	0.935015	243.3383	0.933618	0.966239	0.991508	-1.88822	0.382081	43.06421	7.524685	0
3	1	0.785398	1	0.57955	0.850207	138.2333	0.979861	0.989879	0.994757	-0.1592	0.46795	21.37621	1.826378	0
4	1	0.785398	1	0.512736	0.78669	123.4027	0.986889	0.993423	0.995864	-1.8409	0.233786	16.92467	1.144276	0
5	2	-0.7854	2	0.600553	0.889636	142.2442	0.974008	0.986918	0.994156	1.307986	0.618412	25.2627	2.553406	0
6	2	0.785398	1	0.446992	0.860853	105.9851	0.983136	0.991532	0.995613	-1.23533	0.367392	19.42015	1.505695	0
7	1	0.785398	1	0.443818	0.838083	105.5184	0.984331	0.992135	0.995653	-0.87758	0.405096	17.96316	1.288357	0
8	1	0.785398	1	0.588056	0.859918	140.8427	0.97924	0.989565	0.99489	-0.42893	0.359421	22.31243	1.987473	0
9	2	0.785398	1	0.805296	0.930608	191.3728	0.948341	0.973828	0.992043	0.156501	0.622139	36.95612	5.506378	0

Figure 4.3: Extracted Features (CSV file)

The last step is training the classifier:

```
# Importing the dataset
df = pd.read_csv('H:\Machine_learining_test/Feature_all_opt.csv')

X = df.iloc[:,1:15]
y = df.iloc[:,-1]

# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 0)

# Fitting SVM to the Training set
from sklearn.svm import SVC
classifier = SVC(kernel = 'linear', random_state = 0)
classifier.fit(X_train, y_train)
from sklearn.metrics import accuracy_score
# Predicting the Test set results
y_pred = classifier.predict(X_test)


print("accuracy Score : ",accuracy_score(y_test, y_pred,
                                          ))
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
```

4.5 the system interface

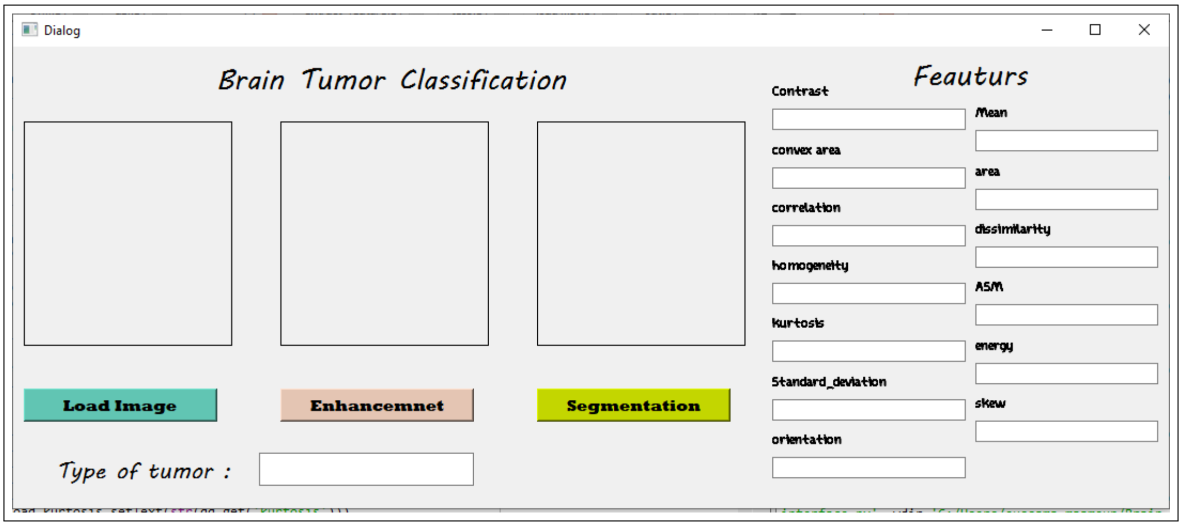

Figure 4.4: The main interface

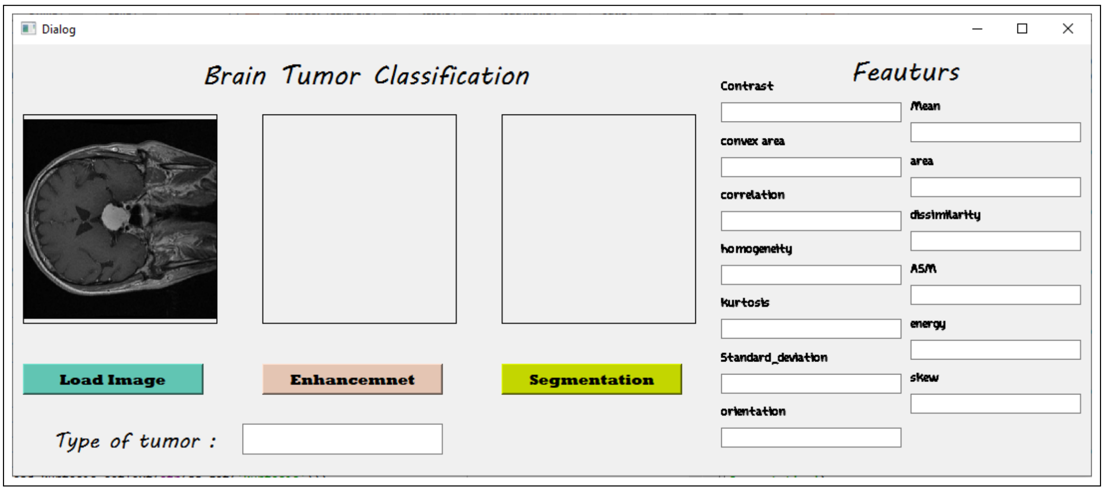

Figure 4.5: load image step interface

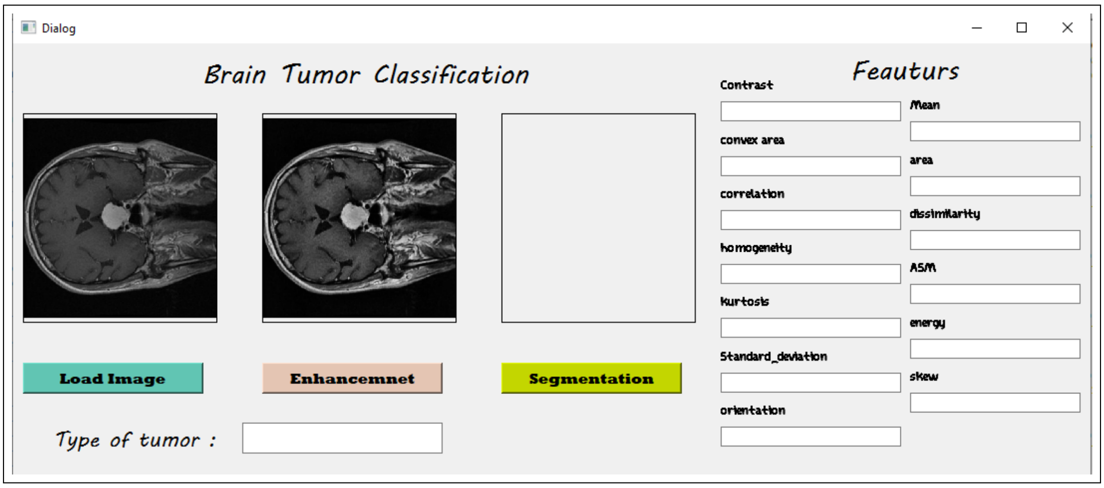

Figure 4.6: Enhancement step interface

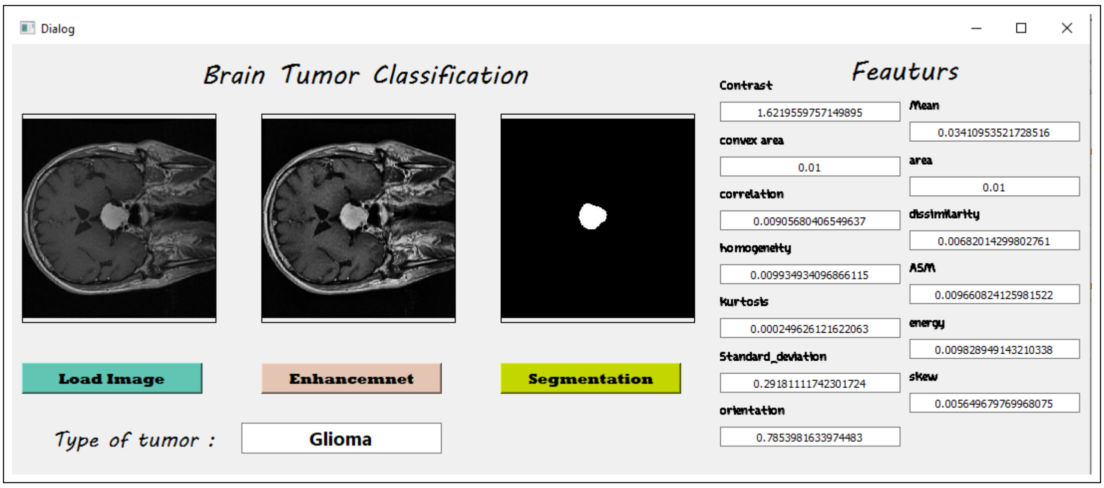

Figure 4.7: Segmentation and result step interface

4.6 Results and Discussion

4.6.1 Segmentation

Figure represents training Loss Function over Epoch:

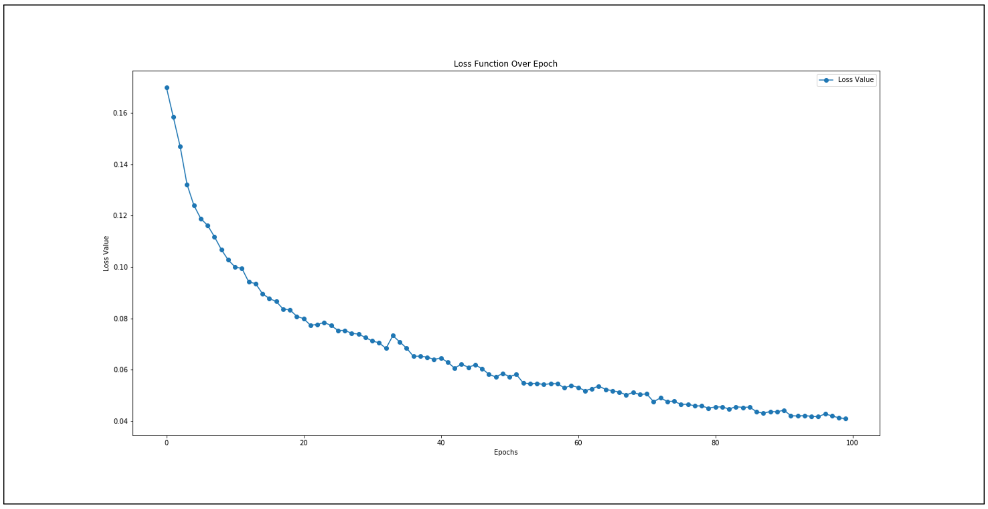

Figure 4.8: Training Loss Function over Epoch

This is an example of the result of segment an image and the dice score of it:

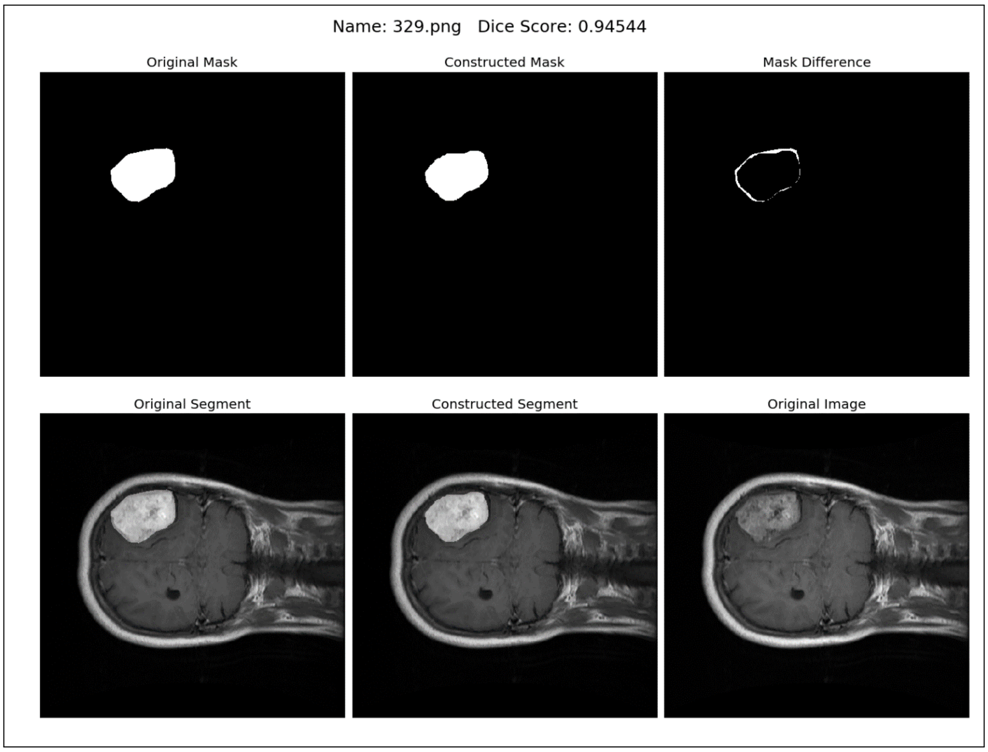

Figure 4.9: Segmentation example and Dice Score

4.6.2 Split the Original Set into Train, Validation and Test Data

Firstly, we split the original dataset into two parts. The first part for training the model and the second part for testing its accuracy in order to predict new samples (80% of the samples for training and 20% for testing). The original data contains 3064 T1-weighted, we chose only 2000 (just meningioma and glioma) samples 1600 samples for training (1100 samples of glioma tumor and 500 samples for meningioma tumor) and 400 samples for the test (280 samples of glioma tumor and 120 samples for meningioma tumor)

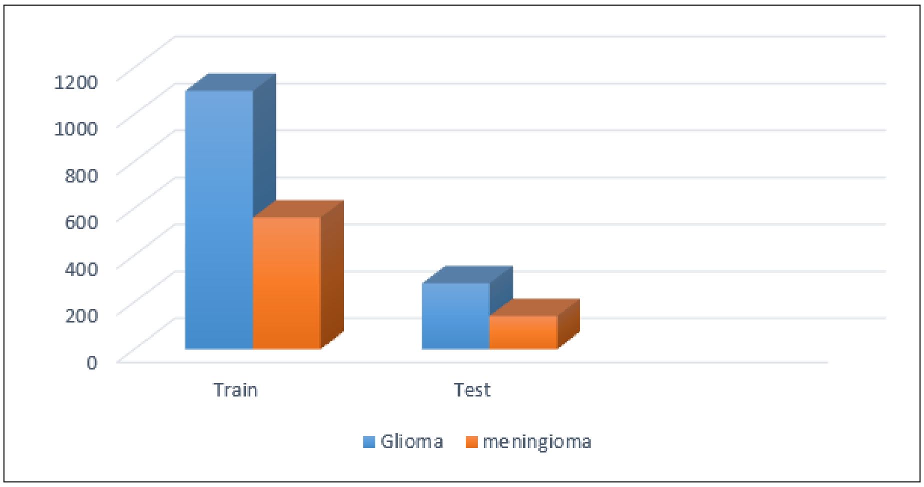

Figure 4.10: Distrubution of Glioma and Meniggioma tumor between Train and Test

Secondly, we split the original train set into two parts. The first part for training the model and the second part for validate the accuracy of the model, where 90% of the train samples for training and 10% for validation,

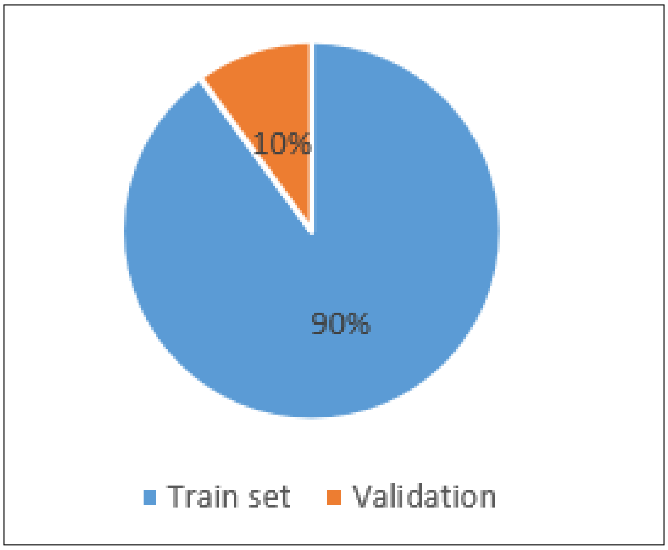

Figure 4.11: Split the train set into train and validation

4.6.3 Evaluating a Classifier

The evaluation of binary classifiers compares two methods of assigning a binary attribute, one of which is usually a standard method and the other is being investigated. There are many metrics that can be used to measure the performance of a classifier or predictor; different fields have different preferences for specific metrics due to different goals. For example, in medicine sensitivity and specificity are often used, while in computer science precision and recall are preferred. An important distinction is between metrics that are independent on the prevalence , and metrics that depend on the prevalence – both types are useful, but they have very different properties.

We try the training with all kernels of SVM:

Kernels	**Accuracy**	**Precision**	**Recall**
Linear	0.964	1.0	0.919
Rbf	0.952	0.995	0.931
Sigmoid	0.672	0.739	0.775
Poly	0.955	1.0	0.931

Table 4.1: training with all kernels of SVM

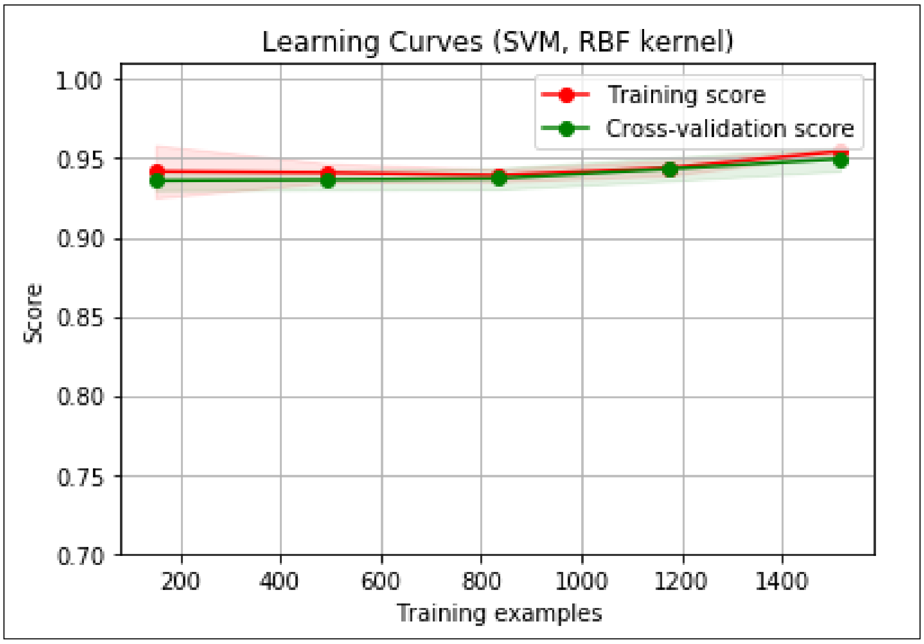

Figure 4.12: RBF kernel curve

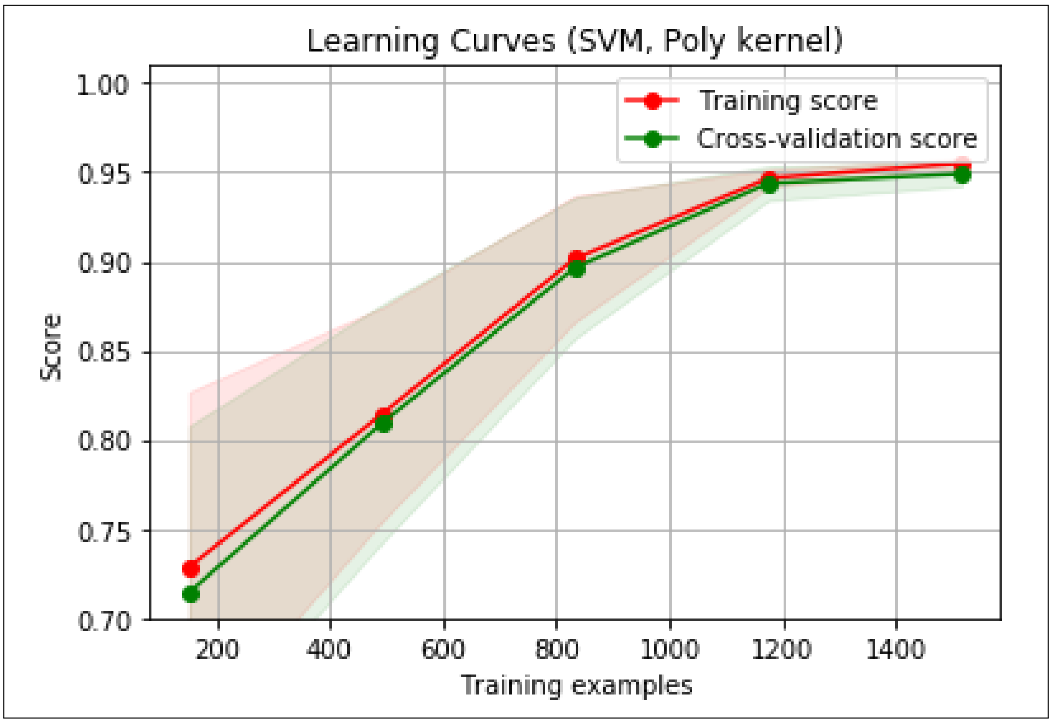

Figure 4.13: poly kernel curve

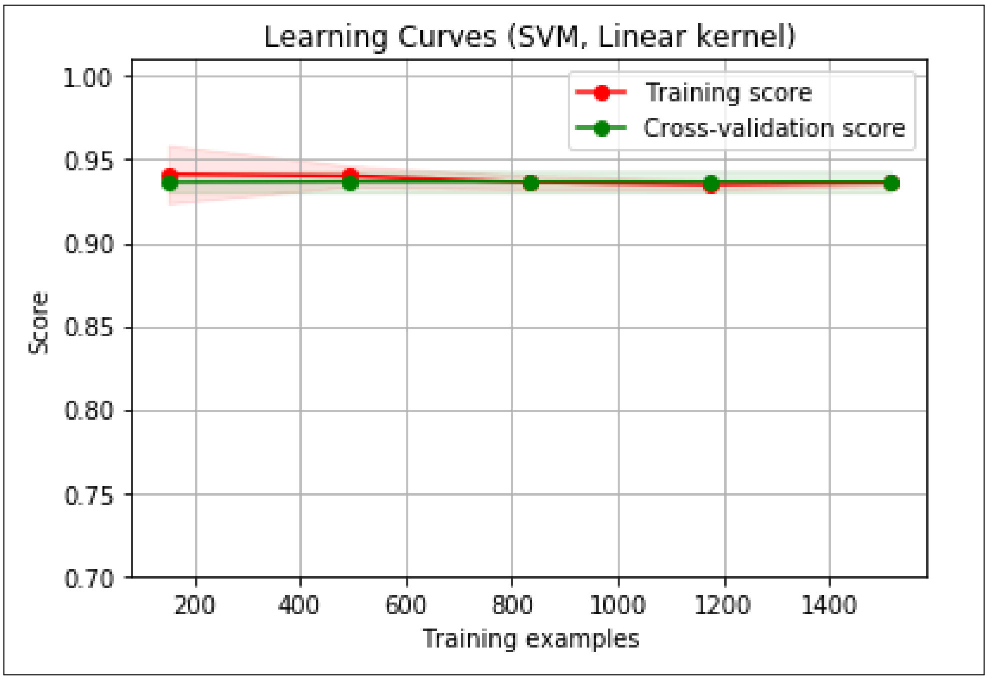

Figure 4.14: Linear kernel curve

	Positive	**Negative**
Positive	131	1
Negative	0	264

Table 4.2: Confusion matrix

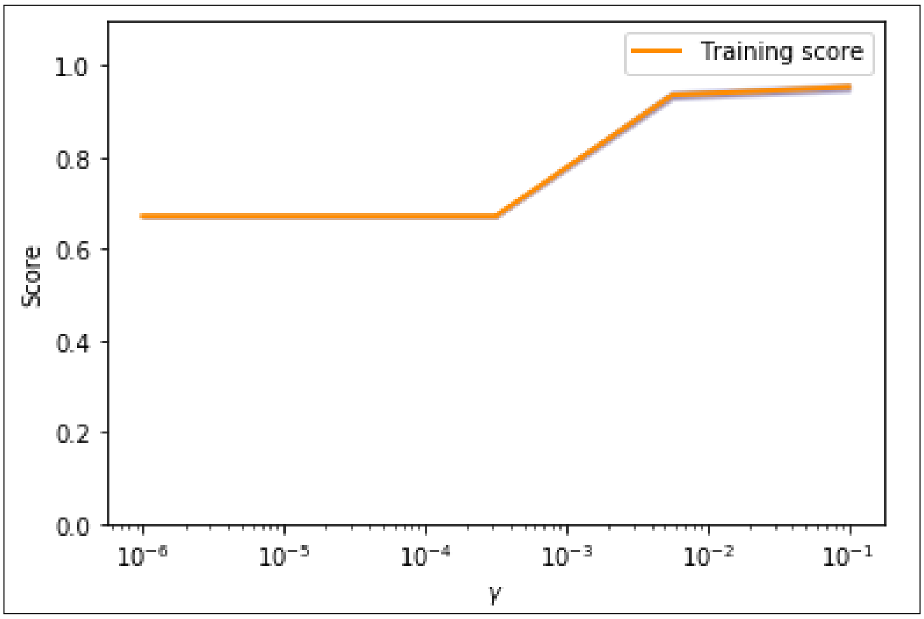

Figure 4.15: Traning accuracy

4.7 Conclusion

In this chapter, we explained the programming language and its tools which were very helpful for our model. Also, the implementation of each step was well explained. Moreover, we try all the SVM kernel which give us a different result and the best choice was linear kernel (96%). In the end, we discussed the obtained results.

GENERAL CONCLUSION

Magnetic resonance imaging (MRI) is a clinical tool allowing in vivo observation of the brain area. It provides a wealth of information about brain tissue through the variety of excitation sequences available.

Computer vision is an interdisciplinary field dealing with how to make computer extract information from images and videos .

In the recent world, the image processing domain involved in the digital biomedical area holds a significant position in two major axes which include improvement in the pictorial information for human studies and processing of this data for storage.

There is nothing specific about brain tumor symptoms which have made this research field an open key of challenges. Also, it is often conflicted about any other common disease. Ultimately, This issue can lead to a delay in the diagnosis which augments the risk factor. Once the affected-regions in MRI are well detected at an early stage is very crucial due to the process would follow either diagnosis or surgery. Several symptoms view nausea, vomiting, severe headache, speech problems, vision impairment, and hearing impairment, the problem in walking, and seizures.[43]

The key issue to adopt the precise treatment once the process of brain tumors detection in very early stages is accurately taken place. The most appropriate therapy, surgery, radiation, or chemotherapy can be elaborated, the stage at which the tumor is identified plays a vital role in the follow-up diagnosis.

In this manuscript and after presenting general notions on brain imaging, image segmentation methods, a state of the art of work carried out around the problem studied was presented. The different phases of the proposed approach are clearly explained there and the various results obtained are discussed and evaluated.

To carry out this study, we have commenced by exposing the essential concepts related to the computer vision following with a brief state of the art of computer-aided of diagnostic illustrating with the anatomy of the healthy brain, pathologies including tumors as well as the ultimate acquisition method of nuclear magnetic resonance imaging.

Also, we reviewed the different existing methods in the field of brain MRI image segmentation and classification. This diversity is representative of the complexity of the problem of segmentation and identification of diseases of brain MRI images. Also, we have highlighted interesting articles as related works that have employed tools of machine learning and different networks of deep learning to improve the accuracy and precision of extracting different tissues in brain MRI.

The main part of this dissertation is the heart of our work which is represented by the modelization of the proposed architecture with the suggestion of four stages.

- Pre-processing step: we have defined to enhance the quality of the image. Image enhancement is the process of modifying a digital image. Image enhancement can be qualitative, quantitative, or a combination of both depending on the type of application. To intensify the quality of lesion affected in MRI brain image and to produce it more contesting for further processing in this work various qualitative techniques are used like: contrast stretching and histogram equalization. Besides, to acquire the quantitative information like edge around the affected area and color variation to highlight the disease-affected region several techniques like median filter and logarithmic transformation are applied to the input image.

  Another method is utilized for knowing the shape is Moments Hue is considered as statistical measures of pixel distribution around the center of gravity of a leaf and allows obtaining the pattern information inside the leaf. They are used to calculate global as

well as geometric information of an image. They used to obtain the information across the entire image rather than providing information at particular boundary [?].
They are used to obtain some global properties which cannot be obtained from boundary-based representations such as image orientation.

- Features extraction step: we have implemented two algorithms: the GLCM method is suitable for estimating image properties related to second-order statistic

- Segmentation step: in this step, we aim to investigate this, we propose a completely programmed strategy for brain tumor division that is created utilizing U-Net based deep convolutional network.
This neuronal network is known a lot quicker because of the thick division of pixels in the image rather than patch classification is an advantage, and offers focused execution, with extracting the region of interests.

- Classification step: here we have realized the classification process with SVM which is one of the famous supervised learning machine, the main role of the use of SVM that generates the best line of decision boundary which can segregate n-dimensional space into classes so that we can easily put the new data and we have compared the three methods using several comparison criteria, to designate the best method. After several performance measurements, we can conclude that none of these methods can be qualified as better, unsatisfactory, or preferred over the other because each has its strengths and weaknesses.
Nevertheless, it is possible to favor one method over the other if we set the comparison criterion and the segmentation domain.

Through this work some perspectives open up as a result of further work:

- Automation of the processing chain there is always a parameter to be adjusted manually (threshold, seed ...) which will change from one cut to another and makes reconstruction quite difficult.

- The Fusion Process due to agglomerating multiple features using different algorithms with a variety of strategies: frequency, spatial, geometry, texture, shape or form,. . . , and for not expending much time with obtaining the best results an optimization algorithm should operate.

- Improved running time, for example by changing the cloud that holds more capacity of material offered {GPU s for accelerating the process} that ameliorates the potential executing time.

- Acquisition of more data to study the effectiveness of detection on tumors lesions of different shapes with different degrees of malignancy.

- The proposed application can be more improved by using an optimization algorithm for classification by providing more symptoms to find out more diseases that reinforced the results in cost time and quality evaluation.

BIBLIOGRAPHY

[1] Nwankpa, Chigozie, Winifred Ijomah, Anthony Gachagan, and Stephen Marshall. "Activation Functions: Comparison of Trends in Practice and Research for Deep Learning." ArXiv:1811.03378 [Cs], November 8, 2018. http://arxiv.org/abs/1811.03378.

[2] My TechDecisions. "Machine Learning Overview: Everything You Need to Know," August 27, 2019. https://mytechdecisions.com/it-infrastructure/machine-learning/.

[3] Dey, Ayon. "Machine Learning Algorithms: A Review" 7 (2016): 6.

[4] "Machine Learning Explained: Understanding Supervised, Unsupervised, and Reinforcement Learning." Accessed September 10, 2020. https://www.linkedin.com/pulse/machine-learning-explained-understanding-supervised-ronald-van-loon.

[5] "Introduction to Logistic Regression | by Ayush Pant | Towards Data Science." Accessed September 27, 2020. https://towardsdatascience.com/introduction-to-logistic-regression-66248243c148.

[6] Géron, Aurélien. "Hands-On Machine Learning with Scikit-Learn and TensorFlow," n.d., 564.

[7] Neural Networks and Introduction to Deep Learning , https://www.math.univ-toulouse.fr/ besse/Wikistat/pdf/st-m-hdstat-rnn-deep-learning.pdf

[8] Zakaria, Magdi, Mabrouka AL-Shebany, and Shahenda Sarhan. Artificial Neural Network: A Brief Overview, 4, no. 2 (2014): 6.

[9] Hijazi, Samer, Rishi Kumar, and Chris Rowen. "Using Convolutional Neural Networks for Image Recognition," n.d., 12.

[10] Kamavisdar, Pooja, Sonam Saluja, and Sonu Agrawal. “A Survey on Image Classification Approaches and Techniques” 2, no. 1 (2013): 5.

[11] Jain, Maneela, and Pushpendra Singh Tomar. “Review of Image Classification Methods and Techniques.” International Journal of Engineering Research 2, no. 8 (2013): 7.

[12] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. “U-Net: Convolutional Networks for Biomedical Image Segmentation.” ArXiv:1505.04597 [Cs], May 18, 2015. http://arxiv.org/abs/1505.04597.

[13] Youssra Riahi, Sara Riahi, Department of Mathematics and Computer Science, Faculty of Sciences, University of ChouaibDoukkali Jabran Khalil JabranAvenu , El jadida 24000, Morocco. “Big Data and Big Data Analytics: Concepts, Types and Technologies.” International Journal of Research and Engineering 5, no. 9 (November 2018): 524–28. https://doi.org/10.21276/ijre.2018.5.9.5.

[14] Mohamed Y. Abdallah, Yousif, and Tariq Alqahtani. “Research in Medical Imaging Using Image Processing Techniques.” In Medical Imaging - Principles and Applications [Working Title]. IntechOpen, 2019. https://doi.org/10.5772/intechopen.84360.

[15] WORLD HEALTH ORGANIZATION. WORLD HEALTH STATISTICS 2019: Monitoring Health for the Sdgs, Sustainable Development Goals. Place of publication not identified: WORLD HEALTH ORGANIZATION, 2019.

[16] Muhammad Waqar Qureshi , Comparison between Medical Imaging Modalities , https://www.academia.edu/4752851/Comparison_between_Medical_Imaging_Modalities

[17] “Integrating Big Data with Medical Imaging.” International Journal of Engineering and Advanced Technology 8, no. 6S3 (November 22, 2019): 721–24. https://doi.org/10.35940/ijeat.F1133.0986S319.

[18] Wachinger, Christian, Anna Rieckmann, and Sebastian Pölsterl. “Detect and Correct Bias in Multi-Site Neuroimaging Datasets.” ArXiv:2002.05049 [Cs, Eess], February 12, 2020. http://arxiv.org/abs/2002.05049.

[19] “Performance Metrics for Classification Problems in Machine Learning | by Mohammed Sunasra | Medium.” Accessed September 27, 2020. https://medium.com/@MohammedS/performance-metrics-for-classification-problems-in-machine-learning-part-i-b085d432082b.

[20] "The 5 Classification Evaluation Metrics Every Data Scientist Must Know | by Rahul Agarwal | Towards Data Science." Accessed September 5, 2020. https://towardsdatascience.com/the-5-classification-evaluation-metrics-you-must-know-aa97784ff226.

[21] "Everything You Ever Wanted To Know About Computer Vision. | by Ilija Mihajlovic | Towards Data Science." Accessed September 15, 2020. https://towardsdatascience.com/everything-you-ever-wanted-to-know-about-computer-vision-heres-a-look-why-it-s-so-awesome-e8a58dfb641e.

[22] Doi, Kunio. "Computer-Aided Diagnosis in Medical Imaging: Historical Review, Current Status and Future Potential." Computerized Medical Imaging and Graphics: The Official Journal of the Computerized Medical Imaging Society 31, no. 4–5 (2007): 198–211. https://doi.org/10.1016/j.compmedimag.2007.02.002.

[23] Ramya, G, A S Shanthi, and PG Scholar. "Segmentation Techniques for Image Analysis – A Survey" 2 (2015): 7.

[24] Acharya J, Gadhiya S and Raviya, Segmentation techniques for image analysis: a review, International Journal of Computer Science and Management Research, 2013

[25] Chowdhary, Chiranji Lal, and D. P. Acharjya. "Segmentation and Feature Extraction in Medical Imaging: A Systematic Review." Procedia Computer Science, International Conference on Computational Intelligence and Data Science, 167 (January 1, 2020): 26–36. https://doi.org/10.1016/j.procs.2020.03.179.

[26] Hamdi, Mustafa, Muhammad Kamal, Shoruk Ahmed, Hager Atef, Muhammad Fathi, Samar Muhammad, and AL Shaimaa Taha. "Study of Detection Brain Tumor with Machine Learning, july 2017" n.d., 86.

[27] Kumar, Parasuraman, and B VijayKumar. "Brain Tumor MRI Segmentation and Classification Using Ensemble Classifier" 8, no. 1 (2019): 9.

[28] Krishnan, Athira. "A Survey on Image Segmentation and Feature Extraction Methods for Acute Myelogenous Leukemia Detection in Blood Microscopic Images" 5 (2014): 3.

[29] Özyurt, Fatih, Eser Sert, and Derya Avcı. "An Expert System for Brain Tumor Detection: Fuzzy C-Means with Super Resolution and Convolutional Neural Network

with Extreme Learning Machine." Medical Hypotheses 134 (January 1, 2020): 109433. https://doi.org/10.1016/j.mehy.2019.109433.

[30] Cancer Support Community And The National Brain Tumor Society ,2013,WWW.CANCERSUPPORTCOMMUNITY.ORG

[31] V. Wasule and P. Sonar, "Classification of brain MRI using SVM and KNN classifier," in Proc. 3rd IEEE Int. Conf. Sensing, Signal Process. Secur. ICSSS 2017

[32] Ismael MR, Abdel-Qader I. Brain tumor classification via statistical features and back-propagation neural network. 2018 IEEE International Conference on Electro Information Technology (EIT). IEEE; 2018.

[33] Litjens, G.; Kooi, T.; Bejnordi, B.E.; Setio, A.A.A.; Ciompi, F.; Ghafoorian,M.; Van Der Laak, J.A.; Van Ginneken, B.; Sánchez, C.I. A survey on deep learning in medical image analysis. Med. Image Anal. 2017

[34] Sert E, Özyurt F, Doğantekin A. A new approach for brain tumor diagnosis system: single image super resolution based maximum fuzzy entropy segmentation and convolutional neural network. Med Hypotheses 2019

[35] Kumar, Parasuraman, and B VijayKumar. "Brain Tumor MRI Segmentation and Classification Using Ensemble Classifier" 8, no. 1 (2019): 9.

[36] Python.org. "Welcome to Python.Org." Accessed September 18, 2020. https://www.python.org/about/.

[37] "Colaboratory – Google." Accessed September 24, 2020. https://research.google.com/colaboratory/faq.html.

[38] "About Us — Scikit-Learn 0.23.2 Documentation." Accessed September 20, 2020. https://scikit-learn.org/stable/about.html.

[39] "About." Accessed September 27, 2020. https://opencv.org/about/.

[40] Aryal, Chudamani. "QUERY FOCUSED ABSTRACTIVE SUMMARIZATION USING NEURAL NETWORKS," n.d., 119.

[41] Maini, Raman, and Himanshu Aggarwal. "A Comprehensive Review of Image Enhancement Techniques" 2, no. 3 (2010): 6.

[42] Gupta, Amit. “A Survey on Image Enhancement Based Histogram Equalization Techniques.” International Journal for Research in Applied Science and Engineering Technology V, no. X (October 22, 2017): 395–401. https://doi.org/10.22214/ijraset.2017.10057.

[43] M. Sudharson, S. R. T. Rajapandiyan, and P. U. Ilavarasi, “Brain Tumor Detection by Image Processing Using MATLAB,” Middle-East J. Sci. Res., vol. 24, 2016.