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## THEME

**Segmentation and classification of MRI to detected  
brain tumors used FCM and SVM.**

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## Dedication



We dedicate this modest work To our parents,

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## Dedication



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## GENERAL INTRODUCTION

Medical imaging is rapidly evolving in these heavens which led researchers to multiply automatic processing methods and obtaining the most accurate results in order to facilitate their interpretation. Methods of processing must have a balance between the amounts of structural complexity in the image with the amount of data to be analyzed, especially when the image in process expresses a phrase of a brain structure. The human brain is incredibly complex, requiring consideration of a variety of characteristics such as age, gender, race and personal medical history, that may be harmed which we are focusing on in study.

Tumors are uncontrolled multiplications of abnormal cells. Since high-grade and low-grade tumor cells are usually labeled, it is difficult to teach a computer system to define and partition tumor region because they might change in size, location and kind displaying a range of patterns from benign to malignant. Segmentation (image segmentation) and classification are two of the most common methods for performing medical image analysis.

One of the most significant aspects of medical imaging technologies is brain picture segmentation. Brain images can contain noise, heterogeneity and aberration. Therefore, accurate segmentation of brain images is a difficult task. The difficulty stems from the structural complexity of MRI images as well as the often in sufficient contrast to extract and, also the structure without any prior knowledge of its shape or location. On the other hand it is critical to accurate diagnosis using clinical tools. Regarding the classification task, images of brain tumors are classified after the segmentations process.

The purpose of our project is the realization of effective segmentation based on the fuzzy c-means standard (FCM) algorithm. For the classification we utilize the transport trucks.

## **Problem statement and objective**

Tumor are a used terms to describe a set of problems that affect the human body such as the brain. Tumors can be natural or abnormal. Atypical tumors are one of the leading causes of death worldwide, thus in order to extend the patient's life, these tumors must be detected and removed as soon as feasible. Medical imaging, particularly magnetic resonance imaging, is one of the available options in this field, since it allow the observation of the tumor's activity in images. It can be a challenging for doctors to interpret these images and provide a trustworthy diagnosis of the patient's condition. Due to the difficulty in recognizing the type of lesions, our particular interest is to provide clinicians with a method for assisting in the diagnosis of cérébral tumors by categorizing them into two categories (natural and abnormal tumors) based on the results.

This dissertation is divided into four chapters, allowing us to show the many parts of our work. We accomplished this by following the procedures outlined in the following chapters:

For the sake of evaluation, this thesis is organized as follows: the study is divided into chapters. The structure of the thesis, chapter by chapter is shown below. In the first chapter we explain the concepts related to research in a sequential manner, the understanding of the most fundamental principles of the study. All methods related to segmentation and classification have been explained, this explanation will assist the third chapter in determining the best method for obtaining the best results, in which we will define all of the methods we have chosen in our research. The implementation and findings from the experiment are articulated in Chapter four outcomes and debates. With the help of the final results, discuss the researcher's analysis of this study. We seal the research and makes recommendations for the future.

# CHAPTER 1

## MEDICAL IMAGING AND TUMOR DISEASE CEREBRAL

### 1.1 Introduction

Let's start with a microscopic explanation of the brain in this chapter, and then go through the many tumors that might damage it, along with a complete diagnosis of it. Furthermore, we've covered the medical side of brain image interpretation by discussing diagnostic procedures for brain tumor identification as well as the basic concept of the acquisition technology that allows for good brain imaging: nuclear magnetic resonance imaging (MRI). We conclude this chapter by applying filtering and noise-removal technologies to a brain magnetic resonance imaging (MRI) picture.

### 1.2 Some elements of brain anatomy

#### 1.2.1 Brain

The brain is a mass of nerve tissue located at the front end of an organism. The brain integrates sensory information and guides muscular responses, it is also the learning center in higher animals. The human brain is made up of billions of cells called neurons and weighs about 1.4 kg (3 pounds). Synapses are connections between neurons that allow electrical and chemical instructions to be passed from one neuron to the next in the brain, a process that underpins fundamental sensory processes and is essential for learning, memory, thinking creation, and other cognitive tasks [1].

#### 1.2.2 Marks of brain structure

Three-dimensional biological structure of the brain is used so that any point inside or on brain can be localized on three "axes" or "planes" the x, y and z axes or planes. The

brain is often imaged on two dimensional images (slices). These slices are usually made in one of three orthogonal planes: coronal, horizontal (axial) and sagittal as shown in (Figure 1.1).

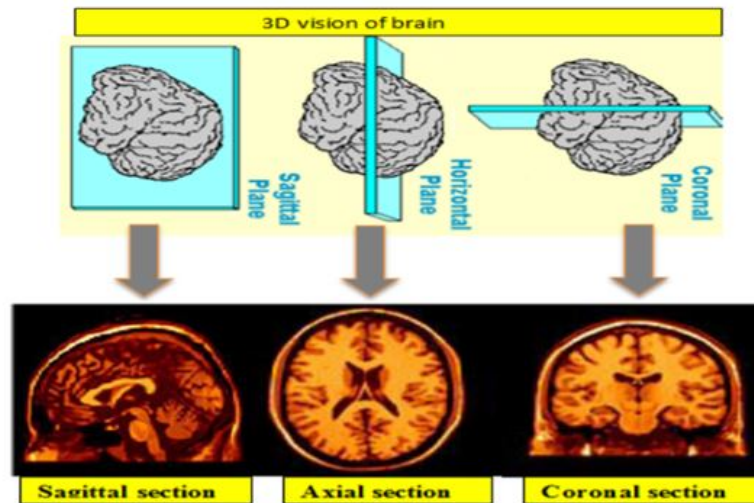


Figure 1.1: 3D and 2D vision brain [2].

### 1.2.3 Brain tissues

When we look at the brain, we can see that it is mostly made up of white and gray matter.

#### 1.2.3.1 The gray matter

Gray matter is the part of the tissues of the central nervous system that concentrates the cell bodies of neurons and glial cells. It appears darker than the rest of the tissue because it contains the cell nuclei. This part of the nervous tissue is the heart of nervous information processing, gray matter is mainly found in the cerebral cortex [3].

#### 1.2.3.2 White matter

Axons, which are extensions of neurons, are found in white matter. These extensions are bordered by a myelin sheath and neuroglia, which are non-nervous cells that contribute to the construction of the neuronal interstitial tissue. The white matter's job is to guarantee that nerve impulses are properly transmitted [4].

#### 1.2.3.3 Cerebrospinal fluid

The cerebrospinal fluid (CSF) or cerebrospinal fluid (CSF) is a clear bodily fluid that surrounds the brain and spinal cord. It is found between the pia mater (which covers the central nervous system) and the arachnoid membrane in the meninges (which lines the

inner side of the dura mater). It's also the fluid that flows in the brain's four ventricles, inside the brain, and in the spinal cord's major channel. It is made up entirely of water. Cerebrospinal fluid absorbs and softens movements or shocks to the brain that may cause injury [4].

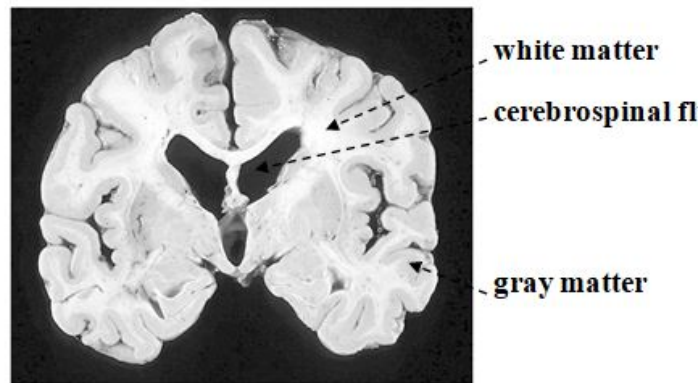


Figure 1.2: The histological section of the brain [5].

## 1.2.4 Types of brain tumors

The World Health Organization's (WHO) recognized categorization of brain tumors is based on cellular origin and malignancy. There are about 120 distinct kinds of brain tumors, lesions and cysts, which are distinguished by their location and the cells that make them up. Some tumors are benign (non-cancerous), while others are malignant (cancerous). We'll go through a few of them here that are relevant to the application we worked on.

### 1.2.4.1 Meningioma

The most prevalent primary brain tumor accounting for more than 30 per cent of all brain tumors is meningioma. The meninges tissue that surround and protect the brain immediately under the skull, are where meningiomas begin. Meningiomas are diagnosed more frequently in women than in males. Meningiomas are slowgrowing, noncancerous tumors that account for around 85 per cent of all meningiomas. Although almost all meningiomas are benign, some of them might be persistent and recur following therapy.

### 1.2.4.2 Glioma

Glioma is a frequent form of tumor that starts in the brain but can occasionally spread to the spinal cord. Gliomas make up around a third of all brain tumors. Glial cells that

surround and support neurons give birth to these malignancies. Glial cells come in a variety of shapes and sizes, therefore there are a variety of gliomas to choose from including:

- **Astrocytomas:** Pilocytic astrocytoma is a benign brain tumor that arises from supporting brain cells and is most commonly encountered in young people or children. If the entire tumor can be removed, surgery can be used to treat it.
- **Glioblastomas:** An especially aggressive tumor type Over time, our understanding of gliomas has progressed. Gliomas can be more or less aggressive depending on the sort of cells that produce them and their genetic abnormalities. A genetic analysis of the tumor is frequently conducted in order to have a better understanding of how it may be have. Diffuse midline gliomas and hemispheric gliomas, for example, are newly identified gliomas with particular mutations linked to a more aggressive character.
- **Metastases:** When cancer cells move from their original location to the brain, this is called a brain metastasis. Any cancer can travel to the brain, but lung, breast, colon, kidney and melanoma are the most likely to produce brain metastases. Brain metastases can result in a single tumor or many malignancies in the brain. As metastatic brain cancers progress, they put pressure on adjacent brain tissue and alter its function. Headaches, personality changes, memory loss and seizures are some of the indications and symptoms. Surgery, radiation therapy, chemotherapy, immunotherapy or a combination of therapies may be used to treat patients whose cancer has progressed to the brain. In some cases, other therapies may be advised. The goal of treatment is usually to alleviate cancer-related pain and discomfort [6].

## 1.3 Some elements of medical imaging

### 1.3.1 Medical imaging

Imaging methods such as brain scintigraphy and magnetic resonance imaging will be used to augment this evaluation. Brain pictures acquired by nuclear magnetic resonance imaging (MRI) are of particular importance to us since they allow us to obtain good images. The general principle of magnetic resonance imaging is presented here [7].

### 1.3.2 Diagnostic techniques of brain tumor

Timely diagnosis helps in treatment procedure. Different techniques are used for the diagnosis tumor and effects of that disease like brain biopsy and brain imaging system (Figure 1.3):

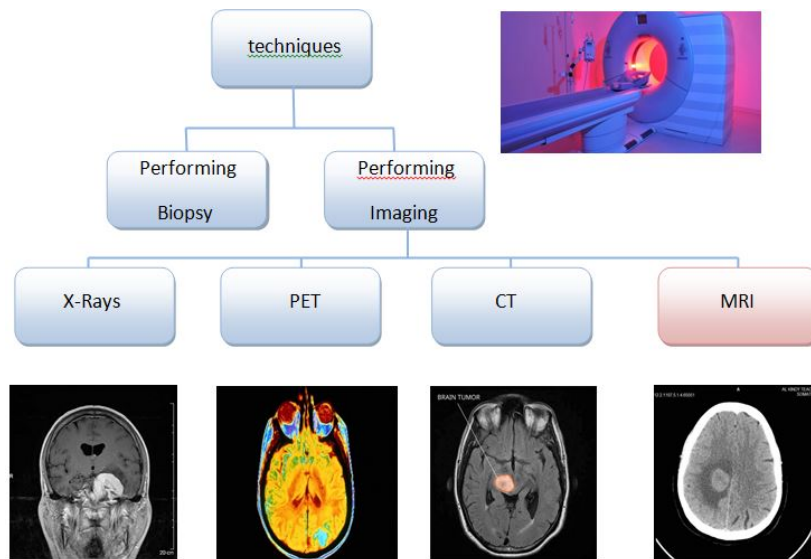


Figure 1.3: Different technique of Brain tumor imaging [8].

### 1.3.3 Magnetic resonance imaging (MRI)

Nuclear Magnetic Resonance Imaging (MRI) is a non-invasive, side-effect-free medical imaging technology that provides a 2D or 3D image of a bodily component, particularly the brain. It is based on nuclear magnetic resonance [7], a scientific phenomena. It's as simple as looking at the nuclear magnetic resonance (NMR) of the body's water protons. The idea is to assess the magnetic properties of living tissues and then rebuild a picture from them. Hydrogen, which is abundant in the human body, is responsible for the latter.



Figure 1.4: The MRI machine [9].

The patient is a All hydrogen atoms orient themselves in the same way when placed in a high magnetic field and they are then stimulated by radio waves for a very brief time. When the stimulation is turned off, the atoms regain the energy they have used in creating a signal, which is then captured and processed as a picture by a computer system [10].

After the stimulation is turned off, the hydrogen atoms recover the energy that has been dissipated in various planes of space due to the magnetic field of love. Other antennas (receiving antennas) collect the energy, which is subsequently evaluated by a computer.

The pictures will differ depending on the water content of the tissues studied as well as any diseases that may exist and the computer will create black and white images with great sensitivity and diagnostic value particularly in the case of tumor or infectious pathology. As a result incisions of any portion of the body can be made in any plane of space [4].

### 1.3.3.1 MRI images sequences

An MRI images sequence in magnetic resonance imaging (MRI) is a particular set of pulse sequences and pulsed field gradients, resulting in a particular image appearance [4]. A multiparametric MRI is a combination of two or more sequences, and including other specialized MRI configurations such as spectroscopy.

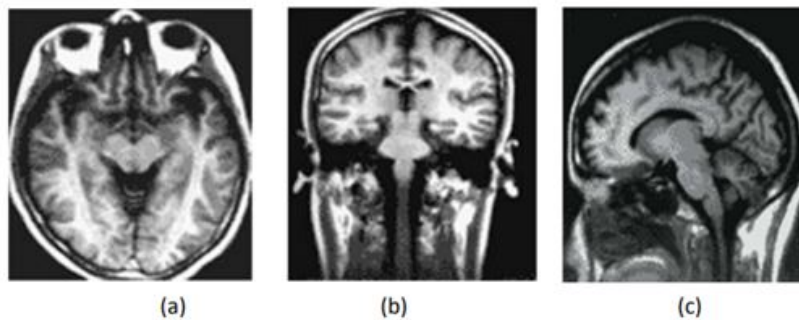


Figure 1.5: The different sections of the brain, (a): Axial section, (b): Coronal section, (c): Sagittal section [11].

- **T1 and T2:** Each tissue returns to its equilibrium state after excitation by the independent relaxation processes of T1 (spin-lattice; that is, magnetization in the same direction as the static magnetic field) and T2 (spin-spin; transverse to the static magnetic field). To create a T1-weighted image, magnetization is allowed to recover before measuring the MR signal by changing the repetition time (TR).

This image weighting is useful for assessing the cerebral cortex, identifying fatty tissue, characterizing focal liver lesions, and in general, obtaining morphological information, as well as for post-contrast imaging. To create a T2-weighted image, magnetization is allowed to decay before measuring the MR signal by changing the echo time (TE). This image weighting is useful for detecting edema and inflammation, revealing white matter lesions, and assessing zonal anatomy in the prostate and uterus.

- **Proton density:** Proton density (PD)- weighted images are created by having a long repetition time (TR) and a short echo time (TE).[4] On images of the brain, this sequence has a more pronounced distinction between gray matter (bright) and white matter (darker gray), but with little contrast between brain and CSF.[4] It is very useful for the detection of joint disease and injury.

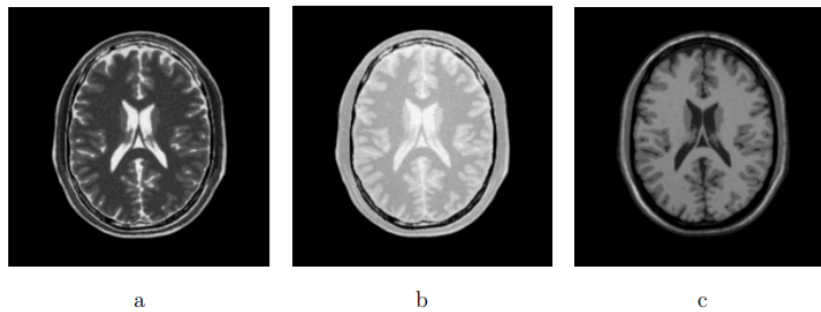


Figure 1.6: MRI sequences. Images of a single cross-section of the human brain, weighted in: (a) T2, (b) density of protons and (c) in T1 [4].

### 1.3.3.2 Artifacts

Artifacts in MRI scans can distort the anatomical picture and/or mimic a disease process [12]. The artifacts are the result of:

#### a) Movement artifact

One of the most commonly encountered artifacts is the movement artifact. It occurs when the segment being investigated is translated in space during the acquisition. There are two kinds of motions that he encounters [9]:

- Breathing, pulse and blood flow are all examples of periodic motions.
- Aperiodic motions include the patient's movements, ocular movements, swallowing movements, digestive peristalsis and cerebrospinal fluid flow.
- They cause signal dispersion, resulting in a fuzzy picture of the moving structure.

**b) RF inhomogeneities**

Inhomogeneity in the distribution of intensities of the picture acquired by MRI can be caused by inhomogeneities in the primary magnetic fields and in the generated field RF pulses, which handicaps solely photometric imaging. For a physician these sorts of artifacts aren't very annoying. It might be troublesome for an automated image processing system due to the disadvantages [13].

**c) Partial volume**

Partial volume scoring is a concept that applies to many imaging methods not only MRI. The resolution of the pictures causes these abnormalities. The application of fine cut at the level of an interface between two fabrics in the direction of cut selection, allows the materials to be effectively separated. A thicker incision on the other hand, contains both tissues at the same time resulting in a signal that is an average of the tissue signals resulting in a loss of contrast information. Because the signal of small structures is averaged with that of nearby structures, it results in a loss of spatial resolution making them undetectable or indistinct [13].

**d) The noise**

The presence of additional information that is randomly added to the details in the collected pictures is referred to as image noise. It is especially noticeable in places with limited illumination and a low signal to noise ratio. As a result, the details lose their clarity.

## 1.4 Conclusion

In brain tumor research, MRI has a significant benefit. We began this chapter with providing some fundamental facts about the human brain, after which we identified brain tumors, their kinds, causes and symptoms. We provided the medical image that defines magnetic resonance imaging (MRI) and its techniques in the second section and we can see the challenges that the fake practitioner faces (movement, partial size effect, etc...). To study these medical photos, the doctor must first understand what has changed and it may be required to examine many photographs before reaching a final conclusion. In the medical profession, precision is critical and in image analysis, precision is required for segmentation. In the next chapter, we will explain segmentation and define its different methods, in addition to mentioning the classification methods related to it.

## 2.1 Introduction

In image processing as well as in image processing and computer vision, picture fragmentation is crucial. On the one hand, we may position this step between improving the image and describing it and on the other hand, we can say that fragmentation should accomplish the arduous work of extracting "valuable" information from a digital image to find and demarcate the entities in the image. The goal of all split methods is to extract characteristics that may be used to differentiate objects. These are the image characteristics points of interest or regions of interest.

This chapter will begin by describing the overall idea of picture fragmentation and its many techniques, followed by a description of the second portion, which will classify images and their methodologies.

## 2.2 Definition of segmentation

Segmentation is a low-level procedure that involves partitioning an image into homogeneous areas based on one or more criteria. According to the same criterion, the areas obtained are distinguished from one another by substantial differences. Following these stages, we can implement sectoral therapy in a variety of ways.

Extracting points, lines or areas is what segmentation is all about. The nature of the picture, the acquisition conditions (noise) and the primitives to be retrieved all influence which segmentation approach is used (outline, texture, ...) [14].

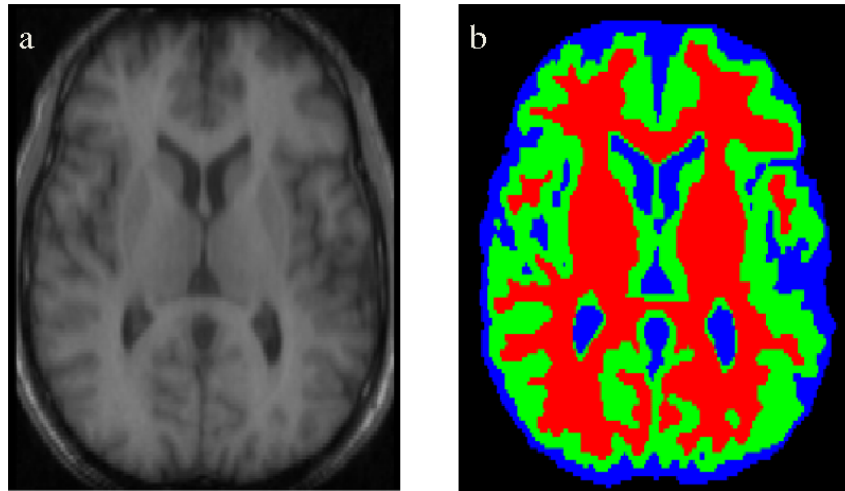


Figure 2.1: Segmentation results of proposed method [15].

- a) Magnetic resonance imaging of the brain.
- b) Result of automatic segmentation.

## 2.3 Objectives of image segmentation

The process of assessing the image and its objects is known as segmentation. It's used to divide the image's contents into segments with similar properties like intensity, color, texture and soon [16]. Image segmentation is one of the most essential criteria for analyzing an image in computer vision. It refers to the process of dividing a digital image into numerous segments such as pixels and determining whether the pixels in an area are homogeneous in terms of color, intensity or texture. As a result, these commonalities are utilized to detect, identify and locate the objects and borders in a photograph [18]. It may also be described as the division of a picture into homogenous groups. According to comparable features, each region is homogenous [17].

Morphometry, functional mapping and visualization are the most common uses of segmentation in medical imaging.

- **Morphometry:** Morphometry is a branch of biometry that examines and analyzes the geometry of organs or brain structures to diagnose, explain and track the course of diseases such as epilepsy, Alzheimer's, autism and schizophrenia.
- **Functional mapping :** The goal of the segmentation of cerebral structures is to explain how the brain works by locating signals, mapping them and visualizing them.

- **Visualization:** It is the location of anatomical structures exterior surfaces. It gives the clinician an accurate (realistic) picture of the brain anatomy to aid in surgical planning (computer-assisted surgery).

### 2.3.1 The purpose of brain image segmentations

Brain structure segmentation is a crucial stage in the interpretation of brain imaging. It allows for the separation of various fabrics of cerebral illnesses (gray matter, white matter, cerebrospinal fluid and soon) as well as potential brain pathologies. Before making a surgical gesture, a proper segmentation aids the doctor in making a final decision.

for example, the main applications of segmentation are morphometry, functional mapping and visualization: morphometry is the quantitative measurement of the positions, shapes and sizes of brain structures it requires the segmentation of these structures before measurement it can be used to identify, understand and track the progression of pathologies such as Alzheimer's or schizophrenia. The two-dimensional structure must next be segmented to find the signals, map them and display the anatomical components (for example in computer-assisted surgery).

## 2.4 The different segmentation methods

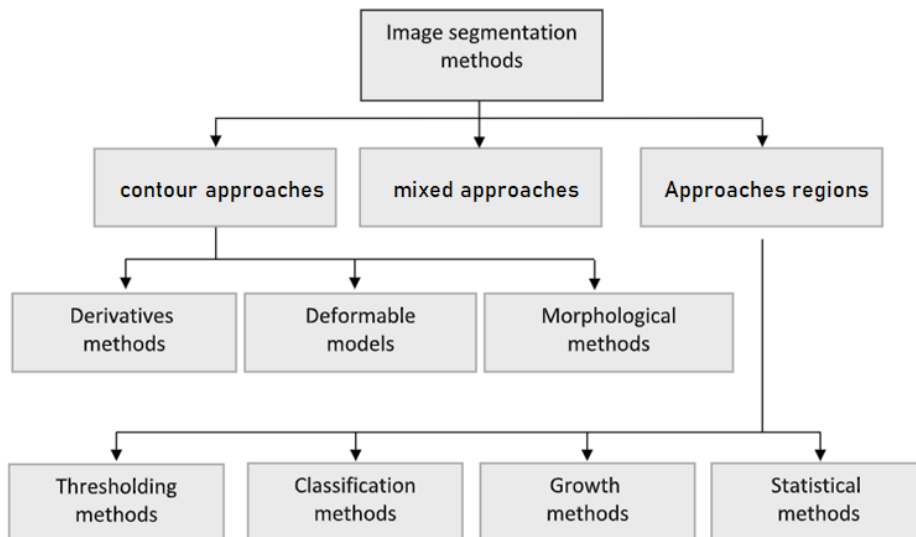


Figure 2.2: The main segmentation methods [19].

### 2.4.1 Segmentation methods based on the contour approach

Contour detection is a technique for detecting spots in a digital picture that correlate to a rapid shift in light intensity. Important events or changes in image characteristics are usually reflected in these changes in image properties.

Discontinuities in-depth, surface orientation, material characteristics and scene illumination are only a few of them. Contour detection is a branch of image processing and computer vision research, specifically in the field of feature extraction.

While retaining essential structural features of an image detecting the contours of an image considerably lowers the quantity of data and removes information that may be regarded as less useful.

Derivative and filtering techniques, morphological approaches and model breakdowns are the three principles that underpin boundary detection methods[6].

#### 2.4.1.1 Derivative methods and filtering techniques

Modeling contours or picture regions with derivative models assume that the digital image is derived from sampling a scalar function with limited support and derivable at every location. Variations in picture intensity may be caused by changes in light (shadows), changes in orientation or distance from the observer, changes in surface reflectance, changes in ray absorption and other factors. All of these values are condensed into a single two- or three-dimensional variable in the processing of a digital picture in the case of monochrome, it is the luminous intensity. These are the perfect curves (Figure 2.4).

- **Stairway:** the contour is sharp (ideal contour).
- **Rampe:** the outline is blurred.
- **Roof:** it is a line on a uniform background.

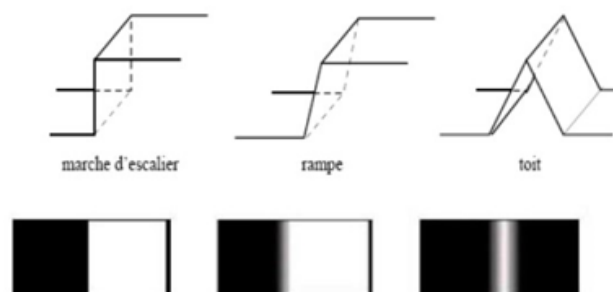


Figure 2.3: Contour models [20].

They provide a gradient and laplacian operator based detection method. These operators are derived from local changes in intensity (Figure 2.3), hence, the gradient is a vector function of the pixels  $[i, j]$ .

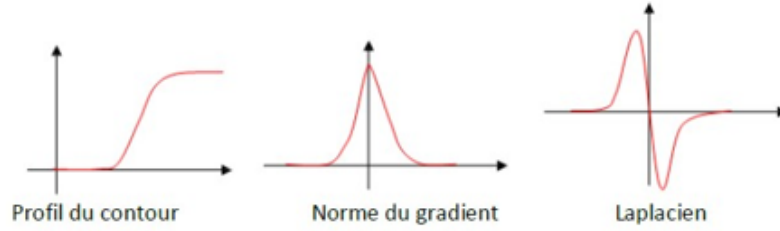


Figure 2.4: Derivative operators [21].

Derivative techniques make use of a derivation operator that can identify a signal's transition. Derivative techniques work by identifying a signal's transition from its derivative [13]. The contour point can be discovered by calculating the maximum gradient standard or examining the laplacian's zero crossing (Figure 2.4).

#### 2.4.1.2 Methods of segmentation by morphological approach

These approaches may be employed directly on the picture if it is thought of as a surface in three dimensional space  $(i, j, I(i, j))$  and B as a structural element.

The morphological technique entails shifting the structuring element at each pixel  $(x, y)$  of the image to be processed  $I(x, y)$  and then analyzing the relationships between the picture and the structuring element B: connections, inclusions...

We call:

- **Expansion:**

$$D(i, j) = \max_{k,l \in B} [I(i - k, j - l) + B(k, l)]$$

- **Erosion:**  $E(i, j) = \min_{k,l \in B} [I(i - k, j - l) + B(k, l)]$

- **Opening:** erosion followed by expansion.

- **Closing:** Expansion followed by erosion.

Stroke detection includes detecting jumps:

- **Erosion Gradient:**  $\nabla_E I(i, j) = I(i, j) - E(i, j)$ .

- **Gradient by expansion:**  $\nabla_D I(i, j) = I(i, j) - D(i, j)$ .

- **Laplacien morphologique :**  $L(I(i, j)) = \nabla_D I(i, j) - \nabla_E I(i, j)$ .

### 2.4.1.3 Segmentation methods by the approach of deformable models

The picture is represented by a function in the deformable model method. Elastic curves are used to represent the contours so that they can adapt as much as possible to the region limits. Energy is related to this aim and its definition is strongly tied to that of the outlines. The contours that best suit the model employed [22], correspond to the local minimum of this energy.

Deformable model based segmentation algorithms offer the benefit of delivering closed outlines over derivative techniques. Active contours and level sets are two of these techniques.

## 2.4.2 Segmentation methods by region approach

The region approach approaches use picture characteristics like color, texture and form to separate regions. These approaches primarily rely on decision criteria to divide a picture into separate areas based on pixel similarity [23].

The different segmentation methods of region type are proposed in the following.

### 2.4.2.1 Segmentation methods by thresholding

Thresholding procedures are the most prevalent regional approach methods. To separate the distinct sections, these approaches aim to obtain an intensity value termed threshold from the histogram of the picture. They work well on photos with a lot of contrast between the different sections [6].

Histogram thresholding may be done in a variety of ways. If the histogram has discrete peaks, the majority of these techniques will work. Furthermore, these approaches were almost often created to cope with the specific scenario of segmentation into two classes (the transition to a binary picture) and their universality in multi-class instances is only very seldom ensured. The Otsu method is one of the reference methods in this class.

### 2.4.2.2 Region growth segmentation methods

This ascending approach starts at the pixel and works its way up to the regions by aggregating pixels based on a homogeneity requirement. The set of pixels not allocated to a region at the start of step  $n$  is the function that characterizes a property of a region  $R_i$  and  $S_n$  [24].

The following is the general region growth algorithm:

- Define the bacteria that live in the GI areas. Germs are pixels or groups of pixels that haven't been allocated to an area. The quality of segmentation is influenced by the terms used. The more a germ is a good representation of a region, the more homogenous the aggregate formed will be.
- As long as  $S_n = 0$ , the pixel element of  $S_n$  is assigned to the  $g_i$  seed which minimizes a function  $W$ .

This function is the sum of fluctuations in the  $\emptyset$  property of the regions.

## 2.5 The different classification methods

The classification of points, lines or areas is known as classification. The nature of the picture, the acquisition conditions (noise) and the primitives to be extracted all influence the classification approach used (contour, texture,. ... ..).

The categorization algorithms are used to divide the MRI picture into several categories. There are two sorts of techniques: supervised and unsupervised (automated) approaches. The following two criteria can be used to assess the classification's quality:

- In terms of certain features, the created classes must be as distinct as possible from one another.
- In terms of the same qualities, each class must be as homogenous as feasible.

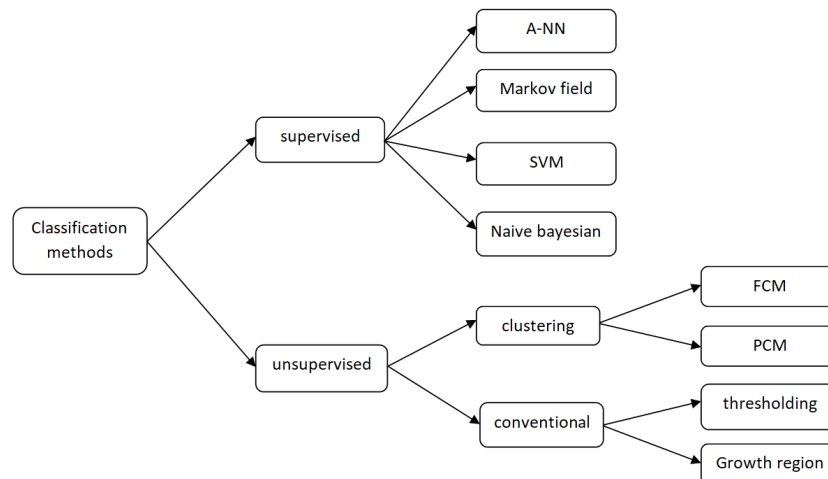


Figure 2.5: Different classification methods [25].

### 2.5.1 Supervised methods

The supervised techniques classify the unlabeled data from the test phase based on the properly labeled data produced during the training phase.

It is divided into two stages:

**Training and testing:** A model is built during the training phase that matches the retrieved data features with the labels or classes.

**During the test phase:** the model is utilized to determine the classes of unlabeled data. The training step necessitates human involvement, which displays the outcomes variability.

In terms of classification accuracy, supervised classification outperforms unsupervised classification [31]. A few classifiers are investigated, including:

#### 2.5.1.1 Bayesian naive beys(NB)

The Naive Bayes (NB) algorithm is a probabilistic data categorization technique [24]. The NAIVE Bayes classifier is simple to use and produces typically decent results. The maximum subsequent choice rule is the name given to this classifier (MAP)[26]. To discover a specific event and the unconditional probability of an occurrence in each class and NB classifier uses the Bayesian theorem. The conditional probability that a Y event corresponds to the variable Xn may be computed using the Bayes theorem and the following (2.1).

$$P(Y | X_n) = \frac{P(X_n | Y) P(Y)}{P(X_n)} \quad (2.1)$$

where:

- $Y$  is a variable indicating the class label.
- $X_n$  is a vector of the dependent element of size  $n$ .
- $P(Y | X_n)$  is the probability that the Y input data belongs to  $X_n$ .

The classifier assumes that the features are statistically independent of any other characteristics present in the data set, given the class variable to estimate  $P(Y | X_n)$  of an instance in a data set using (2.2).

$$P(Y | X_n) = \prod_{i=0}^k P(Y | X_n) \quad (2.2)$$

### 2.5.1.2 Artificial neural networks:

A neural network is an interconnected network of elementary units (nodes) with linear or nonlinear activation functions. For multilayer networks, these nodes are divided into at least two subsets of neurons: an input subset, an output subset and optionally a set of hidden neurons. There are several network models (Hop Field networks, multilayer perception, etc.) [27] in which the various nodes are entirely or partially coupled. The incoming connections of a node are the collection of links that converge on it. Outgoing connections are those that diverge to other nodes. Each link between nodes  $i$  and  $j$  has a weight  $W_{ij}$  that represents the force of node  $i$ 's impact on node  $j$ . The weights are organized into a weight  $W$  vector. An example is a scalar vector  $A$  that appears at all input nodes. This example is also linked to the values  $y$  (the output vector) that one desires to learn. During a learning cycle, the weights of the connections can be changed if desired.

Modifying the output of nodes from their inputs entails first calculating the activation present at the node's input  $e$ , and then calculating the node's output according to the activation function it contains. Three elements may thus be used to create a neural network for each node:

- The total input function  $e$ , which defines the pre-processing  $e(a)$  performed on the inputs. Typically,  $e$  is a linear combination of the weight-weighted inputs of the incoming connections.
- The activation function  $f$  of the node that sets its output state based on the value of  $x$ . Any increasing and odd function is suitable and the sigmoid function is often used. The value of  $f$  in  $x_a$  is redirected outwards or to other nodes where it helps to calculate their activation state.

Finally, two components are required for the network to operate properly: a cost function and a learning algorithm.

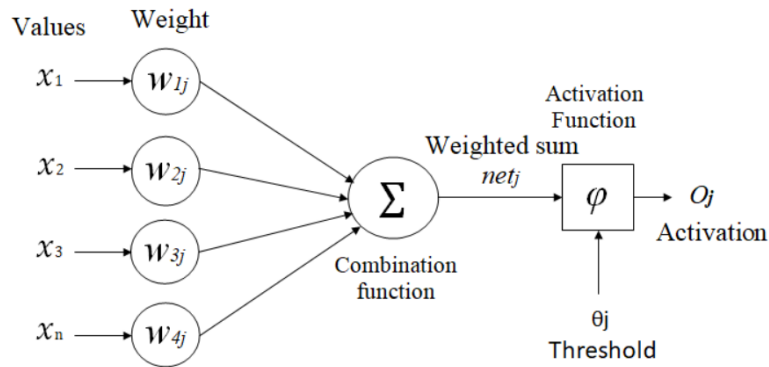


Figure 2.6: Structure of an artificial neuron [28].

Medical image segmentation classifiers are based on neural networks. The values of synapse weights must be correctly adjusted when learning the neural network. This learning is based on a medical picture base, the outcome of which is known ahead of time in the field of medical imaging (supervised learning). The neural network takes an MRI derived characteristic vector as input and outputs the picture classification. To improve the classification's robustness, extra information can be passed in as input, such as the image's volume.

Neural networks are commonly employed as classifiers in the segmentation of medical pictures. Learning from pictures with known segmentation results determines synaptic weights. A supervised neural network is what this is termed. The input neurons are frequently the various MRI pictures that are accessible, and the output neurons are the various search classifications [29].

The stage of learning that involves user intervention to provide this truth terrain that the network needs to compute synaptic weights is the method's primary flaw.

### 2.5.1.3 Large margin separators

Vanik created the support vector machine (also known as the Vast Margin Separation Machine) in 1992 [30]. SVMs are a group of supervised learning algorithms for classification and regression that are used together [31]. They are members of the generalized linear classification family. SVMs have the unique property of minimizing the empirical classification error while also increasing the geometric margin. As a result, SVMs are referred to as maximum margin classifiers.

The SVM is considered to be the most powerful classification algorithm, capable of outperforming other classification algorithms in terms of accuracy [32].

The goal of SVM is to identify the best separation hyper plan across classes by fo-

cusing on training examples that are positioned at the boundary of class descriptors. Its premise is to decrease the structural hazards of statistical learning theory. Support vectors are a type of training example. Other than support vectors, examples of the drive are disallowed. This method not only adjusts the optimum hyperplane but also uses fewer training samples, resulting in excellent classification accuracy with tiny drive assemblies. This is notably useful for remote sensing data sets and even more so for object-based image analysis since object samples are often smaller than in pixel-based techniques [33].

Consider a supervised binary classification task. If the driving data is represented as  $x_i, y_i$ , where  $I = 1, 2, \dots, N$  and  $y_i = -1, +1$ , where  $N$  is the number of training samples, then  $y_i = +1$  for class  $w_1$  and  $y_i = -1$  for class  $w_2$ . Assume that both classes can be separated linearly. This indicates that at least one hyperplane defined by a vector  $w$  with a bias  $w_0$  may be found, allowing the classes to be separated without error:

$$f(x) = w \cdot x + w_0 = 0 \quad (2.3)$$

To identify a hyperplane of this type,  $w$  and  $w_0$  must be approximated to  $y_i (w \cdot x_i + w_0) \geq +1$  pour  $y_i = +1$  (classe  $\omega_1$ ) et  $y_i (w \cdot x_i + w_0) \leq -1$  pour  $y_i = -1$  (classe  $\omega_2$ ). (3.4) may be created by combining these two elements:

$$y_i (w \cdot x_i + w_0) - 1 \geq 0 \quad (2.4)$$

Many hyperplanes might be modified to divide the two classes, but only one is optimum and should generalize better than the others (Figure 2.7).

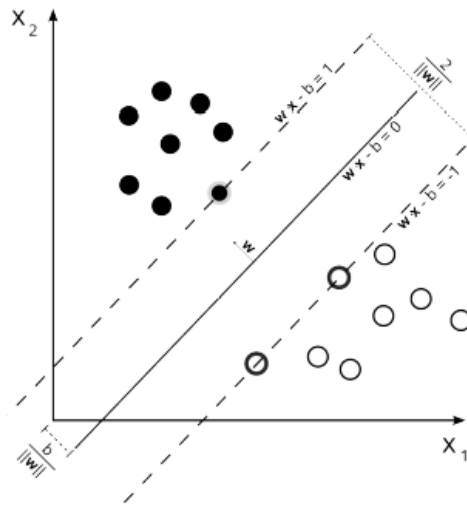


Figure 2.7: Principle of using a vector based machine to solve a non linear problem For a basic linear example, the operational concept of SVMs is illustrated. The separating hyperplane (solid line) separates components of one class (white rounds) from elements of another class (black rounds), maximizing the margin (dashed lines) [33].

The goal is to find the hyper plan that allows for the widest possible gap between courses. The support vectors must be defined before the best hyper plan can be found. Support vectors are located on two parallel hyperplanes to the optimum and are provided by:

$$x_i + w_0 = \pm 1 \quad (2.5)$$

If the hyperplanes  $w$  and  $w_0$  parameters are simply scaled, the margin may be expressed as  $2/|w|$ . The best hyper plan may be found by solving the following optimization problem:

$$\text{Maximize} : \frac{1}{2} \|w\|^2 \quad (2.6)$$

With  $y_i (w \cdot x_i + w_0) - 1 \geq 0, i = 0, 1, \dots, N$

The aforementioned problem may be converted into the following using a Lagrangian formulation:

$$\sum_{i=1}^N \lambda_i - \frac{1}{2} \sum_{i,j=1}^N \lambda_i \lambda_j y_i y_j (x_i \cdot x_j) \quad (2.7)$$

With a total of  $\sum_{i=1}^N \lambda_i y_i = 0$  and  $\lambda_i \geq 0, i = 1, 2, \dots, N$ , where  $\lambda_i$  multiplicateurs.

Under this formulation, the hyper planes optimum discriminant function becomes:

$$f(x) = \sum_{i \in S} \lambda_i y_i (x_i x) + w_0 \quad (2.8)$$

Where  $S$  is a subset of training échantillons that correspond to non zero lagrange multiplicateurs. These training échantillons are known as vectors of support. In the vast majority of examples, the classes are not linearly separable, and (2.4) constraint cannot be met. To handle such cases a cost function may be devised that combines margin maximization with error criterion minimization using a set of variables known as slack variables (Figure 2.7). This cost function is specified as follows:

$$\text{Maximize} : J(w, w_0, \xi) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^N \xi_i \quad (2.9)$$

With  $y_i (w \cdot x + w_0) \geq 1 - \xi_i$

The SVM can also tackle non-linear classification issues by applying kernel functions to match input vectors to a higher dimensional space.

$$\Phi(x)\Phi(z) = K(x, z) \quad (2.10)$$

$K(x, z)$  is referred to as a kernel function. If a  $K$  kernel function can be discovered, it may be utilized to learn without having to know the precise form of  $F(x)$ .

The double optimization issue is now written as follows:

$$\text{Maximiser} : \sum_{i=1}^N \lambda_i - \frac{1}{2} \sum_{i,j=1}^N \lambda_i \lambda_j y_i y_j K(x_i \cdot x_j) \quad (2.11)$$

With  $\sum_{i=1}^N \lambda_i y_i = 0$  and  $\lambda_i \geq 0, i = 1, 2, \dots, N$

As a consequence, the classifier is:

$$f(x) = \sum_{i \in S} \lambda_i y_i K(x_i, x) + w_0 \quad (2.12)$$

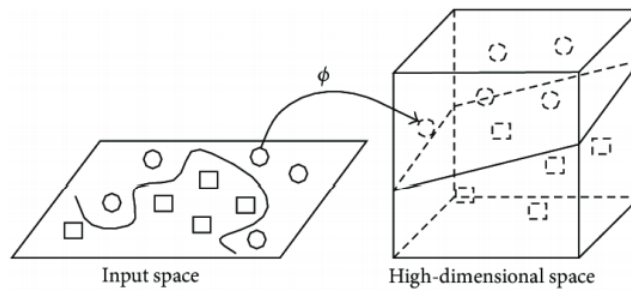


Figure 2.8: Principle of using a vector-based machine to solve a non-linear problem [34].

In SVM models, there are a variety of kernels that may be utilized. Linear and RBF polynomial models are among them. P-order polynomial core:

$$K(x_i, x_j) = (\langle x_i, x_j \rangle + 1)^d \quad (2.13)$$

A polynomial core induces a transformed space of the order  $(p + d)! / p!d!$  where  $p$  is the size of the initial space. Linear core:

$$K(x_i, x_j) = x_i \cdot x_j \quad (2.14)$$

Gaussian bandwidth core:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma}\right) \quad (2.15)$$

The parameter is used to change the gaussian's width. If you choose a large, the resemblance of an example to others surrounding it will be fairly great, but if you choose a small, the example will be unlike any other.

SVM benefits include:

- Highly efficient in high dimension
- They're also useful when the quantity of learning examples exceeds the size of the area.
- Only a portion of the learning examples should be used (the support vectors). As a result, the memory requirements of these methods are reduced.

## 2.5.2 Unsupervised methods

To group pixels with homogenous characteristics, unsupervised segmentation does not require any driving input. An algorithm uses image-based properties such as intensity, gradient and texture to determine the number of classes. These techniques can be used to solve more complicated issues [35]. Unsupervised segmentation algorithms are explained as follows:

### 2.5.2.1 Clustering methods

Unsupervised classification algorithms that split an image into clusters of pixels/voxels of comparable intensity without requiring training pictures are known as clustering methods. Clustering techniques, in reality, train on existing picture data. Iterating between two stages: data clustering and estimate of the characteristics of each tissue type, segmentation and training are done simultaneously [36].

**2.5.2.1.1 Possibilistic C-Means:** Krishnapuram and Keller were the first to suggest PCM [36]. The resultant data partition may be viewed as a possibilistic partition and membership values can be regarded as degrees of the possibility of points belonging to classes, i.e. point compatibilities with class prototypes (Krishnapuram and Keller, 1993) If the classes represented by clouds are regarded to be these fuzzy subsets on the domain, the memberships of any vector  $x_j$  must not be constrained:

$$X = \{x_j, j = 1..N\}$$

Membership degrees must only belong to the range  $[0, 1]$

$$\forall i \in \{1..C\}, \forall j \in \{1..N\} \quad u_{ij} \in [0, 1] \quad (2.16)$$

$$\forall j \in \{1..N\} \left\{ \begin{array}{l} 0 < \sum_{i=1}^C u_{ij} < N \\ \max_i u_{ij} > 0 \end{array} \right. \quad (2.17)$$

The condition (2.17) merely guarantees that the algorithm's fuzzy partition covers the X domain. The U matrix that results is no longer a hazy C partition. By minimizing the

objective function (2.18), and the solutions (2.19), (2.20), the PCM method develops the partition ( Matrix U ):

$$J_m(U, V; X) = \sum_{i=1}^C \sum_{j=1}^N (\mu_{ij})^n (d(x_j, v_i))^2 + \sum_{i=1}^C \eta_i \sum_{j=i}^N (1 - \mu_{ij})^n \quad (2.18)$$

Where:  $U = |\mu_{ij}|_{C \times N}$  is the possible partition matrix.

$$\mu_{ij} = \left( 1 + \left( \frac{d_{ij}^2}{\eta_i} \right)^{1/(m-1)} \right)^{-1} \quad (2.19)$$

$$\forall i \in \{1..C\} \quad v_i = \frac{\sum_{k=1}^n u_{ik}^m x_k}{\sum_{k=1}^n u_{ik}^m} \quad (2.20)$$

Or  $\eta_i$  is a positive parameter that determines the distance between a vector's degree of belonging to class k and 0.5 and it is computed as follows:

$$\forall k \in \{1..C\}, \eta_k = \frac{\sum_{i=1}^N u_{ik}^m \|x_i - V_k\|^2}{\sum_{i=1}^N u_{ik}^m} \quad (2.21)$$

The PCM algorithm:

1. Initialize centers.
2. Set the fuzzy coefficient.
3. Computes the initial fuzzy partition (The membership matrix)
4. Repeat:
  - *Calculation of new centers*
  - *Calculation of the new fuzzy partition*

As long as the shutdown criterion is not verified

The PCM's freedom to disregard noisy points comes at the cost of being extremely sensitive to initializations and occasionally generating coincident clusters. Furthermore, the selections of extra factors I needed by PCM have a significant impact on typologies, i.e. potential adhesions. The above-mentioned flaws in PCM are due to the following facts:

1. The relaxation of the PCM columns' sum restriction renders distinct groups independent, causing the PCM to create identical groups, i.e. the coincident group issue.
2. The PCM is highly delicate during the initialization and indexing of the parameter  $m$  due to the great sensitivity of the potential memberships of the parameters  $\eta_i$  [37]. As a result, these two components of the CFP should be investigated further.

**2.5.2.1.2 Fuzzy c-means** : FCM is a fuzzy classification method that optimizes a quadratic classification criterion [38], with each class represented by its center of gravity. The algorithm requires that the number of classes is known ahead of time and that the classes be generated by an iterative process that minimizes an objective function. As a result, it is feasible to get a fuzzy picture partition by assigning each pixel a degree of belonging to a certain region. The technique works with the pixel set  $A = \{x_1, x_2, \dots, x_n\}$ , where  $x_i$  is a three-component vector and  $c$  is the number of regions. For:  $1 \leq i \leq n, 1 \leq k \leq c$ , where  $u_{ik}$ , indicates the degree of belonging of the pixel  $i$  to the class  $k$ , the membership degree values are grouped in a matrix  $U = [u_{ik}]$ , where  $u_{ik}$  signifies the degree of belonging of the pixel  $i$  to the class  $k$ . The elements of  $U$  are subjected to the following restrictions in order to achieve a suitable partition:

$$u_{ik} \in [0, 1]$$

$$\sum_k u_{ik} = 1; \text{ this } \forall i$$

By minimizing the following objective function, the FCM method develops the partition ( Matrix  $U$  ).

$$J_m(U, C) = \sum_i \sum_k (u_{ik})^m \cdot \|x_i - c_k\|^2 \quad (2.22)$$

Where  $m > 1$  is a blurring control parameter (typically  $m = 2$ );  $c_k$  : is the center of class  $k$ .

The disadvantage of the FCM method is the process of randomly initializing the matrix of degrees of membership, which might have a significant impact on the results achieved (convergence of the functional to a local minimum) [37].

The FCM algorithm:

1. Initialize centers.
2. Set the fuzzy coefficient.
3. Computes the initial fuzzy partition (The membership matrix).
4. Repeat:
  - *New center calculations.*
  - *The new fuzzy partition is calculated.*

As long as the condition for shutdown isn't met,

### 2.5.3 Segmentation by a mixed approach

There are four methods to express the duality between regions and contours:[34][35][36]

- The areas are defined by the outlines. As a result, no contour points exist inside an area.
- A contour point is found on or near the edge of an area border (distance to be determined).
- A contour border is naturally closed.
- On the whole shared boundary between two regions an outline must be located.

This dualism led to image segmentation collaboration. Three distinct techniques may be identified based on how two procedures of segmentation region and contour cooperate: Collaboration in order, cooperation based on the fusion of outcomes, and cooperation [38]:

- One of the segmentation approaches (region or contour) is used first, with the results being used by the second technique to enhance the segmentation criteria or parameters.
- **Results collaboration:** both methods of segmentation are carried out independently. Cooperation should be based on the outcomes to improve segmentation.
- **cooperation:** During the execution phase, the two forms of segmentation work together.

## 2.6 Conclusion

This chapter has merely given a broad overview of available segmentation techniques. Specifically, those of the contour method, the region or cooperative approach, and brain MRI segmentation, as well as their unique characteristics. We also looked at classification techniques to see what their role and purpose were. MRI image segmentation is being worked on. In this way, we gained a broad understanding of all the methods for classifying and segmenting magnetic resonance images, as well as an understanding of how to apply them and get the best results, which we will cover in the following chapter. Mention all the steps and methods that were used and followed in this research.

### 3.1 Introduction

The identification of a brain tumor using magnetic resonance imaging is a critical activity that is frequently performed manually. As a result, automatic segmentation methods have been created to eliminate the need for the user to perform laborious manual effort, and lengthy while delivering a quick and repeatable outcome despite the fact that several techniques have been presented in the literature, picture segmentation remains an open topic of research. The goal of this chapter is to present an effective technique for detecting brain tumors using the FCM algorithm and the SVM classifier.

## 3.2 The proposed approach

The suggested method combines a variety of domains, with different roles and influences on MR image including data/information collection, pre-processing segmentation/division, feature extraction and selection, classification and soon. The suggested strategy's fundamental block diagram is shown in (Figure 3.1).

The architecture of the proposed method is as follows:

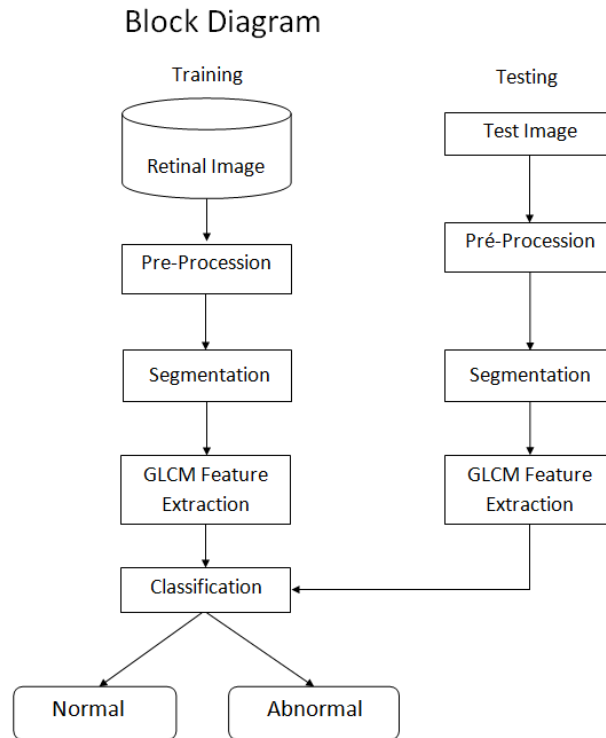


Figure 3.1: Architecture of the proposed methods.

**The steps of our proposal are as follows :**

- a) Select a database containing images of the brain .
- b) Pre-processing step with the median filter.
- c) The segmentation of an image with FCM.
- d) Feature extraction and selection with GLCM.
- e) To recognize brain tumors, we used Support Vector Machine (SVM) to build a classification model.
- f) Then the trained classifier is applied to a new image, it classifies it pixels as tumor or non-tumor.

### 3.2.1 Pre-processing

Pulse noise or isolated pixels with highly differing values from surrounding pixels, is particularly well suppressed by the median filter. The median filter works by sorting all of the values of the window's pixels into a numeric sequence, then replacing the pixels with their median values. It retains brightness variations, which helps to reduce the blurring of regional borders. This technique is also beneficial for visual examination and measurement since it maintains the locations of the image's borders. To find the median, follow the procedures outlined above [39].

1. Read the value of the pixel to be processed with its neighboring pixels.
2. Sort pixel values from smallest to largest.
3. Select the middle value for the new pixel value  $(x, y)$ . The median filtering equation is presented:

$$y[m, n] = \text{median} \{x[i, j], (i, j) \in w\} \quad (3.1)$$

Where  $w$  is a user-defined neighborhood centered on picture coordinates  $[m, n]$ .

### 3.2.2 Segmentation by Fuzzy C-Means principle

Segmentation is the technique of separating an image into multiple slices and object region. The skull stripes images are used in image segmentation. This provides good result for tumor segmentation. In this work, fuzzy c-means algorithm was used in MRI image segmentation. Fuzzy c-means (FCM) algorithm is used to find out the suspicious region from brain MRI image. This fuzzy c-means clustering method provides good segmentation result[40].

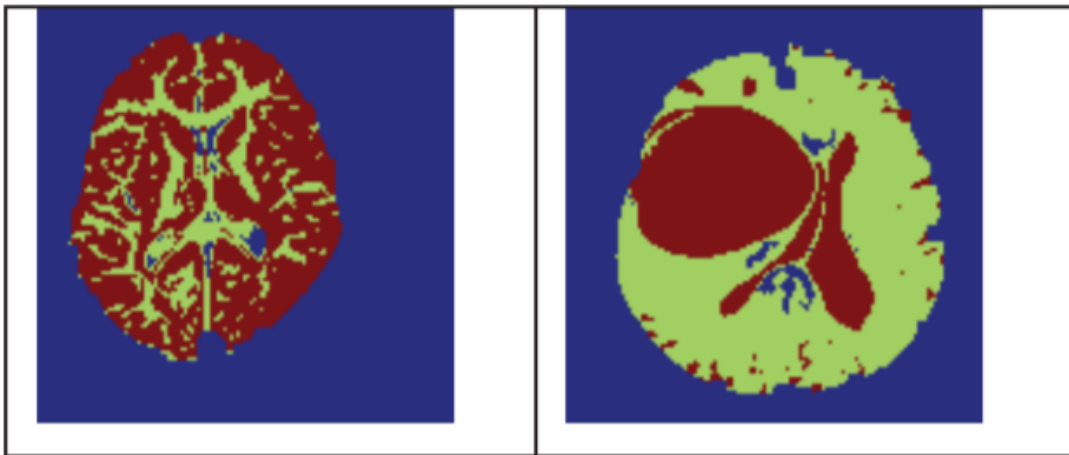


Figure 3.2: Fuzzy c-mean algorithm [40].

### 3.2.2.1 Understanding the FCM algorithm

The FCM algorithm has evolved the partition (Matrix U) by minimizing the following objective function: With:

- **C:** The number of classes, known a priori.
- **N:** The size of the data vector (number of pixels to be classified).
- $u_{ij}$ : The degree of belonging of the pixel  $x_k$  to the class  $i$  known by its center  $v_i$ .
- **D:** The degree of similarity, can be the Euclidean distance.
- **M:** A real  $> 1$  called degree of blur.

And with the following constraints:

$$\forall i \in \{1..N\}, \forall k \in \{1..C\} \sum_{k=1}^C u_{ij} = 1; \sum_{i=1}^N u_{ij} > 0 \quad (3.2)$$

Where  $u_{ij}$  denotes the pixel  $O_i$ 's membership in the  $Z_l$  cluster and  $Z_k$  denotes the cluster's  $Z_l$  center. The Euclidean distance is denoted by. The blur of the resultant division is controlled by the  $m(m > 1)$  option. (3.3) and (3.4) update the membership functions and cluster centers, respectively [41].

$$u_{ki} = \frac{1}{\sum_{l=1}^c \left( \frac{\|o_i - Z_k\|}{\|o_i - Z_l\|} \right)^{2/(m-1)}} \quad (3.3)$$

$$Z_k = \frac{\sum_{i=1}^N u_{ki}^m o_i}{\sum_{i=1}^N u_{ki}^m} \quad (3.4)$$

### 3.2.2.2 Validity of clusters

Cluster validity indices are required to assess the quality of a partition produced by the FCM method. We'll go through four well known metrics, which are as follows:

*The sharing coefficient (PC) is defined as:*

$$PC = \frac{\sum_{i=1}^N \sum_{k=1}^c u_{ki}^2}{N} \quad (3.5)$$

$$PE = \frac{-\sum_{i=1}^N \sum_{k=1}^c u_{ki} \log(u_{ki})}{N} \quad (3.6)$$

The following stages outline the steps of the FCM algorithm:

1. Initialize centers.
2. Set the fuzzy coefficient.

3. Computes the initial fuzzy partition (The membership matrix).
4. Repeat:
  - (a) Calculation of new centers.
  - (b) Calculation of the new fuzzy partition.

As long as the shutdown criterion is not verifie

To separate brain tissue in MRI images, we utilize the FCM segmentation method. To accomplish so, we must first specify the method's many parameters, such as the values of  $m$ ,  $c$  and soon.

- The number of classes  $c = 3$ .
- The size of the data vector  $n$  is determined by the image's dimensions.
- The Euclidean distance is represented by the degree of similarity  $d$ .
- Degree of blur  $m$  and between 1 and 3.
- The stability threshold  $\epsilon$  between 0.01 and 0.1.
- The maximum iteration requirement is 10 to 150 iterations.

### 3.2.2.3 Why Fuzzy C-Mean (FCM)

Regardless of the technique and kind of acquisition, the FCM algorithm has been widely utilized for brain image segmentation (mono or multimodal). Several studies, particularly in magnetic resonance imaging, have been conducted. Because the pixels are represented by their gray levels, the authors have demonstrated that the method is not only equivalent to traditional correlation analysis but also outperforms it (with the advantage of not requiring any a priori knowledge of the paradigm)[42].

### 3.2.3 Feature extraction by GLCM

Image features are the exact characteristics of an image. The problem with most of the previous work is that there are no effective strategies for selecting features. We are building our feature extraction on the gray level redundancy matrix (GLCM), which is a text feature extraction based on Haralick et al [43] [44]. Calculates the common presence matrix for each image in the database by calculating the number of times pixels occur at a given density ( $i$ ) relative to another pixel, a certain distance  $d$  and ( $\theta = 0$ ) direction[45]. Matrix can be calculated for one direction only ( $\theta = 0$ ) and one distance ( $d = 1$ ).The spatial distribution of gray levels in an image object is affected by specific properties

shown by a grayscale matrix. Each feature vector set instance matrix result yields 13 Haralick texture characteristics [46][47][48]. Two qualities are employed in a way that has an active influence on categorization accuracy. As a result, each image's feature vector has fifteen active GLCM features. According to the formula below, GLCM is normalized.

$$P(i, j) = \frac{V_{ij}}{\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} V_{i,j}} \quad (3.7)$$

The number of columns ( $j$ ) and rows ( $i$ ) is equal to the number of gray levels ( $G$ ) used in image and each matrix element  $V(i, j)$ , the value of cell ( $i, j$ ), is normalized as  $P(i, j)$ .

- **Mean:**

$$\mu_i = \sum_{i,j=0}^{G-1} iP(i, j) \quad (3.8)$$

$$\mu_j = \sum_{i,j=0}^{G-1} jP(i, j) \quad (3.9)$$

- **Variance**

$$\sigma_i = \sum_{i,j=0}^{G-1} (i - \mu_i) P(i, j) \quad (3.10)$$

$$\sigma_j = \sum_{i,j=0}^{G-1} (j - \mu_j) P(i, j) \quad (3.11)$$

- **Entropy:**

$$\text{Entropy} = - \sum_{i,j=0}^{G-1} P(i, j) \log(P(i, j)) \quad (3.12)$$

Higher entropy values are extracted from homogeneous scenes and lower ones are from inhomogeneous scenes.

- **Dissimilarity:**

$$\text{Dissimilarity} = \sum_{i,j=0}^{G-1} |i - j| P(i, j) \quad (3.13)$$

Dissimilarity is similar to GLCM contrast and it is high if the local region has high contrast.

- **Contrast:**

$$\text{contrast} = \sum_{i,j=0}^{G-1} (i - j)^2 P(i, j). \quad (3.14)$$

Contrast or local intensity variation measures the distance from the mean diagonal of gray-level cooccurrence matrix and the more the distance the higher the weight that is assigned to  $P(i, j)$ , so contrast exponentially increases when  $i - j$  increases.

- **Inverse Difference Moment (Homogeneity):**

$$\text{IDM} = \sum_{i,j=0}^{G-1} \frac{P(i, j)}{1 + (i - j)^2} \quad (3.15)$$

IDM measures the closeness of distribution of GLCM elements to main diagonal. The more concentration along main diagonal in GLCM leads to more homogeneous area and therefore higher values for IDM [48].

- **Correlation:**

$$\text{correlation} = \sum_{i,j=0}^{G-1} \frac{(i - \mu_i)(j - \mu_j) P(i, j)}{\sigma_i \sigma_j} \quad (3.16)$$

It measures the gray level linear dependency between neighboring pixels.

- **Energy:**

$$\text{ENRGY} = \sum_{i,j=0}^{G-1} (P(i, j))^2 \quad (3.17)$$

- **Cluster shade**

$$\text{SHADE} = \sum_{i,j=0}^{G-1} (i + j - \mu_i - \mu_j)^3 P(i, j) \quad (3.18)$$

- **Cluster prominence**

$$\text{PROM} = \sum_{i,j=0}^{G-1} (i + j - \mu_i - \mu_j)^4 P(i, j) \quad (3.19)$$

- **Sum entropy**

$$\text{SENT} = - \sum_{i=0}^{2G-2} P_{x+y}(i) \log(P_{x+y}(i)) \quad (3.20)$$

- **Sum average**

$$\text{AVRE} = \sum_{i=0}^{2G-2} iP_{x+y}(i) \quad (3.21)$$

- **Difference entropy**

$$\text{DENT} = - \sum_{i=0}^{G-1} P_{x+y}(i) \log(P_{x+y}(i)) \quad (3.22)$$

- **Sum variance**

$$SVAR = \sum_{i=0}^{2G-2} (i - SENT)^2 P_{x+y}(i) \quad (3.23)$$

- **nformation measures of correlation**

### 3.2.4 Classification by Support Vector Machine (SVM)

SVM is a supervised learning method. It is a good tool for data analysis and classification. SVM classifier has a fast learning speed even in large data. SVM is used for two or more class classification problems. Support vector machine is based on the conception of decision planes. A decision plane is one that separates between a set of items having different class memberships. The classification and detection of brain tumor was done by using the support vector machine technique. Classification is done to identify the tumor class present in the image. The use of SVM involves two basic steps of training and testing [49]. In the SVM the classes are assumed to be identified as  $\pm 1$ , and the decision boundary is estimate as  $y=0$ . So using the equation:

$$y = \sum_{i=1}^N w_i x_i + b = x_i w + b \quad (3.24)$$

Where  $x_i$  is the input patterns,  $w$  is the weight vector,  $b$  the offset. Since the classes are defined as  $\pm 1$  the equation for the line dividing the classes will be:

$$x_i w + b \geq 1 \text{ when } y = +1 \quad (3.25)$$

$$x_i w + b \leq -1 \text{ when } y = -1 \quad (3.26)$$

The distance from the hyper-plan ( $x_i w + b = 0$ ) to the origin is  $\sim b/|w|$ , where  $|w|$  is the norm of  $w$ . The distance from the hyper-plane to the origin is:

$$M = \frac{2}{\|w\|} \quad (3.27)$$

Where  $M$  is the margin. So the maximum margin is obtained by minimizing  $|w|$ .

Classification is the process where a given test sample is assigned a class by the classifier during training. We have used the SVM classifier [49].

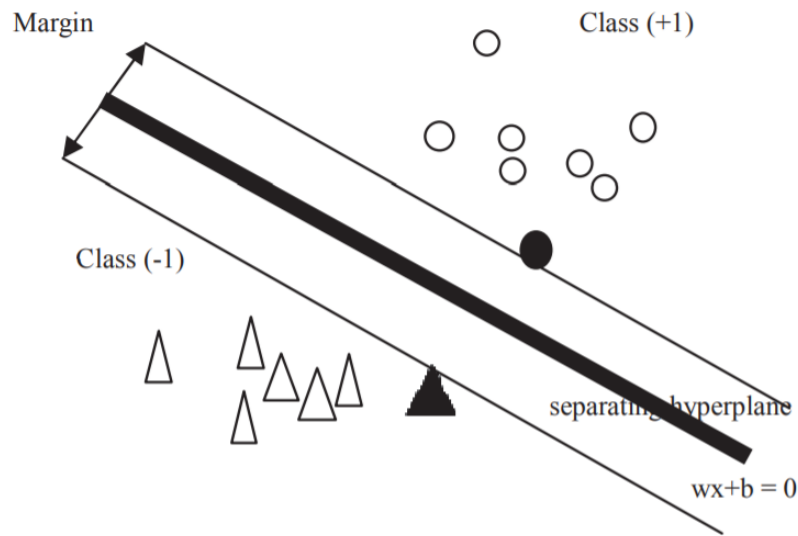


Figure 3.3: SVM classification (the separating margin between the two classes) [48].

### 3.3 Conclusion

In this chapter system brain MR images proved to be a significant way to detect the brain tumor, The hybrid methodology of combining support vector machine and fuzzy c-means clustering for segmentation and classification gives accurate result for identifying the brain tumor. In addition to any a statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. Measures the joint probability occurrence of the specified pixel pairs. In our last chapter, we show the results obtained from our use of all of the above, while proving the quality of the method by giving a simple comparison with other approved methods.

## 4.1 Introduction

In order to understand the result of the methods we discussed earlier, we will apply them to a magnetic resonance imaging of the human brain in this chapter, taking into account all of the factors that contributed to the occurrence of the results we received.

### Implementation environment

#### 4.1.1 Hardware environment

List the computer components that are used to execute all search-related activities:

\* Laptop:

- o Memory (RAM): 8.00GB (7.80GB usable).
- o Processor : Intel (®) core ™ i5-7200U CPU @ 2.50GHz 2.70GHz.
- o System type : 64-bit Operating System, x64-based processor, Microsoft windows 10.

\* Hard disk.

## 4.1.2 Software environment

### 4.1.2.1 MATLAB R2013a

It is a proprietary multi-paradigm programming language and numeric computing environment developed by MathWorks. MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages. Although MATLAB is intended primarily for numeric computing, an optional toolbox uses the MuPAD symbolic engine allowing access to symbolic computing abilities. An additional package, Simulink, adds graphical multi-domain simulation and model-based design for dynamic and embedded systems, Can interact with other languages Such as C, C++, Java and Fortran [50].

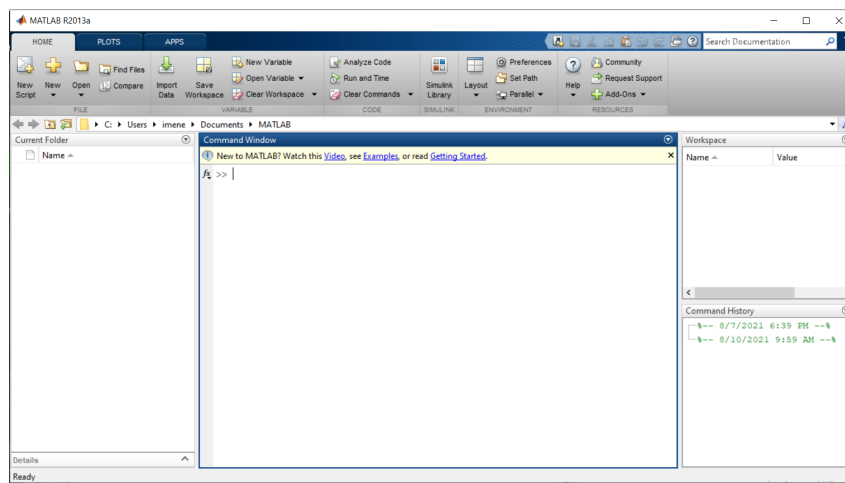


Figure 4.1: MATLAB interface.

### 4.1.2.2 LATEX

Overleaf is a collaborative cloud-based LaTeX editor used for writing, editing and publishing scientific documents. It partners with a wide range of scientific publishers to provide official journal LaTeX templates and direct submission links[51]. Overleaf was originally launched in 2012 as WriteLaTeX by the company WriteLaTeX Limited, co-founded by John Hammersley and John Lees-Miller. Both are mathematicians and were inspired by their own experiences in academia to create a better solution for collaborative scientific writing. They started developing WriteLaTeX in 2011. They launched the beta version of Overleaf on 16 January 2014, at their first "FuturePub" event held at the British Library in London. This is their site [overleaf.com](http://overleaf.com). Overleaf has been discussed as a tool for writing scientific publications in Nature, Science, Red Hat's opensource.com, and the German IT magazine Heise Online. "In 2017, CERN, Europe's particle-physics laboratory near Geneva, Switzerland, adopted Overleaf as its preferred collaborative authoring platform" [52].

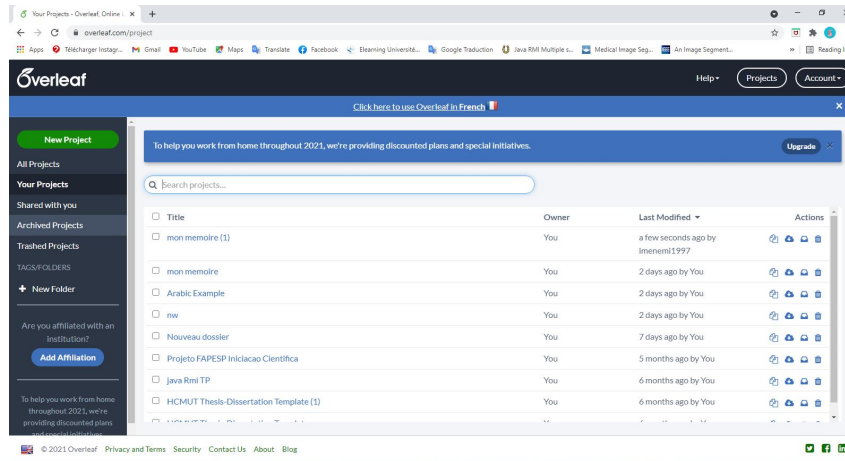


Figure 4.2: Overleaf Interface.

### 4.1.3 Image used

In the last chapter, we said that we needed IRM cerebral pictures, which we could get from the Medical Image repository in the format we needed (.mha). These pictures represent the BRATS 2015's data base. To work with .mha files, you'll need to first read 2D medical data and then attach them to the MATLAB tool.

We have a total of 438 pictures in our database. IRM mode T2 has 222 pictures of brain pathologies and 216 images of healthy brain. Our foundation is split into two parts, with 80 percent dedicated to learning and 30 percent to testing.

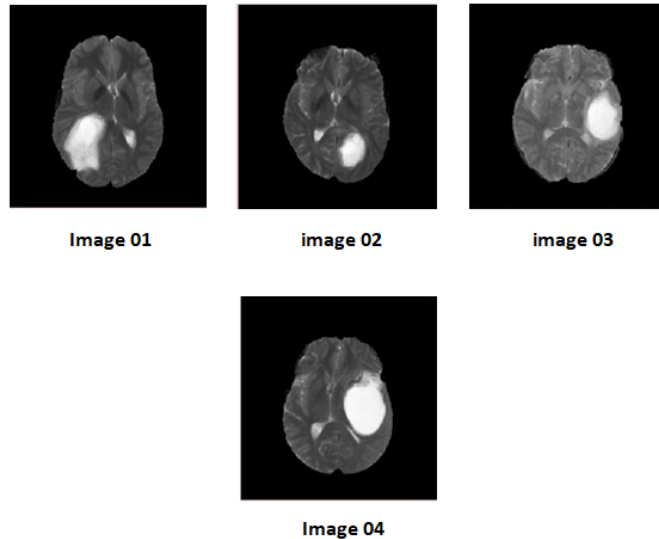


Figure 4.3: A sample of the images used.

#### 4.1.4 Demonstration of the application

This is the primary window that appears when you first open the door(.Fig).

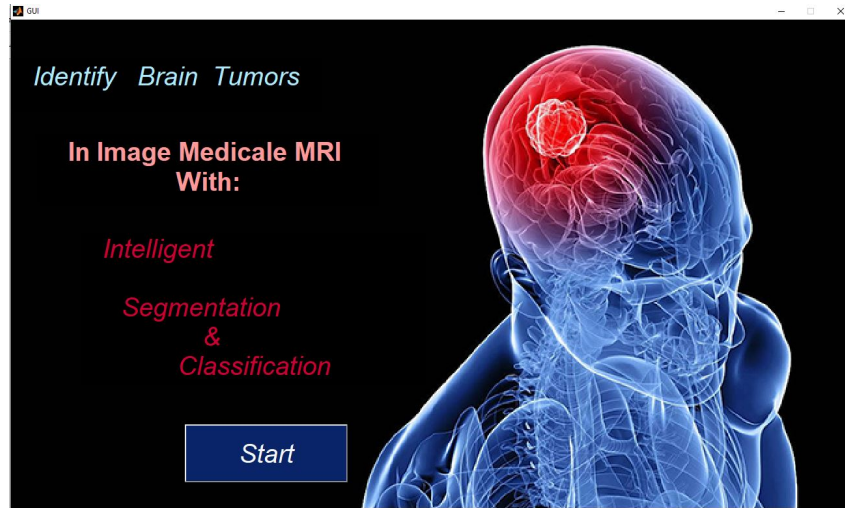


Figure 4.4: Our application's home page.

We press the start button to get to the page where the remainder of the tasks are completed (.Fig).

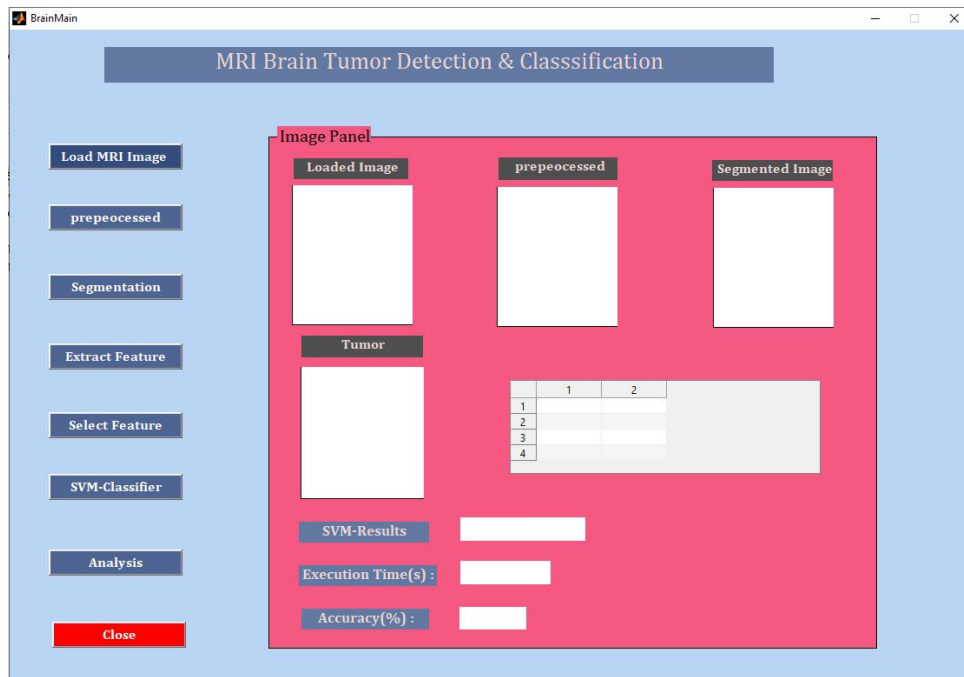


Figure 4.5: Tasks interface.

Before starting the test: we run the training part in order to get the SVM model.

Moving on to the test part: to do a segmentation, press the import button and then choose charger image originale to select the picture to segment (treat). This will open a dialogue box in which you may select an image from a data source (diskette, CD, flash disk, etc.) with the extension mha (Figure 4.6).

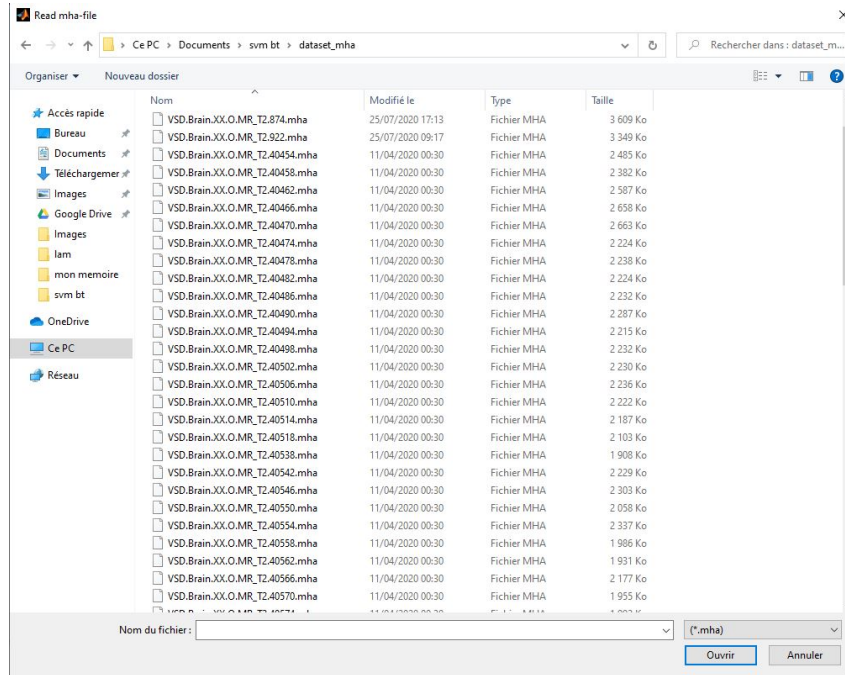


Figure 4.6: A collection of the photos that were used.

We'll download the magnetic resonance images of the brain from the database by clicking on the icon load MRI image. And it appears in our loaded Image screen, as it was captured by magnetic resonance.

Then, by clicking on the preprocessed icon, we start the filtering process and the image appears on the dedicated preprocessed screen without any noise.

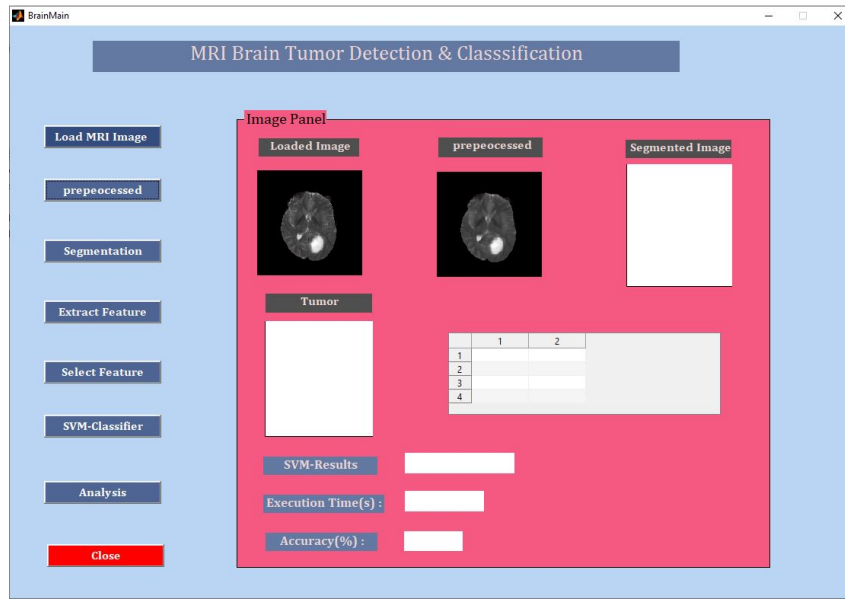


Figure 4.7: Result of the filtered image.

We use the segmentation procedure to separate the tumor, that is, to show its location in the brain if it is present, by clicking on the segmentation button. The segmentation result appears in the picture segmentation screen, with the brain in black and the tumor (foreign body) in white.

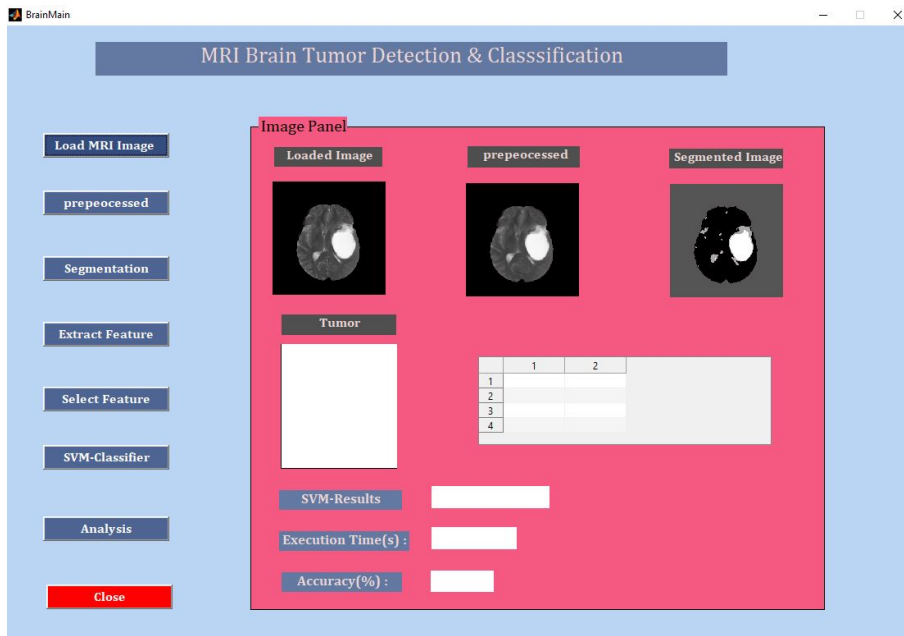


Figure 4.8: Segmentation result.

In this application, a picture of the segmentation process may be displayed, with the FCM algorithm applied, which separates each substance in the brain with a color to determine the most precise separation.

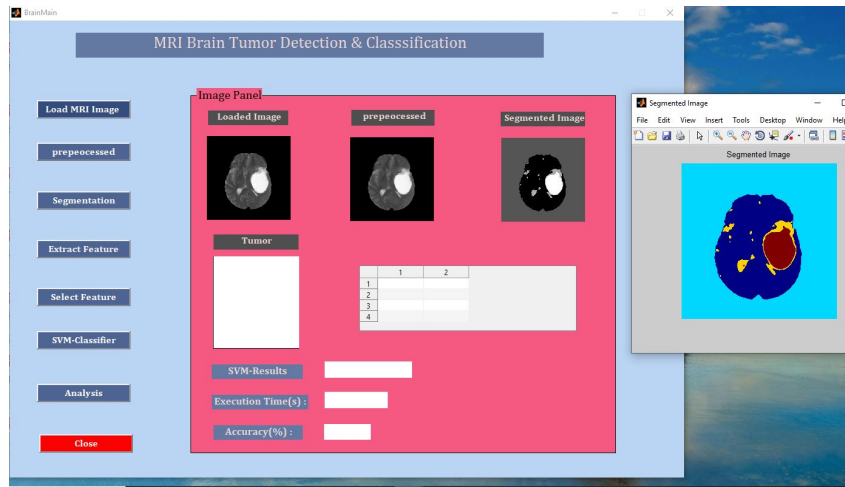


Figure 4.9: FCM segmentation.

We used the code extraction function to apply GLCM to the picture generated from the hachage and to extract second-order texture statistics based on the image's density points.

Despite the importance of features to achieve high accuracy, a large number of features increase the problem of computation time and complexity and waste a large amount of storage memory, so we click on Select that reduces poor accuracy of results. Following that, we classify.

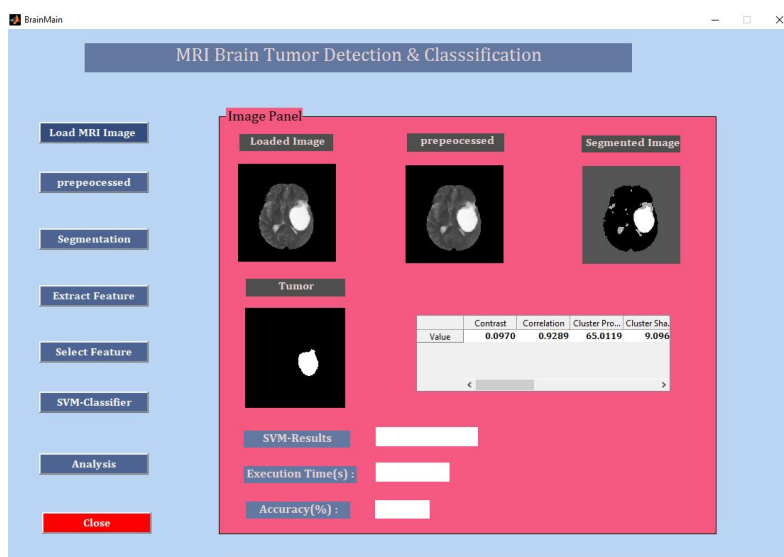


Figure 4.10: GLCM Extract Feature.

- Screen tumoral apparaît black, mince.
- The patient appears on the screen as a white tumeur.

Click on SVM-classifier to get the result, which may be one of these two natural or abnormal brains.

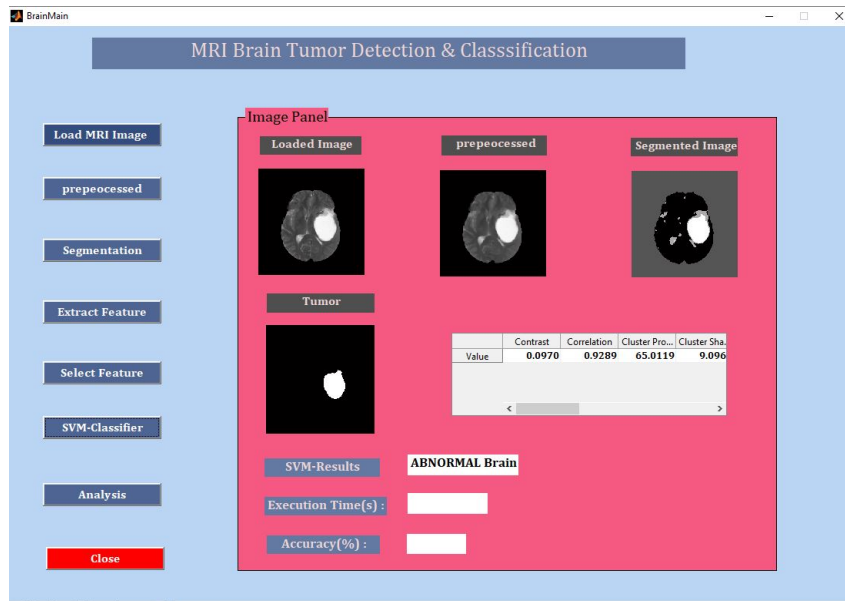


Figure 4.11: SVM Result.

By clicking on the analysis, the results will appear.

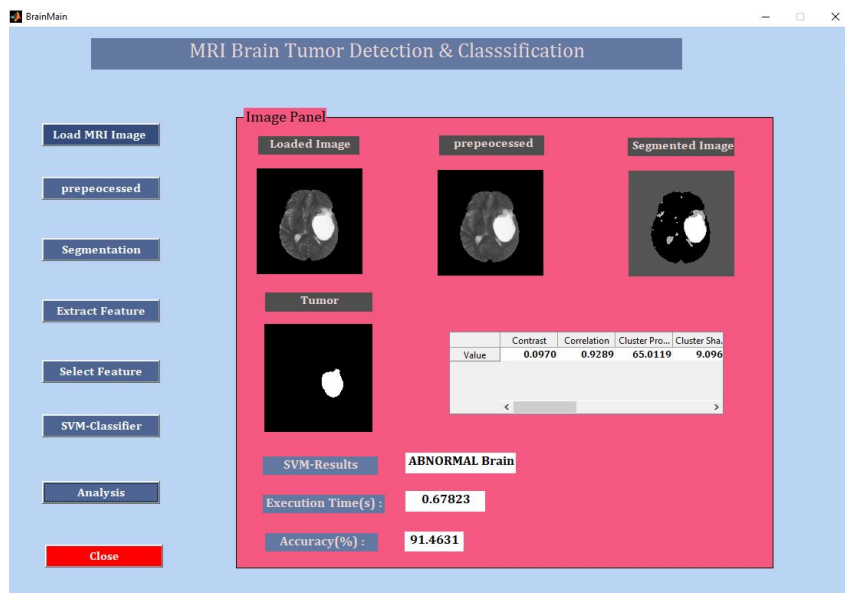


Figure 4.12: The results provided by the analysis.

The image in (Figure 4.13) depicts one of the application's results, which is a natural brain.

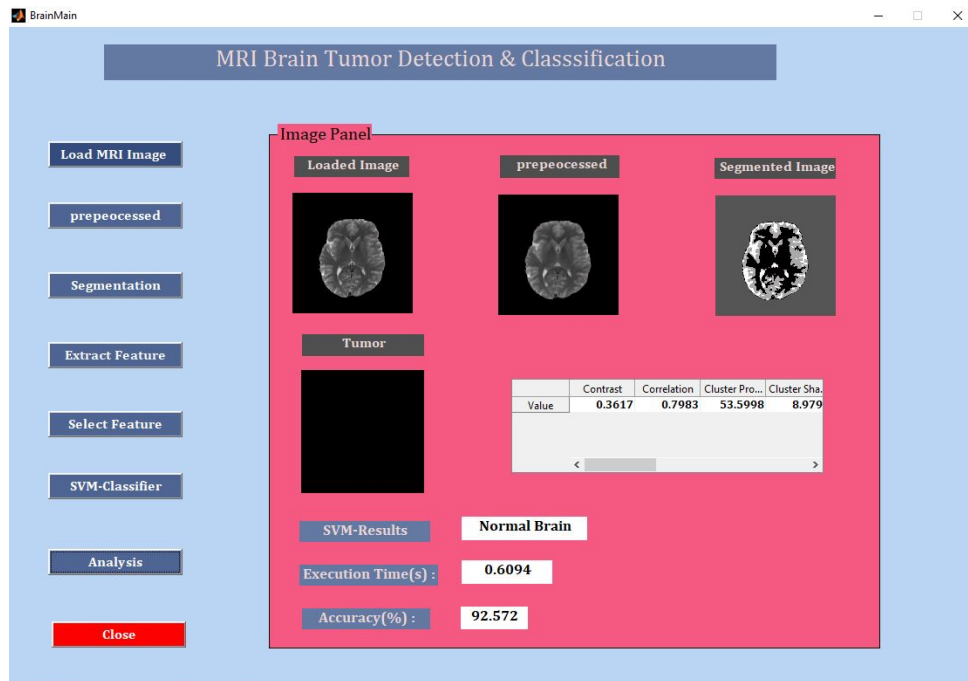


Figure 4.13: Normal brain distance SVM-classification.

-The last screen is the one that allows you to exit the application.

### 4.1.5 Segmentation results

These results are the result of our efforts, and they are IRM picture examples (T2).

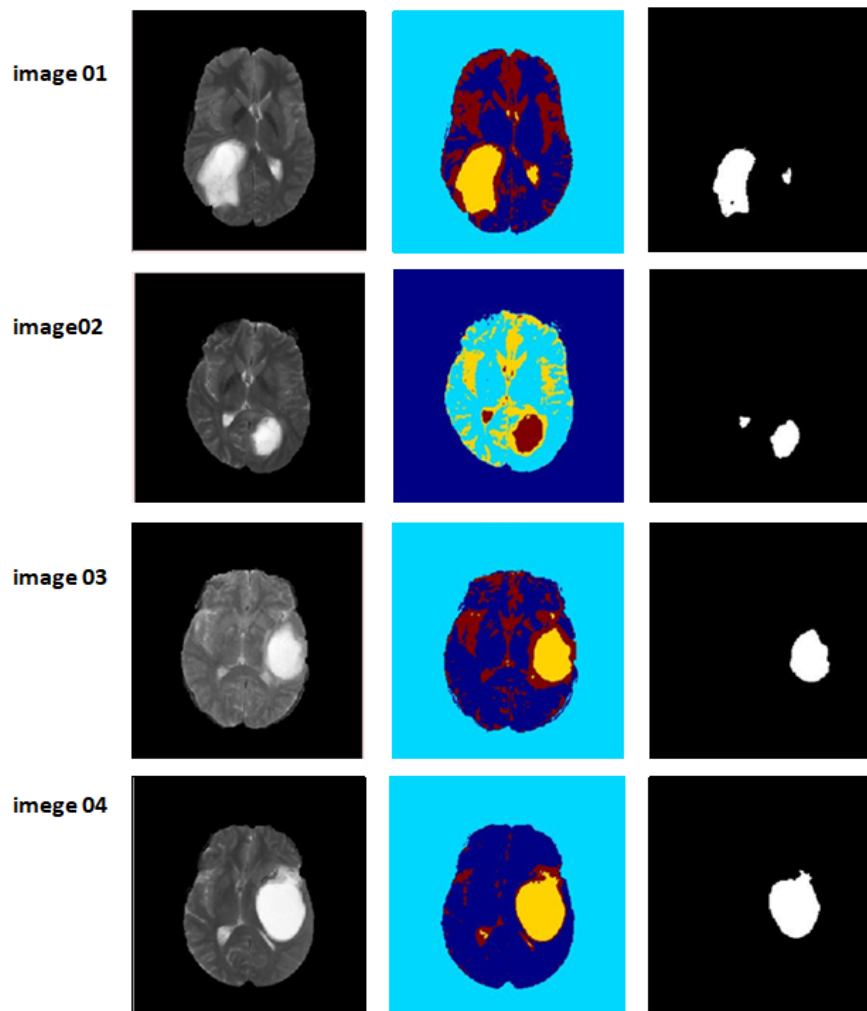


Figure 4.14: Representation results of our proposed method

## 4.1.6 Evaluation of the results

### 4.1.6.1 Signal-to-noise ratio (PSNR)

PSNR (Political Science and National Research Council) (Peak Signal to Noise Ratio)

The PSNR (Peak Signal to Noise Ratio): is the ratio between the maximum power of the signal and the power of the noise which affects the fidelity of its representation. It is defined by the mean square error (MSE) between the two input images  $I$  is the initial image and  $k$  is the restored or improved version of  $I$ . As a result, the higher the PSNR, the better the signal and therefore the restoration or improvement treatment.

$$PSNR = 10 \log_{10} \left( \frac{MAX^2}{MSE} \right) \quad (4.1)$$

Alternatively, the MSE (Mean Squared Error) is:

$$MSE = \frac{\sum_{M,N} [I_1(m, n) - I_2(m, n)]^2}{M * N} \quad (4.2)$$

The numbers  $M$  and  $N$  refer to the number of lines and columns in the entry pictures.

- $I$ : this is the original picture.
- $MAX$ : is the image  $I$ 's highest potential pixel value.
- $K$ : the picture has been segmented.
- The value  $I$  denotes the index of this line, and  $m$  is the number of lines of pixels in the pictures.
- The number of columns of pixels in the image is represented by  $n$ , and index of the column is represented by  $j$ .

### 4.1.6.2 The information entropy IE:

The information entropy (IE) is a criterion that measures the degree of information in a picture; the higher the IE, the more information-dense the image.

$$IE = - \sum_{i=0}^{L-1} P_f(i) * \log_2(P_f(i)) \quad (4.3)$$

The ratio of the number of pixels to the level of grayscale has an effect on the total number of pixels with  $P_f$ .

We evaluated the FCM segmentation results on the BRATS 2015 (4.3) pictures using two criteria: the PNSR and the entropy. The results are shown in (Table 4.1); we found

Images segmentées	Performances	
	PNSR	Entropie
Image 1	24.0416	1.01946222
Image 2	24.3094	0.88963805
Image 3	23.1479	1.00095651
Image 4	23.5841	0.96715669
Moyenne	23,7707	0,9693

Table 4.1: Evaluation table.

that the average PNSR criterion value is 23,7707, and the average entropy criterion value is 0.9693

The obtained classified output from SVM and KNN classifier is resolved through performance metrics like specificity, sensitivity and accuracy.

$$\text{Specificity} = \frac{t_n}{t_n + t_p} \quad (4.4)$$

$$\text{Sensitivity} = \frac{t_p}{t_p + t_n} \quad (4.5)$$

$$\text{Accuracy} = \frac{t_p + t_n}{t_n + t_p + f_p + f_n} \quad (4.6)$$

- True positive (tp): Tumor people correctly identified as having the condition.
- False positive (fp): Normal (healthy) people incorrectly identified as tumor.
- True negative (tn): Normal (healthy) people correctly identified as healthy.
- False negative (fn): Tumor people incorrectly identified as normal (healthy).

The performance metrics sensitivity, specificity and accuracy of SVM classifier KNN classifier with GLCM feature extraction methods is shown in (Table 4.2)

<b>Classifier</b>	<b>Feature extraction</b>	<b>Sensitivity (%)</b>	<b>Specificity (%)</b>	<b>Accuracy (%)</b>	<b>Average(%)</b>
KNN	GLCM	81	74	77	77.33
SVM	GLCM	100	72.17	79	83.72

Table 4.2: Evaluation table.

We provide our findings in (Table 4.2), which shows that it is distinguished by the accuracy with which it recognizes cerebral tissue and that it is effective in classifying cerebral images as normal or abnormal. Based on these findings, the precision of the classification method SVM appears to be more precise. As opposed to the KNN classification method, which is based on the categorization of medical pictures using magnetic resonance imaging.

## 4.2 Conclusion

In this chapter, we've completed our work by providing a description and a list of the steps required for implementation. Our work is based on the use of a filter to remove noise and aid the FCM algorithm in segmenting the image with greater precision as well as the use of a statistical texture function called GLCM to extract characteristics and improve production precision, assisting the SVM classification algorithm in producing a segmentation with 96 percent precision and consistency.

## GENERAL CONCLUSION

Imagery via magnetic resonance is a type of imaging that allows you to see detailed pictures of your organs and tissues within your body. The doctors use it to get a sense of what's going on inside the body and to pinpoint the problem, but this isn't enough because the human body is a complex structure, particularly the human brain, which is frequently affected by a tumor, which can be malignant or benign and determining the latter is difficult. The radiology department needed an effective segmentation method that did not rely on a manual or semi-automated solution with inexact results and a protracted implementation time, as well as a categorization methodology that determines his kind.

Due to the significance of obtaining precise results, a bibliographic review of picture segmentation and classification methods was conducted, allowing us to better understand the variety of methods for segmenting cerebral tissue and classifying its kind. In the literature, several segmentation methods have been proposed, including subsistence segmentation and region segmentation. In terms of the categorization approach, it has been divided into two categories: controlled and uncontrolled.

Our work's goals include obtaining a specific result in a short period, so we followed the steps below: first, filtering an IRM brain image, then segmenting the image that was filtered by the FCM algorithm, which gave us a segmented image that could be used to identify each part of the brain and finally, applying the tagging algorithm. Produced using segmentation to extract the characteristics of a second-order statistical texture based on the density points in an image and fourth, by employing the SVM classification method, which allows us to classify images based on data and determine the outcome.

We presented the results of our research in order to use the best segmentation and classification algorithms for medical pictures in order to improve the quality of brain

tumor detection. All of the steps were carried out on a bidimensional IRM image of the brain, and the result is a collection of pathological data analyses that provide a realistic picture to the clinician.

## ABBREVIATION LIST

- MRI: Magnetic Resonance Imaging.
- NB: Bayesian Naïve.
- PCM: Possibilistic C-Means.
- IDM: Inverse Difference Moment.
- IE: Information Entropy.
- FCM: Fuzzy C-Means.
- GLCM: Gray Level Co-Occurrence Matrix.
- SVM: Support Vector Machine.
- CSF: CerebroSpinal Fluid.
- PNSR: Political Science and National Research.
- MSE: Mean Squared Error.
- KNN: (K-Nearest Neighbor)

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## ملخص

ورم الدماغ هو كتلة او نمو للخلايا الشاذة في الدماغ و يعتبر من الامراض الخطيرة وله انواع متعددة بعضها حميد والآخر خبيث. وهنا قمنا باستعمال التصوير بالرنين المغناطيسي لاعطاء نتيجة قراءة واضحة في الكشف عن الورم، لا يكفي هذا وحده بل يجب الاستعانة بخوارزميات اولها خوارزمية التجزئة فCM لتجزئة الصورة ثم تطبيق GLCM و هذا لاستخراج ميزات النسيج الاحصائي من الدرجة الثانية و تحسين دقة الانتاج للوصول الي الورم و تحديده دون اضافة او نقصان واخيرا خوارزمية التصنيف SVM المسؤولة عن تحديد نوعه .

الكلمات المفتاحية : التجزئة، التصنيف، التصوير بالرنين المغناطيسي، ورم ، FCM ، SVM ، GLCM.

## Résumé

Une tumeur cérébrale est une masse ou une croissance de cellules anormales dans le cerveau. Elle est considérée comme une maladie grave et se présente sous plusieurs formes, certaines bénignes et d'autres malignes. Ici, nous avons utilisé l'imagerie par résonance magnétique (IRM) pour donner un résultat de lecture clair dans la détection de la tumeur, cela seul ne suffit pas, mais nous devons utiliser des algorithmes, dont le premier est l'algorithme de segmentation FCM pour segmenter l'image puis appliquer GLCM pour extraire les caractéristiques du tissu statistique de second ordre et améliorer la précision de la production pour atteindre et identifier la tumeur sans ajouter ni diminuer et enfin l'algorithme de classification SVM chargé de déterminer son type.

Mots-clés : Segmontation, Classification, IRM, Tumeur, FCM, SVM, GLCM.

## Abstract

A brain tumor is a mass or growth of abnormal cells in the brain. It is considered a serious illness and comes in many forms, some benign and others malignant. Here we have used magnetic resonance imaging (MRI) to give a clear reading result in tumor detection, this alone is not enough, but we have to use algorithms, the first of which is FCM segmentation algorithm to segment image then apply GLCM to extract second order statistical tissue characteristics and improve production precision to reach and identify tumor without adding or shrinking and finally SVM classification algorithm to determine its type.

Key-words: Segmontation, Classification, MRI, Tumor, FCM, SVM, GLCM.