Classification of Brain Tumor using Maximum Entropy Thresholding and SVM

Thesis Submitted to
The Superior College, Lahore

In Partial fulfillment of the
Requirement for the Degree of

Master of Philosophy in Computer Science

By
Rabbiya Tahir

Roll No. MSCS-F16-008

Session: 2016-2018

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بسم الله

DEDICATION

This study is wholeheartedly dedicated to ALLAH ALMIGHTY, thanking HIM for the guidance, strength, power of mind, protection and skills and for giving me a healthy life. All of these, I offer to HIM.

After that, I dedicate this to my beloved parents, who have been my source of inspiration and gave me strength when we thought of giving up, who continually provide their moral, spiritual, emotional, and financial support.

And lastly, I dedicated this study to my brothers, sisters, mentor, friends, and classmates who shared their words of advice and encouragement to finish this study.

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In the Name of Allah, the Most Merciful, the Most Compassionate all praise be to Allah, the Lord of the worlds. First and foremost, I must acknowledge my limitless thanks to Allah, the Ever-Magnificent; the Ever-Thankful, for His help and bless. I am totally sure that this work would have never become truth, without His guidance.

I owe a deep debt of gratitude to my university for giving us an opportunity to complete this work. I am grateful to some people, who worked hard with me from the beginning till the completion of the present research particularly my supervisor, Dr. Muhammad Usman Butt, who has been always generous during all phases of the research.

I would like to take this opportunity to say warm thanks to all my beloved friends, who have been so supportive along the way of doing my thesis.

I also would like to express my wholehearted thanks to my family for their generous support they provided me throughout my entire life and particularly through the process of pursuing the master degree. Because of their unconditional love and prayers, I have the chance to complete this thesis.

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ABSTRACT

Medical imaging processing has emerged as an active area of research. In medical imaging, Brain tumor segmentation consists of separating abnormal tissues from normal tissues. Brain tumor detection through Magnetic Resonance Imaging (MRI) is very effective way to help doctors in the diagnosis and treatment of brain tumor – one of the most life-threatening disease, nowadays. In brain tumor studies, the existence of abnormal tissues may be easily detectable most of the time. However, accurate and reproducible segmentation and classification of abnormalities are not straightforward. Brain tumor detection process through MRI images is mostly done manually by experts in an enormous amount of time and includes a large factor of inter observer variability. While on the other hand, both semiautomatic and fully automatic methods have also been proposed. Clinical acceptance of segmentation and classification techniques depends on the simplicity, accuracy and the degree of user interpretation. This research paper will focus to develop a real time novel technique for classification of tumor types (benign, malignant) based on feature extraction in a segmented region of a brain MRI images. The proposed technique will be validated on different Brain MRI datasets and its efficiency, simplicity and accuracy will be evaluated by comparing with existing techniques.

Keywords

Brain Tumor, Magnetic Resonance Images (MRI), Pre Processing, Segmentation, Feature Extraction, Classification.

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Chapter 1
INTRODUCTION

Chapter 1: Introduction

This thesis presents the techniques to monitor tumors in brain and to propose an effective and efficient way to diagnose the type and stage of brain tumors through the robust algorithm. Image processing is a method to perform the necessary operations on images mostly captured by cameras, for the purpose of getting better quality images or to extract certain attribute information from them. The process carried out is a kind of signal processing which takes an image as an input and outputs a more detailed image or characteristics of the image that reveals important information about it.

Today, image processing is one of the fast growing technologies that interest many scientists and researchers [29].It is very popular in engineering and computer science disciplines. Image processing is conducted using three steps as shown below.

1. Preprocess the image using image acquisition tools.
2. Analysis and manipulation of an image.
3. End result which is a better image or a report.

. Computer-aided disease examination is widely used in medical discipline to investigate anatomical and pathological sections from clinical images. Medical imaging procedures will support the early detection and diagnosis of various diseases and also help to reduce the morbidity and mortality rates. In the literature, a number of procedures are proposed and implemented by the researchers to extract significant information from the traditional and medical images [11].

Medical image processing can be carried out in four stages. The first stage is to use a set of images collected from the patients to be investigated. The second stage is to apply image enhancement techniques to obtained better quality images [39]. The third stage to apply image segmentation methods which is the most important part of image processing procedures, and lastly the fourth stage is to extract the necessary features from enhanced

and segmented images which give important information of normality or abnormality of images.

Brain region segmentation plays an important role in accurate diagnosis and efficient treatment of brain related diseases, such as stroke, Alzheimer, and glioblastoma, which has received a lot of attention in the field of computer vision, medical image analysis, and cancer imaging. In medical imaging, segmentation of images plays a vital role in stages which occur before implementing object recognition [15]. Image segmentation helps in diagnosis of brain diseases and helps in qualitative and quantitative analysis of images such as measuring accurate size and volume of detected portion. Accurate measurements in brain diagnosis are quite difficult because of diverse shapes, sizes and appearances of tumors. Tumors can grow abruptly causing defects in neighboring tissues also, which gives an overall abnormal structure for healthy tissues as well [13].Diagnosing neurological disorders is a challenging domain. This is because of highly complex anatomical structure of the brain along with some other factors like variations in size, age, gender etc. [8].

1.1 Tumor

Tumor is formed by the abnormal growth of the tissues, which is a cluster of nerve cells, or neurons, in the brain. Abnormal cell in the form of lump is found in brain are called brain tumor. Normal process of brain is new cells are created and old or damaged cells die. When this process not works fine, old or damaged cells often create a piece of mass tissues called tumor. There are three common types of tumor:

1. Benign
2. Pre-Malignant
3. Malignant (cancer can only be malignant) [7].

Figure 1.1: Illustration of a brain tumor [41]

1.1.1. Benign Tumor: A benign tumor is a tumor that does not expand in an abrupt way, it doesn't affect its neighboring healthy tissues and also does not expand to non-adjacent tissues. When it is detected, it can be treated. It does not spread in other parts of brain but can cause problems as they grow with pressure on surrounding tissue. Some may not come back after treatment but others may need further treatment. Benign tumors may sometimes transform to malignant [7-9]. The most common types of benign brain tumors are given below.

1.1.2. Pre-Malignant Tumor: Premalignant Tumor is a precancerous stage, considered as a disease, if not properly treated it may lead to cancer.

1.1.3. Malignant Tumor*:* Malignant is basically a medical term that describes a severe progressing disease. Malignant tumor is the type of tumor that grows worse with the passage of time and ultimately results in the death of a person. Malignant brain tumors grow faster than benign tumors. They cause problems by spreading into and damaging surrounding brain tissue. These tumors may spread to other parts of the brain or the spinal cord. Malignant brain tumors are more likely to repeat after treatment [19]. The most common types of malignant brain tumors are given below.

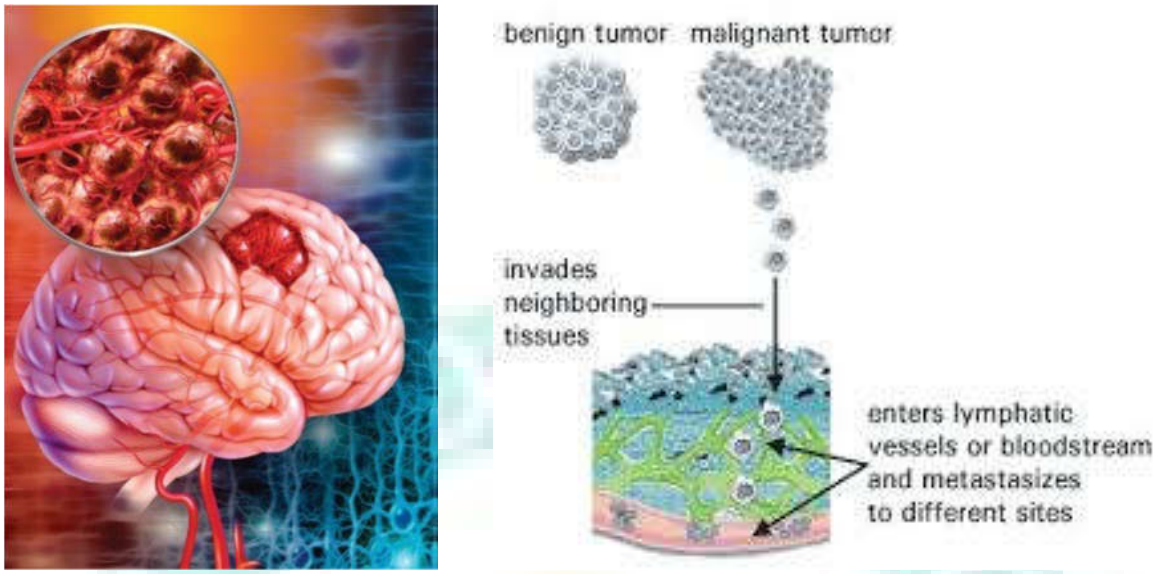

Figure 1.2: Labeled diagram of brain tumor [21]

1.2 Brain Cancer

Brain cancer is a very serious type of malignancy that occurs when there is an uncontrolled growth of cancer cells in the brain. Not all brain tumors are malignant (cancerous). Some types of brain tumors are benign (noncancerous). A tumor may lead to the cancer, which is a major leading cause of death and responsible for around 13% of all deaths world-wide [16].There are mainly two types of brain cancer.

1. Primary Brain Cancer
2. Secondary Brain Cancer

1.2.1. Primary Brain Cancer**:** It is the type of cancer in which the brain cancer originates in the brain itself. Primary brain cancer is the rarest type of brain cancer. It can spread and invade healthy tissues on the brain and spinal cord but rarely spreads to other parts of the body. Primary tumor commonly found in children. It is originating from cells of the brain that support nervous system.

1.2.2. Secondary Brain Cancer: Secondary brain cancer is more common and is caused by a cancer cells that originates in another part of the body, such as lung

cancer which spreads to the brain. Secondary brain cancer is also called metastatic brain cancer.

Brain cancer is most treatable and curable if caught in the earliest stages of the disease but early detection of brain tumors is difficult because the brain is covered by the skull and brain tumors do not exhibit very specific clinical symptoms. Untreated or advanced brain cancer is often difficult to treat, if is not diagnosed properly. This is so because doctors may feel difficulty in suggesting the right treatment. The National Cancer Institute (NCI) had estimated that 22,070 new cases of brain and other central nervous system (CNS) cancers would diagnosed in the United States in 2016. The American Brain Tumor Association (ABTA) clarifies this statistic further estimating that 62,930 new cases of primary brain tumors would be diagnosed. Cancer incidence rate is growing at an alarming rate in the world [9].

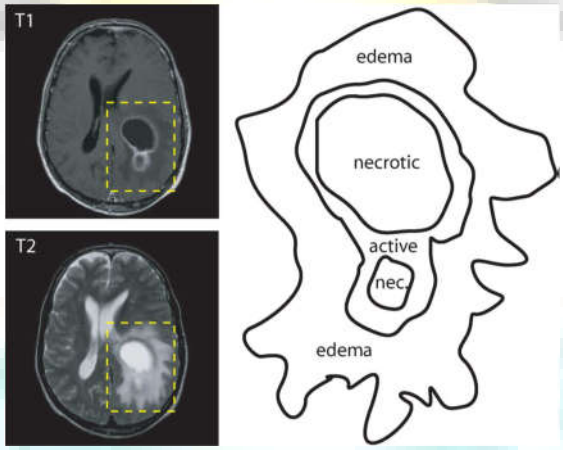

Figure 1.3: Brain tumor modalities [8]

1.3 Grades of the primary brain tumors

The tumor grade is determined by examining the cells through the microscope. Primary brain tumors are divided into four grades and the details of these grades are given below (National Cancer Institute, 2016) [15].

1.3.1. Grade I tumors

The tissue is composed of benign cells. Cells are very similar to normal brain cells and grow slowly. Surgical operations alone are an effective treatment method for such tumors.

1.3.2. Grade II tumors

The tissue is composed of malignant cells. Cells resemble more abnormal cells than cells in Grade I tumors. Such tumors may sometimes be reproduced as a higher grade tumor.

1.3.3. Grade III tumors

The tissue is composed of malignant cells and grows quickly. Grade III tumors are not very different in appearance from Grade II tumors. Such tumors can sometimes be repeated as Grade IV tumors.

1.3.4. Grade IV tumors

The tissue is composed of malignant cells. It grows more rapidly than other tumor grades and can be easily distinguished from normal cells when examined with a microscope. Grade IV gliomas (glioblastomas multiforme) are the most aggressive tumors with a low treatment success rate. They are unfortunately the most common type of glioma.

Primary brain tumors constitute a heterogeneous set of tumors associated with variable behaviors, symptoms, origins and malignancy [4].They are characterized by the type of cell from which they arise and are dominated by gliomas, arising from glial cells. Gliomas are classified by the World Health Organization (WHO) into 4 grades of malignancy based on their histological properties [33]

1.4. Symptoms

In general, three different categories of symptoms for brain tumors can be distinguished. [3] First, increased cranial pressure can lead to headache, vomiting and altered states of consciousness. Second, cognitive and behavioral impairment, personality or emotional changes can be attributed to brain dysfunction. And third, symptoms of irritation like

absences, fatigue or seizures can be observed.

However, all these symptoms are not specific for brain tumors only. Therefore, diagnosis usually starts with an interrogation of the patient for medical history and symptoms. If a brain tumor is suspected, imaging plays a central role.

1.5. Evaluation /Diagnosis

The process of diagnosis and identification of brain tumor MRI images are done manually based on some fixed criteria, measurements etc. from different slices of MRI images. This process requires a long time and still there could be the chance of wrong diagnosis as it involves human interception. Detecting and analyzing brain tumor form MRI scans automatically has therefore a potential as high accuracy rate of detection and classification can be achieved and early therapy plans can also be made. [9, 21]. Manual detection processes performed by the expert radiologists often shows variation while detecting the tumor are especially because sometimes the edges of tumors are not clear and are merged with backgrounds. This effects the accuracy rate of tumor diagnosis and causes more severity in the patients disease.

However, despite the crucial role of imaging, a definitive diagnosis can only be confirmed by histological examination of tumor tissue samples, which have been obtained by biopsy or surgery [22-25]. For better diagnosis of the tumor, the patients are questioned in depth about the symptoms they have noticed and their family history. Some physical examination is also done by the neurologist consultant. After a general examination, the patients is referred to the radiologists for some tests through any modality as per need or requirement. [1]

1.6. Neuro Imaging Modalities

The identification of brain tumor depends upon the accurate segmentation of the MRI

images into the healthy brain cell and the tumor cells [40]. To acquire this, some modalities of brain imaging are being used clinically. Among them, the most popular for Neuroimaging studies are the X-Rays, Computed Tomography (CT), PET (Positron Emission Tomography) and MRI (Magnetic Resonance Imaging). The brief description of these techniques are given below.

1.6.1. X-Rays

X-Rays technology is used to get the detailed information of bones in a human body. This doess not provides information about the soft tissues, muscles etc.it is also reactive and could be harmful if it is used multiple times on same body and place. The only benefit of X-Ray is that this technique is easy to use. [9]

1.6.2. Computed Tomography (CT)

Computed Tomography CT scan [48] is a well-known modality used for neurological diseases because it provides useful information in minimum seconds of time. It is fast and efficient but it does not provide as good contrast of soft tissues as MRI Scanner provides and due to its radioactive nature this is harmful for human body. [17]

1.6.3. Positron Emission Tomography (PET)

Positron Emission Tomography PET uses a radioactive substance to get the image of the brain. This material is injected into the blood to monitor the activity and functions of the brain but this technique is costly and due to the radioactive material this process is harmful. [43]

1.6.4. Magnetic Resonance Imaging (MRI)

MRI Scanner uses the radio frequency signals to capture the image slices of the brain. My dataset comprises of the 2-D MRI images of brain tumor because it offers good soft tissue contrast as compared to others.

Magnetic resonance imaging (MRI) is based on magnetic manipulation of protons to acquire images without ionizing radiation. In an MRI scanner, the patient is placed in a powerful magnetic field, which aligns the magnetic moments of the protons in the patient's body [15]. The radiofrequency signals released during relaxation are detected by receiver coils and processed for subsequent image reconstruction. During image reconstruction, various relaxation parameters can be weighted to attain contrast between distinct tissue types, which makes MRI a remarkably flexible diagnostic tool.

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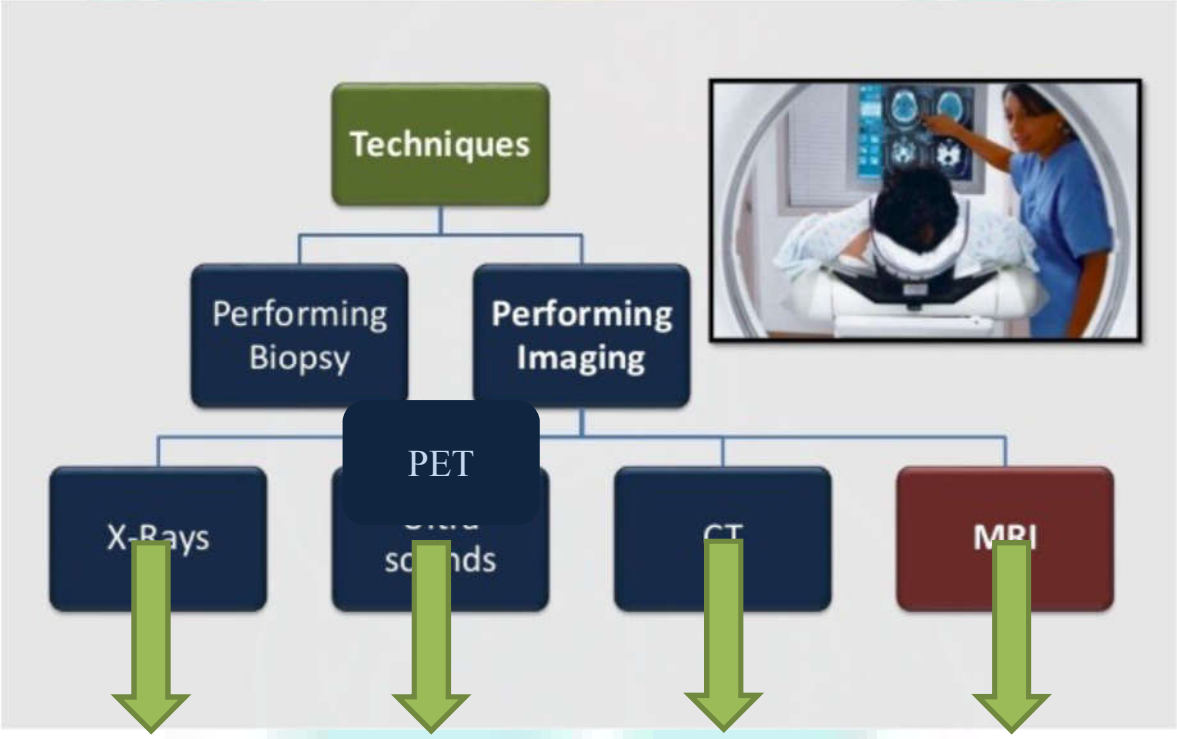

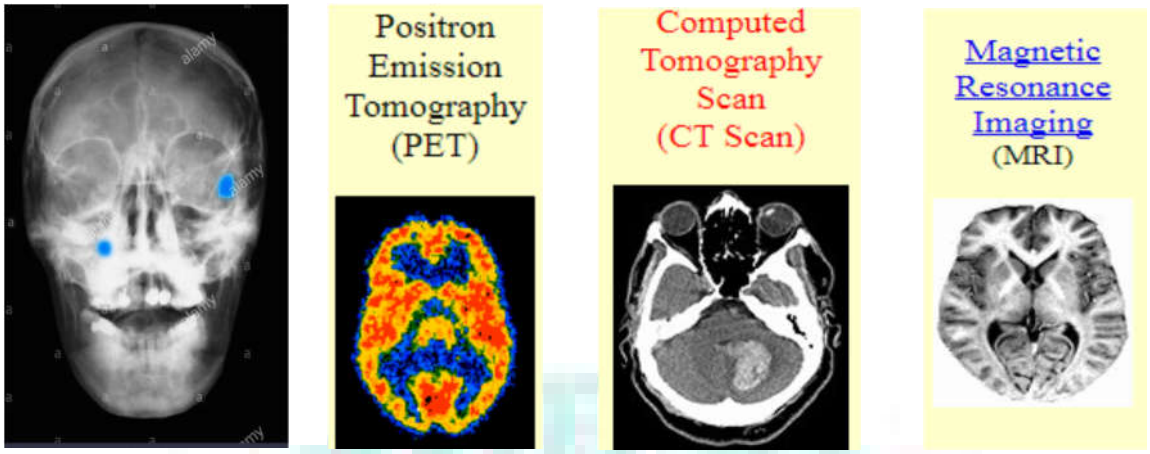

Figure 1.4: Brain Tumor Image Scanning Modalities

1.7. MRI Image Characteristics of brain Tumor

Extracting information from the radiological images is a difficult and time consuming task due to low contrast, blur or diffusive edges etc. MRI Scan and CT scan are diagnostic modality used to show the internal structure of brain. The capability of discrimination of soft tissues and high spatial resolution of MRI makes it advantageous over CT scan and other imaging techniques [12]. Moreover, MRI Scanners does not emit radiations as CT or other imaging techniques emits, so it is not harmful for the human body. It focuses on the soft tissues so it discriminates the normal tissue from the abnormal tissue. MRI is noninvasive so it is very much popular among medical experts for diagnosing tumor size, shape and type etc.

Images taken from MRI Scanner holds enormous information about the brain soft tissues, the information about the brain soft tissues assists to diagnose the tumor existence in brain. The ultimate goal of brain tumor imaging analysis is to extract the patient-specific important clinical information, and their diagnostic disease so that they can plan the accurate treatment of a patient.

Some limitations that are needed to be faced in manual inspection of brain MR Images such as lack of reproducibility, long processing time, and inaccuracies in the diagnosis originates a development of a novel approach that achieves more accuracy in diagnosis, improve the

quality of treatment and reduces the computation time. In the last decades, many researchers in the field of brain oncology and neuro image processing have made significant researches in this field but no technique till now could be clinically implemented because it demands computation efficiency and degree of user supervision.[13]

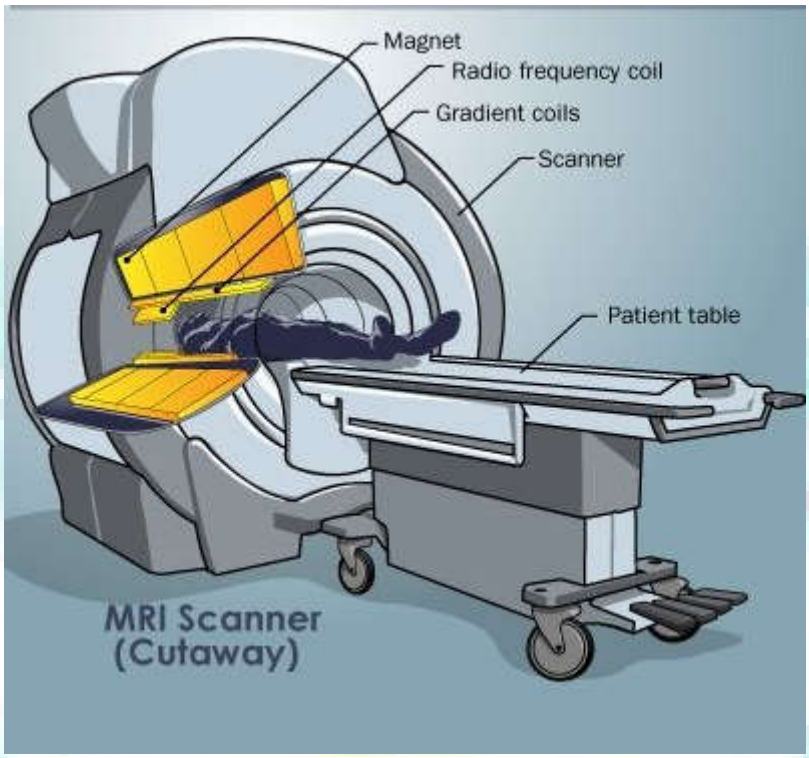

Figure 1.5: MRI Scanner [10]

1.8. Brain Segmentation and Classification

Segmentation is the term used to make separate the slices of an image for analysis and monitoring. This techniques separate the background from the foreground by clustering the pixels into different regions to highlight them. These separated parts are then analyzed and monitored in a better way to study and detect a brain tumor from MRI image.

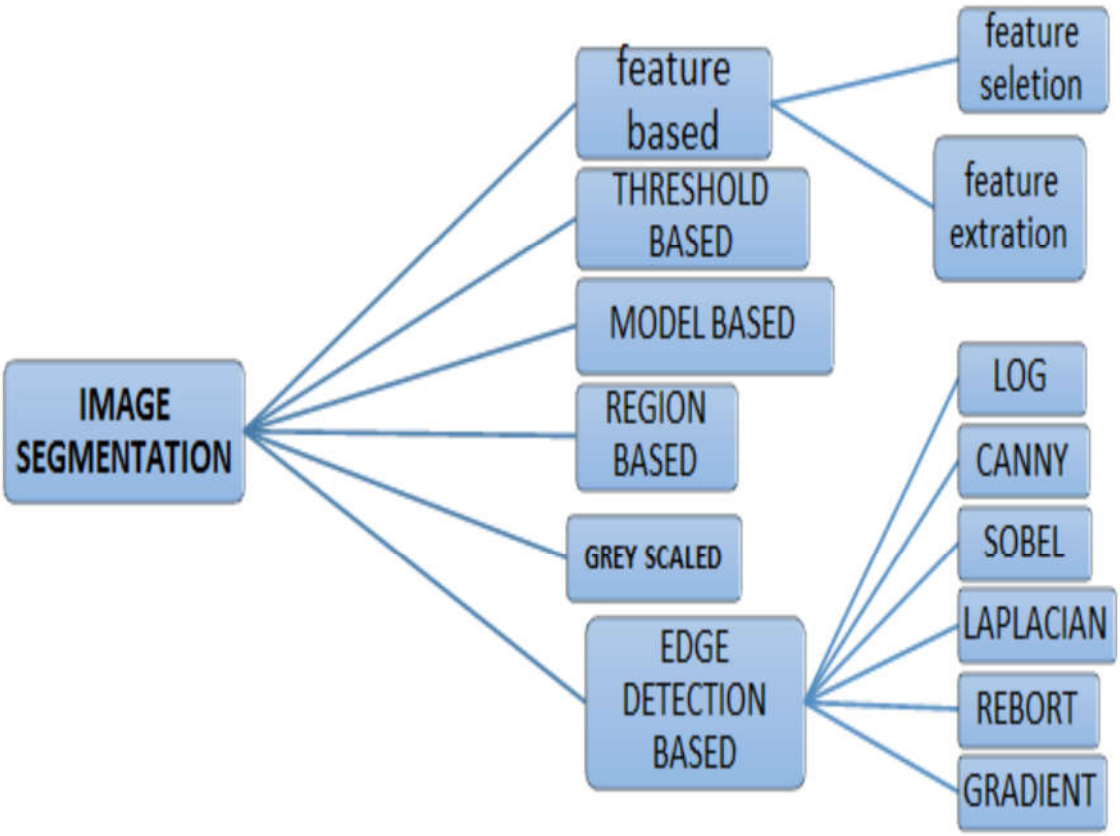

Figure 1.6: Segmentation Techniques [31]

Image classification is a process of extracting the classes of information from the multiband raster images. Basically, two types of classification. [44]

a. Supervised Classification

b. Unsupervised Classification

Segmenting and classifying image manually is one of the critical and time consuming task for the concerned departments. Brain MRI Image segmentation is the process of partitioning a digital image acquired form MRI, CT or other imaging techniques into multiple segments or slices. Basically, all researches are made in this field are the effort to simplify extraction and classification of tumor from brain MRI image by creating a way to make image more meaningful and more information can be extracted from it. Brain image

segmentation is typically used to locate tumors, their boundaries, edges, size shape etc. in MRI images.

1.8.1. Manual Segmentation and Classification

Many different manual techniques and methodologies have been proposed by researchers to detect and analyze the brain tumor through brain MRI images which can broadly be classified in segmentation domain, clustering domain, compression based method etc. [6].

1.8.2. Semi-Automatic Segmentation and Classification

Human interference is needed for initialization in this method. The accuracy of results are also checked manually and sometime needs human interception to correct the result of segmentation and classification of brain tumor.

1.8.3. Automatic Segmentation and Classification

There also exists fully automated techniques for classification of brain tumor detection. These are mainly divided into three categories: 1) Segmentation based 2) Feature Based and 3) Texture based classification approaches.

1.9. Feature Extraction

Feature extraction is the process of extracting some useful information from an image. Features from a brain MRI image can be extracted either through intensity based feature extraction algorithms or texture based feature extraction algorithms. Features are extracted from the initial set of measured data and resulting into the more informative and non-redundant data. An algorithm will be proposed which will extract the required features after segmenting the brain MR Images. Purpose of applying algorithm at this stage is to extract some meaningful information that will help in classifying the Brain MR Image. DWT and GLCM are the two features extraction algorithms to extract texture based features and intensity based features respectively.

1.10. Classification

Image classification is a process of extracting the classes of information from the multiband raster images. After segmenting and extracting features from an image, now it will be easy to classify an image on the basis of shape, size, color, volume and appearance of the tumor. Any probabilistic classifier based approach will be used for classification of human brain magnetic resonance image in to normal class and cancerous classes.

The rest of this paper is organized as follows. Section 2 states the problem statement of my research, section 3 is about the objective while section 4 concludes research significance. Section5 consists of hypothesis questions and section 6 is about the literature study that I have reviewed. My proposed methodology is stated in section 7.

1.11. Problem Statement

Segmentation and Classification of brain MRI images have major impact in diagnosis and treatment of a patient. However, a manual process leads to inter observer variability, human errors, inaccuracies and more time to detect a brain tumor. In critical cases, manual detecting and classifying brain tumor from an MRI image may cause delays which lead to threaten the life of a patient. Automated approaches to classify an image uses supervised and unsupervised Machine Learning (ML) algorithms and deep learning techniques such as Convolutional Neural Networks (CNNs), Neural Networks. And Artificial Intelligence techniques. These techniques are more reliable and accurate, but are computationally expensive and require a large training dataset. This also requires trained and expert staff to use get benefit from these techniques. This process requires not only a large training data, but also requires an accelerated hardware to speed up the entire process. Although Support Vector Machine SVM is a supervised machine learning algorithm that is comparatively less complex and doesn't requires accelerated hardware to classify the images and produces the accurate result based on the boundaries definitions. This is the reason why most of the

current research regarding brain tumor classification is targeted at the SVM algorithms with an intention of having the least human interaction possibility. To minimize the influence of these factors, there arises a strong need to focus on the development of a real time novel technique that comprises of segmenting the tumor along with extracting the features for classification of tumor into benign or malignant.

1.12. Objectives

The objectives of this research are as follow:

- Propose and develop a novel approach for analyzing and segmenting the Brain MRI Images.
- Development of efficient scheme for classification of segmented MRI Images to diagnose whether it is normal brain image, benign tumor image or a malignant tumor image.
- Development of effective, simple, robust scheme which requires minimal human effort with high accuracy.
- To evaluate the performance of proposed approach against other approaches from the literature.

1.13. Significance

Many techniques have been proposed for segmentation and classification of Brain MRI Images. But since there is a dire need for development of an algorithm to meet the challenges such as robustness in automatic detection and segmentation and efficient for classification as well. This research will also help oncologists, pathologists, radiologists to detect and diagnose tumor and will make better treatment procedures to cure if cancerous tumor exists. The major significance of this research work will be to develop a technique for segmenting and classifying the brain MRI images in quick, simple and accurate manner.

The easy, early and precise detection and diagnoses of tumor may save lives of many patients and the morbidity and mortality rates may reduce.

1.14. Research Questions

This research study is set up to answer the following questions on Segmentation Based Feature Extraction Model for Classification in Brain Magnetic Resonance Images (MRI):

- A Robust algorithm to segment and classify Brain MRI Images.
- What type of brain tumors are hard to detect and segment.
- To detect the accuracy and robustness level of proposed model.

1.15. Thesis Organization

Chapter 1 describes introduction and basics of brain tumor segmentation and classification, its categories, problem statement, research questions, objective and significance of research. Chapter 2 describes literature review of existing video brain tumor detection and classification techniques. Chapter 3 describes a step-by-step research methodology used for development of proposed method. Chapter 4 presents a detailed description of datasets and performance evaluation measures used in this study. Experimental works are presented in chapter 5. Chapter 6 presents conclusion of this research.

Chapter 2

RELATED WORK

Chapter 2: Related Work

Brain Tumor segmentation and MRI Classification techniques are considered as one of the pioneer topics among man medical researchers around the globe. Numerous algorithms have been proposed every once in a while to enhance and upgrade the tumor recognition methods. Although, the field still demands better algorithms and techniques to get accurate results. A brief review of a couple of researchers in this field are presented underneath.

Michael Mahesh et al. [8] provided critical analysis based on his reviews about detecting brain tumor through feature extraction techniques, image datasets, implementation tools, evaluation measures and results. The DTI technique which allows the quantitative assessment of isotropic and anisotropic tissue water diffusion components. Perfusion MR imaging is utilized in which is used to measure cerebral blood volume or cerebral blood flow before and after a vasodilatory challenge using agents, such as carbon dioxide or the carbonic anhydrase inhibitor, acetazolamide.

Moitra D. et al. have presented the work that has been carried out with an objective to plan a strategy to identify brain tumors using Artificial Neural Network (ANN) and segmented PET images. He concluded conclude that the Neural Network approach of classification improves the accuracy and the finer information from the individual class is obtained by using textures

Various current methodologies of brain image segmentation using automated algorithms that are accurate and requires little user interaction are reviewed by Selvaraj et al. [20] In this work, the merits and demerits of various automated techniques for brain tumor identification is analyzed in detail. The survey shows that BPN classifier gives fast and accurate classification that can be effectively used for segmenting MRI brain images with high level of accuracy.

S. Goyal et al. [51] presents a framework for disorder prediction and psychological feature

process for patients of cognitive impairment, dementia, or Alzheimer's disease based on automatic segmentation of gray and white matter regions as anatomical features in brain MRI images. Changes in the size or volume of these regions can be correlated to changes in cerebral structure in patients with Alzheimer's, dementia, cognitive impairment, or other neurological disorders. His work proposes the average thickness and volume measurements of the neocortical and non-neocortical regions between the boundaries of the white and gray matter regions, the aggregate of the parts of the regions in both the left and right hemispheres, can be used as the measures with which the cognitive impairment or dementia is quantitatively assessed for a patient, based on their brain MRI scan.

Dubey et al. [31] proposed a new approach to segmentation is proposed that removes the adverse effect on the boundary, which is unwanted especially from the point of view of volume rendering.

This approach provides a lot of correct boundary detection and holes filling once segmentation.

A semi-automatic calculation of meter size of neoplasm has been enforced during this approach.

A comparative analysis of manual, seeded region growing and this advance approach shows more accurate and better performance for 3D volume measurements. The comparisons of volume measure by manual, seeded region growing and AGMRGT ensures that tumor accuracy have been improved using AGMRGT. The results show that volume measurements obtained victimization AGMRGT technique is in smart agreement with manually divided information.

2.1. Manual Segmentation Methods

Mane et al. [25] introduced an efficient image segmentation approach using K-means clustering technique integrated with Fuzzy C-means algorithm. It is followed by threshold

and level set segmentation stages to provide accurate brain tumor detection. The proposed technique can get advantages of the K-means clustering for image segmentation within the aspects of least computation time. In addition, it can get advantages of the Fuzzy C-means in the aspects of accuracy. The performance of the planned image segmentation approach was evaluated by comparison it with some state of the art segmentation algorithms just in case of accuracy, interval, and performance. The accuracy was evaluated by comparing the results with the ground truth of every processed image.

The experimental results clarify the effectiveness of proposed approach to handle a higher range of segmentation problems via improving the segmentation quality and accuracy in minimal execution time. Kumar et al. [23] in their research work the author proposed the concept for brain tumor detection and segmentation. Normally the anatomy of the Brain is viewed by the MRI scan or CT scan. The tomography scanned image is taken for the complete method. The tomography scan is better-off than CT scan for diagnosing. It does not affect the human body. As a results of it does not use any radiation. However they will have some disadvantage in segmentation. In this research work, k-means algorithm is used for segmentation with some morphological operations. So it provides the accurate result for tumor segmentation. The main aim of this research work is to extract optimal features to provide efficient result in segmentation of a brain MR Image. The limitations in these research works is that more improvement in accuracy and algorithm complexity in tumor detection can be done in 3D image and the volume of the tumor can be also calculated.

An Efficient Brain Tumor Detection Algorithm Using Watershed Thresholding Based Segmentation was proposed by Mustaqeem et al. [26]. Brain growth detection helps to find the precise size and placement of tumor. An efficient algorithm is proposed in this paper for tumor detection based on segmentation and morphological operators. Firstly quality of scanned image is enhanced and then morphological operators are applied to detect the tumor

in the scanned image.

Gordillo et al. [34] presented a survey study on MRI brain tumor segmentation in which different existing approaches were compared to find the best approach to segment the MRI Images. They have drawn several general conclusions with regard to elements of a system that can be used to improve performance in brain tumor segmentation. They compared manual segmentation, semi-automated segmentation and fully automated segmentation of brain MRI Images. They found manual segmentation a time consuming, inter-observer variable process. Since the semiautomatic methods use different strategies to combine computers and human's expertise, the outcome of these methods depends on the strategy as much as on computation. These strategies could include involving the user in the initialization of segmentation process, keeping the user in the control during the whole process, or adding intelligent behavior to elevate the abstraction of interaction. Although it's true that by implementing these methods economical brain tumor semiautomatic segmentation ways are often obtained.

Nilesh et al. [40] improved the performance and reduce the complexity involves in the medical image segmentation process, we have investigated Berkeley wavelet transformation (BWT) based brain tumor segmentation. Furthermore, to improve the accuracy and quality rate of the support vector machine (SVM) based classifier, relevant features are extracted from each segmented tissue. The experimental results of proposed technique have been evaluated and validated for performance and quality analysis on magnetic resonance brain images, based on accuracy, sensitivity, specificity, and dice similarity index coefficient. The experimental results also obtained an average of 0.82 dice similarity index coefficient, which indicates better overlap between the automated (machines) extracted tumor region with manually extracted tumor region by radiologists. we investigated texture primarily {based} and bar graph based options with a normally

recognized classifier for the classification of brain tumor from adult male brain pictures.

Varuna Shree et al. [53] have targeting noise removal technique, extraction of gray-level co-occurrence matrix (GLCM) features, DWT-based brain tumor region growing segmentation to reduce the complexity and improve the performance. This was followed by morphological filtering that removes the noise which will be shaped when segmentation. The probabilistic neural network classifier was wont to train and take a look at the performance accuracy within the detection of growth location in brain MRI pictures. The experimental results achieved nearly 100 percent accuracy in distinguishing traditional and abnormal tissues from brain adult male pictures demonstrating the effectiveness of the projected technique.

Reema Mathew et al. [16] presented different steps involved n segmenting tumor through image preprocessing for noise removal, feature extraction, segmentation and classification. Proposed work preprocessed the MRI brain image using anisotropic diffusion filters. In the feature extraction step, discrete wavelet transforms (DWT) based features are extracted. The extracted features was given as input to the segmentation stage. Support Vector Machine (SVM) was used for tumor segmentation and classification. The accuracy of the proposed method is 86%.

Meenakshi Sharma et al. presented the study of this problem that is practically motivated, but has properties that make it an interesting and challenging Masking algorithm. They also introduced a framework that combined ideas from the prior work into a general method to perform this task automatically. They also used many techniques, which helps to remove the noise from the scanning images. The MRI are used in this, which are helpful in finding the tumor location in the brain.

Bandana Bali et al. will be utilizing the bilateral filter technique to eliminate noise from the brain magnetic resonance imaging images, following by applying the improved canny edge

detection algorithm for image segmentation to locate the ridges of tumor areas in them. The last step of hierarchical clustering algorithm application will aid in highlighting the affected area in the images thereby addressing the issues of clear location of tumor cells in the brain MRI images. They worked upon the image segmentation of the brain MRI wherein we made use of the bilateral filter technique to remove the noise from the brain MRI image. In the second step, we applied the canny edge detection algorithm for image segmentation to determine the ridges of tumor area in the image. In the third and final step, we put into use the hierarchical clustering algorithm to highlight the area of brain tumor in the images.

2.2. Semi-Automated Methods

Nicolas Sauwen et al. [50] presented a semi-automated framework for brain tumor segmentation based on non-negative matrix factorization (NMF) that does not require prior training of the method. L1 regularization is incorporated into the NMF objective operate to market abstraction consistency and merging of the tissue abundance maps. The pathological sources are initialized through user-defined voxel selection. Knowledge about the spatial location of the selected voxels is combined with tissue adjacency constraints in a post-processing step to enhance segmentation quality. The method is applied to an MP-MRI dataset of 21 high-grade glioma patients, including conventional, perfusion-weighted and diffusion-weighted MRI. Based on the mean Dice-scores and Hausdorff distances, segmentation results are competitive with state-of-the-art in literature. Robust results were found for most patients, although careful voxel selection is mandatory to avoid sub-optimal segmentation.

2.3. Automated Segmentation Methods

Havaei et al. [7] proposed a novel algorithm technique based on deep neural networks. This research focuses on glioblastomas (both low and high grade) brain tumor MR images.

Due to variance in nature, these tumors can appear anywhere in the brain and have almost any kind of shape, size, and contrast. The exploration of a machine learning solution exploits a flexible, high capacity DNN while being extremely efficient. In this research work, a novel CNN architecture which differs from those traditionally used in computer vision. This networks use a final layer that is a convolutional implementation of a fully connected layer. The experimental results are promising and lay the basis for future works.

Pourreza et al. [38] presented a fully automated segmentation method using deeply-supervised Neural Networks. The classification core of the presented method is a deeply supervised neural network based on HED. Low computational, yet very effective preprocessing and post processing steps were added to the pipeline that highly improved the accuracy of the segmentation. The achieved results are very promising and demonstrate the effectiveness of the presented method in terms of the segmentation accuracy. Moreover, the method has very low computational burden as the neural network.

Corso et al. [22] developed and validated an automated brain tumor segmentation method against manual segmentation with three-dimensional magnetic resonance images in 20 patients with meningiomas and low-grade gliomas. The automated method (operator time, 5–10 minutes) allowed rapid identification of brain and tumor tissue with an accuracy and reproducibility comparable to those of manual segmentation (operator time, 3–5 hours), making automated segmentation practical for low-grade gliomas and meningiomas. The limitation of this research is future clinical studies on the accuracy and reproducibility of this technique in a larger population would be necessary to determine its practical use in a clinical setting.

Ahmad Chaddad et al. [14] presented a novel method for Glioblastoma (GBM) feature extraction based on Gaussian mixture model (GMM) features using MRI. They addressed the task of the new features to identify GBM using T1 and T2 weighted images (T1-WI,

T2-WI) and Fluid-Attenuated Inversion Recovery (FLAIR) MR images. By a comparative study of other features types as PCA and wavelet, this technique resides in its ability to detect GBM automatically with high accuracy performance which was difficult previously.

2.4. Three Dimensional Methods

Ali M. Hasan et al. [48] proposes an automatic technique which will determine neoplasm slices and section the neoplasm across all image slices in volumetrical MRI brain scans. First, a group of algorithms within the pre-processing stage is employed to wash and standardize the collected information. A changed gray-level co-occurrence matrix and Analysis of Variance (ANOVA) area unit used for feature extraction and have choice, severally. A multi-layer perceptron neural network is adopted as a classifier, and a bounding 3D-box-based genetic algorithmic program is employed to spot the situation of pathological tissues within the MRI slices. Finally, the 3D active contour while not edge is applied to section the brain tumors in volumetrical MRI scans. The achieved accuracy was high relative to those of alternative segmentation techniques, the 3DACWE was comparatively slow for tumor segmentation.

Chapter 3
METHODOLOGY

Chapter 3: Proposed Methodology

The goal of this chapter is to contribute to biomedical image analysis domain, by detecting and classifying the brain tumor through MRI images. My methodology is based on the five steps: first step is to pre-process the MRI images. In second step, segmentation of brain tumor through entropy thresholding is done. Method of clustering the segmented images through K-Means clustering is done. In third part. In fourth part features are being extracted through Discrete Wavelet Transformation (DWT)) method. In final part, Data is trained and testing through Support Vectors Machines (SVM) to give accurate and classified results. The aim of this study is to accurately classify the tumor i.e. benign or malignant.

Flow Chart:

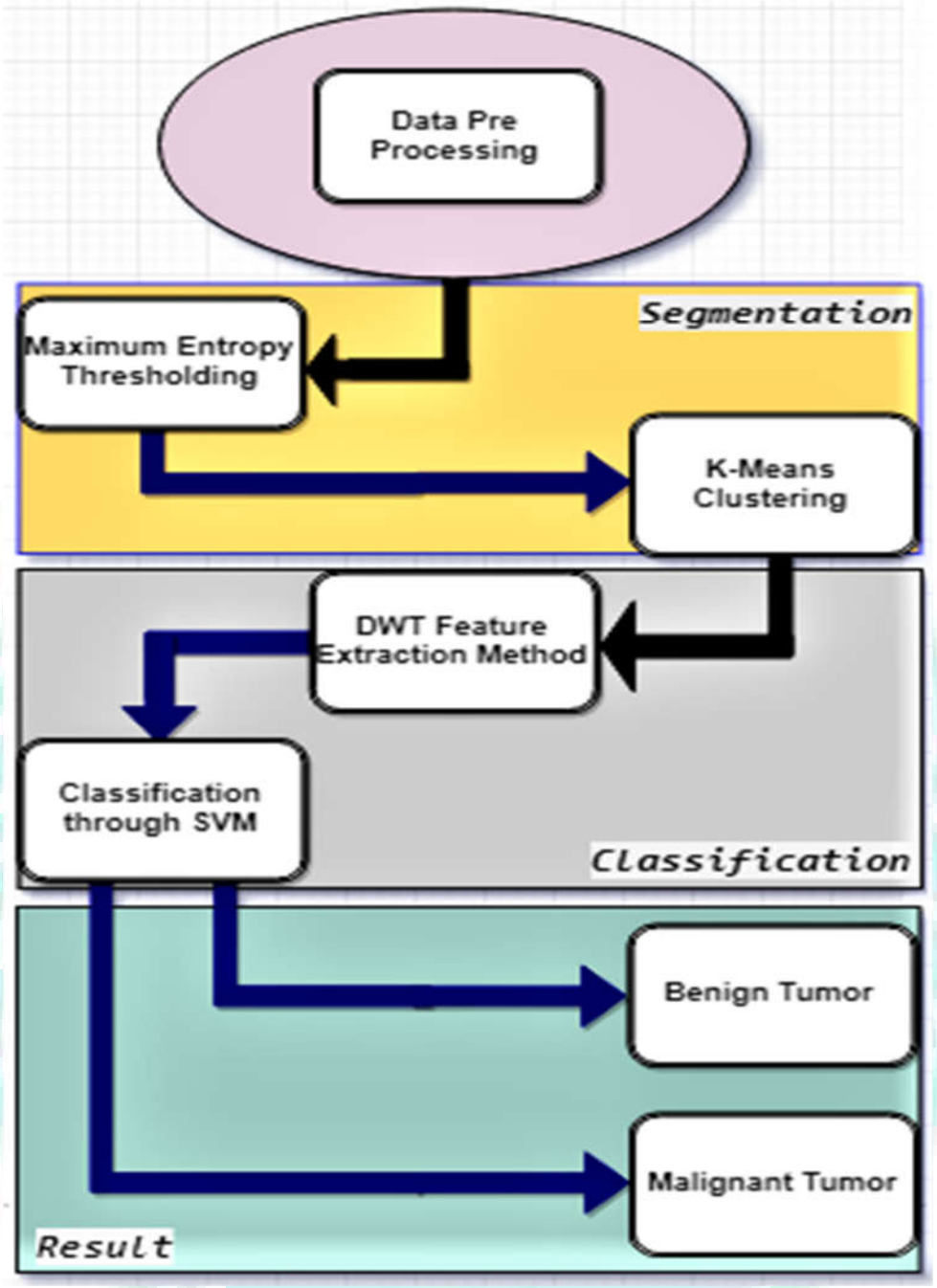

Figure 3.1: My Proposed Methodology

3.1. Data Pre-Processing

In data pre-processing stage, different steps have been performed. MRI scans has been resized and then converted into the gray image. The main artifact that affects the performance of brain tumor segmentation algorithms are the bias field distortion and background noise in MRI scans [43] that causes a slowly changing, inhomogeneous background. This problem has been studied in detail and have presented many solutions to it. Numerous algorithms of noise removal filers have been introduced. In my research, I have used Median filter to remove the background noise and distortion form the brain tumor MRI Scans.

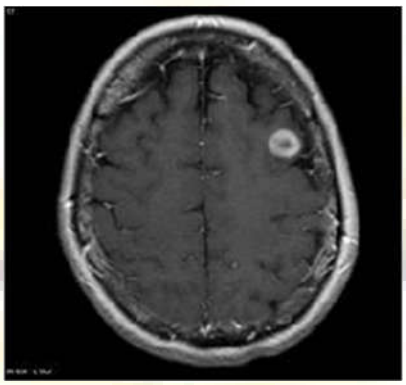

Figure 3.2(a): Original Image

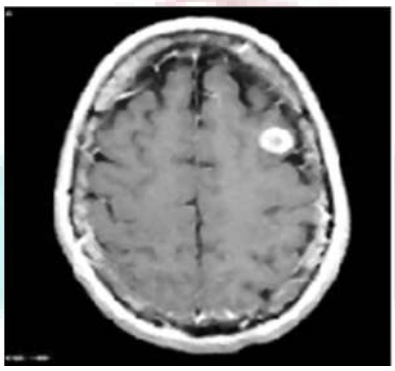

Figure 3.2 (b): Pre Processed Image

3.2. Segmentation

The main focus of this section is to differentiate the brain tumor cells from the healthy brain cell. My proposed technique has two steps to segment the tumor. These steps will help to

segment the tumor more accurately and precisely and to give more accurate classification. The first step is to segment an image by using maximum entropy thresholding technique [38]. To segment the image properly from background, the threshold should match to the response image. Maximum entropy thresholding algorithm is used to extract maximization of the information measure between object and background. It is based on the two dimensional histogram of an image which is composed of average gray level values i.e. gray level values of pixels and average gray level values of neighborhood [54].

The formula of two dimensional histogram is given below:

$$A_{ij} = \frac{n_{ij}}{N \times N}$$

Where N×N denotes images size and the pixels of images are denoted by n_{ij} whereas

- i is the grey level value
- j denotes the local average value.
- n_{ij} is the number of pixels.

Given below is the 2-Dimensional histogram plane of gray level values of each pixel and average gray level values of its neighboring pixels.

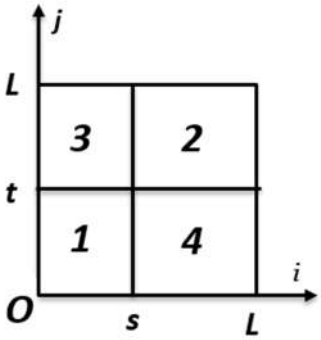

Figure 3.3: The 2D Histogram plane

Field 1 and field 2 in figure 3.3 represents the objects and background of an image while field 3 and field 4 represents the noises and boundaries of an image in histogram graph.

Where as the thresholding is (s, t). Suppose field 1 and field 2 have different probability distribution P1 and P2. Then the discrete entropy function can be defined as:

$$H(1) = \mathrm{H}(1) - \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p_{ij}\, log p_{ij}$$

$$H(2) = \mathrm{H}(2) - \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p_{ij}\, log p_{ij}$$

Field 1 and field 2 in the above given histogram plane has different probability values. The probability of both fields is normalized using posterior probabilities and are thus represented as *pij*. First formula H1 is used for finding the low entropy range whereas second formula H2 is for finding the high entropy range. After calculating both values the best threshold is evaluated by adding the maximum values of both ranges.

$$\varphi(s^*, t^*) = \max\{\varphi(s,t)\}$$

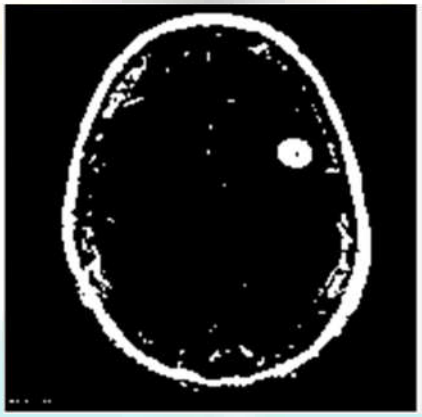

Figure 3.4: Entropy Threshold Image

3.3. K-means Clustering:

The second step is to apply K-means clustering algorithm to the acquired Thresholding brain tumor image. K-means clustering is the least square partitioning method that divides similar data into K groups. This algorithm basically computes the mean and distance of each cluster. This algorithm repeats its iteration until the least value is found **[7].** I have

used K-means clustering after the threshold segmentation to create efficient and soft boundaries for the given datasets.

The K-means clustering in my work is evaluated by the following formula:

$$M = \sum_{j-1}^{k} \sum_{i-1}^{n} \left| \left| x_i^{(j)} - c_j \right| \right|^2$$

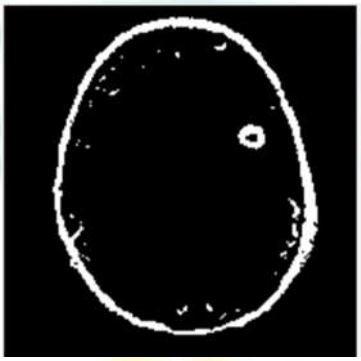

Figure 3.5: K Means Clustering

3.4. 2D Discrete Wavelet Transformation (DWT) Method:

This method is used along with the gray level co-occurrence matrix to extract the texture and intensity features of a brain MRI image.

Table 3.1: Extracted Features of Images

Features	Image 1	Image 2	Image 3
Contrast	0.3323	0.3042	0.2464
Correlation	0.1131	0.1640	0.0688
Energy	0.7812	0.7831	0.7387
Homogeneity	0.9357	0.9380	0.9266
Mean	0.0057	0.0057	0.0053
Standard	0.0896	0.0896	0.0897

Deviation			
Entropy	2.6194	2.8069	3.6152
Variance	0.0080	0.0081	0.0080
Smoothness	0.9549	0.9556	0.9521
Kurtosis	11.996	12.425	6.5725
Skewness	1.2347	1.1531	0.4970

3.5. Support Vector Machine Classification

Support Vector Machines (SVM) is a supervised statistical learning algorithm based on separating hyperplanes for classification and regression analysis. The features that are extracted by the DWT and GLCM method are analyzed and predicted by support vector machine to classify the data. It gives the output of my proposed methodology i.e. the classification of brain MRI images into Benign or Malignant type.

Figure 3.6: Classified Image

Algorithm:

Input: Brain Tumor MRI Image

Output: Classification of brain tumor image into Benign or Malignant

Procedure:

1. Apply preprocessing techniques such as resizing, denoising the image and converting the image in to gray image.
2. Apply Entropy thresholding on the preprocessed image

2.1.Make histogram of the image and normalize it.

a. For loop i=1: to the

i. Determine the lowest range of entropy

b. End of loop

a. Loop i=t+1: 256

i. Determine the highest range entropy

b. End of loop

2.2. Determine the best threshold value by adding both ranges.

a. If Statement entropie(t)>h_max

b. h_max=entropie(t);

c. threshold=t-1;

d. end

3. Determine the cluster of an image by partitioning the same objects into groups

a. for k = 1:nColors

i. colors = I;

ii. colors(rgb_label ~= k) = 0;

iii. segmented_images{k} = colors;

b. end

4. Calculate the texture and intensity based features of brain MRI image by DWT and GLCM methods

5. Run support vector machines algorithm to classify the tumor type existing in the brain MRI image.

Chapter 4

DATASETS AND PERFORMANCE EVALUATION PARAMETERS

Chapter 4 Datasets and Performance Evaluation Parameters

In this chapter, Datasets and performance evaluation parameters that are used in this research study are discussed. The performance of proposed techniques measured on the data sets (references of papers) and evaluate its benefits over existing methods proposed for segmentation and classification of brain tumor images.

4.1. Datasets

The MRI Scans used in this research are the 2D MRI slices of T1 weighted, T2 weighted and Fluid Attenuated Inversion Recovery (FLAIR) sequences. All the images are resized to the same resolution: 200*200 pixels. To expedite the training and test MRI images through SVM, I have divided the data set into two sets and named them as Train set A, B and Test set A, B.

Table 4.1: Detail of Data Sets used for experiments

Data Set ID	Number of Images	Images Format	Image Size
DSTRAIN A	40	.jpg	200*200
DSTRAIN B	40	.jpg	200*200
DSTEST A	40	.jpg	200*200
DSTEST B	40	.jpg	200*200

4.2. Performance Evaluation:

The performance of my proposed classification model is evaluated by confusion matrix [] on the test data whose true values are well-known. Some of the parameters of confusion matrix are discussed here. In 2*2 confusion Matrix, True Positive is the outcome when the positive class is predicted correctly whereas false positive is an outcome when the positive

class is predicted incorrectly. Similarly, True Negative is an outcome when the negative class is predicted correctly and False Negative is an outcome when the negative class is predicted incorrectly [55]. The equations of Sensitivity (True Positive Rate TPR), Specificity (True Negative Rate TNR), Positive Predictive Value PPV, Negative Predictive Value NPV, False Positive Rate FPR, False Negative Rate FNR, False Discovery Rate FDR and accuracy are given below:

Sensitivity:

$$TPR = \frac{TP}{TP + FN} \quad (4.1)$$

Specificity:

$$TNR = \frac{TN}{TN + FP} \quad (4.2)$$

Positive Predictive Value:

$$PPV = \frac{TP}{TP + FP} \quad (4.3)$$

Negative Predictive Value:

$$NPV = \frac{TN}{TN + FN} \quad (4.4)$$

False Positive Rate:

$$FPR = \frac{FP}{FP + TN} \quad (4.5)$$

False Negative Rate:

$$FNR = \frac{FN}{FN + TP} \quad (4.6)$$

False Discovery Rate:

$$FDR = \frac{FP}{FP + TP} \quad (4.7)$$

Accuracy:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \quad (4.8)$$

Chapter 5

EXPERIMENTAL RESULTS AND DISCUSSION

Chapter 5 Experimental Results and Discussion

In this chapter, the results of the proposed technique will be discussed and compared with other techniques used for the segmentation and classification of tumor from brain MRI images. This proposed system of classifying the brain tumor through entropy thresholding is developed using MATLAB version R2017a on Intel ® Core ™ i5 i5-2400 CPU @ 3.10GHz, 64-bit operating system with 6 GB RAM. These requirements were found suitable for this methodology as the MATLAB provides important functions that can simulate segmentation and classification analysis of brain tumor MRI images. Moreover, the MATLAB also provides functionality as a simulation tool for matrix operations.

5.1. Effects of Different Data Sets

In this study, I have used four groups of dataset of 2-D brain tumor MRI images. Each dataset consists of 40 images of T1 weighted, T2 weighted and FLAIR sequences of MRI slices to classify the images into Benign or Malignant brain tumor type. Table 3 shows the performance statistics of these datasets. Every dataset has different performance and quality measurements based on different data sets.

Table 5.1: Performance Statistics of proposed methodology datasets

	In Percentage				
Performance Statistics	**DSTRAIN A**	**DSTRAIN B**	**DSTEST A**	**DSTEST B**	**Average**
Sensitivity (TPR)	97.14	94.29	97.37	94.74	95.88
True Positive Rate (TNR)	66.67	80	100	100	86.66
Positive Predictive Value (PPV)	97.14	97.06	100	100	98.55
Negative Predictive Value (NPV)	80	66.67	66.67	50	65.83
Specificity (FPR)	4.86	4.71	0.98	1.06	2.90
False Negative Rate (FNR)	0.04	0.07	0.03	0.05	0.04
Accuracy (ACC)	96.73	94.50	97.50	96.6	96.33

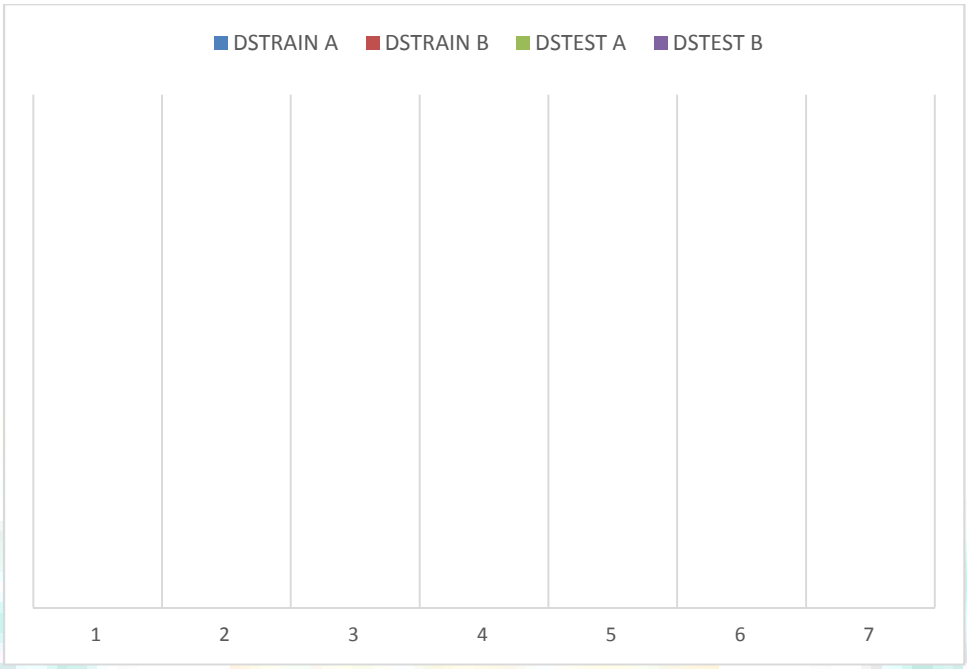

Figure 5.1: Performance Analysis of Datasets

5.2. Effects of Different Types of Classifier

I have used three different classifiers for classification of brain tumor. Table 5.3 illustrates the accuracy rate on DTEST B. Figure 5.2 demonstrate visual description of effects of different type of classifiers on accuracy rate. The best accuracy is achieved using RBF kernel classifier. The RBF kernel classifier itself decides the type of tumor.

Table 5.2: Performance Analysis (%) with different classifiers

Classifier	Sensitivity	Specificity	Accuracy Rate
Linear Kernel	66.74	1.16	66.45

Polynomial kernel	82.4	2.37	82.35
RBF kernel	95.88	2.90	96.33

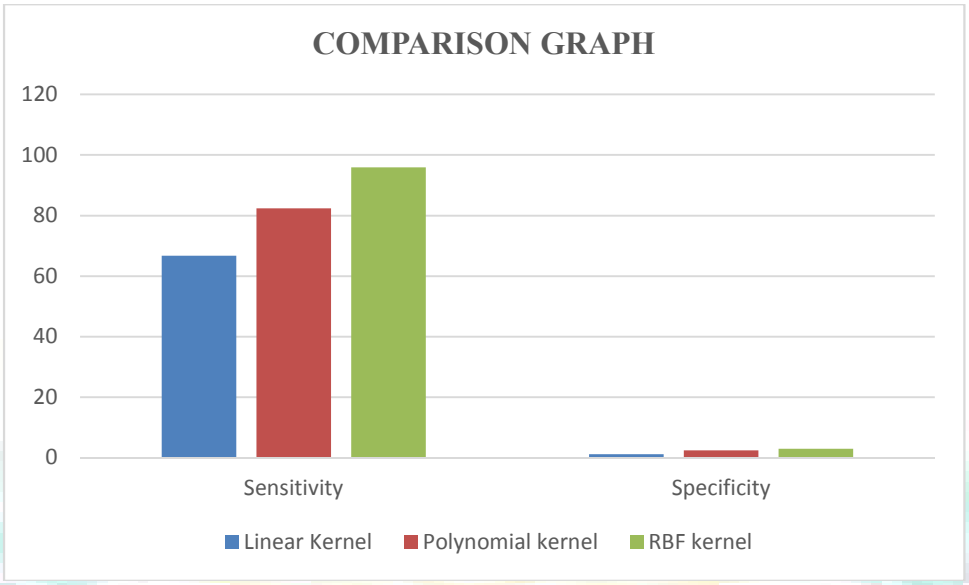

Figure 5.2: Comparison Graph for Sensitivity and Specificity

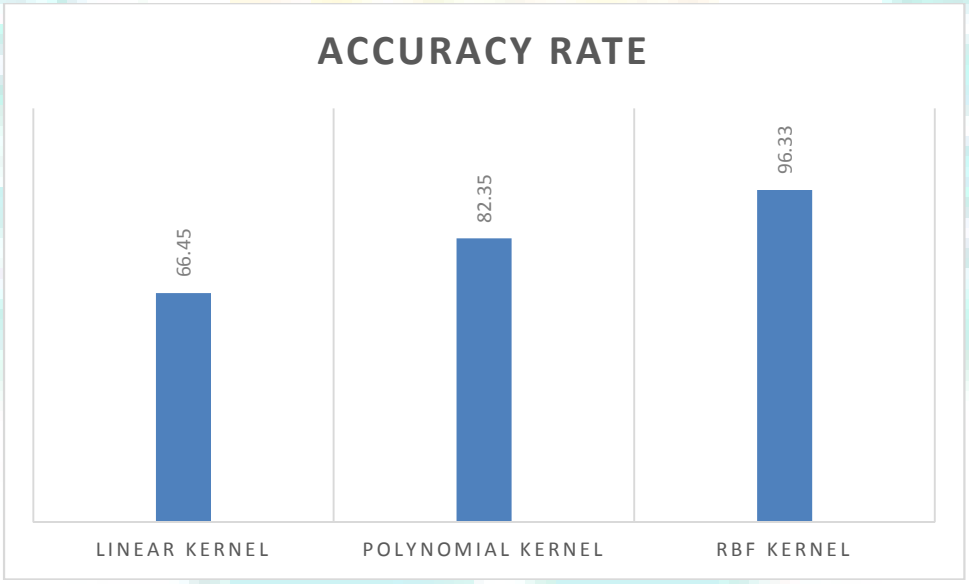

Figure 5.3: Comparison Graph for Accuracy

5.3. Comparison of proposed technique with State of Art

In this section, comparison in terms of accuracy is performed with other state of arts comprising of similar purpose to segment and classify the brain tumor MRI images using different algorithms. I have compared my proposed methodology with Padmanjali et al. [41], Nilesh et al. [40] and Stalin et al. [47]. I have implemented the techniques presented

by these authors to my dataset as the data on which they ran their techniques is not publically available. I found that the algorithm proposed by authors in [47] and [40] was computationally very complex and requires more time. The proposed algorithm is quite efficient and robust. The results obtain from these comparisons are presented below:

Table 5.3: Comparison table for proposed and existing method of accuracy

Methods	True Positive Rate	False Positive Rate	Accuracy (%)
ART Classifier [41]	98.50	2.10	90.42
Genetic Algorithm [40]	68.31	1.92	91.79
Fuzzy Algorithm [47]	59.42	1.37	94.34
Proposed Method	95.88	1.06	96.33

Chapter 6

CONCLUSION AND FUTURE WORK

Chapter 6 Conclusion

This chapter is concluded with the reassessment of the goal I had set out in the chapter 1. In this study, a technique to segment the tumor part of brain MRI images by maximum entropy thresholding to differentiate the foreground objects from background and to determine and softening the boundaries by applying K-Means clustering algorithm to the thresholded dataset .Then, the texture based features and intensity based features are extracted by Discrete Wavelet Transformation (DWT) and Gray Level Co-Occurrence Matrix (GLCM) respectively. Contrast, correlation, homogeneity, entropy, energy, skewness, kurtosis, smoothness, mean and variance are the features that are extracted for the accurate classification of brain tumor through support vector machine. The result of classification is being displayed on the command window of MATLAB. The experimental results of my study concludes that the accuracy measurement of this proposed techniques embraces 97.50 % accurate results.

6.1. Future Directions

Neuro Radiology of brain tumors has attained significant focus in the field of medical imaging. Researchers from all over the globe are proposing advance techniques and algorithms to make a system that could be clinically implemented to diagnose and classify brain tumor within minimum time along with highest accuracy and precision.

This proposed technique can be validated on a large dataset to enhance the accuracy rate. Moreover, Sub classification of benign and malignant tumor types can also be done by extracting the volume of 3-Dimensional brain tumor MRI dataset.

APPENDIX A

Sample Code for segmenting and classifying brain tumor

```
close all
clc
clear all
[filename,pathname] = uigetfile({'*.*';'*.bmp';'*.tif';'*.gif';'*.png'},'Pick an Image File');
im  = imread([pathname,filename]);
figure
subplot(2,2,1)
imshow(im)
title('Original Image');
im = imresize(im,[200,200]);

I = rgb2gray(im);
%
   [n,m]=size(I);
   h=imhist(I);
   %normalize the histogram ==>  hn(k)=h(k)/(n*m) ==> k  in [1 256]
   hn=h/(n*m);

   %Cumulative distribution function
   c(1) = hn(1);
   for l=2:256
      c(l)=c(l-1)+hn(l);
   end

   hl = zeros(1,256);
   hh = zeros(1,256);
   for t=1:256
      %low range entropy
      cl=double(c(t));
      if cl>0
         for i=1:t
            if hn(i)>0
               hl(t) = hl(t)- (hn(i)/cl)*log(hn(i)/cl);
            end
         end
      end

      %high range entropy
      ch=double(1.0-cl);  %constraint cl+ch=1
      if ch>0
         for i=t+1:256
            if hn(i)>0
               hh(t) = hh(t)- (hn(i)/ch)*log(hn(i)/ch);
            end
         end
      end
   end

   % choose best threshold

   h_max =hl(1)+hh(1)
   threshold = 0;
   entropie(1)=h_max;
   for t=2:256
      entropie(t)=hl(t)+hh(t);
      if entropie(t)>h_max
         h_max=entropie(t);
```

```
            threshold=t-1;
        end
    end

    % Display
    I1 = zeros(size(I));
    I1(I<threshold) = 0;
    I1(I>threshold) = 255;
subplot(2,2,2)
    imshow(I1)
    title('Entropy Thresholding')

%%
%%  K means Clustering to segment tumor

cform = makecform('srgb2lab');
% Apply the colorform
lab_he = applycform(im,cform);

%
ab = double(lab_he(:,:,2:3));
nrows = size(ab,1);
ncols = size(ab,2);
ab = reshape(ab,nrows*ncols,2);
nColors = 1;
[cluster_idx cluster_center] = kmeans(ab,nColors,'distance','sqEuclidean', ...
                                'Replicates',1);
[cluster_idx cluster_center] = kmeans(ab,nColors,'distance','sqEuclidean','Replicates',3);

pixel_labels = reshape(cluster_idx,nrows,ncols);

% Create a blank cell array to store the results of clustering
segmented_images = cell(1,3);
% Create RGB label using pixel_labels
rgb_label = repmat(pixel_labels,[1,1,3]);

for k = 1:nColors
    colors = I;
    colors(rgb_label ~= k) = 0;
    segmented_images{k} = colors;
end

seg_img = im2bw(segmented_images{1});
subplot(2,2,3)
imshow(seg_img);title('K-Means Clustering');


 %%  median filter
seg_img1 = medfilt2(seg_img);
subplot(2,2,4)
imshow(seg_img1)
title('Median filter')
    %% % Extract features using DWT
x = double(seg_img);
m = size(seg_img,1);
n = size(seg_img,2);
```

```
signal1 = seg_img(:,:);

[cA1,cH1,cV1,cD1] = dwt2(signal1,'db4');
[cA2,cH2,cV2,cD2] = dwt2(cA1,'db4');
[cA3,cH3,cV3,cD3] = dwt2(cA2,'db4');

DWT_feat = [cA3,cH3,cV3,cD3];
G = pca(DWT_feat);
whos DWT_feat
whos G
g = graycomatrix(G);
stats = graycoprops(g,'Contrast Correlation Energy Homogeneity');
Contrast = stats.Contrast;
Correlation = stats.Correlation;
Energy = stats.Energy;
Homogeneity = stats.Homogeneity;
Mean = mean2(G);
Standard_Deviation = std2(G);
Entropy = entropy(G);
RMS = mean2(rms(G));
%Skewness = skewness(img)
Variance = mean2(var(double(G)));
a = sum(double(G(:)));
Smoothness = 1-(1/(1+a));
Kurtosis = kurtosis(double(G(:)));
Skewness = skewness(double(G(:)));
% Inverse Difference Movement
m = size(G,1);
n = size(G,2);
in_diff = 0;
for i = 1:m
   for j = 1:n
      temp = G(i,j)./(1+(i-j).^2);
      in_diff = in_diff+temp;
   end
end
IDM = double(in_diff);
feat = [Contrast,Correlation,Energy,Homogeneity, Mean, Standard_Deviation, Entropy, RMS, Variance,
Smoothness, Kurtosis, Skewness, IDM];

load Trainset.mat
 xdata = meas;
 group = label;
 svmStruct1 = svmtrain(xdata,group,'kernel_function', 'linear');
 species = svmclassify(svmStruct1,feat,'showplot',false)

% To plot classification graphs, SVM can take only two dimensional data
data1   = [meas(:,1), meas(:,2)];
newfeat = [feat(:,1),feat(:,2)];

 pause
%close all

svmStruct1_new = svmtrain(data1,group,'kernel_function', 'linear','showplot',false);
species_Linear_new = svmclassify(svmStruct1_new,newfeat,'showplot',false);
%
% %%
% Multiple runs for accuracy highest is 90%
```

```
load Trainset.mat
%data   = [meas(:,1), meas(:,2)];
data = meas;
groups = ismember(label,'BENIGN   ');
groups = ismember(label,'MALIGNANT');
[train,test] = crossvalind('HoldOut',groups);
cp = classperf(groups);
%svmStruct = svmtrain(data(train,:),groups(train),'boxconstraint',Inf,'showplot',false,'kernel_function','rbf');
svmStruct = svmtrain(data(train,:),groups(train),'showplot',false,'kernel_function','linear');
classes = svmclassify(svmStruct,data(test,:),'showplot',false);
classperf(cp,classes,test);
Accuracy_Classification = cp.CorrectRate.*100;
sprintf('Accuracy of Linear kernel is: %g%%',Accuracy_Classification)
```

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