Hybrid Approach to Differentiate Healthy and Pathological Tissues from MR Brain Images

Thesis submitted in partial fulfillment of the requirements for
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Submitted by
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CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, "**Hybrid Approach to Differentiate Healthy and Pathological Tissues From MR Brain Images**", in partial fulfilment of the requirements for the award of degree of Master of Engineering in Computer Science and Engineering submitted in Computer Science and Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of **Dr. Rajiv Kumar** and refers other researcher's work which are duly listed in the reference section.

The matter presented in the thesis has not been submitted for award of any other degree of this or any other University.

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This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

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ABSTRACT

Medical image processing is one of the areas in which researchers have an affinity to working. By the advancements in the computer technology, improved techniques of data acquisition newline, analysis, processing, and visualization have a great impact on medical image processing. Magnetic resonance images (MRI) provides information about potential abnormal tissues necessary for medical newline follow up. Brain MRI gets additional importance in medical science as it is the only preliminary method of diagnosing a brain tumor. MRI helps the radiologist to acquire and visualize images of the brain tumor for anatomical judgment in a non-invasive way. A Brain tumor is one of the destructive and devastating types of disease. It can be cure by its detection in early stage followed by the treatment. Therefore, it is necessary to propose the method which can efficiently identify whether the patient is suffering from a brain tumor or not. This thesis addresses the newline problem of detection and classification of brain tumors. The important points in this research have been to develop and implement a robust algorithm for newline the classification of the Brain MRI images as normal or abnormal in this thesis. a hybrid approach has been proposed for detecting and classifying brain tumor using MR Images. The proposed approach comprises of four phases. In the phase-1, pre-processing is done after that in phase-2 thresholding technique is applied. In next phase, feature selection is done using Horlick features and finally in the fourth phase, classification is done using different classifier. The dataset comprises of three MRI scan images that are T1-weighted scan, Proton Density scan and T2-weighted scan. The experimental results of proposed method have been evaluated and validated for performance and quality analysis on brain MRI images based on specificity, accuracy and specificity.

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ABBREVIATIONS

MRI	Magnetic resonance images
PET	Positron emission tomography
CSF	Cerebrospinal Fluid
WM	White Matter
GM	Gray Matter
CLAHE	Contrast Limited Adaptive Histogram Equalization
GLCM	Gray- level Co-occurrence Matrix
DWT	Discrete Wavelet Transform
DCE	Dynamic Contrast Enhanced
PSNR	Peak Signal to Noise Ratio
MSE	Mean Square Error
FLAIR	Fluid Attenuated Inversion Recovery
FCM	Fuzzy C-Means
LDA	Linear Discriminant Analysis
PCA	Principal Component Analysis
SVM	Support Vector Machine
KNN	K-Nearest Neighbor
ANN	Artificial Neural Network
MLP	Multi-layer Perceptron
CAD	Computer Aided Design

Chapter 1

Introduction

The influence and consequences of digital images on this burgeoning society are numerous which has changed the way how people think and operate in a particular phenomenon. They key example of it can be seen in the field of image handling, which is playing a conspicuous role in innovation and development. The rapid advancement in the area of electronic restorative image restoration, investigation procedures and computer-aided diagnosis has impelled therapeutic imaging to a unique position among the critical subfields of scientific imaging. This chapter covers all the basic aspects of the brain tumor and sets the background for the whole thesis work. The knowledge about the brain tissues, diagnosis techniques and other important evaluation measures for detection of the tumor are covered. An improved technique of data acquisition, analysis and visualization have been evolved over a period of time, which is delineated in the thesis.

1.1 Human Brain: Anatomy and Anomalies

The human brain is a delicate mass of steady tissues and nerve cells. The body functions like movement, inhale, coordination, heartbeat are controlled by the central nervous system that forms by the combination of spinal cord and nerve cells. On the basis of the data obtained from American Cancer Society (ASCO) [1], the death rate is increasing very fast and the reason is cancer. There are various reasons of spreading cancer like unhealthy food, modern technology, stressful events. and the symptoms of brain cancer included weight loss, tiredness, sweating, and loss of craving.

The cerebrum is the largest part of the brain. The cerebral cortex is the outermost layer of the cerebrum. The cortex of brain consists of four lobes namely, occipital lobe, frontal lobe, temporal lobe and parietal lobe as shown in Figure1.1 [9]. Occipital lobe processes the visual information and lies at the back of the brain. The frontal lobe, temporal lobe consists of amygdala and hippocampus that are responsible for emotion and memory. Parietal lobe combines the inputs from various senses that are necessary for spatial navigation. Forebrain, midbrain and hindbrain are the three parts where human brain develops. These three sections contain fluid-filled cavities known as ventricles. Forebrain develops in cerebrum where midbrain is part of brainstem and hindbrain boosts the regions of cerebellum and brainstem. Concluding with the fact that brain is responsible for all the neurological activities occurring in the body.

While brain has only weighed about 3 pounds. But it is arguably and important part of the human body so cure of brain tumor and diagnosis at an early stage is important. So that we can perform the actions like feeling and thinking properly. The next section throws light on brain tumor and its types.

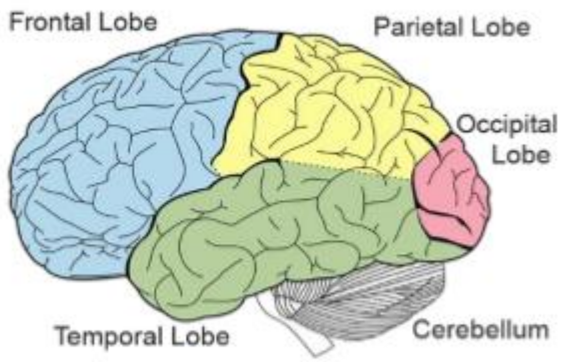

Figure 1.1: Lobes of Human Brain [9]

1.2 Types of Brain Tumor

The cancer of brain is a troupe of unusual and uncontrolled growing cancerous cells. Brain Tumor occurs because when cells damaged and new cells come in place of old cells. If the cell is not properly done, then abnormal multiplications of the cell take place due to this reason tumor spreads. A brain tumor is of two types, benign and malignant, that can influence both kids and adult. The primary tumor belongs to the category of benign category whereas secondary tumor comes under the malignant tumor. Benign and malignant tumors are also categorized according to the grading system. The brief discussion of the tumors are described below:

a) **Benign and malignant tumors**

A benign tumor does not consist of active (non-cancerous) cells and has homogeneity in structure. It can be dangerous in light of the fact that as it broadens it can push on soft tissues that affect their normal working [17]. The benign tumor consists of harmless cells that can be removed completely. But this type of tumor causes permanent damage and unbearable pain in the brain that can cause even death.

Malignant tumor comprises of active (cancerous) cells and has heterogeneity in structure. Cancerous cells may develop gradually or quickly. The malignant tumor is serious and life threatening.

b) Primary and secondary tumor

Primary tumor starts in the brain itself. They delineate all cancer around 1% and all cancer death about 2.5 %. It can either be cancerous or benign.

The secondary tumor occurs as result of metastasis that spreads from other body parts like kidney, breast, and lungs to the brain.

c) Grading tumor

Grading tumor consists of two types low-grade and high-grade tumor as described below

Low-grade tumor-like gliomas and meningioma are an example of this type of tumor and it comes in the category of benign tumors.

High-grade tumor-like glioblastoma and astrocytoma exist under this class of tumor and it comes in the category of malignant tumors.

The world health organization (WHO) classifies the brain cancer into four sections namely, grade I, II, III and IV. The grading scale used from grade I to grade IV for classifying the benign and malignant tumor types. On the basis of the scale grade I and II, glioma fall under the category of benign tumor whereas grade III and IV glioma comes under the category of the malignant tumor [2]. The grade I and II glioma are known as cancer of low grade while grade III and IV are known as cancer of high grade.

The techniques for treating both the type of these tumors are different. Surgery can prove effective in the case of the low-grade I and II glioma. But a proper high defined mechanism is required for the high grade III and IV glioma for treatment. The techniques like chemotherapy, radiotherapy, or using any combination of these can work bliss for curing this type of tumor. In case any low-grade tumor is not detected and treated at an earlier stage it may convert into the high-grade tumor and resulting faulty. The visual depiction of both the types of tumor (benign and malignant) is shown in Figure 1.2.

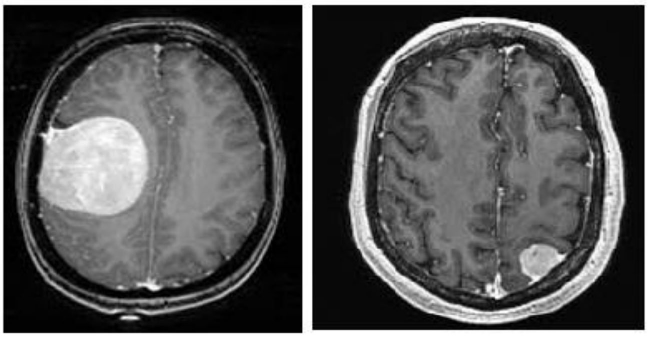

Figure 1.2 Benign and Malignant Tumor

1.3 Diagnosis Techniques Used in Brain Tumor

The researchers have given a lot of evidence about how the existence of tumor can affect the body. The timely diagnosis and detection is the most important target of the radiologist and the surgeons. The mechanisms that assist them in diagnosis are ultrasound scanning, computed Tomography (CT) scanning, X-ray scanning, which makes imaging procedure very effective are shown in Figure 1.3.

The common methods, used for diagnosis in the medical field for cancer detection are namely, biopsy, human prediction, expert view and etc. The biopsy technique used to test whether a person is normal or suffering from abnormality. This process takes around ten to sixteen days which can be a long time for recognition of cancer in the era of modern technology. Human observation may cause an error in some cases. Nevertheless, the computer can deal in a better way without causing any error in the inspection. The digital expertise use in decision support system of medical is very pervasive and huge through medical fields like brain cancer, heart diseases etc. [6]. Expert cannot find conclusion himself rather they take opinion from another expert for final decision in recent time, various techniques are available for diagnosis of disease in medical imaging which includes Computed Tomography (CT) scan, MRI scan, X-ray scan, ultrasound scan which makes imaging procedure very effective these techniques are very accurate, fast and effective as compared to biopsy and other techniques. With the help of these methods, doctors can start their treatment on the very first day of detection the disease.

The tools of imaging that help the doctors to see the inside of the body and attain images of nerves, bones, muscles etc. so that they can find the abnormalities if present in the body. Some of them are discussed below:

- **X-ray scan** also known as radiographs is the most common technique used for diagnosis purpose. It uses the electromagnetic waves and film to view the internal parts of the body. The radiation exposure level of x-ray not so harmful but the doctor still takes precautions while taking x-rays. Orthopedic damage, pneumonia, tumor are detected with the help of x-ray scan.
- **An ultrasound scan** is another technique that uses the high-frequency sound waves to view the internal parts of the body. It is also called sonography. Basically, ultrasound is beneficial for surgeons to perform various biopsies and also helps to recognize the problems in kidney, liver and heart [20]. It's a medical imaging tool that helps the doctors to evaluate and detect the disease.
- **Computed tomography (CT*)*** is one of the tools that are used in medical imaging to produce more detailed and cross-sectional view of the body. It can be applied to each region of the body for reasons of diagnosis and screening. The diagnosis the CT scan works in hands with x-ray scan equipment.

1.4 Magnetic Resonance Imaging (MRI)

The brain plays a vital role in the human body so it is a matter of interest for researchers to work on it. Magnetic resonance imaging (MRI) has proved to be an efficient tool for the diagnosing brain tissues in medical imaging. There are multiple advantages of MRI that provides non-invasive, and takes only 2 minutes to get the data by scanning the entire body. For a better contrast of cancer present in the brain, MRI is preferred [8]. MRI provides comfortable results than other methods of diagnosis because it uses a magnetic field and radio waves instead of any type of radiations which can affect the human body in the wrong manner. It basically calculates the proton changes due to the strong magnetic field and radio frequency. The magnetic field is measured by using the units called Tesla and gauss.

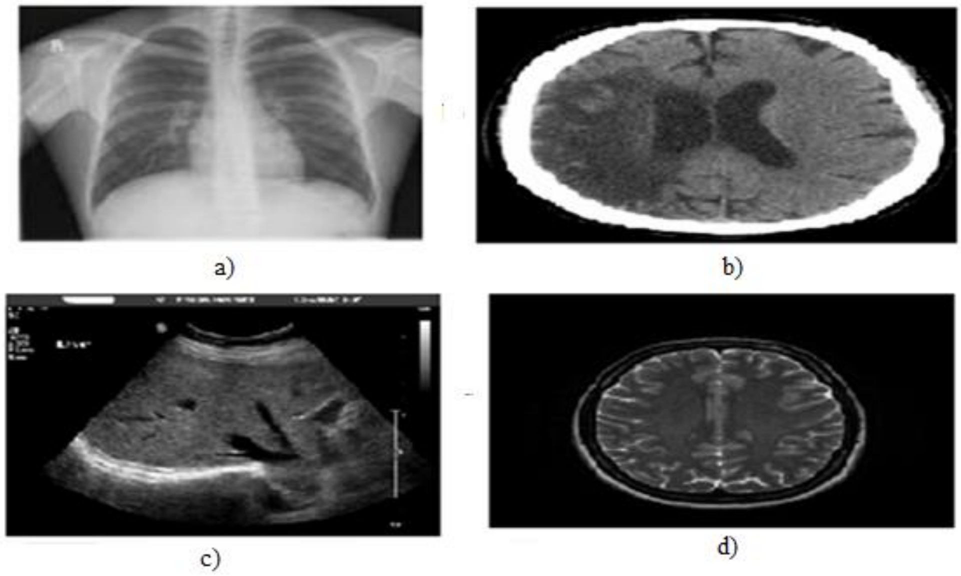

Figure 1.3: The Different Diagnosis Technique a) X-ray of Lungs b) CT of Brain c) Ultrasound of Stomach d) Brain MRI

1.5 Types of MR images

MRI consist of sequence images which are TI-weighted MR image, T2 weighted MR image, FLAIR weighted MR image, proton density (PD) MR image [16]. Most commonly used MRI sequence TI-weighted image and T2 weighted image can be differentiated by looking the CSF. If CSF is looking dark on the image it is called T1 weighted image and bright CSF described the T2 weighted image. The third sequence image of MRI is Fluid Attenuated Inversion Recovery (FLAIR) which easily makes the difference between CSF and brain cancer. Figure 1.4 shows the MRI sequence images.

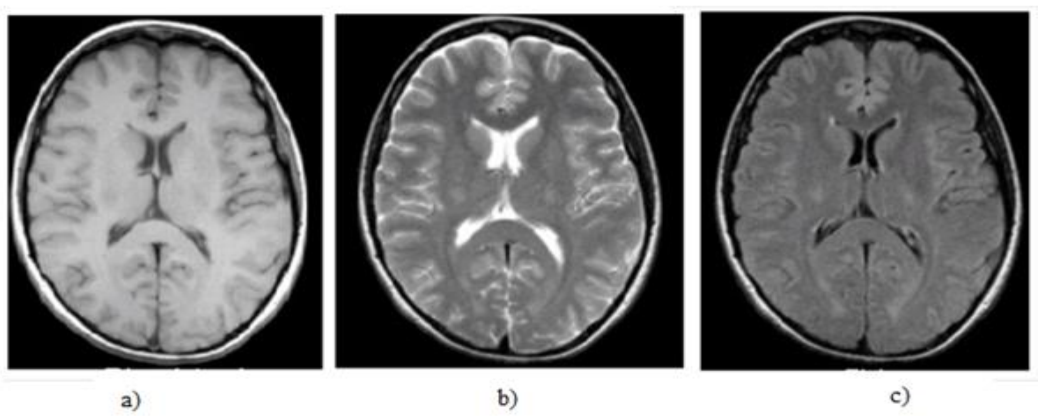

Figure 1.4: MRI Sequences a) T1 weighted scan b) T2 weighted scan c) Flair scan

There are three types of tissues present in the brain called white matter, Gray matter and CSF. If the CSF is bright then it is T2 weighted image and dark represents T1 weighted or FLAIR image. The tissue white matter is light gray it categorizes in T1 weighted image otherwise dark gray color of white matter is either T2 weighted image or FLAIR image. The third tissue gray matter dark delineates the T1 weighted image. The information regarding three tissues of brain MRI has shown in below Table 1.1.

Table 1.1: Details Regarding the Tissues of MRI Brain

Tissues	**TI weighted image**	**T2 weighted image**	**FLAIR image**
White matter	Light gray	Dark gray	Dark gray
CSF	Dark	Bright	Dark
Gray matter	Dark	Bright	Bright

1.6 Planes in MRI Imaging

MRI has three planes to visualize an anatomy are an axial plane, sagittal plane, the coronal plane has shown in Figure 1.5.

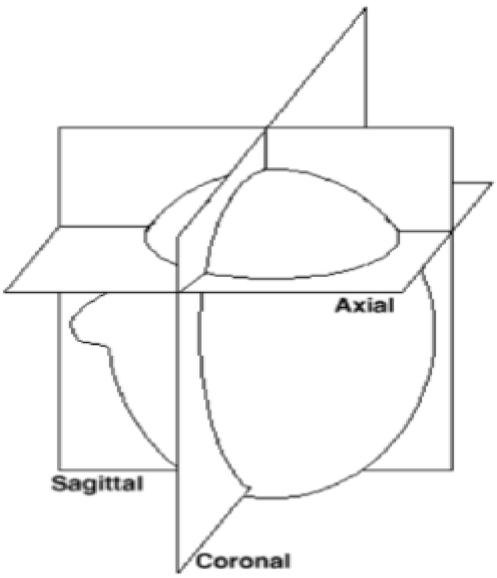

Figure 1.5: Three Planes of MRI

MRI consists of three different planes based on which the visual capturing is done.

X axis – from back to front of person

Y axis – from left arm to right arm of person

Z axis – from head to foot of person

When strong magnetic field used then patient process along the z direction. When proton releases the energy that period is called relaxation time. There are two types of relaxation time called TI and T2. TI is called longitudinal relaxation time while T2 is called transverse relaxation time.

- **Axial plane**

In Radiology, the axial plane is used as standard imaging and this plane is also known as transverse plane. the multiplane reformats (MPR) from the axial plane can be generated for a different view from the same information. The axial plane of three different sequences of MRI images as shown in Figure 1.6.

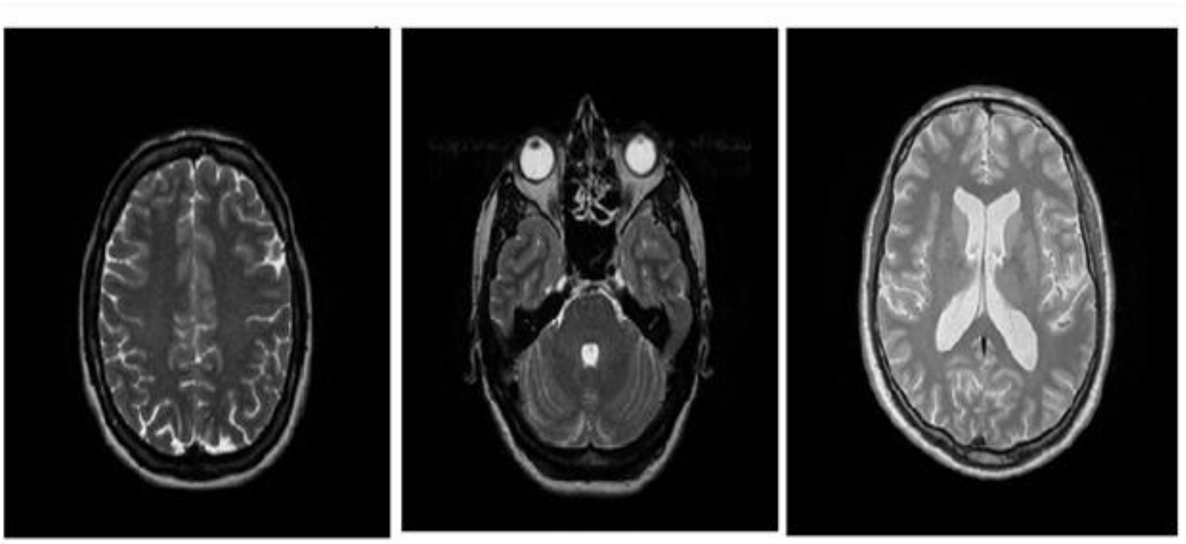

Figure 1.6: Axial MRI Normal Brain

- **Sagittal Plane**

Images of MR brain sagittal plane are taken opposite to the pivotal plane which particular the left and right sides (lateral view). Figure 1.7 shows the sagittal MRI images of normal

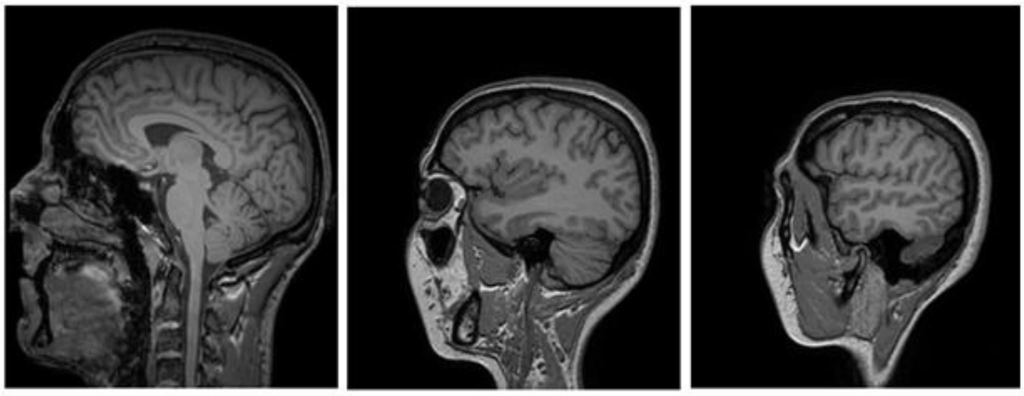

Figure 1.7: Sagittal MRI Normal brain

- **Coronal Plane**

MRI cerebrum Images of the coronal plane taken opposite to the sagittal plane which varies the front from the back. (frontal view). Figure 1.8 shows the coronal view of normal brain

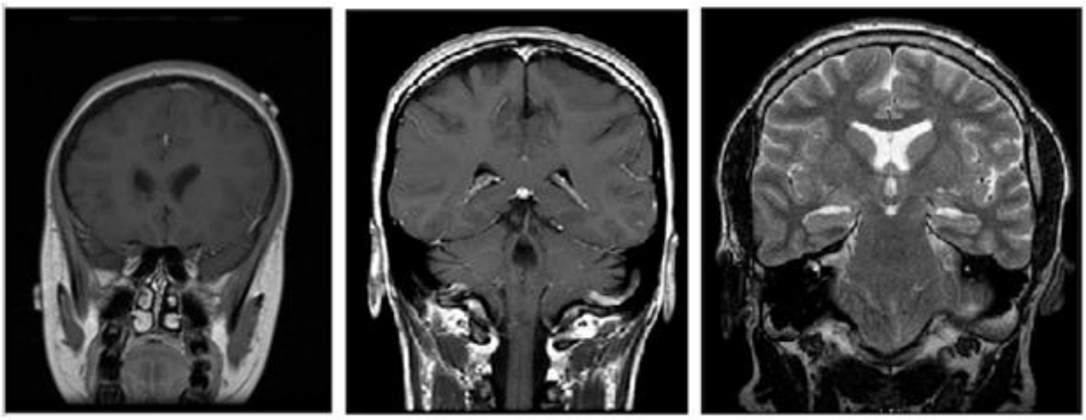

Figure 1.8: Coronal MRI Normal Brain

1.7 Work motivation

The root cause of tumor detection is detecting the abnormal tissues with efficient accuracy is of high interest in medical imaging research. Detection of the tumor is necessary at an early stage because the brain is very sensitive part of human body. In case the tumor spreads and proper diagnosis is not done on time, then it may cause to death. Brain neoplasms characterizing based on histopathologic analysis following surgical biopsy or resection has a limitation which includes sampling error and interpretation variability. So, computer assistance provides a reliable and reproducible procedure for the diagnosis of a tumor in the brain than human readers. The radiological decision depends on imaging like MRI. Sometimes neoplastic tissue shows heterogeneity in imaging and spatial profiles. that creates the problem in tumor characterization. If the approaches are proven accurate for assistance the doctor in the detection of cancer disease, then it can avoid invasive method like biopsy which is time-consuming and expedite the diagnosis. Towards the same goal, many existing techniques like Spatial-Fuzzy C-Means (FCM) for classification benign and malign brain tumor [1] on TI-weighted MRI and T2 weighted MRI. Spectroscopic MR imaging was used in [15] to differentiate normal brain and brain neoplasms by applying a fast bounding box for segmentation and classifier SVM. In [32] compares the two methods namely, Grey Level Statistic Features and Gabor Wavelet features for MRI tumor detection. Global and local thresholding is applied as segmentation [13] on mammograms images. GLCM for features extraction is used in [6] and SVM classifier with 3 kernel radial basis function, polynomial, linear are applied on MRI brain images. Median filter with a hybrid SVM-KNN approach for classification purpose is used. There is no doubt that these techniques are efficient and good for detection but some loopholes are present in these techniques.

Proposed technique tries to cover these loopholes by combining methods for increasing the accuracy of classification and thus, assisting the doctors during surgeries.

1.8 Thesis structure

This thesis composed of six chapters. Chapter 1 gives the introduction on a brain tumor. It explains the types of tumor and its diagnosis techniques and planes in MRI. Chapter 2 gives an overview of an existing algorithm for detection and classification of brain cancer. Chapter 3 reveals the problem definition, gap analysis and objectives. Chapter 4 this chapter discusses the implementation and development of proposed algorithm. Chapter 5 discusses the proposed algorithm results. Chapter 6 this reveals the conclusion of the work and future directions.

To understand the current state of the art, literature has been reviewed and presented in next section.

Chapter 2

Literature survey

Brain tumor identification with MRI pictures is going to be more and more essential within the medical field. The identification method primarily consists of 2 steps specifically, classification and segmentation. Image classification is that the methodology of composing the abnormal pictures into varied bunches on basis of some likeness live. The accuracy of this abnormality identification procedure should be basically high since the treatment arrangement supported this detection. The second step segmentation which is utilized to remove the irregular segment important for volumetric testing. This volumetric examination decides the impact of the treatment on the patient which might be judged from the separated size and state of the strange half. several analysis papers with varied methodologies for image classification and segmentation area unit accounted within the literature. so as to grasp this state of the art during this space, a survey of labour done associated with segmentation and classification of traditional and abnormal MRI pictures has been conferred during this chapter.

Vijayakumar et.al [2007] purposed the method for segmentation of brain cancer on images of an apparent dispersion coefficient and ANN has been used to evaluate of its malignancy state. Initially, the ADC pictures are decayed by multiresolution wavelets, a photograph is decayed by multiresolution ripple, which formed filtered images. Initially, the ADC pictures are decayed by multiresolution wavelets, ripples, which are in this manner specifically recreated to shape wavelet sifted pictures. These wavelets separated pictures alongside FLAIR and T2 weighted pictures have been used as the components component to unsupervised neural system – self-arranging maps (SOM) – to fragment the tumor, edema, CSF and typical tissue mathematical function Som to share the neoplasm, dropsy, CSF and typical tissue paper and grade the threatening condition of the tumor. A novel division algorithm in light of the quantity of hits experienced by Best Matching Units (BMU) on SOM maps is proposed. The outcomes demonstrate that the SOM performs well in separating the tumor, edema, hydrops, CSF and typical tissue design vectors on ADC pictures. Utilizing the prepared SOM and proposed division calculation, reckoning, we can recognize high or second rate tumor, edema, corruption, CSF and typical tissue. The outcomes are approved against physically segmented pictures and affect Initially and got specificity 98% and sensitivity 86%.

Sharma et.al [2008] presented the algorithm for the analysis of medicinal pictures in light of hybridization of syntactic and measurable methodologies, utilizing Artificial neural system (ANN). In this paper, a method for segmentation and characterization of delicate tissues on the premise of textural components of medicinal pictures in view of BAM-sort ANN particularly modified for image handling is set up. The plan of calculation has been founded on the idea that diverse sorts of delicate tissues have distinctive textural highlights, on the premise of which a clinician performs segmentation and characterization; thus conclusion could be made. The conventional ANN was not able to perform well in noisy presence. The modified BAM –type ANN overcomes the problem of noise.

Hemanthl et.al. [2009] purposed the effective fuzzy clustering algorithm for detection of abnormal MR brain image. The fuzzy C-means algorithm has been implemented by utilizing the data compression system without incorporating the weight factor in cluster center updation basis which additionally accelerates the procedure other than yielding extensive segmentation effectiveness. the improved FCM algorithm has utilized for grouping abnormal MR images from four tumor classes specifically, metastases, glioma and astrocytoma. Texture features like, correlation, entropy and energy are extricated from the images and utilized for the algorithm of clustering. convergence rate and segmentation efficiency were the parameters for analyzing the output of segmentation. A relative investigation was performed with the ordinary FCM calculation to demonstrate the unrivaled nature regarding convergence rate. Results concluded that modified FCM got superior results than conventional FCM in terms of convergence rate.

Kumar et.al. [2011] gave the system for classification using PCA-ANN and segmentation by gradient vector flow. In the purposed study, GVF was utilized for separating tumor limits (ROIs). PCA for lessening of the dimensionality of the features and multiclass classification of cerebrum tumors utilizing ANN has been proposed. The execution of PCA-ANN has been assessed for a dataset of 856 ROIs from 428 pictures. The experiment performed comprised of primary tumors and secondary tumors which contrast in each angle in their appearance, area, size, and shape. PCA-ANN has conveyed the overall accuracy of 91.7%.

Qurat -ul-Ain [2010] Proposed framework is produced for diagnosing the cerebrum tumor from mind MR pictures. This framework plays out the diagnosis in different stages. diagnosis first stage was the extraction of the first order and second order texture features. These extricated highlights are utilized for classification. In grouping stage proposed framework utilized ensemble base classifier for arranging mind pictures as malignant and benign. Once the pictures are resolved as harmful these are additionally prepared for tumor extraction from them. Tumor extraction was performed in the division stage. segmentation stage is a multistep stage. It initially expels the skull part of the mind and after that concentrates the tumor area.

Arizmendi et.al. [2011] have developed the method of binary classification of brain cancer by using energy criteria and Discrete Wavelet Transform (DWT). Data pre-preparing has known to be of extraordinary significance in issues of tumor sort classification in light of Magnetic Resonance Spectroscopy (MRS) signal. A blend of the Discrete Wavelet Transform (DWT) for decomposition of signal and for signal reconstruction energy criteria used as a part of this short paper as a past stride to information dimensionality lessening and classification utilizing Bayesian ANNs.

Rathi and Palani [2012] presented an approach for the extraction of function and selection of MR cancer images. Magnetic resonance imaging of brain tumors The classification with selection and extraction of characteristics has been made in the document. The approach recommended in this work was data collection, normalization, intensity, shape and texture extraction characteristics, including determination and classification. In this technique, shape, intensity and texture are extracted and used for grouping. Essential characteristics are chosen to use LDA. The results are contrasted and the strategies of decreasing the PCA measurement. The number of characteristics selected or extracted by PCA and the classification accuracy by SVM obtained 98.87%. In this technique, the framework has been prepared by constant and without persistent information. Therefore, limit the error rate and increase the accuracy of the classification.

Selvakumar et.al. [2012] introduced the use of Simple Segmentation Algorithm for the recognition of the range and state of tumors in the MRI brain imaging. The designed CAD system worked with a combination of two algorithms for the segmentation process. The proposed framework basically has four modules: pre-processing, segmentation, extraction of characteristics and approximate reasoning. The pre-processing step has been completed using the filtration technique. The segmentation was completed by cutting-edge K-calculations and diffuse C-calculations (FCM). The extraction of light was done by a threshold. Finally, the approximate reasoning strategy for perceiving the shape and position of the tumor in the MRI image using the edge placement technique. The proposed technique was mixed with two calculations. In the approximation, the reasoning tumor area was calculated by the binarization technique.

Mohanaiah et.al [2013] presented the technique of texture feature extraction from GLCM. Primitive or low-level image components can be either general elements, for example, color extraction, surface and shape or area particular features. This research work exhibited a consumption of gray level co-occurrence matrix (GLCM) to extricate second order statistical texture components for movement estimation of images. The Four features, in particular, ASM, Correlation, Inverse IDM, and Entropy are figured utilizing Xilinx FPGA. The results reveal that these texture features have great separation accuracy, involves less computation time and consequently proficiently developed for continuing Pattern recognition applications.

Rosy Kumari [2013] purposed an SVM classification based approach for recognition of abnormality in brain MR pictures. The proposed approach comprised of two stages were classification and feature extraction. In first stage extraction of features from images was done with the help of GLCM. In the following stage, extricated features were bolstered as a contribution to classifier called support vector machine. It categorizes the pictures amongst abnormal and normal alongside sort of illness relying on features. For Brain MRI pictures; feature extraction using GLCM offers 98% accuracy rate with SVM radial basis kernel function. Sensitivity and specificity were also used for performance analysis.

Rajeshwari and Sharmila [2013] presented the pre-processing techniques on MR images. The paper focussed on image quality improvement and enhancement in resolution. In this study three filters median, average and Weiner filter were used for denoising the images and for resolution enhancement, the technique called Discrete Wavelet Transform (DWT) based on interpolation was applied. Peak Signal to Noise Ratio (PSNR) and mean square error (MSE) as evaluation metrics for measuring the performance the techniques. The quantitative measure demonstrated that the determination improvement system was having better PSNR contrasted with the denoised images. In this manner, while dissecting image pre-processing both the image denoising and resolution methods were fundamental for enhancing the subjective execution of the images.

Ibrahim et.al. [2013] presented the classification system of MRI brain using a neural network. This paper presented Neural Network systems in order to classify MRI brain images as normal or abnormal. The proposed Neural Network procedure comprised of three phases, pre-processing, dimensionality decrease, and classification. In the first phase, the MR images were obtained and changed it to information shape (encoded data that can be put away, controlled and transmitted by advanced gadgets), in the second stage for dimensionality reduction principal component analysis were applied (PCA), at that point in the order to classify the Back-Propagation Neural Network has been utilized as a classifier to classify subjects as abnormal or normal MRI cerebrum images. In the analysis 3×58 datasets of MRI Brain Sagittal, pictures have been utilized for spoiling and testing the proposed strategy. The consequence of the proposed strategy was contrasted and the aftereffects of benchmark calculations, and it presents legitimacy as aggressive outcomes quality-wise, and demonstrated that the accuracy of purposed technique obtained 96.33%.

Hooda et.al [2014] purposed an automatic system for detection of a tumor in the brain using MR images. The constant database has been taken from Rajiv Gandhi Cancer Institute and Research Center, Delhi, India (RGCI&RC). The paper discussed the performance of various segmentation techniques, viz., Fuzzy C-Means Clustering (FCM), K-Means Clustering, Region Growing for identification of mind tumor from test MRI scan of the cerebrum. The execution assessment of the mentioned systems has been done on the premise of error percentage rate when contrasted with ground truth.

The region of the recognized tumor has compared with territory figured by the algorithms and the outcomes are assessed on the premise of error rate. The results described that FCM provided effective results than other segmentation techniques.

Nandpuru et.al. [2014] purposed automated system for classification of MRI brain cancer. The images from three orientation axial, coronal, sagittal have been taken for the research work.in the paper pre-processing has been done using a median filter to remove the different noises obtained during scanning procedure and after that skull masking has been used. Feature extraction is done by three type of features Gray scale, texture, symmetrical features. PCA used to reduce the dimensionality of data set. SVM with linear, Quadratic and Polynomial kernel has been applied on MRI brain cancer images for classification of normal and abnormal brain tissues.

Torheim et.al. [2014] purposed the system for classification of the dynamic contrast-enhanced MR images of cervical cancer using SVM and texture analysis. The purposed work was to decide that if the result of this treatment for 81 patients with the privately progressed cervical disease could be anticipated from parameters of the Brix pharmacokinetic display gotten from pre-chemo radiotherapy DCE-MRI. First-order statistical components of the Brix parameters were utilized. Moreover, the texture feature of the Brix parameter maps were finished by building gray level co-occurrence matrices (GLCM) from the maps. Clinical components and first-and second-arrange highlights were utilized as logical factors to help vector machine (SVM) classification, with treatment result as a reaction. Classification models were approved utilizing forget one cross-demonstrate validation. An irregular esteem stage test was utilized to assess the show significance. Components gotten from first-arrange measurements couldn't be segregated amongst cured and backslid patients (specificity 0%–20%, p-values near unity). However, second-arrange GLCM elements could significantly foresee treatment result with exactness's (~70%) like the clinical variables tumor volume and stage (69%). The outcomes demonstrate that the spatial relations inside the tumor, quantified by surface components, were more appropriate for result expectation than first-order features.

Machhale et.al. [2015] purposed intellectual classification system to classify the MRI brain cancer. The purposed system used pre-processing steps which included filtering and skull masking. Filtering has been utilized to reduce noise from MRI scan. Therapeutic images are adulterated with rician noise during the scanning procedure. In this purposed work, the median filter has been utilized to evaluate noise. Skull masking removed the non-brain tissues. morphological operations erosion and dilation have been used in skull masking. Three kinds of features namely, texture features, gray scale features, Symmetrical feature are extracted from brain MR cancer images. The research work involved to utilized SVM and hybrid classifier SVM-KNN to identify the given input images into the normal brain or pathological brain images. The exploratory result demonstrated the adequacy of the two models. SVM with Quadratic part accomplished most extreme of 96% classification accuracy and Hybrid classifier (SVM-KNN) accomplished 98% accuracy rate. Results concluded that hybrid classifier provided better accuracy rate 98%, 93.75% specificity rate and 100% sensitivity rate as compared to the SVM classifier with three kernel functions.

G.B and Agrawal [2015] purposed the hybrid approach for classification and detection of brain cancer through magnetic resonance images (MRI). The purposed hybrid approach combined the texture based and region based method for brain tumor detection and classification. GLCM have been utilized as a surface based strategy for include extraction from the MR pictures. LS-SVM classifier alongside Multi-Layer Perceptron (MLP) kernel function was utilized to group the tumorous and non-tumorous images. Fast bounding box algorithm has been utilized as a region based strategy for segmentation of tumor. The purposed approach provided better results which were measured on performance metrics specificity, accuracy, standard error and area under curve the purposed approach got 81.3%specificity, 96.6% accuracy 0.9467 area under the curve and 0.0210 standard error with MLP kernel function.

Emre et.al. [2015] designed a computer-aided system (CAD) to identify the tumor in the brain as benign and malignant with the assistance of computer utilizing T1 and T2 weighted MR images. The system consists of phases pre-processing and enhancement, skull stripping, feature extraction, and classification. In pre-pre-processing stage to reduce the misleading results for further analysis, the median filter of window size 3x3 is used to remove the noise and parasites. Histogram equalization is done for enhancement. MNTA thresholding method used for skull stripping. The intended system segments the brain tumor region using the clustering technique called Spatial-

Fuzzy C-Means(FCM). For extraction of tumor features, GLCM and shape features are used and for feature selection, PCA technique was applied. Thusly, support vector machine(SVM) with different kernels is utilized for identification of benign and malignant tumors in the CAD framework. The results concluded that the proposed CAD framework perceives cerebrum tumors with 91.49% accuracy, 90.79% sensitivity and 94.74% specificity.

Halder and Dobe [2016] presented the technique to categorize the MRI brain as normal when the tumor is not present and MRI brain as abnormal in present. Tumor-free and tumor infected MRI scan differentiation has been done by a set of features. FCM used for feature selection purpose. In paper three parameters accuracy, sensitivity and specificity have described for the effectiveness of purposed method. Supervised learning has done with the help of SVM classifier to classify into two categories normal scan or abnormal scan.

Pritam et.al. [2016] described the methods of feature selection and classification to predict the Recurrence of breast cancer. The paper focused on finding the recurring probability of breast cancer with the help of data mining techniques. Wisconsin dataset has been used that contained 35 attributes in which SVM, decision tree, C4.5, Naive Bayes has been applied and for performance evaluation, accuracy parameter has been used. An efficient feature selection helped in the improvement of accurate prediction has been discussed. The results concluded that SVM provided better output in both cases of before and after feature selection and Naive Bayes and decision tree work well after feature selection.

Sumithra and Deepa [2016] bestowed the techniques of segmentation to discover the abnormality of the brain. to get rid of the salt and pepper noise and speckle noise at 5dB background level present in MRI and PET brain pictures. independent component analysis (ICA) has been utilized in pre-processing step. Mean Shift (MS), Fuzzy C-Means (FCM), Hough rework (HT), Normalized Graph Cut (NGC), Thresholding by the histogram (ThH) and Support Vector Machine (SVM) has been taken for analyzing the performance. The results suggested that, for PET images, pathology identification is discovered nice whereas utilizing ICA as denoising strategy for evacuating salt and pepper and speckle clamor at 5dB and SVM as segmentation procedure. although for

MRI pictures the execution of each ThH and SVM goes as an indivisible unit as a segmentation technique with ICA as noise evacuation strategy. The assessment live utilised were Jaccard and Dice coefficient, Peak Signal to Noise ratio (PSNR), global Consistency Error (GCE), beneath Segmentation (UnS), Over division (OvS) and Incorrect Segmentation (InC), property, Specificity, Accuracy, Positive discerning esteem (PPV) and Negative prescient esteem (NPV). The results terminated that SVM provides a higher outcome for the placement of mellow psychological incapacity in PET output pictures and each SVM and ThH is performing arts helpful for mind tumour recognition in MRI pictures, while not influencing the image quality.

Hasan et.al [2016] presented the comparison of Grey Level Statistic and Gabor Wavelet features of MRI brain cancer screening. The purposed algorithm started with the med-sagittal plane (MSP) detection and correction. After detection and correction by Gabor and gray level has been applied. The modified gray level co-occurrence matrix (MGLCM) features were determined for co-occurrence matrix. With the help of MGLCM 190 features were extracted and 655360 features from Gabor wavelet were extracted. And after extraction of feature, ANOVA technique applied for the selection procedure. Three classifiers Linear Discriminant Analysis (LDA), Multi-layer Perceptron Neural Network (MLP), SVM for classification of extracted features into abnormal or normal MRI brain scan has been used. The results provided that MGLCM features gave higher accuracy and performance for differentiating the normal or abnormal brain MRI tissues.

Kailash et.al [2016] presented the system that focused on feature extraction from MR images to detect the abnormal tissues in the brain. The system comprised of various stages. The stages included pre-processing for improving the MR image quality. The processed data then were gone for transformation into features called feature extraction. Texture, shape, intensity features are extracted for further processing. Important features are selected called feature selection, in the purposed work, feature selection has done by using two techniques called principal component analysis (PCA) and spatial gray level dependence matrix (SGLDM). Classification has been done by support vector machine (SVM) to classify the MR brain images into normal or abnormal

Chaubey [2016] delineated the thresholding methods for Mammogram image segmentation. The paper has proposed a technique for applying global threshold and threshold locally acquired from Otsu's calculation on a Benign and Malignant Breast tumor affected images. In this paper, local thresholding is done by dividing the mammogram image into 16 equally and then Otsu's algorithm applied on each part. the ultrasound image was the input in the pgm design acquired from MIAS database. the outcomes were gotten utilizing the global and local thresholding techniques utilizing Max of Mean and the Otsu's calculation.

Bhima and Jagan [2016] purposed the effective technique for identification of brain abnormality. The method is based on EMGM and Watershed techniques. Proposed Method has discovered for detecting the anomalies in cerebrum magnetic resonance images. the work has been done by utilizing the BRATS dataset of MR brain cancer that contained the cerebrum check MR images alongside their ground truth picture. The accuracy of purposed research was measured by judgement of the correlation between the anomalies separated from input Brain MR Image and the ground truth image of the parallel information image that was displayed in BRATS mind MR image datasets.

Aslam and Cui [2017] reviewed the various techniques with their weaknesses and strengths. The various tasks required for detection and extraction of brain tumor from MR images have been grouped them into various categories, pre-processing, segmentation and morphological operations. Three processes have been described for extraction of tumor in the brain from MR images. Image pre-processing completed by using enhancement. Next process post processing comprised of the first step as thresholding for segmentation after thresholding segmentation watershed segmentation applied and then Morphological Operations has also been explained.

Bahadure et.al. [2017] proposed an approach for tumor extraction from MR images. For improving the segmentation process Berkeley wavelet transformation (BWT) have investigated for segmentation of normal brain and abnormal brain tissues like gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). The approach used the pre-processing for improvement in signal-to-noise ratio and to reduce the effects the unwanted noise in MR images. Thresholding based technique skull stripping used to improve the performance of skull stripping. Furthermore, the technique utilized

BWT to segment the images of MR and support vector machine used for classification purpose of a brain tumor. The technique explored the features based on texture and histogram based with a normally perceived classifier to classify cerebrum tumor from MR brain images. The exploratory consequences of proposed procedure have been assessed and approved for execution and quality examination on MR brain images, in view of accuracy, sensitivity, specificity, and Dice similarity index coefficient. the result from purposed work accomplished 96.51% accuracy, 94.2% specificity, and sensitivity 97.72%, showing the adequacy of the proposed system for recognizing ordinary and irregular tissues from brain MR images.

From this tremendous investigation of writing an overview, it is discovered that a wide range of algorithms was provided by many researchers for detection and classification of brain cancer from MR images. But there are some loopholes in their work and not any algorithm provided satisfactory results in terms of accuracy for detection and classification of normal and pathological tissues in the brain. So to deal with the loopholes, a study has been proposed where the efficient and effective algorithm has developed and implemented.

Chapter 3

Problem Definition

A brain tumor is a serious and life threating disease. Therefore, the study of brain cancer using imaging sequences has become important in the radiology department. To increase the survival of the infected person, an early and accurate detection is a must. Many algorithms have been performed for classification and detection purpose. An attempt is made to classify an infected and normal person using the MRI images. To increase the effectiveness of the approach the issues regarding the accuracy and noise are undertaken. To analyze and develop robust techniques for the classification of the abnormal or normal brain tissues is of prior importance.

3.1 Gap Analysis and Objectives

There has been a prominent influence in the field of medical imaging by the progression in digital technology innovation. MRI provides the details regarding the pathological tissues important for medical examination. The conspicuous anomaly in brain MRI is a tumor or not can be decided by using the available and forthcoming methods of Artificial Intelligence and these techniques can be used as assistance for radiologist department. This thesis addresses the issues in classification and detection of normal and abnormal brain tissues from MRI images and tries to find an effective and efficient solution. The precise problem definition is enrolled below. Dealing briefly with the drawbacks of techniques like region based, K-means require a manual activation seed points is required. KNN is highly sensitive to reluctant features. The FCM, KNN requires huge computation time whereas the K-means affects the accuracy. Such issues are very common in most of the techniques.

Based on the issues linked with accuracy the research work can be moved with the motivation of satisfying the following objections. These objectives are obtained basically from the inefficiency and incompetence of the existing techniques.

Objectives

- To study and analysis various existing techniques to detect infected region.

- To develop an efficient approach for detection and classification from brain tumor using MRI images.
- To test the proposed algorithm on various evaluation parameters.
- Comparative study of the existing best algorithms with the proposed one and to verify those on the accuracy bases.

CHAPTER 4

Development and Implementation of Proposed Algorithm

The chapter delineates the phases involved in proposed algorithm as shown in Figure 4.3. The proposed method comprises of four phases. In the first phase image pre-processing is done using bilateral filter for noise removal and for image enhancement CLAHE is used. In the next phase, segmentation is done using thresholding technique which segments the tumorous region. Further proceeding for feature extraction using GLCM (Gray Level Co-occurrence Matrix). And at last phase, classification of brain MR images is performed with different classifier.

4.1 Pre-processing

The Quality of MR images is often deteriorated due to many noises like speckle noise, salts & pepper noise, Gaussian noises etc. Some other parameters like problems with data acquisition process, poor image sensors, transmission errors, imperfect instruments, and interfering natural phenomena also influence the images. The significant sources of debasement of images in MRI are the affectability inhomogeneity of the recipient loops, curl tuning, angle whirlpool streams, RF standing wave impacts, and RF entrance impacts. A typical issue that emerges because of these sources is power inhomogeneity (predisposition field), picture debasement with a gradually shifting multiplicative spatial field over the pictures. Force inhomogeneity is not generally obvious to a human onlooker, but rather it causes critical tissue misclassification issues when power based division is utilized. Along these lines, it is required to adjust force inhomogeneity in the cerebrum MR picture preceding tumor location and segmentation The need of pre-processing is due to Rician noise added during scanning devices of MR images. Moreover, pre-processing enhances certain parameters of MR pictures, like enhancing signal-to-noise ratio, improving the visual appearance of MR picture, evacuating the unimportant noise and undesired parts out of sight, smoothing the internal piece of the district, and protecting its edges. Pre-processing is used to reduce the noise by filtering and improve the quality of images by enhancement for detection of tumor process to enhance the quality of the MR images and to remove the noise image pre-processing is done. Figure 4.2 shows the pre-processing on tumor free and tumor affected MRI images. The main goal of image pre-processing is to enhance the quality of the MR images and make it in a form suited for further processing by human or machine vision system. Pre-processing steps involved in this research study consist of two phases are described below.

4.1.1 Bilateral Filter

As bilateral filter is good in preserving edge details while removing the noise and also causes smoothing of images [28]. The bilateral filter was developed by Tomasi and Manduchi [44] and it is a nonlinear filter. It is basically a product of domain and range filter. domain filter weight coefficient is related to the spatial distance of pixel around its neighborhood. The working of bilateral shown in Figure 4.1. While range filter weights are proportional to the radiometric distance of pixel around the neighborhood. The output of bilateral filtering at pixel location z is given as [24]. The equation of bilateral filter described as

$$B[I]_p = \frac{1}{K_p} \sum_{y \in S} g_{\sigma_{sp}}(\|p - y\|)\, g_{\sigma_{ra}}(|\, I_p - I_y \,|) I_y \qquad (4.1)$$

Where K_p normalization factor weight sum to 1.0:

$$K_p = \sum_{y \in S} g_{\sigma_{sp}}(\|p - y\|)\, g_{\sigma_{ra}}(|\, I_p - I_y \,|).$$

$g_{\sigma_{sp}}$ described as domain filter and $g_{\sigma_{ra}}$as range filter. Product of these range and domain filter known as bilateral filter.

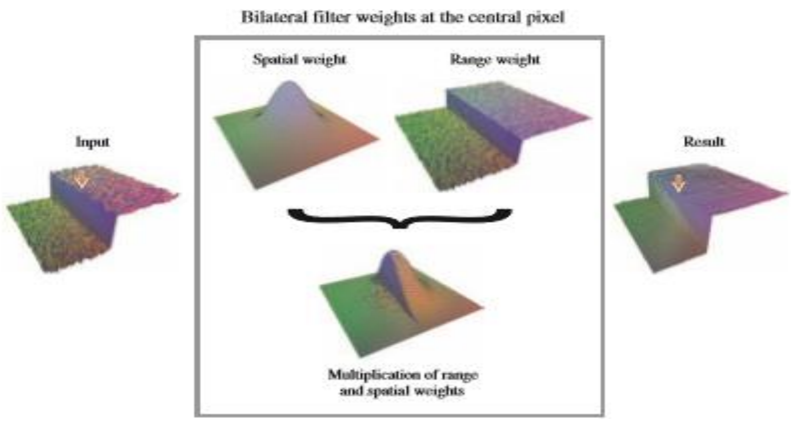

Figure 4.1: Working of Bilateral filter

4.1.2 CLAHE (contrast limited adaptive histogram equalization)

Another pre-processing technique called CLAHE has used in pre-processing. It is local contrast enhancement technique to improve the contrast of an image. It contrasts from histogram in the regard that the versatile strategy registers a few histograms, each relating to an unmistakable segment of the image, and uses them to redistribute the delicacy estimations of the image. CLAHE varies from customary versatile histogram adjustment in its differentiation restricting. This element can likewise be connected to worldwide histogram evening out, offering to ascend to differentiate restricted histogram balance (CLAHE), which is seldom utilized as a part of training. On account of CLAHE, the difference restricting methodology must be connected for every area from which a changing work is determined. CLAHE was developed to keep the over-amplification of clamor that versatile histogram leveling can offer ascent to So to improve the enhancement of Brain MR images, CLAHE is used. So that brain muscles and tumors can be differentiated easily.

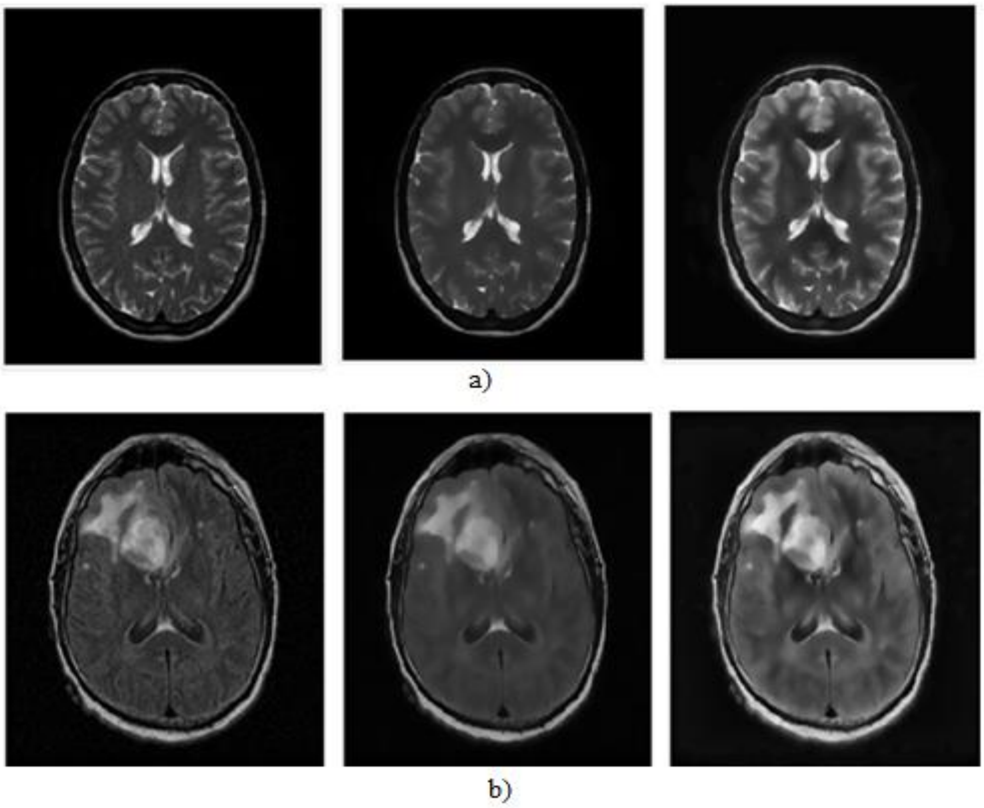

Figure 4.2 a) Pre-processing on Tumor Free Images b) Pre-processing on Tumor Affected images

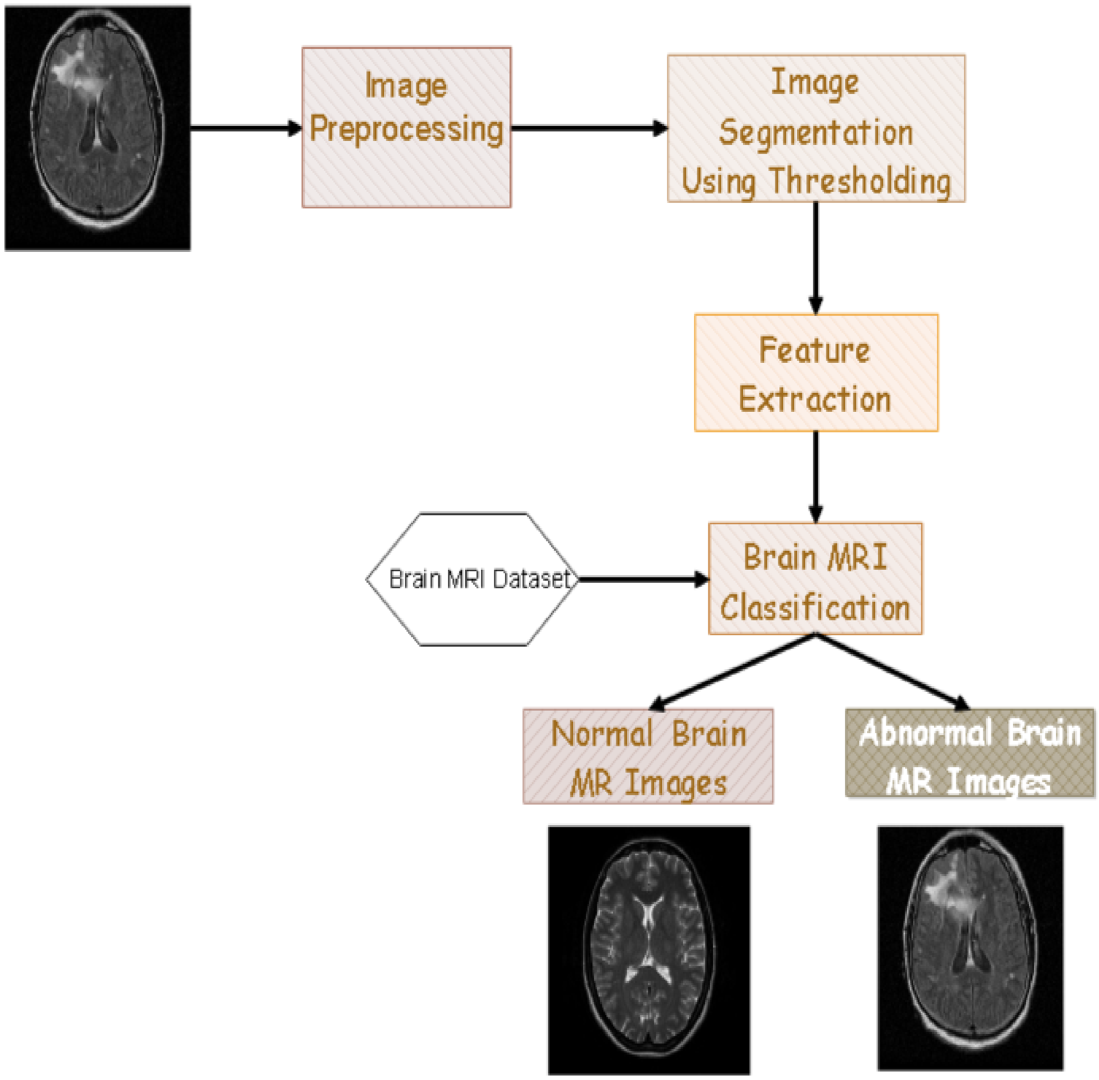

Figure 4.3: Steps Used in Proposed Method to Detect Tumor Using Brain MR Images

4.2 Segmentation

After image pre-processing, Brain MR images undergo image segmentation. Image Segmentation is a data and model-based process used in computer vision for partitioning a digital image into multiple segments for further easier analysis. Most commonly, thresholding is a standout amongst the most by and large utilized and most established techniques for image segmentation. In thresholding approach, image segmentation depends on dark level power estimation of pixels. Histogram of the image is comprising of pinnacles and valleys, where each pinnacle presents to one region. The valley between the pinnacles speaks to a limit esteem. Histogram thresholding [31] technique depends on an idea that partitions the image into two equivalent parts and histograms are contrasted with distinguishing the tumor and editing strategy is utilized to locate an appropriate physical measurement of mind tumor. The edge method settles on choice in view of the neighborhood crude pixel data. Thresholding is regularly utilized as an underlying stride in a succession of image segmentation procedure. The methodology of dividing an image into different chunk holding each pixel with same features is defined as Segmentation. The main aim of this phase is to segment the tumors on MR images. In the proposed methodology, image segmentation has done so that the purpose of effectively differentiate the object and background can be achieved. Thresholding can be Global Threshold and Local Threshold which is explained below

$$T = T[M, P, M(M, P), N(M, P)] \tag{4.2}$$

Where T defines the threshold value, $M(R, P)$ represents the local property and $N(R, P)$ is gray level image pixel [13] [45].

$$\mathrm{G(R, S)} = \begin{Bmatrix} 0 \; if N(M, P) < T \\ 1 \; if N(M, P) \geq T \end{Bmatrix} \tag{4.3}$$

If $\mathrm{G(M, P)}$ is a threshold version of $N(M, P)$ at some global threshold T, G is equal to 1 if $N(M, P) \geq T$ and zero if $N(M, P) < T$ [27].

The global thresholding uses single threshold value for the whole image whereas, in local thresholding, the value of the threshold for each pixel is based on the content in its neighborhood is calculated [42] [45]. The local thresholding strategy is distributed the original image into littler sub-images and a limit esteem is resolved for each of the sub-images. In this research study, thresholding is used for segmentation of brain tumor so that tumor can be calculated. Thresholding techniques are of two types global thresholding and local thresholding. In global thresholding method, Otsu’s technique mostly used for segmentation purpose. Otsu's technique scans for an edge that limits the intra-class changes of the segmented image and can accomplish great outcomes when the histogram of the first image has two particular peaks, one has a place with the foreground, and alternate has a place with the background. The Otsu's limit is found via seeking over the entire scope of the pixel estimations of the image until the intra-class fluctuations achieve their base. As it is characterized, the edge dictated by Otsu's strategy is all the more significantly controlled by the class that has the bigger variance, be it the background or the foreground area [27]. Otsu's method is a traditional technique used for extracting the object for further analysis. In this method, an array is created which contains the intensities of the pixels. By using total mean and variance, the threshold value is calculated. Depending upon this threshold value each pixel is set to either 1 or 0. i.e. foreground or background. Thus here the change of image takes place only once. Most of the results from Otsu have too much of noise in the form of the background being detected as foreground. So local thresholding can provide some optimum results. A threshold T (M, P) is a value such that

$$\mathrm{L(M,P)} = \begin{Bmatrix} 0\ if\ I(M,P) \leq T \\ 1\ otherwise \end{Bmatrix} \tag{4.4}$$

Where $\mathrm{L(M,P)}$ binarized image $I(M,P) \in [0,1]$ intensity pixel at location (M, P) of an image I. In local adaptive method an edge is computed for every pixel, in view of some neighbourhood insights like range, variance, or surface-fitting parameters of the area pixel. Niblack algorithm threshold value for each pixel is determined by sliding a rectangular window over the image. The size of the rectangle window may vary [42] depending on the local mean M and standard deviation SD of all the pixels in the window, to calculate the threshold. Equation for Threshold computation is shown below

$$T_{niblack} = M + K\sqrt{\frac{1}{np}\sum(p_i} + M)^2 \tag{4.5}$$

Gray image pixels defined by np, threshold value presented by T, average value of pixel is represented by M. weight value K is fixed to -0.2.

4.3 Feature Extraction

The Feature extraction is a procedure to gather the important details of an image like contrast, texture, and color. The response of the feature extraction stage will be an input vector comprising of applicable image properties which will be sustained into the classifier. In fact, texture features are an important parameter for consideration in medical imaging because it aids in human visual perception and machine learning system [2] [15]. It efficiently help in accurate diagnosis that patient is normal or suffering from the disease. Gray Level Co-occurrence Matrix (GLCM) and texture feature are introduced by Horlick et al. [33] for image analysis. The proposed technique consists of two phases in feature extraction. In first phase, GLCM is calculated, and in other phase, texture features are calculated from GLCM. Therefore, for finding the tumor at an earlier stage, extraction of features is an important task for supporting decision system. GLCM is a method which extracts feature in the pattern of a matrix in which a number of gray levels G in the image, is equal to the number of columns and rows [15]. The formulas for statistics features [8] are given below

a) **Contrast (C_{on})**

Contrast indicate the sensitivity of the textures in relation to alteration in the intensity. For a constant image, it is 0. It is the amount of local deviation present in an image and is defined as

$$C_{on} = \sum_{a=0}^{r-1} \sum_{b=0}^{s-1} (a-b)^2 f(a,b) \tag{4.6}$$

b) **Inverse Difference Moment (IDM) or Homogeneity**

IDM measure the similarity of an image. It is 1 in the case of diagonal gray level co-occurrence matrix. When there are minimal changes in local texture, IDM becomes large. It may have single or range of values so as to determine whether the image is textured or non-textured.

$$IDM = \sum_{a=0}^{r-1} \sum_{b=0}^{s-1} \frac{1}{1+(a+b)^2} f(a,b) \tag{4.7}$$

c) **Correlation (C_{orr})**

Correlation feature describes the spatial dependencies between the pixel and is defined as

$$\mathrm{C_{orr}} = \frac{\sum_{a=0}^{r-1} \sum_{b=0}^{s-1} (a-b) f(a,b) - M_a M_b}{\sigma_a \sigma_b} \tag{4.8}$$

where Ma and σ_a are mean and standard deviation in the horizontal spatial domain and Mb and $\sigma_b$are mean and standard deviation in the vertical spatial domain.

d) **Directional Moment (DM)**

DM is the textural property of the image calculated by considering the alignment of the image as a measure in term of the angle and is defined as

$$\mathrm{DM} = \sum_{a=0}^{r-1} \sum_{b=0}^{s-1} f(a,b) mod(a-b) \quad (4.9)$$

e) Entropy (E)

Entropy is calculated to characterize the randomness of textural image and is explained as

$$E = -\sum_{a=0}^{r-1} \sum_{b=0}^{s-1} f(a,b) log_2 f(a,b) \quad (4.10)$$

f) Skewness (S_k)

Skewness is the measure of symmetry or the lack of symmetry. The Skewness of random variable X is defined as

$$S_k(X) = (\frac{1}{r*s}) \frac{\sum f(a,b)-M)^3}{SD^3} \quad (4.11)$$

g) Kurtosis ($K_{urt}(Y)$)

The shape of random variable's probability distribution is described by the parameter called Kurtosis. For the Kurtosis for random variable, Y is defined as

$$K_{urt}(Y) = \left(\frac{1}{r*s}\right) \frac{\sum f(a,b)-M)^4}{SD^4} \quad (4.12)$$

h) Energy (E_n)

Energy is defined as a quantifiable amount of the extent of pixel pair repetitions. Energy is the parameter to measure the similarity of an image. If energy is defined by Horlicks GLCM feature, then it is also referred to as angular second moment, and is explained as:

$$E_n = \sqrt{\sum_{a=0}^{r-1} \sum_{b=0}^{s-1} f^2(a,b)} \quad (4.13)$$

i) Mean (M)

The mean of an image is determined by adding all the pixel values of an image divided by all the pixels present in the image.

$$M = \frac{1}{r*s} \sum_{a=0}^{r-1} \sum_{b=0}^{s-1} f(a,b) \quad (4.14)$$

j) Standard Deviation (SD)

The SD is the second central moment describing probability distribution of an observed population and can serve as a measure of inhomogeneity. A higher value indicates better intensity level and high contrast of edges of an image**.**

$$\mathrm{SD}(\sigma) = \sqrt{\left(\frac{1}{\mathrm{p}*\mathrm{q}}\right)\sum_{\boldsymbol{p=0}}^{\boldsymbol{p-1}}\sum_{\boldsymbol{q=0}}^{\boldsymbol{q-1}}(\mathrm{f}(\mathrm{a},\mathrm{b}) - M)^2} \tag{4.15}$$

k) Coarseness (C_{ness})

The image textural analysis roughness is measured by Coarseness. For a fixed window measure a surface with fewer surface components is said to be coarser than the one with a bigger number. the higher value of coarseness defines that texture is rougher. The lower value of coarseness means finer texture. It is calculated as

$$\mathrm{C}_{\mathrm{ness}} = \frac{1}{2^{\mathrm{r+s}}}\sum_{\mathrm{a=0}}^{\mathrm{r-1}}\sum_{\mathrm{b=0}}^{\mathrm{s-1}}\mathrm{f}(\mathrm{a},\mathrm{b}) \tag{4.16}$$

l) Variance (V)

It is defined as variations in intensity of gray levels and explained below

$$\mathrm{V}(\sigma^{\mathbf{2}}) = \sum_{\boldsymbol{a=0}}^{\boldsymbol{r-1}}\sum_{\boldsymbol{b=0}}^{\boldsymbol{s-1}}(1 - \mathrm{M})^2\mathrm{f}(\mathrm{a},\mathrm{b}) \tag{4.17}$$

4.4 Classification

The main goal of Image classification is to categorize input brain MR images into tumor infected image or tumor free. The input feed to classification phase is the output obtained from feature extraction in form of Horlick texture features. In this phase, determination of accuracy, sensitivity, specificity has done by applying five classifiers. The classifier Support Vector Machine (SVM) is binary classifier based on supervised learning. SVM is firstly developed by Vapnik and Learner in 1963 [18]. In proposed algorithm, SVM is used with linear and polynomial two kernel functions for the classification purpose [15] [43]. And corresponding equations are given below

- Linear kernel defined as [46]

$$z_k = f(y, y') \tag{4.18}$$

z_k is linear kernel function whereas y and y' are sample vectors.

- Polynomial kernel [46]

$$K(y, y') = (1 + y.y')^k \tag{4.19}$$

Where y and y' are sample vectors.

KNN (k- nearest neighbor) is all about voting function and distance function in k nearest function. The KNN classifier is an ordinary non-parametric supervised model which provides good performance for optimum values of k [37]. KNN comprise of two stages training and testing. In training stage data points with their class have labels. In the testing stage, the algorithm provides k nearest points and unlabeled data points and working of KNN shown in Figure 4.4 [41].

Adaboost is adaptive boosting which is developed by Yoav Freund and Robert Schapire and got a gold prize in 2003. It is boosting algorithm for binary classification and an ensemble classifier which combines J48 based classifier [34]. Ctree (Conditional Inference Trees) uses the party package to classify object into the normal and abnormal dataset. The pseudo code of purposed algorithm has given below

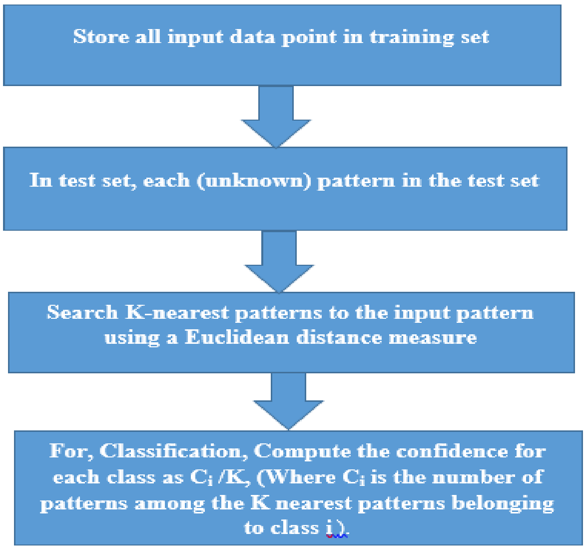

Figure 4.4: KNN Algorithm [41]

Pseudo code of proposed algorithms

Algorithm-1

Pseudo-code:
 	
Input: A RGB MR Brain image (I)
 	
Variables: I_B is image after applying bilateral filter, I_C as image after clahe enhancement and in this image the pixel values are stored in an array named as P, ranging from 0 to 255. I_{A1} as image and in I_{A1} image the pixel value is stored in array named as P_0 ranging from 0 to 255
 	
1. I_G = Convert I to gray scale image.
 	
2. I_R = Resize I_G 255 x 255-pixel size.
 	
3.
a) Apply bilateral filter to I_R for noise removal and then store the image to I_B.
b) Apply CLAHE to I_B for enhancement of image and store to I_C.
 	
4.
Set T = AVERAGE(I_C),
FOR I = 0 to 255
If (P[I].value>T)
P_0[I].value = 255
Else
P_0[I].value=0
ENDIF
NEXT I
 	
5. Apply GLCM (Gray- level Co-occurrence Matrix) on I_{A1} (output of step 4) for extraction of Horlicks features and store the extracted features in I_{G1}.
 	
6. Apply five classifiers on I_{G1} to classify the normal and abnormal tissues of MRI brain.

Algorithm-2

Pseudo-code:

Input: A RGB MR Brain image (I_2)

Variables: I_{B2} is image after applying bilateral filter, I_{C2} as image after clahe enhancement and in this image $_{the}$ pixel values are stored in an array named as P, ranging from 0 to 255. I_{A2} as image and in I_{A2} image the pixel value is stored in array named as P_N ranging from0 to 255

1. I_{G2} – Convert I_2 to gray scale image.

2. I_{R2}- Resize I_{G2} 255 x 255-pixel size.

3.
   a) Apply bilateral filter to I_{R2} for noise removal and then store the image to I_{B2}.

   b) Apply CLAHE to I_{B2} for enhancement of image and store to I_{C2}

4.
```
Sum  0, K  -0.2
    For I  0 to 255
      Sum  Sum + P[I].value
    NEXT I
    M  Sum / I
      N_P = I
  FOR I   0 to 255
    SD  (P[I].value-M) * (P[I].value-M)
  Next I
    T_N = M + K * sqrt (SD /N_P)
            For I   0 to 255
              If (P[I].value>T_N)
                P_N[I].value   255
              Else
                P_N[I].value  0
              End IF
    Next I
```

5. Apply GLCM (Gray- level Co-occurrence Matrix) on I_{A2} (output step 4) for extraction of Horlicks features and store the extracted features I_{G2}.

6. Apply five classifiers I_{G2} to classify the normal and abnormal tissues of MRI brain

The proposed algorithms are applied to many MR brain images using MATLAB and R and the algorithms provide better results. In the next chapter, results obtained from the proposed algorithms are shown and discussed.

CHAPTER 5

RESULTS AND COMPARISON

The performance of the proposed algorithm has been analyzed by using the dataset of 255 x 255 pixel MRI brain images. The dataset has been taken from IXI [47] that comprised of three different types of modalities namely, T1-weighted (T1W), T2-weighted (T2W), and PD-weighted images for the analysis. The collected DICOM dataset consists of 250 images out of which 50 are abnormal brain images and 200 images are of healthy patient brain images taken from all planes (axial, coronal, sagittal). The pathological brain image set comprises of the image of cerebrum influenced by cerebrum sore. The symmetry in axial, sagittal, coronal brain images is an important feature for consideration that human brain is normal whereas asymmetry in brain images strongly shows about the abnormality. The visual appearance of normal and abnormal axial MR images is shown below in Figure 5.1. The proposed algorithm is implemented in MATLAB 2016a software and R. The system runs on operating system window 7 and has Intel Core i5 processor, 4GB memory. Parameters used to evaluate the results of the comparison of two algorithms are described in next section.

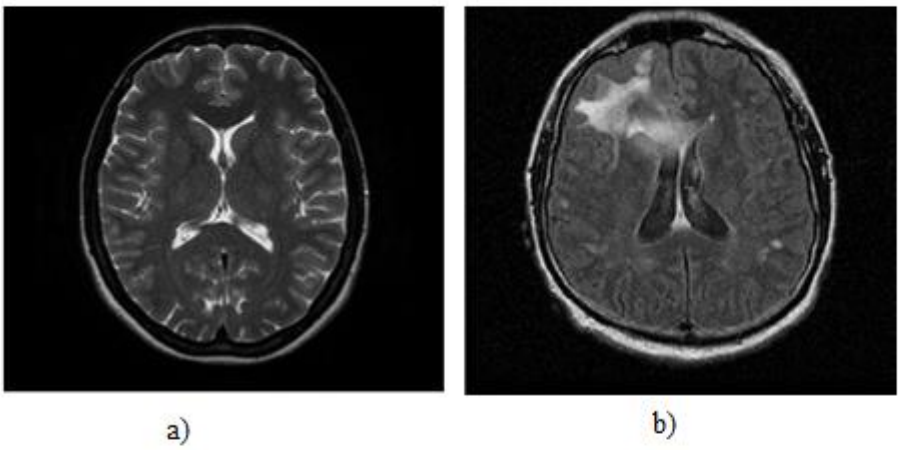

Figure 5.1 a) Normal Brain b) Abnormal Brain

5.1 Evaluation Parameters

To know the performance of the purposed approach some evaluation criteria is required. And for that purpose evaluation parameters are required on the basis of which we evaluated the effectiveness of our proposed work with the other existing work.

Before dealing with the performance metric, the confusion matrix should be known. The "fresh data" formed by a classification system during testing are counts of the normal and abnormal classifications from each class [39]. This information is then normally displayed in form of confusion matrix. A confusion matrix is an arrangement of contingency table showing the differences between the true and predicted classes as shown in Table 5.1 which includes true positive rate, true negative rate, false positive rate, false negative rate which are used to calculate the accuracy, sensitivity, specificity parameters for the classification [38]. The explanation is given below

$$\text{True positive rate } (T_{pr}) = \frac{\textbf{Number of MRI images having brain tumor}}{\textbf{total number of MRI images having tumor or tumor free}} \quad (5.1)$$

$$\text{True negative rate } (T_{nr}) = \frac{\textbf{Number of tumor free MRI images}}{\textbf{total number of MRI images having tumor or tumor free}} \quad (5.2)$$

$$\text{False positive rate } (F_{pr}) = \frac{\textbf{MRI images which are tumor free but detected as brain tumor}}{\textbf{total number of MRI images having tumor or tumor free}} \quad (5.3)$$

$$\text{False negative rate } (F_{nr}) = \frac{\textbf{MRI images having brain tumor but detected as tumor free}}{\textbf{total number of MRI images having tumor or tumor free}} \quad (5.4)$$

The parameters used to measure and evaluate the performance of proposed algorithms are sensitivity, specificity and accuracy. The sensitivity is known as true positive ratio (Tpr) or recall that defines the probability of normal identified for a diagnostic test. The specificity is termed as true negative ratio (Tnr) and defines the probability of abnormal identified for a diagnostic test. Similarly, the accuracy which is the most influential parameter defines the probability that diagnostic test is performed correctly [18]. The formulas of these parameter are defined in the mathematical form below:

$$\text{Sensitivity}= \frac{\text{Tpr}}{\text{Tpr+Fnr}} * 100 \quad (5.5)$$

$$\text{Specificity}= \frac{\text{Tnr}}{\text{Tnr+Fpr}} * 100 \quad (5.6)$$

$$\text{Accuracy}= \frac{\text{Tpr+Tnr}}{\text{Tnr+Fnr+Tpr+Fpr}} * 100 \quad (5.7)$$

Table 5.1: Confusion Matrix

True class	**Predicted class**	
	Predicted normal (-)	**Cancer (+)**
Actual normal	Tnr	Fpr
Actual cancer	Fnr	Tpr

5.2 Comparative Analysis of Algorithm

The comparative analysis of Algorithm-1 and Algorithm-2 on the basis of different factors such as accuracy, sensitivity, specificity using various models are explained below.

5.2.1 Results of Algorithm-1

The results of the comparative study which perspective to different parameters (sensitivity, specificity, accuracy) and the 5 classifiers namely, Adaboost, Ctree, KNN, SVM linear and SVM polynomial for testing the proposed algorithm shown in Table 5.2 below. Observation is made that accuracy rate is higher in Adaboost classifier whereas the worst is shown by Ctree classifier. The matter of study is the SVM polynomial where we found that the sensitivity is really low as compared to all other parameters and classifiers.

Table 5.2: Comparison of Parameters with Different Classifier Using Algorithm-1

Classifiers	Parameters for evaluation		
	Sensitivity(%)	Specificity(%)	Accuracy(%)
Adaboost	76.5	81.2	94.74
Ctree	66.7	93.1	65.79
KNN	21.4	94.2	67.11
SVM linear	16.7	98.4	85.53
SVM polynomial	15.4	98.4	84.24

The detailed analysis of algorithm-1 in graphical representation has shown in Figure 5.2. The results of SVM with polynomial kernel showed 88.16% accuracy, SVM with linear kernel accuracy rate 85.53%, KNN classifier with 67.11%, Ctree provided 65.79% accuracy and Adaboost achieved 94.74% accuracy which attained highest classification rate as compared to other classifiers.

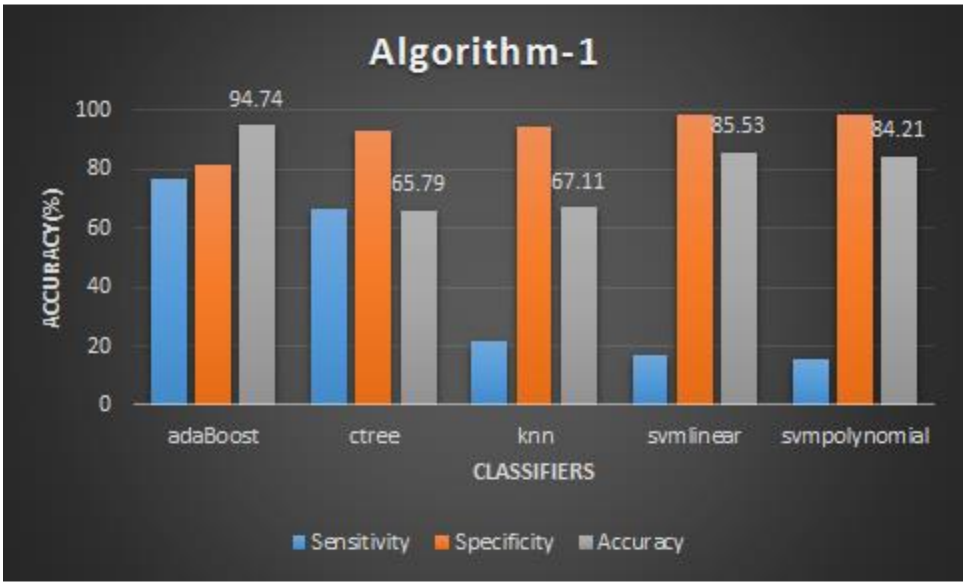

Figure 5.2: Comparative Analysis of Classifier Using Algorithm-1

5.2.1 Results of Algorithm-2

Table 5.3 gives the comparative result of the parameters and the classifiers using niblack thresholding. The higher sensitivity, accuracy and lower specificity indicate better performance. It is lucid from the table that Adaboost provides better results as a comparison to other classifiers whereas SVM polynomial achieved 25% sensitivity whereas in terms of accuracy it is second lowest. Ctree performance is not as good as compared to another classifier in the case of Algorithm-2. Furthermore, higher sensitivity, accuracy and lower specificity indicate better performance.

Table 5.3: Comparison of Accuracy with Different Classifier Algorithm-2

Classifiers	**Parameters for evaluation**		
	Sensitivity(%)	**Specificity(%)**	**Accuracy(%)**
Adaboost	94.1	92.7	98.68
Ctree	81.3	94.7	81.58
KNN	90.4	94.2	90.79
SVM linear	88.2	92.4	97.37
SVM polynomial	25.1	98.5	88.16

Figure 5.3 shows the results which lead to the conclusion that Algorithm-2 with Adaboost classifier came up by 98.68 % accuracy rate. It provides effective and superior results as compared to Algorithm-1 on the basis of performance metrics. While Ctree performance in Algorithm-2 is very poor as compared to another classifier.

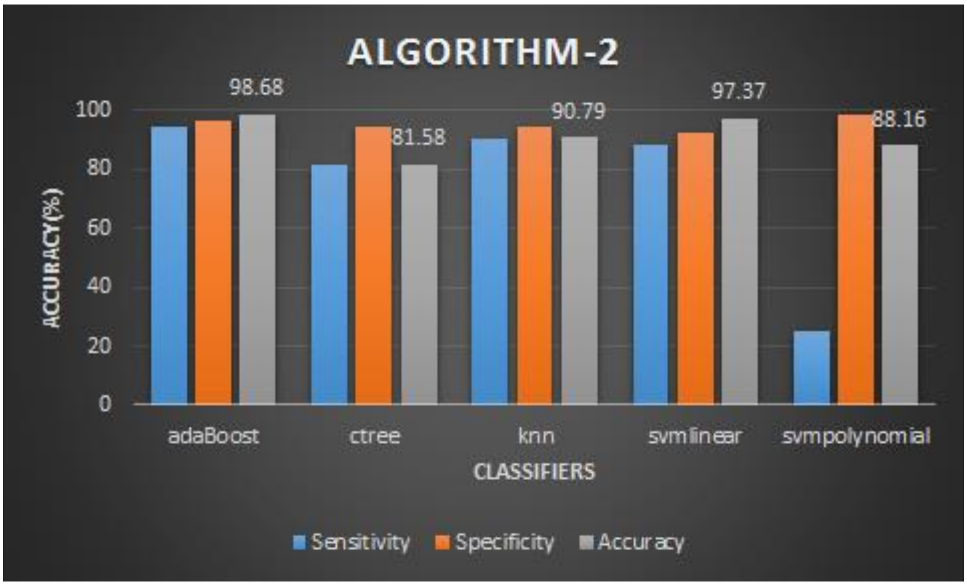

Figure 5.2: Comparative Analysis of Classifier Using Algorithm-2

Further the results are concluded on the basis of another parameter named as the area under the curve which is known to be as ROC curve. The ROC (receiver operating system) curve used for classification accuracy of the proposed approach is shown below. ROC curve is an optimum method which consistently equates the accuracy of diagnostic assessment. ROC curve is a chart representation that provides binary classifier performance [36]. ROC graphically delineates the trade-off between false negative ratio and false positive ratio. The success rate of diagnosis goes higher as the area under the ROC curve goes higher [2] [39]. ROC curve of Adaboost classifier of Algorithm-1 has shown in Figure 5.4 and Algorithm-2 ROC curve of Adaboost classifier has shown in Figure 5.5

On the basis of the above-discussed algorithms, it can be concluded that performance can be improved and can be quick with Adaboost classifier using purposed work. Results demonstrate that proposed algorithm can help the medical specialist to deliver accurate detection of Alzheimer's disease (brain tumor).

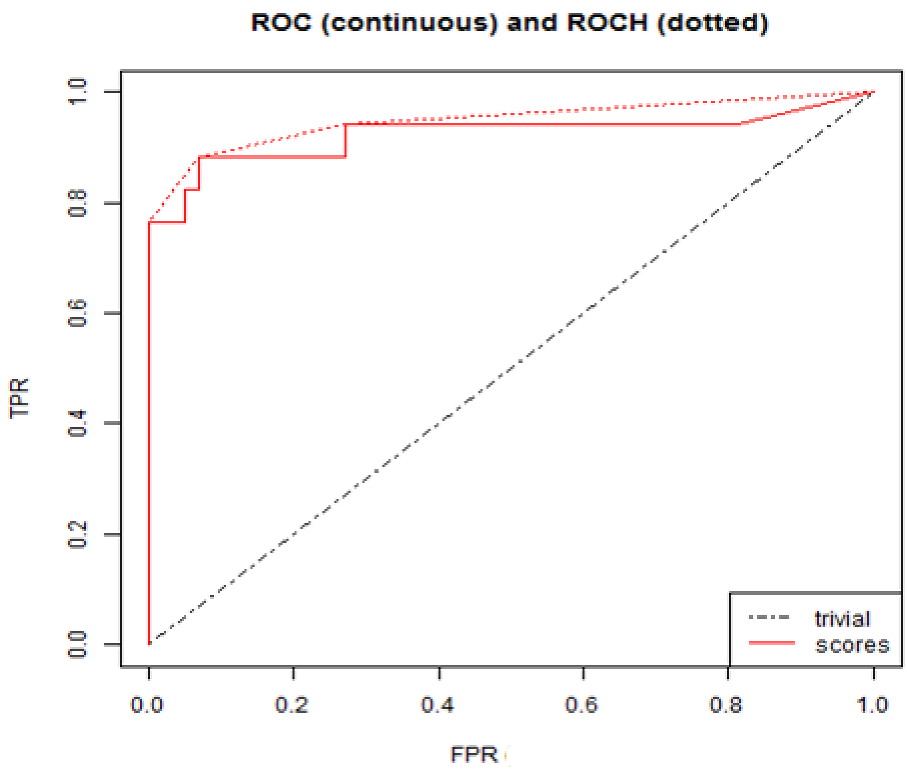

Figure 5.4: Adaboost ROC curve of Algorithm-1

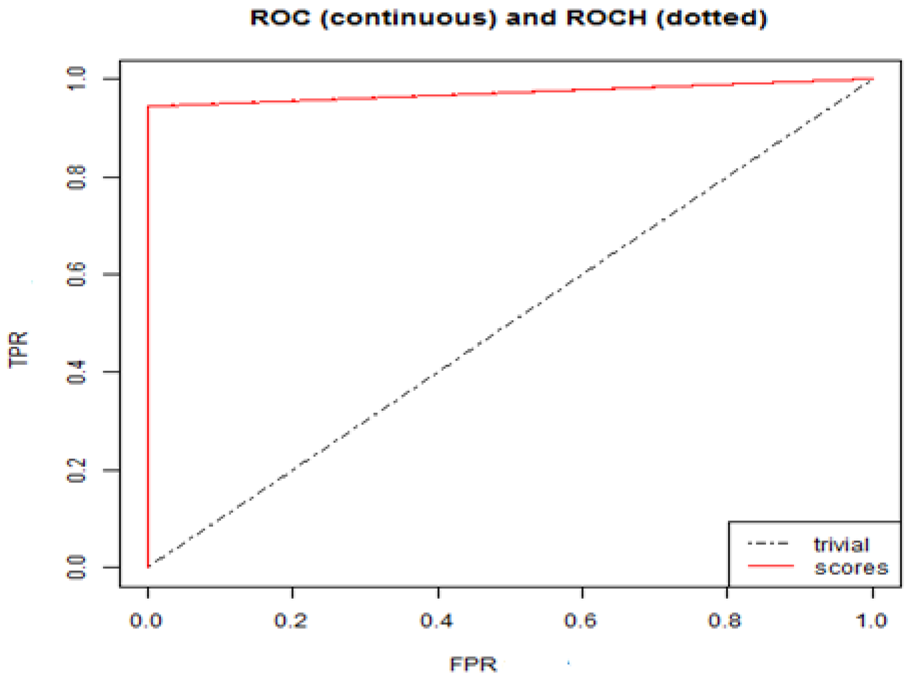

Figure 5.5: Adaboost ROC curve of Algorithm-2

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

There has been the eminent effect on the field of therapeutic imaging by the progression in digital technology innovation. The information acquisition, analysis, handling, and perception are in a phase of improvement for effective diagnosis. In the present study, an algorithm is proposed constituting of the phases that include initially starts from pre-processing. These pre-processed images are then forwarded to Algorithm-1 and Algorithm-2 for further analysis. Feature extraction is also done in next phase by Horlick's features from GLCM. Further, 5 different classifiers are used for the identification of the tumor from MR images. The results obtained are compared on the basis of the parameters like accuracy, sensitivity and specificity. It is observed that Algorithm-2 is more robust and efficient for the detection and classification of normal and abnormal brain tissues. The accuracy rate of Algorithm-2 is 98% which is comparable more than the accuracy rate of Algorithm-1 which turn to be 94%. The efficiency of the proposed algorithm is improved. It is worthy to coordinate clinical decision support system for primary screening and recognition by the radiologists or therapeutic experts.

6.2 Future scope

There is no end to research, and the same is applicable to this work also.

- The proposed approach can be improved and extended by making it as a CAD system for providing assistance to doctors and acting as a second opinion is the decision making.
- The purposed approach can be extended to different parts of the body like lung cancer, diabetic retinopathy etc.
- The purposed approach can be used for classification of different types of tumor.

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List of Publications

1. K. Harjeet, K. Garima, K. Rajiv," Comparative Analysis of Denoising Techniques in Medical Images,"3^{rd} *International Conference on Next Generation Computing Technologies, 2017.*

   [Communicated]

2. K. Harjeet, K. Garima, K. Rajiv, "An Efficient Method for Detection and Classification of Tumor in Brain MRI, "*Computerized Medical Imaging and Graphics, 2017.*

   [Communicated]