Brain Tumor Segmentation

A Dissertation

Submitted in partial fulfillment of

the requirements for the award of the degree

of

MASTER OF TECHNOLOGY

in

ELECTRONICS AND COMMUNICATION ENGINEERING

(With Specialization in Communication Systems)

By

SIDHAMPARAM PRASHANTHI

(Enrollment No. 17531016)

DEPTT. OF ELECTRONICS AND COMMUNICATION ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY,ROORKEE

ROORKEE-247667(INDIA)

JUNE 2019

CANDIDATE'S DECLARATION

I hereby declare that the work carried out in this report entitled Brain Tumor Segmentation is presented on behalf of partial fulfillment of the requirement for the award of the degree of Master of Technology with specialization in Department of Electronics and Communication, submitted to the Department of Electronics and Communication, Indian Institute of Technology, Roorkee, India, under the supervision and guidance of Dr.Vinod Pankajakshan, Assistant Professor, ECE, IIT Roorkee. The content of this dissertation has not been submitted by me for the award of any other degree of this or any other institute.

DATE : .... SIGNATURE:

PLACE: Roorkee (Sidhamparam Prashanthi)

CERTIFICATE

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

DATE : .... SIGNATURE:

(Dr. Vinod Pankajakshan)

Assistant Professor

Dept. of ECE

IIT Roorkee

ACKNOWLEDGEMENT

On completion of my dissertation, I would like to express my deepest gratitude to my supervisor, Dr. Vinod Pankajakshan (Assistant Professor, Department of ECE) for his constant guidance, motivation and support. Throughout my thesis working period he provided me encouragement, good teaching and ideas. I would like to express my profound gratitude to my guide not only for his academic guidance but also for his interest in my project.

I must express my sincere thanks to my teachers Dr.Ajit K Chaturvedi, Professor and Director of IITR, Dr.Debashis Ghosh, Professor and HOD of Dept of ECE, Dr.Sugata Gangopadhyay, Professor Dept of CSE, Dr.Meenakshi Rawat, Assiatant Professor Dept of ECE, Dr.P.M.Pradhan, Assistant Professor Dept of ECE and Dr.Anshul Tyagi, Assiatant Professor Dept of ECE, for their support and guidance during my studies.

I would like to express my appreciation to my senior students Ms.Priya Gupta, Mr.Chothmal Kumawat, Ms.Mallika and Mr. Navneet Nayan reading Ph.D. in Dept of ECE, who always ready to help regarding my research and relative studies. Also, I would like to thank research scholars, officers in Signal Processing and Communication Lab, My classmates and seniors who have been always helpful and understanding.

I must remember to thank Staffs of District Secretariat-Jaffna, Department of Government Information, Ministry of Mass Media and Ministry of Higher Education, Government of Democratic Socialist Republic of Sri Lanka for giving this opportunity to do Masters program in India. Also I am indebted to thank Indian Council for Cultural Relations(ICCR), Ministry of External Affairs, Government of India for providing financial sponsorship throughout the programme.

I would like to thank my family members for their continuous support during my studies.

Sidhamparam Prashanthi

Abbreviations

ANN	Artificial Neural Network
DN	Deep Network
DT	Decision Tree
FFNN	Feed Forward Neural Network
FBNN	Feed Back Neural Network
KNN	K-Nearest Neighbours
ReLU	Rectified Linear Unit
SDAE	Stacked Denoising Auto Encoder
SVM	Support Vector Machine

ABSTRACT

Computer vision and machine learning are growing fields especially, in medical image processing. It helps in the research of brain tumor prediction, biopsy guidance, prognosis monitoring, disease stage identification, therapy planning, and therapy response. The Tumor is the accumulation of abnormal cells. It is the second most common cancer in children and young people. In the case of Glioma, It is the most common form of the malignant tumor. which are heterogeneous in nature. starting the diagnosis earlier will help them to extend their valuable life. Nowadays fully automatic methods have been able to achieve state-of-art results using Magnetic Resonance Image which can give better tissue images.

In this thesis, a hybrid algorithm used to detect, classify and segment the brain tumor. Three main procedures are done in this research they are pre-processing classification and post-processing. Gray level co-occurrence matrix and Discrete wavelet transform used to excerpt the highlevel ideal attribute from the input. After the classification by Hybrid methodology post-processing is done using a morphological process.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Brain Tumour

Brain tumour is the second most common cancers in children. There are 130 different types of tumors found. Brain tumor rates increase with age but, unlike most other cancers occur relatively frequently across all age groups. The Tumor is a mass of tissue that is formed by the accumulation of abnormal cells. Brain tumors sort of fall into two categories. One is those that are within the substance of the brain and other outside the brain pushing on the brain. the most common one is glioma in which tumors that form inside the brain. Metastatic tumors are tumors that come from some other part of the body or organ and land in the brain. Pituitary adenomas begin in the pituitary gland and These tumors can affect the pituitary hormones with effects throughout the body. Primitive neuroectodermal tumors are rare cancerous embryonic cells in the brain they can occur anywhere in the brain. The tumors that are outside the brain pushing on the brain are called meningiomas. They fall under the general classification of a brain tumor. The symptoms that generated from those tumors are different. The treatments are different that depends on tumor appears on the scan report. Those images are inhomogeneity of the location, size, shape of the tumor and also varying the types of cells which are edema, necrotic, non enhancing and enhancing which combine to form the whole tumor, enhancing tumor and whole tumor.

Diagnosis of a brain tumor is done by a neurologic exam,using imaging modalities like CT (computer tomography scan), Positron Emission Tomography (PET), magnetic resonance imaging, Angiogram , Biopsy and Spinal tap. After getting the results from those imaging modalities can find the are different grades of tumor. which really just describe what is the growth potential and what are the sort of biology of the tumor is. That dictates what treatment would be for that person.For low-grade glioma patient first observation is the diagnosis radiation and chemotherapy for High-grade glioma patient.For metastatic tumors that treatment involves surgery followed by focused radiation. After surgery involves observation for meningioma patients. Magnetic resonance imaging is proved to provide

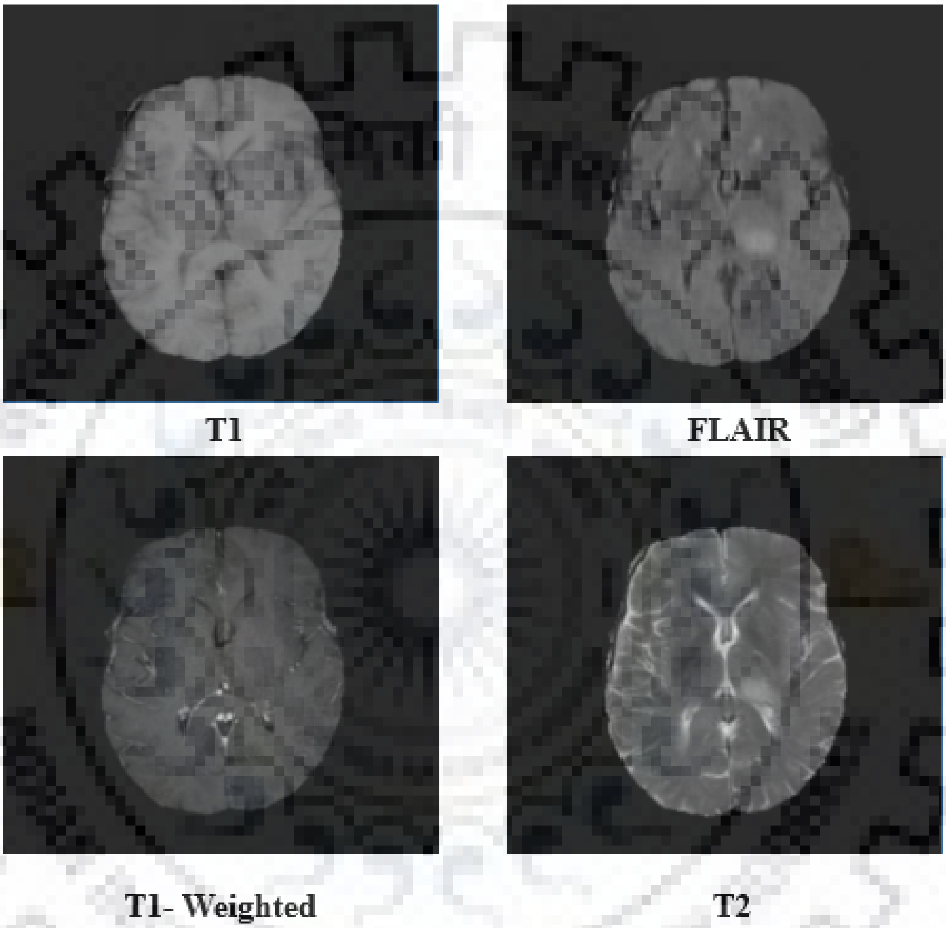


Fig. 1.1. MRI Images

quality data or information about the tumor especially gliomas.Magnetic resonance imaging is proved to provide quality data or information about the tumor especially gliomas from the glial cells. MRI scans of four different types are used to capture contrasted images. four models used in this modality are Fluid Attenuation Inversion Recovery, native T1, T2 weighted (T2), T1-weighted(T1ce). Every four modalities corresponding to the particular patient provides a total of 155 2D images to represent the three-dimensional shape of the brain. the two-dimensional image slice is a 240 x 240 image, therefore, each modality generating a total of 155 x 240 x 240 images for a patient.

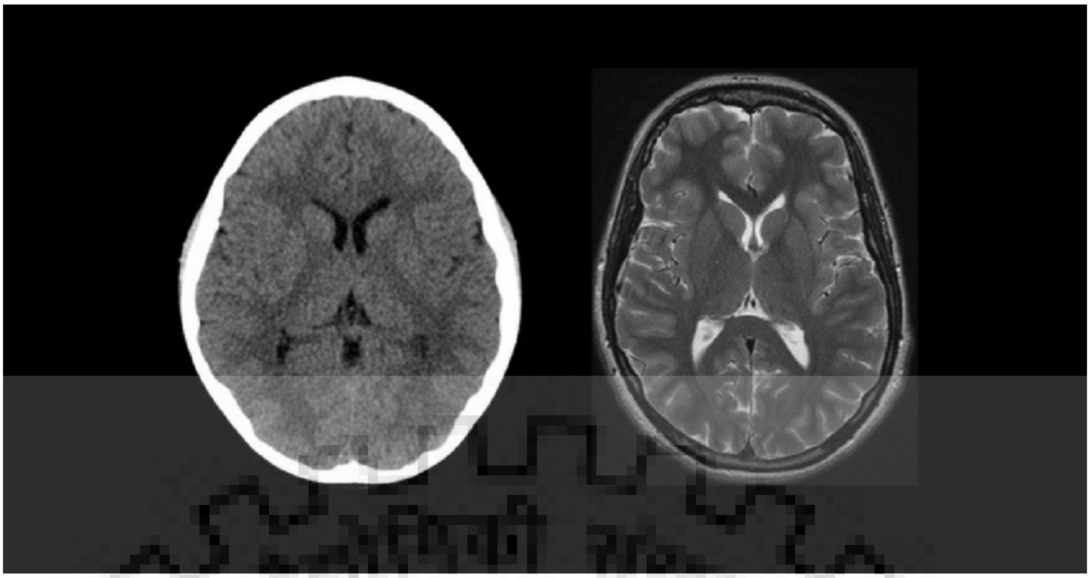


Fig. 1.2. CT image vs MRI image

1.2 Motivation

In this populated world diseases also increasing gradually. Especially cancers and tumors. Doctors have no time to segment the tumors manually they get very less time to diagnosis the patient.The average survival rate of patients suffering from a brain tumor and under proper medical treatment if found to be less than 14 months. If the patient gets treatment early he can extend his life period according to his tumor type. And also Nowadays the machine has been involving from past experience for many years. On the other hand, the era of the machine has just begun. now we are living in the primitive age of machines while the future of machines enormous and is beyond the scope of imagination. After the continuous learning machine can do a thing more accurately than a human. The biomedical image processing joined with this machine learning for zero human involvement, reduction of time consumption, High performance, and for their complex feature learning ability. Brain tumor segmentation is one of the most challenging tasks in biomedical imaging. As an engineer, I wanted to contribute my support by improving the software to improve the accuracy of brain tumor classification and segmentation using the hybrid algorithm.

1.3 Problem Statement

1. Mostly children and young people are affected in this disease. The outcome would be if the problem was not solved is doctors will suffer to start their diagnosis in

time. The problem need to be fixed by improving the diagnosis starting time as soon as possible. This Brain tumor is not a short term problem and cannot cure completely.

2. The primary aim of this research is to develop an algorithm which should be able to take a magnetic resonance image as an input and should give better classification than other algorithms.

3. Improving speed of classification

4. The Continuation of the Brain tumor Segmentation Using Deep Learning, developing the accuracy of the classification and segmentation.

1.4 Outline of Thesis

- Chapter 2 covers the Detailed study has been carriedout for this research.
- Chapter 3 covers the literature review for the thesis.
- Chapter 4 covers the methodology for the implementation for proposed algorithm.
- Chapter 5 covers the results of Deep Learning method and proposed method comparison results.
- Chapter 6 for conclusion and future scope .

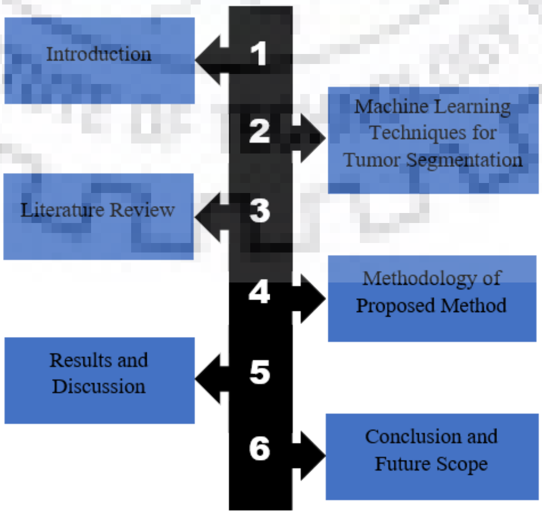


Fig. 1.3. Outline of Thesis

Chapter 2

Machine Learning Techiques for Tumour Segmentation

This chapter covers the relative study for this research.

2.1 Machine Learning

Machine Learning is a concept which allows the machine to learn from examples and experience. And that too without being explicitly programmed. so, instead of writing the code feed the data to the generic algorithm and the algorithm for the machine will still logic based on the given data. Features of machine learning are that it uses the data to detects a pattern in a data set and add just the program action accordingly. It focuses on the development of computer programs that can teach themselves to grow and change when exposed to new data. It enables the computer to find hidden insights using iterative algorithm without being explicitly program. so, machine learning plays an important role in our life.The machine learning is broadly classified into three major tasks which are the Supervised Learning, Unsupervised Learning and Reinforcement Learning.

2.1.1 Supervised Learning

The simplest form of machine learning is supervised learning. It is the one where the input variable x and output variable y. Here using an algorithm to learn the mapping function from the input to the output so in simple terms it implies,

$$y = f(x) \tag{2.1}$$

The goal is to approximate the mapping functions. Supervised learning every instance of the training data set consists of input attributes and expected outputs. The training data set can take any kind of data as input like values of data sets the pixel of an image or audio frequency histogram. The machine continuously predicts the result on the basis of training data. Learning continuously until the algorithm is an acceptable level of performance. Examples for supervised learning are bio metric attendance,speech recognition.

2.1.2 Unsupervised Learning

The command data is unstructured and unlabeled so it becomes very difficult to classify that data into different categories. so, unsupervised learning helps to solve this problem now this learning is used to cluster the input data into classes on the basis of the statistical properties. Now the training data is the collection of information without any label.Now, mathematically unsupervised learning was where only have the input data x and no corresponding output variable. Now the goal of the unsupervised is to model the underlining structure or the distribution in the data in order to learn more about the data so, clustering models focus on identifying groups of similar records and labeling the records according to the which this belongs and this is done without the benefit of prior knowledge about the groups and their characteristics, in fact, we may not even know exactly how many groups to look for. But, the models are often referred to as unsupervised learning model. Since there is no external standard by which to judge the model's classification performance there no right or wrong answers to these models example market basket analysis.

2.1.3 Reinforcement Learning

Reinforcement Learning is a part of machine learning where an agent is put in an environment and he learning to behave in this environment by performing certain tasks and observing the rewards which it gets from those actions. This reinforcement learning is all about taking appropriate action in order to maximize the reward in a particular situation. in supervised learning, the training data comprises of the input and so the model is trained with the expected output itself but when it comes to reinforcement learning there is no expected output the reinforcement agent decides what action to take in order to perform a given task in the absence of a training dataset. It is bound to learn from its own experience. many hurdles between the agent are supposed to find the best possible path to reach the reward example alpha go game.

2.2 Classification

The process, by adding the label dividing the dataset into subgroups called classification. The procedure of classification is first taking the data analysing it and on the basis of some condition finally, divide into various categories. classification is done to get an effective or productive analysis. There are several ways to perform the same task. The main machine learning algorithms used for classification of brain tumor segmentation is discussed in following sections.

2.2.1 Artificial Neural Network

Artificial Neural Network is also known as a neural network. As an artificial neural network consists of a collection of nodes called neurons. Neurons attempt to mimic the functioning of the neurons inside the human brain. Every node connected to one another. The data or information transfer between these nodes like synapses in the brain. Connections between nodes called as edges. These artificial neurons and edges have a value associated with weight.

The weight of a neuron is adjusted during the learning process to increase the signal strength at the connection. the neurons grouped into layers. First layer is inputlayer in this layer getting inputfeatures from outside sources through user. This layer will not do any calculation, the nodes that pass the information to the hidden layers. The nodes of these layers are not visible to the open-air. Calculates all characteristics of the hidden layer and input layerand replaces the output layer. Output layer brings information to the outside through the network. An Artificial Neural Network classify better than other classification methods. In terms of higher dimensional features. ANN needs high consumption of central processing unit, memory and Graphics processing unit.

Feed Forward Neural Network is one of the simplest types of Artificial Neural network. The name arrives from the direction of the data propagation. Which means that the data or information travel in one direction only. The data first passes through the input nodes at the start of the neural network and finally end up in the output nodes at the neural network. These types of the neural network may or may not have a hidden layer of nodes

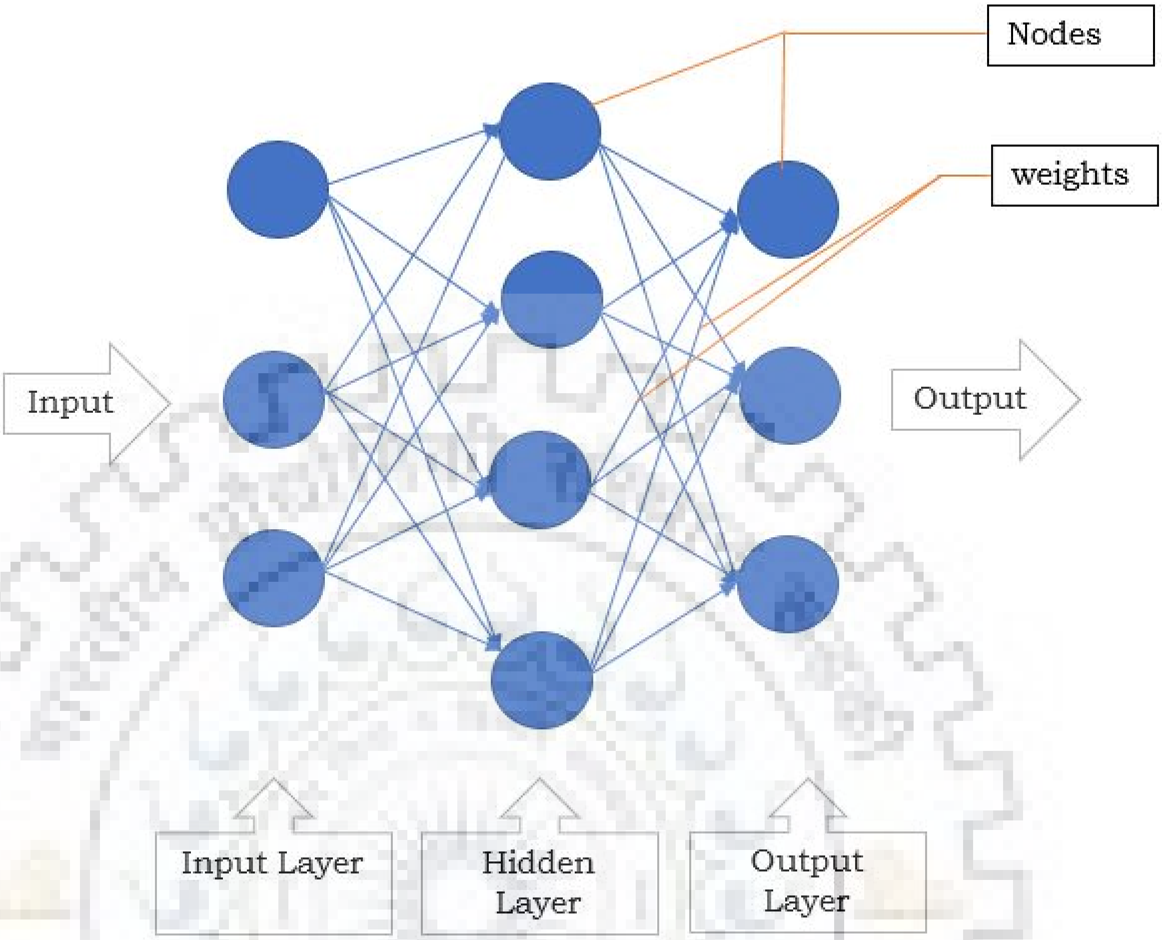


Fig. 2.1. Artificial Neural Network

that facilitate better processing. All nodes and edges in various layers of the network are weight dependent and their value changes according to the introduced problem and while the learning algorithm is applied. These types of Artificial Neural Network used in many fields like image and speech recognition and computer vision.

Feed Back Network having a feedback path. In this method signal has the ability to flow in both directions. It varieties a nonlinear dynamic structure it varies endlessly until it reaches state of equilibrium. It is separated into these types. A Feed Back network with a closed loop called Recurrent network. It has to major subdivisions called fully recurrent network and Jordan network. All nodes connected to other all nodes and every node act as input as well as output is FRN. In Jordan network, the output connect back to the input. This has the opposite type loop to FRN.

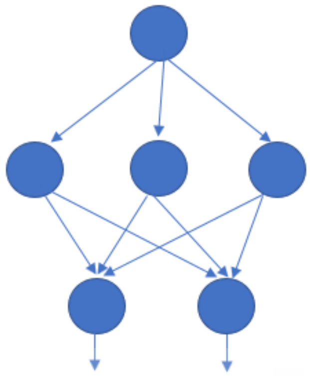


Fig. 2.2. Feed Forward Neural Network

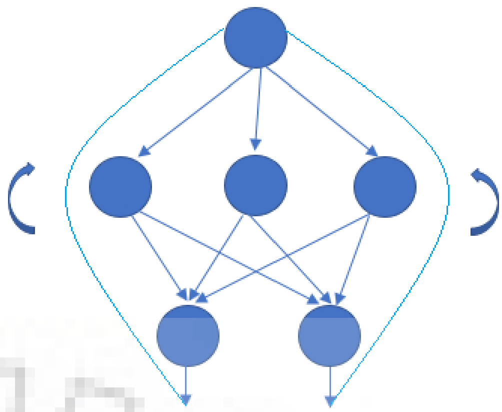


Fig. 2.3. Feed Back Neural Network

2.2.2 Support Vector Machine

Support Vector Machine (SVM) is primarily a smart method that performs classification tasks by constructing hyperplanes in a multidimensional space that separates cases of different class labels. SVM supports both regression and classification tasks and can handle multiple continuous and categorical variables. For categorical variables, a dummy variable is created with case values as either 0 or 1.

2.2.3 Decision Tree

Decision tree comes under supervised learning. It is a graphical representation of all the possible solution to a decision. If the dataset is huge one decision tree is overfitted to that. Therefore in the case should move to the random forest. Decision tree starts with a root and then branches to a number of the solution just like a tree keeps on growing with an increasing number of decision and the conditions. Quantify the amount of uncertainty at a single using a metric called Gini impurity. How much question reduces uncertainty using a concept called information gain. Entropy is just a metric which measures the impurity of something impurity is a degree of randomness. Root entire sample divided into two or more homogeneous set. A leaf node is the one when reaching the end of the tree splitting is dividing the root node into different subpart on the basis of some condition branch or subtree get formed when splitting the tree suppose when spit a root node it gets divided into two branches or subtrees. pruning is just the opposite of splitting just removing the subnode of a DT. The node which is in root is always parent node. All top nodes belong to a parent node. all other nodes associated with that known as a child node.

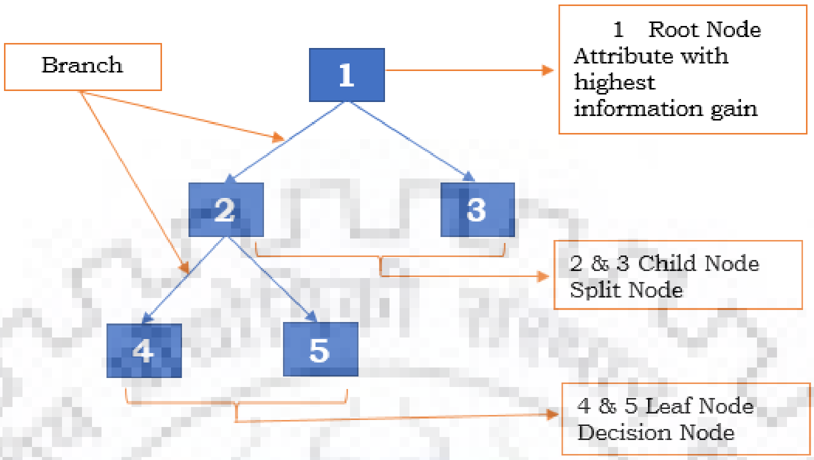


Fig. 2.4. Decision Tree Model

2.2.4 Random Forest

Random forest builds many decision trees and merges them together to get a more accurate and stable prediction. Most of the time the random forest is strained with a bagging method. The bagging method is based on the idea that the combination of learning model increases the overall result. For the huge dataset, the training set categorized into subsamples and create a decision for each subsample. and finally, club the vote to get the decision.

2.2.5 K-Nearest Neighbor

The k-nearest neighbor classifier a very simple way to classify data. If I have more data. Starting with a data set known category then should cluster that data like by using PCA. Then adding a new data all with unknown category to the clot. To figure out which datatype its most similar to. Classify the new data by looking at nearest annotated datat ypes. If k=1, nearest neighbor 1 take and say that data falls into that the datatype that is closest to the unknown data. If k=10 pick the category that gets the most votes. The low value of k can be a noisy and a high value of k is smooth.

2.2.6 Naive Bayes

Naive Bayes classifier one of the most important things in probability and it is very useful in machine learning. Once I have many events and I do not know how to handle them, In that time naive Bayes assumptions that I can make on them to make the maths calculation easier. Naive Bayes classifier is a combination of Bayes theorem and naive assumption that two events are going to be independent when they may not be. Naive Bayes helps us to combine a bunch of different features into creating a model that calculates the probability that something is abnormal and these features get combined in a nice way.

2.3 Methods for Segmentation

Brain tumor segmentation methods can classified as manual segmentation, semi automatic segmentation and fully automatic segmentation.

2.3.1 Manual Segmentation

Manual segmentation method a radiologist practitioner should segment the damaged tissue from the normal tissue with his experience and knowledge in anatomy. It is a time consuming task and difficult. should go through each and every slices one by one pixel by pixel. Patients suffering from HGG have very less survival period so for them fast work is needed without human errors. The manually segmented slices are used as a ground truth image during the training of the MRI images.

2.3.2 Semi Automatic Segmentation

In semi automatic methods at the time of initialization user mainly intervenes an iterative algorithm. During feedback by the algorithm to set proper weights to the feed back and finally at the time of result. During the initialization step first draw a ROI approximately containing the tumour in each of the slices, then during the run of the iterative algorithm user can steer the results towards optimum by adjusting the parameters.This process is faster than manual segmentation method but still user dependent. Hence a shift towards fully automatic segmentation was necessary.

2.3.3 Automatic Segmentation

This type of method is based on developing a model which takes multi model MRI image as input and outputs a lebelled image depicting different tumour sub regions. So, the method is expected to establish the connection between the ground truth and input image. The main steps of these methods are pre processing , feature extraction, segmentation and post processing. Pre processing is done to remove noise and perform intensity bias correction across all the patients. After this extracting features from given MRI image slices which are correct representative of each tissue type. Various image processing methods are engaged to extract those features. Now, these features from as input to classifiers such as Support Vector Machine, Neural Network etc. segmentation results are produced. One of the major problems with traditional classification methods is the selection of the features which correctly represent the data. So, the new trend is to use deep learning based algorithms which have capability of representation or feature learning from raw data along with the classification ability. Therefore, it completely eliminates the need for an explicit feature extraction process. In recent times, many fully automatic methods have been able to achieve state-of-art results.

2.4 Techniques for Segmentation

Various segmentation techniques used for brain tumor segmentation notable advantages and limitation discussed below.

Threshold Technique

Threshold method is a simple method. This method based on the histogram peaks of the image to find a particular threshold value. No need for previous information. Limitations of this method is highly dependent on peaks and spatial details are not considered.

Edge Based Technique

Edge based method is based on discontinuity detection. This method good for images having better contrast between objects. If the image has too many edges this method not suitable.

Clustering Method

Clustering Method based on division into homogeneous clusters advantages of this method are fuzzy uses partial membership therefore more useful for real problems. Determining membership function is not easy is the limitation.

Region Based Technique

Region Based Method based on partitioning image into homogeneous regions more immune to noise,useful when it is easy to define similarity criteria. Limitation of this technique is expensive method in terms of time and memory.

Watershed Technique

Watershed Method based on topological interpretation results are more stable and detected boundaries are continuous complex calculation of gradients.

PDE Based Method

PDE Based Method based on the working of differential equations fastest method, best for time critical applications. More computational complexity is the limitation.

Artificial Neural Network

Disscussed briefly in the section 2.2.1.

2.5 Types of Noises Present in Medical Images

2.5.1 Gaussian Noise

Gaussian noise is additive in nature and statistical in nature existence of Additive White Gaussian Noise in the medical images can be due to bad quality of image capturing, This thing happens only sometimes. Noisy surroundings and noise within communication channels.Since probability density function of Gaussian noise equivalent to that of the normal distribution. Thus, it is called the gaussian distribution. Gaussian noise homogeneously scattered over the signal. Every pixel in the noisy image can be summarized as the total of the actual value of the pixel and arbitrary amount of Gaussian scattered noise.

2.5.2 Salt and Pepper Noise

Salt and pepper noise also called spike noise or impulsive noise. It has luminations pixels in the dark region if the image and dark pixel in the bright region of the image. The values can attainable from salt and pepper noise is a high value and a low value. It basically arises due to conversion errors from analog to digital and also due to bit errors in communication. Important data entrenched in the original image harshly degraded due to salt and pepper noise.

2.5.3 Speckle Noise

Speckle noise deteriorates the standard of the image remarkably and convolutes the decision for identification or recognition for biasing in minute details in ultrasound images. It is a type of manifold noise. Speckle noise can be defined as a grainy noise which deteriorates the standard of medical ultrasound images. Speckle noise persues a gamma distribution.

2.6 Feature Extraction

In machine learning pattern recognition and Image processing feature extraction start from an initial set of measures data and builds to write values intended to be informative. No redundant facilitating the subsequent learning and generalization steps. In some cases leading to better human interpretations, feature extractions are related to dimensionality reduction when input data to an algorithm is too large to be processed and it is suspected to be redundant. Then it can be transformed into a reduced set of features. This process is called feature extraction. Instead of complete initial data, general feature extraction involves reducing the number of resources required to describe a large set of data. When performing analysis of complex data, one of the major problems items from the number of variables involved. Analysis of a large number of variable generally requires a large space of memory, computation power or classification algorithm which overfits the training sample and generalizes poorly to new samples. Feature extraction is a general term for constructing combinations of the variables to get around these problems. While still describing the data with sufficient accuracy. The best results are achieved when the expert constructs set of application dependent features.

2.7 Types of Activation Function

2.7.1 Linear Function

The linear activation function is also called identity function is used at just one place that is in the output layer. The equation of this layer is like a straight line equation. If I differentiate linear function to supply nonlinearity then the result will not rely on the input. Not introduce any pioneering behaviour to the algorithm because the function will become constant.

$$F(x) = x \tag{2.2}$$

2.7.2 Sigmoid Function

Nature of this sigmoid function is nonlinear. Used in the output layer for binary classification Sigmoid functions and their combinations generally work better. It can show 'S' form of graph.This function has vanishing gradient problem. It has two types they are Binary sigmoidal function. it is positive in nature The output cannot be less than zero and more than one.

$$F(x) = sigm(x) = \frac{1}{1 + e(-x)} \tag{2.3}$$

second type is Bipolar sigmoidal function.It can be positive or negative and strictly increasing in nature.

$$F(x) = sigm(x) = \frac{1 - e(x)}{1 + e(x)} \tag{2.4}$$

2.7.3 Tanh Function

Tanh function is non linear in nature. value range from -1 to 1. This function used in hidden layers of a neural network as it's valued lies between -1 to 1 hence the mean of the hiddenlayer comes out to be 0 or very close to it, therefore helps in centering the data by bringing mean close to 0. This makes learning for the next layer much easier.This function also has vanishing gradient problem like sigmoid function.

$$/F(x) = tanh(x) = \frac{2}{(1 + e^{-}2x) - 1} \tag{2.5}$$

2.7.4 Rectified Linear Unit Function

Nowadays the general activation function ReLU is used in many cases. It is implemented in hidden layers of Artificial Neural network. The value ranges from 0 to infinity.Non linear in nature so,can back propagate the errors and have multiple layers of neurons being activated by the ReLU function.ReLu is having less computational expense comparing to sigmoid and tanh.Less computations. At the time only a few neurons are activated making the network sparse making it efficient and easy computation. Dead neurons found in the networks they should use the leaky ReLU function. Relu function used only in hidden layers.It will give the output x if x is positive and 0 else where.

$$F(x) = max(0, x) \tag{2.6}$$

Chapter 3

Literature Survey

This chapter covers the literature review of various techniques that have been used in past for brain tumor segmentation and related studies.

3.1 Review of Machine Learning Based Methods

A tumor detection method was proposed by Natarajan et al. [1] for MRI brain images. Pre processing is the first step brain MRI images using median filter after which threshold technique is used to perform segmentation task. Here morphological techniques can also be used where at the final step tumor regions are obtained by subtractive or difference image technique using Gray level cooccurrence matrix method. Amin et al. [2] used neural networks based solution where the features are first computed from principle component analysis and then it is fed to a multilayer learning perceptron to be trained using backpropagation from the predicted and provided ground truth images. Hence from these machine learning based approaches I can say that most of them uses texture as on of the primary features as well as symmetry of the brain tumor.

V. Anitha et al. [3] proposed an approach of a two-tier classification process. At first, segmentation was done by using adaptive pillar k-means clustering algorithm. Discrete Wavelet Transform coefficients have been used as a set of the feature vector. For tumor classification, SOM neural network and KNN classification algorithms have been used. PS. Jushi et al [4] proposed a method to do fast bounding box approach for boundary detection of brain tumors. And then applied active contour and random walker methods to segment the tumor. Among these two algorithms between those two methods, they finalized FBB applied on random walker technique is the better one. Hasan AM et al. [5]

proposed a technique for detecting abnormal or normal. This method finds the inherent symmetry of two hemispheres of a healthy brain. Modified GLCM matrix based on symmetric concurrences of the pixels. 21 features have been extracted from the modified GLCM matrix. Advantages mentioned is less computational complexity giving effective results. K.skogen et al. [6] proposed method for HGG and LGG dataset. Tumor heterogeneity is characterized using filtration histogram technique with the help of TexRAD. This study used contrast-enhanced texture analysis to quantify the relationship between heterogeneity and grade of gliomas.

Skogen et al. [7] Authors quantify heterogeneity as standard deviation with or without filtration. Tumour size, heterogeneity, and attenuation were correlated with tumor grades. Authors found that the correlation between tumors heterogeneity and grades are significant but there is a moderate correlation between tumor size and attenuation with tumor grade. In [8] authors proposed a method to find the grades of astrocytoma images. Preprocessing by PCNN, feature extracted using DWT and GLCM. Canny edge detection.RBFNN and DNN for classification. Author [9] proposed a two-level hierarchical method for grading the astrocytoma using decision tree and SVM. Three steps used images digitized and segmented to isolate nuclei from surrounding tissue. Then, illustrative variables related to chromatin distribution and DNA content were generated to encode the degree of tumor malignancy. The final step is examining hunt carried out to find the best feature combination. S. Ghanavathi et al. [10] proposed a method for Automatic tumor detection in MRI. Features they used are texture feature, the intensity, the shape, and the symmetry. But this method limitedly applicable to enhace tumor because of features varies for all tumor images.

Naik et al. [11]proposed a technique to classify the medical images. pre-processing followed by feature extraction and association rule mining and the classification for tumor detection in MRI. median filter applied in preprocessing. Wanted features extracted from an image with a texture feature method. Using Decision Tree classification technique Mining of association rules are done from the extracted feature. They concluded that their technique is increases the efficiency. Proposed a super pixel extremely randomised trees based method for detection and segmentation of brain tumor using FLAIR MR image [12]. Varun Jain proposed a method in which MRI benign and malign tumor classified by a hybrid method it includes a discrete wavelet transform process for extracting the features and for reducing the features Genetic algorithm used. Radial Basis Function Neural Network. They showed its Root Mean Square error minimized compared to other methods. [13] greedy layer wise initialization In the first step training the first layer as an auto encoder to reduce the average reconstruction error. the second step is that first hidden layer's description is used as the input of the second hidden layer, and trained to be the second auto encoder. Then the third layer will be trained in a similar way. After a few layers have been trained, the last hidden layer output will be treated as the input of the output layer.Its pyramid structure help to find the nonlinear relations in input nodes. [14]proposed a method for every get trained to reduce the reconstruction cross entropy.

Xiao et al. [15] proposed a method for training the layer as staked auto denoising encoder is first, The input vector x map it to a latent representation y through a deterministic mapping.The resulting latent representation y is then get mapped back to a reconstructed vector Z by another deterministic mapping.Therefore, every training speciman Xi is mapped to a corresponding latent representation y, and a reconstruction vector Zi.

$$y = sigm(Wx + b) \tag{3.1}$$

where,b is a bias vector and W is weight matrix

$$z = sigm(W'y + b') \tag{3.2}$$

$$\theta^*, \theta'^* = arg, \min_{\theta,\theta'} \frac{1}{n} \sum_{i=1}^{n} L(x_i, z_i) \tag{1}$$

$$= arg, \min_{\theta,\theta'} \frac{1}{n} \sum_{i=1}^{n} L(x_i, g'_\theta(f_\theta(x_i))) \tag{3.3}$$

$$L(x, z) = -\sum_{k=1}^{d} [x_k log z_k + (1 - x_k) log(1 - z_k)] \tag{2}$$

The denoising auto-encoder to train it to reconstruct a clean repaired input from a partially destroyed one. This method corrupts the initial input x' to get a partially destroyed version x'.The AE retained to fill in the blanks.Then map and reconstructthe representation of y.z will becomes the deterministic function of y. The equation given below

$$arg \min_{\theta,\theta'} \frac{1}{n} \sum_{i=1}^{n} L(x_i, g'_\theta(f_\theta(x'_i))) \tag{3}$$

Where, x' qD(x'—x) For the classification method,Deep neural network with many hidden layers used.Trained the first denoising autoencoder, which is composed by the input layer and trained the first hidden layer using the image patches. The output of the first hidden layer becomes the input of the second autoencoder. The training will continue in this process. The input layer and hidden layers are the same in number in this SDAE. From this can get improved parameters for the stacked denoising autoencoder. Next step, using the SDAE to start the Feedforward Neural Network. This FFNN is made of one input layer one output layer and many hidden layers. The figure shown here the output layer is used to signify the various category of the input illustration. Thus, the numbers of output later set as two. one group designates midpoint of the image patches are fitting to the brain tumor side. The remaining is fit into the normal tissue. Then additionally enhance this network by engaging the backpropagation with the technique of the stochastic gradient descent. Applying this new classification methodology for the classification of the test image. At last, class label of imagepatches treated as the midpoint classlabel for getting test image to binary image [15]. The results of this method shown in chapter five and compared it with proposed method.

3.2 Review of Hybrid Based Methods

Idrissi et al. [16] used a hybrid methodology for tumor segmentation with a morphological operator and the watershed method. After the process of noise removal, contrast stretching, and thresholding the MRI image is enhanced and the hybrid approach applied to it. They used the images of tumors in the cerebral. [17]did highpass filtering and sharpening to the images then using Otsu thresholding and morphological method to segment the tumor. then, adding this image to the input MRI image and got the result. [18] support vector machine and fuzzy c-means for the projection of a brain tumor. Skull stripping is done by double thresholding and morphological operations. FCM used to find the tumor area and then GLRLM used for extracting features.at last SVM used to classification. [19] Proposed a method using Fuzzy C Means grouping with Artificial Bee Colony and they got efficiently classified results.

Chapter 4

Proposed Methodology for Classification

4.1 Modification and Justification

To overcome some disadvantages of existing methods, I made these modifications, and the Justification for the mofication that I made in this reserch disussed below.

1. A hybrid algorithm, which I proposed is in classification Combined old algorithm with decision tree algorithm. Because, when hybriding two algorithms the detection and classification rate will increase compare to using one algorithm. It happened in this proposed method.

2. MRI images are not perfect everytime therefore, I used filters to remove the noise present in the images which helped for the better performance of the new method.

3. Eventhough the classification accuracy was 95.24 percentage in old implementation the accuracy is not sufficient for dealing with medical image.

4. Machine Learning based techniques always need more dataset to train the machine. If we increase the amount of data machine will work very accurately. But, the main problem is medical datasets not available in open source. Therefore this method is help to sort out the problem.

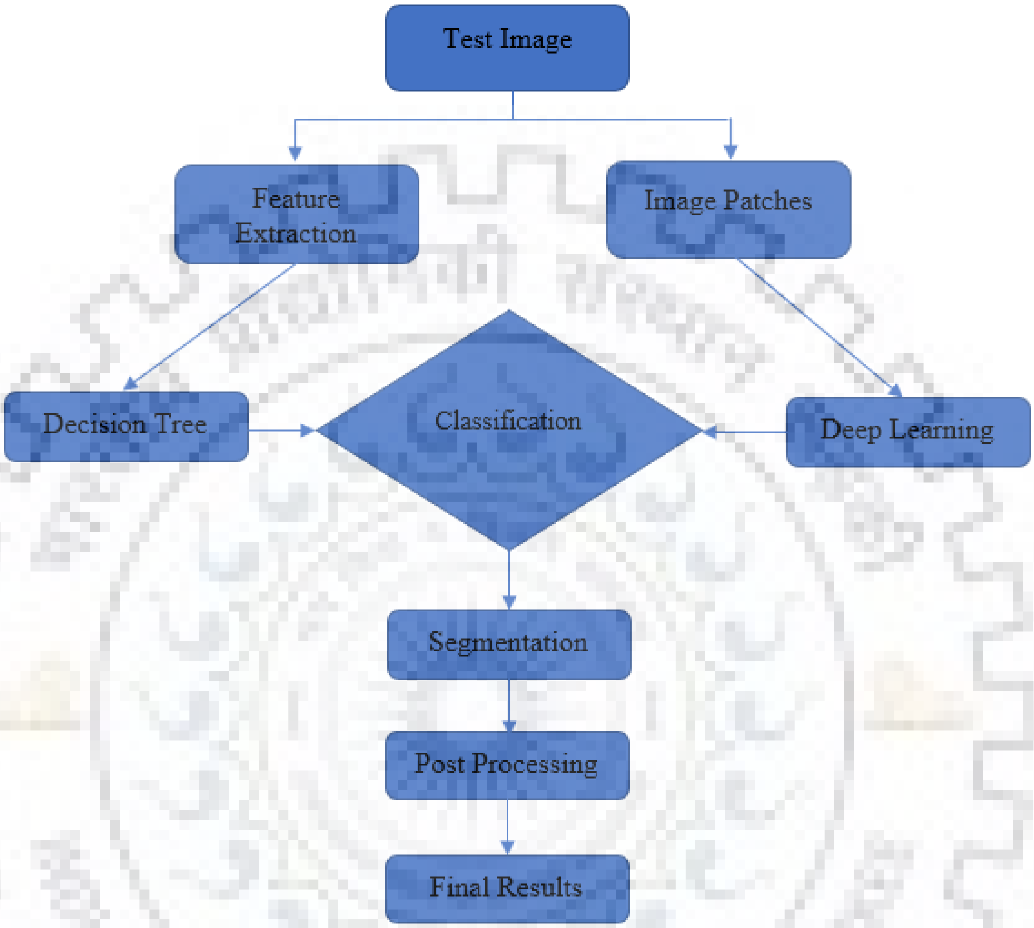
4.1.1 Why Decision Trees?

Decision tree has some better advantages over other classification methods. Here, I disscussed the reason for choosing Decision Tree.

- The decision tree structure is transparent in nature. It states clearly all possible options and indications each option to its conclusion in a single view, allowing for easy comparison among the various options. The use of separate nodes to denote user defined decisions, uncertainties and end of the process gives further clarity and transparency.
- They are white boxes, the obtained knowledge can be expressed in a readable form, while K Nearest Neighbour, Support Vector Machine and Neural Network are black boxes, cannot read the obtained knowledge in an understandable way.Thus, Decision tree has Interpretability.
- It is used for continuous as well as a discrete value inputs.
- It has the capacity to allocate particular values to the problem, decisions, and outcomes of each decision. This decreases uncertainty in making the decision. Every possible framework from a decision finds representation by a clear fork and node, enabling viewing all possible solutions clearly in a single view.This shows the specificity of decision tree.
- Easy to use. It gives a graphical illustration of the problem and different illustrations very simply.Simple mathematics and equations can explain decisions contained in the decision tree easily.
- It is comprehensive Nature. It is a better anticipate model as it allows for a comprehensive review of the outcome of every achievable decision.
- It is flexible compares to other methods. It deals with noisy data, compliated data and incomplete data. once the decion nodes and the tree made classification process happen very quickly.

4.2 Scematic Diagram

Scematic Diagram of the proposed method given below. And the explanation of this diagram discussed in following sections.



4.3 Pre-Processing and Feature Extraction

For training data pre-processing is done. First resized all the images to reduce the computational difficulty. Then adjust the brightness of images to maintain the consistency.noise removal done using Wiener filter which method is mostly used for denoising the two dimensional images. Noise removal shown in figure 4.1 and 4.2. And wiener filter equation for mean and variance given in 4.1 and 4.2. After this step for labeled images manually did ground truthing. For this method I extracted statistical and texture features. Feature of an image can be extracted from its content, by Quanitifying some wanted properties of the image to reduce the extra data from original image. Contents like colour, shape texture position, dominant edges, region etc. The feature of the detected tumor region will extracted by using Gray Level Co Occurrence Matrix and also used Discrete Wavelet Transform [20].The classifier get input characteristics from extracted features. Features that are the great advantageous for efficient diagnosis are skewness, energy, homogeneity, and kurtosis. The feature Mean can be represented as the average intensity level of the image.Variance describes the pixel intensity deviation from its mean value. Histogram symmetry about the mean is described by skewness (darker or lighter pixels as compared to average). The positive skewness specifies that there are more pixels below the mean as compared to above. The relative flatness of the histogram can be calculated by kurtosis which indicates the uniformity of the gray level distribution in comparison to a normal distribution. The positive value indicates that the distribution is peaked and negative kurtosis indicates a flat distribution. Homogeneity is also called Inverse Difference Moment. It is a measure of a local homogeneity of an image. It may be represented by a single value or more values, to determine whether the image is textured or not. These parameters are listed under the category of first-order statistical parameters because they can be calculated by using pixel values and do not depend on inter relationships between pixels [21–23, 23, 24]. Discrete Wavelet Transform(DWT) is used which decompose the signal into mutually orthogonal wavelet functions. It preserves both time and frequency domain of the signal. In numerical analysis and functional analysis, a discrete wavelet transform is a wavelet transform for which the wavelets are discretely sampled as with other wavelet transforms. A key advantage it has over Fourier transforms is a temporal resolution. It captures both frequency and location information. Haar is first DWT, for an input represented by a list of numbers, the Haar wavelet transform may be considered to pair up input values storing the difference and passing the sum. This process repeated recursively pairing up the sums to provide the next scale which leads to differences in the final sum.

$$\mu = \frac{1}{NM} \sum_{n_1, n_2 \in n} a(n_1, n_2) \tag{4.1}$$

$$\sigma^2 = \frac{1}{NM} \sum_{n_1, n_2 \in n} a^2(n_1, n_2) - \mu^2 \tag{4.2}$$

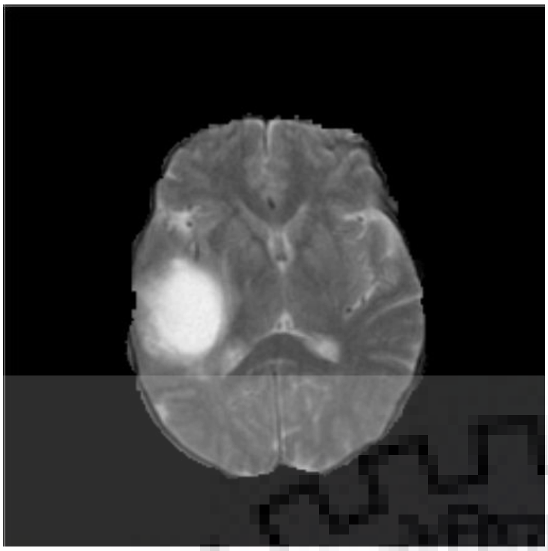


Fig. 4.1. Image Before Filtering

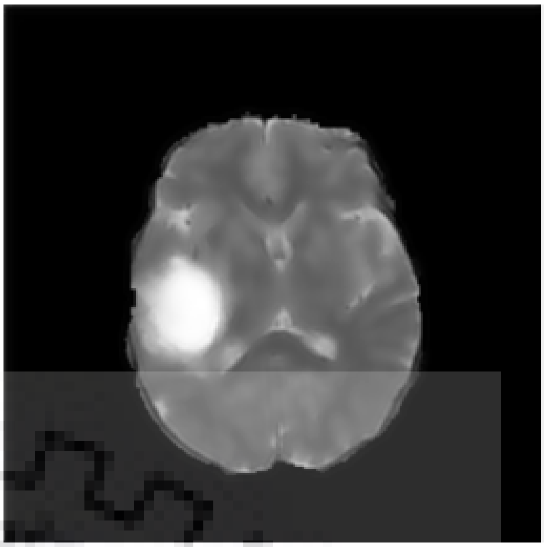


Fig. 4.2. Wiener Filtered Image

4.4 Classification using Hybrid Algorithm

In this hybrid methodology, I used decision tree algorithm along with the Deep Learning. In the medical area decision making plays an prime role and also help the physician to diagnose the patient as soon as possible. Decision making based on different types. Giving a quick answer or response and giving accurate and reliable results is the best decision making. Three basic types of decision trees are single decision tree, boosted decision tree and decision tree forest Decision tree classification gives a quick and productive process of dividing data sets.The first step is data collection. After collecting data next step is wrangling which is the process of cleaning and converting the new data into wanted format. After the data have been cleaned and converted into a particular format the data is analyzed to select and filter the data required to prepare them all. Because not all the data is required for a particular model have to select certain feature now after selecting the pattern and the rules which the algorithm understands the pattern and the rules which govern the data after this the testing dataset determines the accuracy of the model and after that model is ready. So, the final stage comes is that the speed and the accuracy of the model should be deployed. In the real system and after the model is deployed based upon its performance the model is retrained. In the same procedure Decision making is executed. First one is training the classifier with the feature. For training, I selected an attribute or question that the patient has a brain tumor, which I set as the root node. Enropy and information gain shown the formula 4.3 and 4.4. In subsets one side is for Tumor or abnormal tissues in the brain. Another side for normal brain or no tumor. Though I used the same dataset I used earlier, abnormal Higher Grade Glioma images trained. The second one is testing. I add this decision tree classification into neural network classification algorithm. While giving the test image first I will do the classification through deep network and then decision tree will check whether the output or prediction from deep network is correct or not. Decision Tree can work perfectly with less dataset also. After the result comparison deccision, it will save the results for accuracy prediction using the matrix. The production rate of the suggested methodology is evaluated in terms of accuracy, sensitivity, specificity and confusion matrix.

$$Entropy = \frac{-p}{(p+n)}\log_2\frac{p}{(p+n)} + \frac{-n}{(p+n)}\log_2\frac{n}{p+n} \tag{4.3}$$

$$E(s) = -\sum Pi\log_2 Pi \tag{4.4}$$

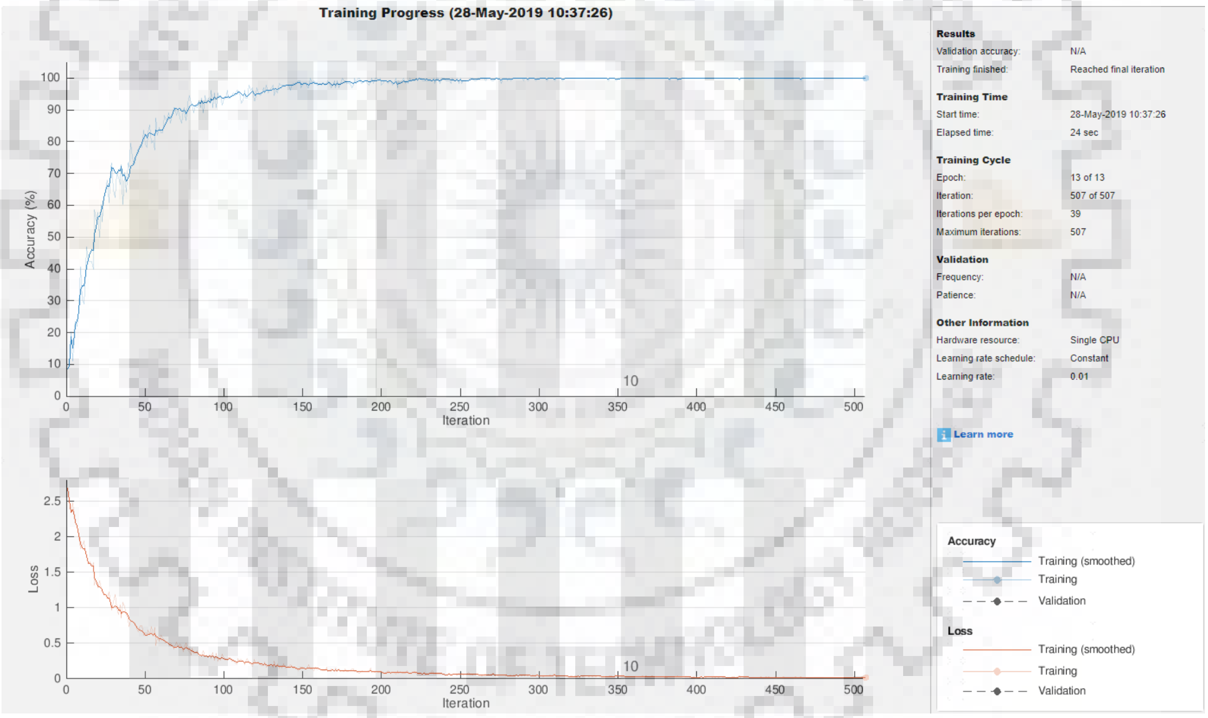


Fig. 4.3. Training Accuracy and Loss Graph

4.5 Post Processing

Morphological processing is dealing with tools. It is a study of an object. There are four types in this method. They are 1. dilation 2. erosion 3. opening 4. closing. The Dilation will increase the white pixels of an image and the black pixels reduces. therefore, holes will get reduced. In erosion white pixels reduced and black pixels will get increased.

Therefore, holes will increase. In opening first erosion followed by dilation should be done. In the close process first dilation and then followed by erosion. The open operate often disconnects narrow gaps and eliminates the small bumps. The close operation can smooth the outline of the image, fuse the narrow gap and fill in the hole [15]. The structuring element is similar to the filter mask.

Chapter 5

Results and Disscusion

5.1 Description of Dataset

In this experiment I used the dataset which is from MICCAI BRATS challenge for the year of 2017. This Dataset consists of three dimensional MRI images from High grade glioma patients. For the uniform comparison among all methods the train data and test data split for all methods taken same. I used 80:20 training testing split for those experiments. For training I selected 300 patients images and, for testing I used 60 images.

5.2 Results from Deep Learning method

The result of Brain Tumour segmentation method using Deep Learning is shown below. Here, trained the layer as staked auto denoising encoder. The detailed procedure discussed in Chapter 3. At first input image is given. From that the results of Tumor Region , Tumor outline, Segmentation of the tumor and performance graph shown. The performance graph shows the Mean Square Error Decreased and the best performance in epoch 2.

Fig. 5.1. Brain Tumor Segmentation Using Deep Learning

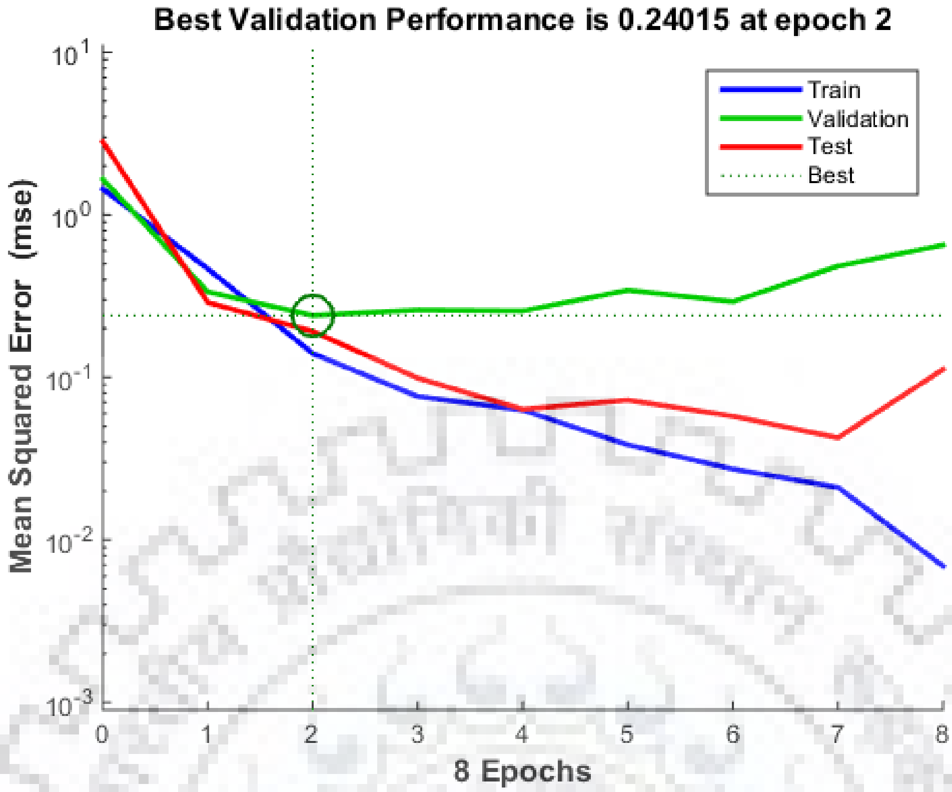


Fig. 5.2. Performance Graph

5.3 Results from Proposed method

In this section the results of proposed method shown. The result of three magnetic Resonance Image Shown below. At first test image given Fig 5.3, fig 5.12, fig 5.19 Which is filtered using Wiener filter fig 5.4 fig 5.12 fig 5.20 shows filtered Image. And following images shows DWT feature extraction, Tumor outline, Tumor detected area, Tumor outline, Segmented Tumor, and Morphological Operation results respectively. Finally the MSE graph also shown. The procedure for these operations discussed in chapter 4.

5.3.1 Tumor segmentation Results for Test Image 1

Fig. 5.3. Test Image 1

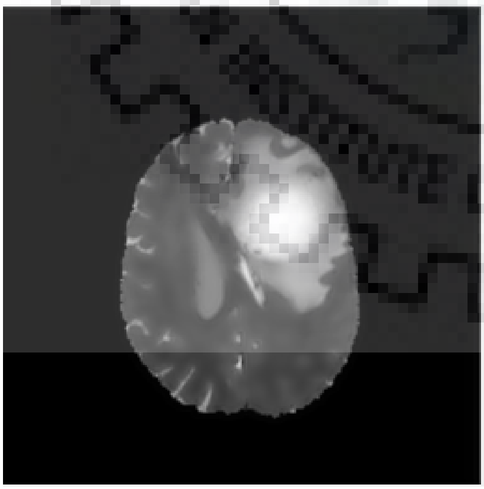


Fig. 5.4. Wiener Filterd Image

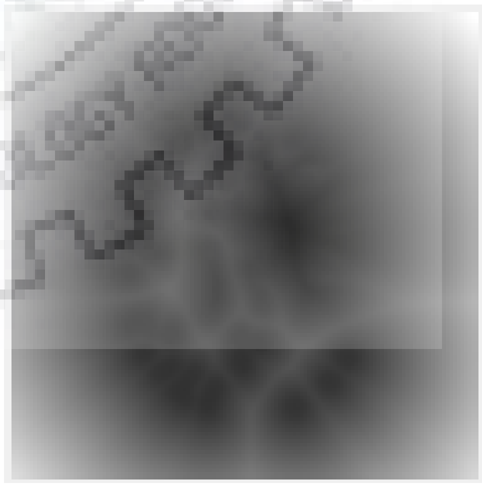


Fig. 5.5. Feature Extracted Image

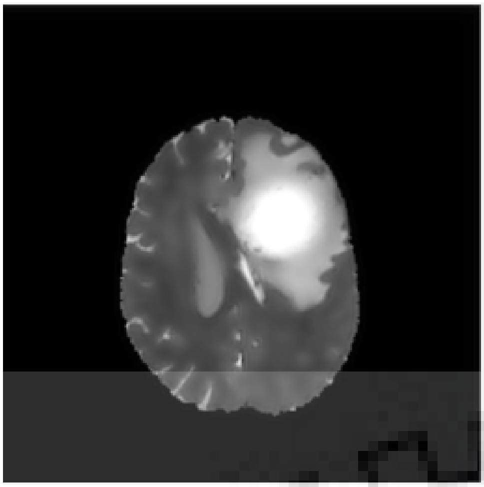


Fig. 5.6. Contrast stretching

Fig. 5.7. Morphological Dilation

Fig. 5.8. Erosion

Fig. 5.9. Thinning

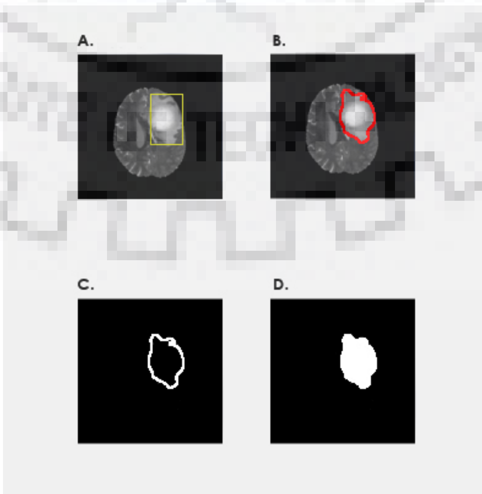


Fig. 5.10. Segmentation of Image 1

A.Tumor outline B. Tuomr detected area C. Tumor outline D. Segmented Tumor

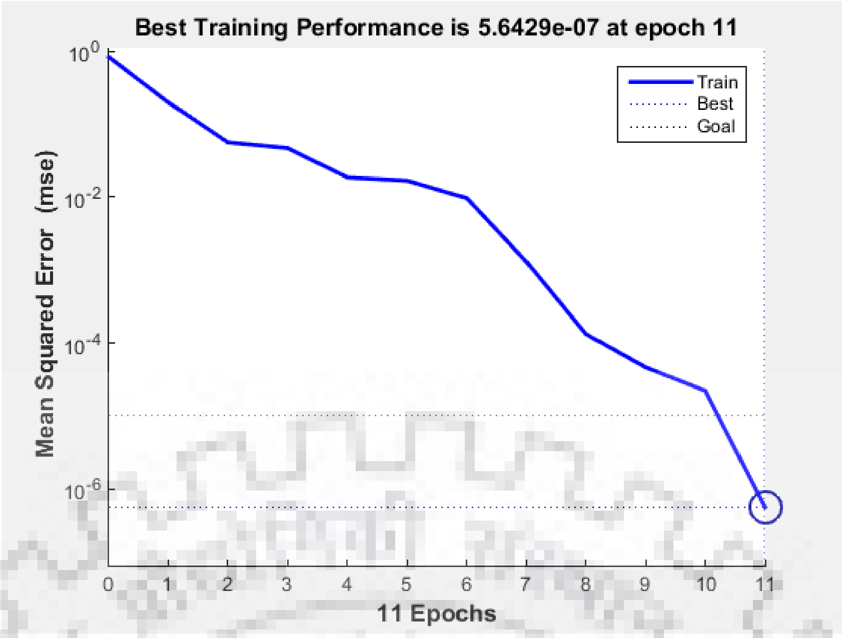


Fig. 5.11. Performance Graph

5.3.2 Tumor segmentation Results for Test Image 2

Fig. 5.12. Test Image 2

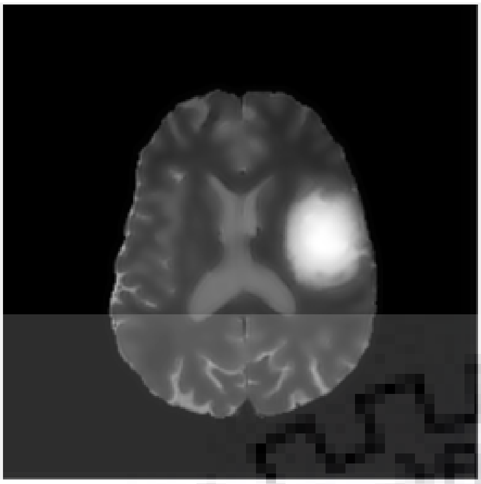


Fig. 5.13. Wiener Filtered Image

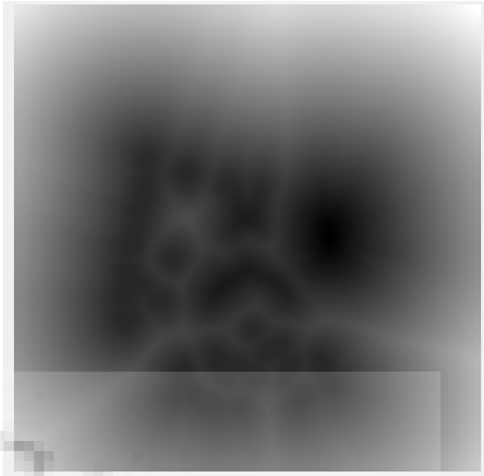


Fig. 5.14. Feature Extracted Image

Fig. 5.15. Contrast stretching

Fig. 5.16. Morphological Dilation

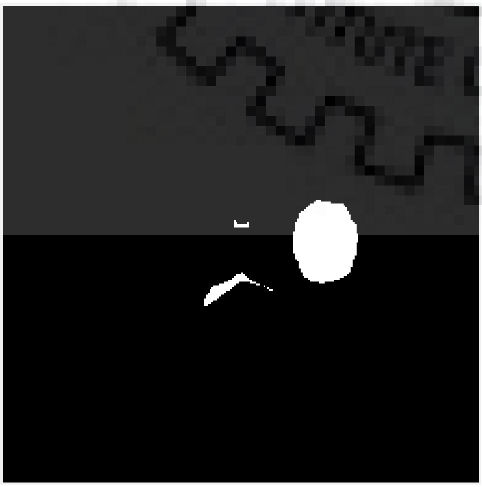


Fig. 5.17. Morphological Erosion

Fig. 5.18. Thinning

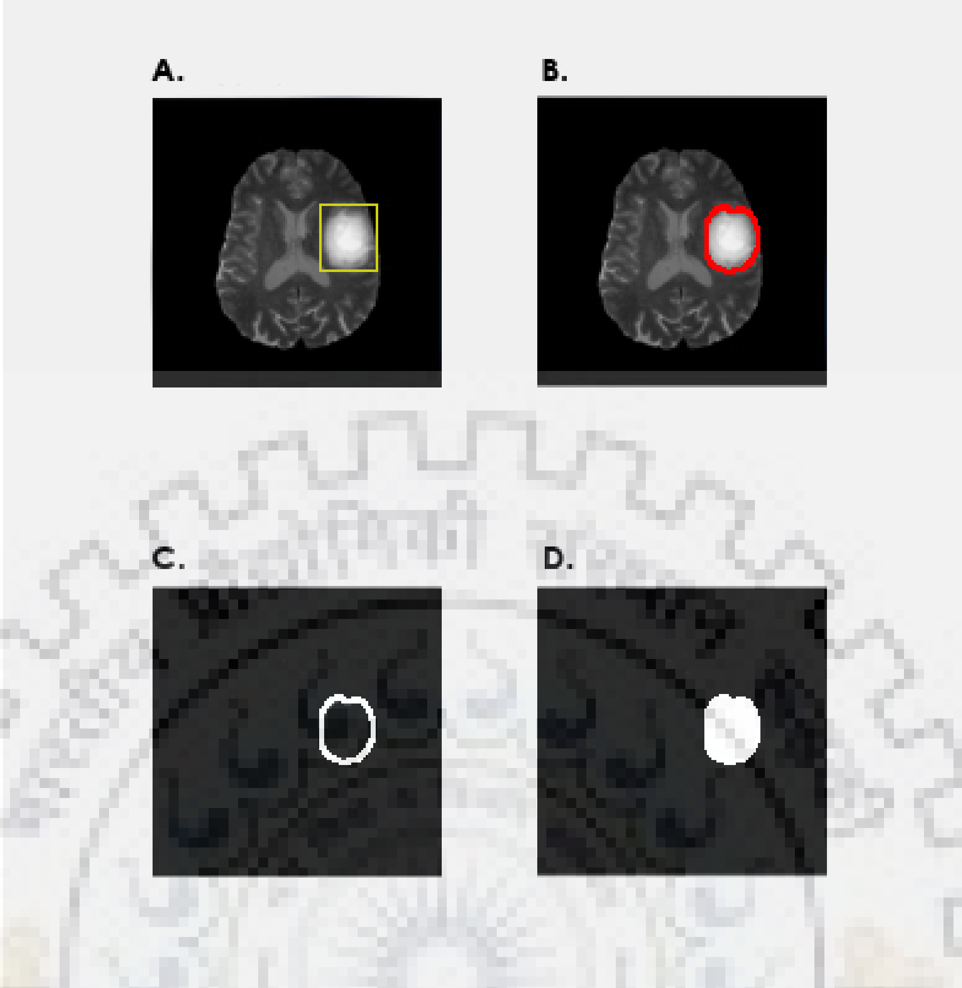


Fig. 5.19. Segmentation of Image 2

A.Tumor outline B. Tuomr detected area C. Tumor outline D. Segmented Tumor

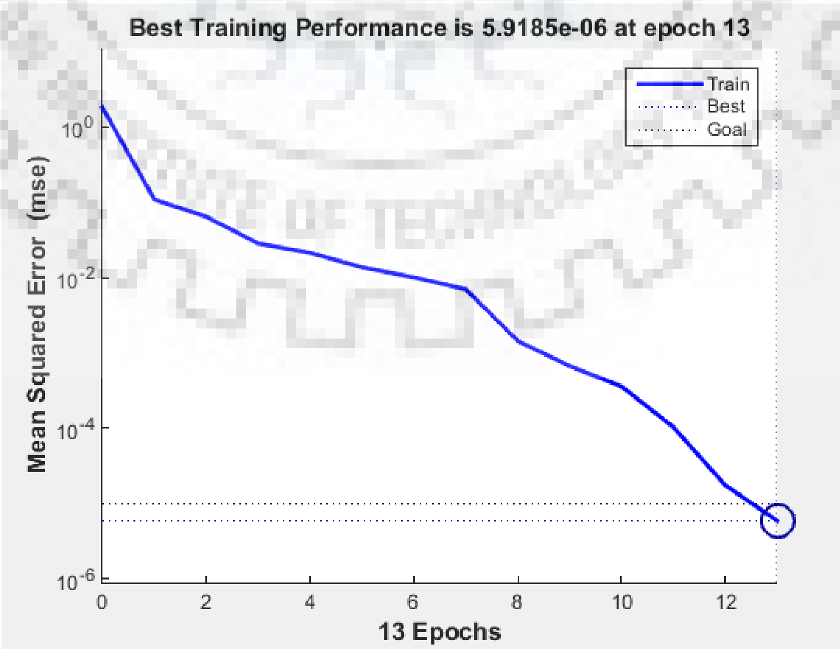


Fig. 5.20. Performance Graph

5.3.3 Tumor segmentation Results for Test Image 3

Fig. 5.21. Test Image 3

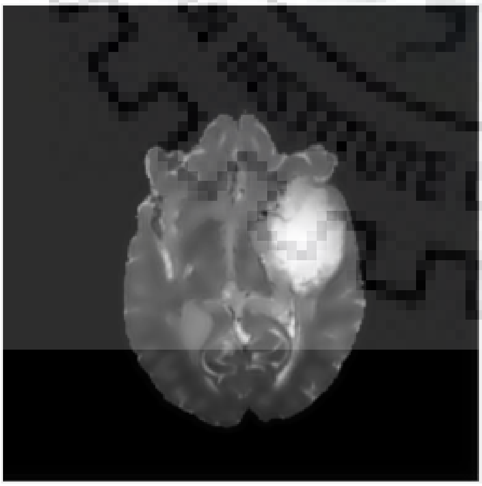


Fig. 5.22. Wiener Filterd Image

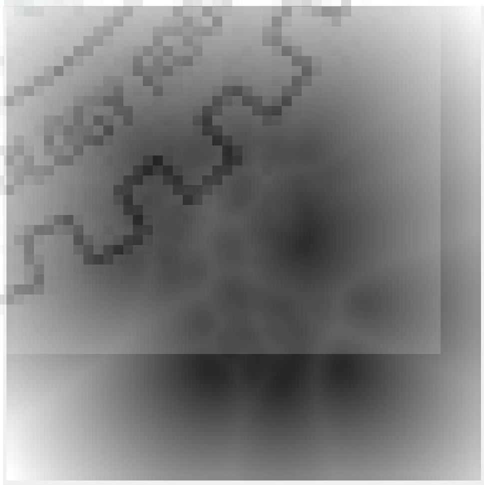


Fig. 5.23. Feature Extracted

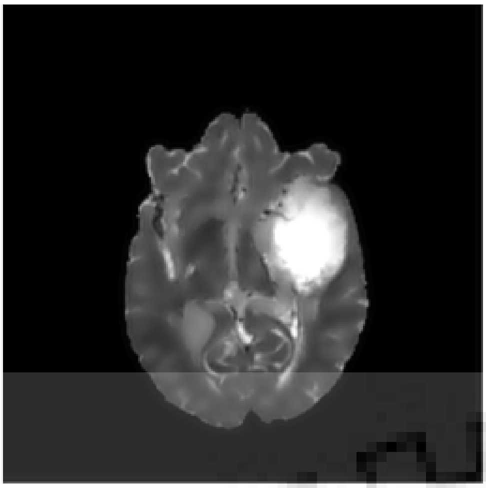


Fig. 5.24. Contrast stretching

Fig. 5.25. Morphological Dilation

Fig. 5.26. Morphological Erosion

Fig. 5.27. Thinning

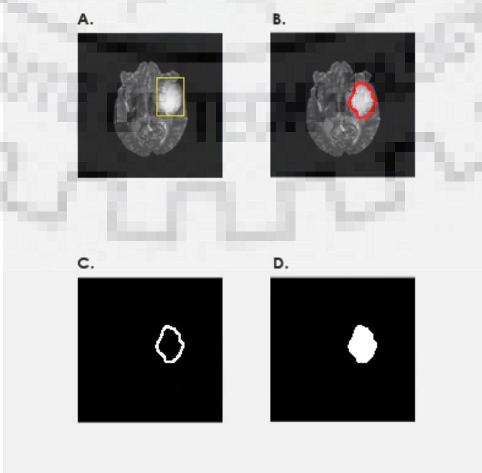


Fig. 5.28. Segmentation of Image 3

A.Tumor outline B. Tuomr detected area C. Tumor outline D. Segmented Tumor

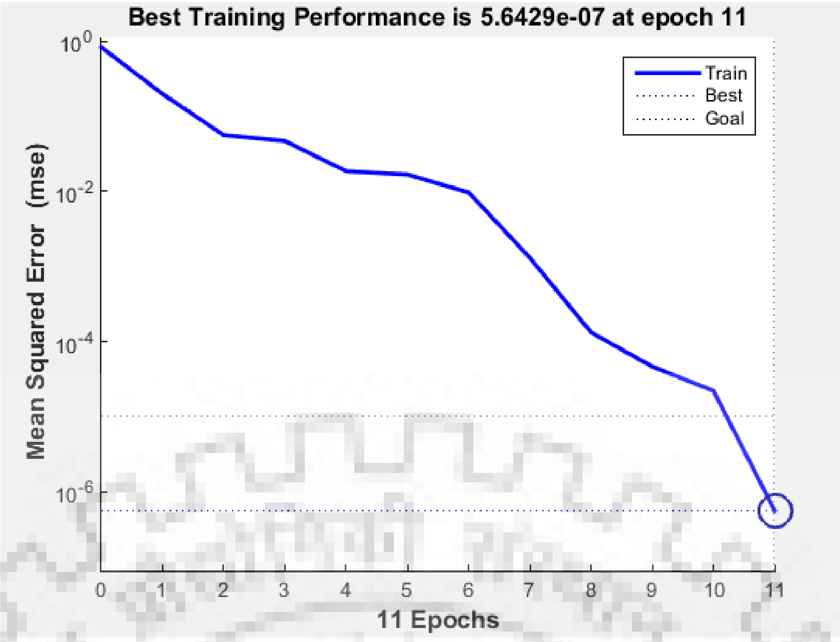


Fig. 5.29. Performance Graph

5.3.4 Confusion Matrix

The confusion matrix is used to describe the performance of a model. In the case of classification, the value of testing data known to the tester. It will appear like a table format. It's a very simple and effective way to check the performance. True positives are the cases in which should predict yes if they have the tumor. In True negatives, should predict negative when image do not have the tumor. In False positives, should predicted yes, but they do not really have the tumor. This is also called as Type I error. In false negatives, should predict no, but they really do have the disease. This is also called as a Type II error Error rate also called as misclassification rate , sensitivity also named as true positive rate and specificity also named as true negative rate The equation for calculating the accuracy, Error rate, Sensitivity and specificity are given below.

Table 5.1: Confusion Matrix

	Actual Yes	Actual No
Predicted Yes	58	2
Predicted No	0	40

$$Accuracy = \frac{(TruePositive + TrueNegative)}{Total} \tag{5.1}$$

$$Errorrate = \frac{(FalsePositive + FalseNegative)}{Total} \tag{5.2}$$

$$Sensitivity = \frac{Truepositive}{(TruePositive + FalseNegative)} \tag{5.3}$$

$$Specificity = \frac{TrueNegative}{(TrueNegative + FalsePositive)} \tag{5.4}$$

$$Recall = \frac{TruePositive}{(TruePositive + FalseNegative)} \tag{5.5}$$

$$Precision = \frac{TruePositive}{(TruePositive + FalsePositive)} \tag{5.6}$$

$$FMeasure = 2 * \frac{Precision * Recall}{(Precision + Recall)} \tag{5.7}$$

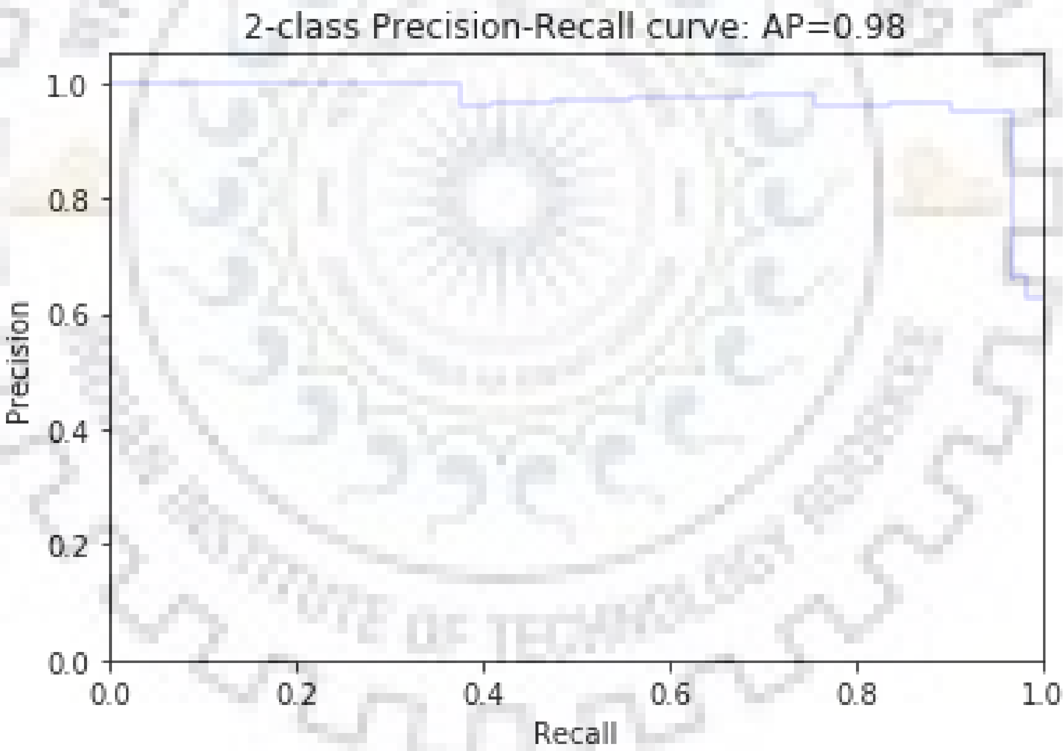


Fig. 5.30. precision-Recall Curve

5.4 Comparing the Results of Deep Learning and Proposed Method

The table 5.2 is showing the comparison result of the accuracy, sensitivity and specificity comparison using confusion matrix.

Table 5.2: Comparison Results using Confusion Matrix

Classifiers	Accuracy	Sensitivity	Specificity
Deep Network	95.24	100	90.91
Proposed Method	98	100	98

Chapter 6

Conclusion and Future Scope

The proposed hybrid algorithm using decision tree and the Deep Netwok for the classification and segmentation of the brain tumor is implemented for the standard dataset from MICCAI BraTs challenge which has shown significant improvement in the result. The GLCM and DWT used to extract the statistical and texture features for Decision Tree classification method.Using those features it is able to classify and segment image accurately. My proposed methodology is applicable for less dataset.

The future work for this project is to experiment on large scale data based on the complex tumor images. And developing the classification method for other types of cancers.

Bibliography

[1] P. Natarajan, N. Krishnan, N. S. Kenkre, S. Nancy, and B. P. Singh, "Tumor detection using threshold operation in mri brain images," in *2012 IEEE International Conference on Computational Intelligence and Computing Research*. IEEE, 2012, pp. 1–4.

[2] S. E. Amin and M. Megeed, "Brain tumor diagnosis systems based on artificial neural networks and segmentation using mri," in *2012 8th International Conference on Informatics and Systems (INFOS)*. IEEE, 2012, pp. MM–119.

[3] V. Anitha and S. Murugavalli, "Brain tumour classification using two-tier classifier with adaptive segmentation technique," *IET computer vision*, vol. 10, no. 1, pp. 9–17, 2016.

[4] P. Juhi and S. Kumar, "Bounding box based automatic segmentation of brain tumors using random walker and active contours from brain mri," in *2014 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT)*. IEEE, 2014, pp. 700–704.

[5] A. M. Hasan and F. Meziane, "Automated screening of mri brain scanning using grey level statistics," *Computers & Electrical Engineering*, vol. 53, pp. 276–291, 2016.

[6] K. Skogen, A. Schulz, J. B. Dormagen, B. Ganeshan, E. Helseth, and A. Server, "Diagnostic performance of texture analysis on mri in grading cerebral gliomas," *European journal of radiology*, vol. 85, no. 4, pp. 824–829, 2016.

[7] K. Skogen, B. Ganeshan, C. Good, G. Critchley, and K. Miles, "Measurements of heterogeneity in gliomas on computed tomography relationship to tumour grade," *Journal of neuro-oncology*, vol. 111, no. 2, pp. 213–219, 2013.

[8] S. Suja, N. George, and A. George, "Classification of grades of astrocytoma images from mri using deep neural network," in *2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI)*. IEEE, 2018, pp. 1257–1262.

[9] D. Glotsos, P. Spyridonos, P. Petalas, D. Cavouras, V. Zolota, P. Dadioti, I. Lekka, and G. Nikiforidis, "A hierarchical decision tree classification scheme for brain tumour astrocytoma grading using support vector machines," in *3rd International Symposium on Image and Signal Processing and Analysis, 2003. ISPA 2003. Proceedings of the*, vol. 2. IEEE, 2003, pp. 1034–1038.

[10] S. Ghanavati, J. Li, T. Liu, P. S. Babyn, W. Doda, and G. Lampropoulos, "Automatic brain tumor detection in magnetic resonance images," in *2012 9th IEEE International Symposium on Biomedical Imaging (ISBI)*. IEEE, 2012, pp. 574–577.

[11] J. Naik and S. Patel, "Tumor detection and classification using decision tree in brain mri," *International Journal of Computer Science and Network Security (IJCSNS)*, vol. 14, no. 6, p. 87, 2014.

[12] M. Soltaninejad, G. Yang, T. Lambrou, N. Allinson, T. L. Jones, T. R. Barrick, F. A. Howe, and X. Ye, "Automated brain tumour detection and segmentation using superpixel-based extremely randomized trees in flair mri," *International journal of computer assisted radiology and surgery*, vol. 12, no. 2, pp. 183–203, 2017.

[13] Y. Bengio, P. Lamblin, D. Popovici, and H. Larochelle, "Greedy layer-wise training of deep networks," in *Advances in neural information processing systems*, 2007, pp. 153–160.

[14] P. Vincent, H. Larochelle, Y. Bengio, and P.-A. Manzagol, "Extracting and composing robust features with denoising autoencoders," in *Proceedings of the 25th international conference on Machine learning*. ACM, 2008, pp. 1096–1103.

[15] Z. Xiao, R. Huang, Y. Ding, T. Lan, R. Dong, Z. Qin, X. Zhang, and W. Wang, "A deep learning-based segmentation method for brain tumor in mr images," in *2016 IEEE 6th International Conference on Computational Advances in Bio and Medical Sciences (ICCABS)*. IEEE, 2016, pp. 1–6.

[16] N. Idrissi and F. E. Ajmi, "A hybrid segmentation approach for brain tumor extraction and detection," in *2014 International Conference on Multimedia Computing and Systems (ICMCS)*. IEEE, 2014, pp. 235–240.

[17] A. Vidyarthi and N. Mittal, "A hybrid model for extraction of brain tumor in mr images," in *2013 INTERNATIONAL CONFERENCE ON SIGNAL PROCESSING AND COMMUNICATION (ICSC)*. IEEE, 2013, pp. 202–206.

[18] A. Singh *et al.*, "Detection of brain tumor in mri images, using combination of fuzzy c-means and svm," in *2015 2nd International Conference on Signal Processing and Integrated Networks (SPIN)*. IEEE, 2015, pp. 98–102.

[19] G. Gopika, J. Shanthini, and S. Karthik, "Hybrid approach for the brain tumors detection & segmentation using artificial bee colony optimization with fcm," in *2018 International Conference on Soft-computing and Network Security (ICSNS)*. IEEE, 2018, pp. 1–5.

[20] E. Sergaki, G. Spiliotis, I. O. Vardiambasis, T. Kapetanakis, A. Krasoudakis, G. C. Giakos, M. Zervakis, and A. Polydorou, "Application of ann and anfis for detection of brain tumors in mris by using dwt and glcm texture analysis," in *2018 IEEE International Conference on Imaging Systems and Techniques (IST)*. IEEE, 2018, pp. 1–6.

[21] S. A. Shah and N. Chauhan, "Techniques for detection and analysis of tumours from brain mri images: a review," *Journal of Biomedical Engineering and Medical Imaging*, vol. 3, no. 1, p. 09, 2016.

[22] M. Soltaninejad, X. Ye, G. Yang, N. Allinson, T. Lambrou *et al.*, "An image analysis approach to mri brain tumour grading," *Oncology News*, vol. 9, no. 6, pp. 204–207, 2015.

[23] E. I. Zacharaki, S. Wang, S. Chawla, D. Soo Yoo, R. Wolf, E. R. Melhem, and C. Davatzikos, "Classification of brain tumor type and grade using mri texture and shape in a machine learning scheme," *Magnetic Resonance in Medicine: An Official Journal of the International Society for Magnetic Resonance in Medicine*, vol. 62, no. 6, pp. 1609–1618, 2009.

[24] E. D. Angelini, J. Delon, A. B. Bah, L. Capelle, and E. Mandonnet, "Differential mri analysis for quantification of low grade glioma growth," *Medical image analysis*, vol. 16, no. 1, pp. 114–126, 2012.