Automated Identification of Brain Tumor using Image Transformation Methods

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Article Info
Page Number: 8061 - 8077
Publication Issue:
Vol 71 No. 4 (2022)

Abstract

In medical image processing, automated detection and classification of Brain Tumor Images (BTI) is very important. Tumors are nothing but the abnormal cells which grow in the brain and directly affect all the healthy cells. In young generation the effect of brain tumor is rapidly increasing. Manual detection and classification of brain tumors can cause human errors. Automated detection and classification of tumor is required as it reduces the burden of human observer and the accuracy also will not be affected due to use of large number of images. Accurate detection and classification of the tumors is required for diagnosis and subsequent treatment planning .Generally, electronic equipment is used in brain tumor diagnosis. The efficient and most popular technique used for diagnosing the brain tumor is Magnetic Resonance Imaging (MRI).This paper uses an image transformation technique named Discrete Cosine Transform (DCT) to obtain the test data results as normal or abnormal images by using the trained dataset images and calculate the percentage of accuracy, sensitivity and specificity using the confusion matrix attributes. Then the obtained abnormal images are further classified by a novel method of segmentation. In this process Otsu's Binirization technique is used to obtain the binary transformation of an image and clustering algorithm named k-means clustering is used to segment the required area of an image. A Discrete Cosine Transform (DCT) is employed for obtaining the features of the image and these extracted features are given to kernel SVM and the Cross validation method is used for enhancement and SVM generalization to classify the Benign and Malignant tumors. These methods are helpful for early detection and also assist doctors in identifying the severity of tumor.

Article History
Article Received*: 25 March 2022*
Revised*: 30 April 2022*
Accepted*: 15 June 2022*
Publication*: 19 August 2022*

Keywords-Brain Tumor; DCT; Magnetic Resonance Imaging (MRI); Otsu Binirization technique; SVM Classification

I. INTRODUCTION

Brain is a complex organ and any effect on it causes lifelong changes. It is the main part which efficiently controls the activities of all the body parts. Brain Tumor is the development of abnormal cell in the brain. The skull surrounding the brain is very rigid and any abnormal growth inside it causes serious problems. Brain Tumor can be Cancerous or Non-Cancerous. The tumor growth inside the brain may cause damage to the brain and also may affect the human survival. The early identification of these tumors is very important to select the most convenient method of treatment to save patients life. Classifying the normal and abnormal tumors with high accuracy is a challenging task in automated tumor identification and use of classifiers for better classification is the major focus of this research study. Early identification of tumor can help the radiologist or the clinical experts to take correct decisions which may help in increasing the survival rate of the affected patients.

Among all the imaging modalities like Biopsy, MRI and CT scan, Magnetic Resonance Imaging (MRI) is a non-invasive method which has no radiation impact on the human body, and produces anatomical structures of the images with high resolution and good quality and also produces more information which can be helpful in biomedical research and clinical diagnosis. So, doctors generally prefer MRI brain tumor imaging technique for brain tumor diagnosis. Manual method of tumor identification and classification can consume more time and also has the chance of producing human error, and these factors are to be reduced in order to get the results with good accuracy rate. The main objective of using medical imaging methods in brain tumor identification and classification is to get accurate information from the images with less number of errors and also able to identify the absence or presence of tumor and also to identify whether the tumor is cancerous or non-cancerous.The numbers of false negatives are to be minimized and a computerized diagnosis model for tumor detection and classification is proposed to identify different types of brain tumor images. The method proposedhelps the clinical experts in correct diagnosis of abnormal areas with less time and also able to classify the normal and abnormal images with high accuracy level.

II. BLOCKDIAGRAM FOR IMAGE DETECTION AND CLASSIFICATION

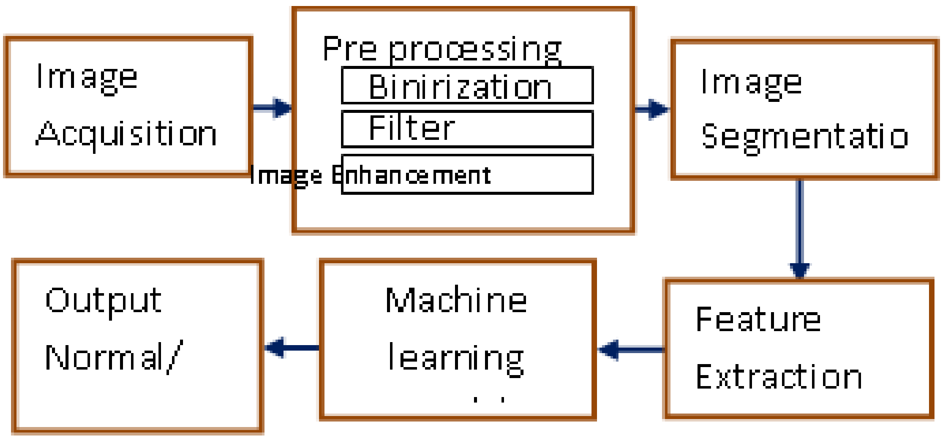


Figure 1. Block diagram of Image Detection and classification

A. *Image Acquisition*

The first step used is the acquisition of MRI image. These images are stored in two dimensional matrix forms which store the pixels in the form of elements. These images are obtained as gray scale images where the values will range from Zero to one (0-1)in which ‘1’ indicates total white and ‘0’indcates total black colour and the values between 0-1 vary in intensity from 0 to 1.The pre-processing includes enhancement of the image, filtering operation and image segmentation.

B. *Image Enhancement*

The first step in image pre-processing is image enhancement. The method named contrast stretching is used as it performs better on gray scale images and also the intensity values can be set in the range of 0 to 1 by which contrast level can be increased which reduces the ambiguity appearing in different portion of the image.

C. *Filter Operation*

The filtering operation is performed to increase the edge enhancement, smoothness and also the sharpness of the image. It is used to preserve the edges and also to reduce the noise.

D. *Image Segmentation*

Segmentation is used for division of images into objects and regions which correspond to the real world areas or objects and this sub division is done based on specific application. It is also used for the dividing the images into regions using similar attributes. It can also be used to obtain some additional features of the image for further analysis. With these segmentation methods, doctors can obtain size, shape and correct location of the tumor. The different methods of brain tumor segmentation based on human interaction are manual segmentation methods, Semi-automated methods and automated methods and the methods based on manually labelled training data are supervised and unsupervised methods and the methods based on conventional method are thresholding and region growing. In manual segmentation the identification of brain tumor from imaging modalities like MRI, CT Scan is a primary concern, but it is a tedious and time taking process for clinical supervisors or radiologists and also it depends on the radiologist and it varies from expert to expert as it depends on the efficiency of the expert and also the operator needs a lot of experience. The semi-automated method combines human experience and computer and this requires human intervention for initialization and correcting the errors and modifies the output for obtaining efficient segmentation. However by intervention of human, the segmentation results may change from expert to expert and also with the same expert. In automated methods, with the introduction of computerized technology in medical imaging and development in the e-health care system helps radiologists to provide efficient treatment to the patients. In automated methods computers determine the identification and classification process without any human intervention. This requires anatomic knowledge such as size, shape, area and position of the tumor to construct a model for performing the task.

E. *Image Identification*

The main step in this process is to obtain the region of interest (ROI). This ROI is obtained from the features obtained using the feature extraction methods. Different ranges of size such as diameter, solidity, area are set as the features to detect the tumor part. When the tumor falls within the range, then ROI can be successfully extracted.

F. *Related Work*

In Digital Image processing images are acquired using image acquisition and segmentation is done using different segmentation techniques for extracting the required information. Segmentation of an image is nothing but the partition of the image into multiple segments. A reverse segmentation is required for an alternate representation of an image which is very efficient and can be easily analyzed for identifying the abnormality of the brain [1].The literature survey of the recent segmentation methods for brain tumor of different MRI images is explained. In this review the hybrid method which uses conditional random field along with conventional neural network and CRF is explained which is more effective to fulfil the requirements of tumor segmentation [2]. A technique is developed for tumor detection and classification from MRI which is automated and uses marker-based watershed algorithm for segmentation and feature selection [3]. By using gamma based contrast stretching the contrast can be improved and a segmentation accuracy of 92.26% with sensitivity rate of 91.01% is achieved. The brain tumor detection using this method is fast and accurate when compared with the manual methods performed by the radiologists for different experiments [4]. The proposed algorithm which considers various performance measures provides better results in improving certain parameters like sensitivity, specificity, dice coefficient and accuracy [5].

The results after experimentation achieved an accuracy of 90.51% in identifying abnormal and normal tumors. MRI Brain Images are generally used in the detection of the tumors [6] and various medical image processing methods are analyzed to detect a brain tumor from scanned MRI images. They employed thresholding technique to differentiate the tumor affected regions and a clustering algorithm named K-means is used for identifying the tumor. The textural based features [7] are obtained and a Weka tool is used for classifying the images. The textural based features include energy, contrast, correlation and homogeneity which are extracted using GLCM algorithm. The Naive Bayes gives less accuracy and it is less accurate compared to MLP which gives more accuracy, but this method takes more time for building a model. When the human life is involved more accuracy is desirable. A classification method is proposed to identify normal and abnormal images and it used Support Vector Machine (SVM) for brain tumor classification to produce an outcome with a high accuracy and low error rate. This research work gave more accurate results compared with the previous research work as it involves different SVM kernel functions to classify the given input MRI images [8].

Generally various types of segmentation techniques are used and the one with good segmentation score is considered. For automatic classification of tumor stage, a genetic algorithm is employed. In this if the area of the tumor is less than 8mm2, then it is no tumor or non-cancerous, otherwise it is cancerous. The performance of this algorithm can be evaluated in terms of accuracy, sensitivity and specificity and the performance results indicate that the approach considered is accurate. It has timely detection along with the identification of exact location of tumor [9].

Automated brain tumor identification [10] and classification task has enormous benefits to improve the diagnosis, treatment planning and follow up consultations of patients. By using different techniques like conventional image processing, machine and deep learning techniques, a very good improvement has been achieved in automated brain tumor detection and classification techniques. It also provides a description of the three brain tumor detection and classification techniques like region growing, machine learning and deep learning.

One of the techniques called Otsu’s technique proposed by Otsu Nobuyuki is used in image processing and computer vision to perform automatic image thresholding. Raja guru proposed a simple method for the identification of the abnormal patterns with SVM classifier for brain MRI images. But in this method the error rate was very high which is not suitable for diagnosis process of classifying tumor regions. A lot of approaches are being proposed by many researchers which can be classified into two categories. The first one includes support vector machine (SVM) and k-nearest neighbour (KNN) which are supervised classification method and the second one includes k-means clusteringand fuzzy C-means clustering which are unsupervised classification methods. The supervised methods perform better than unsupervised methods when classification accuracy is considered though all these methods achieve good results.

III. PROPOSED METHOD AND RESULTS

Identification of normal and abnormal images

A. *Database:*

To validate the proposed algorithm'sperformance, one data set is obtained from the radiologists, which include sample data images of 20 patients. For analysis purpose the MRI images are obtained from Kaggle Dataset and these images are used to evaluate the accuracy and evaluate the performance metrics. There are 240 images in the database with 90 normal and 150 abnormal (without and with tumor) MRI brain images. All the images used are 150x150 pixels, of size 10.7 kB and in JPG format.

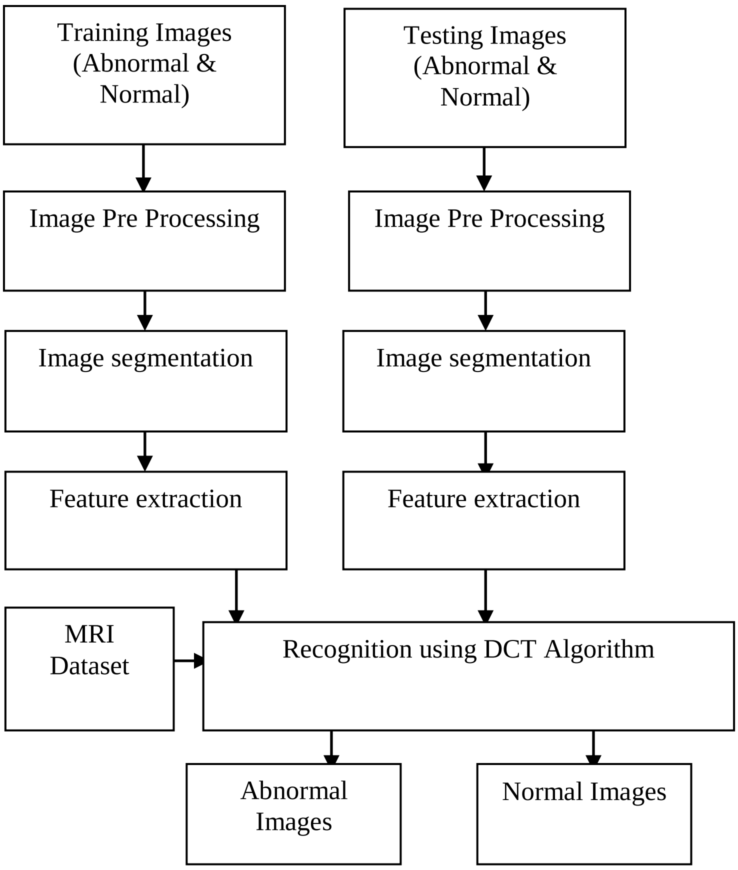


Figure 2: Block diagram for image classification

B. *System Performance*

All the images in the database are used for testing in order to evaluate the system accuracy, sensitivity, specificity and also the error rate and these are the following attributes used for calculation:

True Positive (TP) - In this the abnormal brain is correctly identified as abnormal (obtained a positive result)

True Negative (TN) - In this the normal brain is correctly identified as normal (obtained a negative result)

False Positive (FP) - In this the normal brain is wrongly identified as abnormal(obtained a positive result)

False Negative (FN) - In this the abnormal brain is wrongly identified as normal(obtained a negative result)

In the dataset of 240 sample images, 90 images (without tumor) and 150 images with tumor are analyzed from these dataset 20 percent of normal and abnormal images are considered as testing dataset and rest of the images are givenas training data

The three sets of images (each of 50) testing images are consideredand the output results are obtained using DCT algorithm and all the parameters are calculated from these obtained attributes and are given as follows

Confusion Matrix: It is a matrix of size 2 x 2 for binary classification with actual values on one axis and predicted values on other axis which considers TP, TN, FP, and FN attributes as its elements.

TABLE I. OUTPUT WITH DCT

Test Images	TP	TN	FP	FN
Batch1(50)	28	17	01	04
Batch2(50)	24	22	02	02
Batch3((50)	31	18	00	01

The attributes are calculated using the above parametric measures

- **Sensitivity -** It is the parameter used to measure the determination of true positive rate (person witha tumor) and is given by

$$\boxed{\boldsymbol{Sensitivity}(\%) = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}}}$$

- **Specificity** – It is the parameter used to measure thedetermination of true negative rate (person without tumor) and is given by

$$\boxed{\boldsymbol{Specficity}(\%) = \frac{\boldsymbol{TN}}{\boldsymbol{TN + FP}} * \mathbf{100}}$$

- **Accuracy –** It is a parameter used to measure the successful classification rate and it is given by

$$\boxed{\boldsymbol{Accuracy}(\%) = \frac{\boldsymbol{TP + TN}}{\boldsymbol{TP + TN + FP + FN}}}$$

- **Precision** –It is a ratio of true positives with respect to the predicted positive result.

$$P = \frac{TP}{\text{Predicted Yes}}$$

- **Recall**–It is a ratio of true positives with respect to the actual positive result.

$$R = \frac{TP}{\text{Actual Yes}}$$

- **False Positive Rate (FPR)** –It is a ratio of false positives with respect to the actual negatives.

$$FPR = \frac{FP}{FP + TN}$$

- **False Negative Rate (FNR)** –It is a ratio of false negatives with respect to the actual positives.

$$FNR = \frac{FN}{FN + TP}$$

- **F1-Score**–It is the harmonic mean of precision and recall and given by.

$$F1\text{-}Score = \frac{2PR}{P + R}$$

- **Error Rate**–It is a ratio of incorrect prediction by the total number of predication and given by.

$$\text{Error Rate} = \frac{FP + FN}{TP + TN + FP + FN}$$

TABLE II. PARAMETRIC MEASURES USING DCT

	with DCT		
Parameters	Sensitivity	Specificity	Accuracy
Batch1(50)	0.875	0.94	0.90
Batch2(50)	0.92	0.91	0.92
Batch3((50)	0.97	1.00	0.98
Average	0.92	0.95	0.93

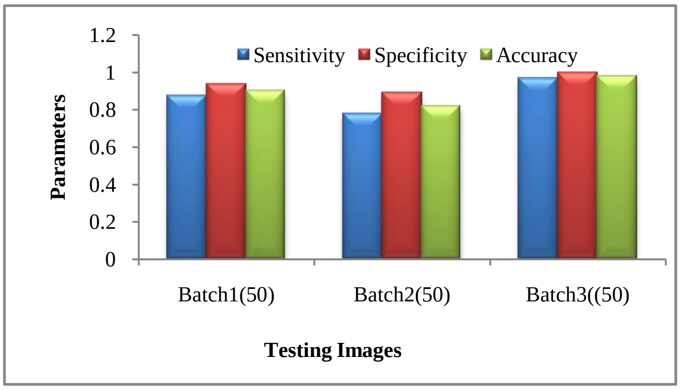


Figure 2. Parametric Measures using DCT

TABLE III. PERFORMANCE METRICS WITH DCT

Parameters/ Test images	Error rate	Precision	Recall	F-1 Score	FPR	FNR
Batch1(50)	0.1	0.965	0.875	0.917	0.06	0.12
Batch2(50)	0.08	0.923	0.923	0.923	0.08	0.07
Batch3(50)	0.02	1.00	0.968	0.983	0.00	0.03
Average	0.06	0.963	0.922	0.941	0.04	0.07

Identification of Benign and Malignant Tumor

Discrete cosine Transform is one of the efficient methods used for extracting the features as it is helpful in analyzing the images with different resolution levels. So, the features are extracted using DCT ad these features are given to a SVM Classifier which is able to identify the type of tumor i.e.whether the tumor is benign or malignant.

The Flow chart for classifying the Benign and Malignant tumors is given as follows:

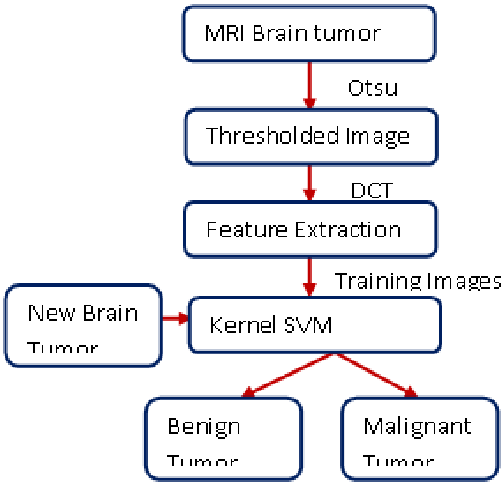


Figure 3. Flow Chart

MRI Images are taken and thresholding is done with Otsu thresholding method and feature extraction is done with the help of DCT and the features extracted are applied to the trained kernel SVM to classify the type of affected tumori.e. to classify whether the tumor is Benign or malignant.

C. Feature Extraction:

D. Statistical Features

- **Entropy (E)**–It is used to calculate to the random value of the textural image and is given as

Figure 4. $E = -\sum_{a=0}^{b-1}\sum_{b=0}^{a-1} f(b,a)\log_2 f(b,a)$

- **Contrast (C_{on})**–It is ameasure of intensity contrast between a pixel and its neighbour pixel over the whole image and it is in the range [0,1], and it is given by

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

- **Correlation (C_{orr})**–It gives a measure of how correlated a pixel to its neighbour over the whole image and it range from [0, 1], and it is given by

$$\boldsymbol{C_{orr} = \frac{\sum_{a=0}^{m-1}\sum_{b=0}^{n-1}(a,b)f(a,b) - M_a M_b}{\sigma_a \sigma_b}}$$

- **Homogeneity** - It is a measure of closeness of distribution of element in matrix to its diagonal element and its range is [0, 1], and it is given by

$$IDM = \sum_{x=0}^{m-1}\sum_{y=0}^{n-1}\frac{1}{1+(x-y)^2}$$

By the single or range of values it also helps to identify textured or non-textured images.

- **Energy (En)** - It gives a measure of pixel pair repetitions that is a measure of textural uniformity and its range is [0,1], and it is given by

$$E_n = \sqrt{\sum_{a=0}^{m-1}\sum_{b=0}^{n-1} f^2(a,b)}$$

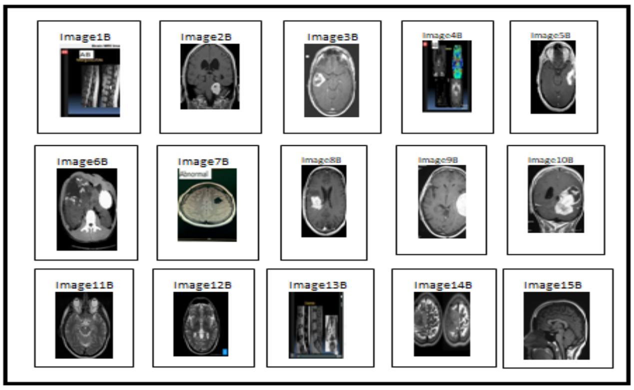
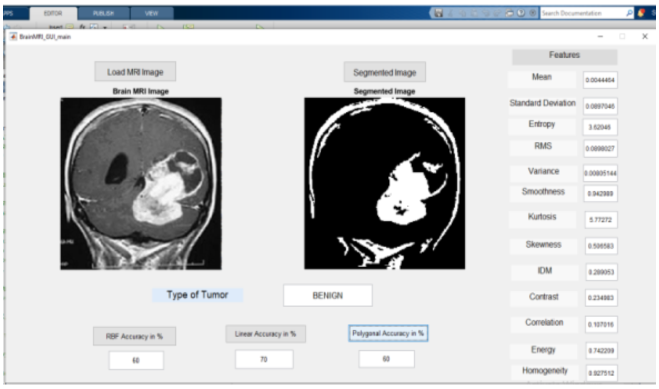


Figure 5. MRI images of Brain Tumor

The output result displaying Benign Tumor



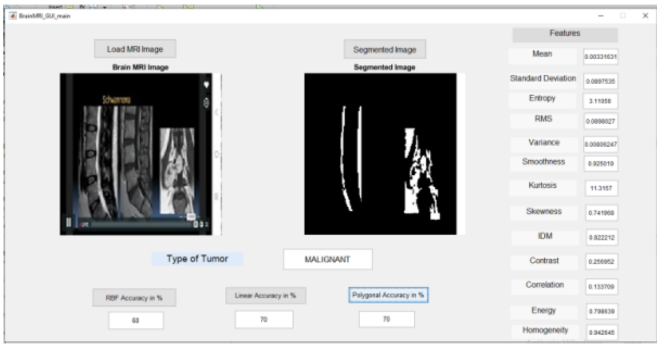


Figure 6. Output Result Displaying Malignant Tumor

TABLE IV. STATISTICAL FEATUREVALUES

Figure	**Entropy**	**Contrast**	**Correlation**	**Homogeneity**	**Energy**
Figure1	3.29447	0.266407	0.174093	0.933746	0.759353
Figure2	3.60323	0.217464	0.096256	0.931614	0.751146
Figure3	3.32064	0.21802	0.139399	0.931822	0.749107
Figure4	3.4053	0.26307	0.128781	0.932124	0.760517
Figure5	3.01511	0.258065	0.150437	0.930984	0.750905
Figure6	3.36215	0.270857	0.080376	0.929143	0.747883
Figure7	3.52175	0.239433	0.126949	0.932594	0.755016
Figure8	3.54859	0.234427	0.098156	0.926214	0.733932
Figure9	3.70932	0.223582	0.078493	0.927721	0.739306
Figure10	3.62046	0.234983	0.107016	0.927512	0.742209
Figure11	3.17551	0.262792	0.095046	0.925867	0.730997
Figure12	3.09742	0.280311	0.158538	0.930265	0.751183
Figure13	3.11056	0.256952	0.133709	0.942645	0.798639
Figure14	3.51182	0.290323	0.058194	0.939183	0.781209
Figure15	3.48034	0.281146	0.078227	0.937319	0.781774

E. Intensity Based Features

- **Standard Deviation (SD) –** It is a measure of in homogeneity or data distribution around the mean. A higher value describes better contrast and intensity level of an image.

$$\boldsymbol{SD = \sqrt{\frac{1}{a*b}\sum_{0}^{n-1}\sum_{0}^{m-1}(f(n,m)-M)^2}}$$

- **Skewness (S_k)** -It is a metric to measure a lack of symmetry or presence of symmetry. The data set or distribution is said to be symmetric if it is same at the right side and left side of the center point.

$$S_k = (\frac{1}{m*n})\frac{\sum|(f(n,m)-M)^3|}{SD^3}$$

- **Kurtosis (S_k)** -It is a measure of the degree of flatness or peak ness in the region of a curve which is the shape measure of a real value random variable and it is calculated by

$$K_{urt} = \left(\frac{1}{m*n}\right)\frac{\sum|(f(n,m)-M)^4|}{SD^4}$$

Smoothness is a technique used to reduce and suppress image noises. The extracted features of the image are given to a classifier for identifyingthe tumor in the MRI brain images

TABLE V. INTENSITY BASED FEATURES:

Figure	Standard Deviation	Skewness	Kurtosis
Figure1	0.089535	0.870931	10.0996
Figure2	0.089772	0.54016	5.993
Figure3	0.089752	0.361323	6.085
Figure4	0.089744	0.774517	8.346
Figure5	0.089755	0.636997	7.497
Figure6	0.089742	0.738333	7.905
Figure7	0.089778	0.633405	7.551
Figure8	0.089697	0.479549	5.824
Figure9	0.089715	0.386773	5.429
Figure10	0.089704	0.506583	5.772
Figure11	0.089718	0.721147	7.412
Figure12	0.089655	1.10438	10.220
Figure13	0.089753	0.741968	11.315
Figure14	0.089767	1.089	11.788
Figure15	0.089727	0.909774	10.856

IV. PERFORMANCE METRICS

The mathematical function used for transformation is known as the kernel function.The kernel types supported by SVM are:

- Gaussian Radial Base Function(RBF)
- Linear
- Polynomial

Accuracy: It is used as a metric for evaluating classification models. The nearness to the true value is called accuracy. It is the fraction of prediction of the correct values.

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP} + \boldsymbol{TN}}{\boldsymbol{TP} + \boldsymbol{TN} + \boldsymbol{FP} + \boldsymbol{FN}}$$

GRBF (Gaussian Radial Base Function) Accuracy–

This is a kernel function which is used in kernalized learning algorithms and it is generally used for classification in SVM. The GRBF kernel with sample images Y and Y^1 which are given as input space feature vectors are defined as

$$\boxed{K(Y, Y1) = \exp(-||Y-Y^1||^2/2\sigma^2}$$

Where $||y-y^1||^2$– feature vectors Euclidean distance which is squared.

Kernel Polynomial Accuracy – It gives the similarity polynomials feature space of the original images and the training images which makes to learn non-linear models. For a 'd' degree polynomial, the kernel polynomial can be given as

$$K(a, b) = (a^T+c)^d$$

Where a,b are vectors of input space and these vectors are computed by the training and testing samplesand the value of c ,which is a free parameter and its value greater than zero effects the lower and higher order terms of the polynomial.

Kernel Linear Accuracy- it is used to classify data into two classes by separating the data linearly using a straight line Such a type of data is called linearly separable data and in this a Linear SVM Classifier is used for classification.

$$K(\alpha, \alpha_\iota) = \sigma\upsilon\mu(\alpha * \alpha_\iota)$$

The obtained distance is a measure of similarity which is a linear combination of inputs and also dot product of a linear kernel.

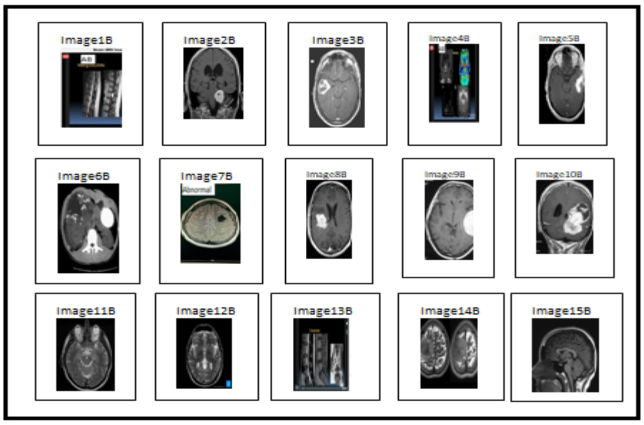


Figure 7. MRI Images of Brain Tumor

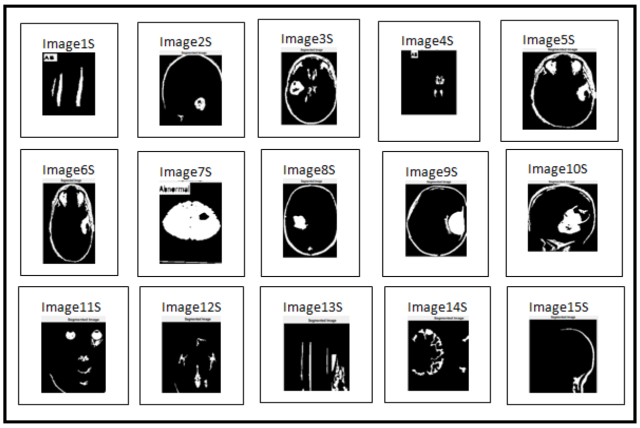
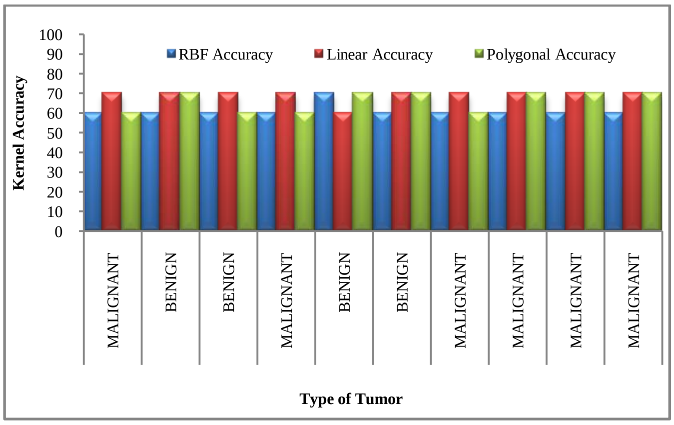


Figure 8. Segmented Imagesof Brain Tumor

TABLE VI. IDENTIFICATION OF TYPE OF TUMOR AND ITS KERNEL ACCURACIES

Figure	Type of Tumor	RBF Accuracy	Linear Accuracy	Polygonal Accuracy
Figure1	MALIGNANT	60	70	60
Figure2	BENIGN	60	70	70
Figure3	BENIGN	60	70	60
Figure4	MALIGNANT	60	70	60
Figure5	BENIGN	70	60	70
Figure6	BENIGN	60	70	70
Figure7	MALIGNANT	50	70	70
Figure8	BENIGN	60	60	70
Figure9	BENIGN	60	70	60
Figure10	BENIGN	60	70	60
Figure11	BENIGN	60	70	70
Figure12	MALIGNANT	60	70	60
Figure13	MALIGNANT	60	70	70
Figure14	MALIGNANT	60	70	70
Figure15	MALIGNANT	60	70	70



V. RESULTS AND DISCUSSION

The given MRI Image along with its Threshold, Clustered and Segmented outputs are displayed below:

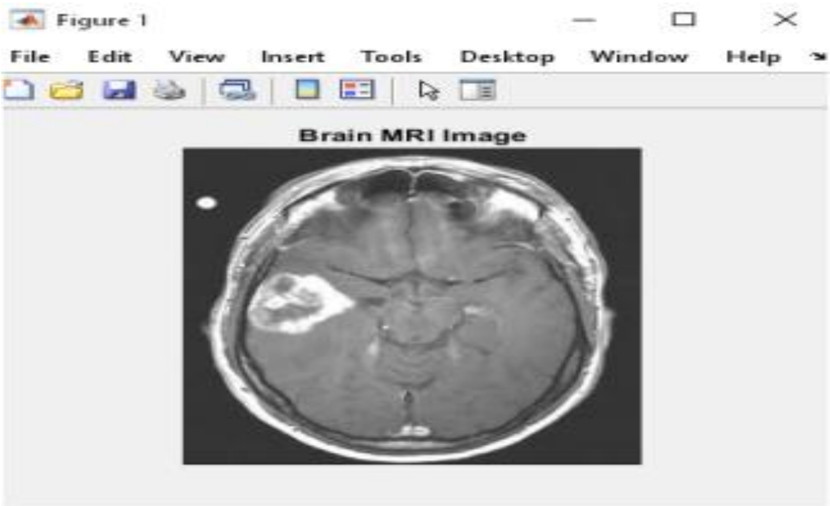


Figure 9. Brain MRI Image

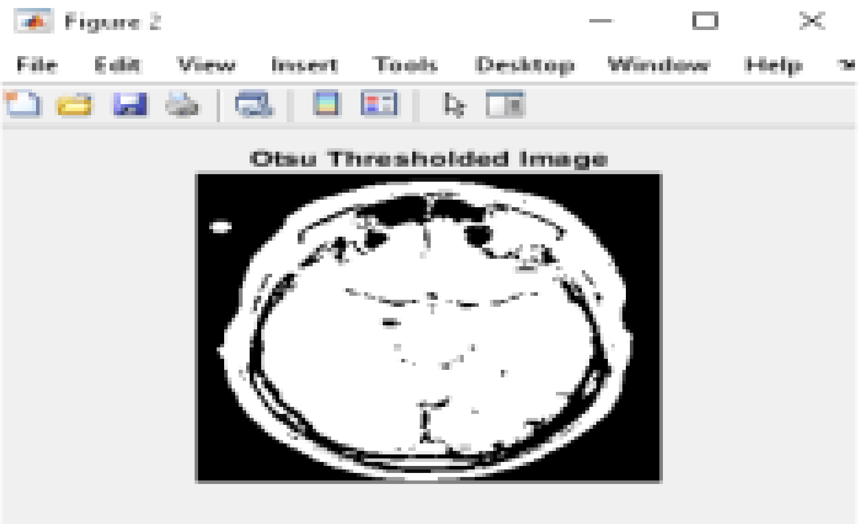


Figure 10. Otsuthresholded Image

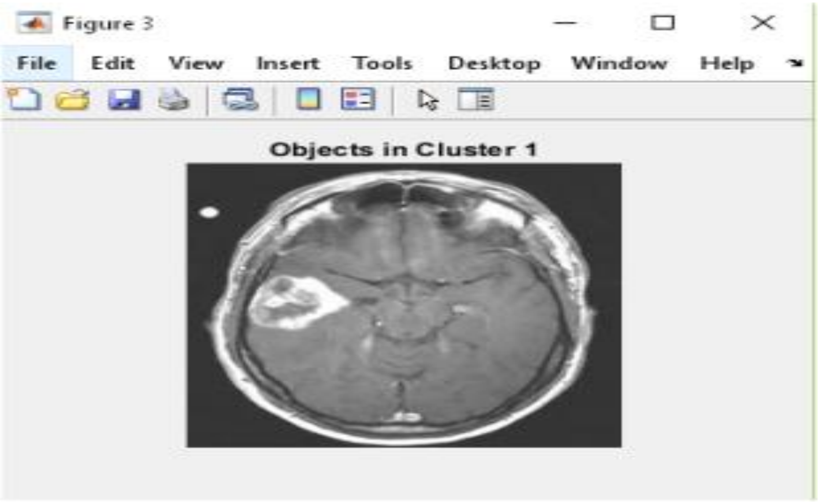


Figure 11. Clustered Image

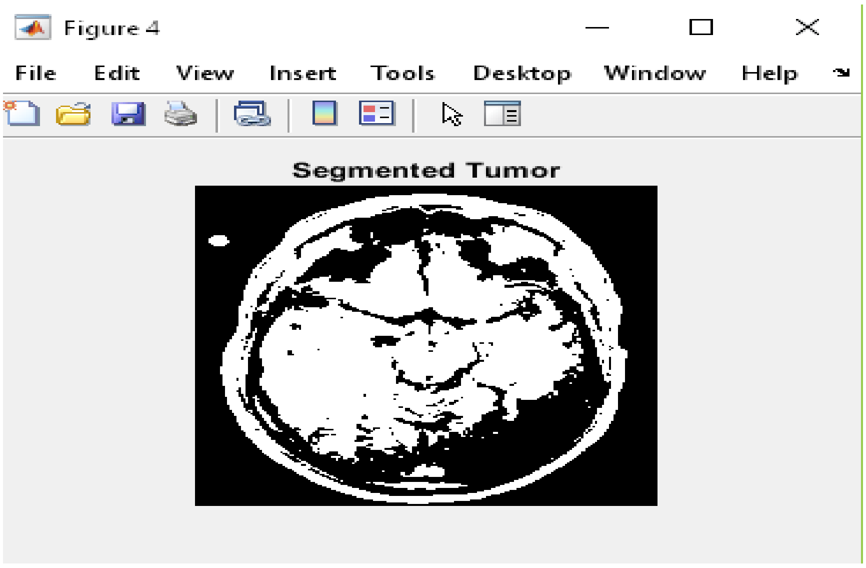


Figure 12. Segmented Tumor

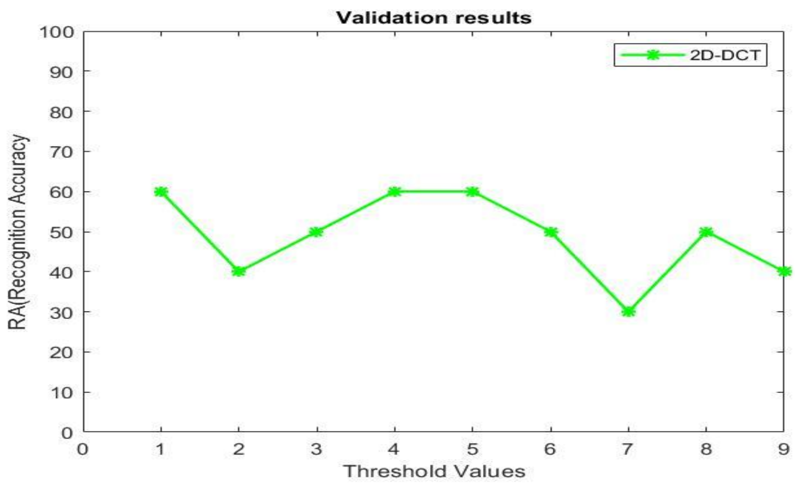


Figure 13. Graphs displaying the validation Results

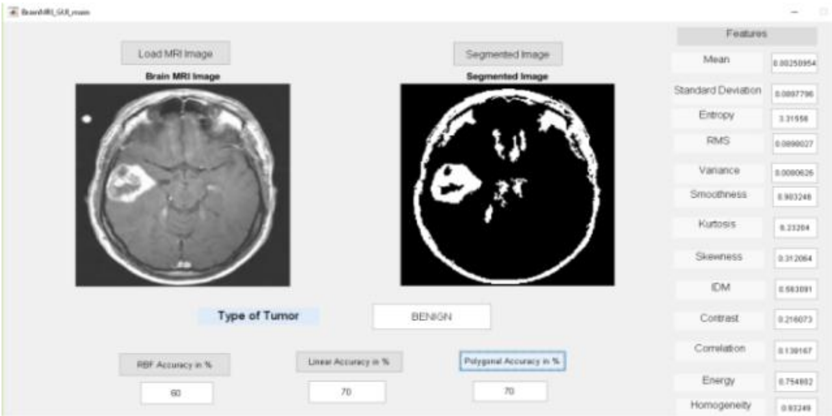


Figure 14. Feature extraction Values and Kernel Accuracies of the tumor Image

CONCLUSION

Manually detecting a brain tumor is not a complicated process but the analysis depends on the person who is examining it whereas automated methods requires minimum amount of time but it has many complex approaches. In this proposed method the recognition accuracy is improved compared to other methods. This project deals with image detection and classification using different techniques like Otsu's thresholding method, Clustering (K-Means method), DCT for feature extraction and Kernel SVM (Support Vector Machine) methods. These accuracies can also be further increased by using the methods of neural networks which improve the rate of accuracy and also reduce the execution time. In medical imaging, concept of deep learning is very important for making a complete automated system with high accuracy and efficiency.

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