An Efficient Brain Tumor Classification Based on SOBS Method for MRI Brain Images

M. Mohamed Sathik, E. Synthiya Judith Gnanaselvi

Abstract: In the field of medical imaging, the segmentation and classification of brain tumors is a complex and important area of studies because it is essential for the intention of early tumor diagnosing and treatment of brain tumors and other neurologic complaints. Earlier segmentation methods require huge number of iterations, longer time and a reduced accuracy. Therefore, this article proposes a multi-stage strategy whereby tumor segmentation and classification can be accurately performed with lower error rate. The proposed system incorporates three phases such as prediction, segmentation along with morphological operations to solve the discontinuities. The proposed segmentation method is named as Self Organisation Based Segmentation (SOBS) method. It is compared with some of the deformable models in literature. Next Use the Gray Level Co-occurrence Matrix to extract features. Finally Use the Gray Level Co-occurrence Matrix to extract features and classify them into normal or abnormal. If it is classified as abnormal, then again classify into glioma or meningioma. The performance metrics such as accuracy, PSNR and MSE are used for scrutinize the performance of these methods. From the investigational outcomes, the classification accuracy was found to be very high using the proposed segmentation method SOBS with the Random Forest (RF) Classifier.

Keywords
Random Forest, Radial Basis Function, segmentation, classification, Self Organisation Based Segmentation (SOBS).

I. INTRODUCTION

Brain is the body's imperative component in the structure of the human body and has a completely complex structure. The brain tumor causes the abnormal development of uncontrolled tissue of cancer in the brain. There are two kinds of brain tumors, first of which are primary brain tumors, second of which are metastatic brain tumors. Some of the primary brain tumors commonly found includes glioma, meningioma, pituitary adenomas, and nerve sheath tumors. [26] [2]. This paper identifies in the analysis only glioma and meningioma.

Glial cells are the most bountiful kinds of cells in the central nervous system. The neurons are surrounded and insulated by these glial cells. A tumor observed in glial cells is called a tumor of glioma. Meningioma are commonly benign in nature, however a minor fraction of them are malignant and are more common in 45 to 55 year old population [1] [13].
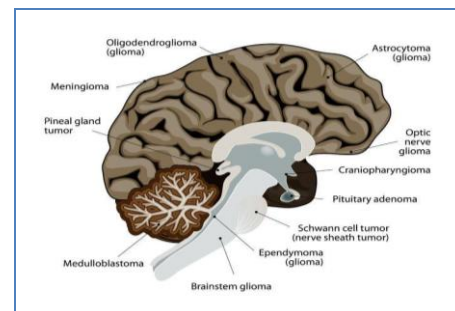

Fig.1. Primary Brain Tumors

Two imaging modalities, such as computed tomography (CT) and Magnetic Resonance Imaging (MRI), allow doctors and researchers to analyze the brain non-invasively.

Using this MRI, essential information on the anatomy of human soft tissue is recognized. MRI supports the relevant brain tumor diagnosis. Four parameters depend on the image intensity of the MRI. One is the density of protons (PD), which is determined by the concentration of relative water molecules. T1, T2 and T2 * relaxation are three other parameters, reflecting distinct local features of the individual protons. [26] [4].

In current days, Research work on automatic segmentation and classification of brain tumors has risen, resulting in demand for this area of research and it is still in progress. There is quite a lot of methods have been proposed in the literature for segmentation and classification of tumors in MRI images [5]. Image segmentation is a process of dividing an image into different homogeneous districts, with the objective of acquiring important picture information and performing unique examination on that portioned picture.

Phyo Thant Thant Aung et al[10] portrayed a fresh segmentation technique based on an active contour model based on a region in which the level set strategy is used to retrieve an image compression scheme based on the region of interest (ROI). This method can segment the MR brain images in all views like axial view, sagittal view and coronal view. The region based Active Contour Method (ACM) for segmentation method by A. Shenbagarajan et al.[11], presents high accuracy, and sensitivity, specificity measures. Moreover, the region based models are less perceptive to preliminary contours. They fail to segment images with intensity inhomogeneity [24]. Vicent caselles et al.[28] proposed a Geodesic Active Contour model in which an edge based active contour model is used to detect object boundaries and is based on active contours that evolve over time in accordance with inherent geometric measures of the image. Van-Truong Pham et al.[25] presented a method which implants the Geodesic Active Contour (GAC) model into the region based method because in the original Geodesic Active Contour model, only the edge information is considered. This paper exhibits that the proposed region aided GAC method is much more effective than the

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existing, especially when dealing with images with holes, weak edges and noises. Ayşe Demirhan et al. suggested SOM method for segmenting images in a competitive, unsupervised technique of practice. The The output images indicate more segmented information of the input images produced by the suggested technique [19] [21].

A comparative analysis have been made in the previous paper by the same authors of this paper [12] which concluded that SOM method provide good segmentation for brain MRI. Although it is useful for segmentation of the medical image, SOM demonstrates some disadvantages. SOM's excellence relies on the feature vectors used to train. Another factor affecting SOM[22] is the fixed map size.

Robert Crandall [27] ascertained the Chan-Vese algorithm for image segmentation which is very effective on a range of images. This technique is particularly functional in instances where an edge-based segmentation algorithm is not sufficient because it depends on global characteristics such as areas, gray level intensities, contour lengths such as gradients to some extent. Also this method is very useful for noisy and blurry images. For some applications, it is very slow depending on the type and size of the image and the number of iterations required, the segmentation can take several seconds [27].

Xiuming Li et al.[15] establishes that it is very hard to segment MR images with intensity inhomogeneity by using the Chan-Vese (CV) model. So a new segmentation method is proposed in this paper which overcomes the problems in traditional methods.

Mohammed M. Abdelsamea et al. provided a survey of SOM based Active Contour Models for image segmentation in which to facilitate improving the healthiness of edge based ACMs to the blur and ill defined edge information; SOMs have been used in combination with ACMs. SOM method was used because of its ability to learn the edge map information via their topology preservation property [20].

Mohammed M. Abdelsamea et al. proposed a new SOM-based Chan-Vese image segmentation model combining the advantages of the self - organizing map (SOM) within the state-of - the-art global ACM, the Chan-Vese (C-V) model[6]. A new segmentation method Self Organisation Based Segmentation (SOBS) method was proposed by the same authors of this paper which combined the SOM and Chan-Vese methods. In that SOBS method, a segmented area is predicted from the given MRI image by using SOM method and the Chan-Vese method is applied within that the predicted area for better accuracy in reduced time. Finally, the morphological operation is carried out to solve discontinuities in segmentation process [1].

Feature extraction is the method of reducing the size of the image data by acquiring the required image information from the segmented image. From the extracted features, it is feasible to demarcate between normal and abnormal MRI brain. After segmentation of the MRI tumor regions, the features of the segmented regions will be analyzed. The properties that describe the entire image are called features. The process of extracting features trims down the original MRI data in a set of functions which is also known as a feature vector. The fundamental inputs for any classification algorithm are these feature vectors [9][29][16]. This paper uses the Gray Level Co-occurrence Matrix (GLCM) to extract five texture features.

Afterwards these feature vectors are provided as the input to the classification algorithms to classify the tumor. Supervised and unsupervised classification techniques are used to classify images into tumorous and non-tumorous types. In supervised classification, the input feature vectors are divided into different categories by comparing them with an input training set. R. Anitha et al. proposed a computer-aided detection and segmentation methodology to perceive and segment the abnormal patterns in brain MR images in which the features are classified into either tumor or non-tumor by using random forest classifier [7]. Praveen. G.B et al. proposed a multi stage approach for the segmentation and classification of brain tumor in which the Random Forest (RF) classification method yields the high accuracy over other classification methods [13]. Geethu Mohan et al. states that the natural capability of RF in managing huge feature vectors, rapid computation and multi-class problems made it well-liked than other classification algorithms[3].

This paper proposes an efficient classification method using a combination of SOBS and RF methods. The remaining paper is presented as follows. In section 2, we present system architecture for proposed method. Section 3 presents a proposed method for classification of brain tumor with the use of SOBS method. The results and discussions are discussed in Section 4. The conclusions are finally made in section 5.

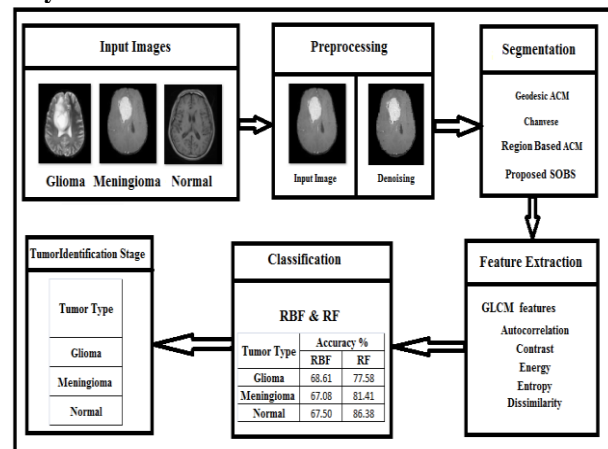## II. MATERIALS AND METHODS

2.1 System Architecture

Fig. 2. Overview of segmentation & classification of brain MRI

2.2 Proposed Method
2.2.1 Preprocessing:
Owing to the MR image quality, pre-processing is the most important step in brain tumor analysis. Here the Gaussian filter is used to remove the noise. [14].

2.2.2 Segmentation
In this paper, the SOBS method is used for segmentation. In this method, initially the segmented area is predicted and afterwards the segmentation is performed. Finally the morphological operations are carried out[1].

2.2.2.1 SOBS
This method combines the SOM and Chan-Vese methods. In this SOBS method, the following steps are carried out.

1. Input the MRI image (consider image intensity value is neuron)
2. The variables sigma, weight vector, winning neuron are initialized.
    Sigma=number of neighborhood pixels
3. find the neighborhood function using Nf(i)=Img(i)-img(i+1)*sigma(i)
4. find the weight vector using Wi(i+1)=wi+Nf(i)*img(i)-w(i)
5. find the winning neuron using Wn=max(wn,img(i)-w(img(i))
6. segmentation of som
Img(i)>=wn then img(i)=1
Else Img(i)=img(i)
7. Develop the custom boundary mask.
8. After creating the mask, start the initial brain counter.
9. Process the number of iterations in the square and elliptical form of the infected brain.
10. Decide the probable area of the brain.
11. Segmenting the probable brain area [1].

2.2.3 Feature Extraction

Five features are extracted from Gray Level Co-occurrence Matrix(GLCM) in feature extraction step. Let the co-occurrence matrix be p(i,j) and the size of the matrix is NxN. And μ and σ are the mean and standard deviation of p.

2.2.3.1 Contrast

The contrast of an image or the amount of local variations present in an image determined by the feature contrast.

$$Contrast = \sum_{i,j=0}^{N-1} p(i,j)(i-j)^2$$

2.2.3.2 Entropy

Entropy gives you an amount of information of the image which is desirable for the image compression. It measures the loss of information in a transmitted signal and also computes the image information. Entropy is inversely proportional to GLCM energy.

$$Entropy = -\sum_{i,j=0}^{N-1} p(i-j)\log p(i,j)$$

2.2.3.3 Energy

Energy means uniformity. If the image has the large energy value then the image is more homogeneous. When energy equals to 1, the image is believed to be a constant image.

$$Energy = \sum_{i,j=0}^{N-1} p(i,j)^2$$

2.2.3.4 Dissimilarity

Dissimilarity is a measure of evenness between two groups.

$$Dissimilarity = \sum_{i,j=0}^{N-1} p(i,j)\,|i-j|$$

2.2.3.5 Autocorrelation

It measures the joint probability occurrence of the specified pixel pairs.

$$Autocorrelation = \sum_{i,j=0}^{N-1} p(i,j) \frac{\left[(i-\mu)_i(j-\mu)_j\right]}{\sqrt{(\sigma_i)^2(j)^2}}$$

2.2.4 Classification

2.2.4.1 Random Forest

A Random Forest (RF) is among the most prevalent classifiers and is a multi-decision trees ensemble. Bootstrap set and OOB set (Out - Of-Bag set) are used to fabricate RF. The bootstrap set contains the instances for building a tree and the OOB set contains test instances which are not included in bootstrap set. The dividing criterion applied in each node is regarded in this technique to maximize information gain. Each node divides the incoming instances into two sets by applying this criterion. To evaluate the gain of information in this RF method, among all existing variables(M) only a small number of variables (mtries) are used in each node. At first these mtries variables are preferred randomly and then the splitting criterion is maximized by using these variables. There are two main parameters in the RF algorithm, such as the number of trees used in the forest and the number of variables randomly selected in each node mtries. The aim of an optimization framework is to determine the appropriate values for these variables [8][17].

2.2.4.2 Radial Basis Function

A Radial Basis function takes advantage of radial base functions as functions for activation. The network output is a linear permutation of input and neuron parameter radial basis functions. An RBF is classified by measuring the similarity of the input to the training set instances. Each RBF neuron stores a "prototype," which is only one of the training set's models. The Euclidean distance between the input and its prototype is calculated by each neuron while we want to classify a fresh input. If the entry is closer to class A prototypes than class B prototypes, it will be classified as class A[23].

The input vector is the categorized n-dimensional vector. Each RBF neuron stores one vector as a "prototype" from the training set that is also called the "center" of the vector neuron. The input vector is contrasted with its prototype by each RBF neuron and produces a value between 0 and 1 that is a similarity metric. If the input is equivalent to the prototype, the output of that RBF neuron is 1. Like that, despite the reality that the distance between input and prototype increases, the response decreases exponentially to 0. The neuron's response value is also called its activation value. The network output comprises of a set of nodes to be categorized, one per category. Each output node calculates a kind of score for the related category. A classification choice is normally produced by assigning the entry to the class with the highest score. A weighted sum of the activation values is used to calculate the score from each RBF neuron. By weighted sum we imply that an output node combines a weight value with each RBF neuron and multiplies the activation of the neuron by this weight before adding it to the overall reaction. By weighted sum we imply that an output node combines a weight value with each RBF neuron and multiplies the activation of the neuron by this weight before adding it to the overall reaction. By weighted sum we imply that an output node combines a weight value with each RBF neuron and multiplies the activation of the neuron by this weight before adding it to the overall response[23].

2.2.5 Dataset

The dataset is a combination of Real time MRI scans obtained from well equipped medical scan centre. The algorithm is implemented in MATLAB 2015a using a 1.80GHz, AMD windows OS machine. The algorithm has

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been tested on glioma, and meningioma.

III. RESULTS

3. 1. Performance Metrics

The performances of all the methods are predicted by using the performance metrics like accuracy, Mean Square Error and PSNR [18]. The formulas are given below.

3.1.1. Accuracy

Accuracy means the percentage of instances correctly classified.

$$Accuracy = \frac{\#(TP) + \#(TN)}{\#(TP) + \#(TN) + \#(FP) + \#(FN)}$$

3.1.2. Mean Square Error

The mean square error (MSE) measures the average of the square of the difference between the the segmented image and the original one. The MSE can be computed by using the formula,

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (I\_seg_i - I\_orig_i)^2$$

3.1.3. Peak Signal-to-Noise-Ratio (PSNR)

A measure of reconstruction quality is termed as peak signal-to-noise ratio (PSNR). The formula of the PSNR is described as:

$$PSNR = 10 \log_{10} \frac{maximum\ intensity^2}{MSE}$$

3.2 Result Analysis

Table 1. Performance evaluation for type of tumor based on different algorithms with classifiers

Algorithms	Classification	Accuracy %			PSNR			MSE		
		Glioma	Meningioma	Normal	Glioma	Meningioma	Normal	Glioma	Meningioma	Normal
Geo_Desic	RBF	66.95	66.89	66.95	51.79	51.90	51.43	0.431	0.420	0.468
	RF	74.49	78.70	86.46	51.96	52.02	52.56	0.414	0.408	0.361
Chan_Vese	RBF	66.85	66.95	66.95	51.53	51.84	52.05	0.457	0.425	0.405
	RF	76.12	81.24	86.43	55.87	54.14	52.56	0.168	0.251	0.361
Region	RBF	66.85	66.95	66.95	51.51	51.86	52.05	0.460	0.423	0.406
	RF	75.91	81.60	82.92	55.87	54.14	52.56	0.168	0.251	0.361
SOBS(Proposed)	RBF	73.78	67.53	69.17	55.88	53.54	52.29	0.168	0.288	0.384
	RF	83.81	84.09	89.73	56.04	54.13	52.80	0.162	0.251	0.341

Table 1 shows that the type of tumor affected such as glioma, meningioma and normal based on different algorithms such as Geodesic, Chan Vese, Region and proposed SOBS with the classifiers like RF and RBF. From the scores in Table 1, it can be seen that that proposed algorithm performs better than other methods. . It clearly shows that on comparing with other methods, proposed SOBS got highest accuracy and PSNR value while using RF classification method. Also the SOBS method yields the lowest MSE value when use RF classification method compared with RBF classification method.

Table2. Performance evaluation for type of tumor by different classifiers based on different features

Features	Classification	Accuracy %			PSNR			MSE		
		Glioma	Meningioma	Normal	Glioma	Meningioma	Normal	Glioma	Meningioma	Normal
Autocorrelation	RBF	67.30	68.73	68.41	54.96	53.80	52.21	0.207	0.271	0.391
	RF	70.66	70.27	70.97	55.62	54.00	52.53	0.178	0.259	0.363
Contrast	RBF	67.73	68.13	72.49	51.18	51.60	52.39	0.495	0.450	0.375
	RF	74.03	79.83	88.89	54.15	53.30	52.70	0.250	0.304	0.349
Energy	RBF	69.58	70.91	73.70	52.57	52.06	51.32	0.360	0.405	0.480
	RF	87.80	82.10	80.72	53.99	53.19	52.51	0.260	0.312	0.365
Entropy	RBF	69.04	70.86	72.86	52.75	52.57	51.75	0.345	0.360	0.435
	RF	76.79	79.58	79.57	54.24	53.44	52.52	0.245	0.294	0.364
Dissimilarity	RBF	69.38	70.73	73.20	51.25	51.53	52.14	0.488	0.458	0.398
	RF	78.63	81.29	88.62	54.97	53.61	52.82	0.207	0.283	0.340

Table 2 shows that the performance analysis based on kind of tumor distressed such as glioma, meningioma and normal by using the classifiers RF and RBF with the consideration of diverse features such as autocorrelation, contrast, energy, entropy and dissimilarity. For example, from the results obtained, it is clearly proves that on comparing with RBF method, the RF method acquired the improved accuracy for glioma, meningioma affected brain and normal brain which are all having the difference value of 3.36, 1.54 and 2.56 respectively while considering autocorrelation feature.

Table 3. Overall classification performance based on different algorithms

Algorithm	Accuracy %		PSNR		MSE	
	RBF	RF	RBF	RF	RBF	RF
Geo_Desic	66.93	79.88	51.71	52.18	0.428	0.397
Chan_Vese	66.92	81.26	51.81	54.19	0.360	0.260
Region	66.92	80.14	51.81	54.19	0.393	0.269
Proposed(SOBS)	70.16	85.87	53.90	54.32	0.304	0.249

Table 3 exemplifies that the overall classification performance based on different algorithms like Geodesic, Chan-Vese, Region Based ACM and the proposed SOBS. From the results obtained in table 6, it can be clearly proves that the proposed SOBS acts upon better than other methods. It undoubtedly proves that the accuracy value of the proposed algorithm got higher value to the extent of 3.24 for both Chan-Vese and region based ACM respectively

for the RBF classification method. Also the proposed method receives higher accuracy value which is differing by 3.23 than the geodesic method. Similarly, when processed with RF classification method, the proposed algorithm acquired the superior value as much as 5.99, 4.61 and 5.73

correspondingly while compared with geodesic, Chan-Vese and region based ACM methods. When comparing the RF and RBF classification methods, it noticeably confirms that the proposed SOBS method got the highest accuracy value (85.57) in RF method.

Table 4. Overall classification performance based on features

Features	Accuracy %		PSNR		MSE	
	RBF	RF	RBF	RF	RBF	RF
Autocorrelation	68.15	70.63	53.66	54.05	0.290	0.262
Contrast	69.45	80.92	51.72	53.39	0.440	0.277
Energy	71.40	83.54	51.98	53.23	0.415	0.312
Entropy	70.92	78.65	52.36	53.40	0.380	0.301
Dissimilarity	71.10	82.85	51.64	53.80	0.448	0.306

Table 4 illustrates the overall classification performance based on the features like autocorrelation, contrast, energy, entropy and dissimilarity. It obviously demonstrates that the RF method got the ultimate accuracy value that is improved by means of 2.48 and advanced PSNR value by 0.39 than RBF method while performance evaluated based on the feature autocorrelation. Additionally the RF method acquired the lower MSE value than RBF which is diminished with the value of 0.028. Whilst the performance is evaluated based on the contrast and energy, it undoubtedly proves that the RF method acquired the expanded accuracy value which is differ by 11.47, 12.14, foremost PSNR value increased by 1.67, 1.25 and the

reduced MSE value diverged by 0.163, 0.103 respectively on comparing with RF method. While considering the entropy as a performance measure, the RF method obtained the increased accuracy value with the difference of 7.73, improved PSNR value by the divergence of 1.04 and the diminished MSE value with the difference of 0.079 on compared with RBF method. Also it clearly proved that the RF method secured the highest accuracy value increased via 11.75, enhanced PSNR value increased by means of 2.16 and the reduced MSE value by 0.142 while comparing with RBF method. While considering the overall result, RF method proved its superiority.

Table 5. Overall classification performance for different types of tumor

Tumor Type	Accuracy %		PSNR		MSE	
	RBF	RF	RBF	RF	RBF	RF
Glioma	68.61	77.58	52.68	54.94	0.379	0.228
Meningioma	67.08	81.41	52.29	53.61	0.389	0.29
Normal	67.5	86.38	51.95	52.62	0.416	0.356

Table 5 depicts that the overall classification performance for different types of tumor. From the above table, it has proved that the RF method possess the highest accuracy value of 77.58 which is increased by 8.97 for glioma affected brain. Also the RF method enlarged than RBF by 14.33, 18.88 for brain affected with Meningioma and normal brain respectively. While considering with PSNR value, RF method increased by 2.26, 1.32 and 0.67 on compared with RBF method for glioma, Meningioma and normal brain images. Also RF method obtained the lowest MSE value than RBF method which is diminished by 0.151, 0.099 and 0.06 correspondingly for glioma affected brain, Meningioma affected brain and normal brain.
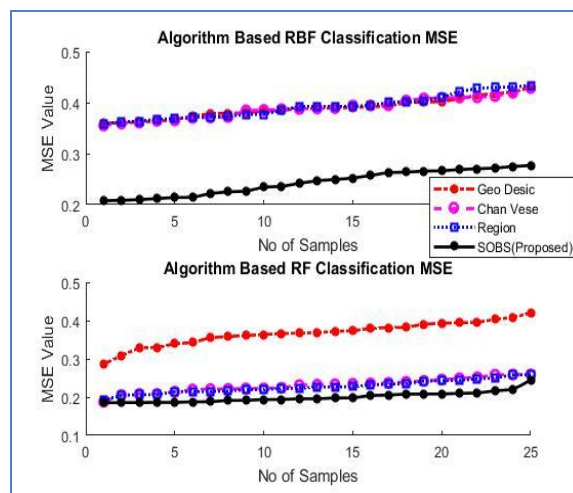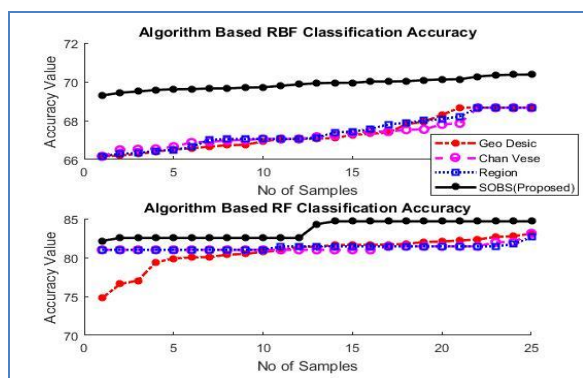
III. DISCUSSION

Figure 3a: Algorithm based RBF & RF classification Accuracy   Figure 3b: Algorithm based RBF & RF classification MSE
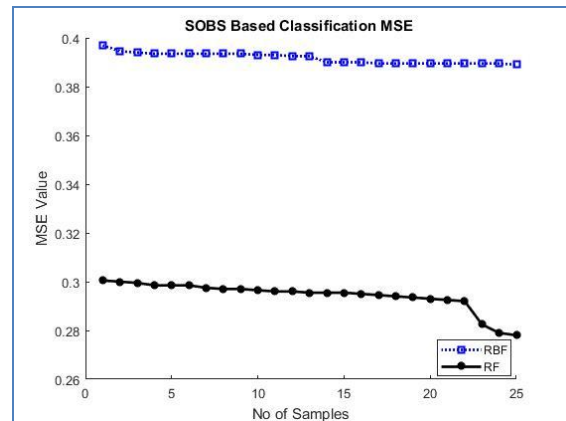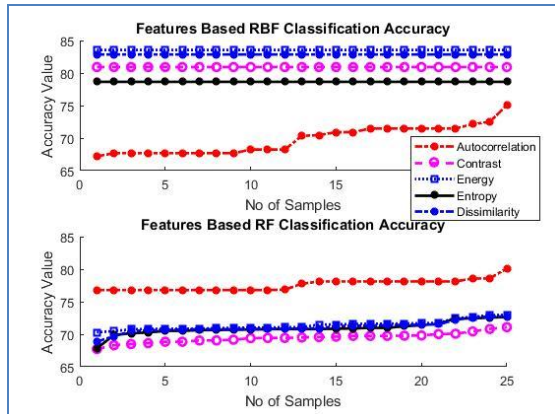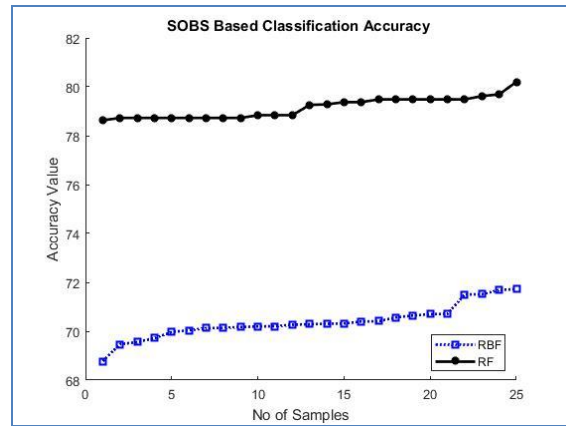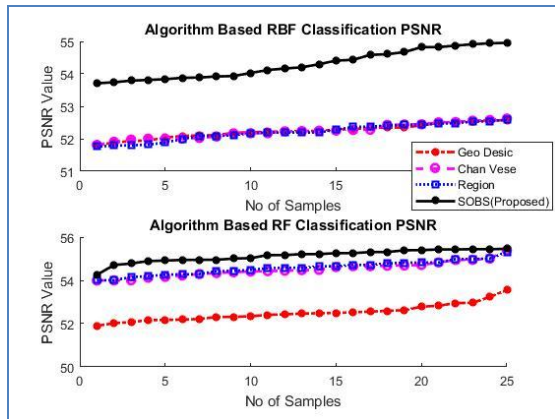
Figure 3c: Algorithm based RBF & RF classification PSNR
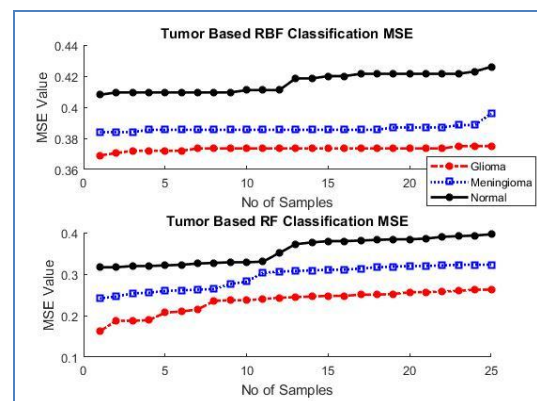**Figure 3d: Features based RBF & RF classification Accuracy**

Figure 3e: Features based RBF & RF classification MSE   Figure 3f: Features based RBF & RF classification PSNR

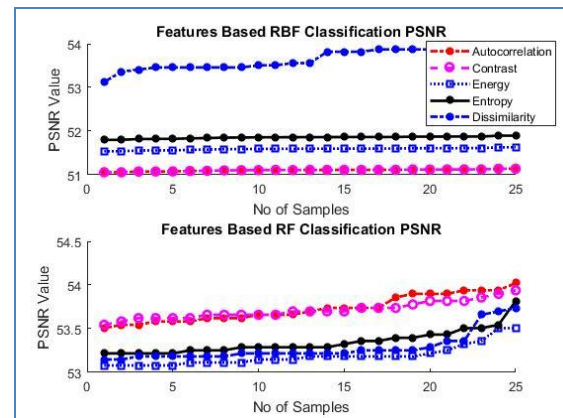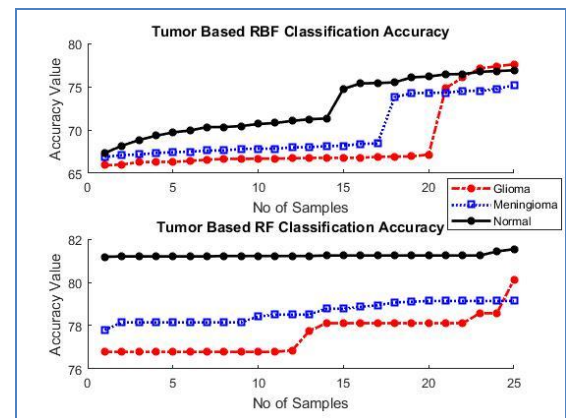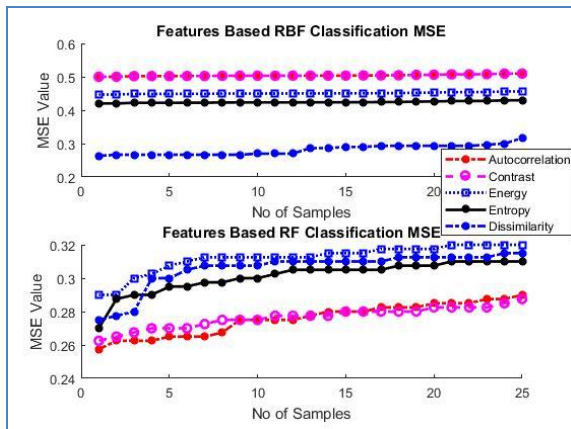**Figure 3g: SOBS based classification Accuracy   Figure 3h: SOBS based classification MSE**

Figure 3i: Tumor based RBF & RF classification Accuracy Figure 3j: Tumor based RBF & RF classification MSE

Figure 3: Graphs showing the performance analysis of classification of brain tumor based on different features by using different algorithms

Figure 3a, 3b and 3c shows the algorithm based classification accuracy, MSE and PSNR respectively for RBF and RF algorithms in which x axis represents the number of samples and y axis represents the accuracy value. The above all three figures compares four algorithms like Geodesic, Chan Vese, Region based and proposed SOBS and demonstrates that the proposed SOBS got high accuracy and PSNR value and lower MSE value. Figure 3d, 3e and 3f shows the features based classification accuracy, MSE and PSNR correspondingly for RBF and RF algorithms in which x axis represents the number of samples and y axis represents the accuracy value. The above all three figures compares four features like autocorrelation, contrast, energy, entropy and dissimilarity value. Figure 3g and 3h shows the SOBS based classification accuracy and MSE for RBF and RF algorithms in which x axis represents the number of samples and y axis represents the accuracy value.

Also the figure 3i and 3j shows that the tumor based RBF and RF classification accuracy and MSE respectively in which x axis denotes the number of samples and y axis denotes the accuracy value.

IV. CONCLUSION

In this paper, a multi level approach by means of segmenting using the proposed SOBS method and random forest method for brain tumor classification has been implemented. The GLCM texture feature extraction methodologies are used in this work to enable correct tumor classification. The accuracy, PSNR and MSE of the proposed methodology are analyses. The performance of the proposed technique is compared with RF & RBF classifiers for Glioma, meningioma and normal tumor type. An important observation in this work is that multi stage approach uses Random Forest (RF) classification method with Proposed SOBS which boosts performance (85.87% accuracy) significantly. The results concluded that multi level approach which includes the proposed Self Organisation Based Segmentation (SOBS) method and Random Forest (RF) classification method outperforms the existing methods and achieves better accuracy in classifying glioma, meningioma or normal.

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