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RESEARCH ARTICLE

Segmentation Method of Deterministic Feature Clustering for Identification of Brain Tumor Using MRI

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ABSTRACT The features play an important role for identification of the region of interest. Different kind of features exist, it is also essential to identify the accurate class of the features, challenging dataset like MICCAI BraTs brain tumor contains many tumor images. Features are helpful to detect the region of tumor with some of their characteristic. But due to many images and their information, the issue of data complexity is raised. because the data was found to be complex. Thus, due to the complexity, higher dimension features are reduced to low dimension features. Hence, there is a need for improved feature selection method. Furthermore, it is also essential to enhance the method for the SOM Map for the selection of deterministic feature after the extraction. The goal of the work is not only to select the accurate feature of tumor but also to segment the tumor intensity with the confidence element. The objective under umbrella of this work is to improve the feature selection method by using confidence element of interest through the determination of the best feature using the SOFM with FCM. The method works with the selection of the best features with higher accuracy. Those higher accurate Features are called the deterministic Features. These deterministic features are selected through improved weighted SOM. This improved SOM is further combined with FCM to cluster the Confidence element. Evaluation is made with comparison to ground truth reality images; Results show; DOI is 0.94, JI is 0.91, MSE is 0.058db and PSNR is 17.94db; MSE with small number highlights the performance of method. It can be compared with the state of the art or it can be compared with benchmark studies. Testing parameters from benchmark studies were JI, DOI, MSE and PSNR: JI accuracy value was 31.5%, DOI accuracy value was 47.3%, MSE value was 2.5dB and PSNR value was 40dB.A better region of interest is proposed method to determine the confidence element. The average accuracy over the dataset is determined in form of confidence element (ROI), overlap is for complex cases and average value is 94 percent.

INDEX TERMS SOFM, feature, clustering, dice over index, Jaccard index, feature selection, feature extraction, feature reduction, clustering.

I. INTRODUCTION

Feature plays an important role for recognition of the objects. Based on characteristics or properties, feature identifies the region of interest. For sake of segmentation, Region of interest is identified accurately When features of specific object are extracted, it consists of higher dimension. For easiness, it needs to be reduced and also needs to select the relevant features.

In field of medical imaging, different kind of images are existing, and these images are associating to different disease. Like MRI is one medical imaging modality, it is very close and important for brain tumor visualization. IT consists of different sequences of images like Flair, T1, T2 and Flair [48].

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These sequences of images pertain different intensity. The MRI imaging of brain tumor are low pass images. Region of interest become vague in these images. Relevant brain tumor MRI Feature extraction plays its role for detection. These brain tumor relevant extracted features are based on shape, texture, and intensity. From this class of feature, it is also important to reduce and select the relevant features.

From the discussion of above paragraph, due to data complexity and a large imaging dataset [2], the handling of values has emerged as an issue to contend with specifically features were applied to identify the data. Thus, there were numerous dataset features extracted. It has been difficult to identify the relevant features. Even though Self-Organization Feature Map (SOFM) are able to perform dimension reduction, but there are still issue of irrelevant feature selection that cannot be resolved by SOFM. Hence, feature selection becomes challenging during the selection of relevant features. A proposed method selects corresponding features according to the dataset. Thus, the proposed feature selection method has improved the SOFM feature selection method. These features are knowing as deterministic feature when they are combing clustering technique so the confidence element segmentation of brain tumor boundaries from brain can be seen more accurately.

II. LITERATURE REWIEWS

The research studies in this articles are varying and more focus is on features, features are like shape, texture and intensity. They have played an important role, as an intermediate process is image enhancement from input to the segmentation. Features extracted from dataset and complex information from dataset with some particular values were identified or detected. Moreover, for accurate classification of features, they were reduced from feature vector with some defined phenomena or criteria. Classification for segmentation helped for accurate segmentation. For this purpose, the study needed certain feature selection criteria. In the line of above, extracted features were combined with other supervised and unsupervised algorithms. A better segmentation was achieved through the best texture-based feature by checking the entropy. With the SVM feature classification, the tumorous and non- tumorous images were identified [1], [52]. In one referenced study, SOM was improved with its weights, and therefore its capabilities were improved for relevant feature selection [2], [51].

Furthermore, Weighted SOM was improved at this level and it did not require pre-processing. Furthermore, a higher classification accuracy feature was selected in a study by [3]. Further to this, in referenced study by [4], algorithm contained accounts about the multi-kernel that selected the relevant features from the dataset. In a referenced study by [5], the feature selection method was an important step that was improved by using the Gaussian function that resulted in good performance. In another study, by [6], a Gaussian Mixture Model (GMM) had resulted the best feature accuracy on the heterogeneous tumor region as compared to the latest technology of PCA and Wavelet.

In a study by [7], shape-based features were extracted with major axis, minor axis, area, circularity and two classifiers like decision tree algorithm and C4.5. The multi- layer perceptron showcased the best classification accuracy. This kind of study was helpful in the analysis of image enhancement. At first, the image is segmented through the Berkeley wavelet algorithm. Next, the texture features were extracted and classified. The image was classified as tumorous and non-tumorous accurately [8]. The major portion of this referenced stud was about the analysis of an image labelled as tumorous and non-tumorous. The first image was segmented through the execution of morphological operation, and the next image then underwent a texture features extraction. Those extracted features were classified as tumorous and non-tumorous [9].

The reference work by [10] made the claim that the approach had improved segmentation by combining the Histogram of Oriented Gradients (HOG) feature to capture the fluctuation in pixel values with those pixel values, using the HOG features, which were classed through the SVM. In this reference study, segmentation was carried out using the Spiking Pulse-Coupled Neural Network (SPCNN) and Feature Extraction (FE), FE was carried out using the Fast Discrete Curvelet Transformation, reduction was carried out using PCA+LDA (linear discriminant analysis), and classification was carried out using the Probabilistic Neural Network [11]. The features were extracted using a two-dimensional discrete transformation wavelet, reduced using probabilistic Principal Component Analysis (PCA), and the image was classed using the AdaBoost algorithm in the work mentioned above [12]. Four classifiers based on SVM were improved in this referenced study, where SWT and PCA were integrated for dimension reduction [2], [10], [11], [12], [13]. Shape, texture, and intensity-based features were extracted, reduced, then classification is performed. in the mentioned reference study Principal Component Analysis (PCA) was utilised for feature reduction. The computation time and storage space will increase as a result of the images' high dimensionality. Additionally, they are 2D extracted characteristics, but 3D extraction will take more time [14]. In one referenced work, multi-contrast images were analysed using an unsupervised algorithm, and effective brain tumour structure was obtained [15].

The researchers in this particular study [16], [21] had combined binary Particle Swarm Optimization with mutation time variations to choose the best characteristics. In addition, the HOG feature-based classifier was recommended in this other investigation to identify images of brain tumours [22]. Based on a study by [13], study presented an improved Self Organization Map that gave better feature classification than the state-of-the-art Self Organization Map. A study by [23] found that the retrieved features were reduced by PCA, and the PCA engaged in classification by using the SVM to identify both tumorous and non-tumorous slices. In this referenced study, the nuclei-based neural network had classified the tumor with the help of the proposed features [24]. From a referenced study, improved classification was proposed from the selected feature, and it was also found to be helpful in the segmentation of brain tumor [25]. Moreover, textural features were helpful for the detection of tumor types such as malignant or benign [26].

However, no study was provided for choosing the optimum deterministic feature for segmentation, according to the evaluation of the references techniques used are named as region-based, classification, or hybrid methods [27], and analyses the region. Additionally, the dataset can be segmented using sound statistical analysis, computational application, and confusion matrix [28]. In one referenced study, traditional segmentation technique that uses filters to remove noise from MR image boundaries [29]. Automatic segmentation becomes challenging if there are a variety of tumor tissues in the image [30], [31], [32], Furthermore, in another study by [33] an image was segmented through two phases, phase one is to calculate the threshold of the image using a histogram. The second phase involved the extraction of the tumor where an automatic seed was automatically adjusted. In addition to these studies, image registration was considered to be a faster technique for segmentation as compared to active contour.

Additionally, the registration performance improves with the skull-stripped (cranium removal) of brain image. Through a longitudinal analysis of the image, the referenced study [34] was able to determine the whole augmentation of the tumor shape. Moreover, this technique provided favorable results because of random regularization of image energy method. Therefore, variation of intensities was easily managed [34]. In a work by [35], a tiny lesion was quantified for clinical use using a hyper-intense MRI image called Flair. The little lesion was important for allowing the tumor's small, heterogeneous lesion to be seen. According to a referenced study, the T2 weighted image contains the heterogonous problem, but the same intensity also detected the flare and a minor lesion, was identified using the Gaussian mix model.

This method of detection was identifying intensity deviations from the mean pixel value [9], [20]. In this reference study, unsupervised learning was used to assess the left and right halves of the brain for a single axial image. The second contribution involved making it possible to independently normalise an image's intensity, and the third involved segmenting an brain tumour from image using CNN [36]. This referenced [37] research, the Multi Cascaded Convolution Neural Network (MCCNN) and coarse and fine-grain segments are combined and created a segmentation, and the linked conditional random field (CRF) further improved this segmentation. The problem of overfitting was also handled with the parameter reduction [38]. The study selects the fine contour, and extract the description from an image block. This approach finds adaptive matching. For the segmentation of brain tumours, this procedure was entirely automatic [39].

Another study explained a two-part approach; in phase one, a categorised segmentation was produced by the random forest method and merged with the level set for delineating the tumour boundaries [40]. The improvement of the area of interest was good with the help of the strategy mentioned. It lessened the signal-to-noise ratio's noise. The GLCM and DWT were first used in the de-noising process.

A probabilistic neural network was then employed to determine the patch's identity. Following that, classification was used to do the segmentation analysis [41]. A significant segmentation was achieved with the help of contrast Fuzzy C-means, spatial model. This combination also handles addressed the outliner problem [42]. In this study, the SOM performed an initial clustering that took into account the FKM and memberships at an average, two Soft Computing techniques that have been used for modern biological applications in addition to artificial intelligence. The state-of-the-art performance measuring methodologies were then compared to the soft computing techniques [43].

Deep learning Neural Network (DNN) utilizes the local as well as global features to segment the shape and position of tumor with accuracy [44]. In this reference study, a review was conducted on an Atlas-based, hybrid-based, and learning- based segmentation with reference to evaluation parameters of Dice and Jacquard are discussed [45]. In this referenced study, the PSO method is seen as compared to EDPSO algorithm which is combination of enhancement, segmentation and classification of image [46], [53]. Referring to a study by [47], [48], [49], and [50] a semi supervised learning algorithm was proposed. The reason behind this proposal is to develop an multi objective approach. In one referenced study [58], Optimised color based segmentation is proposed, it is a good technique to get the cancer shape information.. In one another reference study [59], the tumour pixels are classified with the help of more important feature classification. In another reference study, multi class issue is resolve with the combination of high value feature along genetic algorithm for feature selection and classification is performed using multiclass SVM cubic classifier.

At this point, a new strategy was formed to generate the clusters and the target pixels were only segmented. Segmentation methods play an important role for identification of cancer disease [54], [57]. Different state of the art works is done but not a single one has tackled with the data complexity issue. The issue is mentioned as due to many features, data become complex. Therefore, higher dimension features are reduced to low dimension features. Self-Organization Feature Map (SOFM) is a feature selection algorithm. That needs to improve its SOM Map for selection of deterministic feature. From extracted features, confidence element is also missing. But due to number of images and their huge information, issue of data complexity is rising. because the data was found to be complicated. Thus, due to the complexity, higher dimension features are reduced to low dimension features. Hence, there is a need for improved feature selection method.

TABLE 1. MACCAI BraTs 2017-2013 dataset (https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9166508).

Categories	Patients(no. of patients*sequences)	Sub Total
HGG	210*4*155	130200
LGG	75*4*155	46500
Tagged	285*1*155	44175
Subtotal	46*1*155	28520
Grand total	220875	

As mentioned above, it is also important to enhance the algorithm for the SOM Map for the selection of deterministic feature after the extraction.

III. SYSTEM METHODOLOGY

The sequence of images of MICCAI BraTs brain tumor dataset was experimented. Four sequences were names as Flair, T1, T2, T1Ce. High Grade Glioma (HGG) images were extracted. From dataset 209 patients were experimented. Each patients' images can be seen from perspective of four sequences (T1, T2, Flair, T1Ce). If one patient belongs to T1 then patient will have 155 images, same way is for T2, Flair, T1Ce therefore one hundred twenty-nine thousand and give account of hundred eighty 1,29,580 images. From this count, specific sequence was extracted. For purpose of validation each patient has one segmented image. Method Consists of Feature extraction over the bundle of images, those extracted features are reduces, after reduction feature selection is performed. Selected best features are combined with cluster for better region of interest. Table 1 is taken from [48] reference Shape Circularity and Pixel Orientation.

These features are extracting across each image of the dataset. At first, method will extract twenty (19) features from the image. This study specifically targeted on two sequences, named as flair and T1. For revision point of view, we need to check the detail. For mentioned sequences, they covered the extraction of the whole dataset set where 209 patients with High-grade glioma brain tumor were recorded, and every patient had 155 images.

The total HGG images which were extracted from the whole dataset in the count were one hundred twenty-nine thousand, five hundred and eighty (129,580) images. They were all extracted, and feature intensity mean was calculated for every image. If the intensity of the image were more than 80 per cent tumor intensities present in the image, they were labelled as tumorous and they were assigned with a label of 1, otherwise they were labelled as 0. These intensity images were further compared to ground truth image. For comparison, they were labelled as tumorous or non-tumorous.

Every image is extracted with three types of features such as Shape, Intensity and Texture. The names of the extracted features are intensity-based (Mode, Contrast, Mean, Range, Kurtosis, Variance, Correlation, Smoothness, Skewness, and Root Mean Square), texture-based (Entropy, Energy, Inverse Difference Moment (IDM), and Homogeneity,), shape-based (Area, Perimeter, Irregular-Shaped Features, Shape Circularity, Pixel Orientation, Shape Index). Next, every image label is checked. On the basis of the mean intensity feature of the image, the algorithm decides whether an image is tumorous or non-tumorous. The tumorous image is labelled as 1 whereas a non-tumorous image is labelled as 0. Therefore, every image is extracted across 20 features and along with its label.

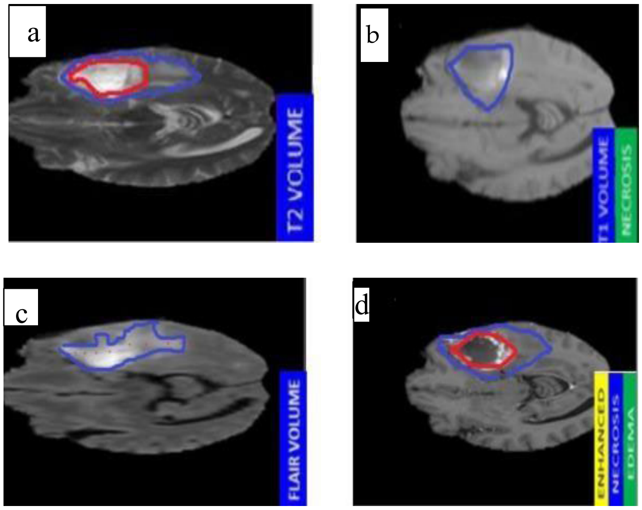


FIGURE 1. Dataset Label.

a) T2 Sequence,
b) T1 sequence,
c) Flair sequence, is an enhancing, Necrosis and edema, represent complete image and it is assigned with label 3.
d) T1 sequence and a necrosis tumor with label 4.

The three main set of features are shapes-based, intensity-based and texture based. The associated features that are intensity-based are Contrast, Mean, Range, Kurtosis, Variance, Correlation, Smoothness, Skewness, and Root Mean Square. Meanwhile the texture-based features are Entropy, Energy, Inverse Difference Moment (IDM), and Homogeneity. As for the shape-based features, they are: Area, Perimeter, Irregular Shape Features, Shape Circularity, Pixel Orientation, and Shape Index. These features and extraction can be seen in Figure 1. For the whole dataset, one hundred twenty-nine thousand, five hundred and eighty images (129,580) were extracted using the aforementioned features

A. IMPROVEMENT OF SOFM

Due to the intention of discard irrelevant features and relevant feature selection, it is ascertained that SOFM requires improvement. Hence an updated Weighted SOM Map is proposed. The improvement of SOFM is possible with SOM Random Weight Initialization, SOM Architecture, and Self Organization Map (SOM). A weighted SOM (WSOM) is proposed in this current study. The steps include a) train classifier b) reduce feature and SOM Map with selected feature

c) deterministic feature and clustering. Overfitting issue is resolving with the selection of highly accurate features for dataset

B. PROCESS OF FEATURE SELECTION

As for Feature Map (SOFM) method., the feature selection procedure starts after the feature reduction. The features reduction is performed recursively. The recursive executions perform through recursion and this recursion reduce the feature vector. Self-Organization Feature Map (SOFM) needs improvement for the selection of relevant features as it was selecting irrelevant features previously.

The solution is Weighted Self Organization Map (WSOM), as it gives deterministic feature after Feature Selection (FS); which is helpful for the ROI extraction detection; and is one of the proposed component Zis associated with highly classified feature. This is important because it expedited the selection procedure.

This parameter is found in random weight initialization. WSOM highly selects accuracy column from feature vector after various comparisons. This column values are the best representation of relevant feature map over the whole dataset. Relevant feature results into tumor detection with greater accuracy.

It is important to have an insight into SOFM. The input to the SOFM is trained to the extracted feature along labels. Firstly, the SOFM Architecture is defined, and the weights are then assigned to the trained extracted features of the proposed updated weighted SOM Map. It reduces the features. It assigns classification accuracies to every individual extracted feature. Next, it defines the threshold where each individual feature accuracy is compared. This comparison is performed recursively.

If this condition is true, then the feature column selects and adds to the resultant feature vector. Otherwise, the feature is discarded from the resultant feature vector space. A resultant feature vector space is obtained. In this step, weights are assigned to every feature and higher accuracy feature is selected. This is termed as the best feature. The middle-weighted features are known as average features, and the lowest values are termed as bad features. Finally, the best feature is selected and termed as deterministic feature.

Hence, the weighted SOM Map returns the deterministic feature, and this approach is an automatic feature selection method for covering the state-of the-art deficiencies. With such dimension reduction and automatic selection system, the computation cost is decreased. The rest of the SOFM steps are to find the best match, compute neighbour and update weights. However, the best extracted feature that extracts an image and accompanies the cluster is given in the following Figure 1. It illustrates the weighted updated SOM map, that produces confident element within ROI. It can be proved when the deterministic feature is combined with clustering algorithm FCM.In Figure 2 the proposed SOM Map is defined and then compared. From the state-of-the-art studies, they performed features selection and their SOM Map assigned weight and also trained the feature, but the selection of feature progress is compromising. The automatic feature selection process is not opted by SOM Map. Due to this issue, the execution cost increases (Ahmad & Starkey, 2018).

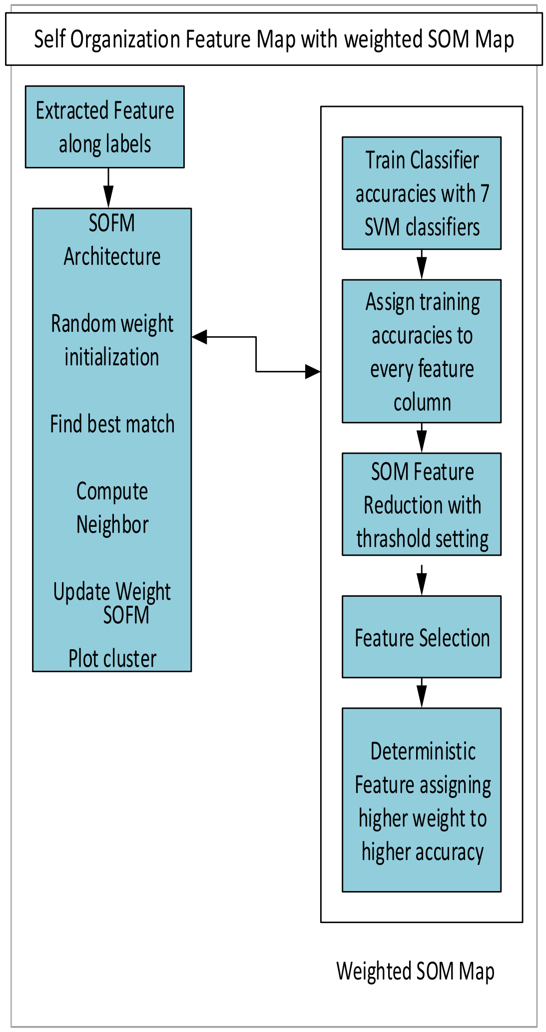


FIGURE 2. **SOFM with Weighted SOM Map.**

The extraction feature vector is trained by 20 features across the 129,580 images. Every feature is assigned the trained feature accuracy by weighted SOM Map. The next step is the determination of hypothesis. This hypothesis is calculated according to the values of the lowest feature accuracy and highest accuracy. Thus, the hypothesis is set by defined phenomena. Based on relative grading or value, the hypothesis is set. Here the higher trained accuracy feature is assigned a weight value as 100, and a lowest criterion is 50 per cent and rest of features are weighted accordingly. In feature reduction, if the weight of the feature does not satisfy the hypothesis, then it will be discarded. Otherwise, the feature selection process selects the successful one in a feature space. This process is performed recursively. Table 5.1 shows T1 and Flair images of the MICCAI BraTS dataset.

TABLE 2. Extracted Features Classification Accuracy of MACCAI BraTS dataset images of sequences T1, Flair.

Sr-no.	Feature Name	Flair Sequence	T1 Sequence
1	Energy	0.67	0.51
2	Homogeneit y	0.43	0.32
3	Root mean square	0.32	0.60
4	Smoothness	0.53	0.52
5	Skewness	0.55	0.41
6	Entropy	0.59	0.57
7	Irregular Feature	0.39	0.54
8	Shape Index	0.37	0.49
9	Shape Circularity	0.60	0.34
10	Pixel Orientation	0.54	0.69
11	Mean	0.998	0.99
12	Mode	0.83	0.96
13	Range	0.83	0.96
14	Area	0.73	0.63
15	Perimeter	0.64	0.43
16	Kurtosis	0.44	0.62
17	Variance	0.75	0.97
18	IDM	0.49	0.80
19	Contrast	0.66	0.40
20	Correlation	0.54	0.50

With the traditional SOM Map, 20 features were given, thus, not a single feature was reduced. Whereas the contributed weighted SOM Map reduces the features to 14 features only. Subsequently, the weighted SOM Map apply the maximum sort on the 14 features with this automatic feature selection, and finally, it selects one feature which is the best, and it is known as deterministic feature (DF). This DF use feature with clustering for the ROI.

C. SOM ARCHITECTURE

In SOM Architecture, the SOFM prepares the input parameters by processing those parameters. This is the second important step where the extracted features are combined with the target label. The extracted feature along the target label is an input parameter. It is also known as feature vector. Random vector is formed by random weight initialisation module. This module trains randomly the extracted feature vector. This module has also formed a Map. The topological neighbour size is defined. The learning rate is also defined for time variation. They are further sent to other phases of the algorithm.

TABLE 3. Table of Feature Reduction.

	Name of the Features	Flair	T1
1	Mean	0.99	0.99
2	Mode	0.83	0.964
3	Range	0.82	0.96;
4	Area	0.73	0.63;
5	Perimeter	0.64	0.62;
6	Kurtosis		0.62
7	Variance	0.74	0.97;
8	IDM		0.8043
9	Contrast	0.66	
10	Correlation	0.54	0.50
11	Energy	0.67	0.51
13	Root mean square		0.61
14	Smoothness	0.52	0.52
15	Skewness	0.54	
16	Entropy	0.59	0.57
17	Irregular feature		0.54
19	Shape Circularity	0.60	0.54
20	Pixel Orientation	0.54	0.69

TABLE 4. Table of Feature Selection.

Feature Name	T1	Flair
Mean	0.998,	0.99

D. SOM RANDOM WEIGHT INITIALIZATION

SOM Random Weight Initialization constitute the main part of the SOFM algorithm. Features are fed to this portion from the SOM architecture. It assigns weight to every single value in the matrix. This portion is the backbone of SOFM or the main entry point of the algorithm. It is important to assign weights to the appropriate features. In such a case, the weighted SOM Map plays a more important role in SOM random Weight Initialization.

TABLE 5. Results of DFC for T1 Sequence.

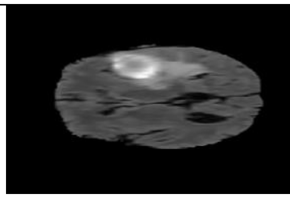
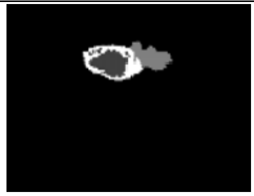
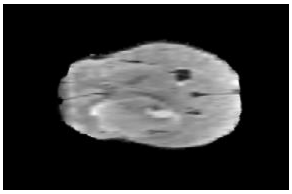
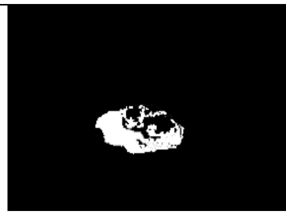
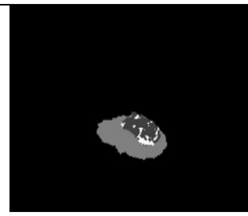
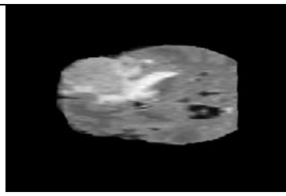
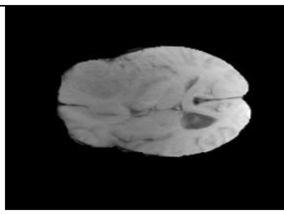
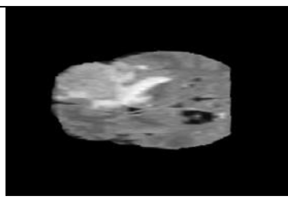
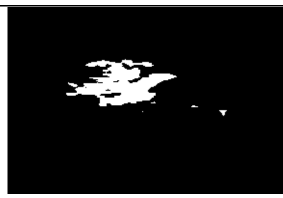
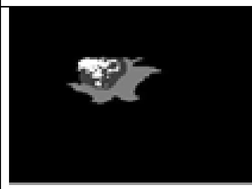
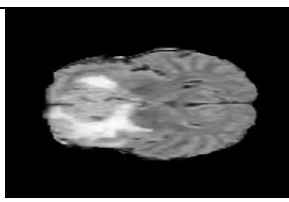
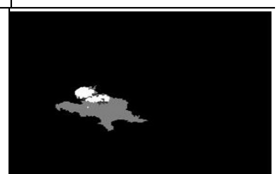
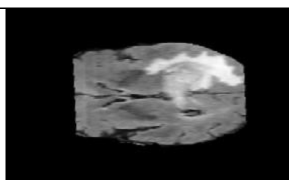
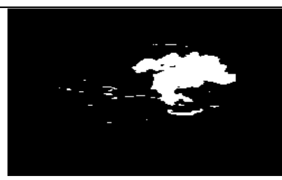
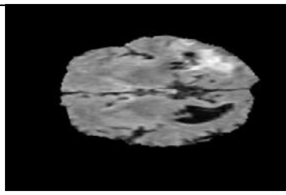
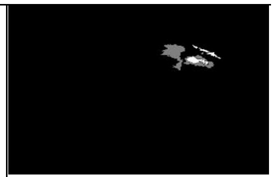
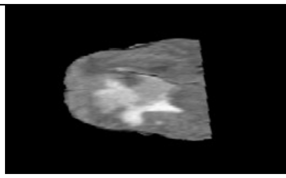
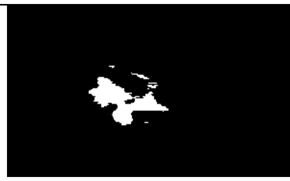
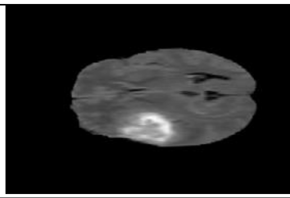
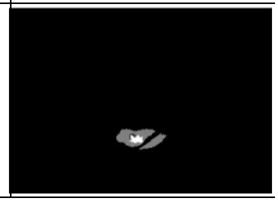
Name of Image	Input Image (a)	DFC Image (b)	Ground Truth Image (c)
Vol_Fl air_1			
Vol_Fl air_2			
Vol_Fl air_3			
Vol_Fl air_4			
Vol_Fl air_5			
Vol_Fl air_6			
Vol_Fl air_7			

TABLE 5. *(Continued.)* **Results of DFC for T1 Sequence.**

Vol_Fl air_8			
Vol_Flair_9			
Vol_Flair_10			

Basically, the SOM Random Weight Initialization takes an input of a combination of features and labels. This combination is called a feature vector. The SOM Random Weight initialization assigns random weights to the feature vector values individually. This is stored in the weighted SOM Map. The first step is to Update Weighted SOM Map, followed by Train Classifier accuracy, reduce feature and SOM MAP for feature selection and finally clustering performed by deterministic feature and clustering.

E. WEIGHTED SOM MAP

Feature is an important process for the selection of related features. This step is also important because it handles features at the entry point to the feature matrix. The traditional workflow involved the feature vector selection and the determination a feature. However, it did not attempt to reduce or select the features automatically.

Therefore, this study found that there is a need for an improved SOM Map, and thus. the weighted SOM Map was proposed. In weighted SOM Map, the feature is determined and selected with a certain contributed step like Train classifier, SOM reduction of features and Deterministic features with clustering that tests the features because the scope of the work is segmentation.

F. TRAIN CLASSIFIER ACCURACY

Train Classifier accuracy determines the classification accuracy of every trained feature. The SVM seven types of classifiers are applied over two types of a sequence of dataset like Flair and T1. It produces a trained accuracy of every feature. With a series of steps, this Trained Classifier accuracy is produced.

In method, the perfect classification accuracy of the input features is produced. In step one, every feature is stored in a specific column. This process is repeated until all features are not stored in one column. These features are stored recursively in the input table known as predictor. Therefore, Columns 1 to 20 are stored in a table. Column 21 is called the label column. Then the predictor is passed to seven types of SVM classifiers where they are selected accordingly. From the predictor, every column is sent to the flavor of the SVM structure. The SVM structure then makes a selection of from column 1 till column 20. It cross-checks with column 21. K-fold is also applied for validation. The value of K fold is 5.

After the validation the Trained Classifier accuracy is produced for every column. The columns are in fact representations of the features. Hence, the study retrieves 20 trained accuracies. These accuracies are appended at feature vector. Firstly, method calls the feature training to get the classification accuracy of the feature; secondly, it performs feature reduction and finally the feature selection is performed.

Table 2 gives the feature classification accuracy and the scale from 0 to 1. The mean accuracy of classification for T1 is 0.99 which means 99 per cent of these features are Deterministic Feature. They are the best features of the dataset whereas the bad feature is with minimum intensity where the value is 0.322. Likewise, is the case for Flair based image. A complete algorithm is discussed in the following sub sections

G. REDUCTION FEATURE AND WEIGHTED SOM MAP FOR FEATURE SELECTION

This is another phase of the weighted SOM Map. Here, the features are reduced recursively. A threshold of 80 per cent is set. Threshold of 80 per cent is determined due to the

TABLE 6. Results of DFC for T1 Sequence.

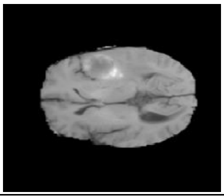
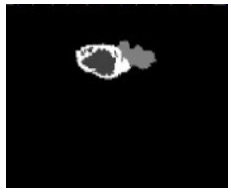
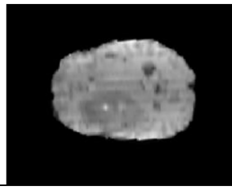
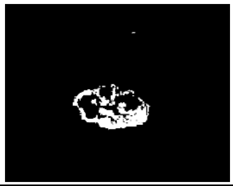
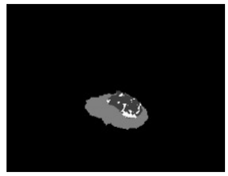
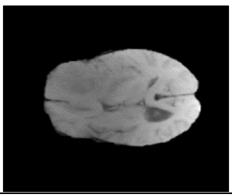
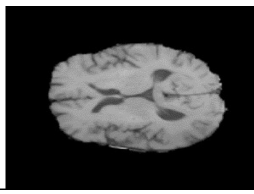
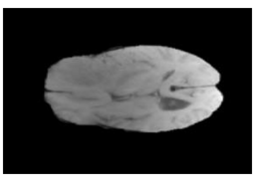
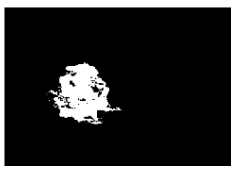
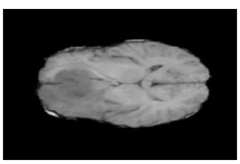
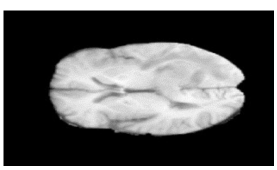
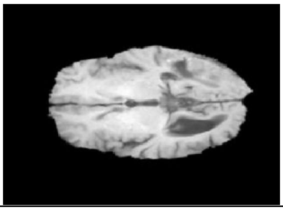
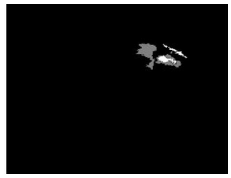
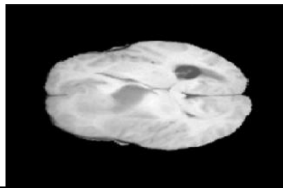
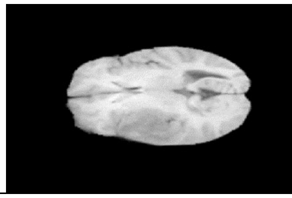
Name of Image	Input Image (a)	DFC Image (b)	Ground Truth Image (c)
Vol_T1_1			
Vol_T1_2			
Vol_T1_3			
Vol_T1_4			
Vol_T1_5			
Vol_T1_6			
Vol_T1_7			

TABLE 6. ***(Continued.)*** **Results of DFC for T1 Sequence.**

Vol_T1_8			
Vol_T1_9			
Vol_T1_10			

strongest categorization of the feature. In every call, the New SOM Map checks every column's accuracy. If it is equal or more than 80 per cent, the feature selects and adds to the new feature space, otherwise it is discarded. This process is repeated for all of 19 features. Therefore, the best features are selected from the dataset. Then the rest of the SOFM steps are performed. Particularly, the trained SVM classifier accuracy portion plays an important role.

In method, the SOM Reduction for T1 sequence shows the overall picture of the reduction of a feature. In step 1, the feature map executes the selection. Moreover, their target labels are associated with them. Next, the SOM architecture attempts the features' input to the random weight initialization module of SOFM where the suggested weighted SOM Map improves the SOFM with the Train Classifier, SOM reduction and the other phases of SOFM are addressed to find the best match, compute neighbours and update neighbours. The minimum learning rate is adjusted at 0.2.

In the SOM Reduction algorithm, all the feature accuracies are fed from column 1 until column 20. Moreover, the accuracies are appended to the feature vector. If the appended feature vector training accuracy value is equal or more than 80, then this feature will be selected to a new feature vector space. This check is performed till the last column, and a new feature vector space is produced by the New SOM Map. Hence, from this New SOM Map, the maximum accuracy feature is selected.

H. DETERMINISTIC FEATURES AND CLUSTERING

New SOM Map determines the maximum accuracy feature known as Deterministic Feature (DF). The weight of this deterministic feature is higher as compared to other features. With a combination of clustering and this deterministic feature; a ROI with the better brain tumor segmentation is produced. This proposed segmentation is resolving the issue of the under fitting. This step proves the weighted SOM Map self- confidence feature, which determines the region of interest. In above table, the features that result in a higher score are selected as discriminatory features and these discriminatory features are used for further processing. In method, the max accuracy feature is selected. This feature is applied to every single image for the best accuracy. This feature highlights the ROI (tumor) in the input image. The FCM is combined with the maximum accuracy feature to segment the portion of the tumor and defines labels to show the intensities. Those labels are divided into two classes and are evaluated one-by-one because they provide different intensities of pixel. Therefore, the Deterministic Feature Clustering helps in segmenting the image.

We can see in Table 1. Three sets of features termed as Intensity-based, Texture-based and Shape- based are extracted on High Grade Glioma (HGG) images. The Intensity features are Contrast, Mean, Range, Kurtosis, Variance, Correlation, Smoothness, Skewness, and Root Mean Square. The Texture-based features are Entropy, Energy, Inverse Difference Moment (IDM), and Homogeneity. Shaped-based features are Area, Perimeter, Irregular-shaped features, Shape Circularity, Pixel Orientation, Shape Index. The grand total of the HGG images are one hundred twenty-nine thousand, five hundred and eighty (129,580) images are extracted, where the subtotal of the T1 images of sequence are thirty-two thousand and three hundred and ninety-five (32,395), the T2 sequences

TABLE 7. Results of DFC for T1CE Sequence.

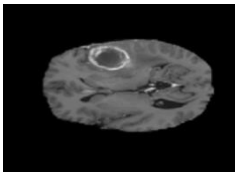
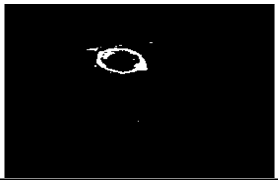
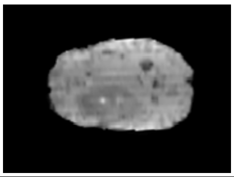
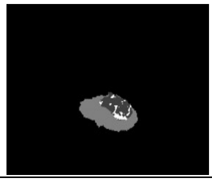
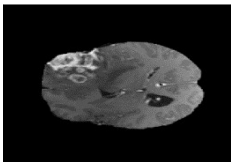
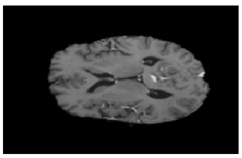
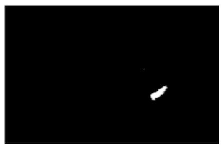
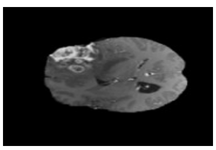
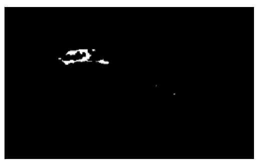
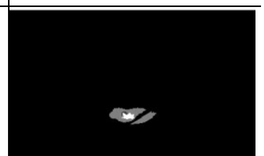
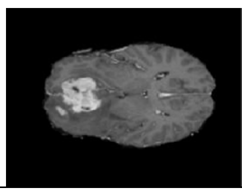
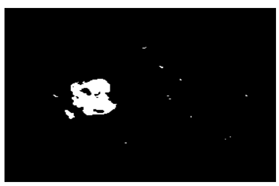
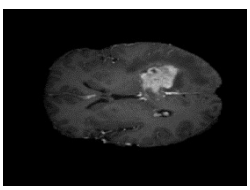
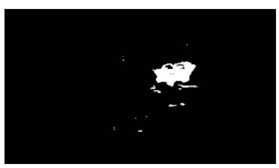
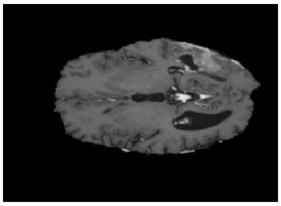
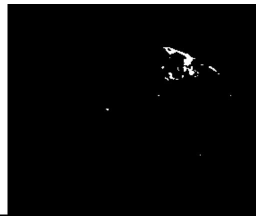
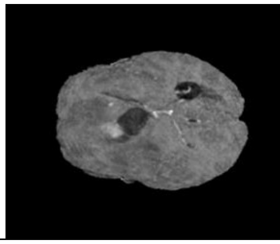
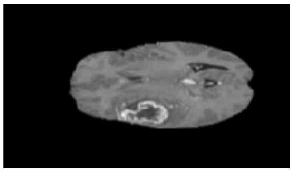
Name of Image	Input Image (a)	DFC Image (b)	Ground Truth Image (c)
Vol_T1C_1 e			
Vol_T1Ce_2			
Vol_T1Ce_3			
Vol_T1Ce_4			
Vol_T1CE_5			
Vol_T1CE_6			
Vol_T1Ce_7			

TABLE 7. ***(Continued.)*** **Results of DFC for T1CE Sequence.**

Vol_T1Ce_8			
Vol_T1Ce_9			
Vol_T1 Ce_10			

images are thirty two thousand, three hundred and ninety-five (32,395), the T1CE sequence images are thirty-two thousand, three hundred and ninety-five (32,395) and the sequence of the Flair images are thirty- two thousand, three hundred and ninety- five (32,395). In Table 2 reduced feature across T1 and Flair sequences are mentioned.

IV. RESULT'S AND DISCUSSION

In this Results section, it is important to check the feature extraction, feature reduction and feature selection process, where the feature selection is then combined with clustering to determine the element of the region of interest. The results are found after experimentation. The setup consists of the core i5 system with 16 GB RAM, 3 GHz processor using 2017B version MATLAB. Feature has their own importance. Experiment is conducted on MICCAI Brats brain tumor dataset. In this challenge dataset the images are present with higher dimension of MR images. The technique deterministic Feature is extracting the 1,29,580 images and 20 closed Features to MACCAI dataset from three classes of features, they are extracting, on basis of classification accuracy, they are features are reducing. One threshold is adjusted which directs the Deterministic Features. One clustering technique (FCM) is combined with Deterministic Feature for segmentation of accurate shape of brain tumor. The technique is known as Deterministic Feature Clustering (DFC). The segmentation result of DFC is compared with given ground truth reality images. For sake of comparison the testing parameters are used. They are named as Dice over Index (DOI), Jaccard Index (JI) and for better visibility Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) are used.

In Table 3 is showing the selected Feature. Table 4 is consisting of Flair images. In each row volume(image) is input in first column of the same row, in second columns segmented image after using Deterministic Feature Clustering is mentioned and Last column is consisting of the ground truth reality images. Table 5 is consisting for sequence T1 using DFC. Table 6 is consisting for sequence of T1CE using DFC. Table 7 is consisting for sequence of T2 using DFC. Results of Deterministic Feature Clustering over sequences of T1, T2, Flair, T1CE using DOI, JI, MSE and PSNR can be seen in Table 8.

It can be seen in Table2. Based on features accuracy, a new feature vector is formed. For feature reduction, one criterion is defined. Criteria checks the grade of feature accuracy, if the values are equal or greater than 50 (0.5), then the features will be added to the feature vector. Otherwise, they will be discarded from the feature vector. The resultant feature vector is reduced to 14 features from 20. The new Feature vector becomes 129,580∗14. The twenty features are reduced to 14 features. The values can be seen of reduced features in Table 2.

Result of Feature selection can be seen in Table 4. Deterministic Feature is found after the selection of high accuracy

TABLE 8. Results of DFC for T2 Sequence.

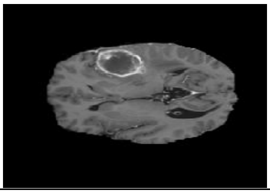
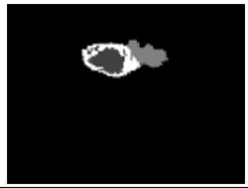
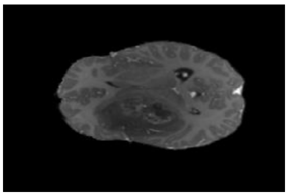
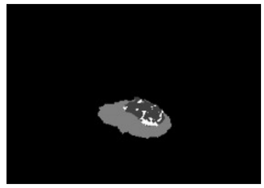
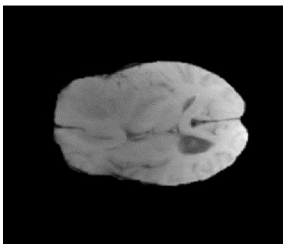
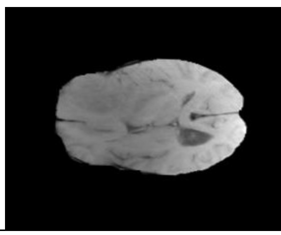
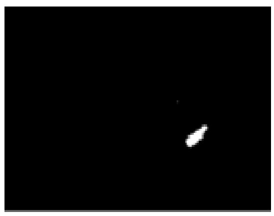
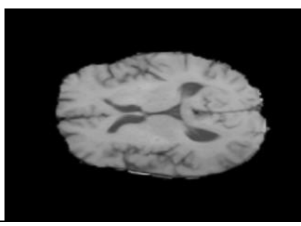
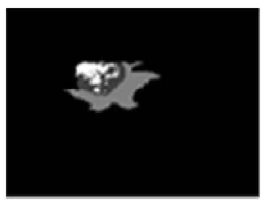
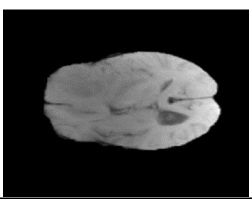
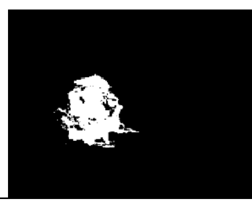
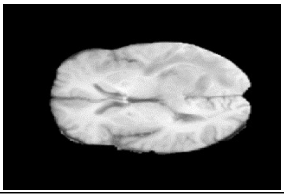
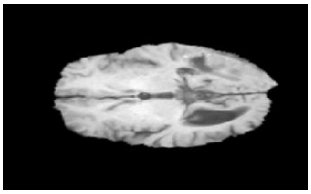
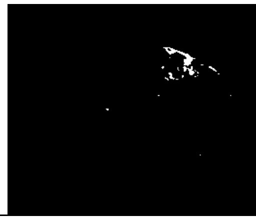
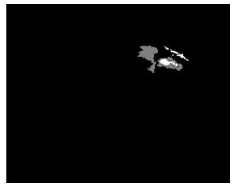
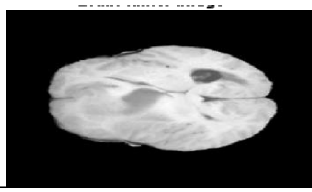
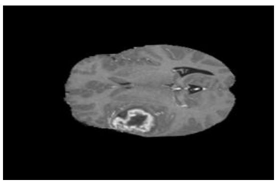
Name of Image	Input Image (a)	DFC Image (b)	Ground Truth Image (c)
Vol_T2_1			
Vol_T2_2			
Vol_T2_3			
Vol_T2_4			
Vol_T2_5			
Vol_T2_6			

TABLE 8. ***(Continued.)*** **Results of DFC for T2 Sequence.**

Vol_T2_7			
Vol_T2_8			
Vol_T2_9			
Vol_T2_10			

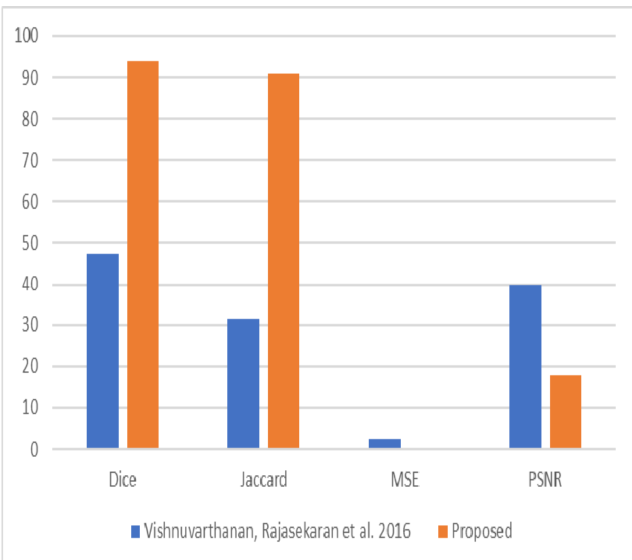


FIGURE 3. **Proposed technique Comparison with Bench mark.**

feature. Deterministic feature is selected from the dataset. Mean feature is 99 per cent. We can see the values in table 4 Which show the procedure on Feature selection. With the Deterministic Feature (DF), clustering is combined with deterministic feature for highly accurate segmentation. Dice (99%), Jaccard (99%) are helpful to the confidence element of tumour. Deterministic Feature is found after the selection of high accuracy feature. Deterministic feature is selected from the dataset. Mean feature is 99 per cent. With the Deterministic Feature (DF), clustering is combined with deterministic feature for highly accurate segmentation. Dice (99%), Jaccard (99%) are helpful to the confidence element of tumour. 0.99 mean 99 percent because the discrete values are mentioned in Tables.

Figure 2 shows the image input from the dataset then the features are determined from the above-mentioned algorithm. The Improved SOFM is identified to be a highly accurate texture feature. This texture feature is called a deterministic feature. From Table 5 to Table 9, Flair Sequence, T1 sequence, T1Ce sequence and T2 sequences, white intensities of the tumor can be clearly visualized, and the Region of Interest (ROI) is highlighting the tumor boundaries with the combination of deterministic features and clustering segments of the tumor. It shows the segmentation with confidence element. In Table 9, these white intensities values are evaluated

TABLE 9. Results of Deterministic Feature Clustering for sequences flair, T1CE, T2, T1.

Data set	DOI	JI	MSE	PSNR
Vol_1_flair	1	1	0.041	19.047
Vol_1_T1CE	1.000	1.000	0.019	19.05
Vol_1_T2	1	1	0.027	19.05
Vol_1_T1	0.95	0.91	0.09	19.05
Vol_2_flair	0.48	0.68	0.01	17.57
Vol_2_T1CE	0.94	0.89	0.11	17.57
Vol_2_T2	0.95	0.91	0.02	17.57
Vol_2_T1	0.96	0.92	0.09	17.57
Vol_3_flair	0.95	0.90	0.03	17.24
Vol_3_T1CE	0.97	0.93	0.03	17.24
Vol_3_T2	0.90	0.82	0.04	17.24
Vol_3_T1	0.93	0.87	0.09	17.24
Vol_4_flair	0.95	0.90	0.03	17.24
Vol_4_T1CE	0.95	0.91	0.01	18.66
Vol_4_T2	0.95	0.91	0.01	18.66
Vol_4_T1	0.93	0.86	0.09	18.66
Vol_5_flair	0.72	0.56	0.03	17.24
Vol_5_T1CE	0.98	0.95	0.03	17.24
Vol_5_T2	0.90	0.82	0.04	17.24
Vol_5_T1	0.93	0.87	0.09	17.24
Vol_6_flair	0.98	0.97	0.06	16.06
Vol_6_T1CE	1.00	0.99	0.06	16.06
Vol_6_T2	0.98	0.95	0.08	16.06
Vol_6_T1	0.92	0.84	0.10	16.06
Vol_7_flair	1.00	1.00	0.05	18.89
Vol_7_T1CE	1.00	1.00	0.03	18.89
Vol_7_T2	0.92	0.85	0.05	18.89
Vol_7_T1	0.91	0.84	0.17	18.89
Vol_8_flair	1.00	1.00	0.03	16.17
Vol_8_T1CE	1.00	1.00	0.03	18.89
Vol_8_T2	0.97	0.94	0.06	18.89
Vol_8_T1	0.96	0.93	0.15	16.17
Vol_9_flair	0.99	0.97	0.04	19.18
Vol_9_T1CE	0.99	0.99	0.01	19.18
Vol_9_T2	0.99	0.98	0.05	19.18
Vol_9_T1	0.9	0.9	0.2	19.2
Vol_10_flair	1.00	1.00	0.02	18.32
Vol_10_T1CE	0.98	0.97	0.02	18.32
Vol_10_T2	1.00	0.99	0.04	18.32
Vol_10_T1	0.96	0.93	0.15	18.32
Average	0.94	0.91	0.058	17.94

as compared to the testing parameter named as Dice, Jaccard, MSE and PSNR. The technique segmentation is comparted to the ground truth reality images of MICCIA brain tumor dataset. From Volume Vol_flair_1 to Vol_flair_10 across DOI, JI, MSE, and PSNR can be seen. From Volume Vol_T1_1 to Vol_T1_10 across DOI, JI, MSE, and PSNR can be seen. From Volume Vol_T2_1 to Vol_T2_10 across DOI, JI, MSE, and PSNR can be seen from Volume Vol_T1CE_1 to Vol_T1CE_10 across DOI, JI, MSE, and PSNR can be seen. In Figure 3, the comparison among proposed and benchmark techniques can be seen. The benchmarks values are 47.5 for Dice, 31.5 for Jaccard, 2.5db for MSE and 40db for PSNR whereas Dice of proposed is 94, JI is 91, MSE is 0.05 and PSNR is 17.45. three parameters are remarkably comparing with benchmark. Quantisation error is deal with the Mean square error. As mentioned above, average value of DOI is 0.94, JI is 0.91, MSE is 0.058, PSNR is 17.94, these results are calculated on complex variation of intensity images.

V. RECAPITULATION

The Figure 3 gives comparison of proposed method (DFC) with benchmark studies. Proposed algorithm (DFC) is compared with existing methods such as SOFM and FKM, Deep learning neural network along with features (DPLNN+Faatures), Deep learning neural network with classifiers (DNN and Classifier), Hybrid (KFCM and HCSD). The results of the proposed method are, average DOI similarity of the complete tumour is 0.94, Jaccard Tanimoto Coefficient Index (TC) is 0.91, Peak signal to noise ratio (PSNR) is 17.94dB and Mean Squared Error (MSE) is 0.058dB. How fine similarity has been achieved as compared to the state-of-the-art studies. In Figure number 3, accuracy of DFC is compared with state-of-the-art techniques.

VI. CONCLUSION

A novel Deterministic Feature Clustering (DFC) is proposed, one hundred twenty-nine five hundred and eighty HGG images are extracted through classes of features. The extracted classes of features are texture based, statistical based and shape based. In DFC, one proposed parameter named as weighted SOM in SOFM which select the best feature with higher accuracy on the dataset., hence a feature selection is improved. Selected features are given name as Deterministic Feature (DF). Those DF are combined with the FCM for clustering. Hence a better segmentation is proposed which segment with element with confidence. This combination is checked over whole dataset. The results are evaluated using the parameter like DOI, JI, MSE and PSNR. The results look to be much prominent as compared to the benchmark. The above work is contributed using HGG images, space of work is also available for LGG images. Every good work contributes more but limitation always remained. At first, three classes of features have been extracted in this work.; these features are more closed to MRI. In future work, we are looking forward to adding more classes of features because with addition of more features, we can achieve better accuracy and more improved mechanism of segmentation should be added so that DFC can be more efficient. Deep learning Neural Network model can give better results. In this work, experimental images are HGG but LGG images are missing so we can add LGG images in future.

DATA AVAILABILITY

The data used to support the findings of this study are available from the corresponding author upon request.

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