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An improved GABOR wavelet transform and rough k-means clustering algorithm for MRI BRAIN tumor image segmentation

B. Chinna Rao[1] · K. Raju[2] · G. Ramesh Babu[1] · Chandra Sekhar Pittala[3]

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Abstract
Our Proposed research is about tumor identification in the human brain. Here, MRI images are considered as the key factor in this research. There are five stages included in this proposed research and the very first stage is pre-processing followed by feature extraction, feature selection, classification, and finally segmentation. The input images are changed into transforming domain, then it happens with the assistance of Improved Gabor Wavelet Transform (IGWT). By Oppositional fruit fly algorithm (OFFA), the features called GLCM reside features are extracted and predominant features are also got chosen. To confirm whether the images look normal or abnormal, the chosen features are handed over to the SVM (Support Vector Machine) classifier. Once the classification process gets completed, the abnormally looking images are then picked out and the images are sent to the next process called segmentation. We used a rough k-means algorithm for the successful segmentation process. In comparison with other existing researches, our work seems structured and efficient. And Based on some evaluation metrics we estimated our efficiency and performance.

Keywords Oppositional fruit fly algorithm · Image segmentation · Rough K-means · Gabor wavelet transform · Feature extraction · Preprocessing

1 Introduction

In medical sciences, image processing & its segmentation can be observed as significant and one of the captivating processes. As to know the inside structure of our body and tissues MRI

✉ B. Chinna Rao
chinnaraob84@gmail.com

[1] Department of ECE, Raghu Engineering College, Visakhapatnam, Andhra Pradesh, India

[2] Department of ECE, Narasaraopeta Engineering College (Autonomous), Narasaraopeta, Andhra Pradesh, India

[3] Department of ECE, MLR Institute of Technology, Hyderabad, India

& CT scans plays a crucial role. We can be able to get precise visualization by the scanning process. When compared with CT scan MRI provides exact results and it doesn't harm our body both inside and outside [20]. As we know the brain is a very sensitive and significant organ of the human body. Our human body is formed up of numerous kinds of cells, hence there is a huge possibility that we could be affected by brain diseases such as brain cancers or tumors and a lot more. Brain tumors are considered as one of the disastrous diseases that affect our human body to the core [28]. In this, a mass number of anomalous cells are grown up in the brain. Here, numerous brain tumors could be observed in the medical sciences. Some tumors are less harmful to the human body which are called 'Benign' tumors in medical terms. Some are considered as disastrous and that is called 'Malignant' tumors [5]. Here we have MRI tools in medical sciences and its primary job is to identify and segment the tumor cells and deliver us a detailed picture of the affected area [17].

Some functions are needed to take place to detect certain values in image processing. Wavelet Transform is employed to deal with this data and it's also useful in detecting the tumor cells. As to maintain the spatial domain we used decomposing operations [13]. To observe the inside structures, Gabor wavelets are utilized with regard to the spatial frequencies, Selecting orientation, and spatial localization. We used this in the research areas like image segmentation & texture analysis [7, 25]. In spatial frequency domains, Gabor wavelet analysis is utilized to extract the features of MRI and to obtain the join resolution [21, 23]. The clustering approach has been implemented as MRI is considered as the time is taken task and its segmentation relies on the tumor's placement and its structure. In this way, MRI & its segmentation have their drawbacks. As to identify same objects classification, cluster analysis is utilized then in larger data sets, it's useful for location arrangement of patterns [19].

Clustering is defined as the grouping of patterns that is converted into clusters. Image segmentation is implemented with clustering. Numerous clustering complications are solved using cluster techniques. Here, we used unsupervised learning methods to resolve the issues. Some of the unsupervised learning techniques are fuzzy c means algorithm, k means algorithm, etc. Here, the k-means algorithm is considered as one of the optimal methods to solve the clustering issues and it tends to believe that, it's one of the simplest forms of unsupervised approach [16]. This algorithm is utilized for the grouping of objects which is k no. of groups and it relies on its attributes or its features. This grouping is based on Euclidean's distance i.e., the distance is between cluster centroid & data [4]. In geology, target recognition, astronomy, medical imaging, and image segmentation, fuzzy c means is utilized. And it's observed as one of the unsupervised techniques that work to solve real-world problems. The clustering approach is very crucial as we know that medical images have limited features, then it has poorer contrast images and it also has noise and it doesn't have uniformity [22, 24]. In some cases, the edges of MR images look awful and confused. So as to resolve these kinds of issues clearly, we can say that clustering provides us efficient results [14].

2 Related works

"Some of the related works relates to Brain Tumor is viewed in this section"

In 2020, Tarhini et al. [27] had suggested to use an effective method based on the threshold segmentation technique and some morphological procedures. First, the MRI picture's quality was improved. Next, threshold segmentation was used to categories the pixels into groups. Finally, morphological operators are used to identify the region of the image that contains the tumor with the greatest intensity.

In 2018, Angulakshmi et al. [3] had employed spectral clustering produces high-quality clusters, to segment brain tumor tissues from Magnetic Resonance Imaging (MRI). Massive data-driven dense similarity matrix creation hurts spectral clustering. The proposed method performs the brain tumor segmentation by locating the tumorous region designated as Region of Interest (ROI) using super pixel-based spectral clustering, and brain tumor tissues are then segmented by performing spectral clustering over the obtained ROI of MRI. This overcomes the disadvantage of spectral clustering. The computational load of spectral clustering is reduced by the identification of ROI. For the purpose of segmenting brain tumors, spectral clustering is used to segment ROI.

In 2018, Soltaninejad et al. [26] had suggested a brand-new 3D supervoxel-based learning technique for tumor segmentation in multimodal MRI brain images. The data from the multimodal MRI dataset is used to create supervoxels. First order intensity statistical features are retrieved for each supervoxel together with histograms of the texton descriptor, which are computed using a collection of Gabor filters of various sizes and orientations. To categorize each super voxel as a tumor core, oedema, or healthy brain tissue, those features are loaded into a Random Forests (RF) classifier.

In 2018, Adjei et al. [1] had implemented a straightforward approach for automatic brain tumor segmentation. Computer tomography and magnetic resonance imaging are frequently used in clinical settings to diagnose brain tumours. The segmentation of brain pictures based on their spatial and color proximity was accomplished through Simple Linear Iterative Clustering (SLIC). To select the best threshold value, the mean and variance of the image pixels are compared. After thresholding, there occurred region merging.

In 2022, Chen et al. [6] had introduced Bayesian and diffeomorphic TransMorph variations. The Bayesian variant generates a well-calibrated registration uncertainty estimate, while the diffeomorphic variants guarantee topology-preserving deformations and thoroughly evaluated the suggested models using 3D medical pictures from three applications, including phantom-to-CT registration, inter-patient and atlas-to-patient brain MRI registration. The proposed models were compared to several existing registration techniques and Transformer architectures for evaluation. Qualitative and quantitative findings show that the suggested Transformer-based model significantly outperforms the baseline approaches, supporting the usefulness of Transformers for medical image registration.

In 2018, Dour et al. [2] had proposed an effective clustering fusion-based fully automatic brain tissue segmentation system. The pixel intensity value was scaled throughout the algorithm's training phase to improve the contrast of the image. Using a superpixel algorithm, related intensity pixels from the brain image are then organized into items. Additionally, each object was segmented via tri clustering approaches. A Neural Network (NN) model was fed with features extracted from the picture objects for each clustering technique and it trained using the labels generated by that clustering technique.

In 2022, Iqbal et al. [15] had used a superpixel-based segmentation algorithm to automatically separate the tumour from brain MRI images. FALIR MRI preprocessing methods were used to remove outliers from slices in order to separate out the tumours because they have an impact on the overall process. Applying super pixel segmentation to the slices with better parameter values. The most crucial factor in superpixel-based segmentation was choosed the best size for the superpixel, and where the compactness parameter was crucial. Large superpixel sizes will allow for the presence of many classes, which will lead to inaccurate classification. Similar to this, a potential unique class was discovered if the size of the superpixel was small also suggests the ideal superpixel size for a more accurate tumour categorization in brain MRI imaging.

In 2019, Khalili et al. [18] Had described a Convolutional Neural Network (CNN) -based automatic technique for foetal MRI brain tissue segmentation into seven tissue classes. By adding synthetic intensity inhomogeneity artefacts to the training data and showed that the suggested technique learns to deal with these artefacts. The segmentation performance could be greatly enhanced by replacing or enhancing preprocessing processes like bias field adjustments.

3 Problem statement

In medical sciences segmenting images considers as a major hindrance to medical imaging. There are numerous segmentation methods based on MRIs are available to detect the tumors. However, it has its drawbacks. They are,

- K-means clustering approaches have been executed for the segmentation task. This ultimate goal is to segment the tumor cells from various MR images. The disadvantage of this is, it generates various results for different kinds of clusters. Previous knowledge about the handling of clusters and then having the capability to take over the noisy data are the required skills for this. In this, they failed to find out the edges which are considered as not enough for robustness.
- Next for segmentation, we used region based method has been utilized. This method seems time consuming also it has noise and intensity gives segmentation higher. As a result, this level of intensity gives sometimes holes or leads to higher segmentation. Also, it might not vary from the original image. The main disadvantages could be noise detection & higher computational cost.
- Thresholding approach among one of the simplest techniques in segmenting brain images. But the problem is we could able to produce only two number of classes and could not able to generate more than two.
- In medical imaging, region based growing technique has been implemented for segmenting the brain cells. As to choose the seed point values, we need UI (user interface) in every area. Also, this method is observed as time taking task.
- Edge detecting techniques are also another easiest technique for segmenting the brain tissues in medical sciences. Though it has simple techniques it has greater disadvantages too like it consumes more time, it’s very sensitive towards the noise, and then it doesn’t obtain greater accuracy.

Hence above are some of the drawbacks related to segmentation in the existing studies. This helps us not to repeat the faults in our proposed methodologies. Also, we tend to achieve a suitable segmentation method to attain greater accuracy in Magnetic Resonance Images.

4 Proposed methodology

The main objective of this paper is to develop and design the appropriate approach for brain image segmentation using MR images. For that, we tend to locate the tumor from magnetic resonance images in a productive, efficient, and accurate way. Segmentation has been taking place when we applied our method effectively and need to have the capability to differentiate the normal tissues with tumor cells. But still in the present medical scenarios what a clinical expert does is manually segment the brain tumor images. As we know, this manual process is considered time consuming, apart from this behavior, this process relies on the difficult side depending on the individual handlers. There are numerous promising approaches related to segmentation that have been proposed in the literature. The primary goal is to segment efficiently the MRI images using proposed techniques is shown in Figs. 1, 2, 3, 4 and 5. The very first step is to preprocess the images to make them suitable for segmentation. Secondly, feature extraction is happening right after preprocessing. This extraction process here employed our suggested approach Gabor Wavelet Transform ((IGWT). After that, each

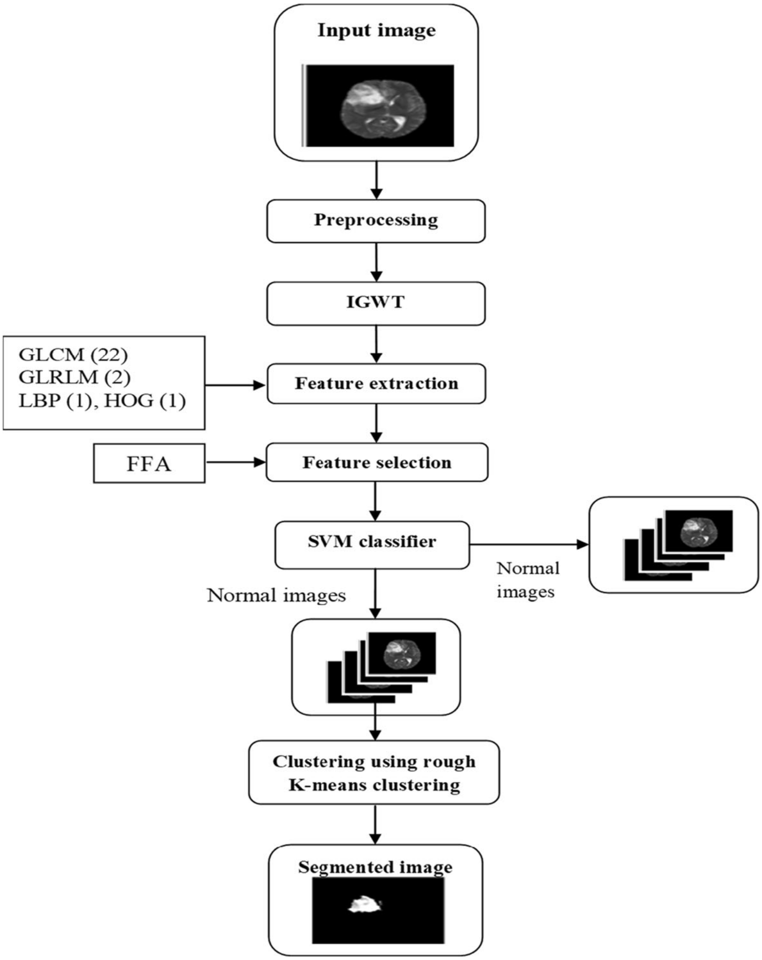

Fig. 1 MRI Image Tumor Segmentation In human brain

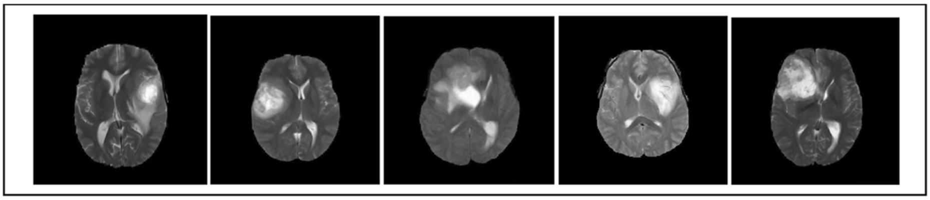

Fig. 2 Input MRI Images

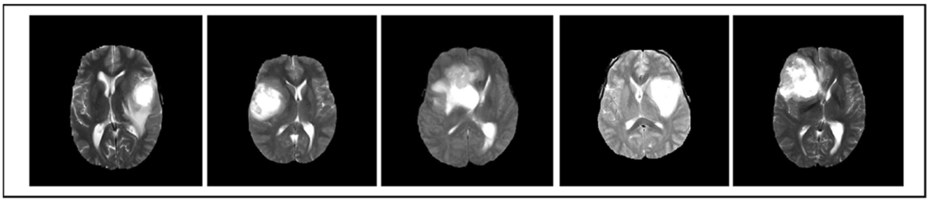

Fig. 3 Preprocessed MRI images

and all images are then extracted from the data warehouse. The next process is classification, but to make it happen we avoid a large number of features used. As a result, we choose only the significant features with OFFA, then the chosen features are sent to the immediate next process called classification. In this step, unusual image results are identified and handed over

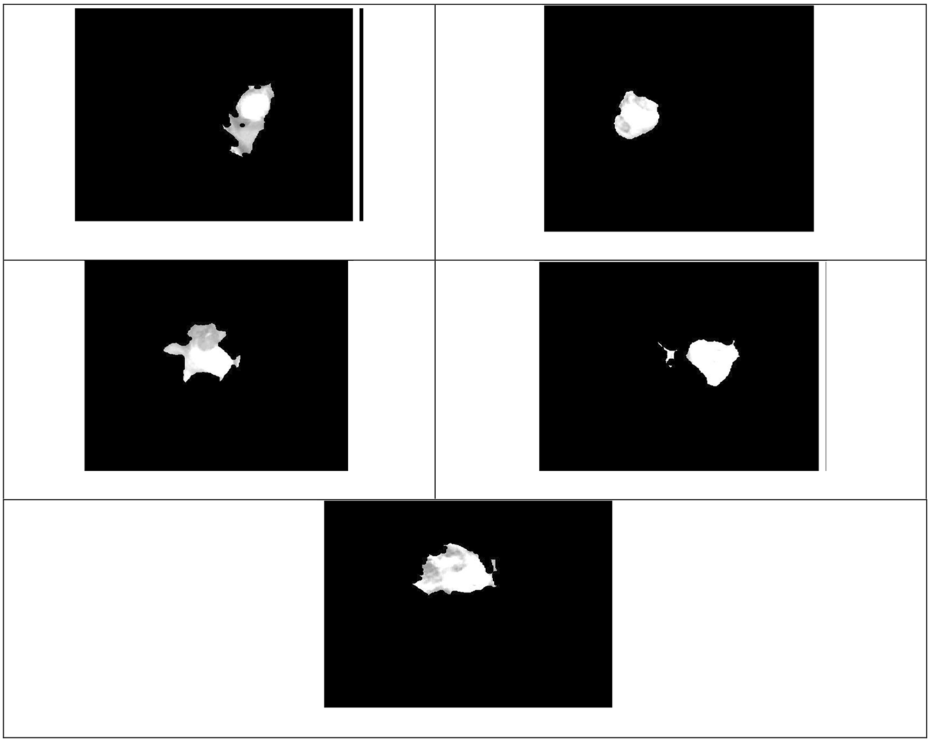

Fig. 4 Segmented MRI Images

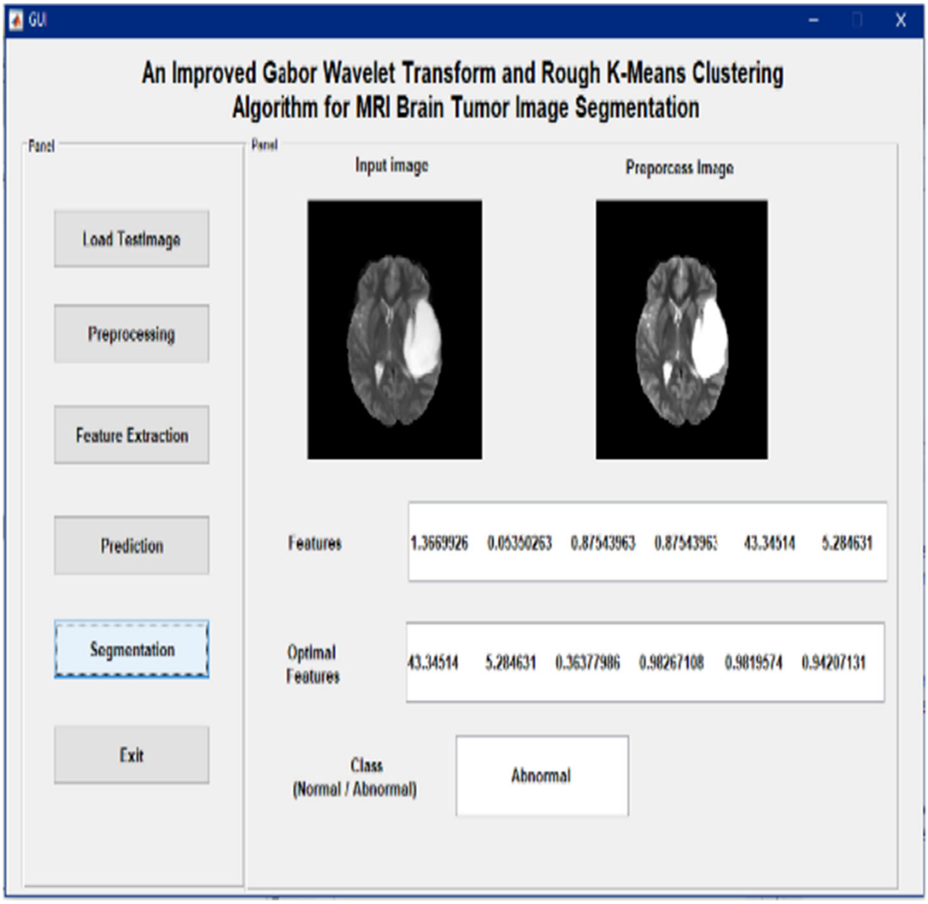

Fig. 5 Image feature extraction using proposed algorithm

to the algorithm, for that we are using a rough k-means algorithm. This algorithm segments the ROI-related portions. By the rough group selection, our clustering algorithm gets upgraded. Upper & lower approximation can be utilized in the design. Our suggested method is executed in MATLAB setup. The performance is calculated based on how greater the accuracy is in terms of segmentation.

4.1 Preprocessing

Preprocessing should be done to get standards in segmentation. For that, we have constraints to follow the process but, in some cases, it affects the quality & clarity of the segmented brain images [8]. As to rectify these segmentation rules we perform manual corrections. By doing these corrections and all we are ready for the next process as we have standard images for the further steps. The processed images are then taken to the next steps once the previous steps get accomplished. For next we tend to implement IGWT (Improved Gabor Wavelet Transform). Here only the feature extraction happens for the following steps. Preprocessing the MRI brain images is the key factor in our proposed system. The reason for preprocessing is mainly for the noise reduction in the brain and to make clear ways for the next steps. To tell more about this preprocessing, it gives a clear and standard image to attain the next step successfully also it gives the ease in detecting the tumors.

4.2 Improved Gabor wavelet transform

To obtain the optimization technique, we reframe the Gabor Wavelet Transform. With the opposition fruit fly algorithm, the effective Gabor filter is enhanced. This improved GWT is utilized in the preprocessed images in the first step. Below is the mathematical brief of IGWT.

The basic wavelet of IGWT is,

$$g(t)=\frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{t^2}{2\sigma^2}+j2\pi t\right),(\sigma>0) \tag{1}$$

$$\int_{-\infty}^{\infty}|g(t)|dt=1 \tag{2}$$

$\{g, f, \tau\}$ Is made using scaling & translating Eq. 3 in the IGW, which is expressed as,

$$g_{f,\tau}(t)=|f|g[f(t-\tau)]=\frac{|f|}{\sigma\sqrt{2\pi}}exp\left[-\frac{f^2(t-\tau)^2}{2\sigma^2}+j2\pi f(t-\tau)\right] \tag{3}$$

Where,

f – Dominant factor
σ – Resolution Factor

Instead of using 1/a for scaling purpose, IGWT eq. (4) is utilized as compared to the equation of GWT. The 4th equation is given as,

$$\widehat{g}_{f,0}(\gamma)=\int_{-\infty}^{\infty}g_{f,0}(t)e^{-j2\pi\gamma t}dt=exp\left[-\frac{2\pi^2\sigma^2(\gamma-f)^2}{f^2}\right] \tag{4}$$

To attain feature extraction, $g_{f,\tau}(\gamma)$ observed as the Fourier transform of $g_{f,\tau}(t)$.

4.3 Feature extraction

The features text is being extracted only when the segmentation process gets accomplished [12]. Here we have 4 types of features are there such,

- GLCM
- GLRLM
- LBP
- HOG

From each image there are 26 features are observed.

4.4 Feature selection

The oppositional fruit fly algorithm is considered as a feature selection technique. This algorithm explained the searching behavior of the fruit flies [10]. This algorithm is utilized for global search optimization which is considered as the novel goal of the algorithm. First, it starts with the behavior of the flies. Fruit flies are considered as one of the greater food hunters who have greater vision & osphresis towards food. To get a food source these flies are roaming around food fragrances that are floating towards the flies. After finding out where their food is, they might get close to the destination and grab it with clear vision. Optima give a representation of food and the searching methodology relies on the optima in OFFA, which provides efficient results and performance gets improved. The bit-by-bit process of the feature selection is expressed below.

- Extracted features are observed as input
- Optimal features are to be results

Step 1:

Initialized the parameters: The major parameters of FOA: Total evolution number & block's position low variant. In our proposed research fruit fly algorithm provides us with a low variant. (PX_axis, PY_axis) observed as the random location of low variant initially.

Step 2:

The traditional oppositional approach gets established to modify the fruit fly algorithms. Tizhoosh initiated the opposition base learning as OBL. According to this, the active agent and the contrasting agents could be known at the same time to obtain the optimal results for the agent solution. When compared to the active agent the opposite agent gets easy access to the optimal solution. The components define the opposite variant blocks.

$$OP_m = \left[op_m^1 + op_m^2, \cdots op_m^d\right] \tag{5}$$

Where,

$OP_m = Low_m + Up_m - P_m$ With $OP_m \in [Low_m, Up_m]$ is considered position of m^{th} low variance blocks.

$OP_m = d^{th}$ dimension of oppositional blocks.

Step 3:

This step explains the low variant block selection & arbitrary path.

Where,

$P_m = m^{th}$ position of low variant block.

$$P_m(x,y) = (PX_m, PY_m)^T \tag{6}$$

$$\mathrm{PX}_m = PX\_axis + RandomValue \tag{7}$$

$$\mathrm{PY}_m = PY\_axis + RandomValue \tag{8}$$

Step 4:

Suggested technique's place evaluation,

$$\mathrm{BP}_m = EC \tag{9}$$

Step 5:

Replace low variant block position with fitness function

$$bestblock = function(MinBP_m) \tag{10}$$

Step 6:

Identify low variant block's position

$$[\text{Excellent block Excellent selection}] = min\ e\ rror \tag{11}$$

Step 7:

This step holds the optimal position of the low variant block also x and y are interrelated. The flies make use of the visual direction of position and it flutters towards the direction.

$$selectedblock = min\ e\ rror \tag{12}$$

$$\mathrm{PX}\_axis = PX(Excellentindex) \tag{13}$$

$$\mathrm{PY}\_axis = PY(Excellentindex) \tag{14}$$

Step 8:

To execute stages three to six, need to validate consecutive optimization. We tend to decide whether the selected features are optimal or not compared to the existing feature selections.

Execute task seven only if it executes correctly. The feature values are taken to the classification process once the features get to choose.

4.5 SVM based classification

The classification takes place once the features selection has been completed. For this, we perform SVM classification to classify the images as normal or abnormally looking images. SVM is also observed as a sampling technique in which the researchers do the sampling based on subjective research rather than random search [9]. Using hyperplanes, the calculations are defined whether it's linear or non-linear. SVM's major objective is to place the hyperplane preferably. To achieve the full margin, we need to segregate two classes, that could be expressed as the objective of the support vector machine, also the range between the support vectors reaches its core extent. Another well-known form of the hyperplane is OSH as an optimal separating hyperplane. The images are segregated as abnormal or normal images in this stage. The unusual images are then taken out and submitted for segmentation.

4.6 Rough K-means clustering

To obtain the constructive clustering process k-means techniques have been suggested. It has k-means clustering & rough set features, as it could get greater results compared to other techniques [11]. To tackle the confusion in the clustering technique these rough k-means are considered as the optimal approach. The upper & lower approximation values are considered as the major thing in cluster k means. To increase the upper and lower bounds efficacy, estimations of the cluster's centroid could be modified. In this way rough k means varies from the usual k -means algorithm. To understand the concept better we narrated all the related things and their meanings.

Here,

V =	finite ordinary set (V = {objn| n = 1, N})
VI =	i^{th} cluster.
ceni =	Center., ceni, i = 1, 2,…, k.
$\underline{A}$VI =	Low approximation.
$\overline{A}$VI =	Upper approximation.
|$\overline{A}$Vi –$\underline{A}$Vi| =	No.of objects in rough area.
objn =	Every object.
lin =	Range between objn & ceni.

Here we have step by process of the rough k means.

Step 1: **Initialization**

Firstly, all the parameters are initialized towards the no.of clusters k and the parameters wb.approx & wl.approx and also towards threshold Δ.

Step 2: **Computing new Centroids**

The v_i cluster using this calculation for newly created cluster center.

$$cen_i = \begin{cases} w_{l.approx} \times \frac{\sum_{obj_n \in \underline{A}V_i} obj_n}{|\underline{A}V_i|} + w_{b.approx} \times \frac{\sum_{obj_n \left(\overline{A}V_i - \underline{A}V_i\right)} obj_n}{\left|\overline{A}V_i - \underline{A}V_i\right|} & if \left(\overline{A}V_i - \underline{A}V_i\right) \neq \varnothing \\ w_{l.approx} \times \frac{\sum_{obj_n \in \underline{A}V_i} obj_n}{|\underline{A}V_i|} & otherwise \end{cases}$$

Step 3: **Object Assigning**

For every objn, allocate the objects to the approximation process. The obj_n's nearby center is considered as cen_i the variations are lin-ljn, $1 \le$ i, j $\le$ k.obj_n is used to determine the membership function.if lin -ljn $\le \Delta$, is happened for the provided threshold, for cluster pairs(Vi,Vj) after that objn $\in \overline{A}$Vi & objn$\in$ also obj_n could not be considered as a low approximation. $1 \le$ i $\le$ k is a mini for objn$\in \underline{A}$Vi & objn $\in \overline{A}$Vi.

Step 4: **Process repeats until it reaches destination**

We repeat the process until it reaches its uniformity. There are no such new objects are found for the assignments. To assign the segmentation processes modified clustering algorithm of k - means is utilized. By the rough set selection, k means clustering is modified. By that lower & upper approximation algorithms could be utilized in cluster k means.

5 Result and discussion

Modified k means clustering is utilized for the input brain image segmentation. The measures used in the segmentation processes are

- Sensitivity
- Sensitivity
- Specificity
- True positive
- True negative
- False positive

5.1 Dataset description

On the Data Request page, we follow the rule and instructions to obtain the BraTS 2018 data values. In this dataset, the updated versions of data are provided. The updated data are clinically obtained 3 T multimodal MRI scans since BraTS'16, then all of the truth tables are revised manually by experts. For this year's challenge BraTS, GBM/HGG & LGG are used to know the diagnosis. Also, this is useful in the training, validating as well as testing process.

The resulting validated data is revealed on the 1st of July via email to the leaderboard. This leads participants to get their prelims results with unknown data also they submit the papers with reported results. This provides cross-validation results over the training data. The truth data of the validated data should not be handed over to the participants however they allow CBICA's IPP which is an online evaluation platform. Finally,On 30th July-20 all participants got the similar test reports,which comes through email for a time window of fourty eight hours. This all processes happened before uploading the final results. For the BraTS challenges the selected candidates called to prepare the slides about the presentation before august.

Sensitivity The portion of positive is measured by recognizing the sensitivity. By performing test results we could measure the positive results.

$$Sensitivity = \frac{Number\ of\ true\ positives}{Number\ of\ true\ positives + Number\ of\ false\ negatives} \times 100$$

Specificity The proportion of negative causes the specificity measures. By performing an ability test we could identify the negative outcomes.

$$Sensitivity = \frac{Number\ of\ true\ negatives}{Number\ of\ true\ negatives + Number\ of\ false\ positives} \times 100$$

Accuracy As given below we could evaluate the accuracy from sensitivity & specificity measures.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

These above metrices are useful to measure the brain MRI image segmentation.

Positive predictive rate Here" True positive" defines the positive event prediction. Also, the subject refers to positive under test. Then "false positive "event explains about the positive prediction on test, here also the subject has a negative resultant under certain standards.

$$PPV = \frac{NoofTP}{NoofTP + NoofFP} \times 100$$

Negative predictive value This "true negative" defines the prediction of negative results, then the subject points to the subject upon the gold standard rules. Next "false negative" is observed as an event that provides the negative test results, here the subject points the positive outcome over the standards.

$$NPV = \frac{NoofTN}{NoofTP + NoofFP} \times 100$$

False positive rate These metrics refer to the calculation between two those are the ratio between several negative events which are categorized wrongly as positive considered as false positives, another one is between the number of actual negative events regards with classification. False-negative ratio is defined by the false positive rate.

$$FPR = \frac{NoofFP}{NoofTP + NoofFP} \times 100$$

False negative rate This refers to the positive proportions which give us negative test outcomes with the test, which tells that the probability of negative test provides the condition is looking for.

$$FNR = \frac{NoofFN}{NoofTN + NoofFN} \times 100$$

The feature extraction process could be attained by using the fruit flies algorithm & Gabor filter algorithm. The above pictorial demonstrates the feature and optimal values.

The efficiency of our presented method was obtained by using some evaluation metrics such as TP, TN, PPV, NPV, FPR, & FNR. In the above Table 1 evaluation measures are shown. In this article first, we are inserted an input image 1. For that, we get the values like 4491 for TP, 256843 for TN, 40 for PPV, 0.8536 for NPV, 0.9998 for FPR, and 0.0088 for FNR. The input image 2 generates 6719 for TP, 253638 for TN, 1731 for FP, 56 for FN, 0.7951 for PPV, 0.9997 for NPV, 0.0067 for FPR and 0.0082 for FNR. In input image 3, we get an evaluation measure TP as 4883, TN as 251,794, FP as 5348, FN as 119, PPV as 0.4772, NPV as 0.9995, FPR as 0.0207, and FNR as 0.023. An input image 4. Produce 6786 for TP, 252106 for TN, 2807 for FP, 445 for FN, 0.7073 for PPV, 0.9982 for NPV, 0.0110 for FPR and 0.0615 for FNR. For an input image 4 and 5, we get TP as12016 and 12,347, TN as 248,775 and 248,022, FP as 1312 and 1454, FN as 41 and 321, PPV as 0.9015 and 0.8946, FPR as 0.0052 and 0.0058, FNR as 0.0034 and 0.0253.

From the tabulation2. We get sensitivity, specificity and accuracy of our presented method. These values are obtained based on the input images. For the input image 1, 2, 3, 4, 5 and 6 we get different types of sensitivity values such as 0.991, 0.9917, 0.9762, 0.9384, 0.9965 and 0.9746. The specificity of our proposed method gets 0.9970 for image 1, 0.9932 for image 2, 0.9792 for image 3, 0.9875 for image 4, 0.9947 for image 5 and 0.9941 for image 6. For the input image 1, 2, 3, 4, 5 and 6 we get various types of accuracy values such as 0.9969, 0.9931, 0.9791, 0.9875, 0.9948 and 0.9932.

Table 1 Evaluation Metrics of proposed study

Input Images	True Positive	True Negative	False Positive	False Negative	Positive Predictive Value	Negative Predictive Value	False Positive Rate	False Negative Rate
1	4491	256,843	770	40	0.8536	0.9998	0.0029	0.0088
2	6719	253,638	1731	56	0.7951	0.9997	0.0067	0.0082
3	4883	251,794	5348	119	0.4772	0.9995	0.0207	0.023
4	6786	252,106	2807	445	0.7073	0.9982	0.0110	0.0615
5	12,016	248,775	1312	41	0.9015	0.9998	0.0052	0.0034
6	12,347	248,022	1454	321	0.8946	0.9987	0.0058	0.0253

Table 2 Sensitivity, Specificity & Accuracy measures of proposed research

MRI images	Sensitivity	Specificity	Accuracy
Image 1	0.9911	0.9970	0.9969
Image 2	0.9917	0.9932	0.9931
Image 3	0.9762	0.9792	0.9791
Image 4	0.9384	0.9889	0.9875
Image 5	0.9965	0.9947	0.9948
Image 6	0.9746	0.9941	0.9932

5.2 Comparative analysis

In our proposed improved image segmentation scheme, we highly focus to attain very good results for effectively executing the MRI image segmentation process. Therefore, we compare our proposed technique with the existing technique to evaluate and prove its efficiency and performance. However, our proposed work shows better results than the existing technique. Here, we provide the Table 2 and graphical Figs. 6, 7, 8, 9, 10, 11 and 12 for showing the comparison of proposed and existing techniques based on results of sensitivity, specificity, and accuracy it will help to understand the better performance of our proposed work.

In our proposed methodology we focus mainly on image segmentation using magnetic resonance images. This process is considered more promising as compared with other techniques, as a result, we got efficient results. As to get the maximum efficiency & performance our resulting approach gets compared with other state of art approaches. From the comparison outcomes, we could say that our methods give optimal and accurate results for segmenting the brain tumor tissues. We provide tabulation and graphical representation to know about the resultant techniques. Accuracy, sensitivity & specificity are provided by our techniques to understand the results easier.

As to prove that our proposed method provides optimal results, the above figure demonstrated between rough k means & existing clustering method of k means.

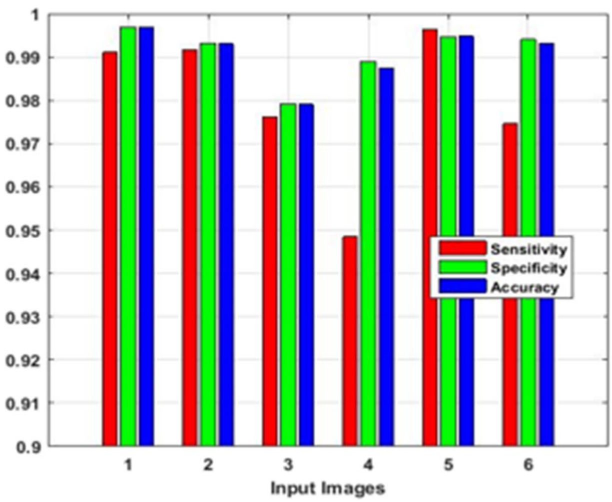

Fig. 6 Graph representation of overall sensitivity, specificity & accuracy

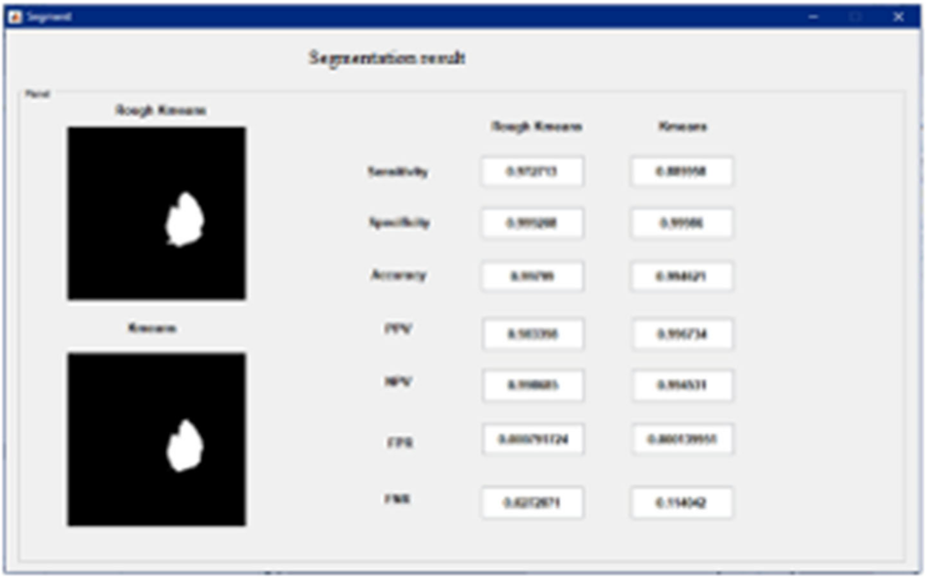

Fig. 7 Optimal results using K means

To demonstrate the performance & efficiency of proposed and existing techniques the above Table 3 narrates the measures. Here we executed some of the evaluation metrics. From this, we have proof that our proposed techniques give obvious results than the existing ones comparatively.

Table 4 shows sensitivity measure of the proposed rough k-means with existing k-means technique. Our presented Rough K-means technique obtains the sensitivity values such as 0.99117, 0.99173, 0.97620, 0.93845, 0.9965 and 0.97466 for image 1, 2, 3, 4, 5 and 6. Our off techniques K-means have produced sensitivity values such as 0.56521, 0.56073, 0.58056, 0.52828, 0.50219 and 0.50473 for input images 1, 2, 3, 4, 5 and 6. From the above Table 4, our presented technique sensitivity is better compared to our off technique.

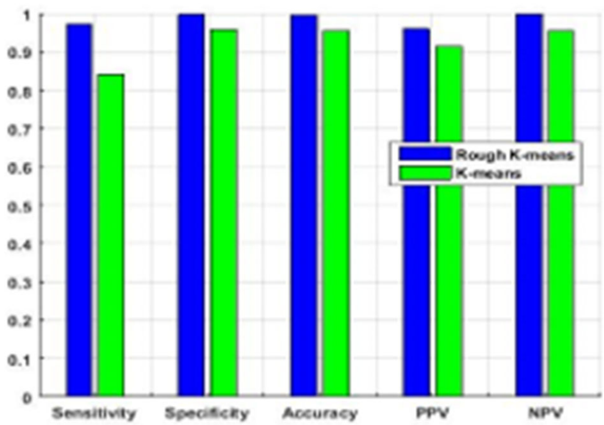

Fig. 8 Graph representation on existing Evaluation measures & proposed study

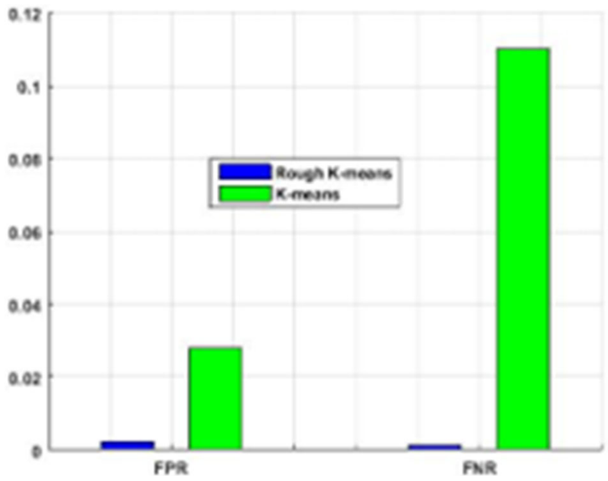

Fig. 9 Graph representation of proposed & existing FPR and FNR Evaluation measures

In Table 5 we have seen that the specificity comparison between existing k means & rough k means techniques. Below are the specificity results of ON rough k means.

Input 1 = 0.99918
Input 2 = 0.99815
Input 3 = 0.99240
Input 4 = 0.99556
Input 5 = 0.99906
Input 6 = 0.99903

Also,our proposed OFF k means are.

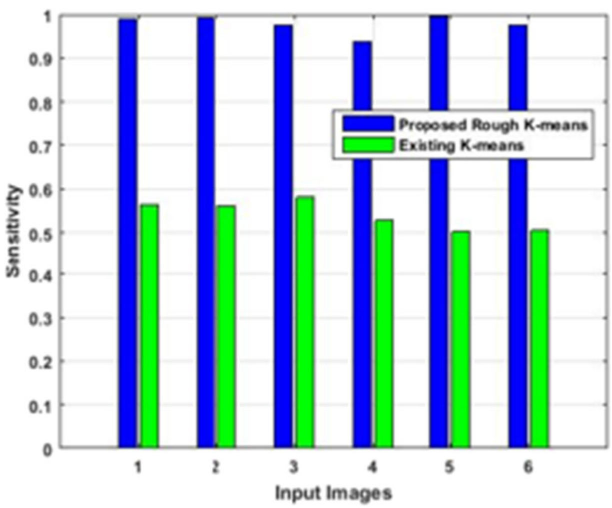

Fig. 10 Graph demonstration of proposed & existing sensitivity measures

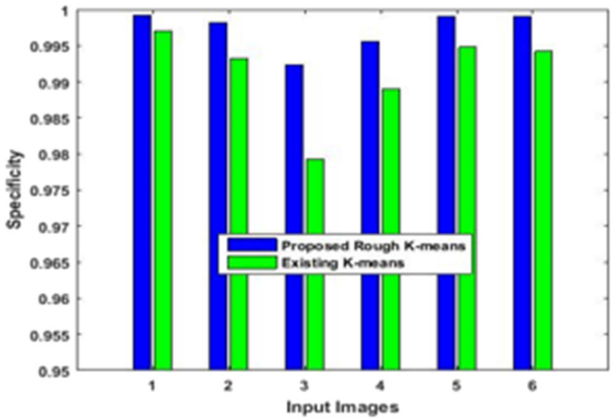

Fig. 11 Graph representation of proposed & existing specificity measures

Input 1 = 0.99701
Input 2 = 0.99322
Input 3 = 0.97920
Input 4 = 0.98898
Input 5 = 0.99475
Input 6 = 0.99417

When compare with other results our proposed research provides greater specificity results and accuracy.

In assistance with the previous k means technique, Table 6 demonstrated the results of accuracy in the proposed k means technique. We attain the accuracy of 0.99691 for the input image 1 over the proposed k –means. we got the accuracy as 0.99168 as existing k means. We attained 0.99318 accuracies for the second input image & 0.98685 for the existing approach. We got 0.97914 as the third input & 0.98454 ask- means algorithm. We optimized 0.98759 accuracies as the fourth input & 0.98267 for existing k-means. For fifth input image got an

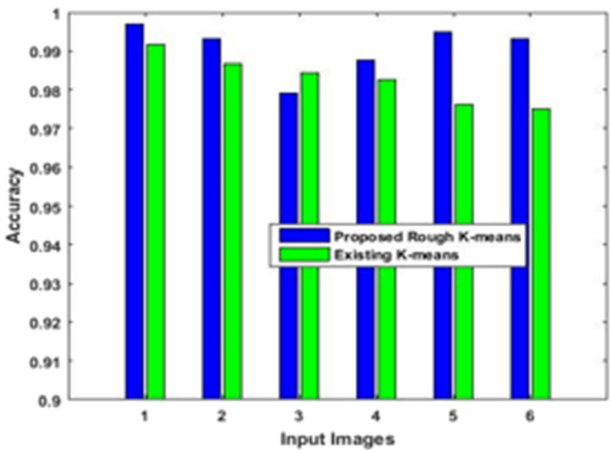

Fig. 12 Proposed & existing measures as a graph representation

Table 3 Comparison of Existing & Proposed Estimation Metrics

MRI Images	True Positive	True Negative	False Positive	False Negative	Positive Predictive Value	Negative Predictive Value	False Positive Rate	False Negative Rate
Rough K-Means	8378.076	250,384.0769	3074.7692	307.0769	0.899918	0.999859	0.00534	0.00290
K-means	3797.230	252,793.1538	665.69230	4887.923077	0.946038	0.97684	0.00139	0.49108

Table 4 Proposed & existing sensitivity measures comparison

MRI Images	Proposed Rough K-means	Existing K-means
Image 1	0.99117	0.56521
Image 2	0.99173	0.56073
Image 3	0.97620	0.58056
Image 4	0.93845	0.52828
Image 5	0.9965	0.50219
Image 6	0.97466	0.50473

Table 5 Comparison of Proposed & existing Specificity Measures

MRI Images	Proposed Rough K-means	Existing K-means
Image 1	0.99918	0.99701
Image 2	0.99815	0.99322
Image 3	0.99240	0.97920
Image 4	0.99556	0.98898
Image 5	0.99906	0.99475
Image 6	0.99903	0.99417

accuracy 0.99483 and the k –means technique got the accuracy range of 0.97621. For the rough k –means they obtained 0.97466 also 0.97466 as the sixth input image.

6 Conclusion

Image processing in the medical field consider as one of the significant processes and this technology helps to rectify the patient's health issues and take further steps to get rid of the medical issues. Here, segmentation plays a crucial role in this technique also experts get a detailed overview of the brain images. Effective image processing approaches are needed in the medical sciences however there exist numerous modalities like CT scan, X-rays MRI. When compared with other techniques MRI gives optimal and accurate results. In this, we implemented the proposed methodology for effectively identifying the tumor cells. After that we tend to utilize improved Gabor wavelet transform with rough k –means cluster technique to improvising the MRI segmentation. By using the fruit flies algorithm we certainly enhanced the Gabor filter efficacy also with the optimization technique IGWT also gets improvised. Once feature selection has been accomplished, values with respect to features are then extracted for the further clustering steps. This step executes the segmentation phase for the

Table 6 Existing & proposed research accuracy measures

MRI Images	Proposed Rough K-means	Existing K-means
Image 1	0.99691	0.99168
Image 2	0.99318	0.98685
Image 3	0.97914	0.98454
Image 4	0.98759	0.98267
Image 5	0.99483	0.97621
Image 6	0.99322	0.97515

further steps. For the segmentation process, the clustering approach rough k means is utilized. We believed that using the performance metrics brings greater and efficient results in segmentation. As we already knew, our proposed approaches produce greater results than the previous segmentation techniques.

Data availability Not applicable.

Declaration

Conflict of interest The authors declare that we have no conflict of interest.

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