Improved Rough-fuzzy C-means Clustering and Optimum Fuzzy Interference System for MRI Brain Image Segmentation

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***Abstract*—The categorization of brain tissues plays a vital role in various neuro-anatomical identification and implementations. In manual detection, misidentification of location and sound of unwanted tissues may occur due to visual fatigue by humans. Also, it consumes more time and may exhibit enormous partially inner or outer the manipulator. At present, automatic identification of brain tissues in MRI is vital for investigation and healing applications. This work proposed MRI image tissue segmentation using Improved Rough Fuzzy C Means (IRFCM) algorithm and classification using multiple fuzzy systems. Proposed research work comprises four modules: pre-processing, segmentation, categorization, and extracting features. Initially, the elimination of boisterous occur in the given image is done through pre-processing. After the pre-processing, segmentation is carried out for the pre-processed brain image to segment the tissue based on clustering concept using Improved Rough Fuzzy C Means algorithm. Later, the features of Gray-Level Co-Occurrence Matrix (GLCM) are extracted from segmentation, and the features extracted from segmented images are applied to Optimum Fuzzy Interference System (OFIS). Then the entire system parameters are optimized using Enhanced Grasshopper Optimization Algorithm (EGOA). Finally, the novel OFIS classifier helps to classify the brain-based tissue images as Gray Matter (GM), White Matter (WM), Cerebrospinal Fluid (CSF), and Tumor Tissues (TT). The results using MRI data sets are analyzed and compared with other existing techniques through performance metrics to show the superiority of the proposed methodology.**

Keywords*—Cerebrospinal fluid; fuzzy interference system; enhanced grasshopper optimization algorithm; improved rough fuzzy c-means clustering

I. Introduction

In abnormal and normal brain tissues studies, Automatic classification of brain tissue from MRI is very important [1]. The troop of unidentified cells that are grown in the brain or around the brain is said to be a brain tumor, and it is the maximum cause of increasing impermanence among adults as well as children across the world. Few brain tumors are benign (non-cancerous), and some are malignant (cancerous) [2]. The main aim of identifying images in the brain-based tumor is to separate the sufferer-specific clinical information and their distinctive characteristics. The collected information was inserted in multidimensional image data; after detection and locality of disease, it instructs and monitors the interventions, and it undergoes disease treatment, clinical observation, and analyzes the stage of disease [3]. In any part of the body, if there are uncontrolled tissues grown is said to be a tumor. It is classified into two stages: primary and secondary. If it is starting stage, then it is said to be primary and if the tumor spreads around and grown in their own way is known to be secondary. Moreover, CSF (Cerebrospinal Fluid) is mainly affected by the tumor [4-5]. The automatic identification and separation of brain tumors is a difficult task and faces many issues in identification. In an automatic computerized system, the separation is a challenging task in brain tumors, and it involves the nature of the disease, intensity, and identification of the shape of MRI images.

The most used object in image segmentation which was shown that mutually exclusive regions which consist of pixels and other regions included homogenous, has implemented with predefined criteria [6]. Brain tumor segmentation has involved different methods of separating different tumor tissue, which consists of GM, WM, and CSF [7]. Its goal in segmentation has shown that changing the depiction in the image is more meaningful and easier to find out. It was used to order the local object and its boundary images. Finally, the result says that the seat of regions mostly covers the entire image [8]. There are many challenging issues in the image segment, which has been developed by a modified approach, and it is mostly implemented in all types of applications and figures. Moreover, the choice has the proper method to find out the image in difficult problems [9]. The major issue in the brain tumor segment indicates that the tumor varies its shape, size, and location-based on image intensities [10]. The manual segment of a brain tumor was derived by the human experts, and it has to be long time, which makes clearer that a computer-aided system for a brain tumor has observed an advisable method.

Clustering is mostly used in MRI image segments. The clustering process is defined by a grouping of pattern arrangements. Cluster analysis says various unsupervised learning techniques that are applied to resolve the changes in cluster problems. There are many various unsupervised instruction techniques such as s k was indicated by Fuzzy C means algorithm etc. and it indicates the K as simplest [11]. To group the objects, K-means clustering is implemented, and it confides on the ascribe characteristic into k no of groups. In k-means clustering, trooping is implemented on Euclidean distance among the cluster center and information [12]. In real-time problem solving such as target identification, image separation, mineralogy, uranology, and images in medical Fuzzy C-Means clustering is used, and it acts as a clear training method. The clustering methods are very important since the images in medical are limited pixel quantity, poor distinction, boisterous, and the variation is non-uniform [13-14]. In the brain image of MRI, the edges of several tissues are unclear. So, clustering methods are commonly applied for the identification and detection of brain tumors.

Research work helps to identify the tissue type of MRI brain images. For the purpose of tissue classification, at first, speckle noise removal is applied in the pre-processing stage. Next to pre-processing, segmentation-based clustering is carried out by means of the Improved RFCM method based on pixel similarity. Then GLCM has extracted the particular characteristics of the improved method. After the feature extraction stage, the OFIS classifier is performed to classify the brain tissue images where its parameters are optimally selected using Enhanced GOA. The remaining sections of the proposed work are discussed below, and the related work of several researchers is described in Section 2. Problem definition and contribution of the research work are given in Section 3, and Section 4 highlights the overall background of the study. Section 5 elaborates the proposed methodology. In Section 6, the result is summarized, and the conclusion of the presented work is provided in Section 7.

II. Literature Survey

In current days, recognition of tumors and their classification system is the most developing research area. Hence, Hao Dong et al. [15] has developed an automatic detection of brain tumor and segmentation approach. Here, this developed approach is utilizing the deep convolution framework based on the U-Net methodology. Moreover, the proposed method segmentation process is compared with various physically defined ground accuracies. The comparison demonstrates segmentation process is robust and effective. In addition, to validate the effectiveness, the entire tumor areas, and higher tumor areas outcomes are compared with core tumor areas. Here, the developed method provides the brain tumor segmentation of particularly affected persons without physical intrusion. Also, this approach is significant permits the objective injury analysis for medical responsibilities like that patient observing diagnosis, arrangement of treatment, and diagnosis. Besides, this method is evaluation is mainly based on the multimodal image segmentation dataset. These datasets include higher and lower grades of brain tumor cases as 220 and 54, respectively. To verify the efficiency of the segmentation procedure, cross-validation is taken.

Recognition of tumors in the brain is the most significant performance in these modern days. Hence, the automatic detection system is developed by Soltaninejad et al. [16]. Moreover, this detection scheme detects the brain tumor in the abnormal tissue related to the segmentation process. This approach mainly bases on the Fluid- Attenuated Inversion Recovery (FLAIR) with MRI image segmentation. Here, the experimental outcomes are having high segmentation performance and higher recognition ratio. Moreover, the performances are validated based on the ERT classifier system. Consequently, the detection sensitivity, error rate, and overlap measure of the proposed technique have attained 6%, 89.48%, and 0.88% separately. In addition, multimodal tumor segmentation performance outcomes are summarized below, 88.09% detection sensitivity, 6% of error rate, and 0.88% dice overlap amount. Here, the developed detection sachems take the original brain tumor images. To classify the images superpixel approach is utilized. Moreover, the original brain tumor image features consist of four types of classification. That is, curvatures, intensity bases feature classification, Gabor textons, and fractal examination.

Cabria et al. [17] has developed a Potential Field Segmentation (PFS) algorithm based original MRI brain tumor segmentation process. Also, the author presents and investigates the outcomes of the created PFS and other approaches to attain the bonded segmentation. Here, the proposed PFS method is mainly based on the Potential Field Clustering (PFC) and other recently proposed clustering approaches concept is incorporated with PFS. Moreover, the term “mass” is represented as a potential field to create the intensity of the MRI pixel vision. Particularly, each and every pixel of MRI is estimated, and a smaller area of the brain tumor pixel was related to the adaptive potential threshold. Moreover, the segmentation condition is “small potential”. It is automatically verifying the brain tumor pixels for a long time. Therefore, there is no “mass” and larger potential surroundings are much larger than the segmentation criteria. Then, the attained performances results are compared with different approaches consist of MRI bases benchmark dataset with multimodal tumor segmentation.

Mohammad et al. [18] have proposed a Deep Neural Networks (DNNs) bases automatic brain detection method is utilized. In this method, take the MR images to perform the low and high-grade networks. Consequently, the brain tumor is affecting is appeared in anywhere of the brain region. Also, the brain tumor is classified based on the size, shape, and divergence; these are the issues in the machine learning methodologies. In addition, the low flexibility and lower ability are the surveyed problems of ML techniques. To overcome these types of issues Convolution Neural framework (CNF) is developed through the Deep Neural Networks. Moreover, the newly proposed CNF structure is totally different from the conventional methods. The process of CNF is initially done with the local features and global contextual features. Implementations are done in the 40 fold speed up with a fully connected layer of the CNF. Finally, the outcomes of the CNF have validated bases on the comparison of the additional source of the dataset for succeeding CNF.

Rajinikanth et al. [19] have developed an innovative algorithm depend on the meta-heuristic optimization method. To evaluate the MRI brain tumor classification, the proposed method is utilized. Moreover, the proposed method improves the mines tumor core, as well as edema sector of the Teaching Learning Based Optimization (TLBO), based brain MRI integrating. Additionally, entropy examination and level set examination-based segmentation procedures are taken to execute the entire process efficiently. Here, the proposed approaches are implemented in flair, T1C, and T2 modalities. Also, the experimental performances are estimated using CEREBRIX and BRAINIX datasets. Furthermore, the optimization algorithm is validated based on the MICCAI separation of brain tumors by multimodal image separation challenge at the 2012 dataset. Attained outcomes are compared with Jaccard index values in terms of accuracy, precision, specificity, and sensitivity. Therefore, the developed segmentation process is medically important.

The accurate identification of tumors in the brain is a difficult and challenging task. To address this issue, Soltaninejad et al. [20] presented a 3D supermodel-based training method for the identification of tumors in multimodal MRI. Collected information and characteristics from multimodal MRI includes systemic MRI, and it results in accurate identification of brain images. Super voxels were created for applying the information, and a variety of characteristics is calculated by Gabor filters for every super voxel. The calculated characteristics are applied to the RF (random forest) classifier to categorize the tumor. The result shows that it gives better results in the separation of tumors. For increasing accuracy, the multimodal MRI is added, and it shows improvement in accuracy, and it provides better delineation among all tumor grades. The detection of brain tumor using multimodal MRI, it is the fastest method; it gives high accuracy and classifies the brain tissue as healthy or brain edema.

Nabizadeh et al. [21] had presented an automated identification of brain tumors in MRI for evaluation of the changeability and difficulty of the position, size, form, and appearance. Some techniques were used in multi-spectral anatomical MRI because of the similarities in intensity between the tissues normally found and injured brains. However, in multi-spectral MRI, there are some limitations in cost and time, and it faces some difficulties; to conquer this, a single-spectral anatomical MRI was developed to detect the tumor tissues. Also, he presented a fully automatic system it detects the tumor area and describes the portion which is damaged. As a result, the experiment shows that it successfully segments the tissues with less difficulty in computation and high accuracy. The benefit of a single contrast mechanism is separating the tissue segments, and it can able to identify the tumor tissues. Furthermore, it also includes an overview that evaluates the benefits of statistical characteristics over Gabor wavelet characterization by applying various classifiers.

III. Problem Definition

Brain tissue categorization in MRI is a vital stage in identifying the disease, diagnosis, planning for surgery, and process of treatment. In present days, MRI classification is a challenging task despite several existing artifacts such as boisterous, complexity in images, and incomplete volume effect. In automatic brain classification, some of the methods are complex, and few are not sufficiently accurate for a certain application. The proposed works contributions are described below:

- The main principle of proposed work is to analyze which type of tissue is occurred in the brain is analyzed from MRI images collected from the database.
- For segmentation, clustering is carried out to segment the brain tissue using Improved RFCM. Here the improved technique manages overlapping clusters.
- Five GLCM features, namely interaction, distinction, energy, disarray, and quantity variance alone, are extracted for the optimum solution.
- To obtain the optimal solution, EGOA is utilized in FIS, which helps to classify brain tissue MRI by optimizing the system structure.

IV. Background of the Study

Several processing methods were proposed by the existing researchers for the separation and categorization of tissues in the brain for MRI. In early researches, numerous techniques were developed and discussed for identifying the brain tissues in MRI; fully automated detection, extraction of features, segmentation, and categorization is essential. A series of steps involved in image processing is utilized on MRI images to do brain tissue segmentation, and categorization of images that were inspired from proposed algorithms, and its background knowledge is analyzed in this section.

A. Fuzzy C-Means Clustering Algorithm

Generally, C-Means are the commonly used and most known clustering models because it is a smallest square model. Fuzzy C-Means is very widespread due to its handling capability of overlying clusters when compared with C-Means clustering algorithm. Based on fuzzy integration, FCM instructs each pixel (data points) to clusters. Let $Y = \{y_1, y_2, \ldots, y_l, \ldots, y_O\}$ be the set of O objects and $W = \{w_j, \ldots, w_j, \ldots, w_d\}$ be the set of d centroids; where $Y = \{y_1, y_2, \ldots, y_l, \ldots, y_O\}$ be the set of d centroids; where $y_l \in S^n$, $w_j \in S^n$and $w_j \in Y$. It separates Yinto $d$clusters by iteratively reducing the function of objectives:

$$K = \sum_{i=1}^{d} \sum_{y_l \in C(Y)} (\eta_{jl})^x \|y_l - w_i\|^2 \qquad (1)$$

Where $1 \leq n < \infty$ is the operator in fuzzifier, w_i represents the j^{th} centre of force correlated to cluster Y_j, $\eta_{jl} \in [0,1]$ is the patterns fuzzy integration y_l to cluster Y_j, and distance criteria is represented as $\|\bullet\|$. The resulting partition is controlled by fuzziness parameter n, where $n = 2$ is used. The pixel near to a centre of cluster achieve membership value as high then the function of objective is reduced and those distant from it are designate the membership value as low. The value of membership depends on the proportional distance of the object to centre of cluster as inverse. Algorithm is outlined as follows:

- Allot initial centre of force w_j, $j \in 1$ to $d$for clusters.
- Find d value of membership for O pixel by following:

$$\eta_{jl} = \frac{1}{\sum_{i=1}^{d} \left(\frac{\|y_l - w_j\|}{\|y_l - w_i\|} \right)^{\frac{2}{n-1}}} \qquad (2)$$

And update cluster centers as,

$$w_j = \frac{\sum_{l=1}^{O} \eta_{jl} \times y_l}{\sum_{l=1}^{O} \eta_{jl}} \quad (3)$$

Subjected to

$$\sum_{j=1}^{d} \eta_{jl} = 1 \nabla l and 0 < \sum_{l=1}^{O} \eta_{jl} < 1 \quad (4)$$

In a cluster, each dataset is assigned, and it carries the membership value is high. If the membership value is low, then the belongingness is also low. Iterate steps two again until the center of gravity stabilizes that are the previous iteration is identical to the present iteration, and there is no additional work. The point which is to be noted is the dependency of FCM on proportional interval among the centre of clusters and the data points, which makes it delicate to boisterous.

B. Rough Set Theory

Rough set theory is based on idea of space of approximation and it is designated by two attributes. Lower estimation, $S_U(Y)$, Upper estimation of the Rough set, $S_L(Y)$ is describe as, Here, subset is denoted as $Y \subseteq Uni$,and Uni is represented as universe, S is the Uni connection of equivalent then we have:

$$S_U(Y) = Uni\{Z \in Uni/S|Z \subseteq Y\} \quad (5)$$

$$S_L(Y) = Uni\{Z \in Uni/S|Z \cup Y\} \neq \varphi \quad (6)$$

Where φ represents empty set.

The lower approximation $S_L(Y)$ is the union of all the elementary sets which are subsets of $Y$and the upper approximation $S_U(Y)$ is the union of all the elementary sets which have a non-empty intersection with Y. The interval $B(Y) = [S_L(Y), S_U(Y)]$ is the delineation of a normal set Yin the space of approximation $< Uni, S >$ or simply it is called Y rough set. The bottom set of approximation describes that all elements were surely refer to Y, whereas in approximation is upper, and then it is a collection of those elements that definitely belong to Y. An object y_l can be lower most part of any approximation. If $y_l \in S_L(Y)$ of cluster Y then simultaneously $y_l \in S(Y)$. If y_l is not a part of any lower approximation, then it belongs to two or more upper approximations.

C. Grasshopper Optimization Algorithm

Optimization refers to attain the best result in a solution space in regard to some predetermined norms. Among several optimization algorithms, GOA is considered to be the efficient technique to find out the best solution. Generally, Grasshopper is a catastrophic insect in agriculture, and it has two stages, nymph and adulthood. Normally, the nymph Grasshopper has no wings, and it eats all vegetation in its path. After a period of time, the wings were grown slowly, and it flies in the air and moves to a large distance in a certain time. Moreover, the grasshoppers' nature is individual; and grasshoppers were joining as a big hive of all beings. The measurements of the hive may be of small size, and it is incubus for farmers. The behavior of hive is found in both phases of grasshoppers, and it is a unique aspect of grasshoppers. The key distinctive of the hive is a slow movement in their phase of larval, and it is the fewer steps for grasshoppers. Distant range and sudden motion is the necessary characteristic of the troop in adulthood. The other characteristic of grasshopper troops is searching of foods by dividing their process of search into two, namely exploration and exploitation. Here each Grasshopper illustrates an answer in the community. Fig. 1 shows the general framework of the grasshopper optimization algorithm:

To replicate the swarming behavior of grasshopper, mathematical model is done and is represented as follows:

$$Y_j = R_j + H_j + A_j \quad (7)$$

Where,Y_j represents the $j - th$ grasshopper position, R_j is the interaction on social, H_j is the $j - th$ grasshopper gravity force, and A_j shows the advection of wind.

1) Social interaction: The element fully replicates the movement of grasshoppers, yet the component which is mainly originated from the grasshoppers and it is discussed below:

$$R_j = \sum_{\substack{i=1 \\ i \neq j}}^{M} t(e_{ji})\, \hat{e}_{ji} \quad (8)$$

Where, distance between $j - th$ grasshopper and $e_{ji}$is $i - th$ grasshopper and it is defined as,

$$e_{ji} = |y_i - y_j| \quad (9)$$

Here, t is a function to define the social forces strength, as shown in equation (9) and e_{ji} is a unit vector from the $j - th$ grasshopper to the $i - th$ grasshopper which can be defined as,

$$\hat{e}_{ji} = \frac{y_i - y_j}{e_{ji}} \quad (10)$$

The function, t defines the social force, is calculated as follows:

$$t(s) = g f^{\frac{-v}{m}} - f^{-s} \quad (11)$$

where g indicates the intensity of attraction and l is the attractive length scale. The grasshopper's impact on social interface is shown as function t. The parameters were adjusted for social force g and m which is not suitable for applying strong forces among grasshoppers with large distances among them.

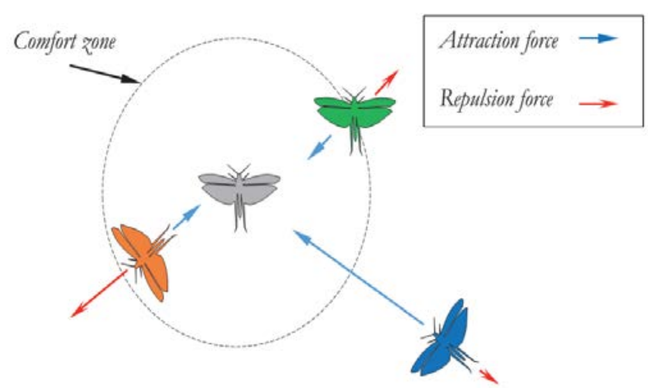


Fig. 1. Generalized Framework of Grasshopper Optimization Algorithm.

For providing random behavior, the equation can be describe as

$$Y_j = s_1 R_j + s_2 H_j + s_3 A_j \tag{12}$$

Where s_1, s_2 and s_3 are random numbers in [0, 1].

2) Gravitational force: The enhanced grasshopper force of gravity is represented below:

$$H_j = -h\hat{f}_h \tag{13}$$

Where h is the constant value in gravitational and $\hat{f}_h$ shows a union vector towards the center of gravity.

3) Wind advection: The grasshopper advection can be calculated as follows:

$$A_j = v\hat{f}_w \tag{14}$$

where, v is constant drift and $\hat{f}_w$ is a unity vector in the direction of wind. Movements of grasshoppers are coordinate with the direction of wind because it has no wings. The values of $T, H\&B$ are substituted in equation (7) and is expanded as follows:

$$Y_j = \sum_{\substack{i=1 \\ i\neq j}}^{M} t(|y_i - y_j|)\frac{y_i - y_j}{e_{ji}} - h\hat{f}_h + v\hat{f}_w \tag{15}$$

where, M represent the number of grasshopper.

V. Proposed Brain Tumor Tissue Detection Methodologies

The primary objective is to outline and build up a technique for classifying MRI brain images using various stages. The redundant data will be reduced by the rough sets and also reduced data to achieve information dimension and also reduction in accuracy and sensitivity. And also, problems in the definition of fuzzy similarity relations. These limitations need to overcome. Therefore, to achieve a better outcome, the Improved Rough FCM is used. The block illustration of the proposed methodology is demonstrated in Fig. 2. Subsequently, a novel brain tissue classification method using MRI images is presented by utilizing Improved Rough Fuzzy C Means algorithm and optimal fuzzy interference system (OFIS) to classify the brain tumor as background (BG), gray matter (GM), White matter (WM), Cerebrospinal Fluid (CSF), and tumor tissues (TT). To accomplish this, the proposed framework is comprised of five modules, namely,

- Pre-processing by speckle noise removal
- Segmentation using Improved RFCM.
- GLCM based feature extraction.
- Brain tissue Classification by OFIS.
- Optimization by means of EGOA.

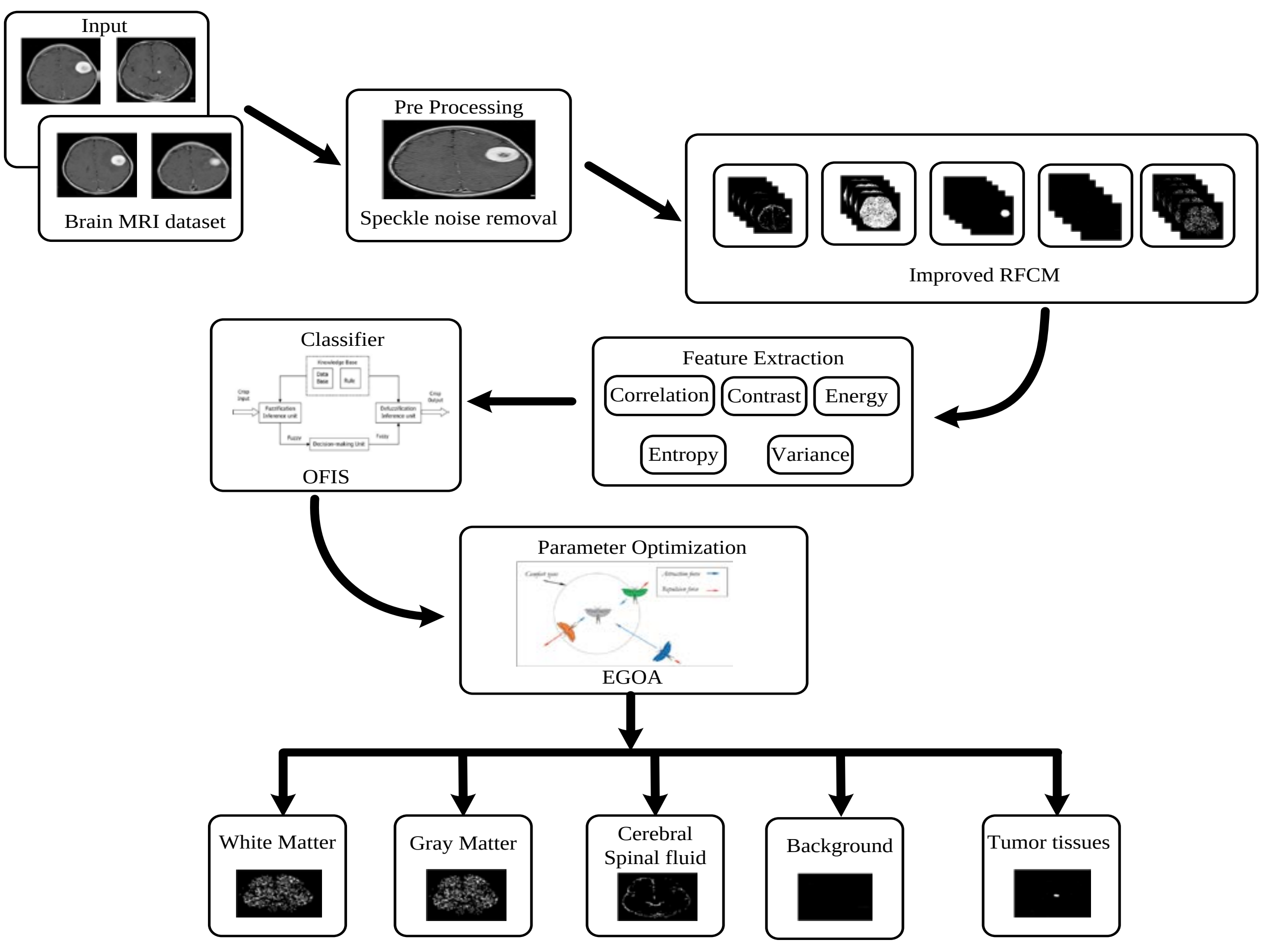


Fig. 2. Block Diagram of the Proposed Methodology.

Initially, the brain MRIs are given to the pre-processing stage, where speckle noise removal is applied to remove the noisy content of the input image. Further segmentation is carried out to segment the tissue based on clustering using Improved RFCM. Then the features are extracted using GLCM. The OFIS classifier is generated for those extracted features, and its parameter gets optimized through EGOA, where the brain tissues are classified as WM, GM, CSF, BW, and TT. The proposed methodology is briefly clarified in the below sections.

A. Pre-Processing

Pre-processing is carried out to eliminate contaminants or noisy data from the picture. Moreover, one of the primary challenges in the processing of medical images is to reduce noise. Different techniques for noise reduction were addressed in prior works. Speckle noise is usually observed in medical pictures. This noise can affect the segmentation quality of the image. The mathematical model of the speckle noise can be represented as:

$$h(o,n) = \xi(o,m) + g(o,n) * v(o,n) \tag{16}$$

Where, $h(o,n)$ defines the input image observed from MRI, $v(o,n)$ represents the multiplicative and the speckle noise additive element is denoted as $\xi(o,n)$, the sample image both axis is represented as $v(o,n)$. The additive noise element is neglected for the noise elimination, which is expressed in equation (17).

$$h(o,n) = g(o,n) * v(o,n) \tag{17}$$

The above equation defines to be the noise eliminated image. After reducing the noise, the image is segmented based on pixel similarity using Improved RFCM algorithm.

B. Tissue Segmentation using Improved Rough Fuzzy C-Means Clustering Algorithm

After pre-processing, the brain MRI images are formed as a cluster concept for the function of tissue segmentation. Novel improved fuzzy C-Means method is used to segment the brain tissue types based on pixel similarity. Consequently, the hybrid rough fuzzy C-Means algorithm is compared with the other methods for validating the effectiveness of the developed model in segmenting brain MRI images.

1) Improved rough fuzzy c-means clustering: A Rough Fuzzy based clustering procedure is a combination of rough sets along with fuzzy sets methods. The rough sets approximation of upper and lower in addition to the concept of the membership of the Fuzzy set is integrated into the C-means clustering. The RFCM partitions a set of objects as o into clusters d by minimizing the objective function.

$$K(Uni,W) = \begin{cases} \psi_{low} \times \beta + \psi_{high} \times \alpha, if S_L(Y_j) \neq \varphi, C(Y_j) \neq \varphi \\ \alpha, if S_L(Y_j) \neq \varphi \\ \beta, if S_L(Y_j) \neq \varphi \end{cases} \tag{18}$$

where

$$\beta \Rightarrow \sum_{j=1}^{d} \sum_{y_l \in S_L(Y)} \left\| y_l - w_j \right\|^2 \tag{19}$$

$$\alpha \Rightarrow \sum_{j=1}^{d} \sum_{y_l \in C(Y)} \left\| y_l - w_j \right\|^2 \tag{20}$$

Where W_j denotes the j^{th}cluster Y_j centroid, the ψ_{low} and ψ_{high} parameter corresponds to the qualified position of lower bound and border area, that leads to $\psi_{low} + \psi_{high} = 1$. Consider that η_{jl} has the identical membership function by means of that placed in fuzzy C-Means. From the computation of β using equation (19) that weights of objects in below approximation are fuzzified in RFCM. To some extent, the centroids updating using equation (19) may lessen the significance of objects in lower approximation and cause the subsequent centroids to float away from right areas [22]. To avoid this problem, a new centroids equation is proposed. The centroids updating for IRFCM is given in equation (21).

$$K(Uni,W) = \begin{cases} \psi_{low} \times \beta + \psi_{high} \times \alpha, if S_L^C(Y_j) \neq \varphi, C_1(Y_j) \neq \varphi \\ \alpha, if S_L^C(Y_j) \neq \varphi, C_1(Y_j) = \varphi \\ \beta, if S_L^C(Y_j) = \varphi, C_1(Y_j) \neq \varphi \end{cases} \tag{21}$$

$$\beta = \frac{1}{|S_L^C(Y_j)|} \sum_{x_j \in S_L^C(Y_j)} x_j \tag{22}$$

$$\alpha = \frac{1}{n_j} \sum_{x_j \in C_1(Y_j)} (\mu_{ij})^m x_j \tag{23}$$

$$n_j = \sum_{x_j \in C_1(Y_j)} (\mu_{ij})^m \tag{24}$$

Using this function, we can improve the clustering accuracy.

C. GLCM based Feature Extraction

After clustering, the feature extraction process is done to the segmented image. The functional extraction phase aims to reduce the original data set by identifying the essential characteristics. By selecting ideal characteristics, classification outcomes are strongly affected. The GLCM based extraction approach is used in this proposed study. Moreover, Haralick's GLCM calculated texture features are a typical approach for representing picture texture as they are easy to implement and result in a collection of interpretable texture descriptors. GLCM is a pixel pitch and direction statistical approach which analyses the picture texture through the spatial connection of the pixels. Let consider, GLCM $(p_{prob}, q, \varphi, r, s)$ regulates the pixel with intensity 'r' ensues in compared with another pixel 's' at distance 'q' and direction 'φ'. Also, the GLCM feature extraction can control up to 14 features. At this period, several of the most significant texture characteristics were determined such as correlation, energy, contrast, and entropy.

1) Correlation (F1): Correlation is defined as the duration of the link between pixels and their nearby pixels. Also, the correlation is estimated by the equation (25) as,

$$Corr = \sum_{r=0}^{P-1} \sum_{s=0}^{P-1} \frac{[r*s]*log(M(r,s)) - [\mu_b * \mu_c]}{\sigma_b * \sigma_c} \tag{25}$$

Where, μ_b, $\mu_c$and σ_b^2, is the mean and σ_c^2 is the variance of r, s, are given as,

$$\mu_b = \sum_{r=0}^{P-1} r \sum_{s=0}^{P-1} M(r,s); \mu_c = \sum_{r=0}^{P-1} s \sum_{s=0}^{P-1} M(r,s) \tag{26}$$

$$\sigma_b^2 = \sum_{r=0}^{P-1} (I_b(r) - \mu_b(r))^2;$$

$$\sigma_c^2 = \sum_{s=0}^{P-1}(I_c(s) - \mu_c(s))^2 \quad (27)$$

2) Contrast (F2): Because of the local similarity of a picture, contrast is stated as the change in luminance. Furthermore, it is estimated using the following equation (28).

$$Cont = \sum_{p=0}^{P-1} p^2 \{\sum_{r=1}^{P}\sum_{s=1}^{P} M(r,s)\}, |r-s| = p \quad (28)$$

where, $M(r,s)$ is represented as Co-occurrence Matrix.

3) Energy(F3): The energy also influences the uniformity of the images. Energy is defined as the total of the GLCM Angular Second Moment entry squares. The second angular moment is large if the picture is extremely homogeneous otherwise if pixels are very similar. The energy is calculated by the equation (28) as follows:

$$Ene = \sum_{r=0}^{P-1}\sum_{s=0}^{P-1} M(r,s)^2 \quad (29)$$

4) Entropy(F4): Entropy is defined as showing the quantity of image data to enable compression by evaluating image data loss. Consequently, the entropy can be articulated as equation (30) as follows:

$$Ent = -\sum_{r=0}^{P-1}\sum_{s=0}^{P-1} M(r,s) * log_2(M(r,s)) \quad (30)$$

5) Sum of Squares (F5): Variance or Sum of squares is an arithmetical system, and it is used in regression study to found the dissemination of data location.

$$V = \sum_{r=0}^{P-1}\sum_{s=0}^{P-1}(r-\mu)^2 \quad M(r,s) \quad (31)$$

This feature places relatively high weights on components which differ from the typical standard value which is referred as $M(r,s)$.

D. Optimal Fuzzy Inference System(OFIS) for Classification

To achieve the optimal classification, the correlation, energy, contrast, sum of square variances and entropy of extracted features are provided to the FIS method. There are three main operations performed in the fuzzy inference scheme: initial Fuzzification, evaluation of rule, and the process of Defuzzification. Fuzzy inference is the technique to map with a fuzzy logic from a given input to an output. Then the mapping offers a framework for making judgments or discerning trends. In the fuzzy inference scheme function, different types of process are proceed such as Logical Operations, Membership Functions (MF) and the rule of If-Then. For performing fuzzification process, collected all the extracted features values of segmented images and estimated all feature minimum (m_n) and maximum (m_x) values. The performance of fuzzification operated by the subsequent equations (32) and (33):

$$m_n L^{(Corr)} = m_{in} + \left(\frac{m_x - m_n}{3}\right) \quad (32)$$

$$m_x L^{(Corr)} = m_n L^{(Corr)} + \left(\frac{m_x - m_n}{3}\right) \quad (33)$$

Where $m_x L^{(Corr)}$ and $m_n L^{(Corr)}$ are the maximum and minimum limit standards of the feature $Corr$. The similar derivation are utilized for the features such as$(Cont)$, (Ene), (Ent) and (V) are required to compute the minimum and maximum limit values. The schematic diagram of the fuzzy inference system (FIS) is shown in Fig. 3.

In the fuzzification stage, the input crisp values of five features namely correlation $(Corr)$, contrast $(Cont)$, energy (Ene), entropy (Ent) and variances (V) are given to the OFIS classifiers which are transformed into fuzzy variables. Also, the membership function (MF) is evaluated for all fuzzy variable in this system. For each feature, fuzzy variables are classified in the range [0, 1] and are classified as Low (L), Lowest (LL), medium (M), high (H) and Highest (HH). Moreover, the fuzzy variables of the output are WM, GM, CSF, BG and TT. Triangular MF and Trapezoidal MF are used in this model to get optimal outcomes. These triangular MF and Trapezoidal MF are used for a boundary as well as intermediate variables. Fig. 4 and 5 shows the MF of fuzzy variables for the input variables and MF of the output variable.

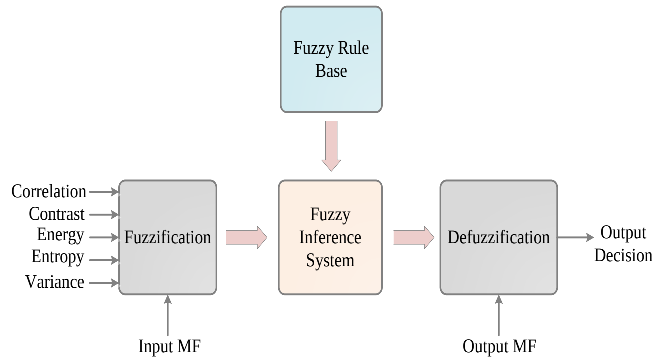


Fig. 3. Fuzzy Inference System Structure.

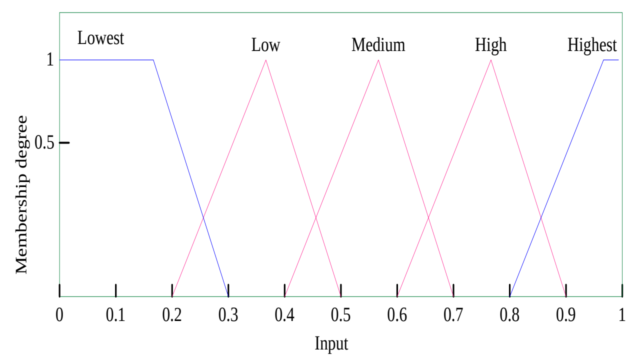


Fig. 4. Membership Function of Input Features.

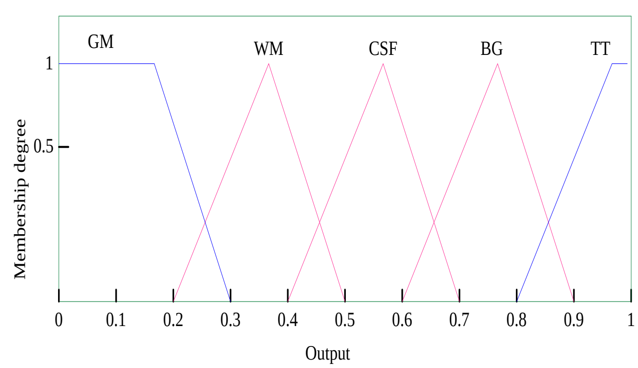


Fig. 5. Output Features of Membership Function.

In the Defuzzification (Z) stage, there are five processes provided to convert the fuzzy set of images into crisp rates for defuzzification. The techniques used for defuzzification are provided as follows as Last of Maxima Method (LOM), Bisector of Area Method (BOA), Mean of Maxima Method (MOM), Center of gravity (COG), and First of Maxima Method (FOM). Then, the sample function of fuzzy rules is demonstrated in Table I.

TABLE I. SAMPLE FUNCTION OF FUZZY RULE

Rule No.	F1	F2	F3	F4	F5	output
1	M	H	L	HH	LL	CSF
2	LL	M	H	L	HH	GM
3	L	H	L	HH	M	WM
4	H	LL	M	L	HH	WM
5	H	LL	M	LL	H	TT
6	HH	L	LL	HH	M	GM
7	M	H	H	M	L	TT
8	L	M	H	HH	HH	CSF
….	….	….	….	….	….	….
n	LL	H	HH	H	M	WM

As shown in Table I, F1, F2, F3, F4, and F5 represent the features for the given image. The rule basis of the FIS system should be updated for each time with the input and output parameters of the MFs altered. Therefore, optimum incorporation of these factors is highly important. The subsequent parameters of the FIS system must be optimized in this approach:

The input variable in triangular MFs must be optimized. For instance, if the triangular shape is assumed as three peak rates like p, q and s, which is illustrated in Fig. 6. The demonstration shows that the variables s and q are fixed when altered the value of p. In this developed FIS function, the triangular shapes are considered to all input variables and those parameters should be optimized for further processing.

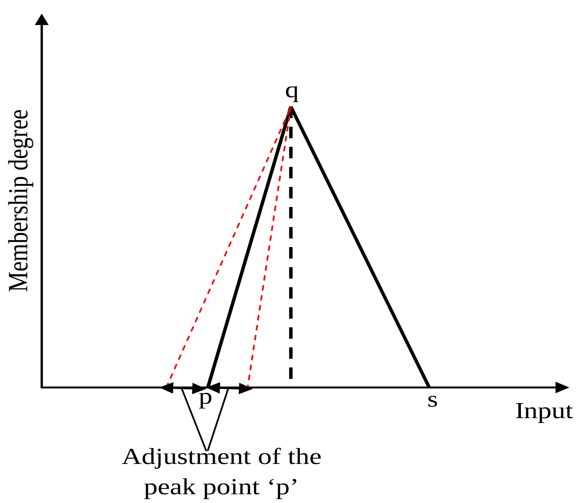


Fig. 6. Triangular MF Peak Points Position.

The optimal fuzzy rules are optimally chosen by the mid fuzzy rules. Consequently, optimal defuzzification process estimated along with the defuzzification methods (Z) and these parameters.

Thus, the FIS parameter has been chosen as the first solution. The selection of the best available solution provides maximum network accuracy. Therefore, an optimization technique is developed for FIS design difficulties that should be given, so that identify an ideal FIS and reduce preliminary modification time. A novel EGOA method is provided in this technique for the optimization of the FIS system parameters.

1) Parameter optimization by Enhanced Grasshopper Optimization Algorithm (EGOA): The parameter used in the FIS method is significantly optimized by the developed EGOA method for enhancing the performance of brain tissue, which is described in this section. The developed EGOA algorithm linked FIS system scheme step by step process is explained as follows:

a) Initialization: Initially, the parameters of FIS system is initialized arbitrarily and the EGOA parameters are also initialized. Furthermore, the population size N along with the candidate outcomes and agent's location is also initialized. The configuration of solution is represented in Fig. 7.

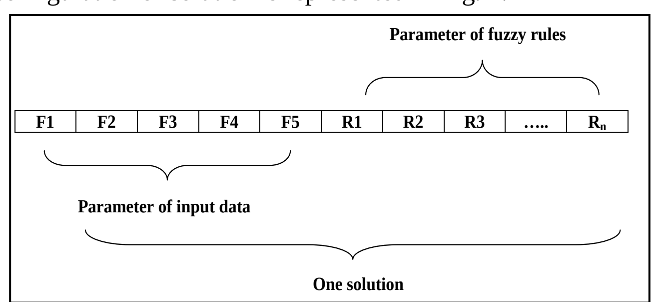


Fig. 7. Generalized Structure of the Solution.

Consider, d dimensional space for the initialized candidate solutions and agents location using equation (34).

$$Y = \{FIS_1, FIS_2, FIS_3 ....., FIS_d\} \tag{34}$$

Where, d^{th} dimension of optimal FIS solution or the agent location is denoted as FIS_d. Then, constraints of the input parameter are given as follows:

$$\{p_n \le x_n \le s_n; \quad n = 1,2,3,4 \tag{35}$$

b) Fitness calculation: After finishing the primary solution of generation process, the fitness value is evaluated. In this work, the utmost accuracy is considered as a fitness function. Also, the fitness rate of this proposed system is estimated by given equation (36).

$$Fitness = m_{ax}(Accuracy) \tag{36}$$

$$Accuracy = \frac{Total.TN + Total.TP}{Total.TN + Total.FN + Total.TP + Total.FP} \times 100 \tag{37}$$

c) Updation of using GOA parameters: Subsequently, the outcomes are updated using GOA parameters after the estimation of fitness value. The Updation function is given in equation (38).

$$Y_j = T_j + H_j + B_j \tag{38}$$

d) Crossover operator: To enhance the GOA, the cross over operator is added to GOA. The crossover operator is the function that is used to choose the genes from the chromosomes of parent and generate fresh offspring constraints. The operation in crossover is articulated by the various parameters such as permutation encoding, binary encoding, tree encoding and value encoding. The Fig. 8 shows cross over process.

e) Mutation operator: After the operation of cross over function, the better solution is updated via mutation. Also, the mutation operator is in compared to crossover that can seek for new regions. The Fig. 9 shows mutation operator. The exploitation fitness is considered as crossover operator and the exploration fitness function is worked by the mutation operator.

f) Termination criteria: Up to the ideal solution, the optimal FIS system, procedures are continued. Once the optimal FIS system has been achieved, the algorithm has closed the process of segmentation. This improved FIS system is utilized as a system for tissue categorization, which enhances the system's overall accuracy. The proposed EGOA method pseudo-code is demonstrated in Algorithm 1.

Algorithm 1: Pseudo code of proposed EGOA

Input : Parameter of FIS and parameter of GOA,

mutation rate 0.2, Crossover rate 0.1.

Output: optimized FIS.

Start:

Initialization: population size($\boldsymbol{M}$),$\boldsymbol{c_{max}}$, $\boldsymbol{c_{min}}$and maximum number of iteration ($\boldsymbol{s_{max}}()$)

Generate a random population ($\boldsymbol{Y}$)

Set the current iteration $\boldsymbol{s = 1}$

While ($\boldsymbol{s} < \boldsymbol{s_{max}}()$) do

Evaluate the fitness of each solution by equation (37)

Renew the value of solution by equation (38)

Apply crossover operator

Apply mutation operator

$s = s + 1$

End while

End

Output: Optimized FIS

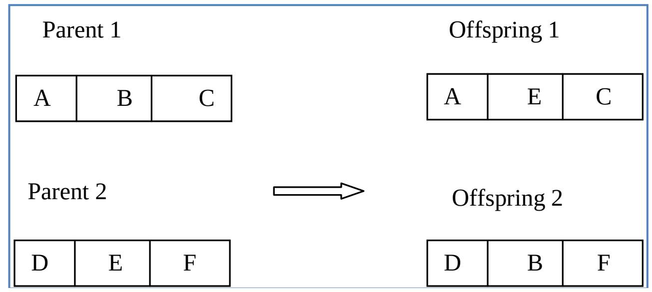


Fig. 8. Crossover Process.

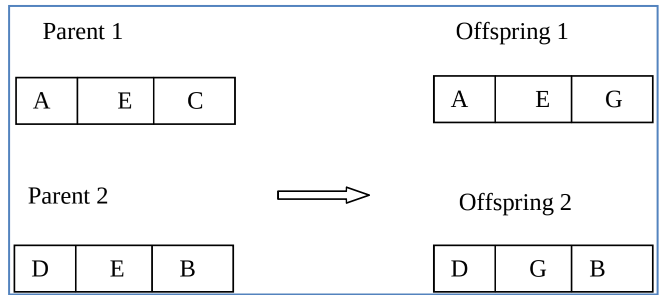


Fig. 9. Mutation Operator.

VI. Results and Discussion

In this section, the consequences and discussion around brain tissue segmentation and classification by using Improved RFCM and OFIS. The proposed configuration has been tested on the data sets of brain MRI named as BRATS 2017. Consequently, the performance of the proposed system is evaluated by the comparison of developed model outcomes with the conventional like Default FIS and KNN.

Accuracy is the proportion of true results among the total number of cases examined. Precision is a valid choice of evaluation metric when we want to be very sure of our prediction. True Positive, True Negative, False Positive, False Negative, sensitivity, and selectivity are the metrics used to know whether correctly predicted or incorrectly predicted the tumor. With these the decision can be taken that the tumor is detected properly or not.

A. Evaluation Metrics

The performance of the developed system is analyzed via the estimation of different evaluation metrics like, Specificity, Sensitivity, PPV, Accuracy, FNR, NPV, and FPR, which are detailed in the subsequent descriptions:

1) Sensitivity: The value of sensitivity is defined as the ratio of total true positives to the summation of total false negative and false positive value.

$$Sensitivity = \frac{Total.TP \rightleftarrows value}{Total.FN + Total. \rightleftarrows \rightleftarrows TP} \tag{39}$$

2) Specificity: The parameter of specificity is defined as the ratio of total true negatives to the summation of total true negative and false positive value.

$$Specificity = \frac{Total.TN}{Total.FP + Total.TN} \tag{40}$$

3) Accuracy: The accuracy metrics are estimated by the parameters value of specificity and sensitivity, which is expressed by equation(41).

$$Accuracy = \frac{Total.TN+Total.TP}{Total.TN+Total.FN+Total.TP+Total.FP} \quad (41)$$

4) Positive Predictive Value (PPV): The rate of PPV is estimated for the positive proportion of experimental and numerical results, which is articulated in equation(42).

$$PPV = \frac{Total.TP}{Total.TP+Total.FP} \quad (42)$$

5) Negative Predictive Value (NPV): The rate of NPV is estimated for the negative proportion of experimental and numerical results, which is articulated in equation(42).

$$NPV = \frac{Total.TN}{Total.TN+Total.FN} \quad (43)$$

6) False Positive Rate (FPR): The rate of FPR is estimated as the ratio of amount of overall incorrect positive forecast to the summation of overall true negative and false positive values. Also, it is estimated from the specificity as referred as 1-specificity value.

$$FPR = \frac{Total.FP}{Total.FP+Total.TN} \quad (44)$$

7) False Negative Rate (FNR): The rate of FNR is estimated as the ratio of amount of overall incorrect negative forecast to the summation of overall true positive and false negative values.

$$FNR = \frac{Total\ FN}{Total\ FN+Total\ TP} \quad (45)$$

B. *Experimental Setup*

The main innovation of this proposed methodology is tissue classification in MRI brain images by multiple phases. Moreover, the performance of the proposed multiple stage execution is validated with the use of various evaluation metrics estimation. In this article, the functions have been characterized the performance measure based on considered tissue types. The foremost aim of the proposed work is to recognize the type of brain tissue in input MRI's. Also, the comparative analysis is provided between the proposed OFIS technique with prevailing methodologies such Default FIS and KNN techniques. The sample collected image is specified in Fig. 10.

Initially, pre-processing is applied to the taken input images to remove the noisy content. Segmentation is carried out for the pre-processed images using the Improved RFCM algorithm. Consequently, the GLCM method is used for the extraction of foremost features from the pre-processed images. Finally, a novel OFIS classifier is executed to classify brain tissue images. The obtained segmented results for the given input images with proposed Improved RFCM technique is shown in Table II.

The proposed segmentation algorithm performance is validated in terms of segmentation, specificity as well as accuracy which are shown in Table III. In this article, IRFCM algorithm is utilized for the purpose of segmentation. IRFCM is a combination of roughest and fuzzy C-Means which is overcome the challenges present in the individual FCM method and rough set theory. While examining Table III, it shows that the proposed approach attains the utmost accuracy of 0.972. However, using rough FCM method has attained only 0.970 and 0.969 is achieved for the use of Rough K-Means algorithm. Similarly, sensitivity and specificity also proposed approach attain the better results.

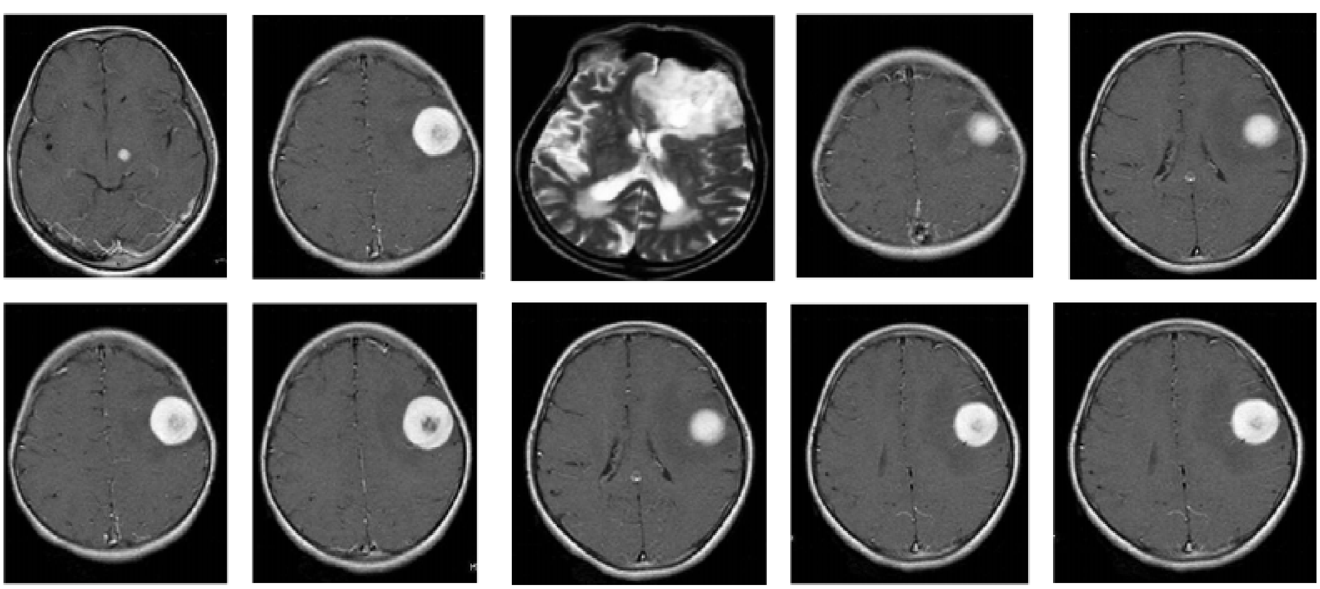


Fig. 10. Set of Sample Brain MRI Images.

TABLE II. INPUT AND SEGMENTED BRAIN TISSUE IMAGES

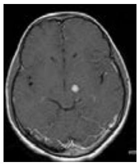
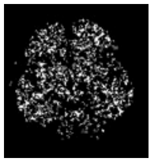
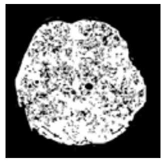
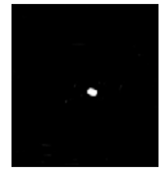
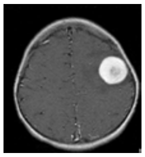
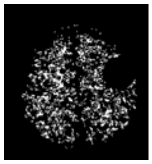
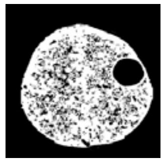
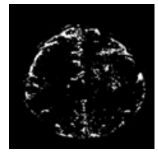
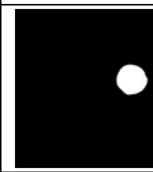
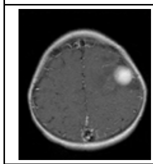
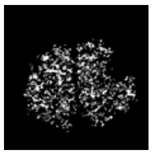
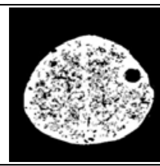
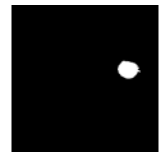
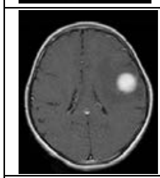
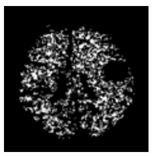
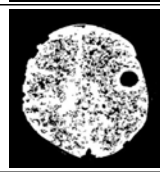
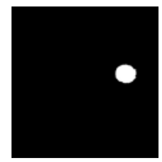
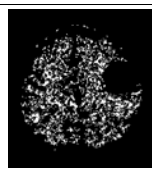
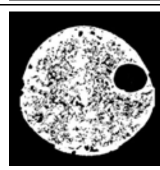
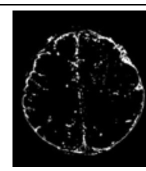
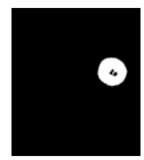
Input image	***WM***	***GM***	***CSF***	***TT***
				
				
				
				
				

TABLE III. COMPARATIVE ANALYSIS OF EXISTING AND PROPOSED IRFCM TECHNIQUE

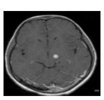
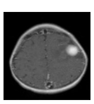
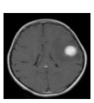
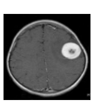
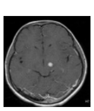
Input Image	**Class**	**Rough K-Means**			**Rough FCM**			**Improved RFCM**		
		Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy
	CSF	0.978	0.998	0.997	0.978	0.998	0.997	0.987	1.000	0.999
	GM	0.768	0.976	0.899	0.769	0.981	0.902	0.776	0.981	0.905
	WM	0.938	0.985	0.980	0.938	0.985	0.981	0.947	0.988	0.984
	TT	0.990	1.000	1.000	0.990	1.000	1.000	1.000	1.000	1.000
	CSF	0.989	0.998	0.998	0.989	0.998	0.998	0.999	1.000	1.000
	GM	0.799	0.990	0.911	0.799	0.990	0.911	0.806	0.990	0.914
	WM	0.943	0.984	0.979	0.943	0.984	0.979	0.952	0.987	0.983
	TT	0.987	1.000	1.000	0.987	1.000	1.000	0.997	1.000	1.000
	CSF	0.970	0.998	0.996	0.970	0.998	0.997	0.980	1.000	0.999
	GM	0.774	0.963	0.889	0.774	0.969	0.893	0.782	0.969	0.896
	WM	0.936	0.982	0.978	0.936	0.982	0.978	0.945	0.986	0.982
	TT	0.989	1.000	1.000	0.989	1.000	1.000	1.000	1.000	1.000
	TT	0.990	0.999	0.998	0.990	0.999	0.998	1.000	1.000	1.000
	CSF	0.790	0.920	0.874	0.791	0.934	0.883	0.798	0.933	0.885
	GM	0.960	0.980	0.978	0.960	0.980	0.978	0.970	0.983	0.982
	WM	0.988	1.000	1.000	0.988	1.000	1.000	0.998	1.000	1.000
	TT	0.990	0.998	0.998	0.989	0.998	0.998	0.999	1.000	1.000
	CSF	0.827	0.979	0.918	0.827	0.979	0.918	0.835	0.979	0.921
	GM	0.939	0.986	0.980	0.939	0.986	0.980	0.948	0.989	0.985
	WM	0.987	1.000	1.000	0.987	1.000	1.000	0.997	1.000	1.000
	TT	0.978	0.998	0.997	0.978	0.998	0.997	0.987	1.000	0.999
Average of Tissues		0.927	0.987	0.969	0.927	0.988	0.970	0.936	0.989	0.972

Fig. 11 illustrates the average measure obtained by the proposed IRFCM and existing RFCM and RK-means techniques for FPR and FNR measures. In the proposed method, the MR image is initially segmented by Improved RFCM. Then successfully, the tissue parts of brain MR images are classified by choosing the parameters optimally. The proposed system is mainly developed for the association of brain images tissue identification.

Fig. 12 describes the segmentation outcome of different measures like sensitivity, specificity, accuracy, PPV and NPV for proposed and existing technique. Thus, the developed IRFCM method achieves the efficient result than existing techniques.

An input sample image is tested by the proposed approach in GUI representation is shown.

The Graphical User Interface (GUI) based sample output and taken input test image is demonstrated in Fig. 13. Since, the test image of input is uploaded, then it provides the classification and segmentation consequences in the display. Thus, this GUI linked proposed approach can shows the corresponding outputs even varying the input test image of different MRI brain pictures.

Fig. 14 and 15 is a GUI example for the different images given. The results of this are evaluated by changing the input image. The resultant values obtained by the evaluation metrics such as Specificity, Sensitivity, PPV, Accuracy, FPR NPV, and FNR for existing Default FIS, KNN and the proposed OFIS technique under a sample test images. By analyzing the performance metrics, the sensitivity of proposed methodology is 0.95, accuracy is 0.975, PPV is 0.95 which is more superior than other existing techniques. Similarly, NPV, FPR and FNR give better performance for proposed technique than existing techniques.

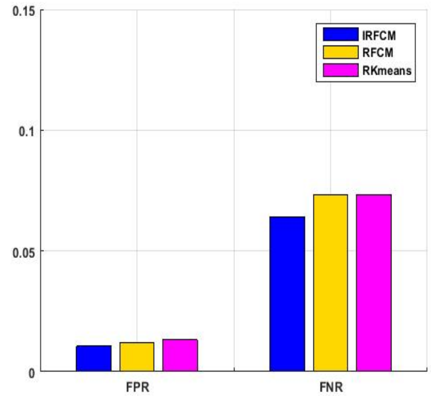


Fig. 11. Segmentation Result for FPR and FNR.

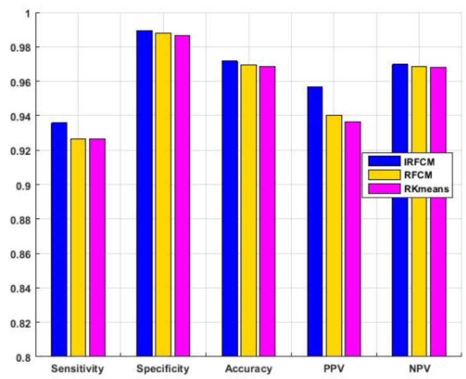


Fig. 12. Evaluation Metrics Segmentation Result.

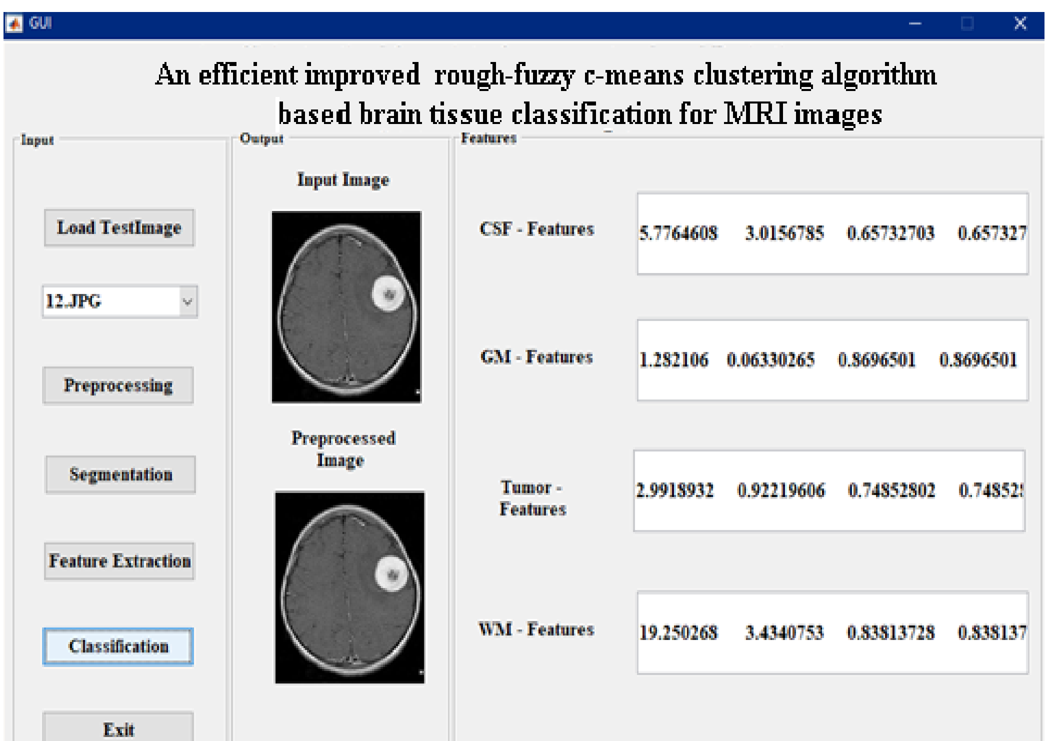


Fig. 13. Sample GUI Representation for Brain Tissue Classification.

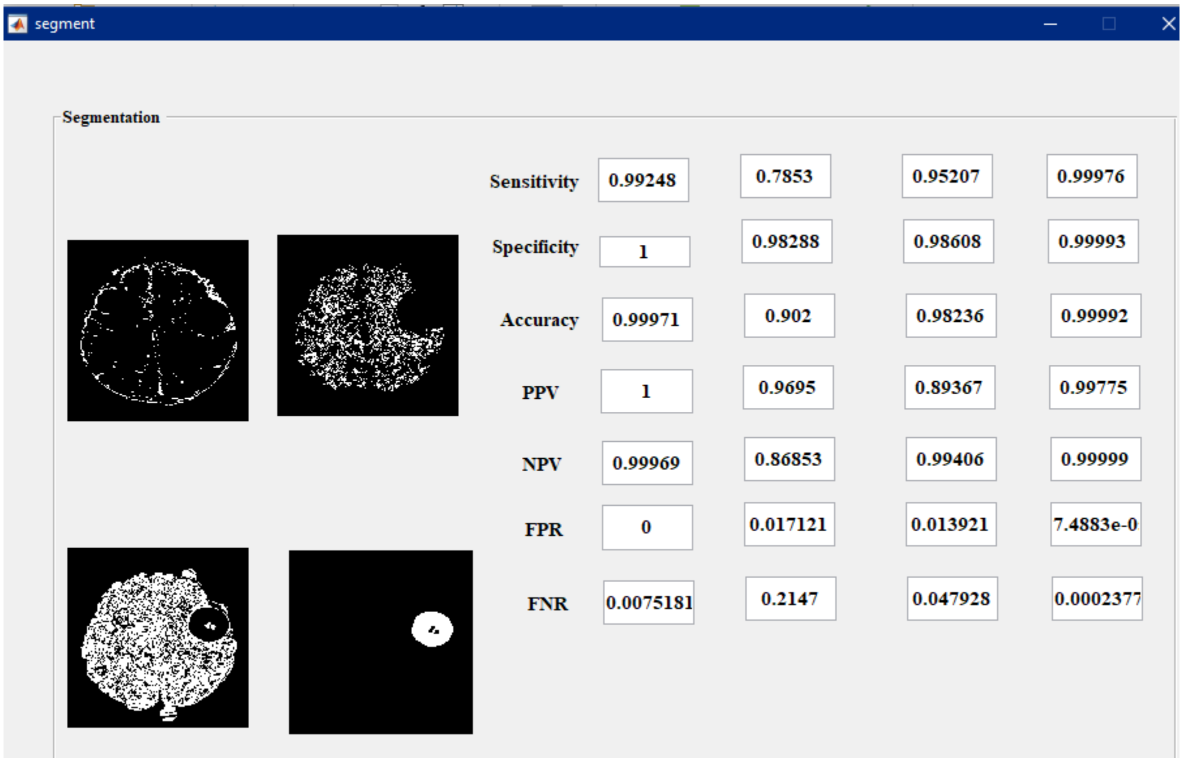


Fig. 14. Segmented MRI Images and its Performance Metrics.

classify

Classification Measure

	Proposed	Default - FIS	KNN
Sensitivity	0.95	0.775	0.775
Sepecificity	0.98333	0.94167	0.925
Accuracy	0.975	0.9	0.8875
PPV	0.95	0.81579	0.775
NPV	0.98333	0.92623	0.925
FPR	0.016667	0.058333	0.075
FNR	0.05	0.225	0.225

Fig. 15. Performance Metrics Rates for Proposed and Existing System.

TABLE IV. COMPARISON BETWEEN PROPOSED AND EXISTING METHODS FOR DIFFERENT METRICS

Evaluation metrics	KNN	FIS	*Proposed OFIS*
PPV	0.77	0.81	0.95
NPV	0.925	0.926	0.98
FPR	0.075	0.058	0.01
FNR	0.225	0.225	0.05

The obtained experimental results of the MRI images for the proposed OFIS and different existing technique for metrics PPV, FPR, NPV, and FNR are shown in Table IV. Thus, the comparative analysis from the graph shows that the proposed technique function is significantly enhanced, which is finest for identifying the portion of tissues in brain MRI images.

VII. CONCLUSION

Brain tissue classifications are the foremost challenging feature in the diagnosis of diseases via medical images. In this work, an efficient approach is proposed to identify the type of brain tissue of MR images. To this classification, primarily, the input of MRI brain image is pre-processed by speckle noise removal method to eliminate the noisy contents contemporaneous in the input image. The pre-processed image is then segmented using an Improved RFCM algorithm based on the clustering mechanism. Next to this, significant texture features are alone extracted by the use of the GLCM feature extraction technique. Afterward, the features were extracted from the previous function are fed into the stage of classification. In that place, OFIS is applied to classify images as WM, GM, CSF, BG, and TT. In OFIS, its parameter is optimally chosen via EGOA for optimally classifying brain tissue. The whole work is executed in the working of MATLAB® platform. The performance of the developed model is analyzed by the evaluation metrics to differentiate the developed and conventional approaches. The complete analysis shows that it is clear that the proposed technique accomplishes an efficient outcome over existing techniques. In future work, the extra information can be added to improve the system as more sensitive; the data for the analysis will consider from the location or textures. In addition to this, future work can be focused on the pathological investigations of classification with the basic goals of monitoring as well as locating the lesions in tissues of the brain.

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