



Performance Analysis of Entropy based methods and Clustering methods for Brain Tumor Segmentation

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Abstract-Brain tumor is the most deadly disease that affects human life span. To segment the brain tumor part, many segmentation techniques have been emerged in image processing like region based Segmentation, Boundary based segmentation. In this paper, several entropies based methods and several cluster techniques are compared and analyzed for brain tumor segmentation. Several entropies such as rough entropy, Shannon entropy, Renyi entropy, Min entropy, Log Energy, entropy and several clustering methods such as K-Means segmentation, Fuzzy C-Means segmentation and improved Fuzzy C-Means clustering based on measure of medium truth degree are applied for segmentation of brain tumor MRI image and the result is compared and analyzed. Entropy and clustering methods are applied to segment the different parts of the image based on threshold. The proposed segmentation gives higher accuracy when compared with other methods like Region based segmentation, pixel based segmentation. Image accuracy is calculated using Peak Signal noise ratio (PSNR), Mean square error (MSE) for each entropy method and for each clustering method and the results show that Rough entropy gives better result for segmentation.

Keywords-Filter, Rough Entropy, Shannon entropy, Renyi Entropy, Min Entropy, Log Energy Entropy, K-Means, Fuzzy C-Means, Improved Fuzzy C-Means Clustering, PSNR, MSE

I. INTRODUCTION

Brain cancer is one of the leading causes of death from cancer. There are two main types of brain cancer. They include primary brain cancer, in which the brain cancer originates in the brain itself. Primary brain cancer is the rare type of brain cancer. It can spread and invade healthy tissues on the brain and spinal cord but rarely spreads to other parts of the body. Secondary brain cancer is more common and is caused by a cancer that has begun in another part of the body, such as lung cancer or breast cancer that spreads to the brain. Secondary brain cancer is also called metastatic brain cancer [1].

In medical image processing and especially in tumor segmentation task, it is very important to preprocess the image. Proper detection and segmentation of the tumor leads to exact extraction of features and classification of those tumors. Preprocessing is carried out using median Filter and average filter and morphological operations are carried out to further process the image.

Data sets are collected from meddb.info website where brain atlas database consists of normal MRI brain images and tumor affected brain images. Image preprocessing is done using filters and processed images are then segmented using entropy. Several images of brain tumor are collected and segmentation based on entropy measures such as rough entropy. Rough Entropy, Shannon entropy, Renyi's entropy, Min Entropy, Log Energy Entropy results are compared.

II. LITERATURE REVIEW

Dariusz Małyszko et al. (2010) proposed adaptive rough entropy clustering algorithms in image segmentation. Incorporating the most important image data information into the segmentation process has resulted in the development of innovative frameworks such as fuzzy systems, rough systems and recently rough - fuzzy systems. Rough entropy framework proposed in has been dedicated for application in clustering systems, especially for image segmentation systems [2].

Prasanna K.Sahoo et al. (2008) proposed textured renyi entropy for image thresholding. This paper introduces textured renyi entropy for image thresholding based on a novel combination mechanism. The renyi entropy is extended by modifying its priory, while still preserving overall functionality. an optional priori is introduced to improve accuracy [3].

Prasanna K. Sahooa (2004) proposed a thresholding method based on two-dimensional renyi entropy in this paper, we present a new thresholding technique based on two-dimensional renyi's entropy. The two-dimensional renyi entropy was obtained from the two-dimensional histogram which was determined by using the gray value of the pixels and the local average gray value of the pixels [4].

Nit in chamoli (2014) survey and comparative analysis of entropy usage for several applications in computer vision. This paper presents a thorough study of different types of entropies; application and comparison of various entropies have been considered with their effectiveness and suitability in different applications being explored. The usage of entropy in the fields of image thresholding, image reconstruction, image segmentation, and incorporation of entropy in tackling real life problems have been mentioned categories. a comparative analysis of different forms of entropy accordingly to their suitability for various applications has been discussed [5].

Sankar K. Pal et al. (2005) proposed granular computing, rough entropy and object extraction the problem of image object extraction in the framework of rough sets and granular computing is addressed. a measure called "rough entropy of image" is defined based on the concept of image granules. its maximization results in minimization of roughness in both object and background regions; thereby determining the threshold of partitioning methods of selecting the appropriate granule size and efficient computation of rough entropy are described [6].

Debashis Sen. (2009) proposed generalized rough sets, entropy, and image ambiguity measures quantifying ambiguities in images using fuzzy set theory have been of utmost interest to researchers in the field of image processing. in this paper, we present the use of rough set theory and it's certain generalizations for quantifying ambiguities in images and compares it to the use of fuzzy set theory. we propose classes of entropy measures based on rough set theory and it's certain generalizations, and performs rigorous theoretical analysis to provide some properties which they satisfy [7].

III. METHODOLY

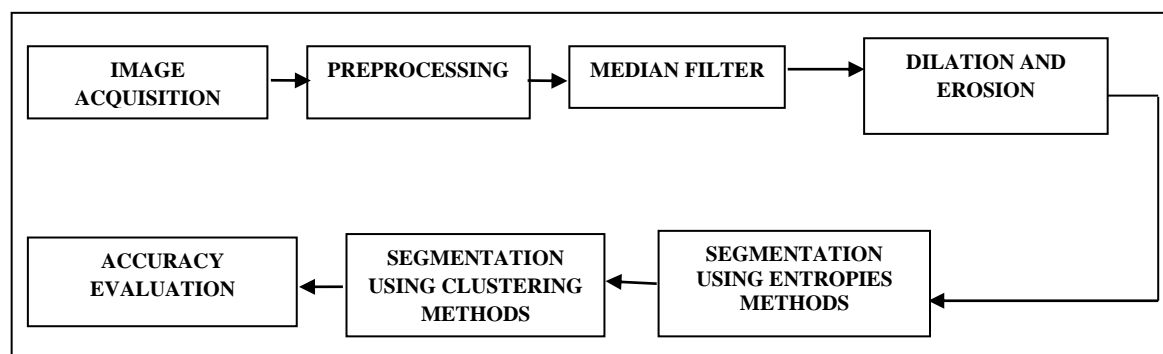


Figure 1. Framework for Brain tumor Segmentation using entropy and clustering methods

A. Image Preprocessing

In medical image processing and especially in tumor segmentation task, it is very important to preprocess the image [8]. Proper detection and segmentation of the tumor leads to exact extraction of features and classification of those tumors. The accurate tumor segmentation is possible if image is pre-processed as per image size and quality. This paper describes the pre-processing method consisting of two phases. In the first phase, we remove the film artifact by using median filter. In the second phase, we introduce an algorithm that uses morphological operations to remove unwanted skull/ribcage portion. This reduces the false positive results in the later stages of processing in the computer aided diagnostic systems.

B. Median Filter

The best known order-statistics filter is the median filter [9], which replaces the value of a pixel by the median of the gray levels in the neighborhood of that pixel.

$$B = \text{medfilt2}(A, [m, n]) \quad (1)$$

Where B is the output image, A is the input image, and m x n is the size of the neighborhood to be used for median determination. If m = n, the neighborhood will be square.

C. Morphological Operations

Morphology has two fundamental operations[10], dilation, which fills holes and smoothens the contour lines, and erosion which removes small objects and disconnects objects connected by a small bridge. Such operations are defined in terms of a structuring element, a small window that scans the image and alters the pixels in function of its window content.

IV. PROPOSED WORK

A. Brain tumor Segmentation

In recent years, many computer vision techniques have been applied to image segmentation, some have been adapted specifically for medical image computing. Brain Tumor segmentation is very important in medical imaging analysis. According to the segmentation results, it is easier to distinguish different diseases clinically; brain MRI segmentation has two purposes. The first one is to segment MR brain images into different tumor classes which are important for image registration and 2D visualization. The second one is to extract abnormal ROIs from the segmented tissues. It not only assists physicians in diagnosis, qualitative and classification the disease, but also to make a therapeutic strategy by measuring and analyzing the shape, boundary, and area of ROIs. Segmenting of brain tumors in MRI is very useful in clinical diagnosis.

In this proposed work, two types of segmentation methods are applied. The first type of segmentation methods is an Entropy based method for brain tumor segmentation. The second type of segmentation methods is clustering method for brain tumor segmentation.

B. Entropy based brain tumor segmentation methods

1) ROUGH ENTROPY

Rough entropy [11] measures calculation of the cluster centers which is based on lower and upper approximation generated by assignment of data objects to the cluster centers. Roughness of the cluster center is calculated from lower and upper approximations of each cluster center. In the next step, rough entropy is calculated as the sum of all entropies of cluster center roughness values. Higher roughness measure value describes the cluster model with more uncertainty at the border. The rough entropy is an effective measure of uncertainty, the rough entropy, proposed by Shannon, and has been a useful mechanism for characterizing the information content in various modes and applications in many diverse fields. In order to measure the uncertainty in rough sets, many researchers have applied the entropy to rough sets, and proposed different entropy models in rough sets. Rough entropy is extended entropy to measure the uncertainty in rough sets. In Rough entropy measure calculation of the cluster centers is based on lower and upper approximation generated by assignments data objects to the cluster centers.

Roughness of the cluster center is calculated from lower and upper approximations of each cluster center. In the next step, rough entropy is calculated as the sum of all entropies of cluster center roughness values. Higher roughness measure value describes the cluster model with more uncertainty at the border.

$$H(X) = - \sum_{j=1}^m p(a_j) \sum_{i=1}^n p(c_i/a_j) \log p(c_i/a_j) \quad (2)$$

Where c_i is the number of occurrences of pixels in each gray level and a_j is the total number of occurrence in the image, (i,j) is the intensity of the pixel in row i and column j , m, n size of the image, X is an entire image.

2) SHANNON ENTROPY

Shannon entropy was introduced by Shannon as a basic concept in information theory, measuring the average missing information on a random source [12]. Let X is a random intensity value of an image with associated probability distribution $P(X)$. Then, the Shannon entropy H of X is defined as

$$H(X) = - \sum_{x \in X} P_X(x) \log P_X(x) \quad (3)$$

H is a measure of uncertainty in Entropy, X is an Entire Image, x is an image intensity values and $P(x)$ is a probability of image.

3) RENYI ENTROPY

Alfred Renyi was introduced by the renyi entropy. Let X is a random intensity value of an image. Then, the Renyi entropy H_α of X order $\alpha \in (0, 1) \cup (1, \infty)$ is defined as in [13]

$$H_\alpha(X) = -\log(\text{Ren}_\alpha(X)) \quad (4)$$

Where the Renyi's probability of X of order α is defined as

$$\text{Ren}_\alpha(X) = \sum_{x \in X} P_X(x)^\alpha \quad (5)$$

4) MIN ENTROPY

The name Min-Entropy stems from the fact that is the smallest entropy measure in the family of renyi entropies. In particular, the min- entropy is never larger than the Shannon entropy. Let X be a random intensity value of an image. Define the min entropy H_∞ of X as Follows [14].

$$H_{\infty}(X) = -\log \max_{x \in X} \{P_x(x)\} \quad (6)$$

Where the maximum of the probability is chosen is an Entire Image; x is an image intensity value, order of image ∞ . Probability of intensity P_x

5) LOG ENERGY ENTROPY

Let x be a random intensity value of an image. Define the entropy H_{∞} of X as follows

$$H_{\infty}(X) = -\log \left(\sum_{x \in X} \{P_x(x)^2\} \right) \quad (7)$$

X is an Entire Image, x is an image intensity value, Log is an minimize the values. P_x Probability of intensity values.

C. PROPOSED ALGORITHM

Step1: Collect Brain tumor images

Step2: Preprocess the image using median filter to remove noise

Step 3: Apply morphological operations such as dilation, erosion to further process the image.

Step4: Apply Rough Entropy, Shannon Entropy, Renyi Entropy, Min Entropy, and Log Energy Entropy to segment the brain tumor

Step 5: Calculate Processed image accuracy using PSNR and MSE for all the entropy measures.

Step 6: Compare which entropy gives higher accuracy.

D. Clustering

Clustering is a type of unsupervised machine learning. A cluster is a collection of objects which are similar in some way, clustering is the process of grouping similar objects into groups. Clustering based brain tumor segmentation methods are as follows.

1) K-Means clustering

The K-Means algorithm (Macqueen, 1967) is one of a group of algorithms called partitioning methods. One of the most widely used clustering techniques. It is a heuristic method where each cluster is represented by the center of the cluster (i.e. the centroids). The K-Means algorithm is very simple and can be easily implemented in solving many practical problems. The K-Means algorithm is the best-known squared error-based clustering algorithm [15].

2) K-Means Clustering Algorithm

Step 1: Give the no of cluster value as K .

Step 2: Randomly choose the K cluster centers

Step 3: Calculate mean or center of the cluster

Step 4: Calculate the distance between each pixel to each cluster center

Step 5: If the distance is near to the center then move to that cluster

Step 6: Otherwise move to next cluster.

3) Fuzzy C-Means clustering Algorithm

The Fuzzy Clustering provides a flexible and robust method for handling natural data with vagueness and uncertainty. [16] In Fuzzy clustering, each data point will have an associated degree of membership for each cluster. The membership value is in the range zero to one and indicates the strength of its association in that cluster.

Step 1: Randomly initialize the membership matrix

Step 2: Calculate centroids

Step 3: Compute dissimilarity between centroids and data points.

Step 4: Compute a new membership matrix.

Step 5: Go back to step 2 unless the centroids are not changing.

4) An Improved FCM Medical Image Segmentation Algorithm Based on MMTD

This algorithm introduces medium mathematics system which is employed to process Fuzzy information for image segmentation. It establishes the medium similarity measure based on the measure of medium truth degree (MMTD) and uses the correlation of the pixel and its neighbors to define the medium membership function. An improved FCM medical image segmentation algorithm based on MMTD which takes some spatial features into account is proposed in this algorithm. The experimental results show that the proposed algorithm is more anti noise than the standard FCM, with more certainty and less fuzziness [17].

- Step 1: Randomly initialize the membership matrix
- Step 2: Compute the fuzzy membership of every pixel
- Step 3: Compute the mean fuzzy membership between the pixel and its neighbors
- Step 4: Compute the medium membership of every pixel
- Step 5: Update the Cluster centre matrix
- Step 6: Go to step 4

V. EXPERIMENTAL RESULTS

A. Data Source

In this experimental analysis, accuracy of the segmentation methods is analyzed. In this thesis entropy method such as rough entropy, Shannon entropy, renyi entropy, min entropy, log energy and clustering based methods such as K-Means, Fuzzy C-Means and Improved Fuzzy C-Means are implemented for segmentation. The Brain Tumor Images for the experimental analysis are obtained from the meddb.info website where brain atlas database consists of normal MRI brain images and tumor affected brain images. In this thesis work is implemented and analyzed by Brain MRI Image. In this thesis, 200 raw MRI Brain Tumor Images are taken for segmentation.

Algorithm involves six phases. In the first phase, collect the image database. In the second phase, preprocess the image using median filter to remove noise and third phase is to apply morphological operations such as dilation, erosion to further process the image and fourth phase is to apply Rough Entropy, Shannon Entropy, Renyi Entropy, Min Entropy, and Log Energy Entropy to segment the brain tumor and fifth phase is calculate Processed image accuracy using PSNR and MSE for all the entropies and sixth phase is applied to compare which entropy gives higher accuracy.

B. PEAK SIGNAL TO NOISE RATIO

The Peak Signal to Noise Ratio (PSNR) is the ratio between maximum possible power and corrupting noise that affects representation of image. PSNR is usually expressed as decibel scale. The PSNR is commonly used as measure of quality reconstruction of image [18].

$$\text{PSNR} = 10 \log_{10} [(255)^2 / \text{MSE}] \quad (8)$$

C. MEAN SQUARE ERROR

Mean Square Error can be estimated in one of many ways to quantify the difference between values implied by an estimate and the true quality being certificated. MSE is a risk function corresponding to the expected value of squared error [19].

$$\text{MSE} = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \quad (9)$$

D. ENTROPY METHODS BASED ON BRAIN TUMOR SEGMENTATION RESULTS

Fig. 2 illustrates the step by step process involved in segmenting the tumor part from original image first step involves converting original image is converted to binary so that gray level image [0-255] is changed to binary with [1-0]. Next preprocessing steps are carried out with median filter, average filter and morphological operation, and then entropy is applied for segmentation of tumor part. Entropies are applied both row wise and column wise by calculating probability based on high intensity pixel (white pixel).final image depicts the tumor part where the intensity of pixel is higher both row wise and column wise.

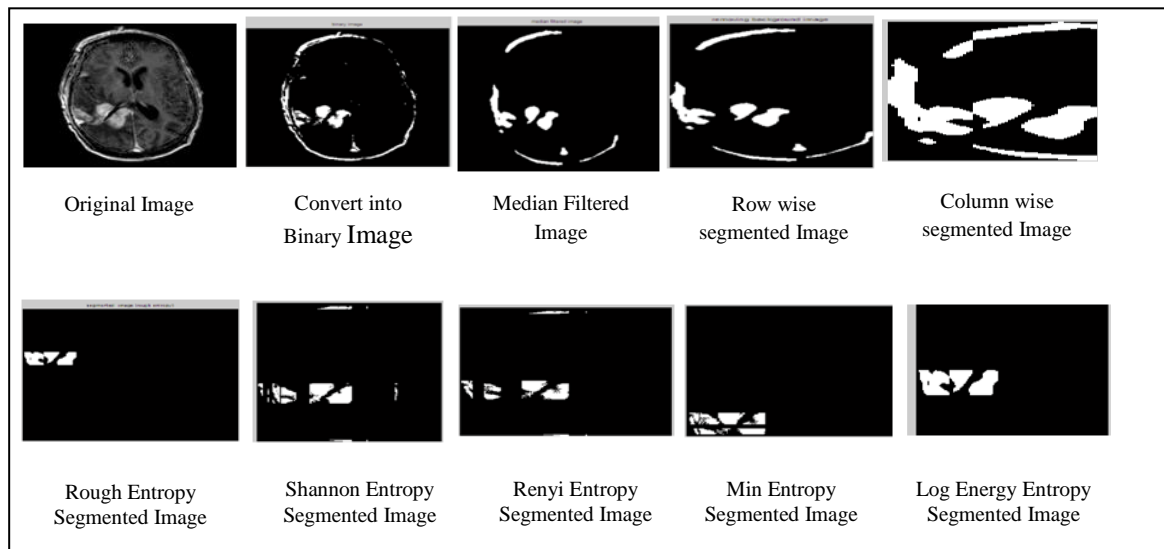


Figure 2. Results of Entropy algorithm for brain tumor segmentation

Table I illustrates the Comparative analysis of Entropy based methods based on PSNR and MSE. This table demonstrates that the rough entropy based on PSNR provides higher accuracy and MSE provides lower accuracy than various entropy methods.

TABLE I. COMPARATIVE ANALYSIS OF ENTROPY METHODS FOR BRAIN TUMOR SEGMENTATION BASED ON PSNR AND MSE

S. No	Algorithm used for segmentation	Average of PSNR	Average of MSE
1	Rough Entropy	139.0595	0.0594
2	Renyi Entropy	82.5132	0.0665
3	Minimum Entropy	82.0881	0.0694
4	Shannon Entropy	76.9504	0.1160
5	Log Energy Entropy	73.0567	0.1713

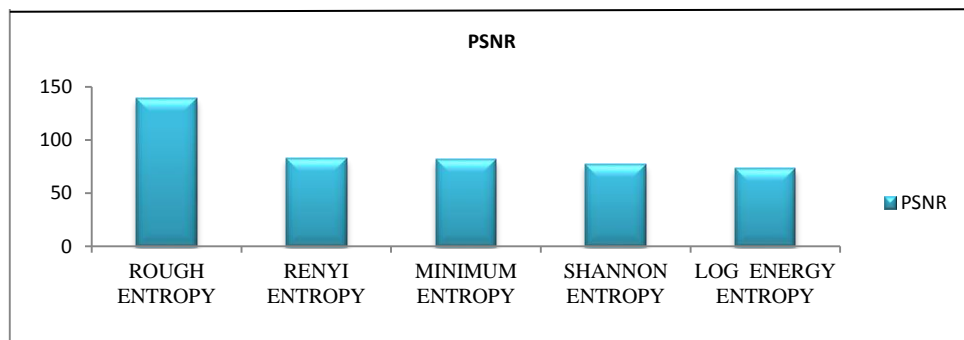


Figure 3. Comparative analysis of Entropy methods for brain tumor segmentation based on PSNR

Fig. 3 and 4 illustrates the Comparative analysis of Entropy methods for brain tumor Segmentation based on PSNR and MSE. Each Data may have various levels to specify their range.

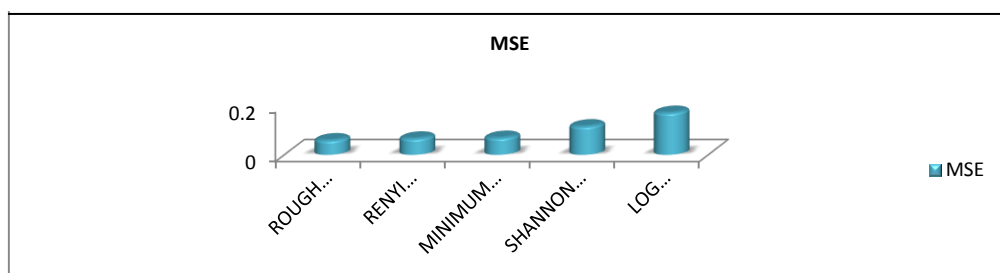


Figure 4. Comparative analysis of Entropy methods for brain tumor segmentation based on MSE

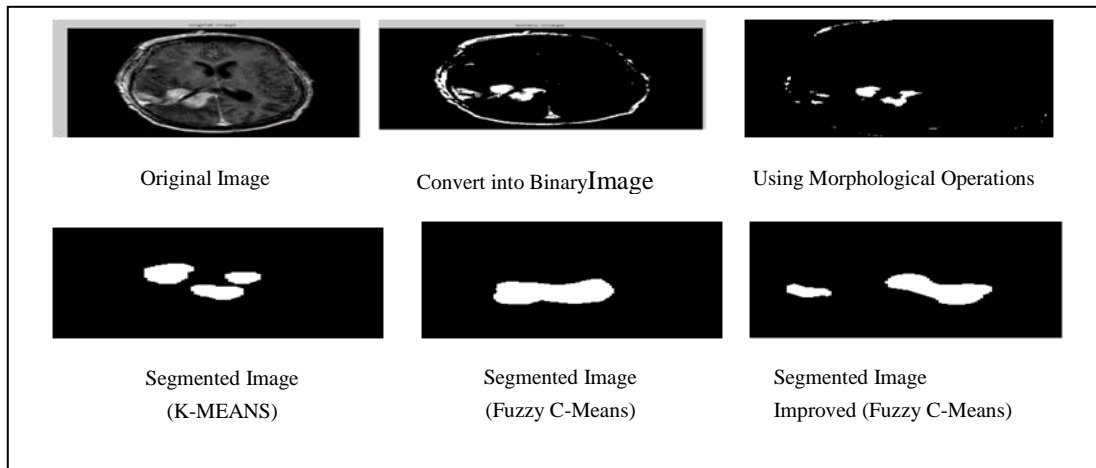


Figure 5. Results of Clustering algorithm for brain tumor segmentation

TABLE II. COMPARATIVE ANALYSIS OF CLUSTERING METHODS FOR BRAIN TUMOR SEGMENTATION BASED ON PSNR AND MSE

S. No	Algorithm used for segmentation	Average of PSNR	Average of MSE
1	K- Means	96.9294	0.1730
2	Fuzzy C-Means	55.4126	0.0567
3	Improved Fuzzy C-Means based on MMTD	87.6430	0.0056

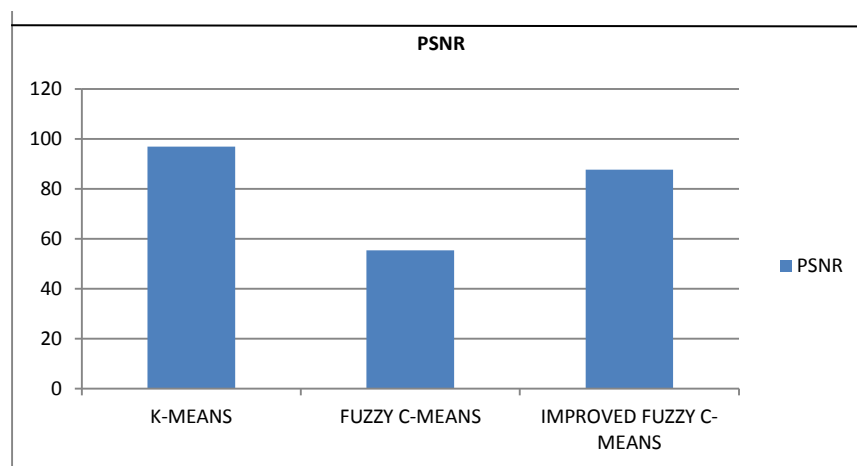


Figure 6. Comparative analysis of clustering methods for brain tumor segmentation based on PSNR

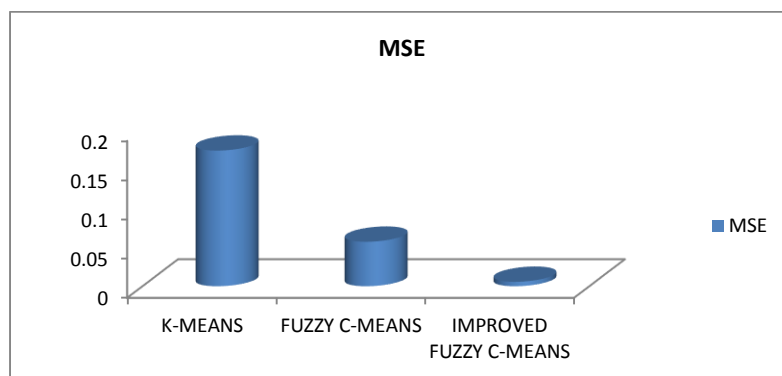


Figure 7. Comparative analysis of clustering methods for brain tumor segmentation based on MSE

VI. CONCLUSION

In this paper, segmentation of brain tumor image is done using entropy based methods and clustering based methods. The Brain MRI image has noise, interference within it and it is to be removed using median filter, average filter and morphological operations and then segmentation is carried out. The experimental results show that the segmentation accuracy based on PSNR (Signal to Noise Ratio) is high for rough entropy and MSE value is minimum in rough entropy. This work illustrates that the rough entropy has higher accuracy compared with Renyi Entropy, Shannon Entropy, Min Entropy and Log Energy, Entropy and K-Means, Fuzzy C-Means and Improved Fuzzy C-Means Based on Medium Measure of Truth Degree clustering approaches.

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