# ADVANCED MACHINE LEARNING TECHNIQUES TO HANDLE BRAIN IMAGE SEGMENTATION AND TUMOR CLASSIFICATION OVER BIO-MEDICAL IMAGES

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**Abstract**

**In real time applications, to evaluate mathematical closely related relations Rough set theory, Fuzzy set theory and rough set theory are the mathematical linear tools for uncertain data elements. Some of the researchers introduced rough sets, rough sets and fuzzy set by connected and combining all set theories together. In this research, we discuss about different combined notations of fuzzy, rough and rough set theories, and also discuss basic methods used to describe about above set theories effectively. We present the concepts related to rough based Rough in tuitionistic fuzzy sets, intuitionist fuzzy rough sets and discuss about basic properties of those set theories effectively. Furthermore, we discuss about classical presentation of rough based intuitionist fuzzy sets in detail with approximate operations in real time synthetic applications. Segmentation of magnetic resonance images is medically complex and important for study and diagnosis of medical brain images, because of its sensitivity in terms of noise for brain medical images. These are the main issues in classification of brain images. Because of uncertainty & vagueness of brain medical images, so that rough sets, fuzzy sets and Rough sets are mathematical tools evaluate and handle uncertainty and vagueness in medical brain images. Traditionally, different type of fuzzy sets, Rough sets and rough sets based approaches were introduced, they have different several drawbacks with respect to different parameters. This research introduces a novel image segmentation (Classification) calculation method i.e. Enhanced and Explored Intuitionistic Rough based Fuzzy C-means Approach (EEISFCMA) with Support Vector machine classifier to estimation of weight bias parameter for brain image segmentation. Intuitionistic Rough based fuzzy sets are generalized form of fuzzy, rough sets and their representative elements are evaluated with non-membership and membership value. Proposed algorithm of this paper consists standard features of existing clustering without spatial weight context data, it defines sensitive of noise in brain images, so that our proposed algorithm deals with intensity and noise reduction of brain image effectively. Furthermore, to reduce iterations in clustering, proposed algorithm initializes cluster centroid based on weight measure using max-dist evaluation method before execution of proposed algorithm. Experimental results of proposed approach carried out efficient image segmentation results compared to existing segmented approaches developed in brain image and other related images. Mainly proposed approach have consists better experimental evaluation based on results.**

## 1. Introduction

In recent times, the introduction of information technology and e-health care system in the medical field helps clinical experts to provide better health care to the patient. Brain tumors affect the humans badly, because of the abnormal growth of cells within the brain. It can disrupt proper brain function and be life-threatening. Two types of brain tumors have been identified as benign tumors and malignant tumors. Benign tumors are less harmful than malignant tumors as malignant are fast developing and harmful while benign are slow growing and less harmful. The various types of medical imaging technologies based on noninvasive approach like; MRI, CT scan, Ultrasound, SPECT, PET and X-ray [1]. When compared to other medical imaging techniques, Magnetic Resonance Imaging (MRI) is majorly used and it provides greater contrast images of the brain and cancerous tissues. Therefore, brain tumor identification can be done through MRI images [2]. This paper focuses on the identification of brain tumor using image processing techniques. The detection of a brain tumor at an early stage is a key issue for providing improved treatment. Once a brain tumor is clinically suspected, radiological evaluation is required to determine its location, its size, and impact on the surrounding areas. On the basis of this information the best therapy, surgery, radiation, or chemotherapy, is decided. It is evident that the chances of survival of a tumor-infected patient can be increased significantly if the tumor is detected accurately in its early stage [3]. As a result, the study of brain tumors using imaging modalities has gained importance in the radiology department. In this paper the brain tumor identification is done by an image processing. In this paper, there are four process are done to identify the brain tumors. The first process is pre processing the image data from the collection of database using median filtering, second stage is segmentation using Fuzzy C-means Clustering Algorithm [4], third stage is feature extraction using Gray Level Co- Occurrence Matrix (GLCM), [5] and the fourth stage is classification using ensemble classifiers is the combination of neural network, Extreme Learning Machine (ELM) and Support Vector Machine classifier (SVM). This will be discussed briefly in this following section.

## 2. Literature Survey

We can observe different data sets like Fuzzy sets, Rough sets and Soft sets notations with mathematical evaluations in real time applications based on different theories and developments. Present day's brain image segmentation is the basic problem to evaluate brain tumor decease in artificial intelligence real time applications. In medical image processing applications, brain tumor detection is a challenging task for real time medical applications. Traditionally some of the research authors introduced different machine learning methods, clustering approaches, classification approaches and filtering approaches to evaluate the basic procedure of the brain image segmentation in both theoretical and practical implementations based on above discussed data sets. All those approaches have some cons and pons in their implementations. In this section, we discuss about each technique implementations using real time data sets in image segmentation. Table 1 gives the brief discussion about all those techniques

| **Segmentation Approach** | **Author** | **Description** | **Advantages** | **Disadvantages** |
|---|---|---|---|---|
| Adaptive Threshold | S. Jansi et.al | Based on image background, divide image into different dynamic regions based on threshold of various pixel | It will be worked based on thresholds | Less accuracy when rotation of different images applied, High time for processing images |
| | | values | | |

| | | | | |
|---|---|---|---|---|
| K-Means Clustering | D.Selvaraj et.al | K-means clustering algorithm worked based on geometric interpretation of data. Based on centroid in images, it can identify brain tumor in images. | Less time for processing brain tumor segmentation, It is iterative process. | Less Accuracy, and Less false positive rate, not worked for large scale datasets |
| Improved K-Means Clustering | P. Vijayalakshmi et.al | Based on initial presentation of clustering identify brain tumor pixels in image segmentation. | It is easiest process, More accurate and high resolution | Less sensitivity and high time for image segmentation. |
| Fuzzy C-Means Clustering | M. Rakesh et.al | Based on given and pre-defined region and based on similarity measure identify brain tumor identification in images | More accurate in image segmentation | Give more time to identify tumor in brain images |
| Adaptive Fuzzy K-means Clustering | S. N. Sulaiman et.al | Based on degree measure relationship in images to identify brain tumor. | It is used to process Magnetic Resonance Images (MRI) Images | It is not applicable for qualitative and quantitative MRI brain images. |
| Region growing | Sudipta Roy et.al | Brain tumor identification is processed based on kindly segmentation | Extraction surface points may cardiac segmentation of | Requires user interface to formulate selection tumor presented surface from |
| | | process applied on medication images | images | segmented images |

| | | | | |
|---|---|---|---|---|
| Mean shift | Vishal B et.al | It is computer vision based non parametric clustering approach in medical image processing | It detect brain tumor on n-dimensional set presentation | Because of iterations in real time presentations, it computes high time complexity in segmentation |
| Watershed segmentation | Deorah et al | To identify foreground and background in image segmentation | Capturing of weak pixel formation in image segmentation, Less time for segmentation | Selection of Seed point selection is low, Increase convergence rate. |
| Level Set Model | Jiang Zhang et.al | To identify brain tumor in images based on surfaces at each dimension | Detection occurred based on level of surface identifications | It is not worked properly if curve was breaking. |
| K-Nearest Neighbour | Warfield et.al | Instance based brain tumor detection in brain image segmentation procedures | It is simplest approach to identify image segmentation, Increase accuracy | Statistical model to identify brain tumor presentations in brain images. |
| Support Vector Machine | Vapnik et.al | It is a supervised machine learning procedure to identify brain tumor presentation in image segmentation | It is an attractive and symmetric method to detect brain tumor image segmentation | Accuracy is very low in classification |
| Principal Component Analysis | Sumitra et al. | Based on principle feature presentation in images, identify the brain tumor classification in image segmentation | Reduce the large dimensionality in image segmentation | Less decomposition rate in image segmentations |

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| | | | | |
|---|---|---|---|---|
| Expectation maximization | Moon et al. | Based on some previously available tumor rules identify detection in brain image segmentation | Differentiate healthy and timorous tissues in brain image segmentation | It have intensity distribution of brain images. |
| Hierarchical clustering | Kshitij et al | Based on grouped tree clustering, identify tumors in brain images. | Accuracy is very high | Time complexity is very low |
| Back Propagation Algorithm | Rumelhard, D et.al | This method works properly in feed forward network ro identify tumor in brain images | Time complexity is less and easily verifiable | Less accuracy with feature extraction based on signal waves |

**Motivation**

Consider the preliminaries present in table 1, we focus on development of advanced techniques to identify brain tumor in brain images based on segmentation/other properties. Our research mainly implement false positive rate, less time complexity and increase the accuracy in brain image segmentation to get better performance results of detection brain tumor in brain images.

**3. Problem Statement**

Fuzzy sets, soft sets and rough sets are the effective data processing frameworks for decision making relative to information processing systems, information retrieval and other conclusive relations present in data, especially in some types of uncertain data events. So it is an efficient concept to process and effective dealing to evaluate uncertain data with different parameters. Consistently, number of researchers orvi and biased field □k setting them into 0 and results of estimation matrixes of X(membership matrix), Y(centroid matrix) and □ (bias matrix). Based on these estimated results, we form our novel calculation and compute the classification of tissue and bias function field. Newly generated function of proposed approach is authors has been introduced number of

K(X,Y,□)□□□

xm||g

□□□□y||2□x□1□□c

xm □

techniques in practical and theory oriented applications.

Define and discuss about different concepts related to fuzzy sets, rough sets and

Where

ikk k k i

i□1 k □1

□gk

x □k

n

□

□ i□1

ik □

□

soft sets theories with their implementation in various fields with existing literature. To further implementation of this work is to develop soft rough within tuitionistic fuzzy sets to generalize properties of real time

Estimation of Bias field

Taking the derivative of K(X, Y,□ ) with respect to □k and assign them into 0 then

we have

□K(X,Y,□)□□□c

□□n

xm(g

□□□ □ y )2□

applications like image segmentation in brain oriented applications. We extend our

□□k

□

□i□1

□□kk □1

ikk k k i□

□

research to support different mathematical evaluations in uncertain data processing in brain image segmentation with practical

implementation.

Second summation of kth term with respect to □kthen us have the following

expression

□□□c

xmg □ □

xm□ g □ □

xmv□ □0

□ ik k ik k k ik k□

## 4. Proposed Methodology

□ i□1

i□1

i□1

□□ □□*

Main objective parameters for defined function i.e. K(X, Y,□ ) to minimize standard representations for c-means for image segmentation in brain medical

images. First we take derived parameters of

Differentiating the distance expression, then we obtain following expression

□□g□c xm□□g□c xm□□c xmv□ □0

□ k ikk k ikik k□

defined function K(X, Y,□ ) with respect to membership parameters xij , cluster centroid

□ i□1

i□1

i□1 □

□ □

□* g □xm□ g □xm□ □xmv

, where i is in between1to N*M, then image X to be represented in IFS as follows:

i□1

i□1

i□1

X□□□ai,□(ai),□(ai))|ai□A}□□

Distance based gradient function for bias field function is as follows:

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with□(ai )□1□(□(ai)□□(ai)),where

□(ai )

□ cxmv□

is membership function and

□ (ai ) is non-

1□

□ ik k □

member function and

□(ai )

is the mean

□k□

□ yk □i□1 □

□k□
□
□

□
i□1

m □
ik □
□

pixel value of image. After evaluating fuzzy image representation update each cluster based on different pixel values of image.

If □ □(0,1) is the weight of membership function, then generated bias data is □ □ 0.007 and increase this from0.001 to□2,□3, ,□10.

Updated Centroid of Cluster

Evaluation of Membership

After minimize the above equation, with different constraints using Lagrange multiplier calculation
L(X,Y,□)□□c □n xm||g□□□□y||2□x □1□□c xm□□□□1□□c u□

Again taking the derivative of K(X, Y,□ )

i□1 k □1

ikk k k i

□
□ i□1

ik□ □
□ □

i□1

ik □
□

with respect yi and setting results is zero,

After taking derivative of

L( X , Y ,□ )

then generated function is

with respect to

xik and set result into

□n m□

zero, then we have

□□xik (gk □ □k□k□ yi)□ □0

□k □1

□ y □ y*

□K(X,Y,□)

m□1 2

m□1

i i
□xik

□□□mxik

| gk □□k□k □ yi || □xmxik

□□□□

□ 0
xik □x*

Where

□ xm(g □□ □ )
y* □k□1

after solving

After solving the above equations based on different parameters for membership

i n
m
ik
k □1
the above equation.

parameter sequences can be re=written as follows:

Intuitionistic Fuzzy based Image

c □□ | g
□ □ □ □ y

1□□1
||2□x □m□1 □

Representation

xik □ □

□k k k i □

j □1 □□

| gk □ □k□k□yi

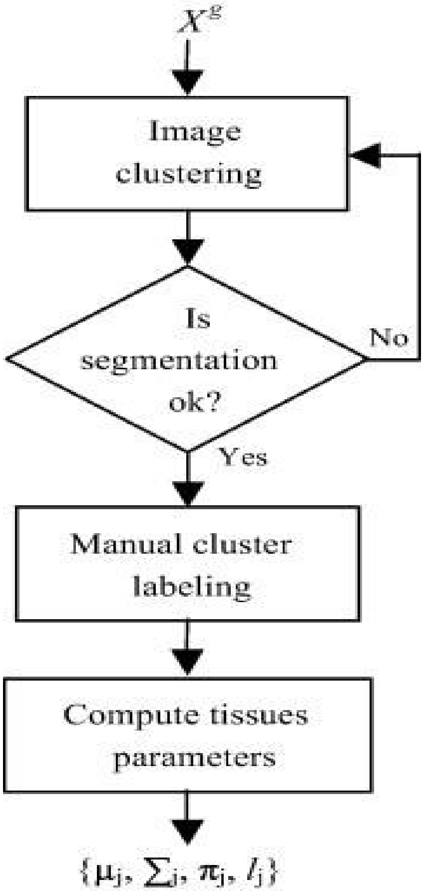
||2□x□ □

Intuitionistic fuzzy sets [IFS] representation of image for image segmentation. The presented image consists N*M size and the

□ □

In the above equation c is number of value of each pixel in image i.e.A □ {ai / ai }
centroid; g is gain function and is constantfor membership functionwith different parameters.
EEISFCMA is evaluated on publicly available brain images, for example we collected brain images from https://www.nitrc.org/frs/?group_id=48&release_id=3124 and http://brainweb.bic.mni.mcgill.ca/brainweb/ with simulated brain image databases. We download these images from web urls and then convert into Matlab readable format and then we can pre-process for feature extraction to segment images using readable Rough ware i.e analysis and visualization of image. Proposed approach can be implemented in Latest Mat lab version with latest system configurations and this section describes implemented results. This section describes experimental results of different traditional approaches like k-means, fuzzy c- Mean, Generalized Fuzzy C-means, Gaussian Kernel based Fuzzy c-Means algorithm (GKFCM) and Rough fuzzy rough sets c-means (SFRCM) with proposed approach at segmentation accuracy and jacquard co-efficient for brain segmented images.

## 5. System Design




Design implementation of brain image segmentation for bio-medical images from different sources.

## 6. References

[1] Anupama Namburu, Srinivas kumar Samay, Srinivasa Reddy Edara, "Rough fuzzy rough set-based MR brain image segmentation", Proceedings in Applied Rough Computing xxx (2016) xxx–xxx. © 2016 Elsevier B.V. All rights reserved.

[2] S. Ramathilagam, R. Pandiyarajan, A. Sathya, R. Devi, S.R. Kannan," Modified fuzzy c-means algorithm for segmentation of T1–T2-weighted brain MRI", ©2010 Elsevier B.V. All rights reserved , Journal of Computational and Applied Mathematics 235 (2011) 1578–1586.

[3] K.V. Leemput, F. Maes, D. Vandermeulen, P. Suetens, Automated model based bias field correction of MR images of the brain, IEEE Trans. Med. Imaging 18 (1999)885–896.

[4] M.N. Ahmed, N.A. Mohamed, A.A. Farag, T. Moriarty, A modified fuzzy c- means algorithm for bias field estimation and segmentation of MRI data, IEEE Trans. Med. Imaging 21 (2002)193–199.

[5] R.L. Cannon, J.V. Dave, J.C. Bezdek, Efficient implementation of the fuzzy c- means clustering algorithms, IEEE Trans. Pattern Anal. Mach. Intell. PAMI-8 (2) (1986)248–255.

[6] Zujun Hou, A review on MR image intensity in homogeneity correction, Int. J. Biomed. Imaging (2006) 1–11. Article ID 49515.

[7] B.R. Condon, J. Patterson, D. Wyper, Image non uniformity in magnetic resonance imaging: its magnitude and methods for its correction, Br. J. Radiol. 60 (1987)83–87.

[8] M. Tincher, C.R. Meyer, R. Gupta, D.M. Williams, Polynomial modeling and reduction of spatial body-coil spatial in homogeneity, IEEE Trans. Med. Imaging 12 (1993)361–365.

[9] S. Lai, M. Fang, A new variational shape-from orientation approach to correcting intensity in homogeneities in MR images, in: Proc. of Workshop on Biomedical Image Analysis CVPR98, 1998, pp.56–63.

[10]S.E. Moyher, D.B. Vigneron, S.J. Nelson, Surface coil MR imaging of the human brain with an analytic reception profile correction, J. Magn. Reson. Imaging 5 (1995)139–144.

[11]S. Krinidis, V. Chatzis, A robust fuzzy local information c-means clustering algorithm, IEEE Trans. Image Process. 19 (5) (2010)1328–1337.

[12]C. Li, J.C. Gore, C. Davatzikos, Multiplicative intrinsic component optimization(MICO) for MRI bias field estimation and tissue segmentation, Magn. Reson. Imaging 32 (7) (2014)913–923.

[13]Z. Pawlak, Rough set approach to knowledge-based decision support, Eur. J.Oper. Res. 99 (1) (1997)48–57.

[14]D. Dubois, H. Prade, Rough fuzzy sets and fuzzy rough sets, Int. J. Gen. Syst. 17(2– 3) (1990) 191–209.[15] P. Lingras, C. West, Interval set clustering of web users with rough k-means, J.Intell. Inf. Syst. 23 (1) (2004)5–16.

[16]P. Maji, S.K. Pal, Rough set based generalized fuzzy c-means algorithm and quantitative indices, IEEE Trans. Syst. Man Cybern. B 37 (6)(2007)1529–1540.