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Hybridization of Fuzzy and Region Growing Segmentation based Tumor detection using trilateral filter

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ABSTRACT: - The brain tumor detection is a critical application of medical image processing. The literature survey has shown that probably the most of existing methods has ignored the indigent quality images like images which are of poor brightness or with noise. In addition, the most of the existing work on tumor detection has neglected the utilization of object-based segmentation. The overall goal of this research work is to propose an efficient brain tumor detection using the feature detection and roundness metric. To enhance the tumor detection rate further we have integrated the proposed hybridization of fuzzy and region growing segmentation based tumor detection with the trilateral filter. The proposed technique has the ability to produce effective results even in case of high density of the noise. The experimental results have clearly shown that the proposed technique outperforms over the available techniques.

KEYWORDS: - Brain Tumor, Segmentation

INTRODUCTION

Medical image analysis is one of the very most critical scopes of work in the field of image processing. Results gained by the analysis are used to guide the flow of diagnosis, treatment planning and administered treatment. Magnetic Resonance Imaging (MRI) is known as a very important tool for researchers. It produces highly quantized images inherent of detailed information regarding delicate structures within human body [1]. Brain tumor is an abnormal growth of cells inside the skull of human body. Normally, the tumor will grow from the cells of the brain, blood vessels, or nerves that emerge from the brain. You can find two kinds of tumor which are benign (non-cancerous) and malignant (cancerous) tumors. The former is described as slow-growing tumors that may exert potentially damaging pressure nonetheless it won't spread into surrounding brain tissue. However, the latter is described as rapid growing tumor and it has the capacity to spread into the surrounding brain. Tumors may damage the standard brain cells by producing inflammation, exerting pressure on elements of brain and increasing pressure within the skull. Fig 1 shows the clear presence of tumor in the brain. Fig 2 shows the MRI consequence of the brain tumor image. [2]

Fig 1: The presence of brain tumor.

Fig 2: MRI brain tumor image.

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Thus there is a need to detect a tumor at early age so that it can be prevented to spread into the surrounding brain. Moreover chance of survival of patient can be increased if the brain tumor is detected at early age and accurately. So need is to develop an automatic brain tumor detection algorithm. Various methods are in use to segment a tumor region from the MRI image such as Region Growing, Histogram Equalization, Using neural networks, Active Contours, K-Means Clustering, Fuzzy C-Means Clustering etc. [3]. You'll find so many challenging issues to image segmentation like development of a single approach that could be applied to all types of images. Even, the choice of a proper technique for a certain sort of image is a difficult problem. Thus, no universal accepted method is there for image segmentation. So, it remains a hardcore problem in image processing and computer vision fields [4].

In this work an automatic detection algorithm is developed based on hybrid clustering of Fuzzy C-means clustering and Region Growing Segmentation Technique with the use of trilateral filter in pre-processing stage. Moreover feature detection is used to calculate the accuracy rate and error rate. Parameters i.e. accuracy rate and error rate of proposed model are compared with accuracy rate and error rate of base paper[5] in which image is segmented with use of hybrid clustering technique of K-means clustering and Fuzzy C-means.

LITERAUTRE SURVEY

Taheri, Sima, et al. [1] introduces a threshold-based method in which level sets for 3D tumor segmentation (TLS) is used. In this method, the particular level set speed function is made employing a global threshold. The threshold is explained on the basis of the concept of confidence interval. It is iteratively updated through the evolution process . **Nie, Jingxin, et al. [2]** has proposed the algorithm based on Spatial accuracy-weighted Hidden Markov random field and Expectation maximization (SHE) approach for both automated tumor and enhanced-tumor segmentation. SHE incorporates the spatial interpolation accuracy of low-resolution images to the optimization procedure of the Hidden Markov Random Field (HMRF) to segment tumor using multi-channel MR images with various resolutions. **Saha, Baidya Nath, et al. [3]** proposes an automated, fast, and approximate segmentation method. The input is an individual study consisting of some MR slices, and its output is really a area of the slices including axis-parallel boxes that circumscribe the tumors. The approach is founded on an unsupervised change detection method that looks for the absolute most dissimilar region (axis-parallel bounding boxes) involving the left and the proper halves of a brain in a axial view MR slice. The change detection process works on the novel score function predicated on Bhattacharya coefficient which is computed with gray level intensity histograms. **Bhattacharjee, Rupsa, et al.[4]** predicated a comparison of two filters based on a study of quality parameter, adaptive median filter is selected for de-noising the images. Image slicing and identification of significant planes are done. To obtain the processed image showing the tumor region accurately various logical operations are applied on selected slices. A guide image reconstruction algorithm is developed on the basis of the application of Principal Components Analysis (PCA). This above mentioned reconstruction algorithm is applied on original raw images as well as on the processed images. **Dhanalakshmi,et al.[5]** uses computer aided technique of detection which means segmentation of brain tumor on the cornerstone of the mixture of two algorithms. This technique allows the segmentation of tumor tissue with accuracy and reproducibility much like manual segmentation. Additionally, it reduces the execution time for analysis. At the end of the procedure the tumor is extracted from the MR image and its exact position and the form also determined. The stage of the tumor is displayed on the cornerstone of the degree of area calculated from the cluster. **El-Dahshan et al.[6]** presents a hybrid method for the classification of the magnetic resonance images (MRI). The proposed hybrid method contains three stages for the detection or segmentation of brain tumor region from the MRI scan image. Various stages are feature extraction, dimensionality reduction, and classification. In the initial stage, features related to MRI images using discrete wavelet transformation (DWT) are obtained. In the next stage, the options that come with magnetic resonance images have now been reduced, using principal component analysis (PCA). In the next stage of classification, two classifiers have now been developed. The first classifier centered on feed forward back-propagation artificial neural network (FP-ANN) and the next classifier is based on *k*-nearest neighbour (*k*-NN). **Perumal et al.[7]** proposed algorithm for detecting the number and model of objects in images. The image is visually examined for detection and analysis of object. To avoid the visually examination, this paper uses computer aided technique for detection which also means segmentation of objects on the basis of the mixture of two algorithms. This technique allows the segmentation of image with accuracy and reproducibility similar to manual segmentation. Additionally, it reduces the execution time for analysis. At the conclusion of the method the item is extracted from the image and its exact position and the design also determined. The truth is analyzed on the basis of the quantity of area calculated from the cluster. **Jose, Alan, et al. [8]** implements a Simple Algorithm for detection of range and shape of tumor in brain MR Images. Following the segmentation, which is done through k-means clustering and fuzzy c-means algorithms mental performance tumor is detected and its exact location is identified. Comparing to another

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algorithm the performance of fuzzy c-means plays a major role. The patient's stage is decided by this method, whether it may be cured with medicine or not. **Harati, Vida, et al. [9**] presented approach is a better fuzzy connectedness (FC) algorithm based on a range in which automatically the seed point is selected. The algorithm does not depend on the tumor type in terms of its intensity of pixels.The evaluation results of Tumor segmentation are predicated on similarity criteria (similarity index (*SI*), extra fraction (*EF*) and overlap fraction (OF) are 92.89%, 3.95%, and 71.95% respectively) indicate a better performance of the proposed technique set alongside the conventional methods, especially in MR images, in tumor regions with low contrast. Thus, the suggested method is helpful for increasing the power of automatic estimation of tumor position and size of brain tissues, which gives more accurate investigation of the necessary surgery, chemotherapy, and radiotherapy procedures. **Dubey, Madasu et al. [10]**, segmentation is conducted manually in clinical environment that's operator dependent and very tedious and frustrating labour intensive work. Whereas, automated tumor segmentation in MRI brain tumor images many challenges pertaining to characteristics of an image. A contrast of three different semi-automated methods, viz., modified gradient magnitude region growing technique (MGRRGT), level set and a marker controlled watershed method is undertaken here for evaluating their relative performance in the segmentation of tumor. **Vasuda,et al.[11]** Segmentation is an essential part of medical image processing, where Clustering approach is widely found in biomedical applications particularly for brain tumor detection in abnormal Magnetic Resonance Images (MRI). Fuzzy clustering using Fuzzy C- Means (FCM) algorithm turned out to be superior over the other clustering approaches in terms of segmentation efficiency. Nevertheless the major drawback of the FCM algorithm may be the huge computational time necessary for convergence. The potency of the FCM algorithm in terms of computational rate is improved by modifying the cluster centre and membership value updating criterion. In this paper, convergence rate is compared between the typical FCM and the Improved FCM. **Jiang, Jun, et al.[12]** Brain tumor segmentation is just a medical requirement for brain tumor diagnosis and for planning of radiotherapy. Automation of this technique is a very challenging work due to the diversity to appear at of tumor tissue among varied patients and the ambiguous boundaries of lesions. The technique is proposed to create a graph by learning the population- and patient-specific feature sets of multimodal magnetic resonance (MR) images and utilizing the graph-cut to reach one last segmentation. The probabilities of every pixel that belongs to the foreground and the back ground are estimated by global and custom type of classifiers which were trained through learning population and patient specific feature sets. **Sachdeva, Jainy, et al.[13]** In this study, a lot of experiments are undertaken to analyze the performance of intensity-based techniques for homogeneous tumors on brain magnetic resonance (MR) images. The analysis shows that the state of art techniques fail to segment tumors which are homogeneous against background which is similiar or when these tumors show partial differences toward the background. They likewise have preconvergence problem in the event of false edges/saddle points. However, the current presence of weak edges and diffused edges results in over segmentation by intensity-based techniques. Therefore, the proposed method which is content-based active contour (CBAC) uses both texture and intensity information present within the active contour to overcome the stated problems capturing large range in a image. **Khotanlou, Hassan, et al.[14]** propose a brand new generalized method for segmentation of brain tumors in 3D magnetic resonance images. This approach is applicable to several types of tumors. First, your brain is segmented utilizing a brand new approach, robust to the present presence of tumors. Then first tumor detection is completed, which is based on selecting areas which are asymmetric with respect to the approximate symmetry plane and fuzzy classification of brain. Its result consists of the initialization of a method of segmentation based on a variety of a model and spatial relations, resulting in a precise segmentation of the tumors. **El-Dahshan, El-Sayed A., et al.[15]** has proposed a cross intelligent machine learning technique for computer-aided detection system for automatic detection of brain tumor through magnetic resonance images. The proposed technique is based on the following computational methods; the feedback pulse-coupled neural network for image segmentation, the discrete wavelet transform for features extraction, the principal component analysis for reducing the dimensionality of the wavelet coefficients, and the feed forward back propagation neural network to classify inputs into normal or abnormal. **Nabizadeh, Nooshin et al.[16]** present an automatic system, which can detect tumor and, to delineate the tumor area. The experimental results on single contrast mechanism demonstrate the efficiancy of /proposed technique in successfully segmenting brain tumor tissues with high accuracy and low computational complexity. Moreover, a study evaluating the efficacy of statistical features over Gabor wavelet features using several classifiers. This contribution fills the gap in the literature, as is the initial ever to compare these sets of features for tumor segmentation applications on single contrast mechanism demonstrate the efficacy of our proposed technique in successfully segmenting brain tumor tissues with high accuracy and low computational complexity. Moreover, we incorporate a study evaluating the efficacy of statistical features over Gabor wavelet features using several classifiers. **Madhukumar, et al.[17]** does the qualitative comparison of Fuzzy C-means (FCM) and k-Means segmentation, with histogram guided initialization, on tumor edema complex MR images. The

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accuracy of any segmentation scheme is influenced by its ability to share with apart different tissue classes, separately. Hence, there is a significant pre-requisite to judge this ability before employing the segmentation scheme on medical images. This paper evaluates the power of FCM and k-Means to segment Gray Matter (GM), White Matter (WM), Cerebro-Spinal Fluid (CSF), Necrotic Focus of Glioblastoma Multiforme (GBM) and the perifocal vasogenic edema from pre-processed T1 contrast axial plane MR images of tumor edema complex. The experiment reveals that FCM identifies the vasogenic edema and the white matter as an individual tissue class and similarly gray matter and necrotic focus, also. K-Means can characterize these regions comparatively a lot better than FCM. FCM identifies only three tissue classes whereas; k-Means identifies all the six classes. The experimental evaluation of k-Means and FCM, with histogram guided initialization is conducted in Matlab .**Rouhi, Rahimeh, et al. [18]** presented two automated methods to diagnose mass types of benign and malignant in mammograms. In the very first proposed method, segmentation is done utilizing an automated region growing whose threshold is obtained by a qualified *artificial neural network* (ANN). In the second proposed method, segmentation is performed with a *cellular neural network* (CNN) whose parameters are determined with a *genetic algorithm* (GA). Intensity, textural, and shape features are extracted from segmented tumors. GA can be used to choose appropriate features from the pair of extracted features. In the next stage, ANNs are accustomed to classify the mammograms as benign or malignant.

PROPOSED METHODOLOGY

There are some image segmentation procedures which use region growing technique for detecting mass tumor in brain [24]. The region growing method can correctly separate the regions that have the same properties and simple to execute on large datasets but it suffers from problem of images with high density of noise. On the other hand, other systems use Fuzzy C-means algorithm because it retains the most of the information which is accurate of the original image to detect malignant tumor cells accurately compared to the K-means [25]. These systems are sensitive to noise and outliers and they take long execution time. In our proposed medical segmentation system, we get benefits from the last two algorithms. As shown in Figure 3, the proposed medical image segmentation system contains hybridization of Fuzzy C means clustering with the region growing segmentation method using trilateral filter in its Pre-processing stage. Moreover features are extracted from the image using roundness matrix. The main idea of accomplishing the integration is to lessen how much iteration done by initializing the right cluster centers to Fuzzy C-means clustering techniques that, obviously, minimizes execution time and give qualitative results. The results of experiments shows that the hybrid clustering method of brain tumor detection can detect a tumor that cannot be detected by only Fuzzy C-means algorithm with less execution time. Moreover there is a need to convert the image into gray scale first. Fig 3 shows the proposed methodology.

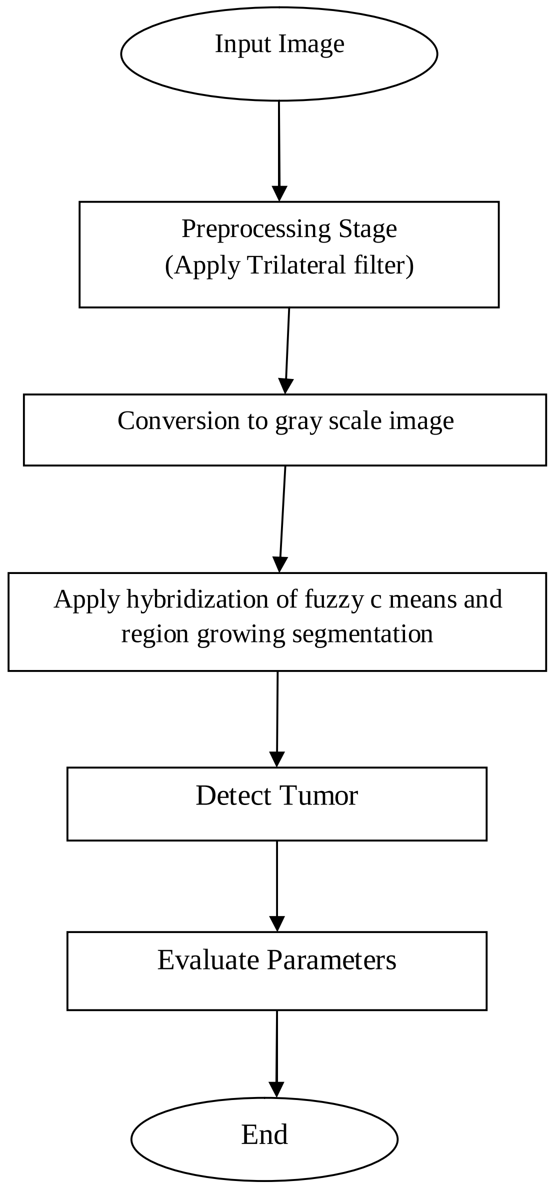

Fig 3: Proposed Methodology

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RESULTS

INPUT IMAGE: Fig 4 shows the input image.

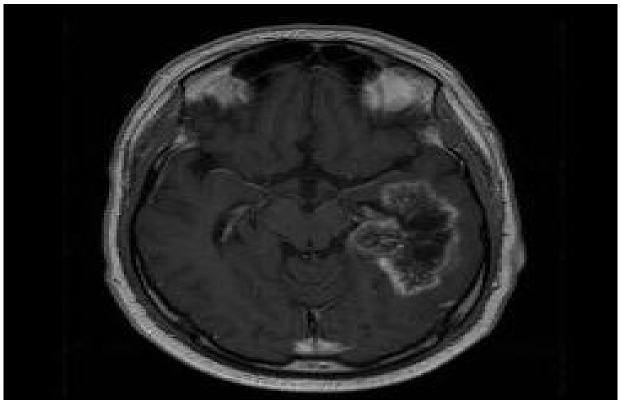

Fig 4: Input image

BASE PAPER SEGMENTED IMAGE: Fig 5 shows the base paper segmented image.

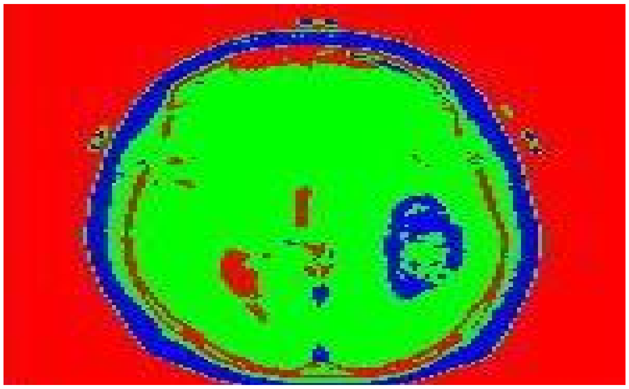

Fig 5: Base paper segmented image

PROPOSED SEGMENTED IMAGE: Fig 6 shows the proposed segmented image of tumor.

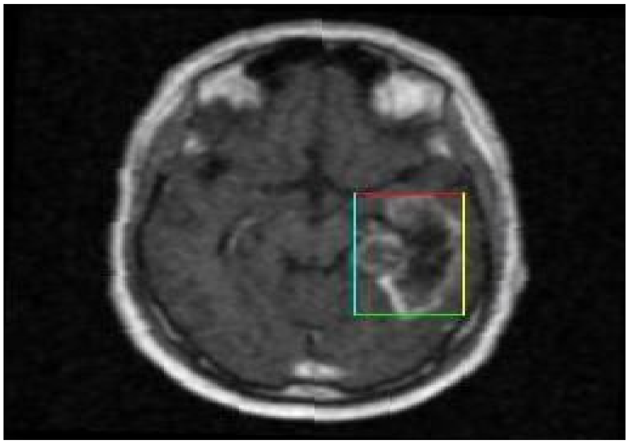

Fig 6: Proposed segmented image

PERFORMANCE EVALUATION

Accuracy Rate and **Error Rate:** The accuracy of a measurement system is the degree of closeness of measurements of a quantity to that quantity's true value. Accuracy is the proximity of measurement results to the true value. Whereas Error Rate means the frequency of errors that occur in the measurement system. Error rate can be calculated from the accuracy rate itself. It is defined as 1-accuracy rate as shown below. The comparison was done between the base technique and proposed technique according to the following performance measures:

$$\text{True Positive (TP)} = \frac{\text{No. of resulted images having brain tumor}}{\text{Total number of images}}$$

$$\text{True Negative (TN)} = \frac{\text{No. of images that have not tumor}}{\text{Total number of images}}$$

$$\text{False Positive (FP)} = \frac{\text{No.of images that have not tumor and detected positive}}{\textit{Total no.of images}}$$

$$\text{False Negative (FN)} = \frac{\text{No.of images have tumor and not detected}}{\textit{Total number of images}}$$

$$\text{Accuracy Rate} = \frac{(TP+TN)}{(TP+TN+FP+FN)}$$

$$\text{Error Rate} = 1 - \text{Accuracy Rate}$$

ACCURACY RATE TABLE AND GRAPH: Table 1 shows the comparison of accuracy rate between base paper results and proposed results. Fig 7 shows the graph of comparison of accuracy rate between base paper accuracy rate results and proposed accuracy rate results.

Table 1: Accuracy rate

IMAGES	BASE PAPER	PROPOSED
1	0.5347	0.9830
2	0.8750	0.9809
3	0.5879	0.9860
4	0.3593	0.9855
5	0.7361	0.9857
6	0.9588	0.9938
7	0.4560	0.9908

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8	0.9607	0.9926
9	0.4203	0.9898
10	0.4424	0.9925
11	0.4162	0.9925

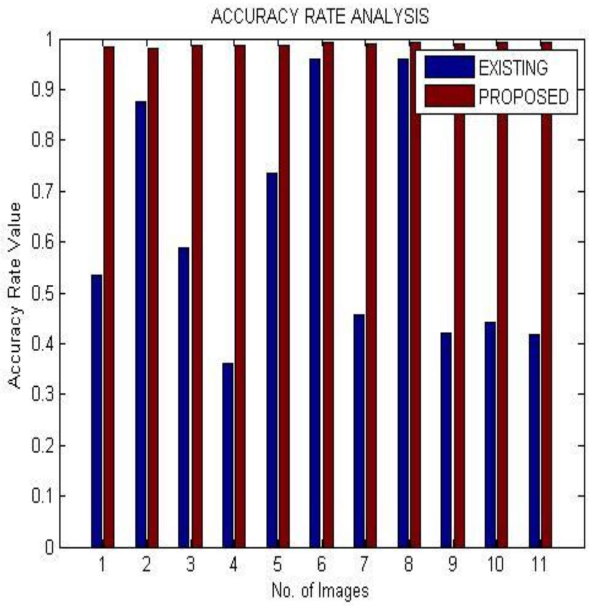

Fig 7: Accuracy Rate Comparison graph

ERROR RATE TABLE AND GRAPH: Table 2 shows the comparison of error rate between base paper results and proposed results. Fig 8 shows the graph of comparison of error rate between base paper error rate results and proposed error rate results.

Table 2: Error rate

IMAGES	BASE PAPER	PROPOSED
1	0.4653	0.017
2	0.125	0.0191
3	0.4121	0.014
4	0.6407	0.0045
5	0.2639	0.0143
6	0.0412	0.0062
7	0.544	0.0092
8	0.0393	0.0074
9	0.5797	0.0102
10	0.5576	0.0075
11	0.5838	0.0075

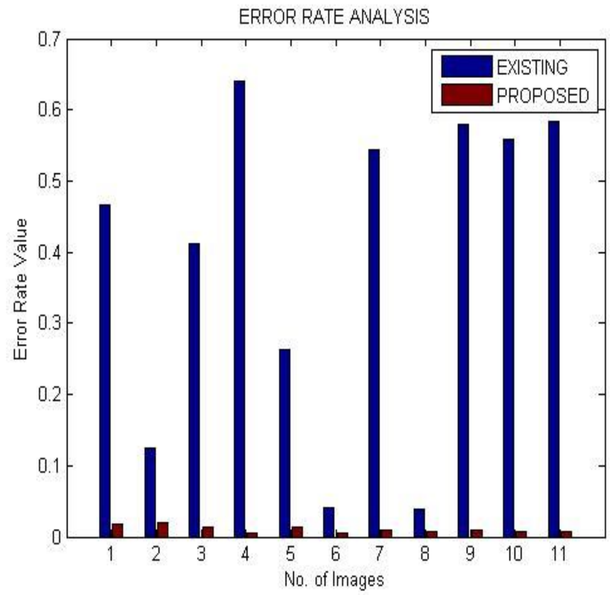

Fig 8: Error rate comparison graph

CONCLUSION AND FUTURE SCOPE

This research work has to proposed an efficient brain tumor detection using the feature detection androundness metric. To enhance the tumor detection rate further an hybridization of fuzzy and region growing segmentation based tumor detection with the trilateral filter is proposed. The proposed technique has the ability to produce effective results even in case of high density of the noise. The proposed technique is designed and implemented in the MATLAB tool along with the help of image processing toolbox. The experimental results has clearly shown that the proposed technique outperforms over the available techniques. This work has not considered the use of particle swarm optimization to segment an image in more proficient manner. So in near future the proposed technique will be enhanced by considering the particle swarm optimization based segmentation.

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