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# COMPARITIVE ANALYSIS OF K++GKFCM CLUSTERING FOR BRAIN TUMOUR DETECTION

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***Abstract:*** **Due to the complicated structure of brain tumors, hazy borders, and outside variables like noise, inferring tumor and edema regions from brain magnetic resonance imaging (MRI) data is still difficult. In this paper, a powerful hybrid clustering technique together with morphological procedures is suggested for segmenting brain tumors in order to reduce noise sensitivity and enhance segmentation stability. The following are the paper's key contributions: initially, adaptive Wiener filtering is employed for de-noising, and morphological procedures are applied for deleting non-brain tissue, thereby minimizing the method's susceptibility to noise. Second, to segment pictures, the fuzzy C-means technique based on a Gaussian kernel is used with K-means++ clustering. This clustering decreases the sensitivity of the clustering parameters while simultaneously enhancing the stability of the algorithm. To produce accurate representations of brain tumours, the retrieved tumour pictures are lastly post processed utilising morphological procedures and median filtering. The suggested approach was also contrasted with other existing segmentation algorithms.**

***Keywords:*** **MRI, K++ means clustering, Gaussian Kernel.**

## I. INTRODUCTION

One of the most dangerous illnesses, brain tumours frequently have fatal effects. The research of brain tumour images is currently receiving more and more attention. These days, brain imaging using MRI is very helpful [1] since it may be done without administering radioisotopes. Multiparameter imaging, which creates diverse pictures by modifying various parameters, is the foundation of magnetic resonance imaging (MRI). The pictures in Fig1 show brain MRI with tumours and were captured using T1, T1c, T2, and FLAIR, among other modalities. The FLAIR modalities are frequently utilised for identifying the expansions of tumours and edemas. Here, we employ FLAIR image segmentation in BRATS 2012 [2].MRI scans typically have low contrast, making it challenging to precisely characterise lesion sites due to noise. Therefore, proper tumour segmentation is crucial. Medical image segmentation is now a common practise using a variety of image segmentation algorithms. Examples include the threshold segmentation method [3], edge-based segmentation techniques [4], and neural network-based segmentation [5].

Based on certain pixel attributes, the segmentation threshold is chosen using the threshold-based segmentation method. To decide which areas of the picture to classify the pixels, the feature values of the pixels are contrasted with the segmentation threshold. It is easy to implement and carry out this strategy.

The pixel features on each side of the border will have quite visible changes since the boundary pixels' attributes are discontinuous. Therefore, the fundamental concept behind the edge-based segmentation technique is to first describe the border directions before applying any way to locate the boundaries. Then, the pixels on one side of the border are separated into one subimage, while the pixels on the other side are regarded to belong to another sub image. Despite the speed of this method while the pixels on the opposite side are thought to be a part of a different subimage. Although this approach is quick, it is noise-sensitive and typically only yields partial results.

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The use of neural networks for picture segmentation has grown in popularity recently. In this method, the architecture and weights of connections between the network's nodes are modified after a neural network has been trained using a training set. A trained neural network is used to segment new picture data. Among the many neural network techniques, convolutional neural networks (CNNs) have gained a lot of popularity [5]. However, building the network is one of the more challenging aspects of neural networks. Implementation of neural networks is difficult since they need a lot of calculation and time.

Clustering techniques are often employed for segmentation of medical pictures. Commonly used clustering techniques include fuzzy C-means clustering (FCM), K-means clustering, and expectation maximisation (EM). The K-means algorithm [7][8] is a hard clustering approach that allocates the image's pixels to classes that correspond to the closest centroid after computing the grey scale means of various clusters repeatedly, measuring the distances between the image's pixels and the cluster centroids. Fuzzy C-means clustering [9] leverages the fuzzy set theory, which provides soft segmentation. Data can be characterized as a combination of probability distributions, according to the EM method. The algorithm then use the maximum likelihood estimation approach and clustering criteria to repeatedly calculate the posterior probability and estimate the mean, covariance, and mixture coefficients [6][11][12].

An efficient clustering segmentation approach is developed in this paper to enhance the unstable clustering and to reduce its sensitivity to noise. The following are this paper's key contributions:

(i) A hybrid clustering technique based on K-means++ and Gaussian kernel-based fuzzy C-means (K++GKFCM) is suggested.
(ii) The clustering centre is initialised using the K-means++ technique, which significantly increases the algorithm's stability.
(iii) Fuzzy C-means with a Gaussian kernel is also included to increase sensitivity to noise.
(iv) To further increase segmentation accuracy, the suggested technique is integrated with morphological procedures for preprocessing and post processing.

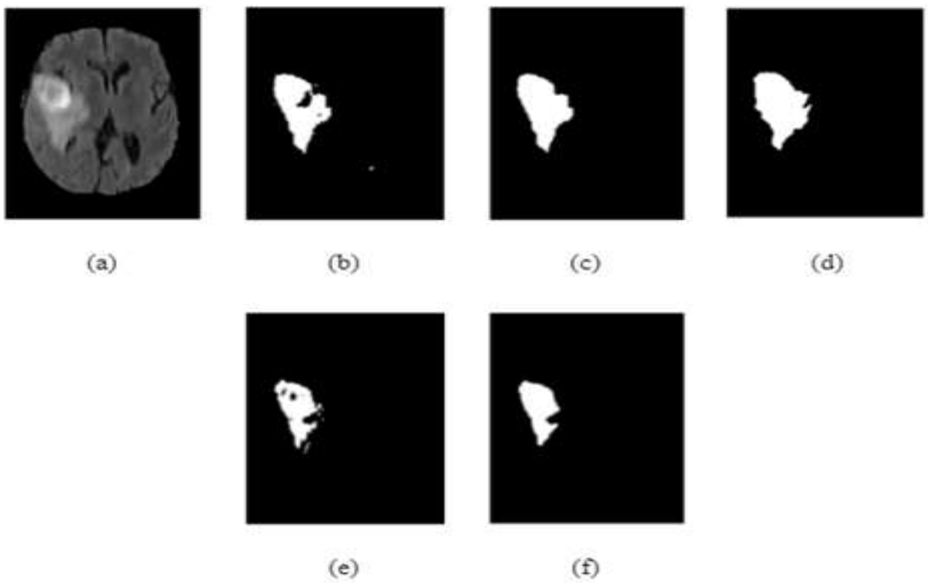
As a consequence, image segmentation accuracy has greatly increased.

## EXPERIMENTAL CLASSIFICATION RESULTS AND ANALYSIS

The proposed method is implemented in Python software, which is run on an Intel Core i3 CPU 2.5 GHz. The algorithm is tested on the BRATS 2012 open source image library which contains brain MR images of different modalities. The work described in this paper is used for segmentation of FLAIR images in BRATS 2012. About 100 pairs of MR images of twenty different patients containing tumors are selected for testing the segmentation algorithm.

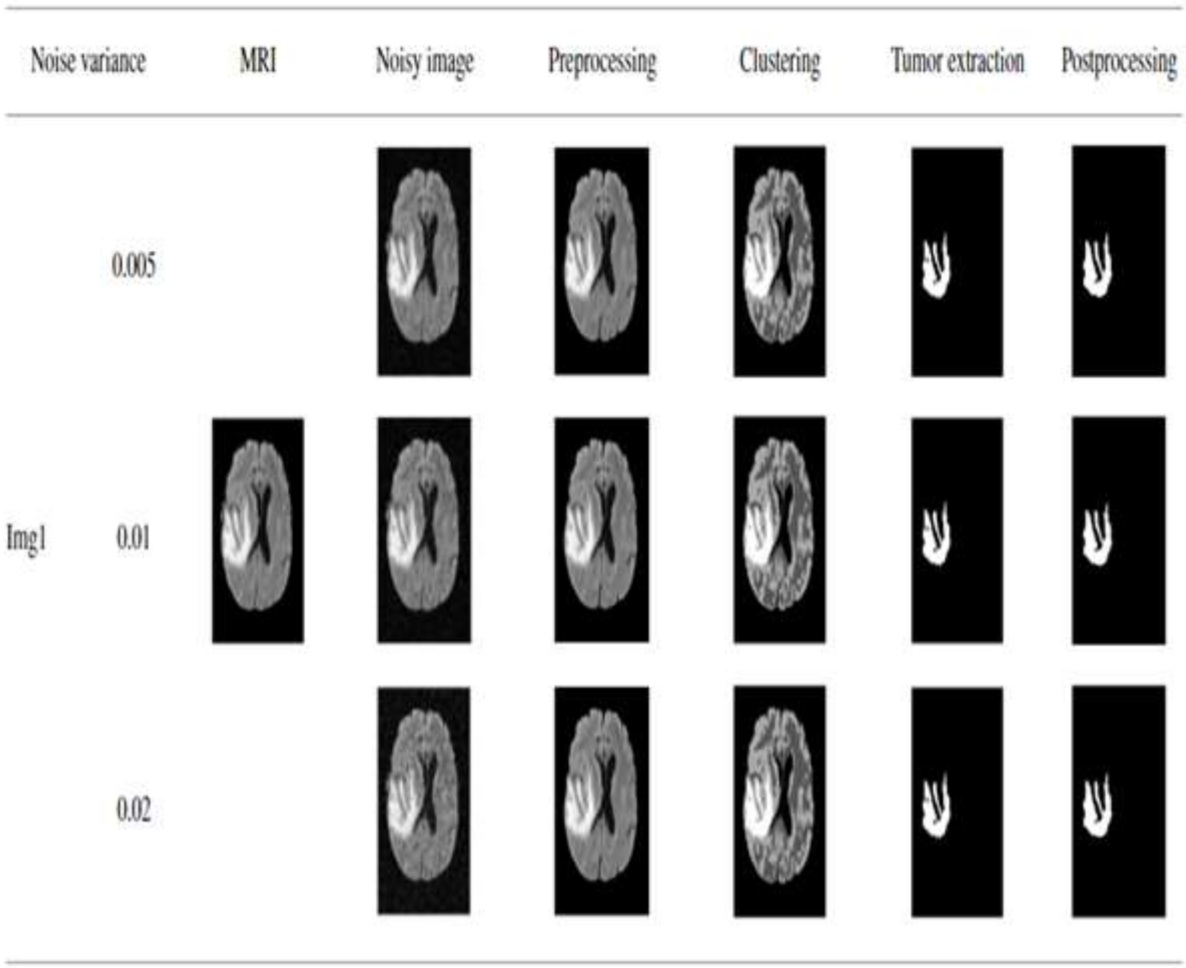
## TESTING THE ALGORITHM'S STABILITY AND ROBUSTNESS TO NOISE

Whether with FCM or K-means clustering, the choice of cluster centroids is uncertain. If K-means is used first for centroid initialization and is then combined with the Gaussian kernel-based FCM clustering algorithm, two different segmentation results are obtainedas shown in below Figure




Generation of two unstable results from cluster centroids using K-means: (a) MR image; (b) tumor region extracted from the first result; (c) tumor region after post processing extracted from the first result; (d) Ground truth image; (e) tumor region extracted from the second result; (f) tumor region after post processing extracted from the second result.

Above Figure shows the two types of results of the segmentation procedure, where Figure (b) shows the first image obtained after post processing and Figure (c) shows the tumor region extracted using the first clustering result. Figure (e) shows the tumor region extracted using the second clustering result, and Figure (f) shows the second result after post processing. Figures (a) and (d) are the original MR image and the ground truth image, respectively. To improve the stability of the segmentation algorithm, this paper proposes to use K-means++ for deterministic initialization of cluster centroids. Experiments show that the proposed method exhibits very good stability. The specific segmentation results are shown in Table below.




Additionally, Gaussian noise, which frequently distorts MR images, has a significant impact on medical image segmentation. However, a typical shortcoming of traditional clustering methods is that they are susceptible to noise. In this paper, preprocessing is done using adaptive Wiener filtering and morphological techniques to address this flaw. Here applied Gaussian noise with variances of 0.005, 0.01, and 0.02, to the MR image to further confirm the resilience of the suggested approach to noise. The impact of adding Gaussian noise with the aforesaid variances is seen in Table above. Over a variety of noise fluctuations, the segmentation findings hold steady. It is clear that the suggested method is very noise-resistant.

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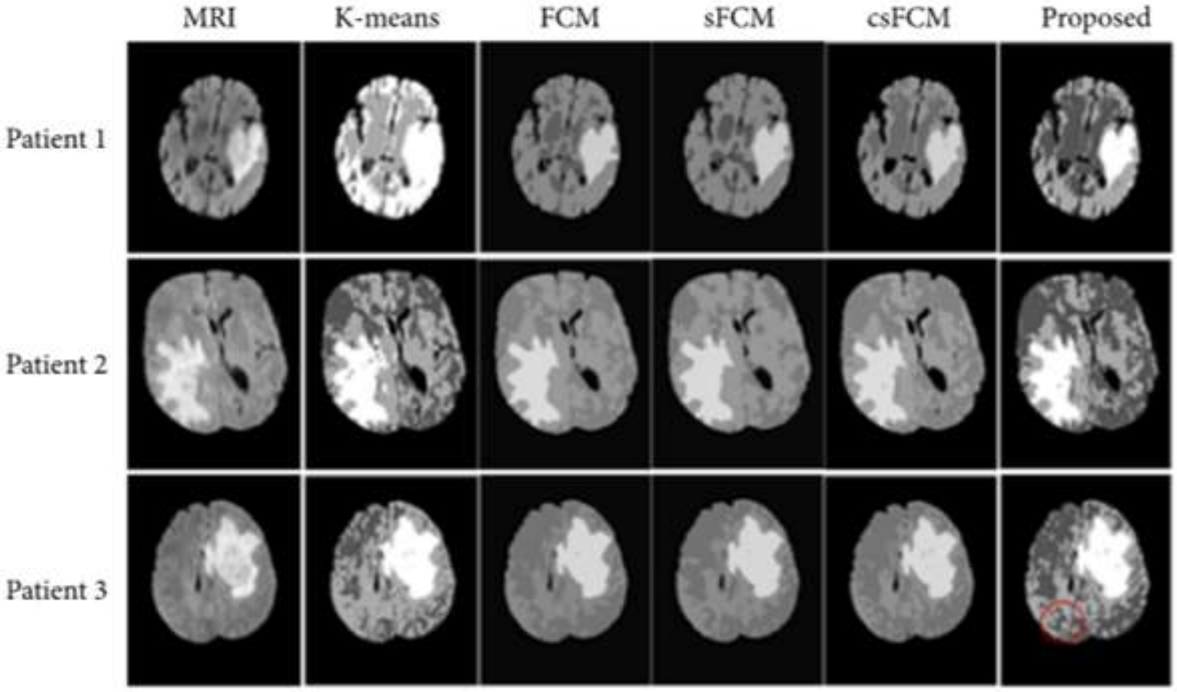


**Comparative Analysis With A Few Recently Proposed Clustering Algorithms**

Recently, a lot of clustering techniques have been presented. To confirm the efficiency of the suggested clustering technique, it is compared it to a few well used clustering methods. For analysis, three brain MR scans were chosen at random. The suggested algorithm's clustering impact is depicted in Figure as shown below, along with a comparison to the clustering performances of FCM, K-means, sFCM, and csFCM. It is clear that the method suggested in this paper treats texture features more precisely than the other techniques. Particularly, the area highlighted in red in Patient 3 is better captured by the clustering approach that is now being suggested.

Four assessment indicators—Dice, Sensitivity, Specificity, and Recall—were utilised to assess the quality of segmentation in order to further confirm the efficacy of the proposed algorithm. The most common evaluation index, the Dice value, shows how much of the total area is occupied by the intersection of two items. A perfect division has a dice value of 1. The amount of pixels that the algorithm properly identifies as being part of the region of interest are known as true positives (TPs), and the more TPs there are, the more sensitive the algorithm is. A larger proportion of false positives (FPs) reduces the specificity since they represent pixels that do not actually belong to the region of interest but are yet categorised as Specificity.

$$\text{Dice} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{TN}}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FN}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Where TP represents tumor exists and is detected correctly, TN represents tumor does not exist and is not detected, FP represents tumor does not exist but is detected, FN represents tumor exists but is not detected.

In order to compare various clustering techniques with the suggested approach, brain scans from three distinct patients were used as examples in this paper. The comparison between the proposed method and the K-means, FCM, sFCM, and csFCM algorithms is shown in Table as shown below. The Dice, Sensitivity, and Specificity indicators show greater values for the suggested method. The suggested method's Recall [10], however, is somewhat lower than that of the FCM, sFCM, and csFCM algorithms.

| Clustering methods | Evaluations | Patient 1 | Patient 2 | Patient 3 |
|---|---|---|---|---|
| K-means | Dice | 0.9001 | 0.9316 | 0.8298 |
| | Sensitivity | 0.9630 | 0.9064 | 0.9424 |
| | Specificity | 0.9952 | 0.9984 | 0.9780 |
| | Recall | 0.8449 | 0.9583 | 0.7412 |
| FCM | Dice | 0.9137 | 0.9341 | 0.9004 |
| | Sensitivity | 0.9263 | 0.8905 | 0.9336 |
| | Specificity | 0.9971 | 0.9994 | 0.9880 |
| | Recall | 0.9015 | 0.9823 | 0.8694 |
| sFCM | Dice | 0.8169 | 0.9258 | 0.9144 |
| | Sensitivity | 0.7112 | 0.8645 | 0.9290 |
| | Specificity | 0.9968 | 0.9994 | 0.9878 |
| | Recall | 0.9597 | 0.9965 | 0.9002 |
| csFCM | Dice | 0.8069 | 0.9179 | 0.9166 |
| | Sensitivity | 0.6960 | 0.8540 | 0.9290 |
| | Specificity | 0.9971 | 0.9996 | 0.9880 |
| | Recall | 0.9597 | 0.9922 | 0.9045 |
| Proposed | Dice | *0.9261* | *0.9400* | *0.8978* |
| | Sensitivity | *0.9622* | *0.9184* | *0.9380* |
| | Specificity | *0.9971* | *0.9996* | *0.9881* |
| | Recall | *0.8926* | *0.9625* | *0.8608* |

## II. CONCLUSION

For segmenting pictures of brain tumours, a hybrid clustering technique including morphological procedures was proposed in this paper. The outside membrane is initially removed by the method using morphological procedures, which lowers the computing difficulty and the quantity of clustering iterations. The K-means++ clustering technique is used during the clustering stage to establish the centroids of the clusters. This approach addresses the issue of unstable clustering, which results from the ambiguity surrounding the initialization of cluster centroids. Only a stable clustering outcome is generated by each cluster. The suggested approach also avoids over fitting. The approach then employs fuzzy C-means clustering with a Gaussian kernel as its foundation. The suggested approach significantly reduces the sensitivity to clustering parameters and further enhances the resilience of the system. Finally, post processing techniques like median filtering and morphological processes are used to further boost segmentation accuracy.

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