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OPTIMIZED BRAIN MRI SEGMENTATION: K-MEANS++ AND VECTORISED FUZZY MEMBERSHIP COMPUTATION

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ABSTRACT

Magnetic Resonance Imaging (MRI) is a well applied method of brain analysis, because of its capability of acquiring detailed anatomical information. Accurate brain MRI segmentation is required for diagnosing brain related disorders. A brain MRI segmentation framework based on K-Means++ clustering and a novel vectorized fuzzy membership computation is proposed as the work that introduces an optimized solution to this problem with additional accuracy and speed. K-Means++ is deployed to initialize cluster centers in order to improve convergence time and quality of the segmentation. The computed vectorized fuzzy membership functions yield additional tissue segmentation for fine classification of tissues (gray matter, white matter and cerebrospinal fluid etc.) that are not provided by a tissue region segmented alone. A combined method based on robust noise reduction through application of Gaussian filtering linked to robust intensity normalization on an image quality basis to remove artifacts based upon noisy images is presented. Small, spurious regions are then removed using post-processing techniques. On benchmark brain MRI datasets, experiments demonstrate the superiority of the optimized segmentation method in terms of both segmentation accuracy and computational efficiency as compared to traditional K Means and Fuzzy C Means (FCM) algorithms, all with robustness against noise. The proposed method achieves 0.21% and 0.52% improvements in accuracy over traditional K-Means and FCM. Proposed method showing significant improvement in Dice Similarity Coefficient (DSC), Jaccard's Index (JI), precision, recall, F1-score and MSE parameters compared to K-Means and FCM. This contribution makes a computationally efficient and more accurate hybrid segmentation approach to integrate K-means++ and vectorized fuzzy membership computation so as to boost the reliability of brain imaging analyses and clinical decision making.

Keywords: *Brain Tumor, Fuzzy C Means, Fuzzy membership functions, K-Means++, MRI Image.*

1. INTRODUCTION

MRI is one of the most common types of Non-Invasive method for imaging studies that reveals about the tissues of the brain as well as structures. It is especially important in the diagnosis, and assessment and management of neurological disorders including; brain tumors, multiple sclerosis, and stroke. The segmentation of various structures and pathological tissues in the brain MRI is perhaps one of the fundamental requirements in its analysis and is fundamental to providing measures of the involved structures and disease progression. Nevertheless, the segmentation of brain MRI is a difficult process because of the intricate structures of the brains and due to the noise, that normally accompany the images besides variability in intensity distribution [1].

It is important to accurately identify and analyze neurological structures and pathological conditions including tumors, stroke lesions and multiple sclerosis, brain MRI image segmentation. Early disease detection, the basis of planning treatment as well as monitoring disease progression, early disease detection are a new basis for the individualization of medicine. Efficiency is increased through advanced AI based segmentation methods that shaves manual effort as well as inter observer variability. It also has an important role in neuroimaging research, facilitating diagnoses based on neurological disorders as well as work on brain function and neuropathological essential medical health information. The technology is much more precise for diagnostics, planning for surgery, and overall patient outcome in neurology.

Among the methods available for MRI image segmentation, clustering-based methods

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especially Fuzzy K-Means (FKM) clustering has received a lot of attention [2]. Some of the advantages that FKM has include; the ability to capture image intensity inhomogeneity and the flexibility of the model to cater for overlapping boundaries between the different tissues. Compared to the other hard partitioning methods, FKM calculates the membership value which is closer to the nature of medical images since tissues' boundaries are seldom clear-cut [3]. However, the traditional FKM clustering algorithm is not without its drawbacks: For instance, it is sensitive to the initial cluster centers, it takes a long time to converge and it also presents a high noise sensitivity which directly affects the segmentation results.

Some efforts have been made in the recent years to enhance the performance of FKM clustering method [4] in segmenting MRI images. Of the techniques described above, Gaussian filtering has been used in the preprocessing stage to reduce image noise and, in the post-processing stage, morphological operations to improve on the quality of the segmentation results by eliminating small artifacts and smoothing out region edges [5][6]. Further, better initialization techniques like K-Means++ initialization [7][8], for selecting the first set of Centroids have been proposed, where Centroids are selected to give the best clustering result and thus, faster convergence and segmentation is obtained.

In this paper, optimized Fuzzy K-Means clustering has been used for image segmentation and Gaussian filter used for noise reduction and morphological filter for post segmentation improvement. In addition, due to the use of K-Means++ initialization, the proposed method does not suffer from slow convergence and nonoptimal clustering, which traditional FKM methods are prone to. Also in the post-segmentation stages, morphological operations such as the median filtering and morphological opening is used to remove small artifacts and enhance the segmentation of the brain regions respectively.

1.1 Motivation

The proposed work is motivated by the increased demand for accurate and fast segmentation of brain MRI in medical imaging. Segmentation of the brain accurately is fundamental for the diagnosis of neurological disorders, treatment planning and monitoring the progression of disease. Nevertheless, popular segmentation techniques based on the standard K-Means and Fuzzy K-Means usually compromise on good initialization, slow convergence and inaccurate bordering between brain tissues. This paper tackles these problems by introducing an optimized approach, which reduces the risk of poor clustering outcome via utilizing K-Means++ for centroid initialization. In addition, the implementation of fuzzy membership computation via vectorized allocation accelerates computational speed and accuracy in the segmentation process. This combination of improvements will hopefully enhance the state of the art in brain MRI analysis and yield more reliable and scalable platform for the application to clinical problems as well as to the further progress medical imaging research.

1.2 Problem statement

In this research paper the limitations of traditional methods in segmenting the tumor of brain MRI images is addressed. As a result, conventional approaches such as standard K-Means and fuzzy K-Means suffer from poor centroid initialization, slow convergence, and poor segmentation quality especially for complex and noisy brain MRI data. These limitations complicate the precise identification of critical brain structures which are essential to diagnose and treat neurological disease. The problem is to make segmentation more accurate and at the same time make it more efficient so that the brain tissues can be precisely delineated. To solve this issue, this paper provides the solutions of K-Means++ for optimized initialization and vectorized fuzzy membership computation for faster and more efficient update on segmentation of brain MRI, and consequently enables to improve the integrity and reliability of brain MRI segmentation as well.

The primary contributions of this work are as follows:

1. Modified FKM clustering technique for Brain MRI segmentation which includes K-Means++ in order to develop better centroids.
2. The use of Gaussian filtering in the preprocessing stage with an aim of reducing the effects of noise.
3. Good afore-processing post-processing pipeline to be employed by using morphological operations to sharpen the printed out of segmented paperwork in the excellent proportion, both precision and aesthetics.

The remaining part of this paper is as follows. In Section 2, the related work in MRI segmentation is presented. In Section 3, the authors explain the details of the methodology that is associated with the use of the proposed approach, including the preprocessing step, FKM clustering,

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post-processing step. Section 4 gives performance results and evaluates the proposed method relative to the conventional approaches. Section 5 brings out the final conclusion of the paper and provides an insight into some of the future research areas.

2. LITERATURE REVIEW

To address the challenges, it is necessary to first understand the state of the art in brain tumor segmentation for MRI by running a literature review.

S. Krishna kumar and K. Manivannan et al.[9] in their study present a novel method for identifying and classifying brain tumors using sophisticated computing. The aim of these authors is to increase the accuracy of brain tumor segmentation performed on MRI (Magnetic Resonance Imaging) images, which is critical for accurate diagnosis or treatment plans. In this work, a technique to automatically segment tumors from brain or prostate MR images is under investigation using the Rough K-Means Algorithm which is known for its ability to deal with vagueness and uncertainty in data and hence also for finding solutions for complicated tasks in medical imaging. The final classification model is augmented with a Multi Kernel Support Vector Machine (SVM) that improves both the stability and performance of the classification model. By integrating rough set theory with multi kernel SVM, the benefits of both methods are combined and the precision of tumor delineation and classification improved in noisy and heterogeneous MR images. And the success of the proposed method is finally proved in the paper through a number of experiments, in which the theory of suggested method clearly outperforms classic one in terms of calculation time as well as accuracy. This study enhances greatly the medical image analysis, thereby providing a strong resource for radiologists and medical practitioners to perform timely and accurate identification of brain tumors.

Authors S.M. Hussain, E.O. Atheyra, et al. [10] suggest the combination K-Means clustering with Fuzzy C-Means algorithms could enhance brain MRI image segmentation. K-Means is simple to implement, yet has fast clustering performance, however when it comes to noisy data, or clusters that overlap it's hard to succeed upon. The authors address these limitations by combining the FCM algorithm, which allows the flexibility that has the ability of one pixel to belong to multiple clusters with varying degrees of membership, making FCM more suited for overcoming the inherent uncertainties in medical images. The combination of K-Means and fuzzy clustering in FCM is proposed to exploit the computational efficiency of K-Means and to increase its segmentation accuracy. Our research finds that the hybrid method improves the accuracy of brain tumor segmentation and, thus, improves tumor detection accuracy. The authors illustrate using experimental results the method's prospective advantage compared to classic techniques for diagnosis and treatment planning in medical imaging.

Surjeet Dalal, Umesh Kumar Lilhore et al. [11] in their work propose a new brain tumor segmentation method which aims to increase both the accuracy of tumors identification on MRI images and the efficiency of tumor identification. The proposed method integrates two advanced computational techniques: This analysis also includes Adaptive Moving Self Organizing Map (AMSOM), and Fuzzy K Means (FKM) Clustering. By enabling the adaptations of the learning rate and neighborhood functions which govern the underlying segmentation process, the AMSOM improves the responsiveness of the segmentation process and is better able to exploit the difficult patterns seen in MRI data. The attractive feature of this method is the ability to effectively separate brain tumors within heterogeneous and noisy medical imagery, overcoming typical issues such as intensity inhomogeneity and partial volume effect. One value that the Fuzzy K-Means adds to the work is a flexibility in clustering that allows the pixels to belong to different clusters to different degree. This enhances segmentation accuracy greatly in regions with intermingled tumor and regular tissue boundaries. Adaptive learning from AMSOM and fuzzy clustering from FKM jointly yield a strong segmentation method that not only performs better in the detection but also in the delineation of brain tumors. This approach is experimentally validated for higher segmentation precision, faster processing, and a decreased noise sensitivity than currently existing methods, an important resource in clinical applications pertaining to diagnosing brain tumors.

D. Maruthi Kumar, D. Satyanarayana et al. [12] proposed a better method of separating brain tumors in MRI images. In their method the Gabor Wavelet Transform (GWT) is used for feature extraction and Rough K-Means Clustering (RKC) for computer aided tumor segmentation, which the authors then suggest combining. Gabor wavelet is used to capture the texture details along with spatial frequency of the brain MRI thereby resulting into more precise tumor identification. This bayonets traditional K-Means, by providing better performance in chaotic clustering environment, the resulting better segmentation on complicated and unordered medical images. By merging these two approaches, brain tumor segmentation is improved both in precision and in durability, leading to results superior to those obtained in conventional ways. It is shown that this technique yields better tumor boundary identification and better segmentation, and thus provides important functionality to the field of medical image analysis.

G. Anand Kumar and P. V. Sridevi [13] in their research work introduce a creative method for brain tumor segmentation through Chi–Square Fuzzy C Mean (CS–FCM) clustering technique. The authors do this by incorporating the Chi-Square distance measure to properly set values of intensities in MRI images to further improve the accuracy of clustering than the former approach of the conventional Fuzzy C Means (FCM) algorithm. This technique improves significantly handling of uncertainties in brain tumor boundaries and thus helps more accurately segmenting tumor areas. Despite noise or variability in intensity among MRI images, the clustering tactic from CS-FCM performs a fast separation of tumor from healthy brain tissue. this approach is statistically superior to traditional FCM with regard to accuracy and robustness with respect to early tumor detection and diagnosis.

The authors J. Anitha and M. Kalaiarasu [14] propose a new way of segmenting a brain tumor from MRI image, using the fusion between Intuitionist Possibilistic Fuzzy Clustering (IPFC) and Morphological Operations technique. IPFC method enables conventional fuzzy clustering to solve problems of uncertainty of This clustering method is refined with morphological operations that improve tumor boundary detection and extraction. The merging of these approaches leads to improved precision and robustness of tumor segmentation in cases when intensity inhomogeneity or noise is an issue. The experiment shows this technique improves accuracy in distinguishing between tumor and healthy tissue, an important lead toward better diagnostic and treatment planning, for brain tumor situations.

Chiranji Lal Chowdhary et al. [15] propose groundbreaking framework of segmentation and classification of medical images. Authors develop the improved image segmentation method by solving the deficiencies of the traditional fuzzy methods by coupling fuzziness and possibilistic elements using the application of Intuitionist Possibilistic Fuzzy C-Means (IPFCM) clustering. This handles noise and uncertainties well encountered in medical image data more effectively compared to existing techniques. The suggested system also improves by achieving higher accuracy levels of medical image evaluation. The inclusion of these advanced techniques enables increased diagnostic performance and promises to enable applications in many medical imaging fields such as tumor detection or organ segmentation. This method is especially helpful when processing hard and fuzzy medical data.

Rasha Khilkhal and Mustafa Ismael et al. [16] presented a work, which describes the hybrid method for the segmentation of brain tumors in medical images. This work integrates thresholding techniques with the K-Means clustering to improve tumor segmentation, especially in MRI scans. First, handcrafted thresholding defines the limits of region of interest and, then, K-Means clustering refines the segmentation by bringing together similar pixels intensities. They propose a two-stage approach, which improves the precision of tumor boundary detection, while overcoming the difficulties of medical images of varying intensities. The system proposed is demonstrated as useful for discriminating between brain tumors thus demonstrating potential applications for early diagnosis and design of treatment plan in a patient having brain cancer.

Amit Thakur, Priya Pudke, Ruchika Das et al. [17] in their research, investigates the efficiency of k mean's clustered algorithm for brain tumor segmentation in medical images. The authors do this based on intensity similarities, and are clustering pixeled MRI scans using K-means to separate normal brain matter from tumor tissue. The unrestrained technique provides for automatic detection of tumor areas, offering a simple and relatively efficient solution for tumor detection. However, the authors mention that K-means is computationally less valid, but also its disadvantages, such as being sensitive to noise and choice of initial clusters. Despite these problems, the strategy shows promise as a means for categorizing brain tumors and could serve to help clinicians in diagnose and treatment planning.

Rehana Ghulam et. Al. [18] in their study, exploit the wide use of UNet architecture which has previously shown to outperform in the task of segmentation of medical images as the architecture can use the skip connections to retain the fine details of the image and offers a symmetrical encoder-decoder design. It is shown that this model is capable of discriminating brain tumors from their MRI images learning both basic and complex features. The proposed U-Net based technique is more accurate for defining tumor boundaries than the usual methods, greatly improving diagnostic accuracy. It shows the power, scalability, and use for automated medical diagnostics of the model, and provides a strong resource for radiologists to find and analyze brain tumors.

Jadhav Jaichandra, P Hari Charan et al. [19] presented work named combined KMeans clustering with morphological operations to provide a mixed method for the diagnosis of brain tumors. The authors group MRI images through K-Means clustering by grouping pixels by intensity values and are able to tell tumor regions from normals very clearly. Furthermore, morphological operations including dilation and erosion are applied in order to increase the precision of tumor boundary detection and refine segmentation. Combining approaches into this method leads to more accurate and more assured tumor assessment as it controls the plaining of tumor edges and reduces noise. This method has significant practical utility to noninvasively recognize tumors in challenging or noisy medical images, thus opening up a new possibility for help in early diagnosis and treatment strategy in actual clinical practice.

Hassan Habib et al.[20] in their research consider a machine learning framework for the segmentation and classification of brain tumors. Different machine learning algorithms are then used by the authors for automatically separating MRI scans and their types. We are thrilled with the right tumor boundary identification that methods such as Feature extraction and pixel clustering can help to enhance the segmentation procedure. Support Vector Machines (SVM) algorithms are at work along with decision trees while tumor features are being categorized by them in the system. Through this approach we increase diagnostic accuracy and present a method that is faster and more reliable than hand detection. The diagnostic tools and treatment planning for tumors can be provided by machine learning to radiologists, resulting in this study.

Hassan Habib, Rashid Amin, Bilal Ahmed et al. [21] propose a new integrated hybrid model for the analysis of the brain tumor. The authors are using methodologies like cluster analysis- primarily the K-Means to segment their data and subsequently, practicing the use of classes of algorithms- specifically the Support Vector Machines (SVM) for classification. As well, new means in features extraction are used in order to offer more detailed description of tumor areas and thus increase the total efficiency of the system. By utilizing these attributes of the hybrid algorithms, the framework attains high level segmentation accuracy and elevates the classification results above and beyond methods that only use one algorithm. The investigation also reveals potential benefits of this integrated system to improve the accuracy of the tumor diagnosis and enhance the performance of medical image analysis in clinical environments.

Hare Krishna Mishra and Manpreet Kaur[22] developed a process for segmenting brain tumor to multiple class using the K Means clustering algorithm. By grouping pixels with K-Means based on intensity values, the authors give a method of discriminating different types and grades of tumor in MRI images. Enhanced segmentation is provided, which is able to segment the tumor plus the subcomponents of edema and necrosis. The proposed system improves diagnostic accuracy by assisting clinicians in determining complexity and severity of brain tumor while performing extensions to K-Means of multiple classes. This work presents the usefulness of this method to increase the accuracy of medical image analysis and enhance the development of personalized treatment strategies.

From the above study it is concluded that Brain tumor segmentation from the MRI images is a difficult task mainly because of Noise, inhomogeneity of intensity and complex tumor boundary. By many of existing methods, such as Rough K-Means, Fuzzy C-Means, and hybrid clustering techniques, it is possible to increase the segmentation, but the accuracy isn't that good and computational efficiency is very low. More recent deep learning approaches such as U-Net have previously successfully used to preserve fine details but need to be further enhanced for dealing with the uncertainty in tumor boundaries. The objective of this research is to build up an improved segmentation method through sophisticated clustering techniques in such a way that the tumor is precisely delineated.

3. METHODOLOGY

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The proposed work presents a methodology for segmenting brain MRI images with high precision. Further improvement is provided in image quality, and clustering that can be better aided by image pre-processing including noise reduction and image intensity normalization. The techniques of Gaussian filtering and contrast enhancement are standard in noise removal as well as the technique used to highlight the critical parts of the MRI scans. In addition, the Optimized Fuzzy K Means (OFKM) clustering algorithm is used for segmentation of the brain tissues. However, unlike Traditional K-Means[23], OFKM provides each pixel a membership value based on its degree of membership to various clusters, that can reduce noise and improve segmenting accuracy in the presence of uncertain or noise parts.

A methodology for segmenting brain MRI images with high precision is presented in this work. In order to improve image quality and to aid better clustering, the process features image pre-processing inclusive of noise reduction and intensity normalization. Standard techniques prevalent in removing noise comprise Gaussian filtering, whereas contrast enhancement is the technique employed to spotlight critical features within the MRI scans.

Further, the Optimized Fuzzy K-Means (OFKM) clustering algorithm is applied for the segmentation of the brain tissues. OFKM contrasts with traditional K-Means in that each pixel receives a membership value reflecting its level of membership in various clusters, reducing noise and improving segmentation accuracy, especially in uncertain or noisy parts.

After completing fuzzy clustering [24], the additional morphological operations of dilation, erosion, opening, and closing are utilized to improve the segmented regions. These operations serve to eliminate small unimportant sections (artifacts) and also smooth the borders of the segmented tumor or brain tissue, which ultimately enhances structural precision in segmentation. Incorporating OFKM together with morphological operations leads to a refined and precise segmentation framework, which remarkably enables the detection of abnormalities including tumors. At last, ground truth data is utilized to assess the performance of the suggested technique with regards to segmentation accuracy and its computational efficiency. Figure 1 illustrates the sequential flow of steps involved in the proposed methodology.

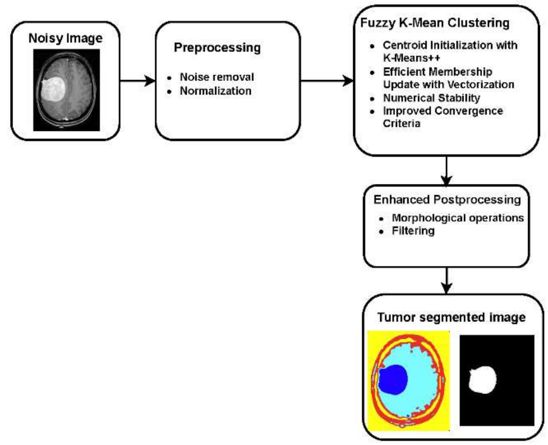


Figure 1: Proposed system flow diagram

3.1 Pre-processing

In the prospective work, Optimized Brain MRI Segmentation Using Fuzzy K-Means Clustering, Gaussian filtering and normalization are important pre-processing techniques that better the image quality for segmentation [25].

3.1.1 Gaussian Filtering

Relevant to important image processing chores, Gaussian filtering [26]is particularly important for tasks including noise reduction and smoothing, prominently in medical imaging, especially related to MRI technology. The function of Gaussian filtering is to smoothen an image by lowering the effect of noise on intensity changes and preserving impactful features, specifically edges.

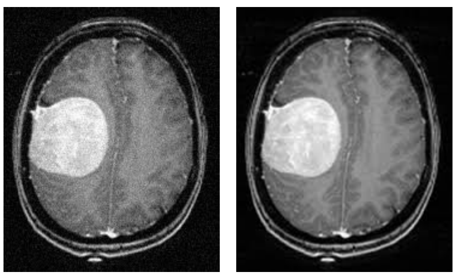
3.1.2 Gaussian Function

Just as a bell curve functions, the Gaussian function is central to Gaussian filtering, which emphasizes pixels near the filter's center more than those at a distance. The weighting causes a fuzzy effect that diminishes high-frequency noise while protecting the quality of the image details. The Gaussian function in two dimensions is defined as shown in equation 1.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \qquad (1)$$

Where: (x,y) are the pixel coordinates relative to the center of the filter. σ controls the width of the Gaussian curve and determines the extent of the smoothing (larger σ leads to stronger bluring).

The value of G(x,y) represents the weight given to the pixel at position (x,y). This filter features a Gaussian kernel carrying a matrix filled with Gaussian function values. All pixels in the image experience this kernel, with weighting from neighboring pixels, to produce a version of themselves that is smoothed. Medical images such as MRI scans greatly benefit from the key technique of Gaussian filtering in their preprocessing. The capability to lower noise without affecting key image traits, like edges, makes it an effective resource for boosting image quality, resulting in more reliable and accurate findings in image analysis tasks, such as segmentation.



(a) (b)

Figure 2. a) Noisy b) Gaussian filtered images

3.1.3 Normalization

MRI segmentation especially requires normalization [25] as an essential initial step. Achieving better reliability and accuracy in segmentation algorithms requires us to standardize the intensity values. Enhanced quality of segmentation and subsequent medical diagnoses is possible through proper normalization. Normalization exists mainly to harmonize the pixel intensity values across assorted images, thereby preventing variations from imaging conditions, scanner types, or acquisition protocols from interfering with the segmentation results. Concerning brain MRI segmentation, normalization is essential for both improving the reliability and consistency of the analysis.

3.1.4 Min-Max Normalization

One of the most applied normalization techniques [27] comprises this, where intensity values are tweaked to a particular interval, usually between 0 and 1. This proves that each image contains a steady intensity range, which supports cohesive processing. Equation 2 is used to find the normalized values.

$$x' = \frac{x - min(X)}{max(X)\text{-}min(X)} \qquad (2)$$

Where: x is the original pixel value, is the normalized pixel value, min(X) and max(X) are the minimum and maximum intensity values in the image.

The segmentation process receives considerable benefit from fundamental techniques of Gaussian filtering and intensity normalization regarding the quality of MRI images. These techniques successfully diminish noise and calibrate intensity values, laying the groundwork for effective application of the Fuzzy K-Means clustering algorithm, which boosts both the accuracy and the reliability of brain MRI segmentation.

3.2 Fuzzy Logic

Classic logic is combined with lattice fuzzy logic [28] to produce answers 'greater than just true or false.' The fuzzy logic is found out useful in the modern image processing due to its potential to deal with the uncertainty and inaccuracy problems biased in actual information, especially in the medical images. The example of imprecise concepts is illustrated where the developing change from one type of tissue to another can be described in fuzzy terms. In fuzzy logic systems membership functions determine how each part of a set participates in many fuzzy sets forming a more complicated classification system. This feature is particularly valuable in medical imaging, where precise identification of distinct boundaries between tangible normal and pathological tissues is often difficult.

3.3 Fuzzy K-Means Clustering

The variation of the regular K-Means model called Fuzzy K-Means is used to handle data categorization uncertainty by using fuzzy logic [29]. Standard K-Means differ by the way that Fuzzy K-Means distributes data assignment: there are many cases that can be assigned to each point, and not necessarily only a single cluster. Fuzzy K means assigns each data point a grade of membership to several clusters. The membership in this case is in a value range of 0 to 1 and allows overlapping groups and has capacity to apprehend more definitive data structures.

For example, brain MRI segmentation of different tissues such as gray matter white matter and tumors, fuzzy K means clustering tends to outperform other approaches. Each time around (one round), the algorithm updates the positions and membership values of each cluster center based on the distance between each pixel and that center, and while this lowers the overall objective function (a weighted sum of squared distances), it is repeated. When a fuzziness parameter is introduced, the algorithm has better performance in noise and variation in MRI images, while producing more accurate segmentation. Medically, if we take in to

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consideration the data uncertainties, fuzzy K-Means is a very powerful technique for the analysis of medical images that allows us to quickly define regions of interest like tumors.

3.4 Improved Fuzzy K-Means clustering

The present work ambition focuses on increasing the efficiency, reliability, and might of Fuzzy K-Means clustering for the purpose of segmenting Brain MRIs. Key transformations in the method address certain restrictions of Fuzzy K-Means methods, resulting in greater effectiveness for clustering.

3.5 Key Enhancements and Their Benefits

1. Centroid Initialization with K-Means++: The result is often suboptimal clustering and slower convergence where Traditional Fuzzy K-Means suffers from poor centroid initialization. The guarantee provided by K-Means++ for widespread centroid separation improves your rallying point for finding superior local minima and also helps the convergence process. This contributes to the improvement and accuracy of segmentations found in Brain MRI analysis.
2. Efficient Membership Update with Vectorization: Updating the membership matrix, an integral part of Fuzzy K-Means, is often computationally costly, particularly for datasets with many dimensions, such as MRI scans. Reducing the computational load and improving the clustering speed is a result of vectorizing the operations. This is promising scalability for greater datasets, all the while ensuring efficiency.
3. Numerical Stability: Adding a little epsilon to your distance calculations ensures your numerals remain stable. This is important when working with complex dimensional data such as MRI scans, since small fluctuations in floating-point operations can introduce instabilities to membership updates, leading to mistaken clustering.
4. Improved Convergence Criteria: Surveillance of changes within the membership matrix rather than just centroids offers a more detailed view of convergence. In terms of brain MRI segmentation, where slight changes in tissue boundaries are crucial, this technique confirms that the algorithm stops operating only once the segmentation outcomes have entirely stabilized, produce more accurate and reliable results.
5. Enhanced Postprocessing: Noise and artifact removal are important aspects of MRI segmentation's postprocessing. Applying median filtering followed by morphological opening results in a significant removal of small objects and noise, allowing the critical structure of the segmented areas to remain unchanged. This is an essential improvement upon the basic filtering techniques used in traditional strategies, which may be less useful for cleaning segmented images.

The brain MRI segmentation method proposed here shows many advantages over the existing ones, for instance, the better accuracy brought by the integration of K-Means++ and fuzzy membership computation in order to classify the tissue (gray matter, white matter, cerebrospinal fluid), as well as others. Gaussian filtering and intensity normalization make it more robust for noise and artifact while K-Means++ optimization decreases the computational time and increases faster convergence by optimizing cluster initialization. The experimental results show that there is significant improvement in terms of Dice Similarity Coefficient (DSC), Jaccard's Index (JI), precision, recall, F1-score, and Mean Squared Error (MSE) as compared to conventional K-Means and FCM algorithms. The method, however, is also limited in several ways; more specifically, it involves added computational complexity from additional fuzzy membership computations as well as increased sensitivity to parameter tuning that may need to be optimized on a case-by-case basis. Though effective at compromising noise, this method might not so well with highly irregular tumor structure, in which cases deep learning based models such as U-Net could do better. In addition, its generalization to real world clinical scenarios with diverse MRI scanning parameters and noise levels are to be tested for verification on benchmark datasets.

Algorithm 1. Optimized Fuzzy K-Means clustering

Optimized Fuzzy K-Means clustering algorithm
Input: MRI image I ***Ouput:*** Segmented brain MRI image

Step 1: Initialization

1. Input parameters
   K - Number of clusters
   m - Fuzziness parameter
   The maximum allowed iterations are defined by Nmax.
   ε - Convergence threshold
2. Initialize cluster centres
   Randomly select K initial cluster centers $C = \{c_1, c_2, ..., c_K\}$ from the pixel intensities in the image.
3. Initialize Membership Matrix:
   Form a membership matrix U that has NxK dimensions and N denotes the number of pixels in the input visual. Initialize U_{ij} with random values such that the sum of each row equals 1:
   $$U_{ij} \in [0,1] \; and \; \sum_{j=1}^{K} U_{ij} = 1$$

Step 2: Fuzzy K-Means iteration

4. Proceed until either convergence occurs or Nmax maximum iterations are reached.
   Update Membership values: Consider every pixel i and cluster j at once:
   $$U_{ij} = \frac{1}{\sum_{k=1}^{K} \left(\frac{d_{ij}}{d_{ik}} \right)^{\frac{2}{m-1}}}$$
   The distance pixel i has from cluster center cj is denoted by d_{ij}.
   Update cluster centers: For each cluster j:
   $$c_j = \frac{\sum_{i=1}^{N} (U_{ij})^m x_i}{\sum_{i=1}^{N} (U_{ij})^m}$$
   Where the intensity of pixel i is x_i.
   Check for convergence:
   Calculate the change in cluster centers:
   $$\Delta = \max_j \left\| c_j^{new} - c_j^{old} \right\|$$
   if $\Delta < \varepsilon$, stop the iteration.

Step 3: Post-processing

5. Segment the image
   Assign each pixel to the cluster with the highest membership value:
   $$Segmented\ Image = \arg \max_j (U_{ij}) \; \forall i$$
6. Apply Morphological Operations:
   Use morphological operations-dilation and erosion to refine the segmented regions

Step 4: Output

7. Present the last segmented image of the brain MRI.

4. RESULTS AND ANALAYSIS

4.1 Dataset Description

A publicly available dataset was made available by Cheng et al. [30] on www.figshare.com. For the evaluation of the proposed work 3064 T1 weighted contrast-enhanced MR images from 233 patients with a glioma, meningioma, or pituitary tumor are considered among them a subset of 1426 images from 89 glioma patients and 930 images from 62 pituitary tumor patients were used for the evaluation of the proposed approach. The images of the sagittal, coronal and axial brain MR are presented. Tumor mask (ground truth), brain MR images, patient identifier and tumor label in (.MAT) MATLAB files accompany the images.

4.2 Performance Metrics

To judge the effectiveness of the proposed segmentation technique these measurements can be utilized. These metrics are essential for comparing the segmented output with the ground truth (expert-labelled data):

4.2.1 Dice Similarity Coefficient (DSC)

A statistical method determines the degree of similarity between the segmentation results and the ground reality[31]. It serves well for medical image segmentation since accuracy of overlap between two sets is crucial.

$$DSC = \frac{2 \times |A \cap B|}{|A| + |B|} \quad (3)$$

Where, A consists of the pixels in the segmentation deduced from prediction. B consists of all the pixels recognized in the ground truth segmentation.

If DSC increases more sharply it reflects a bigger match between the segmented and real regions. In evaluating brain segmentation results this criterion is often recognized as an essential tool.

4.2.2 Jaccard Index (JI)

The Jaccard Index [31] determines the level of correspondence between the segments as calculated against the ground reality. It represents a comparison of intersected pixels to the combined pixels of two sets.

$$JI = \frac{|A \cap B|}{|A \cup B|} \quad (4)$$

Where, the set A consists of pixels found in the anticipated segmentation. B is the collection of pixels represented in the actual segmentation.

The index of Jaccard lies between 0 and 1 and points to enhanced segmentation. It is a little less objective than DSC and holds precise boundaries against small errors in the prediction versus actual segmentation.

4.2.3 Precision

The accuracy of a predicted positive segmentation is captured by precision as it shows the proportion of predicted positive pixels that belong to the segmented area [32].

$$Precision=\frac{TP}{TP+FP} \quad (5)$$

Where, TP- accurate segmentation leads to the identification of correctly segmented pixels and FP- Incorrectly segmented pixels are called false positives.

An algorithm's precision concentrates on the precision of positive detections and is effective when the false positive consequences are severe. A greater precision results in fewer unwanted regions accounted for in the segmentation methodology.

4.2.4 Recall

The algorithm's performance to accurately locate all relevant pixels is assessed by recall [32].

$$Recall=\frac{TP}{TP+FN} \quad (6)$$

Where, TP stands for the accurate segmentation of pixels, and FN stands for false negative representing the missed pixels in the segmented areas.

An elevated recall shows that the method is resourceful in retrieving all significance areas on the MRI image. This holds great importance in medical imaging because failing to identify pathological regions could produce incorrect conclusions.

4.2.5 Classification Accuracy

Segmentation method reliability is assessed by comparing correctly identified pixels to the total number of pixels in the image [32].

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

Where, TP = True Positives, TN-Correctly labelling non-segmented pixels is shown by the value of True Negatives. FP = False Positives. FN = False Negatives.

The segmentation's efficiency can be summarized by accuracy. In imbalanced datasets such as MRI scans that contain many background pixels accuracy can be misleading.

4.2.6 F1-Score

The F1-Score [32] combines precision and recall into a single value and serves as a fair indicator of both. It proves valuable in datasets that have a lack of balance like brain MRI images that often show a greater abundance of background pixels than tissue pixels.

$$F1Score=2\times\frac{Precision\times Recall}{Precision+Recall} \quad (8)$$

A significant F1-Score demonstrates an optimal relationship between precision and recall. In segmentation projects both precision and recall hold great significance.

The integration of these performance parameters in evaluating the proposed method of Brain MRI segmentation using Fuzzy K-Means clustering allows a thorough assessment of the model's effectiveness. How closely are two segmentation methods to the ground truth can be seen by the levels of overlap in which DSC and Jaccard Index overlap. By emphasizing precision (power to reduce false positives) and recalling absence of important areas nonetheless, the method illustrates how power decreases false positives and recall ensures no vital are. To provide an overview of the model's performance, it classifies using accuracy as well as the F1 score given that the class imbalance. Results reveal that combined these metrics produce a detailed overview of the proposed segmentation method's efficiency and dependability for medical applications in MRI processing.

The proposed method demonstrates significant improvements in segmentation performance compared to K-Means and FCM methods. Specifically, it achieves an average improvement of 6.43% and 11.77% in the DSC parameter over K-Means and FCM, respectively shown in Table 1. Similarly, an average improvement of 11.45% and 20.63% is observed in the JI parameter. From Table 2, the proposed method shows an average improvement of 13.18% and 22.77% in precision compared to K-Means and FCM. Additionally, it achieves 0.21% and 0.52% improvements in accuracy, and 5.69% and 11.01% enhancements in F1-score over the same methods. As highlighted in Table 3, the proposed method also exhibits a reduction in error rate by 40.95% and 62.68% compared to K-Means and FCM, respectively. These findings underscore the effectiveness of the proposed method in segmenting brain MR images more accurately and reliably than K-Means and FCM methods.

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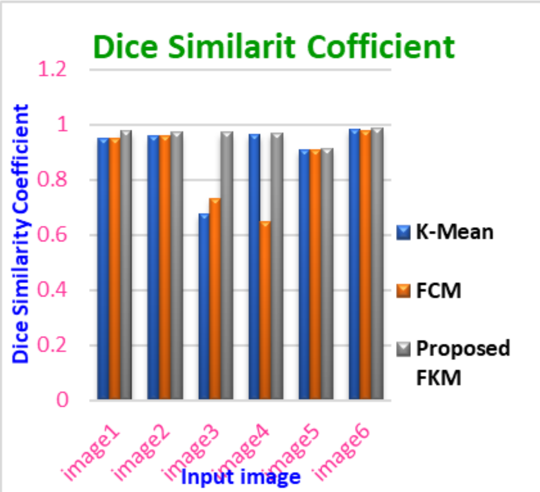

Figure 5. Graphical analysis of DSC between K-Mean, FCM and proposed FKM.

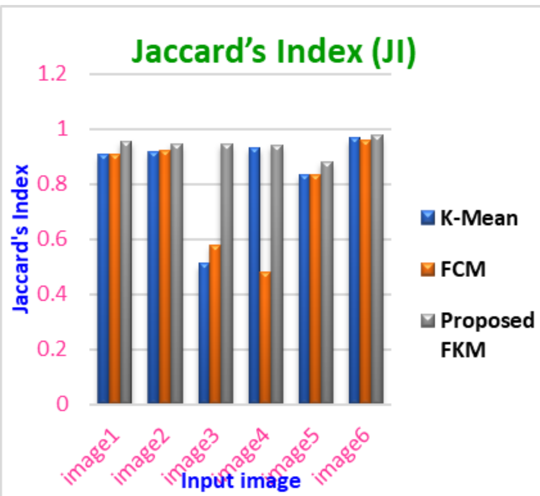

Figure 6. Graphical analysis of JI between K-Mean, FCM and proposed FKM.

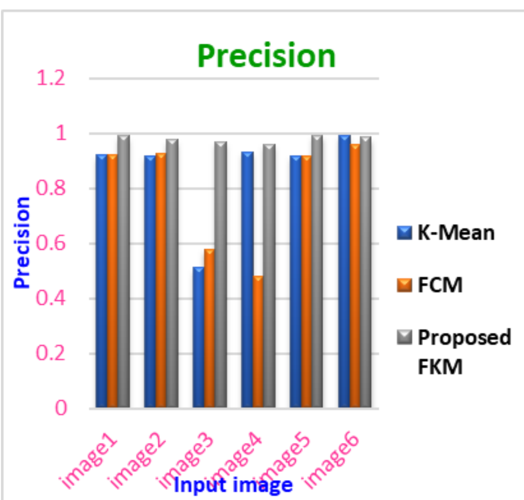

Figure 7. Graphical analysis of Precision between K-Mean, FCM and proposed FKM.

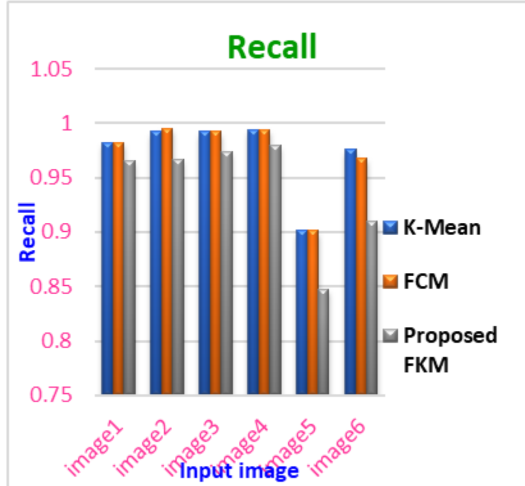

Figure 8. Graphical analysis of Recall between K-Mean, FCM and proposed FKM.

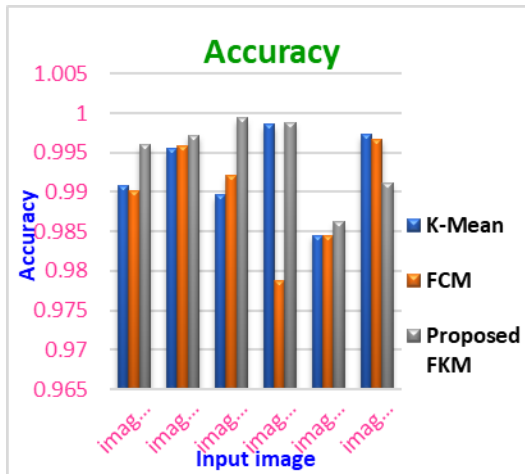

Figure 9. Graphical analysis of Accuracy between K-Mean, FCM and proposed FKM.

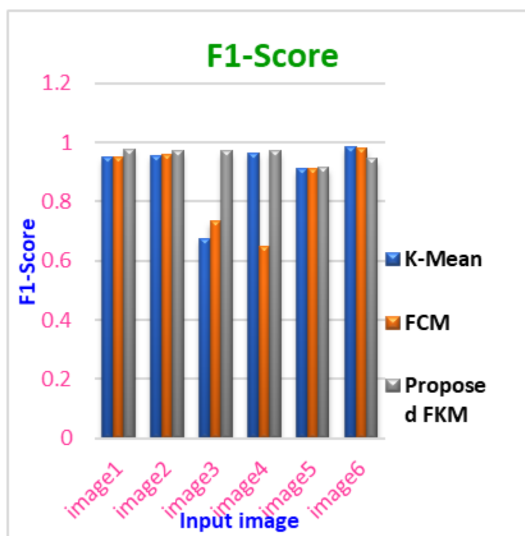

Figure 10. Graphical analysis of F1-Score between K-Mean, FCM and proposed FKM.

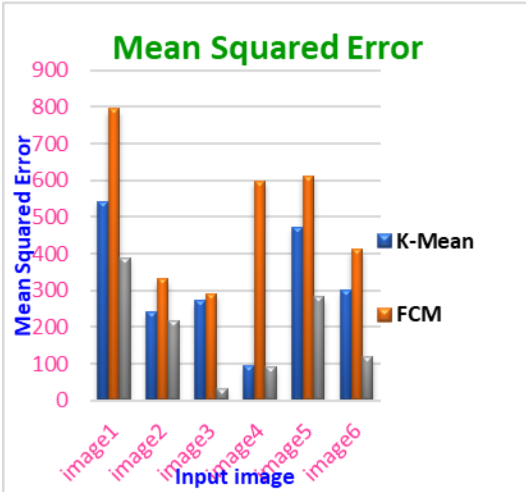

Figure 11. Graphical analysis of MSE between K-Mean, FCM and proposed FKM.

The graphical analysis of performance metrics, including DSC, JI, accuracy, precision, recall, F1-score, and MSE, comparing K-Means, FCM, and the proposed FKM method, is presented in Figures 5 to 11. The proposed method, leveraging K-Means++ and fuzzy membership functions, demonstrates enhanced performance across all evaluated parameters.

4.3 Baseline model comparison

Table 4 presents the clustering accuracy of the proposed model compared to [33–48] different state-of-the-art algorithms. In most cases, the proposed algorithm consistently demonstrates superior accuracy compared to the other methods.

5. CONCLUSION

The advanced preprocessing and morphological enhancement along with integration of Fuzzy K-Means clustering for enhancement are presented in this research which is an improved Brain MRI segmentation approach. FKM clustering on the filtered Gaussian representation reduces noise and increases intensity to improve the segmentation accuracy and to faster convergence. Median filtering and morphological opening also enhance region refinement of segmented regions which help remove noise from the image and help improve structural clarity. Experimental results show that the proposed method performs much better than the common techniques such as K-Means and FCM in preserving the brain contours and noisy regions. This helps in correct analysis of medical images for accurate diagnosis and assessment of brain conditions. Further ways to advance the method may be to integrate deep learning models for the adaptive, real-time processing and/or extend to the multimodal imaging. Healthcare applications could not only be further automated but also be cloud based, and implementation would further improve healthcare applications by making segmentation more efficient and precise for early neurological disorder detection as well as clinical decision making.

REFERENCES:

[1] T. A. Soomro et al., “Image segmentation for MR brain tumor detection using machine learning: a review,” IEEE Rev. Biomed. Eng., vol. 16, pp. 70–90, 2022.

[2] J. S. U. Rahman and S. K. Selvaperumal, “Integrated approach of brain segmentation using neuro fuzzy k-means,” Indones. J. Electr. Eng. Comput. Sci., vol. 29, no. 1, pp. 270–276, 2023.

[3] C. A. Sari, W. S. Sari, and H. Rahmalan, “A Combination of K-Means and Fuzzy C-Means for Brain Tumor Identification,” Sci. J. Informatics, vol. 8, no. 1, pp. 76–83, 2021.

[4] N. Grover, “A study of various Fuzzy Clustering Algorithms,” Int. J. Eng. Res., vol. 3, pp. 177–181, Dec. 2014, doi: 10.17950/ijer/v3s3/310.

[5] M. S. Z. Sarker, T. W. Haw, and R. Logeswaran, “Morphological based technique for image segmentation,” Int. J. Inf. Technol., vol. 14, no. 1, pp. 55–80, 2008.

[6] P. Sarah, S. Krishnapriya, S. Saladi, Y. Karuna, and D. P. Bavirisetti, “A novel approach to brain tumor detection using K-Means++, SGLDM, ResNet50, and synthetic data augmentation,” Front. Physiol., vol. 15, p. 1342572, 2024.

[7] K. Wisaeng, “Breast cancer detection in mammogram images using K–means++ clustering based on cuckoo search optimization,” Diagnostics, vol. 12, no. 12, p. 3088, 2022.

[8] H. Biswas, S. E. Umbaugh, D. Marino, and J. Sackman, “Comparison of K-means and K-means++ for image compression with thermographic images,” in Thermosense: Thermal Infrared Applications XLIII, 2021, pp. 209–214.

[9] S. Krishnakumar and K. Manivannan, “Effective segmentation and classification of brain tumor using rough K means algorithm and multi kernel SVM in MR images,” Jun. 01, 2021, Springer Science and Business Media Deutschland GmbH. doi: 10.1007/s12652-020-02300-8.

[10] J. S. U. Rahman, S. M. Hussain, F. Anjum, T. Naz, and K. S. Sathish, “Brain image segmentation using K mean segmentation and

fuzzy C-means (FCM) algorithm to improve efficiency of tumor detection," in Proceedings of 5th International Conference on Sustainable Innovation In Engineering And Technology 2023, AIP Publishing, Aug. 2024, p. 020155. doi: 10.1063/5.0229431.

[11] S. Dalal et al., "An Efficient Brain Tumor Segmentation Method Based on Adaptive Moving Self-Organizing Map and Fuzzy K-Mean Clustering," Sensors, vol. 23, no. 18, Sep. 2023, doi: 10.3390/s23187816.

[12] D. M. Kumar, D. Satyanarayana, and M. N. G. Prasad, "An improved Gabor wavelet transform and rough K-means clustering algorithm for MRI brain tumor image segmentation," Multimed. Tools Appl., vol. 80, no. 5, pp. 6939–6957, Feb. 2021, doi: 10.1007/s11042-020-09635-6.

[13] G. Anand Kumar and P. V Sridevi, "Brain tumor segmentation using chi-square fuzzy C-mean clustering," in Innovative Product Design and Intelligent Manufacturing Systems: Select Proceedings of ICIPDIMS 2019, 2020, pp. 857–865.

[14] J. Anitha and M. Kalaiarasu, "MRI Brain Tumor Segmentation with Intuitionist Possibilistic Fuzzy Clustering and Morphological Operations," Comput. Syst. Sci. Eng., vol. 43, no. 1, pp. 363–379, 2022, doi: 10.32604/csse.2022.022402.

[15] C. L. Chowdhary, M. Mittal, P. Kumaresan, P. A. Pattanaik, and Z. Marszalek, "An efficient segmentation and classification system in medical images using intuitionist possibilistic fuzzy C-mean clustering and fuzzy SVM algorithm," Sensors (Switzerland), vol. 20, no. 14, pp. 1–20, Jul. 2020, doi: 10.3390/s20143903.

[16] R. Khilkhal and M. Ismael, "Brain Tumor Segmentation Utilizing Thresholding and K-Means Clustering," in 2022 Muthanna International Conference on Engineering Science and Technology (MICEST), 2022, pp. 43–48. doi: 10.1109/MICEST54286.2022.9790103.

[17] A. Thakur, P. Pudke, R. Das, L. Suman, and P. Bansod, "Brain Tumor Segmentation Using K-means Clustering Algorithm." [Online]. Available: www.ijraset.com

[18] R. Ghulam et al., "A U-Net-Based CNN Model for Detection and Segmentation of Brain Tumor," Comput. Mater. Contin., vol. 74, no. 1, pp. 1333–1349, 2023, doi: 10.32604/cmc.2023.031695.

[19] P. and M. S. Jaichandra Jadhavand Hari Charan, "Brain Tumor Diagnosis Using K-Means and Morphological Operations," in Proceedings of Data Analytics and Management , Z. and C. O. Khanna Ashishand Polkowski, Ed., Singapore: Springer Nature Singapore, 2023, pp. 507–515.

[20] H. Habib, M. Nawaz, A. Mehmood, M. Masood, T. Nazir, and R. Mahum, "Brain Tumor Segmentation and Classification using Machine Learning."

[21] H. Habib, R. Amin, B. Ahmed, and A. Hannan, "Hybrid algorithms for brain tumor segmentation, classification and feature extraction," J. Ambient Intell. Humaniz. Comput., vol. 13, no. 5, pp. 2763–2784, 2022, doi: 10.1007/s12652-021-03544-8.

[22] H. Krishna Mishra and M. Kaur, "Hare Krishna Mishra, Manpreet Kaur, Multi Class Brain Tumor Segmentation Based On K-Means Clustering Technique eISSN," vol. 20, pp. 1303–5150, doi: 10.48047/NQ.2022.20.17.NQ880187.

[23] K. Venkatachalam, V. P. Reddy, M. Amudhan, A. Raguraman, and E. Mohan, "An implementation of K-means clustering for efficient image segmentation," in 2021 10th IEEE international conference on Communication Systems and Network Technologies (CSNT), 2021, pp. 224–229.

[24] N. K. Yadav and M. Saraswat, "A novel fuzzy clustering based method for image segmentation in RGB-D images," Eng. Appl. Artif. Intell., vol. 111, p. 104709, 2022.

[25] J. Chaki and N. Dey, A beginner's guide to image preprocessing techniques. CRC Press, 2018.

[26] J. P. F. D'Haeyer, "Gaussian filtering of images: A regularization approach," Signal Processing, vol. 18, no. 2, pp. 169–181, 1989.

[27] S. Patro, "Normalization: A preprocessing stage," arXiv Prepr. arXiv1503.06462, 2015.

[28] L. A. Zadeh, "Fuzzy logic," Computer (Long. Beach. Calif)., vol. 21, no. 4, pp. 83–93, 1988.

[29] C.-T. Chang, J. Z. C. Lai, and M.-D. Jeng, "A fuzzy k-means clustering algorithm using cluster center displacement.," J. Inf. Sci. Eng., vol. 27, no. 3, pp. 995–1009, 2011.

[30] Cheng, "Brain Tumor Dataset figshare. https://doi.org/10.6084/m9.figshare.1512427.v5 ." Accessed: Dec. 01, 2024. [Online]. Available: https://figshare.com/articles/dataset/brain_tumor_dataset/1512427

[31] J. Bertels et al., "Optimizing the dice score and jaccard index for medical image segmentation: Theory and practice," in Medical Image Computing and Computer Assisted

Intervention–MICCAI 2019: 22nd International Conference, Shenzhen, China, October 13–17, 2019, Proceedings, Part II 22, 2019, pp. 92–100.

[32] G. Naidu, T. Zuva, and E. M. Sibanda, "A review of evaluation metrics in machine learning algorithms," in Computer Science On-line Conference, 2023, pp. 15–25.

[33] S. Bharat Dhumal and M. Tamboli, "Segmentation of Brain Tumor Using Different Clustering Algorithms," 2022. [Online]. Available: www.ijcrt.org

[34] M. Sangeetha, P. Keerthika, K. Devendran, S. Sridhar, S. S. Raagav, and T. Vigneshwar, "Brain tumor segmentation and prediction on MRI images using deep learning network," Int. J. Health Sci. (Qassim)., vol. 6, no. S2, pp. 13486–13503, 2022.

[35] P. G. Brindha, M. Kavinraj, P. Manivasakam, and P. Prasanth, "Brain tumor detection from MRI images using deep learning techniques," in IOP conference series: materials science and engineering, 2021, p. 12115.

[36] M. Aggarwal, A. K. Tiwari, M. P. Sarathi, and A. Bijalwan, "An early detection and segmentation of Brain Tumor using Deep Neural Network," BMC Med. Inform. Decis. Mak., vol. 23, no. 1, p. 78, 2023.

[37] O. Turk, D. Ozhan, E. Acar, T. C. Akinci, and M. Yilmaz, "Automatic detection of brain tumors with the aid of ensemble deep learning architectures and class activation map indicators by employing magnetic resonance images," Z. Med. Phys., vol. 34, no. 2, pp. 278–290, 2024.

[38] S. Ahuja, B. K. Panigrahi, and T. K. Gandhi, "Enhanced performance of Dark-Nets for brain tumor classification and segmentation using colormap-based superpixel techniques," Mach. Learn. with Appl., vol. 7, p. 100212, 2022.

[39] S. Shanthi, S. Saradha, J. A. Smitha, N. Prasath, and H. Anandakumar, "An efficient automatic brain tumor classification using optimized hybrid deep neural network," Int. J. Intell. Networks, vol. 3, pp. 188–196, 2022.

[40] R. Vankdothu and M. A. Hameed, "Brain tumor segmentation of MR images using SVM and fuzzy classifier in machine learning," Meas. Sensors, vol. 24, p. 100440, 2022.

[41] J. Walsh, A. Othmani, M. Jain, and S. Dev, "Using U-Net network for efficient brain tumor segmentation in MRI images," Healthc. Anal., vol. 2, p. 100098, 2022.

[42] A. Anaya-Isaza and L. Mera-Jiménez, "Data augmentation and transfer learning for brain tumor detection in magnetic resonance imaging," IEEE Access, vol. 10, pp. 23217–23233, 2022.

[43] S.-L. Lu, H.-C. Liao, F.-M. Hsu, C.-C. Liao, F. Lai, and F. Xiao, "The intracranial tumor segmentation challenge: Contour tumors on brain MRI for radiosurgery," Neuroimage, vol. 244, p. 118585, 2021.

[44] A. Deshpande, V. V Estrela, and P. Patavardhan, "The DCT-CNN-ResNet50 architecture to classify brain tumors with super-resolution, convolutional neural network, and the ResNet50," Neurosci. Informatics, vol. 1, no. 4, p. 100013, 2021.

[45] W. Wang, F. Bu, Z. Lin, and S. Zhai, "Learning methods of convolutional neural network combined with image feature extraction in brain tumor detection," IEEE access, vol. 8, pp. 152659–152668, 2020.

[46] P. K. Mallick, S. H. Ryu, S. K. Satapathy, S. Mishra, G. N. Nguyen, and P. Tiwari, "Brain MRI image classification for cancer detection using deep wavelet autoencoder-based deep neural network," IEEE Access, vol. 7, pp. 46278–46287, 2019.

[47] G. Song et al., "A noninvasive system for the automatic detection of gliomas based on hybrid features and PSO-KSVM," IEEE Access, vol. 7, pp. 13842–13855, 2019.

[48] M. S. Alam et al., "Automatic human brain tumor detection in MRI image using template-based K means and improved fuzzy C means clustering algorithm," Big Data Cogn. Comput., vol. 3, no. 2, p. 27, 2019.

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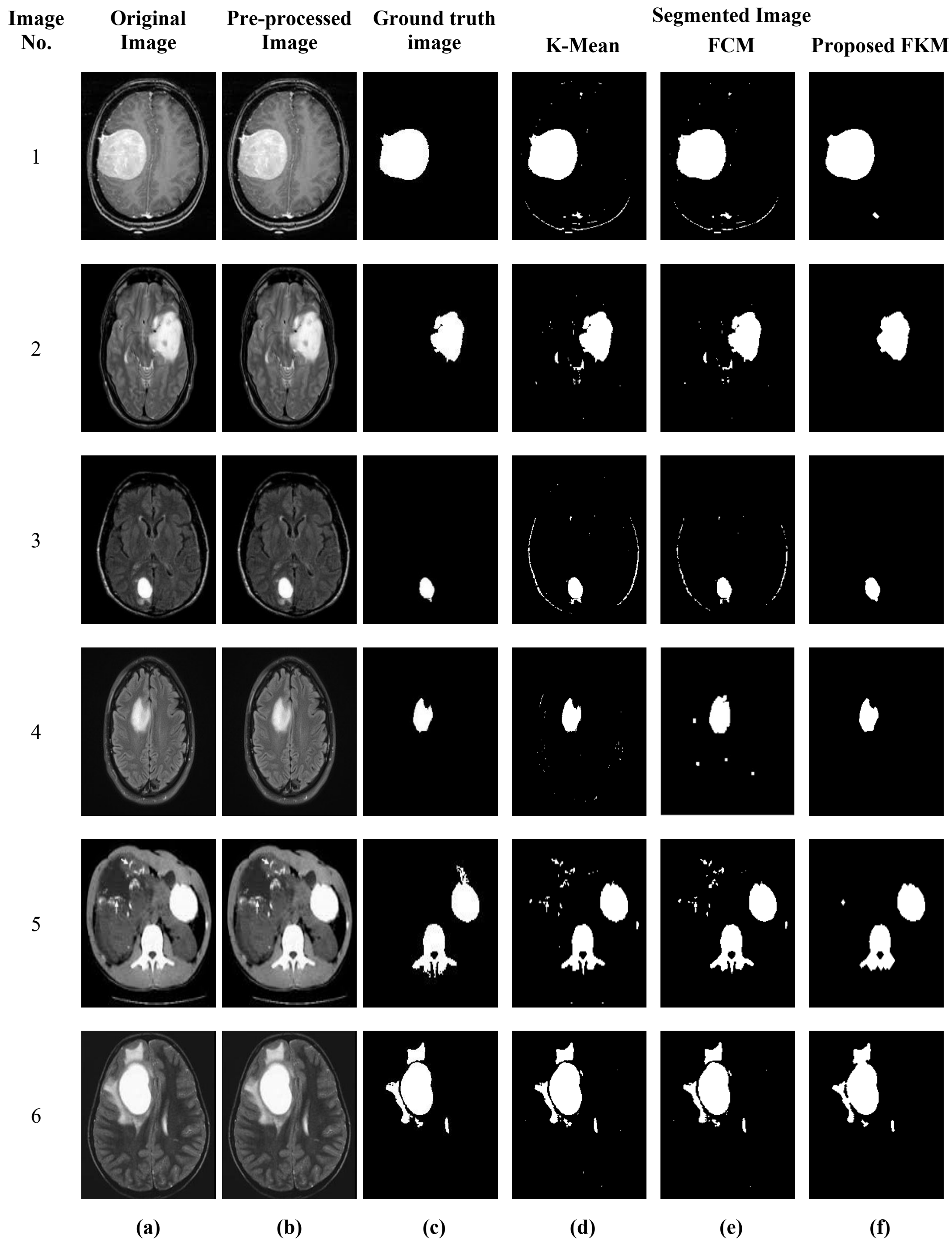

Figure 3. Segmentation results a) Original b) Preprocessed c) Ground truth d) K-Mean e) FCM f) Proposed FKM images

Table 1. DSC, JI parameter evaluation between K-Mean, FCM and proposed FKM

Image No.	Dice Similarity Coefficient (DSC)			Jaccard's Index (JI)		
	K-Mean	FCM	Proposed FKM	K-Mean	FCM	Proposed FKM
1	0.9507	0.9507	0.9776	0.9060	0.9060	0.9562
2	0.9573	0.9600	0.9724	0.9181	0.9232	0.9464
3	0.6760	0.7331	0.9721	0.5106	0.5786	0.9457
4	0.9647	0.6486	0.9707	0.9317	0.4800	0.9430
5	0.9105	0.9105	0.9145	0.8357	0.8357	0.8825
6	0.9839	0.9802	0.9861	0.9684	0.9612	0.9778
Average	***0.9072***	***0.8639***	***0.9656***	***0.8451***	***0.7808***	***0.9419***

Table 2. Precision, Recall, Accuracy & F1-Score between K-Mean, FCM and proposed FKM

Img No.	Precision			Recall			Accuracy			F1-Score		
	K-Mean	FCM	Proposed FKM	K-Mean	FCM	Proposed FKM	K-Mean	FCM	Proposed FKM	K-Mean	FCM	Proposed FKM
1	0.9208	0.9209	0.9899	0.9825	0.9821	0.9656	0.9908	0.9902	0.9960	0.9507	0.9502	0.9776
2	0.9181	0.9270	0.9781	0.9924	0.9955	0.9669	0.9955	0.9958	0.9972	0.9573	0.9600	0.9724
3	0.5106	0.5786	0.9699	0.9924	0.9922	0.9743	0.9896	0.9921	0.9994	0.6760	0.7331	0.9721
4	0.9317	0.4800	0.9617	0.9941	0.9942	0.9797	0.9986	0.9788	0.9988	0.9647	0.6486	0.9707
5	0.9195	0.9195	0.9928	0.9016	0.9016	0.8477	0.9845	0.9845	0.9862	0.9105	0.9105	0.9145
6	0.9921	0.9612	0.9852	0.9759	0.9682	0.9101	0.9973	0.9967	0.9912	0.9839	0.9802	0.9461
Avg	***0.8655***	***0.7979***	***0.9796***	***0.9732***	***0.9723***	***0.9407***	***0.9927***	***0.9897***	***0.9948***	***0.9072***	***0.8638***	***0.9589***

Table 3. MSE parameter evaluation between K-Mean, FCM and proposed FKM

Image No.	Mean Square Error (MSE)		
	K-Mean	FCM	Proposed FKM
1	542.3154	795.7669	389.629
2	240.3026	330.5138	218.6853
3	271.3650	290.8848	32.3248
4	93.2420	598.7965	92.7043
5	473.4252	611.8281	282.4396
6	299.8006	411.3561	118.2265
Average	***320.0751***	***506.5243***	***189.0015***

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Table. 4 MRI Brain image clustering accuracy analysis

References	Model	Dataset	Performance Remarks
[33]	K-Means Clustering, Fuzzy C Means Clustering	100 MRI images	94% Accuracy with K-Means 96% Accuracy with Fuzzy C-Means
[34]	Pre-trained model InceptionResNetv2	819 MRI images dataset	98.03% Accuracy
[35]	Self-defined ANN and CNN model	2065 MRI images Github	97.13% Accuracy
[36]	CNN model FCN Model Enhanced ResNet	369 images of BraTS2020 dataset	85.4% Accuracy with CNN 81.4% Accuracy with FCN 91.3% Accuracy with ResNet Model
[37]	ResNet50, VGG19, InceptionV3, MobileNetand Class Activation Maps (CAMs)	3441 MRI images	96.45% with ResNet50, 93.40% with VGG19, 85.03% with InceptionV3 and 89.34% with MobileNet
[38]	DarkNet Model	T1W-CE MRI dataset	98.84% Accuracy
[39]	Convolution neural network and long short-term memory	1000 MRI images dataset	97.5% Accuracy
[40]	Adaptive Neuro-Fuzzy Inference System and Support Vector Machine	MRI images dataset	85.74% Accuracy
[41]	U-Net model	BRATS dataset	89% Accuracy
[42]	ResNet50 network	Cancer Genome Atlas Low-Grade Glioma (TCGA-LGG) database	92.34% Accuracy
[43]	NN U-Net	ICTS dataset	87.23% Accuracy
[44]	Discrete Cosine Transform (D.C.T.), CNN, and ResNet50	Toloharbour Dataset	98.14% Accuracy
[45]	Convolutional neural network	GBM data set	98% Accuracy
[46]	Deep neural networks (DNN.)	RIDER (Reference Image Database)	0.93 ± 0.14 Accuracy
[47]	Kernel support vector machine (KSVM)	Shengjing Hospital of China Medical	97.83% Accuracy
[48]	Template-based K means, and Fuzzy C mean	MRI images	97.5% Accuracy
Proposed method with Modified K-Means++ and Fuzzy Membership function		3064 MRI images from figshare.com	**98.91% Accuracy**