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A Systematic Review of Brain MRI Segmentation and Uncertainty Modeling Using Evidence Theory with Implementation of Fuzzy Clustering and Fuzzy Inference Systems Methods

Fahad B. Sedeeq*, Hadeel K. Aljobouri, Jamal A. Hasan

Biomedical Engineering Department, College of Engineering, Al-Nahrain University, Baghdad 10011, Iraq

Corresponding Author Email: fahad_alnuaimy@yahoo.com

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ABSTRACT

Image segmentation, the process of partitioning an image into its constituent parts, is a pivotal step in image processing, particularly with respect to brain MRI images. This operation's complexity is magnified due to inherent uncertainties, which may arise from factors such as noise and intensity non-uniformity. In this study, a systematic review of both non-fuzzy and fuzzy medical image segmentation methods, with a focus on brain MRI images, was undertaken. Practical application of fuzzy clustering and fuzzy inference systems were demonstrated using freely accessible simulated data. This paper presents an emphasis on uncertainty modeling techniques, highlighting the potential of belief structure integration as a significant approach for future hybrid medical image segmentation techniques. The fusion of diverse information sources through this combination is posited to enhance both the accuracy and robustness of uncertainty handling, critical aspects in medical image analysis.

1. INTRODUCTION

In the vast landscape of medical diagnostics, imaging technologies play a pivotal role by providing invaluable insights into the human body's internal workings. Within this scope, segmenting medical images, particularly in the context of Magnetic Resonance Imaging (MRI), is a fundamental challenge. MRI image segmentation holds paramount importance as it enables the precise delineation of anatomical structures and lesions, enhancing the diagnostic and clinical utility of medical images. However, this task is complex due to various factors such as intensity non-uniformity (INU), patient movement, and partial volume effect (PVE). These challenges, intertwined with the nuances of pixel brightness intensity, highlight the intricate nature of medical image segmentation, demanding sophisticated techniques to extract meaningful information effectively. Brain MRI segmentation holds immense importance in the medical field due to its pivotal role in precise anatomical mapping and pathological identification. Accurate segmentation allows for detailed analysis of brain structures and lesions, aiding in the diagnosis, treatment planning, and monitoring of various neurological disorders, including tumors, dementia, and stroke. Moreover, it facilitates the assessment of treatment efficacy and disease progression, guiding clinicians in making informed decisions. These applications underscore the critical role of brain MRI segmentation in advancing medical research and improving patient outcomes. Researchers have proposed various hardware and software methods to address these issues and improve brain MRI segmentation [1]. Generally, software-based methods fall into two categories: registration-based and brightness-based. In registration-based methods, also known as atlas-based methods, a transformable atlas is applied to an image, and the tissue labels are transferred. The advantage of atlas-based methods is that brain structures can be extracted without additional costs [2]. However, in some cases, this feature can lead to a simplistic and meaningless segmentation. In brightness-based methods, individual pixels are classified. Interpretation tools are required to address the issue of overlapping brain and non-brain tissues [3]. Other segmentation methods include surface-based approaches such as transformable active contour models, coplanar sets, active template models, and active appearance models [4]. As this work focuses on brightness-based methods, other segmentation methods will not be delved into. Additionally, existing brightness-based methods can be categorized into non-fuzzy and fuzzy methods, but the focus will be on fuzzy methods.

2. BRAIN MRI SEGMENTATION

2.1 Non-fuzzy methods

Non-phased illumination intensity-based methods use standard classifications such as the Gaussian mixture model, K-Means, and nearest neighbor. However, due to uncertainty in expressing pixel brightness, these methods may not perform well without preprocessing. Methods that cannot model uncertainty usually require pre-processing, such as modeling non-uniform illumination intensity. Therefore, the success of non-phased methods depends on appropriate models and methods chosen to improve the non-uniformity of lighting intensity, noise, and other disruptive phenomena [5]. Non-uniform illumination intensity varies drastically between individuals and even between slices of the same individual, making it necessary to correct brightness intensity separately for each image [6]. Proposed models only address a part of the non-uniformity, as the sources of non-uniformity differ, and no single model can completely address the issue. As this research focuses on methods that can model and manage uncertainty, fuzzy methods commonly used in brain MRI segmentation will be investigated further.

2.2 Fuzzy methods

To achieve satisfactory results in brain MRI segmentation, a method capable of dealing with uncertainty is necessary. Non-phased methods relied on pre-processing, but due to the variety of MRI problems and the complexity of modeling error sources in MRI, these methods may not always produce the desired results [7]. Alternatively, researchers have developed fuzzy methods that can model and manage uncertainty. In these methods, different areas of the image are considered fuzzy sets, allowing a pixel (voxel) to potentially belong to multiple classes up to a certain extent. The theory of fuzzy sets [8] is utilized to model effective uncertainty in pixel brightness intensity.

There are several fuzzy segmentation methods in image processing [9, 10]. Among them, fuzzy clustering and methods based on fuzzy rules [11, 12] have received more attention in brain MRI segmentation. Other proposed methods include fuzzy thresholding, fuzzy stochastic Markov, and fuzzy region growth for image segmentation. In the following, two important applications of fuzzy methods in brain MRI segmentation will be examined: methods based on fuzzy clustering and methods based on fuzzy rules as shown in Figure 1.

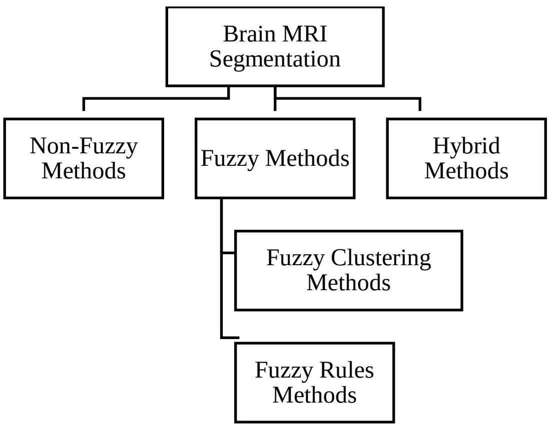


Figure 1. Brain MRI segmentation

2.2.1 Fuzzy clustering in brain MRI segmentation

The segmentation of brain MRI images using fuzzy clustering has been an actively researched topic due to the challenges posed by the non-uniformity of illumination intensity and noise in such images. Many methods have been proposed, each with their strengths and weaknesses. One approach proposed a modified Fuzzy C-Means (*m*-FCM) algorithm for MR brain image segmentation is presented to overcome the uncertainty caused by segmentation into White Matter (WM), Gray Matter (GM) and Cerebrospinal Fluid (CSF) in MR images. The primary issue is the enormous number of chaotic maps that prevent a selection of the most promising chaotic map for some specific problem [13]. Other researchers have focused on incorporating spatial information into fuzzy clustering. For example, a system that used to smooth membership values using spatial information [14]. More recent methods have focused on optimizing the objective function of fuzzy clustering. For example an optimized clustering method by clustering images using hierarchical/agglomerative clustering algorithm [15]. A method known as Bias-corrected fuzzy c-means (BCFCM) was presented. Ahmed's method is more resistant to noise and brightness inconsistency than the classical fuzzy clustering method, but since it uses the information of neighboring pixels linearly, it causes blurring in the final results [16]. However, these methods could cause blurring in the results. To address this issue, another method to improve fuzzy clustering and overcome the blurring of the final image [17], this method called Iterative Fuzzy C-Means (IFCM). In IFCM, a value based on the degree of similarity with the neighborhood was added to the distance of the pixels from the centers of the floors. These improved methods required more time to obtain the result than classic FCM. To address this issue, some researchers have focused on increasing the speed of these methods while maintaining their accuracy. However, these methods still had their limitations, such as the need for parameter tuning [18].

In another study, a method called fuzzy c-means clustering with spatial information (FCMSI) was proposed [19], in which the sum of the membership values of the neighbors of a pixel to each cluster was added to the membership value of that pixel in that respective cluster. Additionally, an algorithm that utilized both local and non-local information simultaneously to enhance resistance against the uncertainty of brain MRI was proposed [20]. Recent studies have combined fuzzy clustering with other techniques to improve segmentation accuracy, although fuzzy clustering optimization alone cannot model the uncertainty in pixel brightness. For instance, in a recent study, a completely automatic method for brain MRI segmentation based on optimized fuzzy clustering was proposed. This method used a homomorphic filter to correct for the non-uniformity of brightness and selected the initial centers of clusters based on the image histogram. Ambiguous pixels, defined as pixels whose membership values to two clusters differed by less than 0.15, were identified, and their neighboring pixels were re-examined to correct the ambiguity at the border between clusters. However, one limitation of this method was that the neighborhood information for ambiguous pixels contained uncertainty and may not have been used explicitly [21].

In other studies, such as pixels of T2-weighted images and proton density PD-weighted images, which are simultaneously prepared from a slice of the brain, are clustered using FCM. Then, by defining certain rules and based on the results obtained from clustering, mass functions are calculated. Finally, the obtained mass functions are combined using fuzzy relations and the result is obtained. Although this method benefited from the use of pixel neighborhood information, its success heavily depended on the coordination of different MRI images, making precise pre-processing necessary [22]. The major weakness of combination-based methods in brain MRI segmentation was their inability to model the uncertainty of pixel brightness.

Alternatively, some researchers explored assigning membership values of samples to the desired cluster. For instance, a clustering algorithm named possibilistic c-means (PCM) was proposed, in which the degree of membership of the i-th sample to the j-th cluster is only a function of the distance of that sample from the desired cluster [23] However, a major weakness of this method was the lack of consideration of pixel neighborhood information.

Inspired by combination of fuzzy-possibilistic c-means (FPCM) information from different images is used for MRI segmentation [24], but this approach still suffered from the lack of neighborhood information and the need for different MRI images.

Another research series based on PCM and evidence theory presented algorithms for information clustering with evidential c-means (ECM) being the only algorithm used for brain MRI segmentation in [25-27]. Despite their flexibility, these algorithms had practical limitations in image segmentation, including the non-use of neighborhood information and the need for multiple MRI images, making them less suitable for brain MRI segmentation.

2.2.2 Fuzzy rules in brain MRI segmentation

Fuzzy rules are fundamental components of fuzzy logic systems used for decision-making and inference. They describe the relationships between input variables, typically using linguistic terms and fuzzy sets, and define how these inputs contribute to the determination of output variables. Fuzzy rules are expressed in the form of "if-then" statements, where the "if" part represents the conditions or antecedents, and the "then" part signifies the consequent or output. By incorporating expert knowledge into a set of fuzzy rules that describe relationships between input variables (e.g., pixel intensities in an MRI image) and output variables (e.g., tissue labels). Each rule consists of linguistic variables and membership functions that quantify the degree of membership of input variables to specific linguistic terms (e.g., "high intensity," "low intensity"). The system then combines these rules using a fuzzy inference engine to make decisions about the output variables, ultimately leading to the segmentation of the MRI image.

A crucial component of fuzzy rule-based systems is the Fuzzy Inference System (FIS). The FIS comprises three main stages: Fuzzification: This stage involves mapping the input data (e.g., pixel intensities) into fuzzy sets using membership functions, converting crisp data into fuzzy linguistic variables. Rule Evaluation: The fuzzy rules, defined by experts, are evaluated based on the degree of match between the input data's fuzzy sets and the linguistic terms in the rules. This process quantifies the applicability of each rule. Defuzzification: Finally, the system combines the results of rule evaluations to produce a crisp output or segmentation result. This stage involves converting the fuzzy output into a usable, quantitative result. The two most common types of FIS are Mamdani and Sugeno (or Tsukamoto). In contrast to the Mamdani FIS, the Sugeno FIS uses linear or constant functions in the consequent part of the rules, allowing it to produce crisp (numerical) outputs rather than fuzzy sets.

One of the first studies to use the idea of fuzzy rules (or a set of if-then rules) in brain MRI image segmentation is a two-stage system was proposed. In the first stage, pixels are assigned to membership functions and then, based on a set of if-then rules, only pixels with high membership values are classified. This classification is used as a preliminary preparation for the next step. In the second stage, uncertain pixels are classified using fuzzy clustering [27].

In another study, a segmentation method based on anatomical knowledge encoded in the form of fuzzy rules was proposed. In the proposed system, the main structures are identified first, and then the segmentation operation is completed using the distance relationships between different areas and targeted areas resulting from the previous step [28].

Another study based on Fuzzy Inference System FIS was proposed to identify the white matter of the brain in elderly people. The proposed system uses the information combination of three categories of T2-weighted images, PD-weighted images, and Fluid Attenuated Inversion Recovery (FLAIR) images for segmentation. The FIS uses three categories of verbal variables to classify pixels [29].

Whereas a fuzzy system based on fuzzy rules was proposed. A combination of image histogram features and features based on neighborhood distance are used. Since one of the parts of FIS is fuzzy rules, the way to obtain these rules can have a significant impact on the performance of the system and its generalization ability. For example, in the last research mentioned above, considering that the rules are obtained manually, there is a fundamental uncertainty about the generalization power of the proposed method [30].

Although fuzzy rule-based systems, powered by Fuzzy Inference Systems, offer a valuable approach for brain MRI segmentation due to their ability to handle uncertainty, adaptability, and potential to incorporate expert knowledge, they also come with complexities and computational considerations that should be carefully managed in practice.

3. EVIDENCE THEORY

Evidence theory, introduced by Dempster and later developed by Shafer which is why it is also named as Dempster-Shafer (DS) Theory [31, 32], has attracted the attention of many researchers. It has different applications in medical diagnosis, object classification, information synthesis and retrieval, goal tracking, process engineering, quality control, e-commerce, securities evaluation, knowledge management, and mineral resources search, among others. In DS, uncertainty is represented using a Basic Probability Assignment (BPA) function, denoted as μ. For a set of possible outcomes (usually referred to as elements of a frame of discernment), this function assigns a mass (probability measure) to each subset of the frame of discernment. Mathematically, for a frame of discernment Ω, the BPA function μ is defined as:

$$\mu: 2^{\Omega} \dashrightarrow [0,1] \; where \; \mu(\phi) = 0 \; and \; \sum_{A \subseteq \Omega} \mu(A) = 1 \qquad (1)$$

where, $\emptyset$ is the null element and $\mu(\emptyset)$ represents the degree of uncertainty or the belief that none of the possible outcomes in the frame of discernment have occurred.

When combining evidence from multiple sources, Dempster's Rule is used to combine the BPAs. Given two BPA functions, μ1 and μ2, Dempster's Rule calculates the combined BPA, μ12, as follows:

$$(\mu 1 \oplus \mu 2)(A) = \sum_{B \cap C = A} \mu 1(B) . \mu 2(C) \qquad (2)$$

From the BPA function, we can derive two important measures: Belief Function (*Bel*) which represents the probability of an event or hypothesis being true. *Bel(A)* is calculated by summing the masses of all subsets that contain

A.

$$Bel(A) = \sum_{B|B\subseteq A} \mu(B), Bel(\emptyset) = 0, Bel(\Omega) = 1 \tag{3}$$

And Plausibility Function (*Pls*) which represents the lower probability bound of an event being true. *Pls*(*A*) is calculated by summing the masses of all subsets that intersect with *A*.

$$Pls(A) = \sum_{B|B\cap A\neq\emptyset} \mu(B), Pls(\emptyset) = 0, Pls(\Omega) = 1 \tag{4}$$

DS evidence theory is valuable in situations where information comes from various sources, each with its own level of reliability and uncertainty. It allows for the integration of evidence to make informed decisions, particularly when traditional probabilistic methods are insufficient due to uncertainty or lack of data. A closer examination of the scientific literature reveals two distinct research areas. In the first category, researchers leverage the theory's benefits, such as knowledge and uncertainty modeling, and the law of evidence combination, to address different problems without delving into the theory's theoretical underpinnings. This approach focuses on investigating sources of human knowledge-related uncertainty in the problem and modeling them based on the theory of evidence. Since the sources of uncertainty can stem from feature extraction, the reasoning that governs the system and the classification output that leads to a decision.

The initial confidence assessments from various classifiers were consolidated using DS evidence theory, considering the accuracy of three specific classifiers: support vector machine (SVM), Random Forest, and k-nearest neighbor (KNN). The effectiveness of the machine learning methods was assessed in relation to accuracy, sensitivity, specificity, and the area under the curve. By leveraging DS evidence theory, the integration of diverse classifier outputs is achieved, effectively addressing the segmentation challenges associated with MRI images [33]. DS evidence theory aids in managing uncertainty related to feature extraction and decision-making processes, thereby achieving precise tumor segmentation which consequently addresses the time-consuming and error-prone task of manually segmenting brain tumors from 3D multimodal magnetic resonance images (MRI). The aim is to develop two automated approaches for accurate segmentation, comparable to manual results. The segmentation process involves using three weighted MR feature images (enhanced T1, (PD), and T2) for each axial slice through the head [34]. All mentioned methods in brain MRI segmentation have been listed with limitations of each type as shown in Table 1.

DS evidence theory is also applied in the identification of anti-personnel mines remaining from wars [35]. In the proposed method, information from two ground-penetrating radar sensors and a metal detector is combined to provide a robust response. The method generates uncertainty depending on human knowledge, resulting from the use of different images with different characteristics, which evidence theory models. Additionally, the theory is used to classify and identify textures in images [36]. Given that texture pixels do not have clear borders, using neighboring pixels' information aids texture identification. The proposed solution models the uncertainty caused by the information of neighboring pixels using evidence theory and then reduces it by using Demaster's law of combination. In the study [37], DS evidence theory is used to investigate hidden corrosion in aircraft covering connections. The proposed algorithm employs statistical features extracted from X-Ray images and a K-Means classifier to obtain preliminary results. The results are then combined using evidence theory. The use of various features extracted from images leads to uncertainty related to human knowledge. Another area where evidence theory finds application is in the safety assessment of spaceship landing sites [38]. The method combines information from several sensors to estimate the safety degree of landing site candidates while managing uncertainty. Compared to other methods, the proposed approach is simple to implement and adaptable to real conditions. Some key features of evidence theory were reviewed. This theory encompasses powerful aspects such as incorporating uncertainty and imprecision into the model, accounting for partial or global ignorance, calculating conflicts between images, and allowing for the incorporation of prior information [39].

The uncertainty related to human knowledge arises from the use of relevant reasoning. This research explores examples that are more consistent with reality than those in previous studies. The study employs two concepts: inconsistency weight assessment and decision frame development. Evidence theory was used to identify abuse in mobile telecommunication networks. Belief functions are estimated using certain rules and input evidence, leading to the generation of B-type uncertainty[40].

4. APPLICATIONS OF SELECTED FUZZY METHODS

In this study, fuzzy logic was applied for MRI brain image edge detection, validated using the Simulated Brain Database (SBD) from Brain Web. The SBD, containing realistic MRI data volumes, served as a known ground truth for evaluation. The method involved interactive thresholding, grayscale conversion, filtering, and masking for skull stripping. A Mamdani-type fuzzy inference system (FIS) with specific rules was employed to highlight edges in the images. This approach, validated against the SBD, demonstrates the efficacy of fuzzy logic in precise edge detection for medical imaging applications [41]. First, the MRI skull strip was done by interactively selecting a threshold value from the image based on a user-selected pixel's intensity, then converting the image to grayscale, thresholds it using the selected value, and then applying filtering, hole filling, and masking, to isolate and restore the largest connected brain region. Then a series of image processing techniques to obtain the gradient image along the x and y axes. Next, this gradient used images as input to a fuzzy logic system for edge detection. Specifically, a Mamdani-type fuzzy inference system (FIS) with two inputs was presented, Imgx and Imgy, representing the gradient image along the x and y axes, respectively. The FIS had one output, Iout, which represented the degree of membership of each pixel to an edge. Gaussian membership functions were used for the input variables and triangular membership functions for the output variable. The FIS consisted of two rules, which defined the conditions for assigning pixels to the white (edge) or black (non-edge) regions. Finally, the FIS was applied to the gradient image to obtain a binary image with edges highlighted. The results of our analysis demonstrate the potential of fuzzy logic systems for edge detection in medical imaging applications.

Table 1. Fuzzy methods in brain MRI segmentations

Author	Fuzzy Method in Segmentations	Limitations
Ghosh et al. [13]	a modified Fuzzy C-Means (*m*-FCM) algorithm for MR brain image segmentation	enormous number of chaotic maps prevent a selection of the most promising chaotic map for some specific problem
Attalah et al. [14]	smoothing membership values using spatial information	Uncertainty
Pathak et al. [15]	optimized clustering method by clustering images using hierarchical/agglomerative	Blurring
Ramudu et al. [16]	Improved FCM (IFCM)	blurring in the final results
Kannan and Anusuya [17]	Hierarchical Fuzzy Clustering Algorithm	Questionable Accuracy
Gomathi et al. [19]	FCMSI	Questionable Accuracy
Abd El Kader et al. [20]	combined fuzzy clustering with other techniques to improve segmentation accuracy	fuzzy clustering optimization alone cannot model the uncertainty in pixel brightness.
Hussain et al. [21]	MRI segmentation based on optimized fuzzy clustering was proposed.	The lack of use of pixel neighborhood information
Mehrotra at al. [22]	FPCM combination	The lack of use of pixel neighborhood information
Almadhoun et al. [23]	clustering algorithm named PCM	lack of consideration of pixel neighborhood information
Praveena et al. [24]	combination of FPCM	lack of neighborhood information
Alagarsamy et al. [27]	two-stage system	only pixels with high membership values are classified
Murugachandravel and Anand [28]	anatomical knowledge encoded in the form of fuzzy rules.	Uncertainty
Zhang [29]	(FIS) proposed to identify the white matter of the brain in elderly people.	Uncertainty
Liu et al. [30]	Fuzzy C-Means + Evidence Theory	Uncertainty
Demidova and Liliya [33]	Evidence theory	Uncertainty
Wafa and Zagrouba [34]	develop two automated approaches for accurate segmentation, comparable	Time consumption

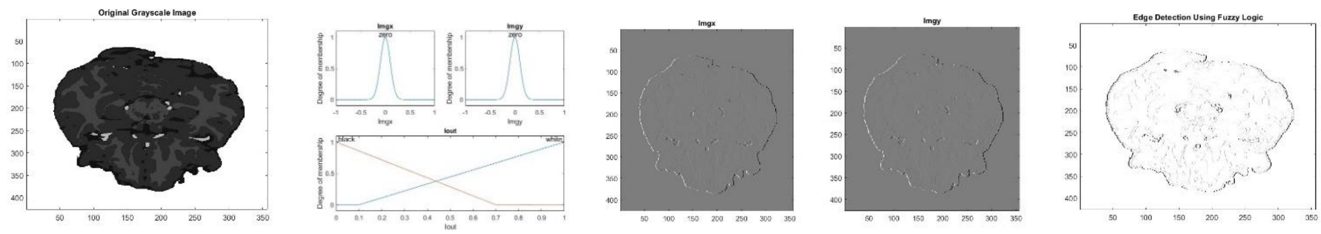
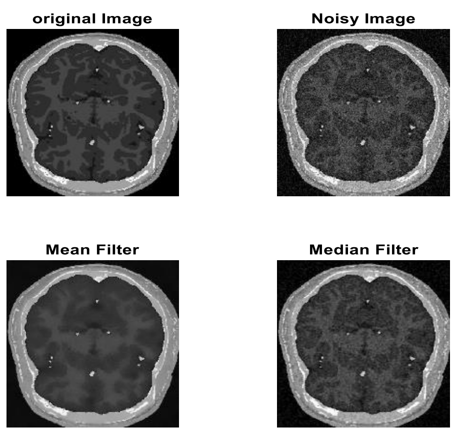


Figure 2. Edge detection using fuzzy rules results

Also, a FIS file, 'Fuzzy Edge' was granted, which can be used to reproduce our analysis or applied to other similar images. As shown in Figure 2.

Next, Gaussian noise was added, and then apply mean and median filters to the noisy image. It then defines a Mamdani-type fuzzy inference system for noise reduction, with mean and median as inputs and image intensity as output. It creates two membership functions for the inputs and three membership functions for the output, which are then used to define two rules for the fuzzy system. Finally, it evaluates the fuzzy system on the noisy image and displays the output. The output of the fuzzy system is saved as a FIS file using the "writeFIS" function. This file can be loaded and used for noise reduction on other images without the need to redefine the system. As shown in Figure 3.

Next, MATLAB code is performing image enhancement using fuzzy logic. It starts by reading an MRI image in color, converting it to grayscale, and adding Gaussian noise to the image. Then, it defines a Mamdani-type fuzzy inference system (FIS) with an input variable called "Img" and an output variable called "Iout". The "Img" variable represents the pixel intensities of the input image, which are classified into three fuzzy sets: "DARK", "GRAY", and "BRIGHT". The "Iout" variable represents the output pixel intensities after enhancement, which are classified into three fuzzy sets: "DARKER", "Gray", and "BRIGHTER". The FIS is constructed with three fuzzy rules, which map the input fuzzy sets to the output fuzzy sets. Finally, the FIS is used to enhance the input image by evaluating the degree of membership of each pixel intensity in the input image to each of the input fuzzy sets and applying the corresponding fuzzy rules to determine the degree of membership of the pixel intensity in the output fuzzy sets. The resulting output fuzzy sets are then mapped to the corresponding output pixel intensities, and the enhanced image is displayed. As shown in Figure 4.



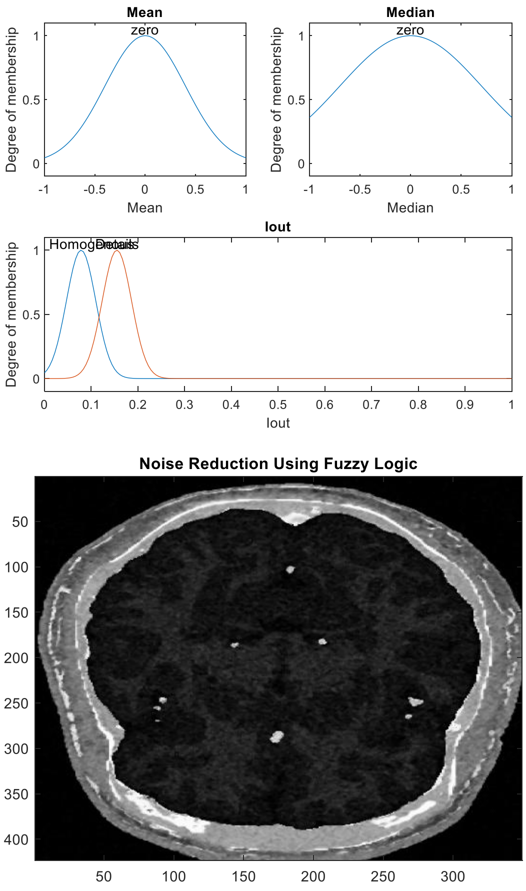


Figure 3. Fuzzy Noise results with mean and median filters applied

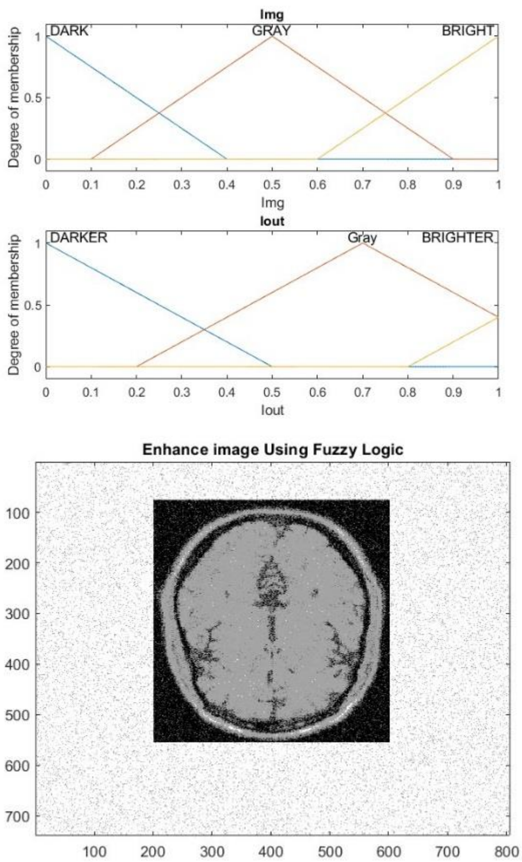


Figure 4. Results of enhancing MRI image

Then, image clustering using the fuzzy C-means (FCM) algorithm was performed. It reads an input image "MRI3.jpg", converts it into a one-dimensional array "Img" and applies the FCM algorithm with four clusters. The resulting clustered one-dimensional array "nn" is then reshaped into four two-dimensional arrays "imIDX1", "imIDX2", "imIDX3", and "imIDX4" representing each cluster. Finally, the code displays the clustered images for each cluster. As shown in Figure 5.

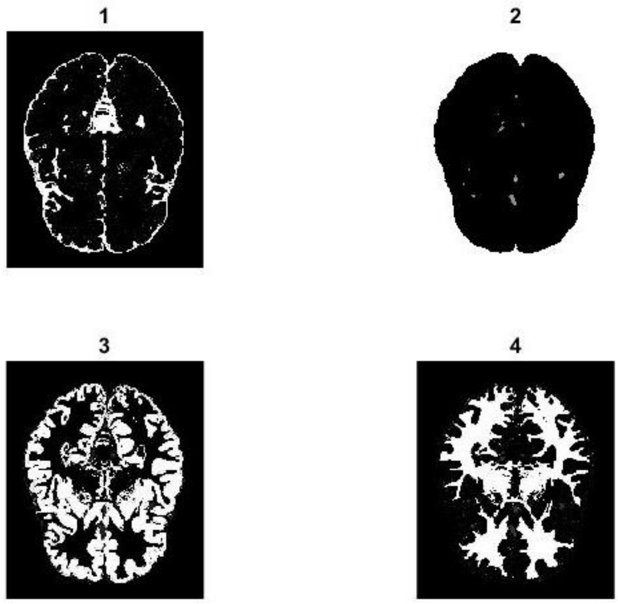


Figure 5. FCM C-mean clustering results

5. HYBRID METHODS

Several research papers have proposed the combination of evidence theory and fuzzy methods for medical data uncertainty modeling and image analysis. For instance, Fuzzy C-Means clustering and DS was utilized to segment brain MRI images [42]. Similarly, Fuzzy C-Means and DS was used to segment T1, T2, and PD MRI images [43, 44]. An alternative approach is to use Fuzzy Inference System (FIS) and DS for data fusion, as demonstrated by Soni and Chaurasia [45]. A proposed a Fuzzy Inference System combined with DS to fuse conflict evidence, while Ullah proposed a data fusion scheme using FIS and DS to extract precise information and infer the result of patients' heterogeneous data in IoT-based healthcare systems [46]. Additionally, Evidential C-Means (EVCLUS) combined with DS in belief functions for image segmentation [47], a hybrid segmentation was proposed structure using FCM and Evidence Theory for single-channel T1 MR Images of multiform benign and malignant tumors [48]. These studies demonstrate the potential of combining evidence theory and fuzzy methods in medical image analysis for improved accuracy and efficiency.

6. CONCLUSIONS

Based on the review of existing methods for the segmentation of brain MRI and the outcomes of the applied fuzzy logic techniques demonstrated by: FCM-based noise reduction, image enhancement, and clustering, along with the Mamdani-type FIS employment for edge detection. It was evident that these techniques effectively enhanced the segmentation task; however, it is important to note that no single method can be considered perfect for brain MRI images. The quality of the segmentation result depends on a variety of factors, including pixel density, color, texture, and intensity leading to inherent uncertainty. Therefore, hybrid solutions incorporating DS evidence theory hold promise for mitigating this uncertainty and improving brain MRI segmentation results.

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