Unsupervised Classification for predicting Malignant Tumor cells in Brain using FCM Method

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Abstract

Physiological effects has a significant impact on human existence. MRI plays a crucial part in our life. Magnetic resonance imaging (MRI) is a crucial tool for spotting brain tumors. In this proposed research work, we introduce a novel approach for predicting brain tumors. One of the great problems of modern medicine is the identification of human brain tumors. In this study, we present an MRI-based model for detecting human brain tumors using the improved fuzzy C means (FCM) algorithm. The suggested approach determines the best segmentation template to use for a given image by analyzing its grayscale intensity. The flexible C-means (FCM) algorithm uses distances from the cluster centroid to the cluster data points to update membership as it gets closer to the optimal solution, and then the upgraded FCM clustering algorithm is applied to tumor detection. The suggested approach outperforms state-of-the-art methods in simulating human brain images with tiny differences in gray-level intensity, as demonstrated by the simulation results. As an added bonus, our system can detect human brain cancers in a matter of seconds, whereas other algorithms can take up to minutes to do so. Tumor detection and extraction from brain MRI scans are performed with the help of MATLAB. The findings show a level of robustness against the presence of noise. Additionally, in some instances of tumor pathology, the accuracy of segmentation was improved by as much as 10-15% compared to the expert estimate.

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1. Introduction

The brain is a massive, intricate organ that regulates the whole nervous system and is home to over 100 billion nerve cells [1]. This vital organ's origins can be traced back to the brain, the processing hub of the nervous system. Therefore, any form of brain disorder may be harmful to human health. Brain tumors are the most life-threatening kind of anomaly. Brain tumors, also known as neoplasm, are malignant growths of cells that can be either primary or secondary. Primary tumors originate in the brain, while secondary tumors spread to the brain via the circulatory system from other areas of the body. When it comes to primary tumors, a misdiagnosis of a glioma or meningioma in the brain can be fatal. Glioma, in fact, is the most prevalent type of human brain tumor [2].

Treatment options for brain tumors vary according to the tumor's stage, size, and type. Surgical removal of a tumor is currently the gold standard for treating brain tumors [3]. Because it is the only non-invasive and non-ionizing modality, MRI is the preferred imaging method for diagnosing brain tumors [4] and [5]. MRI scans can provide important details about the tumor's size, shape, and location in two dimensions (D) and three dimensions (3D). Extraction of the necessary region requires careful preprocessing. Non-brain tissues are removed using the 2D brain extraction algorithm (BEA), the FMRIB software library, and the BSE [6]. Intensity in homogeneity, a result of flaws in the radio frequency coil, causes the bias field, a major issue in magnetic resonance imaging. The issue has been fixed. In different situations, preprocessing techniques such linear, nonlinear, fixed, multi-scale, and pixel-based are employed. Direct image analysis is typically complicated by the minute differences between normal and diseased tissues as a result of noise and artifacts. To segment brain tumors, AFINITI is applied [7]. That's why many of people these days are turning to automated procedures, wherein segmentation is handled by computer software rather than by hand. Automation, both full and partial, is commonly employed. The segmentation techniques can be broken down into the sub-types listed below.

1. Procedures that are considered standard practice.
2. Methods based on machine learning.
3. Shading artifacts and partial volume effects are both caused by MRI noise's various in homogeneities.

Training and testing are conducted using known and unknown samples with classification approaches. Brain tumor detection requires determining not only the location of the tumor within the brain, but also its size, shape, and border. The brain can be imaged using a variety of imaging modalities, including computed tomography, positron emission tomography, magnetic resonance imaging, and others. MRI and CT scans are commonly used to examine the brain tumor's anatomy [8]. However, MRI provides an accurate view of the anatomical structure of brain tissues, whereas CT scans contain radiation that is harmful to human body. A magnetic field and radio waves are used in the MRI machine, which produces high-resolution images of inside organs and tissues [9]. To aid pathologists in their diagnoses, MR image processing is continually under scrutiny by researchers. In this study, we suggest several significant new developments: We propose the algorithm, which will allow for more precise detection of brain tumors of any size. Even with a noisy MR picture, the proposed approach provides superior accuracy and efficiency over alternatives [10]. When compared to traditional algorithms like ANN, which take 7-15 minutes to execute the output results, the suggested algorithm's required execution time is significantly reduced at 40-50 s. This paper continues with a presentation of related works in Section 2. The traditional fuzzy c-means algorithm are described in Section 3 which is the proposed algorithm for classifying brain tumor cells. Section 5 provides a brief overview of the findings and debate, while Section 6 provides a conclusion and suggestions for further research.

2. Literature Survey

DIP involves the collection and processing of pictures for the purposes of segmentation and data extraction. When talking about a digital image, "segmentation" means to divide it up into smaller pieces. Recognizing brain abnormalities and providing an alternative, more meaningful, and easily analyzed picture representation both require accurate segmentation. Thresholding is a common approach to segmenting brain MR images and is useful for image binarization. Threshold is the foundation, however it is used in tandem with various methods like classifiers, clustering, artificial neural networks, etc [11]. This method shines when used on an image that features a uniformly bright area or object set against a more varied grayscale. It divides images into groups based on the grayscale values of their pixels. The grayscale MR picture of the brain can be used to map out specific regions of the brain. One major drawback is that it cannot be used with multi-channel pictures. Large regions are created from pixels or sub regions based on a set of predetermined parameters in region expanding segmentation. To create areas, this method first selects a collection of "seed" points and then draws lines between them to join neighboring pixels that share comparable prominence. The major downsides of this method are the high cost of computing and the need for human involvement in choosing the seed points. Even more so, it is very susceptible to background noise. The process of growing and separating regions is an extreme version of the region growing method. In order to achieve this, it is necessary to split and merge regions of the image that share similar characteristics. When employing the region expanding approach, if a region does not meet the homogeneity criterion, the region is split in order to produce four new regions [12]. The problem of border leakage is the fundamental drawback of this method. In order to divide areas, edge-based segmentation looks for and exploits sharp contrast changes in image values to focus on detecting contour. The main disadvantage of this technique is that it cannot segment images that are either too unclear or too complicated to determine a specific border. A suitable pixel classifier for training data is essential in classifier approaches. Mainstream classifiers include K-nearest-neighbor (KNN), expectation maximisation (EM), and others [13]. To save time and produce precise results, it is preferable to use a classifier and training data that are both effective. KNN is superior than other classifiers for MR images in terms of accuracy and stability. Additionally, KNN does real-time image segmentation due to its faster runtime and relative ease of implementation. When the acquired single neighbor is an outlier of some other class, there is a chance that the algorithm will make a wrong call [14].

Each pixel in a Fuzzy C-means cluster may be partially or fully part of two or more clusters [15]. Finally, the FCM technique detects a tumor in the image using approximate segmentation and exact cluster selection. Unlike K-means clustering, where it is used successfully despite background noise, the traditional FCM is sensitive to noise only. Segmentation is challenging, but it must to be faultless before being applied to the brain's intricate structure. To detect and categories tumors, ANN is now one of the most promising methods. Two distinct types of ANN exist: feed forward neural networks (FFNDs) and recurrent networks (sometimes called feed-backward networks) (FBNN). The ANN method has strong parallel capability and quick computing. From what has been said above, it could be concluded that there is no such thing as a perfect method. However, to achieve the best results in this area, we must lessen the restrictions of the various approaches described here.

3. Methodology

Bezdek presents the FCM clustering algorithm, a clustering method in which each data pixel is assumed to belong to two or more clusters. Locational proximity to a cluster's epicentre is positively correlated with increased membership in that cluster. The FCM algorithm is implemented in this study using the data compression technique without including the weight factor in the cluster centre updating criterion, which both speeds up the process and yields significant segmentation efficiency. Clustering aberrant MR brain images from four tumor types—metastasis, meningioma, glioma, and astrocytoma—is performed using a modified version of the fast clustering method (FCM). The clustering algorithm makes use of retrieved textural information from the photos, such as correlation, contrast, and entropy. The effectiveness and convergence rate of the segmentation are evaluated in an analysis of the segmented results. To demonstrate its superiority in terms of convergence rate, we compare it to the standard FCM method.

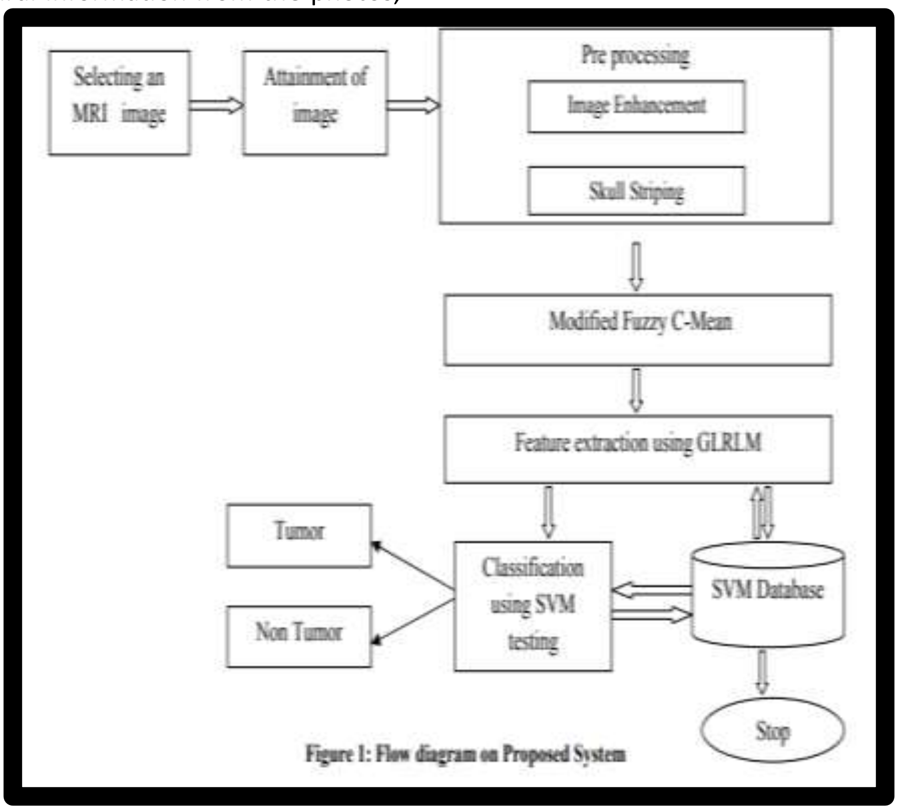

Figure 1. Flowchart of Proposed Architecture

Positive outcomes for the improved FCM algorithm were observed in experimental settings. In order to categorize patterns, clustering is one of the most popular picture segmentation approaches because samples within the same group tend to be more similar to one another than samples belonging to other groups. Fuzzy clustering approaches, which preserve more of the original image than hard ones do, have recently attracted a lot of attention. In order to classify images, the fuzzy C-means approach is commonly used since it permits pixels to be partially in several classes. However, the FCM method has been criticized for being laborious to implement. The existing network has been updated in a number of ways to boost performance. This process includes gathering an MR image database, extracting features from those images, doing an FCM-based segmentation, and finally performing a modified FCM-based segmentation. In we see the methodology for segmenting MR images of brain tumors.

One pixel can be part of many clusters at once with Fuzzy C-means (FCM), a method of clustering. The FCM method aims to divide a set of pixels into "C" fuzzy clusters according to some predetermined criteria. It is possible to employ many similarity measures for class identification, depending on the nature of the data and the task at hand. Distance, connection, and intensity are only a few examples of possible parameters to utilize as comparison standards. These photos are divided into four distinct categories.

The process of segmentation involves cutting a picture into sections or "slices," each of which represents a distinct part of the image or a single object. The segmentation of tumours is improved by this method. The segmentation of magnetic resonance images (MRIs) was performed using the fuzzy c-mean technique in this study. The principle of data compression is at the heart of the updated FCM algorithm. Quantization and aggregation are the two main components of data compression. A lower 'm' bit value of the feature value is masked before the quantization of the feature space is performed. When performing an aggregate operation, feature vectors with similar intensity values are bundled together. The following are the main steps of this revised FCM for brain tissue segmentation.

Algorithm for Fuzzy-C Mean(FCM) for CLassifying Brain tumor cells

Step 1: First, analyze the measured brain volume.

Step 2: Second, you need pre-compute the image's degree of symmetry matrix.

Step 3: Third, decide on the initial cluster centroids and assign to a small value (1105). Finally, enter the number of tissue classifications c.

Step 4: The fourth step is to employ an equation to bring the fuzzy membership uik up to date (6).

Step 5: Phase 5: Refresh i-centers of clusters through equation (7)

Step 6: If (uik new - uik old) , then go to Step 7; otherwise, go back to Step 4.

Step 7: To complete the segmentation process, step seven involves retrieving the maximum fuzzy membership value for each pixel.

Fig. 1 depicts the full workflow of the recently described method for detecting tumors. The procedure begins with the capture of an MR image of a human brain, followed by pre-processing of the input picture and MR image enhancement. In addition, the temper based K-means clustering segmentation is applied to the window's output when the template base window is picked. Then, features are taken out that are necessary. Finally, the tumor is acquired by an enhanced fuzzy C-means method with an updated membership, as indicated by the red line in the figure below. The clustered image, which is selected mechanically based on visual features, is responsible for this.

4. Experimental Results

Fuzzy C-Means is a popular clustering method in the fields of computer vision, pattern recognition, and image processing since it allows for data to potentially belong to many clusters. Using a fuzzy approach, the FCM algorithm is able to get segmentation results. Color-based classification techniques that assign each pixel to a single category. For segmenting images based on color, the FCM method excels. A number of popular segmentation methods take their cues from fuzzy set theory. Each data point's participation in a cluster is determined by its membership degree in the algorithm Fuzzy C-means, a type of clustering. One piece of data can be a part of multiple clusters with the help of the fuzzy c-means (FCM) clustering method. A database of 40 brain tumor images are taken. A variety of high-quality images of brain tumors in various stages of complexity have been collected to create this database. Images were obtained from and preprocessed for use in our algorithmic software. We then used MATLAB 2016(a) to perform the necessary image processing and create the final database. The stage of the tumors depicted in these images makes it difficult for laypeople to diagnose them. Pre-processing of MR images is crucial for improving their visual quality before further analysis. The photos included in the collection are typically of such low quality that noise filtering and sharpening are required before they can be used. The images in the dataset are converted from RGB to grayscale and the acquired image is transformed into a two-dimensional matrix as part of the pre-processing phase. A median filter is used to smooth out the image and get rid of any imperfections as shown in Fig. 2. Adjusted operations, histogram-based operations, and adaptive histogram-based operations are then used to improve the quality of the original image. The most common method of enhancing an image is through increasing its contrast. The next step is the implicit extraction of various features.

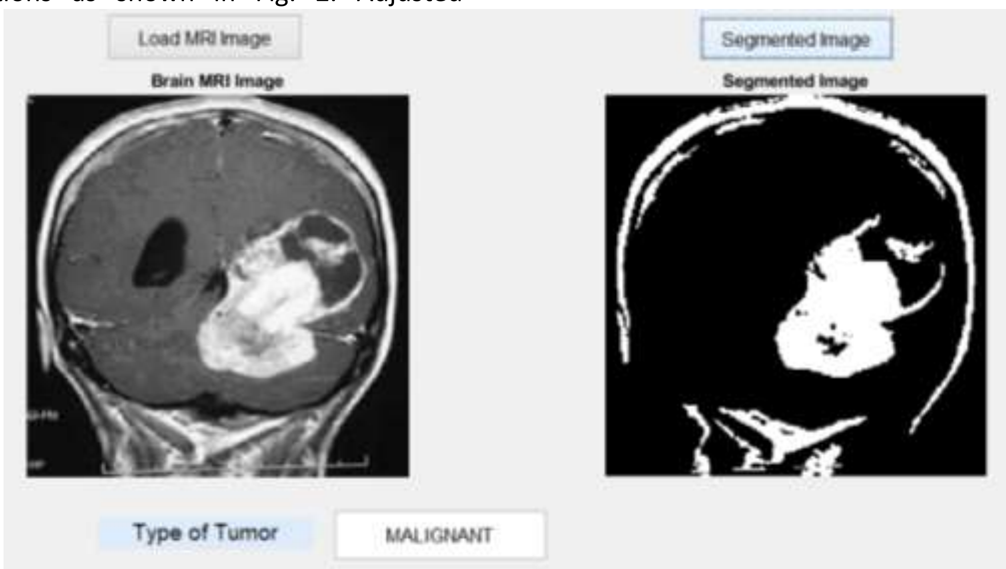

Figure 2. Applying Filter for the MRI image

Once that is done, a variety of features are extracted initially on an implicit basis. No part of the brain tumour may be ignored, so it's necessary to pick the whole thing. The first step is to apply the filters to the input image. The image is then initially segmented using template based K-means (TK), depending on the grey level intensity and color tone, with k equal to 8. Once again, the tumor is filtered by a median filter. Following this, an enhanced FCM algorithm is used to detect the tumor and label it as a red line based on the Euclidean distance from the cluster centre to each data point, which is mostly determined by the various variables. This may help in understanding why this method was modified and included. Tumors in medical pictures can be seen in a wide variety of anatomical places, and can exhibit a wide range of pathologies in terms of their shape, size, density, and the amount of surrounding tissue that they have damaged. Studies were conducted to demonstrate the effectiveness of the proposed methodology in detecting edges and in withstanding an average level of background noise as shown in Fig. 3.

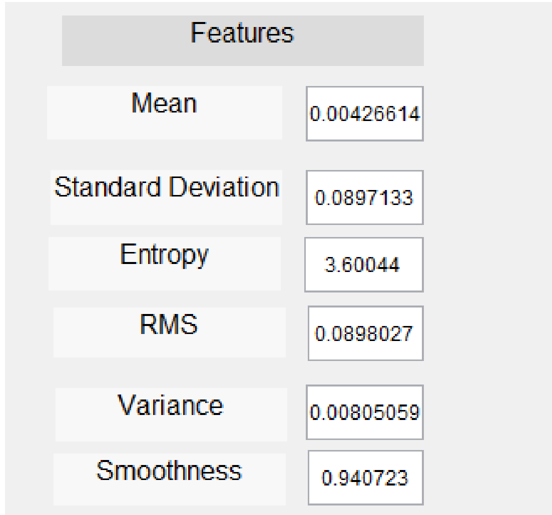

Figure 3. Feature Selection using Filters

The initial analysis will involve contrasting the proposed method with traditional, simple gradient operator-based edge detection techniques like Roberts, Prewitt, and Sobel, as well as more advanced techniques like LoG and Canny. Images with the least noticeable noise influence were chosen for the comparison. Reference photos prepared by a medical expert were used to determine all research evaluation parameters. Pixel Not Detected (PND) is the fraction of undetected pixels. The best possible value for this metric is zero. Various types of accuracy is shown in Table 1 and various images obtained with various filters are depicted in Fig. 4. Various other parameters are also evaluated like the sensitivity of the proposed model and the noise level. They are depicted in Fig. 5 and Fig. 6 respectively.

TABLE 1: Various types of accuracy

Type of Accuracy	Percentage
RBF Accuracy	90
Linear Accuracy	90
Polygonal Accuracy	80
Quadratic Accuracy	90

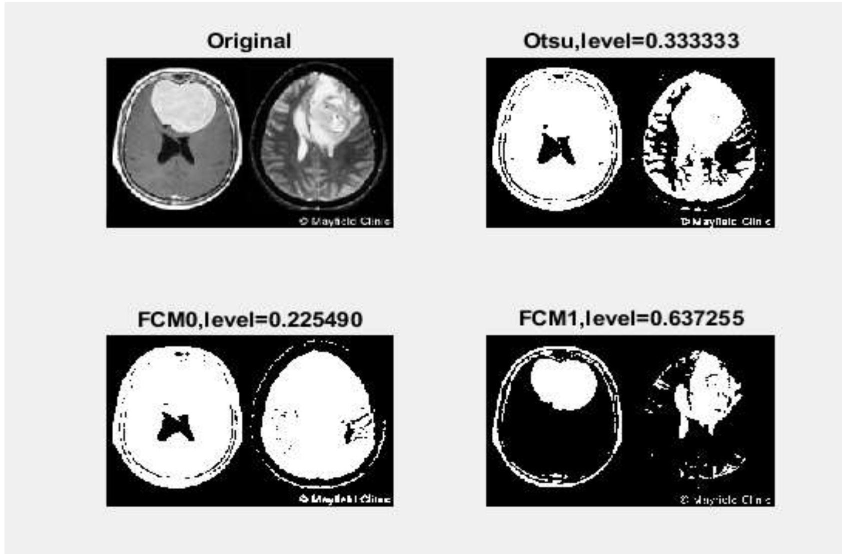

Figure 4. Filter Analysis

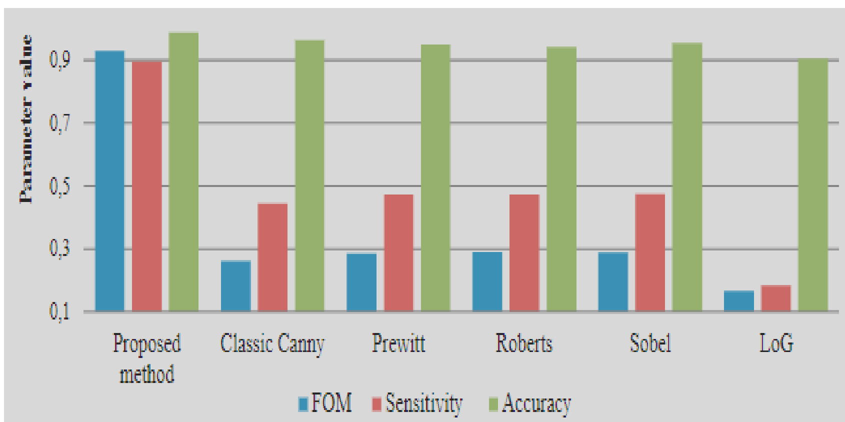

Figure 5. Sensitivity Analysis

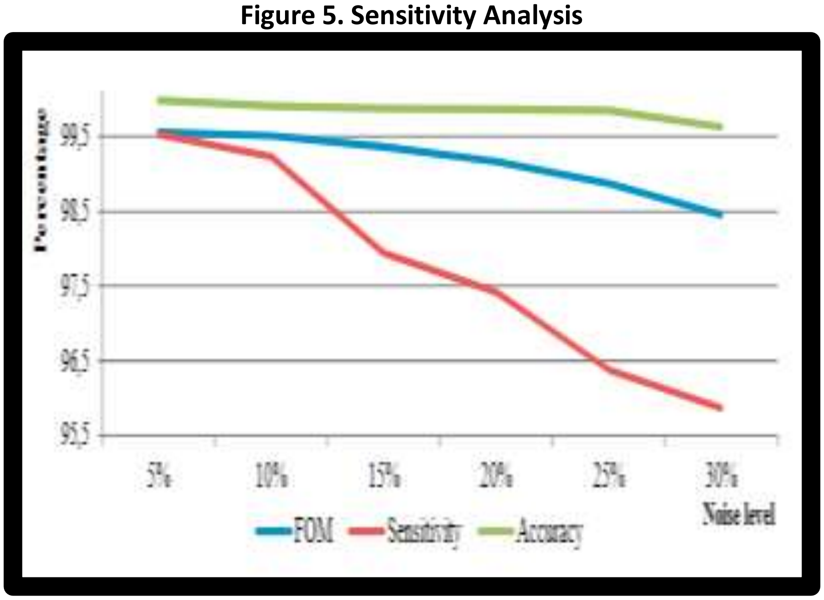

Figure 6. Noise level Analysis of the proposed Method

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5. CONCLUSION

Medical picture edge detection of a brain tumour on MRI aids in the diagnosing process. This is a challenging task because the quality of the source photographs is sometimes low due to technical constraints. So, the method of detecting edges should work well. This research introduces an FCM clustering-based method for detecting the borders of MRI brain tumor images. In order to detect brain tumors, a fuzzy segmentation approach was employed. Weight vector, processing time, and number of tumor-detected pixels are all measures of MRI picture performance. We have presented a number of medical image processing methods, and we have talked about the needs and characteristics of brain tumor detection strategies. More details on FCM segmentation and tumor identification in the brain are provided in this study. By experimentation, he showed that the proposed method yielded an edge map that was robust against noise.

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