Available online www.jsaer.com

Journal of Scientific and Engineering Research, 2022, 9(12):127-137

Rsearch Article

ISSN: 2394-2630
CODEN(USA): JSERBR

Enhancing Fuzzy C-Mean Algorithm for Medical Image Segmentation Process

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Abstract This paper is focus on an enhanced application of Fuzzy C-Means Algorithm in Image Segmentation Process. The application of digital systems in the areas of automated medical diagnosis is no doubt the backbone of any effective decision and treatment that may arise due to the cause of brain tumor. Several researchers have shown that the causes of most death are as a result of incorrect diagnosis of the affected areas of brain arising from brain tumor. It is obvious that the chances of survival can be enhanced if the tumor is detected and classified correctly at its early stage. Segmentation of brain tumors in magnetic resonance images (MRI) is a challenging and difficult task because of the multiplicity of their possible shapes, locations, image intensities. The paper intends to summarize and compare the methods of automatic detection of brain tumor through Magnetic Resonance Image (MRI) Machine by application of an enhanced Fuzzy C-Mean. The proposed method can be successfully applied to detect the contour of the tumor and its geometrical dimension. In this research work we will highlight the ways for detection for both mass and malignant types of tumor cells by use of a 3-D Analyzer tool for more accurate result since the malignant tumor is difficult as compare to mass tumor. We will use the Structural System Analysis and Design Method (SSADM).

Keywords Enhanced, Fuzzy C-Means, Algorithm, filtering technique, Image Segmentation

Introduction

Medical image segmentation has contributed immensely to medical care delivery. With the speedy development of deep learning, medical image segmentation processing based on deep convolutional neutral networks (CNNs) has become a research interest [1]. Most of the problem that is face by man or organization is in the areas of image identification, these problems may arise as a result of complexities in image that is captured from either satellite tv, x-ray or magnetic resonance image machine as the case may be. Hence there is need to perform filtering or de-noising technique on the image before the process of image segmentation [2]. Segmentation is the process of splitting image into different parts for proper analysis. In this study, we will outline the processes that are involve in the used of an enhanced fuzzy c-means algorithms in the domain area of brain tumor to detect the presence of tumor in it early state of formation. Tumors are of two types named *Malignant and Benign or mass* [3].

Related Work

A lot of research papers related to medical image segmentation were studied. Below are the reports of some of the literature survey presented. Akpan *et al*. [4] introduced color-based segmentation using K-Means clustering for the brain tumor detection. The developed algorithm shows better result than canny based edge detection.

Nandha [5] developed an intelligent system to diagnose brain tumor through MRI using image processing clustering algorithms such as fuzzy c-means along with an intelligent optimization tools such as Genetic algorithm (GA), and particle swarm optimization (PSO). Wenli *et al.* [6] also developed a novel image segmentation algorithm called W-SPK which combined watershed and K-means clustering method based on simulated anealign particle swarm optimization which was use to overcome the short realize a fast and accurate image segmentation process. Sasikate *et al.* [7] developed an automated segmentation of malignant types of tumor in magnetic resonance image (MRI) of brain using optimal texture features. In this case, the texture features are extracted from normal and tumor region (ROI) in the brain images under study using spatial gray level dependence method and wavelet transform.

Deep Learning Concept and Applications

Presently complex ANN – based structures exist in clinical task and categorization issues are diverse. Here, Deep Neural Networks is used to denote all models. The observed achievement of DL models, for example, Deep Neural Networks result in a blend of proficient algorithms with vast statistical space. This space composed layers which makes Deep Neural Networks complicated 'black-box' models [8, 9]. Based on the use of ML methods, the lesion detection techniques are automated with convincing precision and human effort [10].

Computer Vision Tasks

Cheng *et al.* [11] in figure 1.0 listed various clinical tasks performed by a computerized – based vision for which DL models are used in medical imaging as follows:

i) *Image Categorisation:* This involves forecasting the labeling of the entire binary image (two classes) or multiclass (more than two).
ii) *Object Detection:* This is the recognition and localisation of precise unit of the element of image.
iii) *Semantic Segmentation:* It allocates individual picture element to exact classes. A typical illustration is that individual picture element in lever can be allocated to parenchyma, tumor, or blood vessel.
iv) *Instance Segmentation:* Refers to the picture element level recognition and demarcation of several objects in the same class, for example, lung nodules independently differentiated on a chest radiograph.

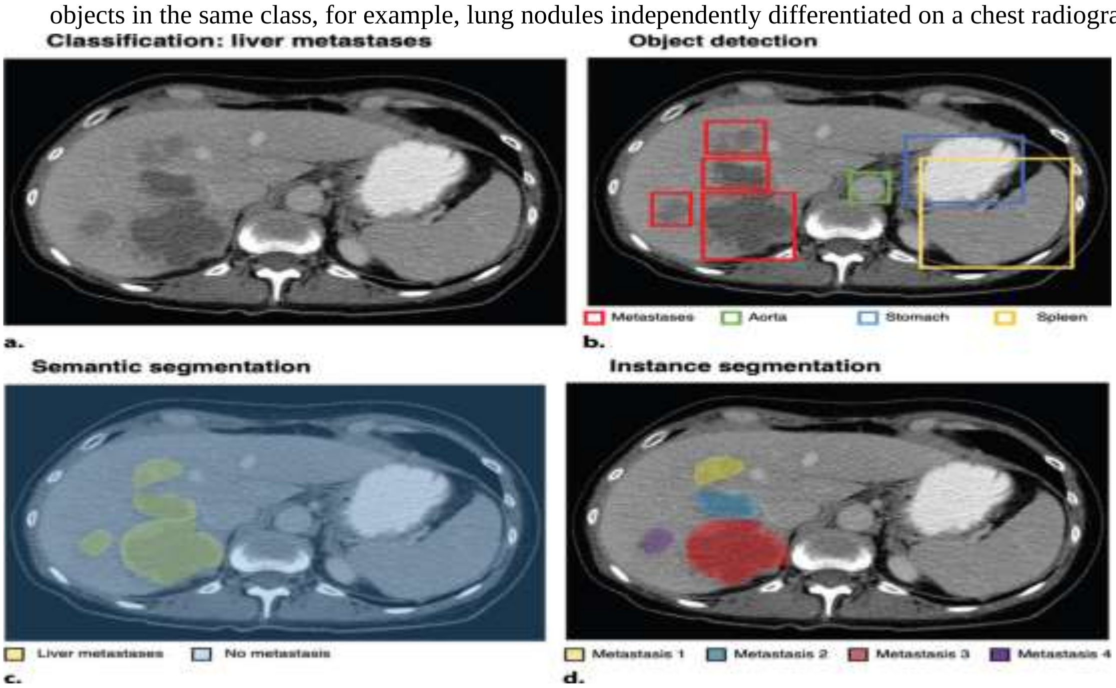

Figure 1.0: Contrast-enhanced CT images showing Computer Vision tasks [11]

From figure 1.0, cheng *et al.* [11] argued that:

a) The categorization of image is to allocate a label from a structure to known image.

b) The detecting of an object aim to situate human organs, lesions area; structures like metastases that are in red, aorta in green, stomach in blue and the spleen in a yellow (all square size).
c) The semantic segmentation allocates an object classification label to individual picture image, for example, liver metastases which have yellow colour.
d) The instance segmentation allocates labels to every picture element, for example, each liver metastases are in sections (i.e., red, blue, purple, and yellow).

Convolutional Neural Networks (CNNs)

CNN is a made up of heap of layers, individually handling a definite operation, for example, convolution, pooling, and calculating loss. Each intermediate layer gets the output of the former layer as its input. Layers get the input layer from past layer as the input. Starting layer becomes the input layer linked to the input image with neurons that are equipment to the pixel numbers in the input image. Next stage are CNN layers showing outcomes of convolving quantities of filters with input data to present feature extraction. The filters are called kernels, and of smaller dimensions, based on the essential part. The neuron reacts to exact region of the former layer, termed receptive field. The yield of each CNN layer is called activation map, emphasising the consequence of using a precise filter on the input. These stretched the idea by applying various imaging modalities, for example, brain MRI, breast MRI, and cardiac CTA for segmentation process [12].

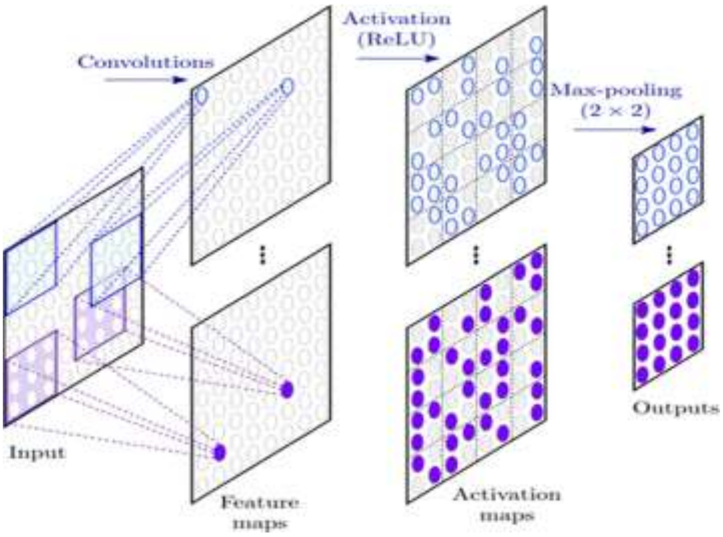

Figure 2.0: The structure of a Convolutional Neural Networks [11]

However, showing 2D convolutions with an isotropic kernel on anisotropic 3D images can be difficult [12]. In detecting, the information represents images denoted with leaping box match up; demarcating traits of interest. Organising object data in ML algorithm process is difficult [10, 13]. Even with inadequate information, the model can be train to forecast labels exactly [14]. The means to increase the training dataset to avert over fitting is image augmentation. Figure 2.0 shows data augmentation process. This involves:

i) *Classic data augmentation:* This involves applying a range of transformations, for example, translating randomly, rotating, flipping, scaling, cropping, bighting and contrasting adjustments to original CT images.
ii) *Artificial data augmentation:* This employ a generative adversarial network (GAN) creating extra artificial images with a numerical distribution.

The illustration in figure 3.0 shows the CycleGAN training to switch contrast-enhanced CT images to non contrast images. The generator afterward supplements early dataset for training on a task segmenting non contrast images [15].

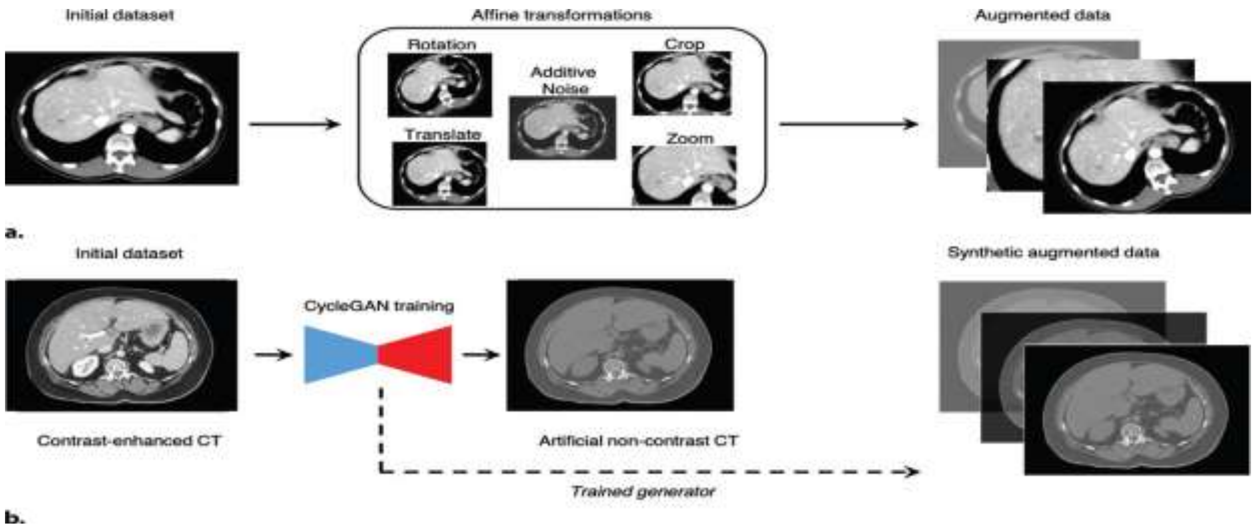

Figure 3.0: Demonstration of data augmentation [11]

Similar process of raising the amount of preparing images involves translating randomly, rotating, flipping, scaling, cropping, bighting, contrasting adjustments. GANs can produce irregular images resembling exact images [16].

Medical Image Segmentation

Segmentation is an important aspect of processing image. Aarish and Devanand [17] posited Medical image segmentation as the practice of facilitating the delineation, characterization and visualization of regions of interest in any medical image. Previous to de-noising an image, it is segmented to recuperate the original image. The major reason for segmentation is to decrease the information for effortless analysis. Numerous techniques for automated segmentation of computed tomography (CT) and magnetic resonance (MRI) images are used in transforming medical practices. Imaging experts are engaged in image elucidation for patients with cancer, obesity, cardiovascular disease, neurodegeneration, osteoporosis, arthritis, etc. These approaches will aid in disease diagnosis, determining the prognosis, selecting the patients for therapy and to observe responses to treatment. Bensalah *et al.* [18] argued that in classifying medical image segmentation, the following approaches should be mentioned. These approaches are:

i) *Semi- automatic vs Automatic Segmentation*: The object, for example, organ, tissue, pathological lesion or other structure is used for the examination or treatment of a particular disease.

ii) Supervised and Unsupervised Segmentation: Supervised segmentation needs prior training, such as intensity normalization and classification. While, unsupervised does not need training and are less accurate.

Medical Image Segmentation Techniques

Dar and Padha [17] listed segmentation methodology to include:

i) *Thresholding:* Local thresholding, Otsu's method, Gausian mixture Approach.

ii) *Region based:* Region merging and Splitting.

iii) *Edge Base/boundary Based:* Edge Detection, Prewitt filter, Sobel filter, Canny filter, Laplacian of Gaussian LOG, Watershed.

iv) *Clustering methods:* k – Means/ Iso – data algorithm, Fuzzy C – means algorithm, Expectation maximization (EM) algorithm.

v) *Other methods:* Level Set method (LSM), artificial neutral networks, Atlas Guided approach, Generic algorithms.

Dar and Padha [17] compared Segmentation methodologies by specifying advantages and disadvantages in table 1.

Table 1.0: Difference in Segmentation Techniques

Methodologies	Advantages	Disadvantages
Local Thresholding	Ease of Implementation No need of prior information.	Produces noisy and blurred edges.
Otsu"s Method	Minimizes inter-class and intra-class variations. No particular histogram shape considered prior. Extendable to multi-level thresholding.	Formation of binary classes in grey-level images. Enhancement in density with increase in levels of threshold. Regions might get fused or varied.
Gaussian Mixture Approach	Used for histogram-based problems. Decreases categorization error probability. Favoured for small size-classes. Iterative model.	All histograms do not follow Gaussian model. Resultant intensities are fixed and non-negative. .
Region Growing	Its support is on similarity and immune to noise.	Costly method.
Region Merging and Splitting	Dividing an image on demand resolution and calculating mean, variance of segment pixel value.	May result in blocky segments.
Edge Detection	Choose a huge region in an image. It uses images with irregular elucidation.	Applicability for basic backgrounds.
Prewitt filter	Calculates edges and their orientations in 8 directions of pixel.	Less accuracy. Sensitive to noise
Sobel filter	Calculates edges in horizontal and vertical orientations. Better noise suppression Isotropical results.	Expensive
Canny filter	Calculates wide range of edges and orientations. Adaptive.	Difficulty in working effectively at curves, corners.
Laplacian of Gaussian (LoG)	Detection of blurry edges and sharp detail.	Complexity in working at corners.
Watershed	Decreases over-segmentation. Division of overlapping objects. Quick and dependable output.	Time consuming and gradient based.
K-Means/ Iso-data algorithm	Quick and easier to used.	Sensitive to variety and initialization of centroids.

Fuzzy C-Means algorithm	Unsupervised and considers vagueness, uncertainty in an image.	Best solution is undefined. Initialization is susceptible. Slightest compatible for noisy images.
Expectation Maximization (EM) algorithm	Unsupervised Iterative and reduced sensitivity.	Results in noise generation and intensity-inhomogeneity. Slow convergence rate. Gets stuck into local optima. High computational cost.
Level Set Method (LSM)	It is efficient, versatile, robust and accurate.	Sensitive, requires considerable design planning for level set function.
Artificial neural networks (ANN)	Ease of implementation. Applicable to diverse problems.	Selection of architecture. Black-box problem.
Atlas Guided approach	Computationally fast. Suited for structures that are constant over populace of study. Labels are transferred during segmentation.	Difficulty in accurate segmentation of complex structures with non-Linear registration methods.
Genetic algorithms	Incremental segmentation. Adaptive to user access patterns. Computationally fast.	Choosing number of generations, population size. It does not always result in optimal solution.

Medical Imaging Modality

In the diagnosis and treatment of patients, imaging assists radiologists to perform diagnosis. A wide range of imaging modalities that is being used for diagnosis and in effective treatment planning currently is in use. The main widely used modalities are spitted into *anatomical* and *functional*. In this study, we discuss about the *anatomical* modality. Digital Images can be represented in 2-D, 3-D and 4-D systems. The elements of an image in 2-D are referred to as pixels, while as in 4-D they are referred to as Voxels. In this study specific medical imaging modalities are presented and emphasis is mainly focused on Ultrasound, MRI, CT and X-Ray. Table 5.2 shows various imaging modalities, their application areas and recommended methods.

i) Computed Tomography (CT):

Computed tomography helps in capturing different sectional planes (tomography) which are difficult to process otherwise. It visualises small density gradients i.e. In case of brain, it distinguishes between grey-matter, white-matter and cerebro-spinal-fluid (CSF).

ii) Ultrasound:

It is a non-invasive imaging process using sound waves to produce computerises images reflected by organs and interior organs of body. It can also be used for interventional procedures. It doesn't have any known harmful effects on human body in clinical imaging. It is inexpensive technique but it cannot visualise the anatomical regions (i.e. Brain).

iii) Magnetic Resonance Imaging (MRI):

MRI uses magnetic fields and radio-frequencies to generate visualisation area of different body organs. The variation in reflected frequencies helps in localization of different body organs with the help of magnetic field. This method is employed to get fine details of organs i.e. brain, liver, chest, pelvis and abdomen.

iv) *X-Ray:*

X-ray is also a non-invasive imaging method and one of the oldest imaging techniques that uses ionizing radiations that are rapid and of shorter duration. This imaging technique is inexpensive as compared to others. It can also be used in interventional procedures for detecting fractures in bones.

Table 5.2: Medical imaging modalities and their application areas

Technique	Recommended Methods	Application Area
Thresholding and region-based segmentation	Abdomen, Appendix, Bladder, Brain, Breast, Chest, Cervix, Kidney, Lungs, Pancreas, Esophagus.	CT Scan
Watershed and region-growing(3D) Clustering (2D)	Neuro-imaging, Cardiovascular, Musculoskeletal, liver, Gastro-Intestinal, Functional, Oncology, Phase Contrast.	MRI
Thresholding Based	Transrectal, Breast, Doppler, Abdominal, Transabdominal, Cranial, Gall-bladder, Spleen.	Ultrasound
Edge-Based and watershed	Radiography, Mammography, Fluoroscopy, Contrast-Radiography, Anthography, Discography, Dexa-Scan, Upper GI.	X-Ray

Fuzzy C-Means

A fuzzy c-means is a data clustering technique in which a dataset is grouped into n clusters with every datapoint in the dataset belonging to every cluster to a certain degree. Let consider a scenario in which a certain datapoint lies close to the centre of a cluster will have a high degree of belonging to that cluster and another datapoint that lies far away from the centre of a cluster will have a low degree of belonging or been a member of that particular cluster. However, medical images are considered fuzzy due to the uncertainty present in terms of region/boundaries, non-uniform intensity variations. Fuzzy c-means is one of the clustering methods that were proposed by J.C. Bezdek [9]**.** But the fuzzy c-means clustering algorithm works well on segmenting most noise free images it fails to segment image corrupted by outliners. The traditional fuzzy c-means (FCM) leads to its own robust mainly due to

i. Not utilizing the spatial information in the image
ii. Use of Euclidean distance.
iii. To overcome the first problem many researcher incorporated the local spatial information into traditional fuzzy c-means (FCM)

Problem Definition

In the existing system there has been different approaches used to detect the presence of brain tumor in it early stage of formation. Pritee [5] applied fuzzy c-means algorithm for brain tumor segmentation, the detection of brain tumor was done on mass type of tumor. In this approach it fails to address the problem of segmentation of malignant tumor which serves as my motivation for this research paper. Prasants [4] developed a Gene-fuzzy c-means clustering technique that was use to detect the presence of brain tumor. In this approach it has a high objective function of computational complexity as result it fails to address the problem of high objective function computational complexity and also do not make use of the 3D representation of brain and 3D analyzer tools in order to obtain a more accurate result in the brain tumor detection.

Proposed Scheme

In this research paper we will improve on an existing fuzzy c-means algorithm that is use in detection of brain tumor at it early stage of formation. The advantages of using enhanced fuzzy c-means clustering technique is to ensure that we obtained a more accurate result through the use of 3D image representation of the brain and the 3D analyzer tools which will be used for analysis.

Multiple Kernel Fuzzy C-Means (MKFCM) with Spatial Biasing

The application of Fuzzy c-means clustering technique will be largely limited to spherical clusters only, but with the application of kernel fuzzy c-means algorithm attempts to solve this problem by mapping data with nonlinear relationships to appropriate feature spaces. Kernel combination, or selection, is crucial for effective kernel clustering. For most of the applications, it is not easy to find the right combination. In this paper a multiple kernel fuzzy c-means (MKFC) algorithm which extends the fuzzy c-means algorithm with a multiple kernel learning setting. By using multiple kernels and automatically adjusting the kernel weights, MKFC is more important to ineffective kernels and irrelevant features. It makes the choice of kernels less crucial. Experiments on both synthetic and real-world data demonstrate the effectiveness of the proposed MKFC algorithm [8]. It has the ability to combine different information from multiple heterogeneous or homogeneous sources in the kernel space. Specifically, in image-segmentation problems, the input data involve properties of image pixels sometimes derived from very different sources. Therefore, we can define different kernel functions purposely for the intensity information and the texture information separately, and we then combine these kernel functions and apply the composite kernel in MKFCM to obtain better image-segmentation results. However, the Multiple Kernel Fuzzy C-Means (MKFCM) still do not provide a spatial neighbor pixel information. Hence, the MKFCM is very sensitive for the noise image segmentation. In order to address this problem of noise in an image segmentation, a novel Multiple-Kernel fuzzy c-means (MKFCM) methodology with spatial information is introduced and is represented as MKFCM-S I and MKFCM-S2. The objective function, cluster centers and cluster centers and membership functions for the proposed method are given below.

$$O_m^G(U,C) = \sum_{i=1}^{c}\sum_{j=1}^{n} U_{ij}^m\left(1 - K_M\left(x_{j,}C_i\right) + \sum_{i=1}^{c}\sum_{j=1}^{n} n_i U_{ij}^m\left(1 - K_M\left(\overline{x_{j,}}C_i\right)\right.\right. \quad (1)$$

Where $K_M(x_j, C_i) = K_1(x_j, C_i) \times K_2(x_j, C_i)$, $K_1\left(x_j, C_i\right) = \exp\left(\frac{-||x_j - c_i||^2}{\sigma_1^2}\right)$

$$K_2\left(x_j, C_i\right) = \exp\left(\frac{-||x_j - c_i||^2}{\sigma_2^2}\right)$$

x is the mean for MKFCM_S1 and median for median for MKFCM_S2 of the neighbor pixels σ_1^2, σ_2^2 are the variances.

$$U_{ij} = \frac{\left(\left(1-K_M\left(x_j,C_i\right)\right)+n_i\left(1-K_M\left(x_j,c_i\right)\right)\right)^{-1/(m-1)}}{\sum_{i=1}^{c}\left(\left(1-K_M\left(x_j,C_i\right)\right)+n_i\left(\overline{x}_j,C_i\right)\right)^{-1/(m-1)}} \; ; i = 1,2, \ldots \ldots C \quad (2)$$

$$C_i = \frac{\sum_{j=1}^{n} U_{ij}^m\left(K_M(x_j,C_i)x_j + n_i K_M(\overline{x}_j,C_i)\overline{x}_j\right)}{\sum_{j=1}^{n} U_{ij}^m\left(K_M(x_j,C_i)x_j + n_i K_M(\overline{x}_j,C_i)\right)} \; ; i = 1, 2 \ldots\ldots C \quad (3)$$

$$n_i = \frac{\min_{i \neq j}(1 - K(c_i, c_i))}{\min_k(1 - K(c_k, \overline{x}))} \; ; i = 1, 2 \ldots\ldots C \quad (4)$$

Proposed Algorithm for MKFCM with Spatial Biasing

Step 1: Browse for the file path; load the 3D image representation from database of MRI machine scanned to be processed (JPEG format)

Step 2: Check if the image is RGB if not then convert the image to gray image.

Step 3: Convert the 3D image representation to double to increase the pixels value

Step 4: For MKFCM, predefine the clusters centre C_i (c= 3 clusters)

Step 5: Get the size of the whole image

Step 6: Convert the input matrix to a vector

Step 7: Compute the membership value by using equation 2

Step 8: Update the cluster centre by using equation 3

Iteration Process Start:

Step 9: Update the membership value U_{ij} by using equation 1

Step 10: Update the cluster center C_i by using equation 2

Step 11: If $| C_{new} - C_{old}| > \varepsilon$; $(\varepsilon = 0.001)$ then goto Step 1

Else stop Assign each pixel to a specific cluster for which the membership is maximal

Detection stage

In this stage, the detection of segmented image will be achieve by using the binarization method in the approximate reasoning step the area of the tumor is calculated. That means the image having two values either white or black (1 or 0). We represent the binary image as a summation of the total number of black and white pixels as given in the formula below:

Image, I $=\sum_{W=0}^{m}\sum_{H=0}^{m}[f(0) + f(1)]$ (5)

Pixels = Height (H) X Width (W)

f (l) = black pixel (digit 1)

f (0) = white pixel (digit 0)

No_of _White, $P = \sum_{w=0}^{m}\sum_{H=0}^{m}[f(0)]$ (6)

Where,

m = maximum image size

P=Total number of white pixels, (height x width)

1 Pixel = 0.264

The formula for area of tumor size

Size_of_Tumor S = $[(\sqrt{P}) \times 0.264]$ mm^2 (7)

Detection Stage Algorithm Steps

The algorithmic steps used for brain tumor detection is as follows:

Step 1: Use .JPEG MRI images from a database or real-time system as input.

Step 2. Checks whether the input image format is as specified and move to step 3

Step 3: Verify that image is gray image. If not then convert to gray-scale using rgbtogray ( ) function in Matlab.

Step 4: Find the edge of the grayscale image using binarization and thresholding method.

Step 5: Calculate the total number of white pixels (digit 0) in the image using equation 6

Step 6: Calculate the Size of the Tumor Using equation 7

Step 7: Test if Tumor Area > 6mm^2 then display message “Abnormal”
else display message “Normal:” .
Test if Tumor = “Mass” then display message “Mass Type”
Else display message “Malignant Type”

Step 8. Stop the process.

Flow Chart Diagram

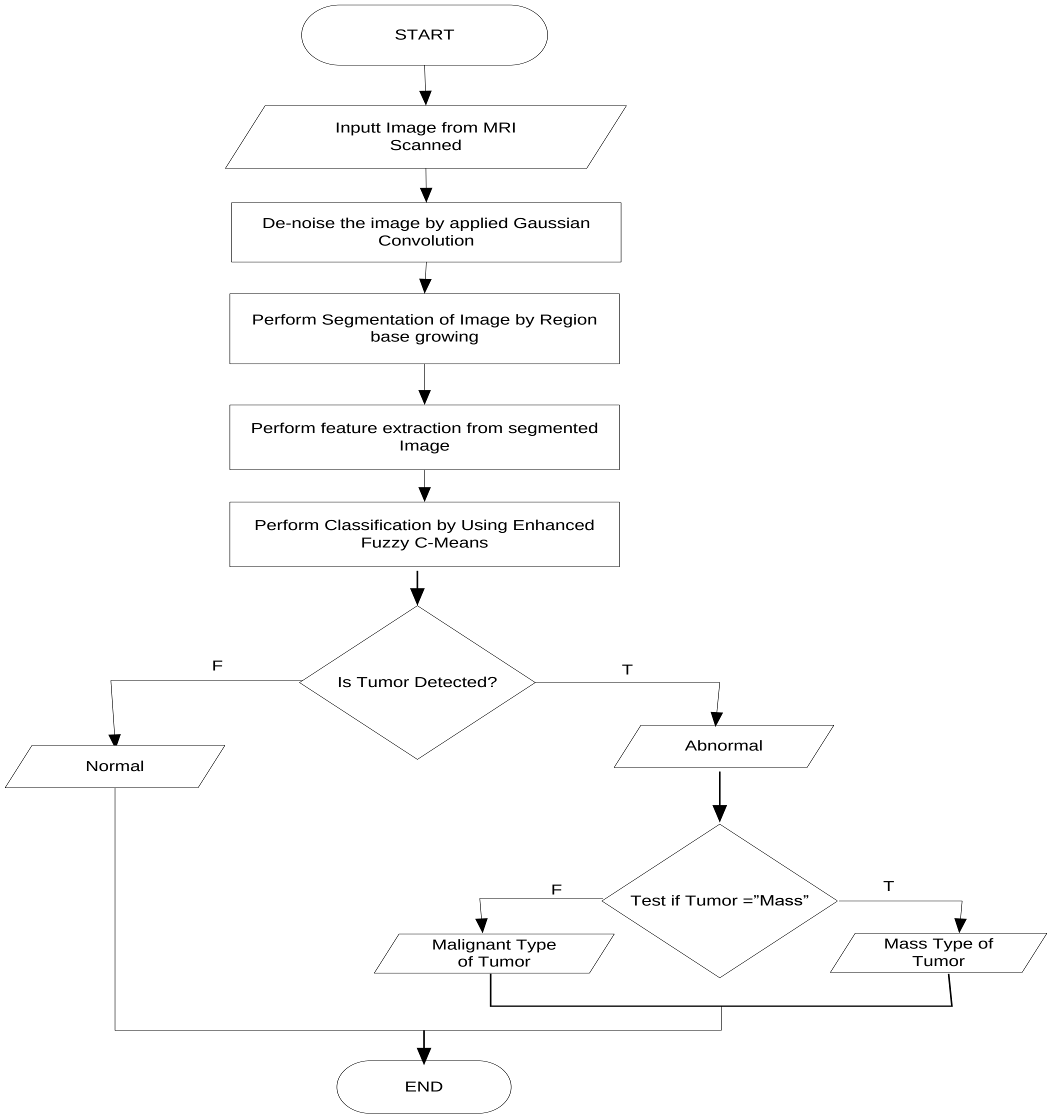

Figure 4.0: A flowchart showing the Brain Tumor Detection

Conclusion

In conclusion, we have discussed the processes that are involved in image segmentation by the application of an enhanced Fuzzy C-Means algorithms which is achieved by Multiple Kernel Fuzzy C-Fuzzy Means with spatial biasing, with the aim to ensure that brain tumor are detected at it early stage of formation and also determine if the tumor detected are either mass or malignant types of tumor before treatment can be administered on patients. We also presented the algorithm for Multiple Kernel Fuzzy C-Means (MKFCM) with spatial biasing, the algorithm for detection for tumor affected area and flow chart showing the detected area of tumor which is geared towards ensuring that we obtained a more accurate result.

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