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A Comparative Study of Detect Brain Tumor Based on K-Means and Fuzzy C-Means Algorithms

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Abstract:
The detection of the tumor region in medical images such as (MRI, CT, X-Ray) a boring and time-consuming task is by radiologists or experts. So, in this review the accuracy is needed for detection the tumor. The area of medical imaging is also reducing complexity and improving diagnostic precision with the growth of information technology. This review paper makes a comparison between the k-mean, and fuzzy c-mean algorithms to display the results and accuracy of them to detection the brain tumor. The execution of the k-mean algorithm is based on centroid, size, split process, threshold, epoch, characteristics, and number of iterations, while Fuzzy C-mean is executed on the basis of the fuzziness value and the termination condition in medical images. In comparing the efficiency parameters with the state-of-the-art processes, the experimental outcomes demonstrate the importance of medical images (MRI, CT and X-Ray) and the accuracy of each algorithm that have been discussed.

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1. Introduction

The brain is a significant component of the human body that regulates via the nervous system (Kapoor & Thakur, 2017). This member regulates several acts, such as ability to heart, breathe, talk, move, and think, alertness and unconscious balance, it is the important part in the human (Zeinalkhani et al., 2018). Therefore, Brain tumor is the development of irregular cells in and around the brain, which is one of the most common causes of increased mortality among children and adults. It consist of two types the benign, and malignant tumors, and divided into tumors two primary, and secondary tumors (Naz & Hameed, 2017), (El-Dahshan et al., 2014). Medical images such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), X-Ray Imaging (X-Ray) may be tested for brain anatomy (Zhang, 2010; Andria et al., 2013; Bargarai et al., 2020; Zebari et al., 2020), for detection the tumor (Abdel-Maksoud et al., 2015). A widely used diagnostic technique is the diagnosis of brain tumors using Magnetic Resonance Imaging (MRI) (Bal et al., 2018; Jafari & Shafaghi, 2012; Zebari et al., 2021). MRI offers valuable knowledge on the anatomy of the brain that is necessary for tumor detection (Gonzales & Woods, 2002). In addition, Computer vision brain tumor segmentation is a method of separating or segmenting an image into regions by dividing the images neighborhood pixels based on certain predefined features or properties of the pixel. (Mardia & Hainsworth, 1988; Krishnakumar & Manivannan, 2020). The primary aim of medical imaging is to extract useful goods and correct image data with the lowest possible error. Two key phases are involved in medical image processing. Preprocessing the picture is the first step (Faris et al., 2019). This step includes performing acts such as noise reduction and filtering, which for the next stage will produce the perfect image (Saha & Hossain, 2017). The purpose of pre-process the image is to improve the images it for further processing, this is achieved by modifying the nature of the image to improve its pictorial details (Singh & Ansari, 2016). The implementation of Segmentation and Morphological Operators is the second step. They assess the tumor's size and location (Parmar & Gondaliya, 2018). Segmentation is a very important process and occupies a crucial role to extract information from complex medical images, in the field of image processing. The primary aim of image segmentation is to divide the digital image into regions that are mutually exclusive (Joseph et al., 2014). In a variety of ways image segmentation can be carried out (Havaei et al., 2016; Ahmed & Sadiq, 2018a). Some of these are region-based segmentation and segmentation of edge detection by using clustering algorithms (Hamamci et al., 2011; Tustison et al., 2015). After processing and segmentation of medical images, need to use features extractions help to differentiate against tumors based on their specific intensity strength or pattern of texture (Viola & Wells III, 1997). In MR images of the brain, the diverse structures of different tumors have led to the extraction of useful features (Dou et al., 2007; Wang et al., 2009; Ahmed, 2013a). In order, Radiologists classify brain tumors on the basis of textural homogeneity or heterogeneity to distinguish between various tumors (Selvaraj et al., 2007; Jahwar & Abdulazeez, 2020). These visually extractable features provide instructions for finding the most suitable descriptors of mathematical features to develop a CAD to distinguish between brain tumors (Kharrat et al., 2010; Zacharaki et al., 2009). The aim of this review is to find the best techniques to detect the brain tumor in early stage by using clustering and classification algorithms and made a comparison between the algorithms to find the best results (Gayathri et al., 2015).

This review based on Clustering algorithms that use for segmentations and feature extraction of the images (Zhang et al., 1997). K-mean, Fuzzy c-mean clustering algorithms were used individually with their classification, and compared to other algorithms (Ji et al., 2012). However, clustering algorithms can be used after extraction of brain tumor features containing any unnecessary parts that can be removed to enhance the image quality (Wetherill et al., 2018; Shakya, 2019).

2. Medical Images

Medical images that involve several type of images that vary from one to another such as Computed Tomography, Magnetic Resonance Imaging, and X-Ray (Toner & Jodrell, 1997 (Modgil & Kaur, 2019). To assess these tumors, MRI is a widely used imaging method, but the vast amount of data generated by MRI prevents manual segmentation in a reasonable amount of time, restricting the use in clinical practice of accurate quantitative measurements (Bauer et al., 2013) . CT imaging is favored over MRI, Due to wider availability, lower cost and early-stock sensitivity. CT contains the information needed to make decisions during an emergency in most cases. A hemorrhage appears in CT images as a bright area of hyper dense contrasted to its surroundings (Chawla et al., 2009). X-ray imaging has played a great role in the cognitive and functional organization of medicine. X-ray is electromagnetic waves are a form of radiation. This is equivalent to microwaves and illumination. To form a 2-D, X-rays penetrate the body. This provides representations of the inside of your body. The images depict parts of the body in various shades of black and white. This is because different tissues consume different levels of radiation (Zhang et al., 2019; Zeebaree et al., 2019b). Moreover, the MRI provides various data on Various structures in the body that are accomplished with The support of an X-ray (Saini & Singh, 2015). In the table 1 below will compare the medical images (Goel et al., 2016).

Table 1: Comparison of Medical Images

	X-Ray	MRI	CT
Resolution	Normal	Best	Moderate
Speed	Short	Long	Moderate
Cost	Low	High	High
Data acquisition	Low	High	High
Effects	Ionizing radiation	No	Ionizing radiation
Availability	Maximum	Less than CT	Without much difficulty

2.1. Pre-processing

The medical images first need a pre-processing to improve the images quality. Here, we begin the process with some constraints that can harm the image quality. Thus, in pre-processing, we perform manual correction. We may then improve the images quality to make it ready for further processing, the purpose of pre-processing is to remove from the brain MR/CT images the film objects and skull portions, And to improve the accuracy of the images to make it easier and safer to identify brain tumors (Patil & Udupi, 2012). The processed images are occupied to the next phase once this process is completed, where to the segmentation and feature extraction is accomplished for further processing to detected the brain tumors and it is type (Patel, 2010; Ahmed, 2013b).

2.2. Segmentation

In several medical imaging algorithms, the segmentation of images plays a key role (Liu et al., 2014). The next step after enhancing the medical images for brain tumor is segmentation methods that can be grouped into various groups, based on different criteria (Pham et al., 2000a). Brain tumor segmentation methods are generally divided into three main categories in the clinic, namely manual, semi-automatic and fully automatic segmentations, depending on the degree of human intervention required (Bauer et al., 2013), (Zeebaree et al., 2019a). It is the mechanism by which an image is divided into regions with various characteristics such as color, texture, brightness, contrast and gray level. A digital gray scale picture is the input to the operation. (MRI or CT) Anomalies are the performance of the operation. The use of segmentation is to provide greater data than is present in medical images. Different methods, such as the k-mean clustering, fuzzy c-mean, used in segmentation to get desired performance data (Pham et al., 2000b).

2.3. Feature Extraction

Extraction of features is a method of collecting an images visual content. the extraction of features is the technique of representing the raw image in its reduced form, to facilitate decision-making, such as pattern recognition. The set of features must be extracted from the input data if the extracted features are carefully chosen to acquire the necessary information to perform the desired task using this small representation instead of the full size input (Egmont-Petersen et al., 2002), (Shukla & Kumar Sharma, 2020). By creating a stronger and more accurate classifier that can act as an expert assistant to medical professionals and has attempted to solve the problem of classifying brain images for MRI and CT (Pushpa Rathi, 2012).

2.4. K-Mean Clustering

K-mean clustering algorithm it is unsupervised machine learning that separates the image intensities depending on the centroid cluster, then calculates the distance between each pixel of the image and the centroid pixel. Based on the minimum distance value, the algorithm assigns each pixel to a particular centroid. By changing the average distance values of the pixels assigned to the centroids, the algorithm also updates the centroids. with respect to new centroids, the distance values are modified and the pixels are reassigned, the algorithm continues until the meaning of the distances from the centroids has modified significantly (Hanuman & Sooknanan, 2018), (R. Zebari et al., 2020). Tumor region clustering obtained after extraction of brain tumor features requires some redundant parts that can be removed to boost precision using the clustering algorithm. The step of k-mean algorithm to present number of cluster (k|), and select the nearest centroid:

1) Position the initial centroids of the cluster |(k).
2) Assign the centroid nearest to each pixel.
3) Once all pixels are assigned, recalculate the new centroids of the k cluster.
4) Repeat the steps 2, and 3 until the convergence criterion has been met that is, until the centroids are no longer moving.

The flowchart below in Figure (1), shows the steps of k-mean, and how it calculates the distance to centroids each point of the image (Tripathy et al., 2013).

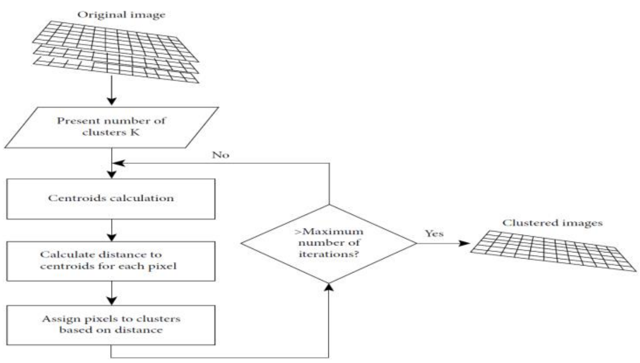

Fig. 1: Flowchart of k-mean clustering algorithm.

2.5. Fuzzy C-Mean

In data clustering the FCM is one of the most powerful procedures. FCM is an unmonitored technique concerned with a wide variety of problems, including examination of characteristics, clustering, and classification. It has a wide range of horticultural architecture, astronomy, chemistry, geography, image research, therapeutic determination, identification of boundaries and objective recognition applications. The partial volume effect (PVE) can be handled well by FCM and the data is segmented into two or more clusters. This only takes the intensity of the segmented image into account and is an iterative operation (Karuna et al., 2020). FCM clustering carries out a clustering that defines the data structure as best as possible, by iteratively searching for a series of fuzzy clusters and associated cluster centres. This enables the current set of power points n to be separated by a given number of fuzzy set (*Citeseer - Full Text PDF*, n.d.), (Nawzat Sadiq Ahmed & Sadiq, 2018b). MRI image segmentation is achieved by combining feature extraction and feature reduction together with modified FCM algorithm (Emblem et al., 2009).

3. Related work

Islam et al., (Islam et al., 2020) Proposed a model that using K-mean technique and an improving of support vector machine (ISVM) classificatory to classify brain tumors. The MRI images is obtained as a dataset in the proposed algorithm that is reprocessed by the median filter; secondly, the processed image is segmented using the K-mean algorithm, lastly the SVM algorithm is used to identify irregular cells tumors. Compared to other traditional systems, the proposed algorithm obtained greater precision from the experimental result. This suggested algorithm also lowers the execution time and can exceed a second within a short period of time to detect a tumor. Nasor et al., (Nasor & Obaid, 2020) Presented an automated machine vision technique to identify and locate brain tumors in MRI images at their very early stages, using a combination of k-means clustering, patch-based image processing, object counting, and tumor evaluation. The technique was tested on twenty real MRI images and found that multiple tumors, including those with very small sizes, can be identified in MRI images regardless of their variations in intensity level, scale, and location. Apart from its use for diagnosis, It is possible to integrate the technique into automated treatment instruments and robotic surgery systems. The proposed technique was able to classify tumors at an early stage in MRI images, irrespective of their variation in magnitude and place size.

Mehidi et al., (Mehidi et al., 2019) Suggested a method for establishing a simple and suitable boundary in the MRI images around the tumor area. Some disadvantages of the standard KM algorithm are discussed by the proposed solution, such as random centroid cluster initialization and noise sensitivity based on the k-mean algorithm. The main objective is to combine the Darwinian Optimization of Particle Swarm (DPSO) technique, the KM algorithm and the operation of morphological reconstruction (MR). For the initialisation of cluster centroids, the DPSO approach is applied to MRI medical images. In addition, the MR filter is used to remove noise and create more compact clusters that are well separated. By comparing it with some state-of-the-art segmentation algorithms, such as the standard KM clustering algorithm and DPSO-based multilevel thresholding, the efficiency of the proposed method was assessed. The results indicate the effectiveness of the approach proposed for early tumor detection. Nitta et al. (2020) Proposed a technique that focused on the MRIs medical images for segmentation. A novel of K-mean cluster algorithm is implemented in this suggested approach by incorporating the images utmost dominant gray level, unlike the methods developed. The problem of selecting k the number of pixels randomly using the dominant gray level of the image was discussed. The experimental results of the proposed method showed that it has improved performance in terms of image accuracy, as opposed to the traditional K-Means approach. (grawal et al. (2018) A hybrid approach was proposed for brain lesion segmentation, by incorporating median filter, k-mean cluster, Sobel edge detection and morphological operations in different imaging modalities of MRI and CT. The median filter is a significant pre-processing stage and is used, followed by k-means segmentation, to remove impulsive noise from the acquired brain images. Using performance measures such as segmentation accuracy and execution time, the performance of the proposed automated system is evaluated on standard datasets. Compared to manual delineation carried out by an expert radiologist, the result showed that it achieves a high accuracy of 94%. ShanmugaPriya & Valarmathi (2018) Proposed work focused on Edema and tumor segmentation Based on skull stripping and on the kernel-based fuzzy c-means process. The clustering process is improved by combining multiple kernels based on spatial information. Our approach to multilevel segmentation relies on global matching information, between image distributions and eliminates the need for pixel-wise information that reduces the difficulty of computation. In this framework, the Graph cut algorithm is implemented as a co-segmentation to define the exact cut-off point between edema and tumor to remove edema from the tumor. In this approach, clearer visualization of edema is possible and additional room is established for the tumor to be properly removed. Results of the simulation indicate that our methodology outperforms the other current full tumor and edema segmentation. Hamad et al. (2018) Introduced a MRI brain tumor detection, based on clustering algorithm of Fuzzy c-mean in the medical images processing system. With a median filter, BCET denotes and enhances the input image. Then the picture is segmented by the FCM clustering process and the edge map of the brain tumor is generated using a canny edge detector. As the canny method is used for ideal input images that have improved quality and are segmented into homogeneous regions for BCET and Fuzzy c-mean, the proposed approach works better. As a result, the recommended approach yields a good outcome and offers high image quality for medical professional testing. The experimental research carried out showed the stability of the edge map produced by the method proposed to influence and decrease the noise. Narmatha et al. (2020) Proposed A system using the fuzzy c-mean, brain-storm optimization algorithm, a mixture of fuzzy and brain-storm optimization techniques, For segmentation and classifications of medical images. Optimizing the brain-storm focuses on the cluster centres and gives them the highest priority, like every other swarm algorithm, it could collapse into local optima. The fuzzy conducts several iterations in order to present an ideal network structure, and the brain-storm optimization seems promising and with better results exceeds the other techniques in this study. The BRATs dataset was used, and the proposed FBSO was successful, robust and mainly decreased the optimization algorithm segmentation time with 93.85 percent accuracy, 94.77% accuracy, 95.77% sensitivity, and 95.42% of F1 score. Latha & Perumal (2018) Showed that the extraction of tumor from MRI uses a fitness feature in the genetic algorithm that based on Fuzzy c-mean, clump and morphological activity. Computer simulations provide a significant improvement over the current methods. however, a tumor is an abnormal development of the body cells. At the initial stage, a brain tumor is difficult to diagnose. Magnetic resonance imaging MRI is now being diagnosed as it differentiates multiple grades of intensity by tumor square calculation. the results show the FCMFF in GA segmentation a better result with more accuracy. Thilagam el al. (2020) Proposed for (MRI and CT) brain tumor segmentation, a new FCM formulation technique (fuzzy c-mean algorithm) called the PIGFCM algorithm was implemented, followed by an image de-noising technique, which is an unavoidable before the phase in image processing. The PSNLM filter (Presmooth Non-Local Means filter) is used to denoise Rican noise, and the PIGFCM algorithm which is an FCM algorithm reformulation (fuzzy C means algorithm) used in the proposed process, which integrates good quality into the segmentation process and is used to denote the Rician noise process, The PIGFCM algorithm utilizes the tumor classes' prior knowledge. the results show reduce de-noising in the medical images, increase segmentation accuracy, and high speed in the proposed process give good result to help detected the tumor.

Table 1: A comparison table to Detect Brain Tumor using K-Means and Fuzzy C-Means

Ref.	Year	Dataset	Techniques	Objective	Result and Accuracy
(Zeebaree et al., 2019a)	2020	MRI images	K-mean ISVM	K-mean and improving SVM help to detected the dieses in early stage in less time "in a second"	The proposed algorithm has achieved 95% accuracy, 94.74% sensitivity and 100% it is better than other techniques
(Pham et al., 2018.-b)	2020	MRI images	K-mean	At the very early stages of their development, the identification of cancerous tumors helps doctors determine the correct treatment and thus increases patients chances of full recovery	From the MRI images, by using the detection data. the result show that for Precision 98.48%, high Accuracy 99.81%, and Specificity 99.99%
(Egmont-Petersen et al., 2002)	2019	MRI images	K-mean	The most goal of this method is to locate the boundary of tumor area present in specified MRI image, to detection the tumor	The proposed algorithm accurately located the boundary of the tumor area present in the specified MRI image and calculated the efficiency of the results and showed the image quality after the proposed noise-free technique was applied.
(Shukla & Kumar Sharma, 2020)	2020	MRI image	K-mean	To enhance the problem of arbitrarily selecting k no pixels using the images dominant gray level method. Instead of taking random initial centroids in K-mean	The improving of k-mean to selected k give the result with more accurately of MRI images from traditional k-mean
(Pushpa Rathi, 2012)	2018	MRI and CT images	K-mean	The main objective is to eliminate noise using a median filter, Using identification of Sobel edge and morphological operations to use the k-means clustering method for segmentation and brain tumor extraction.	It help the radiologist to detected the tumor with it a high accuracy 94%.
(Hanuman & Sooknanan, 2018),	2018	MRI images	Fuzzy c-mean	The aim is to minimize computation time and increase the precision of segmentation based on fuzzy clustering techniques.	The results clearly show that the approach proposed is more effective for better detection of anomalies while maintaining image quality.
(R. Zebari et al., 2020).	2018	MRI images	Fuzzy c-mean	The primary objective is to develop features and achieve better medical images characteristics for the proper diagnosis using BCET	An increase in the accuracy of solving segmentation problems was found to be up to 10%-15% higher than the corresponding expert estimates in some cases of tumor pathology
(Tripathy et al., 2013)	2020	MRI images, BRATs	Fuzzy c-mean	The primary objective of using FBSO was to reduce the segmentation time of the optimization algorithm efficiently, robustly and primarily for medical images	The result shows that the proposed FBSO was efficient, robust and reduced the segmentation time of the optimization algorithm, with an accuracy of 93.85%, an accuracy of 94.77%, sensitivity 95.77% and an F1 score of 95.42%.
(Karuna et al., 2020)	2018	MRI images	Fuzzy c-mean	MR brain medical images assess the intent of this algorithm to expand the accuracy and its efficiency.	This work was improved the methodology to locate brain tumor from medical images with better result and high accuracy.
(Thilagam el al.,2020a)	2020	CT, MRI images	Fuzzy c-mean	The main objective is enhancement the medical images CT and MRI Using a new fuzzy C formulation algorithm means the PIGFCM algorithm is named	the result show the PIGFCM algorithm has proved to be an effective fuzzy algorithm. For segmentation and good speed, the algorithm has good precision

4. Discussion

From the table has been done above, several authors shown desirable results for detected brain tumor and lots of them used MRI images as a dataset in their studies. they depended on clustering algorithms specially k-means, and fuzzy c-mean algorithms for each medical images. The identification of tumors at the very early stages of their development helps doctors determine the correct treatment and thereby increases the chance of full recovery for patients. In (Pham et al., 2018b) k-mean improving to help to detected the brain in early stage with high accuracy and high sensitivity from other techniques depending on MRI images. In other such as the authors (Pushpa Rathi, 2012) depended on MRI, CT as a dataset, the use k-means clustering approach for segmentation and brain tumor extraction, to remove noise of medical images using a filter to detected the tumor in early stage with less time. While other authors depended on Fuzzy c-mean to detected the tumor, such as in (Tripathy et al., 2013) the use MRI images BRATs as a dataset, to reduce the segmentation time of the optimization algorithm efficiently, robustly and primarily for each images. In (Thilagam el al.,2020a) the use MRI, CT as a dataset and fuzzy c-mean algorithm help to using a new formulation algorithm of fuzzy c-means called PIGFCM algorithm that enhancement the fuzzy c-mean algorithm and increase the speed of the algorithm, the help to reduce the noise and enhance the segmentation to detected the tumor. Finally, from this review we compared the two algorithms k-mean, and fuzzy c-mean both of them help to detected the brain tumor, but each one has different accuracy to segmented the images, and reduce the noise of the images.

5. Conclusion

Radiologists or specialists to detect the tumor area in medical images, such as (MRI, CT, X-Ray), a tedious and time-consuming process, assume that K-mean that the algorithm is sufficient to detected it from the brain cells. the K-mean algorithm will help to remove before the phase if there is any noise present in the medical images such as (MRI, CT, X-Ray). The noise-free image is given as an input to the k-means, and the medical image extracts the tumor. And then segmentation using Fuzzy c-mean accurate extraction of malignant tumor form and output thresholding in function extraction. Finally, an approximate explanation for tumor form calculation and location calculation. in this review the results are compared with the k-mean and the fuzzy c-mean algorithms to show the accuracy of each one.

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