International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

A STUDY OF FUZZY BASED AUTOMATIC DETECTION AND CLASSIFICATION APPROACH FOR MRI-BRAIN TUMOR

CANDIDATE NAME= SATYAM KACHHTI
DESIGNATION= RESEARCH SCHOLAR SUNRISE UNIVERSITY ALWAR
GUIDE NAME= DR. VIRENDRA SINGH
DESIGNATION= ASSISTANT PROFESSOR
SUNRISE UNIVERSITY ALWAR RAJASTHAN

ABSTRACT
The goal of this chapter is to develop a method for automatically detecting and classifying brain tumors in MR scans. Pre-processing, tumor identification, picture segmentation, feature extraction, and template-based classification are the steps of the procedure. The fuzzy KNN technique is integrated with other prominent approaches to image processing, such as fuzzy C-means clustering and affine harmonic enhancement (AHE). The suggested method utilizes big MRI images to identify and categorize the brain tumor. Determines whether or not a tumor is present in the supplied picture based on the confidence level assigned to that image. Accuracy is improved over the current method, and efficiency in terms of detection and categorization is shown. Human brain tumors are defined by the abnormal growth of cells that often originate in the brain and spread to nearby structures including the brain's veins and nerves. Alterations in brain anatomy or behavior are two more names for a brain tumor. Brain tumors may be categorized as either benign, premalignant, or malignant. A benign tumor that grows slowly yet has a significant impact on brain tissue is called a "kindhearted tumor." A precancerous tumor is one that has not yet undergone the cancerous process that drives its development, and it may be treated with the right therapy. There is now no real cure for harmful tumors, which is why men continue to die from them.

KEYWORDS: Automatic Detection, MRI-Brain Tumor, fuzzy KNN technique, affine harmonic enhancement

INTRODUCTION

Electronic tomography (CT) and magnetic resonance imaging (MRI) are two of the most common imaging techniques utilized for brain tumor diagnosis. The CT procedure is regarded as the best method for distinguishing cancers among these approaches. Because diagnostic imaging provides fundamental data that guides treatment planning, and because radiation beams may be focused on the tumor while sparing surrounding healthy tissue. One method of separating brain tissue from bone is the skull-stripping mechanism. The tumor cells may be treated directly without affecting any other brain cells because to this separation. This method allows us to accurately identify cancer cells. CBTRUS reports that there were 64,530 new cases of high-risk, high-benefit (i.e. crucial) cancers in the globe in 2011.

Approximately 6 lakhs individuals are now affected by this illness.

Thirty percent of people across the globe have a brain tumor. Tumors form because of the abnormal growth of tissues in the brain, which occurs when cell division is not properly regulated. Radiological images aid doctors in identifying and staging a brain tumor. Therapeutic imaging researchers have been motivated to tackle the challenge of brain tumor segmentation from MRI images so that they can better aid patients. Dangerous tumors spread swiftly, wreak havoc on surrounding tissue, and are difficult to treat. Human life expectancy may be drastically shortened by detecting and removing a brain tumor in its early stages. The primary objective is to naturally divide atypical MRI image pixels from typical ones. Jiang et al. (2004), Greenspan et al. (2006), Yang and Huang (2006), Zhou and Bai (2006), Zhang et al. (2008), Jaya et al. (2009), Prastawa et al. (2008), and Ratan et al. (2009) all agree that pixel intensities are the primary dividing line for classifying brain tumors as benign or malignant.

Tumors are recognized as normal, benign, or malignant based on the input picture. Identifying an existing method requires many phases, such as taking into account an input picture and then using a noise reduction technique, such as a competitive, cooperative, or synoptic weight adaption method. Next, binary operations are applied to the enhanced picture to determine which features should be extracted. In preprocessing, MR pictures are typically de-noised. The speckle noise cancellation method is adopted here. Synthetic aperture radar and medical pictures often include many speckle noises.

Image: In order to advance the picture-splitting process, one of the most critical tasks is to verify that the underlying systems are functioning as expected with supporting visuals. The photographs have different characteristics in terms of scale, composition, dimensions, and tones. The many image types are discussed here. Images are often classified as either raster images, synthetic aperture radar images, or restoration images. Various MRI, CT, fMRI, DTI, PET, and NMRI pictures are used to test various methods of brain tumor detection and classification. The file extension, such as.tif,.jpeg,.bmp,.dicom,.png,.pgm, etc., reveals the image format. Other types of photographs include those that move, those that just show a person's face, and so on. In any event, MRI scans are treated as data images in this work.

SPECKLE NOISE REMOVAL

In medical image processing, reducing noise is the most difficult task. The researchers have laid a plethora of groundwork for noise reduction technique, building on prior work. Medical images often include speckle noise. Filtering strategies were presented for eliminating speckle noise in MRIs. In modern medicine, this imaging method is often utilized for diagnostic purposes. MR scans provide a detailed look into the primary organs within the body, including their size, nerve structure, and any damage. Speckle noise is the most distracting

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

kind in MR pictures and may be frustrating to look at. The following is a representation of speckle noise:

$$g(n, m) = f(n, m) * u(n, m) + \xi(n, m) \quad (1)$$

The MRI input picture is denoted by g n, m, the multiplicative component of the speckle noise is denoted by u n, m, and the additive component of the speckle noise is denoted by n, m. The picture samples are denoted by n, m along both axes. To get rid of noise, just disregard its additive part, which may be stated as:

$$g(n, m) = f(n, m) * u(n, m) + \xi(n, m) - \xi(n, m) \quad (2)$$

$$g(n, m) = f(n, m) * u(n, m) \quad (3)$$

The noise-free version of the picture is given by (4.3). The AHE technique is then used to improve the picture once the noise has been removed. Speckle noise is an unseen quality of synthetic aperture radar, satellite, and MR images caused by wave interference. Noise is produced by a scattering array, which is what the return waves are. We refer to these sounds as textures. To illustrate the model,

$$g(n, m) = f(n, m) * u(n, m) + \xi(n, m) \quad (4)$$

ADAPTIVE HISTOGRAM EQUALIZATION METHOD FOR IMAGE ENHANCEMENT

The contrast levels of the MRI images are improved with the use of AHE. Instead of using a standard histogram equalization approach, AHE rebalances the picture by redistributing the softness estimates of its various parts. As a result, AHE is well-suited for increasing the local complexity of the MRI picture and highlighting finer details. It improves the picture's aesthetic appeal by increasing its contrast. The first step is to convert the color image to black and white. The image's output is fed into a degradation process, which ultimately improves the image's quality.

With AHE, the transform function may be applied to separate sub-images and then combined to generate the final picture. Sub pictures, typically of size N × N, are extracted from the input image. These pictures are used to calculate the histogram equalization. Then, it's up to you to evaluate whether or not each pixel in the supplied picture indicates an interior area. Each pixel was given a weight, and the total of those weights was used in the mapping calculation for the pixel's inclusion in the internal area. If the area represented by the pixel is a border, then two weights must be considered when determining the closest value. The border region's map will be derived from the weighted total. Histogram corner region equalization mapping is performed if pixel stands for that area.

FUZZY C-MEANS CLUSTERING METHOD FOR IMAGE EGMENTION

In the field of soft segmentation methods, FCM is one of the clustering techniques employed. Jiang et al. (2004), Zhang et al. (2008), and others suggest many different families of effective fuzzy based clustering methods.The varied pattern in a batch

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

of data may be uncovered by using clustering algorithms to group comparable pixels [objects]. The fuzzy clustering approach is used by FCM in practical situations. In a nutshell, clustering is a function that, in a self-organized fashion, classifies the feature vectors. If we define x(q) = (x1(q), x2(q),..., xn (q)), where q = 1, 2, 3,..., Q), then we have a Q feature vector with N components. Assigning Q feature vectors to K clusters c (k): k=1,..., K using minimal similarity distance is the whole point of clustering. Within a certain distance from the selected centroid, the similarity between the data is calculated. Each data set should be inside the smallest possible cluster.

This is a form of clustering in which a data slice may be assigned to more than two groups. Pattern recognition relies heavily on it. Fuzzy behavior is characterized by its membership function, which sets limits on the data inside each cluster.

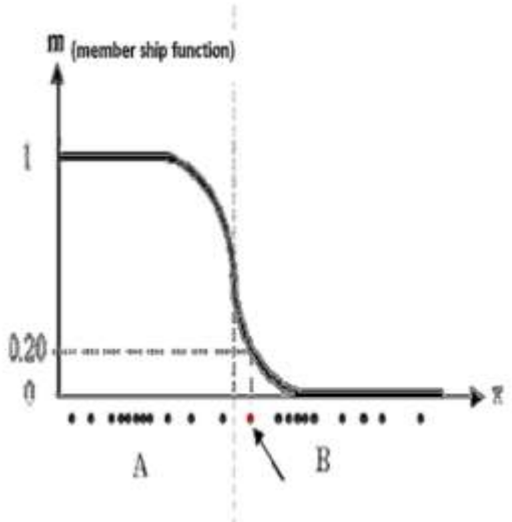

Figure 1 Membership function using in Fuzzy C-means

Fuzzy logic is a kind of logical analysis that uses many values to categorize a huge data collection. It organizes the set by employing close approximations rather than precise and fixed ones, with 0 and 1 serving as the logical values. If X is a collection of data points and A is a fuzzy set, then f(x) = A x would be used to classify X. Every X in the range [0, 1] has a corresponding value for F(x).

TUMOR CLASSIFICATION BY FUZZY-KNN CLASSIFICATION

Generally Fuzzy K-Nearest Neighbors is a supervised technique that may operate with either crisp or fuzzy data. It's a kind of categorization in which groups are distinguished by shared characteristics. Pixels are sorted according to their K-nearest neighbors. It remembers information previously learned regarding the class issue. In most cases, classes should be declared before being used. Each category will have a different total number of components. The Fuzzy-KNN classifier is fed the full set of Gabor feature values that were extracted from the improved version of Image I. The Fuzzy-KNN (33) technique combines KNN with Fuzzy. Clustering begins with established classes. The elements in a class and the clustering results that are processed on top of them may be different. However, class members are nearest neighbors.

CONCLUSION

In this study, a novel, methodical approach is given for identifying and categorizing brain tumors in MRI scans.

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

The overarching goal is to provide the most effective method for improving the effectiveness of the newly constructed system. Optimization techniques allow for even more progress to be made. The Fuzzy KNN classifier determines if an image is normal or abnormal and then displays the tumor's location using FCM clustering. For a set of 100 photos, the suggested method achieves an accuracy of 99%. Experimenting with live hospital photos, photographs from a benchmark database, and ground-truth images all contributed to its development. Tumors are recognized as normal, benign, or malignant based on the input picture. Identifying an existing method requires many phases, such as taking into account an input picture and then using a noise reduction technique, such as a competitive, cooperative, or synoptic weight adaption method. Next, binary operations are applied to the enhanced picture to determine which features should be extracted. In preprocessing, MR pictures are typically de-noised. The speckle noise cancellation method is adopted here. Synthetic aperture radar and medical pictures often include many speckle noises. Here, we take into account the input picture after first processing it to get rid of noise we call speckle. Using an adaptive histogram equalization technique, image enhancement raises the brightness and contrast of a picture. Synthetic aperture radar pictures, satellite photos, and medical imaging all suffer from this speckle noise to varying degrees. The threshold is chosen from among many bands. In the event that no particular frequency range is chosen, the overall threshold is evaluated.

REFERENCES

1. Chaddad, A, Zinn, PO & Colen RR, 2014, 'Brain tumor identification using gaussian mixture model features and decision trees classifier', IEEE- Information Sciences and Systems (CISS), 8th Annual Conference on Univ. of Texas MD Anderson Cancer Center, Houston, TX, USA, pp. 1-4.
2. Chakraborty, D & Nikhil, P 2004, 'A neuro fuzzy scheme for simultaneous feature selection and fuzzy rule based classification', IEEE Transactions on Neural Networks, Vol. 15, pp. 110-123
3. Chandramouli, K & Izquierdo E, 2006 'Image classification using chaotic particle swarm optimization', IEEE International Conference on Image Processing, pp. 3001-3004.
4. Chartier S & Boukadoum M, 2006, ' A bidirectional hetroassociative memory for binary and grey level patterns', IEEE Transactions on Neural Networks, vol. 17, pp. 385-96.
5. Charutha S & Jayashree MJ, 2014, 'An efficient brain tumor detection by integrating modified texture based region growing and cellular automata edge detection', International Conference on Control Instrumentation, Communication and Computational Technologies (ICCICCT), pp. 1193-1199
6. Deb, D, Dutta, B & Roy, SA 2014, 'Noble approach for noise removal from brain image using Region Filling', International Conference on

Advanced Communication Control and Computing Technologies (ICACCCT), pp. 1403-1406.

7. Deorah, S, Charles, L, Zita, A & Timothy R, 2006, 'Trends in brain cancer incidence and survival in the United States: Surveillance', Epidemiology and End results program. Neurosurgery Focus, vol. 20, pp. 1-7.
8. Dou, W, Ruan, S, Chen, Y, Bloyet, D & Constans, J 2007, 'A framework of fuzzy information fusion for the segmentation of brain tumor tissues on MR images', Image and Vision Computing, vol. 25, pp. 164-71.
9. El-Sayed, A & Abdel-Badeeh, M 2009 'Tamer H. A hybrid technique for automatic MRI brain images classification'. Informatica, vol. 54, pp. 55- 67.
10. Eschrich, S, Ke, J, Lawrence H & Dmitry G, 2003 'Fast accurate fuzzy clustering through data reduction', IEEE Transactions on Fuzzy Systems, vol. 11, pp. 262-70.
11. Fan, Y, Shen D & Davatzikos C, 2005 'Classification of structural images via high dimensional image warping, robust feature extraction and SVM', Proceedings of MICCAI, Lecture Notes on Computer Science, vol. 3749, pp. 1-8.
12. Ganesan, R & Radhakrishnan, S 2009, 'Segmentation of computed tomography brain images using genetic algorithm', International Journal of Soft Computing, vol. 4, pp. 157-61.
13. Garcia-Nieto, J & Jourdan, L 2007, 'A comparison of PSO and GA approaches for gene selection and classification of microarray data', Proc. of the 9th Annual conference on Genetic and Evolutionary Computation, pp. 427-429.
14. Georgiadis, P, Cavouras, D, Kalatzis, J, Daskalakis, A, Kagadis, G, Sifaki K& Solomou E 2007, 'Non-linear least square feature transformations for improving the performance of probabilistic neural networks in classifying human brain tumors on MRI', Lecture Notes on Computer Science, vol. 47, no. 07, pp. 239-247.