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Efficient Brain Tumour Segmentation Using Fuzzy Level Set Method and Intensity Normalization

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ABSTRACT- This paper is developed to implement a fuzzy set technique with intensity normalization intended for the identification of location and tumor shape from an MRI image. Normally, the tumor can be an uncontrolled growth of tissue in any portion of the body. Here, different kinds of cancers have various conditions with the treatments. Hence, brain tumor segmentation is an essential topic in medical applications. The fuzzy level set technique is utilized to segment the tumor from the brain MRI images. Additionally, intensity normalization is utilized to enhance image quality. The proposed technique is implemented in MATLAB and the exhibitions are evaluated by performance scores and implementation scales of quality ratings. To recognize the exhibition of the proposed technique, it is compared with the different and conventional strategies, for example, mobilenetv2, resnet18, resnet50, and xception separately.

General Terms: Tumor Segmentation, Fuzzy set technique and Normalization.
Keywords: Brain tumor, Segmentation, Intensity modulation, Fuzzy level set method, Similarity measurements.

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1. INTRODUCTION

Brain tumors can develop from abnormal growth of cells inside the mind or from cells that have spread to the mind from another disease (Havaei et al., 2017) [1]. There are broad classifications of cerebral development, which are characterized by the cells of their origin, and can be classified as a low- or high-quality continuum based on their malignancy and developmental properties. Diagnosis is based on the quality and type of cancer for the best treatment (Ali et al., 2020) [2]. Clinical imaging methods are used to identify and evaluate cancers. Among these clinical imaging methods, magnetic resonance imaging (MRI) is commonly used to assist in determining clinical results, treatment, anticipation, and organization of clinical and radiotherapy (Pinto et al., 2018) [3,17].

Due to the multimedia concept of MRI, there are image types and variations that enhance a vague radiographic assessment of the development type (Khan et al., 2021) [4]. A computer support system is being developed to assist with routine neurological detection and treatment arrangements. Design acknowledgment and image manipulation with machining learning computations are widely used for research as a guide for translating medical images. Segmentation methods have been proposed for a few medical applications. For brain tumors, imaging may help to quickly and objectively assess the extent of cancer, as well as identify patient-specific components that may help confirm and organize treatment (Chen et al., 2020) [5,18].

2. LITERATURE REVIEW

Mohammadreza Soltaninejad et al., (Soltaninejad et al., 2018) [6] have introduced the original super voxel-based based learning technique for differentiating cancer in multimedia MRI images (traditional MRI and DTI). Super voxels were produced using data from a multimodal MRI database. For each super voxel, the classification of features that memorized text histograms for the descriptor determined the use of a set of Gabor channels of different sizes and directions, and the first request force extracted true elements. To compile each superoxide into growth center, oedema, or solid brain tissue, those features are observed in a random forests (RF) classifier.
Amjad Rehman Khan et al., (Khan et al., 2021) [7] have presented deep learning and K-means clustering for brain tumor segmentation with the consideration of synthetic data augmentation. The recommended technique involves three main stages: pre-processing, brain tumor segmentation, clustering using k, and finally, regulation of MRI information in their specific classifications (harmless/dangerous) by microscopic VGG19 (i.e., 19-layer visual geometric group). Sample. In addition, for better classification accuracy, the idea of expanding the information produced was known to increase the amount of information available for categorization and preparation.

Asieh Khosravanian et al., (Khosravanian et al., 2021) [8] have introduced another user given the level set strategy for the medical image segmentation. To the right of the bat, categorize the objective capacity of a superpixel fuzzy clustering. To create superpixel districts, the multiscale morphological gradient reconstruction (MMGR) function was used. Besides, the original fuzzy energy is useful in terms of superpixel segmentation and histogram calculation. Then, the level set conditions are obtained using the angle slope technique. Finally, address the level set conditions using the lattice Boltzmann method (LBM).

P. Ramya et al., (Ramya et al., 2021) [9] have introduced an ensemble method for image segmentation of the developmental area of the MRI image in the brain. For segmentation, images were pre-manipulated by the Laplacian cell automata separation technique and separated by a group of different group techniques, for example, the collection of K-means, fuzzy-based clustering, self-organization map (SOM), and Gaussian mixture model, K-meaning, thought about SOM and their results. This costume cluster name was considered fragmentary and regulates contradictions using an in-depth learning technique.

Prabhjot Kaur Chahal et al., (chahal et al., 2021) [10] have recovered the most significant groups using MR images of a hybrid weighted fuzzy k-means (WFKM) for brain tumor segmentation. It relies on the fuzzification of weights in a spatial setting with a mild membership approach that helps to solve problems with various combinations of pixels and dramatic expansion in the number of rotations. The segmented image is used in addition to the effective development type ID that is vulnerable or intimidating by SVM. Performed trial and error on MR images covering the Digital Imaging and Communications in Medicine (DICOM) database in medicine, showing that the combination of the proposed WFKM and SVM overrides many existing methods. Zaka Ur Rehman et al., [14] have presented a regional level using Random Majority Down-sampling-Synthetic Minority Over-sampling Technique (RMD-SMOTE) for brain tumor segmentation. P. Sriramakrishnan et al., [15] have presented a modified local ternary pattern technique for efficient brain tumor segmentation from the MRI images. Mahnoor ali et al., [16] have presented a 3D convolutional neural network for optimal brain tumor segmentation process.

3. PROPOSED SYSTEM MODEL

Over the past two years, clinical imaging and grouping have become a field that can assist medical professionals and radiologists in diagnosing a variety of chronic diseases, including wellness-related applications. Evaluation. Usually, several planned segmentation strategies are developed by analysts. The efficient and mandatory segmentation is an intriguing review of medical applications. The planned brain tumor segmentation deals with a variety of issues, for example, measuring cerebral development, which is generally small, associated with fluctuating types and tissue abnormalities, and the difference between brain tumors. Furthermore, multi-goal scanners and security strategies expand the developmental and intensity changes between the brain and tumor. In recent years, the fuzzy-based clustering methods are interesting attention to managing different automatic recognition. The block diagram of the projected technique is illustrated in *figure 1*.

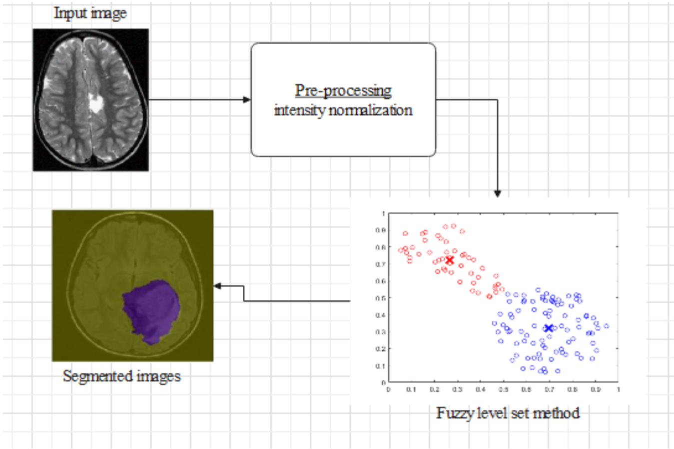

Figure 1: Block diagram of the projected technique

3.1 Pre-processing Stage

In the pre-processing phase, the MRI removes undesirable data from the image and enhances the image quality. The pre-processing techniques for the proposed system are introduced as follows,

(a) Intensity normalization

In the brain MRI image, the basic barrier of the images is that the comparable types of tissues do not have precise intensity. Different MRI arrangements give different key ranges to the soft comparative tissue type inside the comparator. These intensity changes give the complex operation of the image investigation and segmentation process. Therefore, intensity normalization in MRI examination is expected (Sachdeva et al., 2013) [11]. Here, Gaussian intensity normalization is used, which measures power limits by a global direct measurement process. This strategy is operated by the essential properties of the distance by constant deflection of the total key ranges within one of the following,

$$I^{new}=I/\sigma \qquad (1)$$

Where *I* is defined as the primary intensity parameter and σ is defined as the entire scan of standard deviation. Related to the procedure, the MRI image segmentation is attained in the period of [0,1024], without any essential data loss.

3.2 Fuzzy Level Set Technique

In this proposed approach, the FLS technique is used to segments tumor from the MRI image (Khosravanian et al., 2021) [12]. The targeting capability of the FLS strategy is limited to the fuzzy technique that can be used in the section. The membership variable depends on the cluster location associated with the exact district of interest. The exact area of interest depends on the particular cluster. Assembling objects in a group usually depends on objective qualities. The cluster center is selected with the help of irregular resolution. Clusters

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are calculated in light of the mean square deviation of the various pixels introduced below,

$$\sigma_{XD} = \sqrt{\sum D \in nx\{D\} \frac{(G^{`}-G)^2}{M-1}} \qquad (2)$$

Where, $G^{`}$ is defined as the remaining pixel parameter, G is defined as the chosen pixel parameter. The upgrading of the exponential kernel function is presented as follows,

$$W_{XD} = Exp[-(\sigma_{XD} - \frac{\sum D \in nx \sigma_{XD}}{M} \qquad (3)$$

After standardizing the image borders, the pixel variables can be merged with the larger borders recorded on the neighborhood page [18]. Adjusting the boundary for each pixel can be completed by dividing the weight (W) by the total capacity of W. Finally, k is used to regulate the intensity introduced as follows,

$$F_{R1} = \sum_{I=1}^{N} \int |G(X) - G(C)| U_1(X) dx \qquad (4)$$

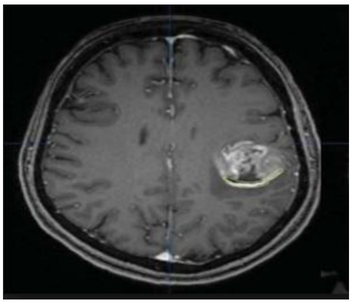
Where, $U_I(X)$ is defined as the region membership function $(R1)$. In the proposed technique, the cluster head is chosen with the consideration of random selection.

4. SECTIONS

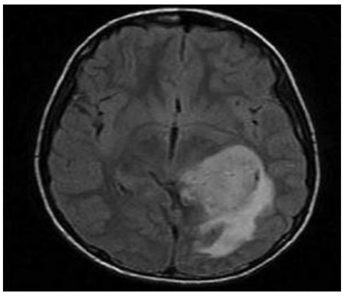
The presentation of the proposed strategy is evaluated and supported in this section. In this section, the planned method exhibitions are recognized by implementation and selection. To acknowledge the existence of a projected MRI brain tumor segmentation, the proposed strategy is carried out on an Intel Core i5-2450M CPU 2.50GHz PC and 6GB RAM. This technique is implemented in MATLAB programming R2016b. To authorize the exhibition of the proposed technique, data are collected from [13] containing 253 images. The planned strategy implementation boundaries are given in *table 1*. The proposed technique is implemented and approved using presentation metrics such as accuracy. The proposed in-depth learning technique is used to distinguish brain cancer from MRI images.

Table 1: Proposed method parameters

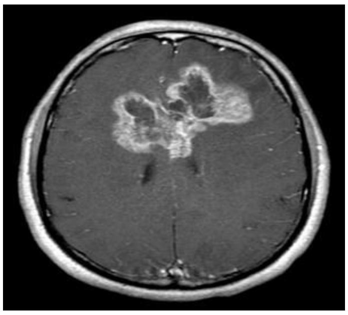
S. No	Description	Value
1	Number of Decision Variables	5
2	Number of Populations	50
3	Upper bound	5.12
4	Lower bound	-5.12
5	Iteration	100



(a)

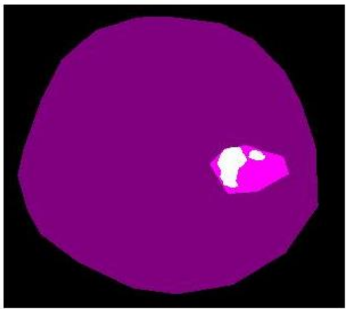


(b)

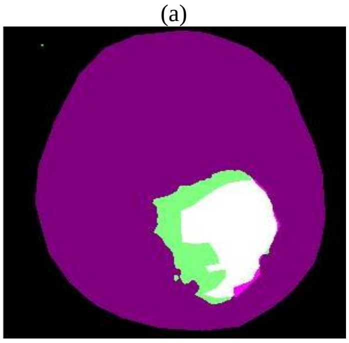


(c)

Figure 2: MRI input images (a) image 1, (b) image 2 and (c) image 3



(a)



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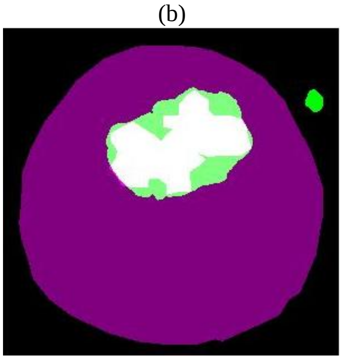
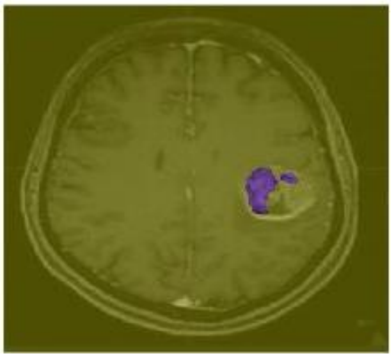
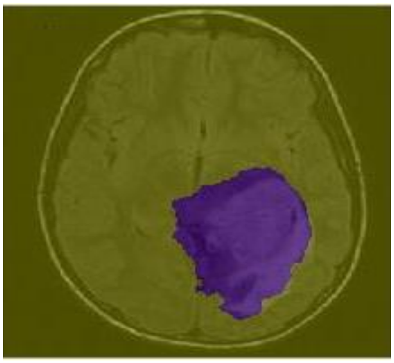


(c)

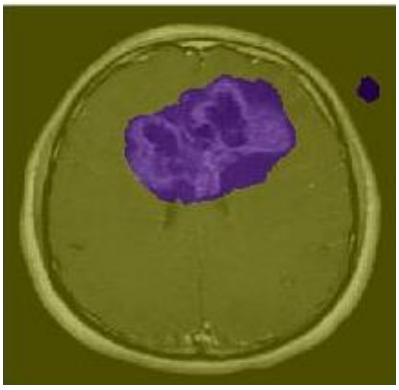
Figure 3: MRI ground truth images (a) image 1, (b) image 2 and c) image 3



(a)



(b)



(c)

Figure 4: MRI segmented images (a) image 1, (b) image 2 and (c) image 3

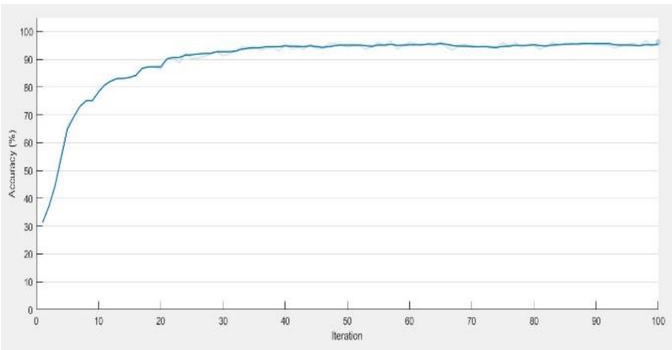


Figure 5: Accuracy of the projected technique

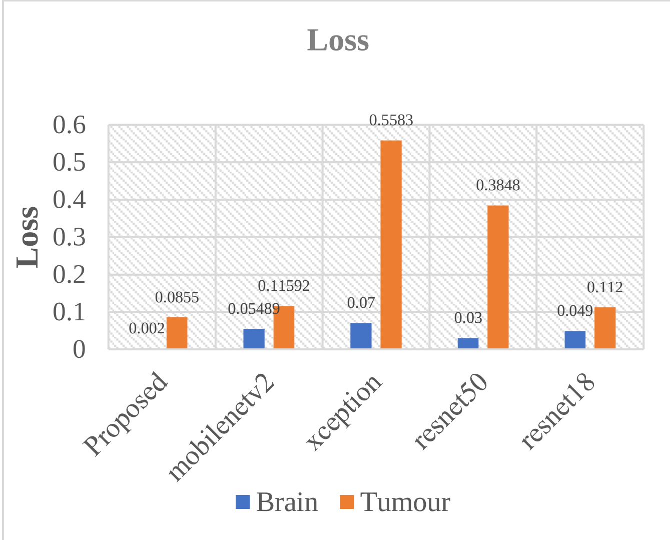


Figure 6: Loss of the system

Example input images of MRI brain tumor are shown in *figure 2*. The basic factual images of the proposed technique are introduced in *figure 3*. Segmented images as a result of the proposed technique are described in *figure 4*. The accuracy of the proposed technique is introduced in *figure 5*, and the proposed technique is executed with 97% accuracy in the segmentation of brain tumor. The loss of the system is illustrated in *figure 6*. From *figure 6*, the proposed technique accomplished a 0.002% loss. mobilenetv2, xception, resnet50 and resnet18 are 0.0548%, 0.07%, 0.03% and 0.049% respectively. From the exam, the proposed technique brings a loss segmentation process.

5. CONCLUSION

Different types of tumors are accessible. They can be mass in the brain or a threat to the brain. If it is a mass, the planned process is sufficient to separate it from the synchronizers. Assuming there was some confusion in the MR image, it was taken before the clustering structure. The non-abrasive image is given as a contribution to the cluster structure and the tumor segments from the MRI image. This paper proposed the intensity normalization and fuzzy level set technique for brain tumor segmentation. The main objective of the research has been segmenting the tumor portions from the brain MRI images. The proposed strategy is to segment the tumor portions of the brain. The proposed technique is implemented in MATLAB and the exhibitions are evaluated by performance scores and implementation scales of quality ratings. To recognize the exhibition of the proposed technique, it is compared with the different and conventional strategies, for example, mobilenetv2, resnet18, resnet50, and xception separately. From the analysis, the proposed technique accomplished a 0.002% loss. mobilenetv2, xception, resnet50 and resnet18 are 0.0548%, 0.07%, 0.03% and 0.049% respectively. Additionally, the projected technique achieved 95% of accuracy in brain tumor segmentation.

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