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An efficient optimized multi-kernel support vector machine-based brain tumor classification and segmentation in MRI

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ABSTRACT

Magnetic resonance (MR) imaging has been playing a vital role in neuroscience research to examine brain conditions related to normal and abnormal brain structures and functions in vivo. In previous years, MRI is observed to play an important role in brain abnormalities research in determining size and location of affected tissues. MRI Image segmentation and classification refers to a process of assigning labels to a set of pixels or multiple regions. It plays a major role in the field of biomedical applications as it is widely used by the radiologists to segment the medical images input into meaningful regions. Thus, various segmentation techniques in medical imaging depending on the region of interest had been proposed. Medical image segmentation problems have been approached with several solution methods by different ranges of applicability such as Region Growing, Self-Organizing Map (SOM) and Fuzzy c-Means (FCM). Some recent progress has been made to create semi-supervised (based on user interaction) or supervised variational methods. In the last decades, many methods have been proposed to segment the brain tumor of MR images, such as neural networks, finite Gaussian mixture model, knowledge-based methods, atlas-based method, active contour model, level set methods, and outlier detection. However, segmentation of medical imagery remains a challenging problem due to the complexity of the images. Brain tissue is a particularly complex structure and its segmentation is an important step for studies in temporal change detection of morphology. Success of MRI in the detection of brain pathologies is very encouraging. However, diagnosis and locations of abnormality are made manually by radiologists. It consumes valuable human resources, is error sensitive and makes it prone to error.

Keywords: *MRI, CT scan, Fuzzy C-Means, Image Segmentation and Classification*

1. INTRODUCTION

MRI (Magnetic resonance Imaging) brain tumour images Classification may be a difficult task thanks to the variance and complexity of tumors. A brain tumour is an intracranial solid neoplasm or abnormal growth of cells within the brain or the central vertebral canal. Brain tumor is one among the foremost common and deadly diseases within the world. Detection of the brain tumour in its early stage is the key to its cure. There are many different types of brain tumors that make the decision very complicated [1]. So, classification of brain tumors is very important, in order to classify which, type of brain tumor the patient really suffered from. A good classification process leads to the right decision and provides good and right treatment [2]. In general, early-stage brain tumor diagnosis mainly includes Computed Tomography (CT) scan, Nerve test, Biopsy etc [3]. At present with the rapid growth of the Artificial Intelligence (AI) development in Biomedicine, computer-aided diagnosis and Magnetic Resonance Imaging (MRl) scans attract more and more attention [4]. Brain cancer is caused by a malignant brain tumour. Not all brain tumors are malignant (cancerous). Some types of brain tumors are benign (non-cancerous). Brain cancer is also called glioma and meningioma. Brain cancer is one of the leading causes of death from cancer. There are two main types of brain cancer such as primary brain tumor and secondary brain tumor [5].

Feature extraction and selection are important steps in carcinoma detection and classification.

An optimum feature set should have effective and discriminating features, while mostly reducing the redundancy of features to avoid "curse of dimensionality" problem [6]. Feature selection strategies often are applied to explore the effect of irrelevant features on the performance of classifier systems [7-9]. In this phase, an optimal subset of features which are necessary and sufficient for solving a drag is chosen. Feature selection improves the accuracy of algorithms by reducing the dimensionality and removing irrelevant features [10] [11]. Moreover, Feature extraction of images is an important step in tumor classification. Several sorts of feature extraction from digital mammograms including position feature, shape feature and texture feature etc. Several techniques have been developed for feature extraction from tumor images. After feature extraction, the feature selection process is more important.

Feature selection (also referred to as subset selection) may be a process commonly utilized in machine learning, wherein a subset of the features available from the info is chosen for application of a learning algorithm. Feature selection algorithms may be divided into filters [12], wrappers [13] and embedded approaches [14]. Filter's method evaluates quality of selected features, independently from the classification algorithm, while wrapper methods require application of a classifier to guage this quality. Embedded methods perform feature selection during learning of optimal parameters.

Classification is the process of allocation of things into groups consistent with type. Image classification requires different features of the image to classify them into different groups. Classification is required for categorizing the brain MR images into normal and tumorous images. Therefore, feature extraction and feature selection from the image is an extremely important task. Different classification methods from statistical and machine learning areas have been applied to cancer classification. Classification is a basic task in data analysis and pattern recognition that requires the construction of a Classifier. Many machine learning techniques have been applied to classify the tumor, including Fisher linear Discriminant analysis [15], k-nearest neighbour [16] decision tree, multilayer perceptron [17], and support vector machine [18]. After this classification, segmentation is performed on the malignant images for tumor region extraction. Different researchers develop a brain tumor image segmentation algorithm such as watershed transform [19], fuzzy partition entropy of 2D histogram [20], fuzzy entropy and morphology [21] etc. Extraction of brain tumour region requires the segmentation of brain MR images into two segments. One segment contains the traditional brain cells and therefore the second segment contains the tumorous brain cells. Correct segmentation of MR images is extremely important because most of the time MR images aren't highly contrasted, thereby these segments are often easily overlapped with one another.

2. RELATED WORKS

In the literature survey, several methods have been proposed for brain tumor classification in image processing. Among the most recently published works are those presented as follows:

Chen, H., et al [22]. have examined an automatically segment brain tumor. DCNN based segmentation arrangements by including symmetric veils in a few layers were proposed. It was approved in the BRATS 2015 database, and they additionally give a few baselines. The outcomes are assessed by the Dice similarity coefficient metric (DSC). The technique accomplished a serious outcome with normal DSC of 0.852. Besides, the strategy just takes about 10.8 s to segment a patient case. In spite of the fact that the strategy was not the best execution in the BRATS 2015 test, supposedly, the technique outflanks other late DCNN-based strategies.

Tong, J., et al [23]. Has developed a brain tumor division based on system features. In this paper, MRIs were pre-processed to minimize noise, increase variability, and correct intensity uniformity. Sparse encoding was performed in the first-order and second-order statistical eigenvectors extracted from the original MRIs, which was a 3 × 3 patch around the voxel. Kernel dictionary learning was used to extract non-linear features to create two adaptive dictionaries for healthy and pathological tissues, respectively. A kernel-clustering algorithm based on dictionary learning was developed to encode the voxels, and then the linear discrimination method was used to classify the target pixels. In conclusion, the flood filling function was used to improve the separation quality. The results demonstrated that the kernel scattering index-based method has high efficiency and low computational cost with high segmentation accuracy.

Zhao, X., et al [24]. have proposed a brain tumor section. In this manner, a deep neural network has been used to cut images. They have evaluated their method based on imaging data provided by the Multimodal Brain Tumor Image Section Challenge (BRATS) 2013, BRATS 2015 and BRATS 2016. Experimental results have demonstrated that this method can produce a segmentation model with player, T1c and T2 scans. And achieve competitive performance as configured with Player, T1, T1C, and T2 scans.

Ponte, S., et al [25]. have analysed brain tumor segmentation in limited data using a local setting. They present a new approach using the Random Forests model, combining voxel-wise structure and abnormal features in T1 and FLAIR MRI. They convert both scans into 275 feature maps. Next, a random forest model computes the probability of belonging to 4 tumor classes or 5 normal classes. Then, a dedicated voxel clustering algorithm provides the final tumor section. They trained the method in the Brats 2013 database and verified it in the Big Brats 2017 dataset. They achieve an average tumor score of 40.9% and 75.0% for defining an active tumor, and 68.4% / 80.1% for the total abnormal area, including edema.

Banerjee, S.,et al [26]. has proposed brain tumor segmentation using visual salinity. The segmentation method was used for publicly available standard BRATS data sets and has been found to achieve the highest accuracy with good reliability (or repeatability) and robustness of results. In terms of weak linear correlations, its robustness was also investigated by measuring the impact of tumor size on segment accuracy. The results demonstrate that the segmentation developed by the algorithm can be applied to high- and low-grade tumors with a precise, consistent definition, compared to many related sophisticated methods involving semi-automated and supervised learning.

Kumar et al [27] had exhibited Optimization driven Deep Convolution Neural Network for brain tumor classification. This work introduces an optimized deep learning mechanism; Q6 named Dolphin-SCA based Deep CNN, to improve the accuracy and to make effective decisions in classification. Initially, the input MRI images are given to the pre-processing and then, subjected to the segmentation process. The segmentation process is carried out using a fuzzy deformable fusion model with Dolphin Echolocation based Sine Cosine Algorithm (Dolphin-SCA). Then, the feature extraction process is performed based on power LDP and statistical features, like mean, variance, and skewness. The extracted features are used in the Deep Convolution Neural Network (Deep CNN) for performing the brain tumor classification with Dolphin-SCA as the training algorithm. The performance of the proposed Dolphin-SCA based Deep CNN is analysed and shows better performance with the accuracy value of 0.963. In future, the performance of the proposed Dolphin-SCA based Deep CNN will be further improved by considering the HoG features, along with Statistical features and LBP features. Also, in future, the proposed method will be further improved by categorizing the tumor cells into malignant and benign.

Kaplan et al [28] had exhibited Brain tumor classification using modified local binary patterns (LBP) feature extraction methods. In this study, two different feature extraction (nLBP and αLBP) approaches were used to classify the most common brain tumor types; Glioma, Meningioma, and Pituitary brain tumors. nLBP is formed based on the relationship for each pixel around the neighbours. The nLBP method has a d parameter that specifies the distance between consecutive neighbours for comparison. Different patterns are obtained for different d parameter values. The αLBP operator calculates the value of each pixel based on an angle value. The angle values used for calculation are 0, 45, 90 and 135. To test the proposed methods, it was applied to images obtained from the brain tumor database collected from Nanfang Hospital, Guangzhou, China, and Tianjin Medical University General Hospital between the years of 2005 and 2010. The classification process was performed by using K-Nearest Neighbour (Knn) and Artificial Neural Networks (ANN), Random Forest (RF), A1DE, Linear Discriminant Analysis (LDA) classification methods, with the feature matrices obtained with nLBP, αLBP and classical LBP from the images in the data set. The highest success rate in brain tumor classification was 95.56% with the nLBPd = 1 feature extraction method and Knn model. Because of low cost, simplicity and easy-to-apply method, our proposed model can be preferred in order to make a decision support system for radiologists.

3. CONCLUSION

The primary goal of this research is to design and develop an approach for brain tumor classification and segmentation. The proposed approach consists of four stages, namely, (i) pre-processing, (ii) feature extraction, (iii) tumor classification and (iv) segmentation. Initially, the image will be given to the pre-processing stage to remove the noise present in the input image. Then, we will extract the texture features of each image. After feature extraction, the selected features will be given to the input of the classifier. For the classification process, an optimized multi-kernel support vector machine (OMKSVM) will be used. To enhance the performance of MKSVM, the parameters will be optimally selected by artificial jellyfish optimization algorithm (AJF). After the classification, the abnormal images will be given to the segmentation stage to segment ROI separately using a level set clustering algorithm. The performance of the proposed approach will be analysed in terms of different metrics. The proposed system will be implemented in MATLAB.**4.**

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