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Delineation and diagnosis of brain tumors from post contrast T1-weighted MR images using rough granular computing and random forest

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ABSTRACT

This paper presents a new approach of delineation and characterization of four different types of brain tumors viz. Glioblastoma multiforme (GBM), metastasis (MET), meningioma (MG) and granuloma (GN) from magnetic resonance imaging (MRI) slices of post contrast T1-weighted (T1C) sequence to improve the computer assistive diagnostic accuracy. An integrated framework of identification and extraction of tumor region, quantification of histogram, shape and textural features followed through pattern classification by machine learning algorithm has been proposed. Rough entropy based thresholding in granular computing paradigm has been adopted for delineation of tumor area. After accomplishing quantitative validation and comparison with existing methods, experimental results prove the efficiency and applicability of proposed segmentation approach. In the next stage, the extracted lesions have been quantified with 86 features to develop the training dataset. Random forest (RF), an ensemble learning scheme has been implemented, which learns the training data for accurate prediction of the class label of a given input. The performance of RF has been evaluated by statistical measures from 3 fold cross-validation and compared with five different classifiers. The same experiment has been repeated over the reduced set of features generated by correlation based feature selection strategy. Experimental results show the superiority of RF (Sensitivity achieved in %: GBM-96.7, MET-96.2, MG-98.1 and GN-97.7) with the complete set of features. The comparison of proposed methodology with the existing works signifies its applicability and effectiveness. Additionally a 10 fold cross-validation has been accomplished to justify the statistical significance of the classification accuracy achieved from proposed methodology.

1. Introduction

At present scenario, the prevalence of brain cancer is increasing rapidly. It develops from brain tumor, which is a solid mass originated by the uncontrolled cell divisions in human brain leading to the abnormal growth of the cells [1]. The early diagnosis of tumor can help in better prognosis. MRI is widely appreciated popular imaging modality for initial diagnosis of brain tumor because of its noninvasive characteristics, radiation free environment and potentiality in providing image of internal body part with impressive soft tissue contrast. MRI follows different protocols viz. T1-weighted (T1), T2-weighted (T2) etc. for imaging. Interestingly, every MRI protocol or sequence provides different characteristics of tumor region. As a consequence, the intensity profile of the tumor tissues changes between sequences. Therefore, the diagnosis through interpreting the multispectral magnetic resonance (MR) images by observing and analysing the visual imaging features becomes a challenging task for radiologists. In fact the typical shape and orientation of tumors, sometimes heterogeneous intensity profile and overlapping intensity in the spatial imaging plane make the diagnosis difficult and confusing to the radiologists. As a result differential diagnosis happens. In the context of brain tumor diagnosis, it is a challenging task of distinguishing one type of tumor from other kinds having look-alike features (for example, GBM is the differential diagnosis of MET). In a regular practice, the manual segmentation of tumor for better interpretation is itself a time consuming procedure; which involves intra-observer variability. On the other hand, the brain biopsy (guided stereotactic surgery) is a surgical procedure of confirmatory diagnosis. But stereotactic biopsy is very risky and invasive surgery. Considering Indian socio-economic status, it is costly too. Under such circumstances, the development of a robust computer vision technique for exact detection of tumor region and the identification of its type from MR image computation can certainly improve the diagnostic process through helping in fast diagnosis, therapeutic and surgical interventions.

GBM and MET both are malignant brain tumors. GBM is a primary tumor as it originates from the glial cells of brain and MET is developed due to the migration of

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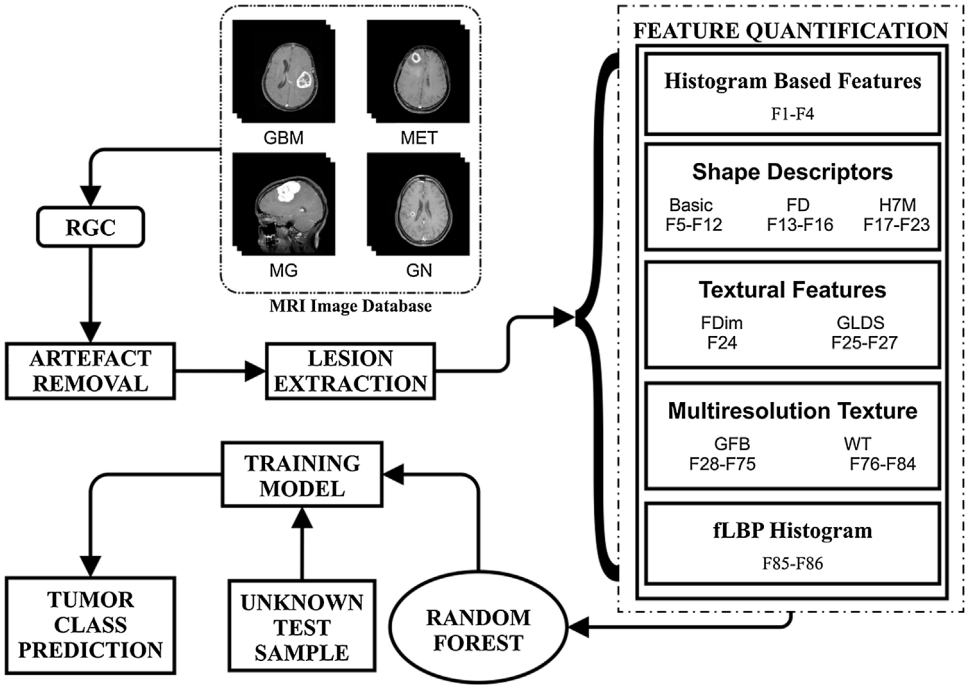

Fig. 1. The block diagram of proposed methodology for brain tumor detection and screening.

the cancer cells from other organ and thus it is a secondary [1]. MG is an extraaxial benign tumor and common in middle aged women. Generally it appears large and compresses and causes damage to brain tissues. Hence it becomes fatal [1]. In this study, the GN lesions represent the small region of inflammation in brain due to the tuberculosis and neurocysticercosis. The tumor and its vascular region develop blood brain barrier, which is eventually the inherent characteristics of tumor. When nonionic gadolinium radiopaque (paramagnetic substance) is injected during T1C MR sequence, the barrier breaks down. In effect, we observe the enhanced visualization of abnormal vascularity in tumor which is referred as the enhancing lesion or active region. The enhancement of vascular region (enhancing lesion) is a common characteristic of all four tumors and it helps in understanding the boundary of tumor. Thus, this imaging sequence is a routinely followed scanning procedure in tumor diagnosis. During the course of T1C, the peripheral enhancement of GBM, MET and GN can be observed and hence they are named as ring enhancing lesions. Owing to this fact, the detection of the enhancing lesion and its contour signifies the boundary of core tumor region. The most threatening characteristic of brain tumor is its mass effect and because this infiltrates brain tissues. As a result, it holds a typical orientation in image. Sometimes in T1C images, the ambiguity exists in the boundary of tumor region. Under such conditions, the radio-diagnostic decision making for tumor evaluation seeks more attention toward minimization of ambiguity. In view of this, we propose a new framework through integrating pattern identification with automated classification of brain tumors by machine learning technique for its computer assistive diagnosis from T1C MR sequence with improved accuracy.

In this section, we discuss the prior arts of tumor detection and characterization from MR images. Knowledge based fuzzy clustering [2,3] and fuzzy clustering [4] are popular techniques for identifying the exact location of abnormal mass from brain MRI and it has been used in various types of tumor segmentation. Warfield et al. developed an adaptive template moderated algorithm consisting of iterated sequence of spatially varying classification and nonlinear registration through embedding k-nearest neighbor (kNN) classifier for automatic segmentation of normal and abnormal anatomy of human brain from MR images [5]. Later, Kaus et al. [6] applied the same algorithm [5] for segmentation of low grade glioma (LGG) and MG and also validated the performance against the manually segmented results. Deformable models like level set, active contour etc. are also popular in tumor segmentation. For example, Ho et al. used intensity based fuzzy segmentation for initial classification of voxels in tumor and background region. According to this, tumor probability map was generated, which drove the automatic initialization of level set curve that generated the three-dimensional segmented region of GBM [7]. Prastawa et al. introduced the expectation maximization (EM) technique on atlas data for GBM segmentation and they reported 49–71% accuracy level over 5 cases [8]. In the next year, the same group proposed a knowledge based framework based on outlier detection for segmenting GBM [9]. In this approach, they considered only T2 MRI for simultaneous segmentation of both tumor and edema. They also discussed the contribution of edema in diagnosis and treatment. Zhang et al. [10] designed one class support vector machine (SVM) for classifying tumors. They also proved the superiority of their unsupervised approach over the supervised two-class SVM. Xie et al. proposed a hybrid level set method by combining region information as a propagation force and boundary information as a stopping function for semi-automated segmentation of brain tumor and edema [11]. In the same year, Lee et al. employed discriminative random fields classifier for detecting GBM and astrocytoma (AST) [12]. Corso et al. developed a novel methodology of segregating GBM from MR images by bridging the gap between affinity based and model based segmentation [13]. Wang et al. designed an integrated framework for segmentation of tumors from T1 MRI. Brain map was generated by Gaussian Bayesian classifier based on normalized Gaussian mixture model. Then 3D fluid vector flow was employed to extract the final contour [14]. Hsieh et al. [15] also developed a hybrid model through integrating fuzzy C-means with region growing for automatic segmentation of MG from non-enhancing lesions appeared in T1 and T2 MRIs. Sachdeva et al. introduced content based active contour model by integrating intensity and texture information for detecting various homogeneous brain tumors. In addition, texture space was generated with gray level co-occurrence matrix [16]. Rajendran and Dhanasekaran proposed possibilistic fuzzy C-means with modified distance metric for initial segmentation of tumor and later on parametric active contour model was implemented to obtain the final contour of tumor from T1C and fluid attenuation inversion recovery (FLAIR) images [17]. Gooya et al. developed a new technique based on EM for simultaneous segmentation and registration of glioma [18]. Georgiadis et al. modified the existing probabilistic neural network (PNN) classifier by introducing a nonlinear least squares features transformation (LSFT) for characterization of brain tumors from T1C MRI with improved performance as compared to PNN alone [19]. In the next year, the same group used LSFT-PNN for two stage classifications of brain tumors from T1C MR images; in the first step primary tumors were differentiated from MET and glioma was characterized from MG in the second step [20]. Five different categories viz., MET, MG, grade II glioma, grade III glioma and GBM were distinguished from MR image database of 102 tumors by three different classifiers viz. kNN, linear discriminant analysis (LDA), and nonlinear SVM [21]. They reached satisfactory classification accuracy for MET and grade II glioma, whereas in case of grade III and GBM accuracy was very poor. Kumar et al. proposed Principal component analysis (PCA) and Artificial neural network (ANN) based classification framework for discriminating various brain tumors and normal region from T1C MR images [22]. Sachdeva et al. introduced a new brain tumor characterization methodology consisting of genetic algorithm (GA) and SVM from T1C MR images [23]. After accomplishing an extensive literature review, it has been observed that no such MR image computing technique has been yet proposed for characterization of GN from brain tumors (viz. GBM, MET and MG). Sometimes the appearance of GN is lookalike to the ring enhancing MET lesion in T1C image and hence it is a challenging task to be solved in computational domain. Therefore, our study has taken up the problem of automated characterization of those brain tumors from MR images with augmented classification accuracy.

The aim of this work is to develop a new computer aided decision support system for brain tumor diagnosis from MR image analysis. In this regard, the accurate detection and automated characterization of tumor can be performed with improved accuracy from the single slice of T1C MR sequence. The slice selection depends on radiologist's interpretation. Fig. 1 represents the block diagram of proposed work. In this study the selected slices are processed to detect and extract the