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Identification of Gliomas from brain MRI through adaptive segmentation and run length of centralized patterns

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ABSTRACT

Brain tumor detection and identification of its severity is a challenging task for radiologists and clinicians. This work aims to develop a novel clinical decision support system to assist radiologists and clinicians efficiently in real-time. The proposed clinical decision support system utilizes fusion of MRI pulse sequences as each of them gives salient information for tumor identification. An adaptive thresholding is proposed for segmentation and centralized patterns are observed from LBP image of so obtained segmented image. Run length matrix extracted from these centralized patterns is used for tumor identification. The developed features successfully identify and classify tumor with Naive Bayes classifier. The proposed decision support system not only detects tumors, but also identifies its grading in terms of severity. As Glioma tumors are the most frequent among brain tumors, the proposed system is tested for the presence of low grade (Astrocytoma and Ependymoma) as well as high grade (Oligodendroglioma and Glioblastoma Multiforme) Glioma tumors on images collected from NSCB Medical College Jabalpur, India and BRATS dataset. The experiments performed on two datasets give more than 96% accuracy. The proposed decision support system is quite sensitive towards the detection and specification of tumors. All the results are verified by domain experts in real time.

1. Introduction

The basic needs and daily routines of a common man in 21st century can never be detached from computers and electronic gadgets. In the digital world, the number of brain tumor patients have been increased and reported on large scale. The radiations from such devices, unhealthy eatings, over-thinking, stressed life, and many more factors create tumorous cells in human body. The report published by Brain Tumor Association of USA estimated around 78,000 cases of brain tumors to be diagnosed at the end of the year 2016 [3]. Recently, a report published by Brain Tumor Foundation of India stated that due to less awareness among people every year around 40,000 to 50,000 death cases are caused by cancerous brain tumors and 20% of those are of children. Also, 90% of such cases are curable, provided that tumors are detected at the earliest and treatment protocol is correctly followed [1].

Abnormal growth of brain tissues generates tumorous cells in brain. Brain tumors are distinguished from each other by intrinsic characteristics of brain tissues. MRI scans, being highly sensitive, are mostly used by the radiologists and researchers for the detection and classification of brain tumors. The most of the cases are determined by pertinent area and signal intensities of MR imaging. Brain tumors are divided into two broad categories; primary and secondary [8]. Primary tumors originate in brain tissues, while secondary tumors are discovered in other parts of the body and spread towards brain cells. Among primary tumors, Glioma tumor intensifies on the glue cells of brain and is the most frequent among brain tumors. Four types of Glioma tumors, Astrocytoma, Ependymoma, Oligodendroglioma, and Glioblastoma Multiforme are considered with respect to severity (Grade I to Grade IV) [13,19]. Astrocytoma and Glioblastoma Multiforme are distinct based on the presence of necrosis and vascular endothelial proliferation. Glioblastoma Multiforme, along with Oligodendroglioma and Ependymoma, has a tendency to bleed, which helps in the differentiation and identification of several features of intra-tumoral hemorrhage. Astrocytomas are homogeneous and arise on white matter. Glioblastomas Multiforme and Ependymoma are often found quite heterogeneous, and

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Oligodendroglioma appears identical with extensive high-intensity surrounding called "edema" [19].

Most of the existing systems are quite promising in terms of detection of tumor from brain MRI, [9,10,12,14,20,23,32,36] but a little efforts have been put to classify tumor after detection [27,28,37]. Moreover, validation on small sized datasets further questions generalization of system usage on any dataset. As a result, it is difficult for radiologists and clinicians to use these systems in daily practice. Based on these facts, the present work is focused on the development of an efficient clinical support system for identification of various types of Glioma tumors from brain MRIs. Apart from testing on a publicly available brain MRI dataset, the proposed system is also tested on a relatively large dataset collected from one of the local government medical college. The system is also tested and endorsed by domain experts in the real time environment.

The paper is organized in five sections. Section 2 includes the literature survey of the existing systems. Section 3 describes the proposed methodology with detailed description of each step. The experimental analysis and validation of the system are covered in Section 4. Finally, Section 5 concludes the work.

2. Literature review

MRI scans appear non-homogeneous in the sense of poor contrast and low illumination [21]. The visual appearances of tumors are different on each pulse sequence of MRI due to the observed intensity pattern of signals affected by surrounding magnetic field and spins of the molecules. The alignment of proton molecules monitors the relaxation time and hence the intensity level. For the detection and classification, MRI scans are mostly used by the radiologists and researchers. MRI scans include four sequences, namely $T1-weighted$ $(T1w)$,, $T2-weighted$ $(T2w)$,, $T1-postcontrast$ $(T1C)$, and Fluid Attenuated Inversion Recovery (*FLAIR*). In *T1w* and *T1C*, tumor appears hypo-intense (lower intensity than normal tissue), while in *T2w* and *FLAIR* it appears hyper-intense (higher intensity than normal tissue) [21]. Generally, *T2w* images are considered to diagnose brain tumor. However, complex anatomy of brain is another unavoidable factor to deal with. To avoid or minimize manual segmentation error, the automatic segmentation and detection of tumor have become the most challenging task for radiologists and clinicians. It has been emerged as intense research area in the medical imaging.

Several non-invasive systems exist in the literature to detect and identify brain tumor. As the first step, preprocessing includes various basic methods to perform enhancement, de-noising, and skull-stripping etc. Block-based selection [12,15], fuzzy c-means [4,27,33], threshold [24], watershed [28], level-set method [36], feedback pulse-coupled neural network [10], incremental supervised neural network [14], morphological operations [28] are quite known for the segmentation of abnormalities from medical images. Gabor coefficients [20,23], discrete wavelet transformation (DWT) [9], local binary patterns (LBP) [23], gray level co-occurrence matrix (GLCM) [37], and Gaussian mixture model (GMM) [6] are used for textural features extraction. Also, Zernike moments [14] and pyramid of histogram of gradients (PHOG) [23] have been frequently used to extract shape of tumors in recent works. In [20], DWT and Gabor filters are used to enhance MRI scans. This is followed by applying global threshold to segment the tumor. In another work, block wise DWT is applied and some statistical features are extracted [15]. DWT and feed forward back-propagation neural network are used to classify tumorous and non-tumorous images in [10]. The dataset used is biased, i.e., only 14 tumorous images out of 101 images.

Tumors are also detected by comparing the mutual information of histograms of two brain hemispheres in [23]. After that, several shape and texture features are extracted and classified by five classifiers separately. Block based segmentation is used to detect the tumor and the threshold for the classification in [12]. In 2016, fuzzy logic is again used for the segmentation of tumors, and various shape and texture features are extracted [28]. Naive Bayes (NB) is used for the classification and tested on only 36 MRI scans. In another work, unsupervised clustering (fuzzy k-means with hybrid self organizing map) is used for the segmentation of tumorous MRI scans [32].

Most of the systems are complex due to the use of some specific sequences and/or different segmentation approaches for different pulse sequences to detect the tumor. Use of too many features [32] and small sized test datasets [10,28] are important issues to be addressed. Also, use of ensemble classifiers in many systems increases execution time unavoidably [2,26] Moving a step further, Astrocytoma, Meningioma, Metastatic bronchogenic carcinoma, and Sarcoma tumors are identified in [37]. Another work [27] focuses on detection and identification of four types of Astrocytomas, e.g., Low grade, Pilocytic, Anaplastic, and Glioblastoma tumors. However, none of these works gave details of the datasets used by them. Further, tumors are identified as low grade/high grade Astrocytoma in [28].

The salient contribution of the proposed clinical decision support system lies in its simple structure, use of each pulse sequence, and fast execution with accurate detection and identification of Gliomas. It is based on the fusion of different MRI pulse sequences as each of them contains different information of brain tumor. Fusion of these images covers most of the minute information and removes the cons of each other, if exists. Also, the adaptive global thresholding used in this work makes the system efficient and generalized one for the segmentation of tumor. The proposed texture features are derived from run length matrix obtained from indexed LBP image. It is demonstrated that this new feature is quite effective for the analysis of tumor texture. Also, instead of ensemble classifier, use of NB classifier results in a faster system.

3. The proposed clinical decision support system

Fig. 1 shows the basic flow of the system developed for tumor detection and identification. The training and testing processes are clearly depicted in the figure.

3.1. Acquisition of datasets and preprocessing

Brain images are collected from NSCB Medical College Jabalpur, India and referred as JMCD hereafter. JMCD contains images of 134 patients sampled by 1.5T GE Health Care USA Scanners. JMCD contains non-tumorous (770) as well as tumorous (570) MR images having low grade (Astrocytoma (200) and Ependymoma (130)) as well as high grade (Oligodendroglioma (150) and Glioblastoma Multiforme (90)) Glioma tumors. Another publicly available Brain Tumor Segmentation (BRATS) challenge dataset [17] considered in this work contains brain MRI data of 80 patients. Its images are classified into non-tumorous (120), low grade (80), and high grade (120) Glioma tumors with no further classification. Both the datasets consist four types of image pulse sequences.

JMCD and BRATS datasets are preprocessed by a method based on Dynamic Stochastic Resonance (DSR) and Anisotropic Diffusion (AD) [11]. The method is found suitable among other existing enhancement techniques for medical images as it not only enhances the visual quality, but also gives smoothen images with sharper tumor boundaries. Anisotropic diffusion deals with edge sharpening and DSR deals with the enhancement required for dark areas. The brightness and contrast are increased in iterative manner by incrementing mean and standard deviation of image, respectively [11]. This enhancement technique is well adaptive and fast.

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