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Glioma detection on brain MRIs using texture and morphological features with ensemble learning

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ABSTRACT

The real time usage of Computer Aided Diagnosis (CAD) systems to detect brain tumors as proposed in the literature is yet to be explored. Gliomas are the most commonly found brain tumors in human. The proposed non-invasive CAD system based on brain Magnetic Resonance Imaging (MRIs) is capable of assisting radiologists and clinicians to detect not only the presence, but also the type of glioma tumors. The system is devised to work irrespective of the image pulse sequence. It uses different segmentation schemes for different pulse sequences, fusion of texture features, and ensemble classifier to perform three levels of classification. Once the tumor is detected at the first level of classification, its location is analyzed using tentorium of brain and it is classified into superatentorial or infratentorial in the next level. Based on the morphological and inherent characteristics of tumor (area, perimeter, solidity, and orientation), the system identifies tumor type at the third level of classification. The system reports average accuracy of 97.76% on JMCD (a dataset collected from local medical college) and 97.13% on BRATS datasets at the first level of classification. Average accuracy of 97.87% for astrocytomas, 94.24% for ependymoma, 96.29% for oligodendroglioma, and 98.69% for glioblastoma multiforme is observed for histologically classified JMCD dataset. The same is observed as 95.45% for low grade and 95.50% for high grade tumors in publically available BRATS dataset. The performance of the proposed CAD system is statistically examined through hypothetical Student's *t*-test and Wilcoxon matched pair test. The performance of the system is also validated by domain experts for its possible real time usage.

1. Introduction

Report of the National Brain Tumor Society of United States mentioned that around 79,270 people are suspected to suffer from brain tumor with survival rate of 34.70% in 2017. It is also estimated that 16,947 people will be diagnosed with malignant brain tumors and will die in 2017 [1]. The same report for the year 2016 suspected 77,670 people suffering from brain tumor with survival rate of 34.40% [2]. Although survival rate is increased by 0.30% due to rising awareness, still 2% increase in the people suffering from brain tumor tells that there is increasing need to diagnose the tumor at an early stage. Gliomas, meningiomas, primitive neuroectodermal, pituitary, pineal, choroid plexus, cyst, etc. are primary brain tumors. Gliomas comprise nearly all intracranial tumors and represent 80% of malignant tumors [2]. Imaging modalities like Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) scans are used to detect tumors. Due to high resolution and large numbers of slices including the redundant ones, the manual examination of CT and MR scans becomes difficult. However, MR scans demonstrate the abnormal threads of brain tissues more clearly [3] and therefore, these scans are preferred to be used. MR scans are used to detect such kinds of tumor as these tumors possess different kind of characteristics and morphological properties in order of appearance/visibility on images [4–6]. Correct interpretation of these abnormalities through a Computer Aided Diagnosis (CAD) system may assist radiologists and help them in pre-operative diagnosis and treatment planning. Further, accurate categorization of tumors is still a challenging problem. Most of the existing CAD systems are able to detect tumor [7–20], but not categorize it. This work aims for accurate assessment of various types of most commonly found glioma tumors from brain MR images.

Characteristics of most common glioma tumors and their characteristics on MRI scans are summarized in Section 2. Existing CAD

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systems for tumor detection are discussed in Section 3. The proposed CAD system is elaborated in Section 4. Results and discussion in detail is given in Section 5 and Section 6 concludes the work.

2. Gliomas and their charactreistics on MRI scans

Glioma is a broad term which includes approximately all tumors arises in glial or supportive tissues of the brain [21,22]. Glial cells are the building block cells of the supportive tissue in the central nervous system. As per histological classification, there are several types of gliomas, including astrocytomas, ependymoma, oligodendroglioma and glioblastoma multiforme. World Health Organization (WHO) classifies these tumors from grade I to IV, where low grade refers to grade I and II, and high grade refers to grade III and IV. Astrocytomas, oligodendrogliomas, and ependymomas may be classified as grade I to III as per their appearance, while glioblastoma multiforme is grade IV tumor [23]. Glioblastoma multiforme is the most common and deadliest malignant brain tumors in adults. Astrocytomas, oligodendrogliomas, and ependymomas comprise nearly half of all intracranial tumors, and almost half of gliomas are glioblastoma multiforme. In the light of these facts, this work focuses on detection and identification of gliomas [24,25].

Astrocytoma arises among cells that nourish and support neurons of the brain. Astrocytoma circumscribed in group and has anatomically strong boundaries [26]. Ependymoma arises on ependymal cells and usually located along, within, or adjacent to the ventricular system. It is more often seen in the posterior fossa or in the spinal cord in adults. They appear as soft tissues and may contain cysts or mineral calcifications [27]. Oligodendroglioma arises from the oligodendrocytes, which wraps around nerve cells and is responsible for required electrical insulation for the successful conduction of nerve impulses [28,29]. Glioblastoma multiforme has features similar to astrocytomas with the addition of necrosis (known as dead cells) as its prognostic factor. Glioblastoma multiformes consist of poorly defined intra axial mass with variegated appearance due to necrosis and hemorrhage on brain [23,30]. Ependymoma, oligodendroglioma, and glioblastoma multiforme appear more infiltrating due to the tendency to invade [31]. In such cases, group of specific intensities are useful to extract the hidden or invisible tumors [24].

Routine MR imaging includes four basic pulse sequences: T1-weighted (T1-w), T2-weighted (T2-w), Fluid Attenuated Inversion Recovery (FLAIR), and T1-post contrast (T1-pc). White Matter (WM) appears brighter, Gray Matter (GM) appears dark, and Cerebrospinal Fluid (CSF) appears almost black in T1-w pulse sequence. In T2-w pulse sequence, CSF appears brighter, GM appears dark, and WM appears almost black. However, CSF is attenuated in FLAIR sequences, but abnormalities or an artifact remain brighter [3,24]. These pulse sequences are used for brain tumor detection as well as for other diseases of the brain or other body parts. However, kind of abnormality could be easily found by T2-w and FLAIR images. FLAIR is more sensitive for the detection of brain pathology as compared to T1-w images. T2-w MR images are most preferred by the radiologists in clinical prognosis [30,32]. Also, T1-pc pulse sequence generally produces a clear visual appearance of tumor edges/boundaries due to the presence of contrast agent.

The majority of astrocytoma appears hypointense on T1-w and hyperintense on T2-w images. A high grade of malignancy and micro calcifications are associated with an increased signal intensity of astrocytoma on T1-w images. However, these factors do not influence signal intensity on T2-w images significantly [33,34]. Ependymomas, including both infratentorial and supratentorial, generally demonstrate low signal intensity in T1-w, high signal intensity in T2-w, and intermediate-to-high signal intensity in FLAIR sequences relative to both gray and white matter [27]. Oligodendroglioma exhibits heterogeneously hyper-intense signal on both T1-w and T2-w images with moderate mass effect. No significant peritumoral edema is noted in general. Calcifications characteristic of oligodendroglioma are less evident on MRI appearing as small, non-specific low signal intensity foci [35]. Glioblastoma multiforme appear as irregular hyperintense lesions on T2-w/FLAIR images and may be seen surrounded by vasogenic oedema, with occasionally found flow voids. However, they appear hypo to isointense on T1-w images [30].

3. CAD systems for brain tumor detection – state of the art

Since 2006 several CAD systems using brain MRI have been developed [36]. Among various textural and shape features, Gabor, Gray Level Co-occurrence Matrices (GLCM), Zernike moments, area, circularity, and wavelet transformation are used. Classifiers like Markov Random Field (MRF), Artificial Neural Network (ANN), and Support Vector Machine (SVM) are used and reported accuracy ranges between 75%–98%. Khayati et al. [37] used spatial information and MRF classifier to classify brain MRIs into three categories, i.e., normal tissues, CSF, and lesion. However, they observed only 75% accuracy on the dataset collected from Koorosh Diagnostics and Medical Imaging Center, Tehran. Wang et al. [38] classified brain tissues into WM, GM, and CSF by using fuzzy c-means and observed 96.01% accuracy on the dataset of McGill University, Canada. They used multi-scale diffusion filtering scheme for the construction of multi-scale images. Zernike moments were used by Iscan et al. [39] and 97% accuracy was achieved with ANN classifier on an unknown dataset. Dahshan et al. [7] used wavelets and reduced these coefficients through PCA to achieve 97% and 98% accuracy through ANN and k-Nearest Neighbors (kNN) classifiers, respectively on the dataset provided by Harvard Medical School website.

GLCMs with feed forward neural network are used by Zulphe and Pawar [8] for tissue characterization, which ultimately leads to tumor detection with 97.50% accuracy. Saha et. al. [9] used centroid coordinates and reported 92% accuracy on the dataset collected from Cross Cancer Institute, Alberta, Canada. Ain et al. [10] used the combination of Anisotropic Diffusion (AD) and Discrete Wavelet Transform (DWT) with SVM to achieve 99.47% accuracy on the dataset collected from MRI and CT Scan Center, Rawalpindi, India. Arakeri et al. [40] used several shape and texture features with ensemble classifier to report 99.09% accuracy on the dataset collected from Shirdi Sai Cancer Hospital, Manipal. They classified images into four classes (astrocytoma, meningioma, metastatic bronchogenic carcinoma, and sarcoma).

Gupta and Khanna [11] examined the performance of several features on the dataset collected from NSCB Medical College, Jabalpur, India with threshold based classification to achieve 97.93% accuracy. Nabizadeh and Kubat [12] proposed Gabor wavelets and statistical features with SVM classifier. They achieved 96.10% accuracy on NCI-MICCAI 2013 challenge dataset. Using textural and shape features in combination with naïve Bayes (NB) classifier, Subashini et al. [14] reported 91.67% accuracy on the dataset collected from MRI & Medical Research Centre Pvt. Ltd, Calicut, India. Vishnuvarthanan et al. [13] used fuzzy k-means and self-organizing mapping with ANN classifier to achieve 97.37% accuracy on Harvard Brain Repository dataset.

Among recent techniques, Soltaninejad et al. [15] used superpixel technique to distinguish tumorous and non-tumorous images using several texture features. They reported 98.28% accuracy on BRATS. In Kaya et al. [17], two clustering algorithms are advanced using PCA dimensionality reduction technique. Cabria et al. [18]