Applied Soft Computing 47 (2016) 151–167

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

A package-SFERCB-"Segmentation, feature extraction, reduction and classification analysis by both SVM and ANN for brain tumors"☆

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ARTICLE INFO

Article history:
Received 21 January 2015
Received in revised form 15 August 2015
Accepted 12 May 2016
Available online 18 May 2016

Keywords:
Genetic Algorithm (GA)
Brain tumors
GA-SVM
GA-ANN

ABSTRACT

The objective of this experimentation is to develop an interactive CAD system for assisting radiologists in multiclass brain tumor classification. The study is performed on a diversified dataset of 428 post contrast T1-weighted MR images of 55 patients and publically available dataset of 260 post contrast T1-weighted MR images of 10 patients. The first dataset includes primary brain tumors such as Astrocytoma (AS), Glioblastoma Multiforme (GBM), childhood tumor-Medulloblastoma (MED) and Meningioma (MEN), along with secondary tumor-Metastatic (MET). The second dataset consists of Astrocytoma (AS), Low Grade Glioma (LGL) and Meningioma (MEN). The tumor regions are marked by content based active contour (CBAC) model. The regions are than saved as segmented regions of interest (SROIs). 71 intensity and texture feature set is extracted from these SROIs. The features are specifically selected based on the pathological details of brain tumors provided by the radiologist. Genetic Algorithm (GA) selects the set of optimal features from this input set. Two hybrid machine learning models are implemented using GA with support vector machine (SVM) and artificial neural network (ANN) (GA-SVM and GA-ANN) and are tested on two different datasets. GA-SVM is proposed for finding preliminary probability in identifying tumor class and GA-ANN is used for confirmation of accuracy. Test results of the first dataset show that the GA optimization technique has enhanced the overall accuracy of SVM from 79.3% to 91.7% and of ANN from 75.6% to 94.9%. Individual class accuracies delivered by GA-SVM are: AS-89.8%, GBM-83.3%, MED-95.6%, MEN-91.8%, and MET-97.1%. Individual class accuracies delivered by GA-ANN classifier are: AS-96.6%, GBM-86.6%, MED-93.3%, MEN-96%, MET-100%. Similar results are obtained for the second dataset. The overall accuracy of SVM has increased from 80.8% to 89% and that of ANN has increased from 77.5% to 94.1%. Individual class accuracies delivered by GA-SVM are: AS-85.3%, LGL-88.8%, MEN-93%. Individual class accuracies delivered by GA-ANN classifier are: AS-92.6%, LGL-94.4%, MED-95.3%. It is observed from the experiments that GA-ANN classifier has provided better results than GA-SVM. Further, it is observed that along with providing finer results, GA-SVM provides advantage in speed whereas GA-ANN provides advantage in accuracy. The combined results from both the classifiers will benefit the radiologists in forming a better decision for classifying brain tumors.

1. Introduction

Brain tumor classification includes categorization of primary and secondary tumors into different classes. Primary tumors originate in the brain itself like Astrocytoma (AS), Glioblastoma Multiforme (GBM), Meningioma (MEN), Medulloblastoma (MED) etc. Secondary brain tumors or metastases (MET) are the cancer cells that originate from another part of the body and have spread to the brain [1].

Magnetic resonance (MR) images obtained from different excitation sequences like T1, T2, post contrast T1, FLAIR provide texture and intensity information of brain tumors. Of all these sequences, post contrast T1 weighted MR images provide better visualization of brain tumors than the other ones. The post contrast T1 images are obtained after intravenous administration of 0.15–0.20 ml/kg of MR

☆ The work has been done as a collaborative project to develop an interactive CAD system to assist radiologists under MOU between IIT Roorkee, India and PGIMER, Chandigarh, India.

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http://dx.doi.org/10.1016/j.asoc.2016.05.020
1568-4946/

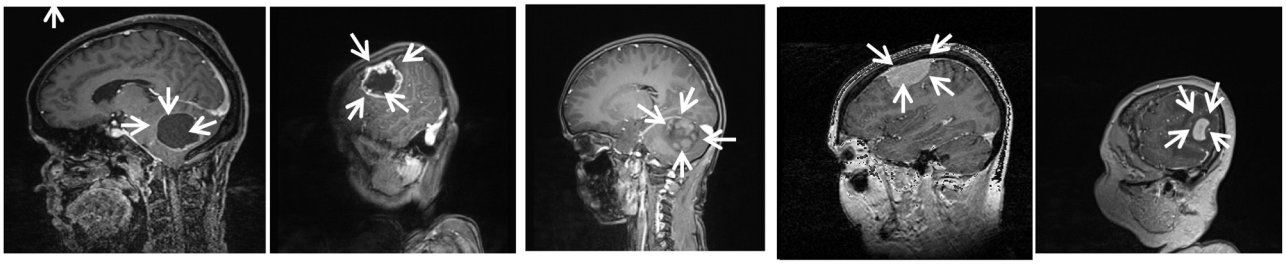

Fig. 1. Appearance of brain tumors on post contrast T1 MR images.

contrast material-(Gadolinium based) in patients. Even though the Gadolinium based contrast material injected is consistent across the patients, the degree of enhancement of tumors is different. Tumors may either show complete solid enhancement or peripheral rim of enhancement or no enhancement as shown in Fig. 1 [2]. A combination of two or more sequences provide better accuracy in delineating and classifying brain tumors; however, these sequences may not always differentiate between the tumor and the associated perilesional oedema. Post contrast T1-weighted images delineate the tumor well along with the demonstration of the extent and character and are thus considered relatively better for brain tumor classification [2,3].

Radiologists according to their clinical experience classify brain tumors in MR images using pathological details which include signal intensities and texture patterns on MR images [1,4,5]. The signal intensities of tumors are defined below:

- Isointense—The tumors which show isointense property have same intensity as that of brain tissues.
- Hypointense—The tumors which illustrate hypointense property are darker than the brain tissues.
- Hyperintense—The tumors which exemplify hyperintense property are brighter than the brain tissues.

The tumor texture may be homogeneous or heterogeneous [4,5]. These terms are defined below:

- Homogenous—Tumors show relatively similar signal intensity/brightness in their entire extent.
- Heterogeneous—Tumors show areas of different signal intensity/brightness (necrotic and cystic part) within themselves.

Pathological details of different tumors on post contrast T1-weighted images are discussed below [1,4,5].

- Astrocytoma—Astrocytoma can be homogenous or heterogeneous lesion. The homogeneous, lesions show a homogeneously similar intensity without significant post contrast enhancement while heterogeneous lesions show variable post contrast enhancement. These lesions especially homogeneous ones are low grade and have good prognosis after surgical resection.
- Glioblastoma Multiforme—It is a heterogeneous intraparenchymal mass showing thick peripheral enhancement. There may be associated central necrosis with significant neo-vascularity.
- Medulloblastoma—It is a childhood tumor, most commonly seen in the posterior fossa. It may be homogenous or heterogeneous lesion in relation to the fourth ventricle with moderate post contrast enhancement.
- Meningioma—Meningioma is a relatively homogenous well defined extra-axial moderately enhancing mass lesion and shows early enhancement which persists into the delayed phase after intravenous administration of contrast. It compresses and displaces the cortex and the subarachnoid space including its contents i.e., blood vessels.
- Metastatic tumor—It is a secondary tumor of brain showing thick ring or solid enhancement. It has well defined margins and causes significant perilesional oedema and mass affect on the adjacent normal brain parenchyma.

The basic knowledge of signal intensity patterns is essential as also the principles by which various sequences describe tumor morphology before one proceeds for brain tumor classification. The different types of tumors taken in this study with their signal intensity, texture pattern and enhancement criteria (solid/peripheral/no) on T1-post contrast images are shown in Fig. 1.

The segmentation, feature extraction and classification are the important aspects of any medical decision support system or computer aided diagnostic (CAD) system. Different Computer Aided Techniques (CATs) proposed for marking brain tumor regions on the images, consist of automatic and semi-automatic segmentation methods [6–15].

Fetcher Heath et al. [6] developed an automatic segmentation method for non enhancing tumors based on fuzzy clustering algorithm. The domain knowledge obtained by training the system and fuzzy clustering were employed for tumor segregation. The segmentation was performed in axial plane of T1, T2 and proton density images. Similar technique was developed by Dou et al. [7] for segmenting Glial cerebral tumors based on fuzzy information collected from different MR sequences. The tumor characteristics, fusion and adjustments were done by employing fuzzy models and operators. However, inputs from different MR sequences were considered.

Yu and Fan [8] partitioned the image into dark, gray and white sub segments by employing fuzzy sets. The image was divided into two groups based on membership functions which lead to the formation of fuzzy sets. The method was able to segment the desired object. Jaffar et al. [9] developed a method of segmenting lung boundaries on CT images. This method was based on fuzzy entropy and morphology. Promising segmentation results were obtained for segregating lungs on CT images. In this technique, optimal threshold was determined by incorporating fuzzy entropy. Similar technique based on knowledge based system was developed by Clark et al. [10]. GBM tumors were segmented based on cluster formation. The cluster centers acted as inputs to a rule-based expert system. Analysis of multispectral histograms separated the tumor region from the normal regions of the brain. However, the time constraint was a major drawback. The above methods took a lot of time for calculating optimal image parameters.

Research based on watershed algorithm segmenting medical images was carried by Grau et al. [11]. The slope information as well as neighboring pixels information was based on the prior knowledge of the pixels. The major limitation of this method is its reliance on prior information.