Technique for Tumor Detection Upon Brain MRI Image by Utilizing Support Vector Machine

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Abstract

Medicinal images assume a key part in the diagnosis of tumors. In a similar way, MRI could be the cutting edge regenerative imaging technology which permits corner sectional perspective of the body, facilitating the specialists to inspect the affected person. The detailed MRI images enable the medical specialists to recognize minor improvements of structures throughout the body, and serve as a basic part in finding and treatment planning. In this paper, we address the issue of classifying a brain MRI image to predict whether it contains a tumorous part or not. We utilize Histogram of Oriented Gradients (HoG) features to train a Support Vector Machine (SVM) to efficiently predict an MRI image to contain a tumorous part. Before applying the trained SVM classifier on the test MRI images, we also perform image enhancement to increase the accuracy of the prediction. Our experimental results show an impressive accuracy of the proposed technique.

Keywords—Brain Tumor, Magnetic Resonance Image (MRI), Image Enhancement, Image segmentation, SVM (support vector machine), Feature Extraction, HoG (Histogram of Oriented Gradients).

1 Introduction

Brain tumor acknowledgment with magnetic resonance images (MRI) is critical in the medicinal determination as it gives organized information on the design outline of a body part. Medical imaging is really a crucial segment connected with countless which helps to conclude. The best component of MRI is that it can create images of diverse features. There are a couple of essential MRI checks out: (i) T1 weighted MRI, and (ii) T2 weighted MRI. T1 images are generally used to take a gander at typical anatomical subtle elements. T1 is suitable for looking at the cerebrum structure on the grounds that fats and tissues seem brilliant and bone marrow contains a lot of fat. T2 is the transverse development of protons and is typically used to take a gander at pathology in the light of the fact that most tissues included in contagion have a tendency to have higher water content than normal. T1 and T2 checkouts have following effects.

- White matter appears light gray in T1, and dark gray in T2.
- Grey matter appears grey in both.
- Cerebrospinal fluid (CSF) appears black in T1, and white in T2.

ISSN: 2523-0379 (Online), ISSN: 1605-8607 (Print)

As we are concentrating on the tumorous area, T1 weighted MRI outputs are most useful for us as they can help us in examining the points of interest of anatomical conduct of tumorous region. Therefore, we utilize T1-weighted images for preparing our model. MRI is one of the most effective diagnostic techniques in medical imaging technology which permits the cross-sectional perspective of the body with uncommon tissue contrast [1]. MRI assumes a vital part in evaluating neurotic states of the lower leg, foot and cerebrum. Additionally, MRI is a non-obtrusive methodology that has been proven to be very instrumental in the investigation of the human cerebrum. The data that MRI gives has enormously expanded information about the ordinary and diseased anatomy about medical research, and is a basic part in the diagnosis and treatment of a disease [2]. A doctor's choice of medicinal treatment depends on the diagnosis

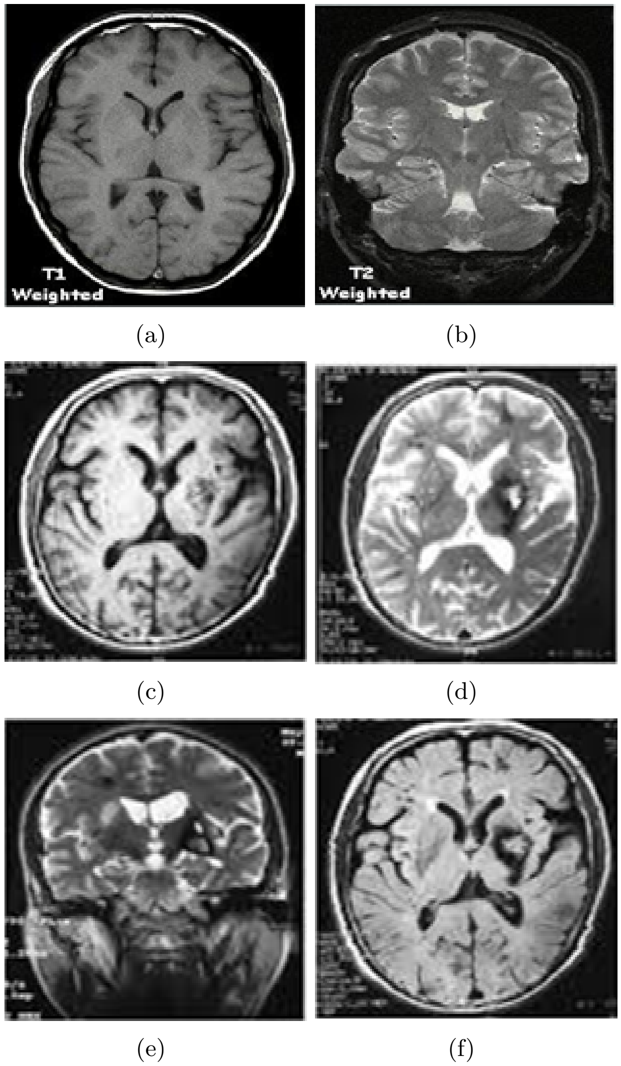


Fig. 1: T1 weighted MRI scans (a, c, e), and T2 weighted MRI scans (b, d, f)

tests. Hence, the precision of an analysis is key in medical care. Fortunately, the properties of the conclusion tests can be measured. For a given disease condition, the most ideal test can be picked in view of these properties. The affectability, specificity and precision are widely used in a demonstrative test. Figure 1 shows the comparison between T1 and weighted MRI scans and T2 weighted MRI scans.

1.1 Tumour Detection in Brain MRI Images

The brain is a soft, spongy mass of tissues which is covered by skull, a hard bone, three thin layers of tissue called meninges, and a watery fluid. The brain is responsible for all the major actions that a human body requires, e.g., thinking, walking, talking, etc. It is also controlled by our senses such as sight, hearing, touching, taste, smell, memory, emotions and personality. Brain has the following three major parts.

1) **Cerebrum** conveys information between the brain and other parts of the body through nerves. It is also responsible for reading, thinking, learning, speech and emotions.
2) **Cerebellum** is responsible for balance, walking standing and other complex actions.
3) **Brain stem** connects the brain with the spinal cord. It controls breathing, body temperature, blood pressure, and other basic functions.

Computer-aided detection of anomalous development of tissues is essentially persuaded by the need of accomplishing most possible accuracy [3]. Most of the cells in the body are generated and then divided in an orderly way to produce further cells in order to keep the human body healthy and working properly. When cells lack the ability to grow or divide evenly, the extra cells produce masses of tissue known as tumor. According to medical science, tumor are of two types: benign and malignant.

1.2 Benign Brain Tumours

This type of tumor does not contain cancer cells. Normally benign tumours can be removed and they seldom re-grow. The border or edge of a benign brain tumour can be clearly seen. Cells from benign tumours do not invade tissues to other parts of the body, but they are also dangerous because they can press on the sensitive areas of brain and make brain to work improperly and cause serious health issues. Very rarely, a benign brain tumor may become malignant.

1.3 Malignant Brain Tumor

Malignant brain tumors is serious and life-threatening for patients. It may be primary (a tumour that mainly originates from the brain tissues) or secondary (metastasis that originates from another part of the body). In both cases, it is likely to grow fast and can invade the surrounding normal brain tissues.
A brain tumour is one of the real reasons for the increase in mortality rate among kids and adults. A tumor is a mass of tissue that becomes uncontrollable by the typical forces that trigger its development [4]. The rate of brain tumor is rapidly increasing, especially in older people than younger once. A brain tumor is an accumulation of anomalous cells within the brain or around the cerebrum. Tumor can specifically crush all healthy brain cells. It can also affect the healthy cells around the tumorous one and affect different parts of the brain by creating inflammation, swelling and generating pressure inside of the skull [6].

Early location and right treatment taking into account precise conclusion are essential strides to enhance the results of diagnosis. Brain irregularities include a wide range of conditions extending from development mistakes to vascular mishaps. This variability results in incalculable potential outcomes of discoveries of prenatal ultrasound, which could make some analytic predicaments.

2 Literature Review

The research on tumour detection is becoming increasingly popular and important these days due to its appealing prospects for analyzing tumour growth history and morphological alterations in the cancer operation [1] [3] [4]. Early tumour detection in brain is particularly important due to the alarmingly high mortality rate caused by brain tumour all over the world [1].

For automatic detection of brain tumours, the widely used techniques are based on traditional image processing. The techniques for tumour detection using image processing studied in the literature can be broadly categorized as automatic and semi-automatic. However, the performance of these techniques usually remains limited due to a number of factors and/or constraints. Some of these factors include presence of noise in input images, poor contrast of images, and occlusions, etc [2] [4] [5].

Scientists have applied different approaches in order to propose an efficient system that can detect a tumor from brain images in which MRI has the best image results. These approaches are proposed for MRI image segmentation such as statistical methods using pixel labeling, threshold based methods, and parametric techniques, to name a few [7] [8] [9]. These strategies name pixels according to the likelihood values, which are resolved according to the intensity distribution of the image.

Varying intensity of tumours in cerebrum MRIs makes the cerebrum of such tumours tremendously difficult. Cerebrum tumour division utilizing an MRI has been extensively researched. Both elements-based and chart book based techniques and also their blends have been proposed for cerebrum tumour division. The authors in [1] state that brain segmentation is computerized utilizing a dual localization strategy. In the initial step of their procedure, scull veil is produced for the MRI images. White matter and tumor area are utilized to ad lib K-implies algorithm. In the last stride of their strategy, they evaluate the breadth and length of the tumor [5]. MRI is valuable for analyzing cerebrum images due to its high precision rate. This technique combines the clustering and arrangement algorithm to minimize the error rate. Segmentation errand is performed utilizing the ortho-normal administrators and characterization utilizing BPN. Images containing a tumor are prepared to utilize K-implies grouping and a precision rate of 75% is acquired [6].

The authors in [7] argue that the segmentation results will not be accurate if the tumor edges are not sharp, and that this case emerge amid the underlying phase of a tumor. A texture-based strategy is proposed in this paper. Alongside cerebrum tumour location, segmentation is likewise done automatically utilizing this technique. In another technique [8], the authors propose a proficient strategy for cerebrum tumour identification. A standout among the most critical strides in tumour discovery is segmentation. A mix of two standard algorithms, first means move and second standardized slice is performed to identify the brain tumor surface zone in MRI. By utilizing a mean move algorithm, a pre-handling step is performed with a specific end goal to shape fragmented districts. In the following stride, district hubs clustering is prepared by the standardized cut strategy. In the last stride, the cerebrum tumour is distinguished through segment investigation.

The authors in [9] propose a programmed brain tumor detection approach utilizing symmetry examination. They first distinguish a tumor, section it and afterwards discover the region of the tumor. One of the vital elements is that subsequent to playing out the quantitative examination, we can distinguish the status of an expansion in the ailment. They recommend a multi-step and secluded drew closer to take care of the intricate MRI division issue. The tumor discovery is the initial step of tumor division. They obtain better results in complex scenarios.

Another approach primarily comprises of four stages: i) Pre-processing, ii) isolation of an area utilizing crop tool, iii) feature extraction of the district by utilizing HoG include, and iv) final grouping utilizing the support vector machine. In the pre-handling stage, channels are utilized to remove picture commotion in the MRI images.

The recent work has focused on machine learning for tumour detection in MRI images due to the growing popularity of machine learning. The authors in [14] first segment image using a pulse-coupled neural network. This is followed by the feature extraction using discrete wavelet transform. Subsequently, a neural network classifies the input image into with or without tumour. In a more recent work [15], the authors use deep neural network architecture utilizing small kernels for tumour segmentation in MRI images.

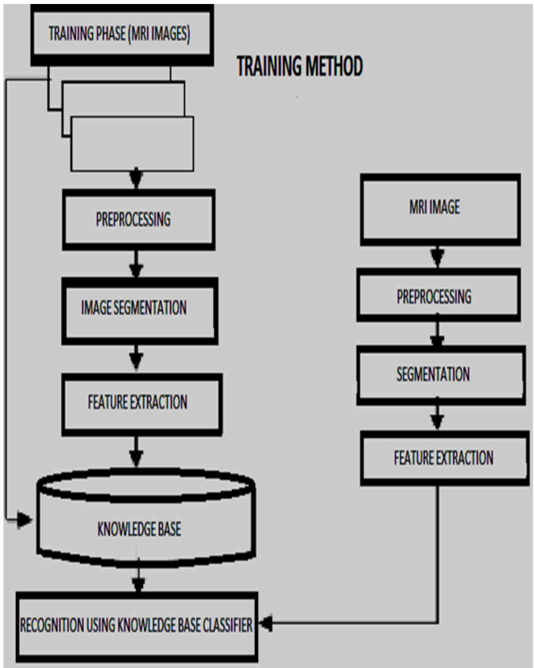


Fig. 2: Proposed methodology for tumor detection in a brain MRI image

2.1 Proposed Technique for Tumor Detection

Our proposed technique is summarized in Figure 2. The individual steps of the proposed technique are explained in the following sections.

2.2 Pre-processing

A few pre-processing steps are utilized to concentrate more on the correct components from MRI images. We utilize dark MRI images so that we can smooth them by an alteration in contrast for better results.

2.3 Image Enhancement

Image enhancement is the procedure of adjusting digital images so that the resulting images are more suitable for further diagnosis. Nowadays, research on tumor has immense focus on account of their potential for separating past advancement arrangements and morphological changes in the development operation [1] [3] [4]. An early area of a tumor in the cerebrum is significant as the death rate is more obvious among individuals actuating brain tumour [1]. Brain tumor area techniques use image processing that has present for recent decades. A couple of researchers have presented systems of modified and semi-automatic image processing approaches to detect tumours regions in cerebrum in which most of the frameworks disregard to deal with the expense of capable and effective results owing to the region of image noise, inconsistency, and low-quality that generally occur in medical images [2] [4] [5]. A number of techniques have been proposed to distinguish a tumour from cerebrum image, among which the techniques working with MRI are shown to be most effective. Most of the techniques prefer to label pixels. Whereas the techniques utilizing edge systems and parametric systems are rarely used [7] [8] [9]. These strategies label pixels based on their probability values which are determined on the premise of power dissemination. Some of them include removing noise from the image, and envisioning the brain cortex territory in MRI images [10]. The particular dark ranges encompassing the brain are removed from the image-enhanced method [11] [12] [13].

2.4 Feature Extraction

After enhancing and adjusting images and selecting the positive and a negative region from MRI image separately, we extract Histogram of Oriented Gradients (HoG) feature of selected regions and label our regions as positive or negative. We then pass the feature vectors to SVM to train our model. Feature extraction is among the most critical steps while we are distinguishing or separating particular region from our image. There are numerous algorithms relying upon the type of features. We implement HoG features to identify the elements of our region of interest. Histogram of Oriented Gradients can be used for object recognition in an image [16]. We apply them so as to attempt to distinguish tumor region in brain cortex. HOG baed object detection is a procedure in which an image detector ïňĄnds image features and decides the location of objects of interest in the image.

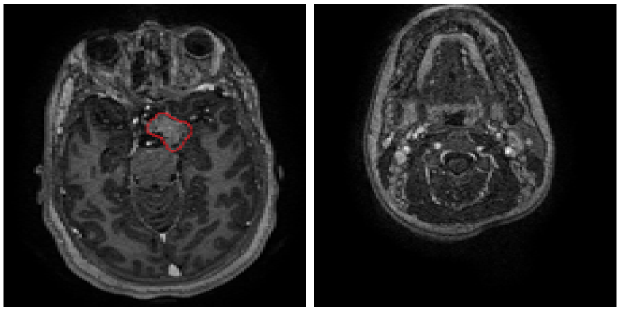
2.5 Classification Using SVM

We train a classifier using Support Vector Machine (SVM) on the training data. The trained classifier is able to classify the brain MRI images as having tumor or not. SVM classifiers are known to solve the 2-class problems effectively. After extracting the HoG features of the region of interest from all the MRI images, we train them using SVM algorithm.

Figure 3a shows an MRI image from our training dataset. It can be seen that the tumorous part is marked as a region of interest. Figure 3b shows an example of an MRI image which has to be tested by the trained SVM classifier.

3 MRI Image Dataset Description

The MRI image dataset that we use in our work is divided in the following two categories.



(a) (b)

Fig. 3: MRI image of (a) training dataset, and (b) test dataset

3.1 Training Dataset

Training dataset is gathered from the publicly accesible online source (www.radiopedia.org) of MRI images with and without tumors that we utilize for training our proposed model. We take about 10 tumorous MRI images for training.

3.2 Testing Dataset

As we are keen to implement our model in a real environment, thus we test our model on a dataset that we have collected from a renowned hospital in Karachi. We acquired the data of seven patients suffering from brain tumor.

4 CONCLUSION

In this paper, we proposed a technique for tumor detection in brain MRI images. It is not trivial for a common man to detect the tumor region easily just by viewing MRI images as Pathologists and MRI technicians are able to judge the tumor area by doing a comparative analysis of an image. We connected characteristic extraction strategy by applying HoG feature to train a SVM classifer to predict the probability of an MRI image having tumor. Our proposed system is further able to detect the correct tumorous region that is also highlighted by a pathologist.

Acknowledgment

Authors are grateful to the Department of Computer Science and Information Technology, Institute of Business Management (IOBM), Karachi, Pakistan and Government of Pakistan for financial support to carry out this work.

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