Brain Tumor Detection Using Shape features and Machine Learning Algorithms

Dena Nader
Al-Mustansiriya University

Hashem Jehlol
Al-Mustansiriya University

Anwer Subhi
Al-Mustansiriya University

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Dena Nadir George, Hashem B. Jehlol, Anwer Subhi Abdulhussein Oleiwi

Abstract— one of the common methods used to detect tumor in the brain is Magnetic Resonance Imaging (MRI). It gives important information used in the process of scanning the internal structure of the human body in detail. The MR Images classification is not easy task because of the variation and complexity of brain tumors. In the proposed technique, the detecting a brain tumor in the MR Images includes a number of steps are sigma filtering, adaptive threshold and detection region. Numbers of shape features are considered consists Major Axis Length, Euler Number, Minor Axis Length, Solidity, Area and Circularity to extract features for MR Images. The proposed method uses two classifiers depend on supervised techniques; the first classifier was C4.5 decision tree algorithm and the second classifier Multi-Layer Perceptron (MLP) algorithm. The classifiers are used for the purpose of classification the brain case to the normal or abnormal; the abnormal brain is classified into one type of benign tumor and five type of malignant tumor. Maximum precision of about 95% is achieved by considering 174 samples of brain MR Images and using MLP algorithm.

Index Terms— Magnetic Resonance Imaging (MRI), Adaptive Threshold, C4.5 decision tree, Detection Region, Multi-Layer Perceptron (MLP).

1 Introduction

Brain tumors are a solid neoplasm inside the skull. These tumors arise as a result of the uncontrolled and abnormal cell division. Usually they grow in the brain itself, but also grow in other places such as in lymphatic tissue, in blood vessels, in the cranial nerves, in the brain envelopes. Brain tumors can also grow as a result of the spread of cancers primarily located in other parts of the body [1]. Classification of brain tumors depends on the tumor location, the type tissue which the tumor created, whether the tumor is malignant or benign, and other considerations [2].

Primary brain tumors are tumors that arise in the brain and are called according to the types of cells that originated them. They can be benign (non-cancerous), meaning that they cannot spread to other places for example Meningioma. They can also be malignant and invasive for example Lymphoma (the classic appearance of lymphoma most often seen as a ring), cystic oligodendroglioma (It consisting of homogeneous, rounded cells with distinct borders and clear cytoplasm surrounding a dense central nucleus, giving them a “fried egg” appearance), Ependymoma (Ependymoma are the tumors that arise from ependymal cells within the brain. This tumor is histologically benign but behaves malignantly) and Anaplastic astrocytoma (Anaplastic astrocytoma are most common tumors of high grade astrocytoma) [3].

Secondary brain tumors or malignant tumor takes its origin from cancer cells that have spread to the brain from elsewhere in the body. In most cases, cancers that spread to the brain to cause secondary brain tumors arise in the kidney, lumy and breast or from melanomas in the skin [2].

A brain scan is a picture of the internal anatomy of the brain. The most common in the brain scans are MRI (Magnetic Resonance Imaging). MR Images provides an unparalleled view inside the human body [4]. Two common techniques used to classify The MR Images, they are supervised techniques such support vector machine, k-nearest neighbors, artificial neural networks, and unsupervised techniques such fuzzy c-means and self-organization map (SOM). Many research used both supervised and unsupervised techniques to classify MR Images either as normal or abnormal. [5].

In this paper, the supervised machine learning techniques are used to classify five types of abnormal brain MR Images such as Ependymoma, Lymphoma, Cystic Oligodendroglioma, Meningioma and Anaplastic Astrocytoma as well as normal type, Fig. 1 illustrates MR Images types of brain tumor that were classified in this paper. Automated classification algorithm for brain MR Images was proposed by using machine learning approach involve C4.5 decision tree algorithms and multi-layer perceptron (MLP).

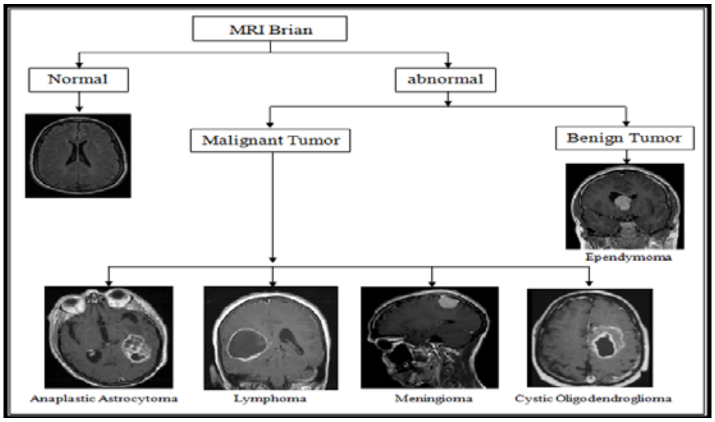

Fig.1 Five Types of MR Images That Were Classified In This Paper

- Dena Nadir George, Al-Mustansiriyah University, Colleg of Education, Department of Computer Science, dena_master2010@yahoo.com
- Hashem B. Jehlol, Al-Mustansiriyah University, Computer Center, hashemhbg@yahoo.com
- Anwer Subhi Abdulhussein Oleiwi, Al-Mustansiriyah University, Avicenna Center for E-learning, anweraljuboury@yahoo.com

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2 Related Work

Hassan Khotanloua et al [6]. proposed a new method to segment brain tumors in 3D MR Images. The first step in the proposed method is the brain MR Images segmentation using a new and powerful approach to detecting tumors. Then tumor detection was performed depend on choosing asymmetric areas. This method considers with the brain symmetry plane and used fuzzy classification. Its result forms the initialization of a segmentation process depend on a combination of a spatial relations and deformable model, leading to accurate segmentation of the brain tumors.

Qiang Wang et al [7]. using the information from magnetic resonance (MR) imaging and magnetic resonance spectroscopy (MRS) to assist in clinical diagnosis. The proposed approach consists of several steps including segmentation, feature extraction, feature selection. Classification model construction for used to classify the brain case to the normal or abnormal. A segmentation technique based on fuzzy connectedness was used. They outline the tumor mass boundaries in the MR Images. The concentric circle technique on the regions of interest was applied to extract features. Feature selection was performing to remove redundant features. Experimental results demonstrate the effectiveness of the proposed approach in classifying brain tumors in MR Images.

Yudong Zhanga et al [8]. proposed approach to classify MR Images as abnormal or normal using neural network. The first step in this method was extracted features from MR brain image by employed wavelet transform. And then reduce the number of features using the technique of principle component analysis. The results are given to a neural network. The method applied on 66 images 18 of them was normal and other abnormal. The classification accuracies were 100%.

Rajeswari S. et at [9]. Proposed a method based on texture features such as Grey Level Co-occurrence Matrix GLCM of MR Images. They use Sequential Forward selection algorithm to select the discriminative features. The proposed method classify MR Images to normal and abnormal by applied Afterwards an advanced kernel based technique such as Support Vector Machine (SVM) .

A. Jayachandran et al [10]. they proposed a hybrid algorithm for detection brain tumor using statistical features and Fuzzy Support Vector Machine classifier. The proposed method consists of four steps. In the first step anisotropic filter was performed for noise reduction. In the second step, the texture features extracted from MR Images. In the third step, the features of MR Images have been reduced using principles component analysis to the most essential features. Final step, the tumor was classified to normal and abnormal by using Supervisor classifier based Fuzzy Support Vector Machine. The accuracy of Classification was 95.80%.

PrachiGadpayle et al [11]. developed System for a brain tumor Detection and Classification. The image processing techniques such as preprocessing, image enhancement, image segmentation, morphological operations and feature extraction have been implemented for the detection of brain tumor in the MRI images. The features texture such Gray Level Co-occurrence Matrix (GLCM) was used in the detected tumor. They classify MRI brain image into abnormal and healthy image using BPNN and K-NN classifier.

N.M. Saad et al [12]. proposed method to detect and classify a brain tumor using thresholding and a rule-based classifier. Four types of brain tumor depend on diffusion-weighted imaging were analysed such acute stroke, solid tumor, chronic stroke and necrosis. In the detection and segmentation stage, the image is divided into 8x8 macro-block regions. Adaptive thresholding technique is applied to segment the tumor's region. Statistical features are measured on the region of interest. The rule based classifier was used to classify four types of lesions. The accuracy of classification obtained from this method was 93%, 73%, 84% and 60% for acute stroke, solid tumor, chronic stroke, and for necrosis respectively.

3 Proposed Method

The architecture of proposed method is illustrated in Fig. 2. MR Image's acquisition was first step in this method. Detection of tumor in the brain MR Images includes a number of methods are Sigma filtering, adaptive threshold and detection region. Shape Features method is used to extract features for MR Images. Two Machine learning algorithm of classification were used to compare their performance involve C4.5 decision tree algorithms and multi-layer perceptron (MLP).

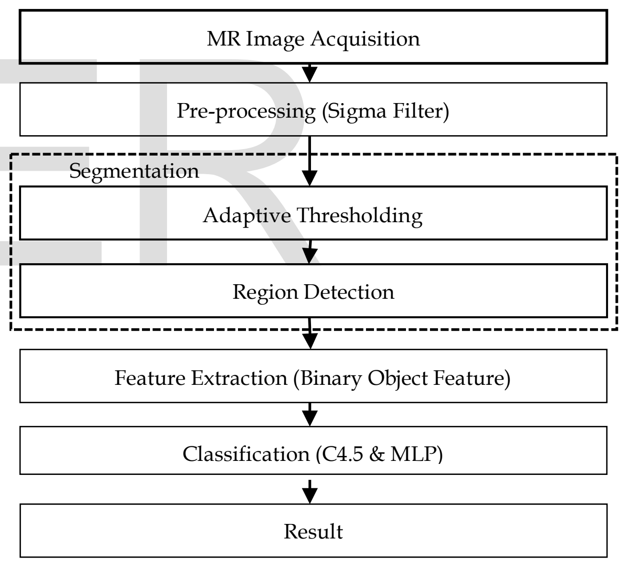

Fig. 2: Diagram of Brain Tumor Classification Method

3.1 Image Acquisition

The proposed method has been implemented on real data for human MR Images dataset, some of them were obtained from the hospitals and the other were obtained from the internet as there are no database is available from these types of tumors that considered in this paper.

3.2 Image Preprocessing

It is well known that the most noise in MR Images is random and Gaussian distribution is used to characterize it statistically. In this paper we are using sigma filter for removing noise from MR Images. The sigma filter finds the average of pixels in the box that have been predetermined size which not deviate too far from the pixel which the box is centred on. Consequently, the difference in the intensity of the pixels by

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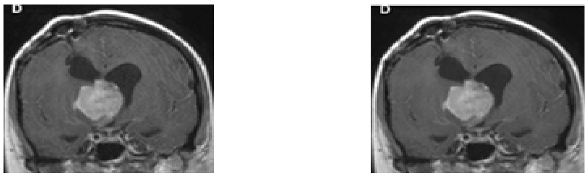
more than two standard deviations of the pixel in the centre box, there is a high probability that this difference is not because of the noise; Therefore Sigma filter ignores such a pixel [13]. Fig 3 illustrates used sigma filter on MR Images.found at:



(a) (b)

Fig. 3: a) MR Image before Using Sigma Filer. b) MR Image after Use Sigma Filter

3.3 Image Segmentation

Generally, The threshold used in the process of image segmentation by putting all the pixels that are higher than the threshold level to a foreground while the other pixels to the background value. Any dynamic change according to the pixel intensity cannot be achieved when using threshold method [14]. In proposed method we used Adaptive threshold that usually take the gray or color images as input and outputs in the form of binary image representing segmentation. Adaptive thresholding techniques used to separate the object of an image from its background. The main different between threshold and Adaptive thresholding is that the Adaptive threshold value is calculated for each pixel in the image. This technique provides more robustness to changes in illumination.

After used adaptive thresholding, the region detection process is performed on the binary image that results from an adaptive thresholding step. Region detection is Image segmentation technique that classifies pixels in the image to one or several separate areas or blob which is an area of touching pixels with the same logic state. The region detection consists of scanning and labeling any new regions, but also merging old regions when they prove to be connected on a lower row. Therefore, the image is scanned and every pixel is individually labeled with an identifier which signifies the region to which it belongs [15]. The binary image result has many object beside the object of tumor, by using the region detection method the biggest area object are extracted (this object is the tumor) and put it in a separate image. Fig. 4 illustrates adaptive thresholding and region area detection.

(a) (b) (c)

Fig. 4: a) MR Images with Sigma Filter. B) Result of MR Images after Used Region Detection Method. C) Object of Tumor

3.4 Features Extraction

After the completion of image segmentation stage, Shapes features are performed on the segmented objects or regions in the scene. For each shape in the binary image the Matlab function regionprops have a number of properties. In this paper used six shape properties which include Major axis length, Minor axis length, Euler Number, Solidity, Area and Circularity. The description of these features is given below:

1. Major axis length: Major axis length is calculated by using the maximum diameter of the shape, which holds the number of pixels in that longest diameter of the ellipse [16].
2. Minor axis length: The minor axis is the shortest diameter. It is calculated by using the minimum diameter of the shape, which holds the number of pixels in that shortest diameter of the ellipse [16].
3. Euler Number: Euler number represents the fundamental relationship between the number of components of the connected object C and the number of holes in the object H [17].

$$\mathrm{E} = \mathrm{C} - \mathrm{H} \qquad (1)$$

It specifies the number of objects in the region minus the total number of holes in those objects.

4. Solidity: the concavity of the particle can be measured by Solidity. The equation 2 give the solidity of particle where the image area, A, divided by the convex hull area, Ac. the particle becomes more solid if the image area and convex hull area approach each other[18].

$$S = \frac{A}{Ac} \qquad (2)$$

5. Area: The area of the object is calculated using the actual total number of pixels which are present inside the object, which describes the area of that region [16].
6. Circularity: Cicularity represents the degree of similarity in the particles to the circular shape. It takes into consideration the degree of smoothness surroundings. This means that the circularity is a measure of particle shape and roughness [18].

$$C = \sqrt{\frac{4\pi A}{P^2}} \qquad (3)$$

3.4 Classifications

In this paper used two type of machine learning algorithm to classify the MR Images of brain tumor and compare their performing, they are MLP and C4.5.

The multi-layer perceptron (MLP): the multi-layer perceptron is a feedforward neural network consisting of an input layer of nodes, followed by two or more layers of perceptron, the last of which is the output layer. The layers between the input layer and output layer are referred to as hidden layers. It has a lot of successful applications in solving complex problems in the real world, consisting of non-linear decision boundaries [19].

MLP does not have any cycles and the output depends only on the input samples therefore it is named feedforward. It depends on supervised learning. Learning process conducted by changing the connection weights after handling each piece of data, based on the amount of error in the output target compared with the expected result. The main goal of a learning step is to reduce the error through improving the current values of the weight associated with each edge. Due to the process of backward changing of the weights, it's called as backpropagation [3].

C4.5 decision tree algorithms: C4.5 algorithm was developed by Quinlan Ross as an extension of the ID3 algorithm. It deals with all of the categorical and continuing attributes to build a decision tree [20]. It performs a depth-first, general to specific search for hypotheses by recessively partitioning the data set at each node of the tree. C4.5 attempts to build a decision tree with a measure of the information gain ratio of each feature and branching on the attribute which returns the maximum information gain ratio. At any point during the search, a chosen attribute is considered to have the highest discriminating ability between the different concepts whose description is being generated [21].Pruning takes place in C4.5 by replacing the internal node with a leaf node thereby reducing the error rate. It has an enhanced method of tree pruning that reduces misclassification errors due noise or too many details in the training data set .C4.5 uses pessimistic pruning for deleting of unnecessary branches in the decision tree due to that accuracy was increased [22].

4 EXPERIMENTAL RESULTS

In this paper, the number of collected samples was 174 brain MR Images. The binary object features such as (Major axis length, Minor axis length, Euler Number, Area and Circularity) for each image are extracted using Matlab program. Weka tools are used for brain MR Images classification. Brain MR Images were classified using the C4.5 algorithm and Multi-Layer Perceptron (MLP) with 55% percentage split. In 55% percentage split, used 55% of the samples in the training process the rest of the samples have been used in the test. It is seen from the table (1) the C4.5 algorithm has the average TP rate and FP rate 0.897 and 0.017 respectively. The precision was of about 91%.

TABLE 1 RESULT OF C4.5 ALGORITHM

Brain tumor type	TP Rate	FP Rate	Precision
Ependymoma	0.923	0.015	0.923
Meningioma	0.818	0.03	0.818
Lymphoma	0.75	0	1
cystic oligodendroglioma	1	0.059	0.914
anaplastic astrocytoma	0.846	0.015	0.917
Normal	1	0	1
Average	0.897	0.017	0.911

The graphical representation of the results obtained from C4.5 algorithm is given in Fig. 5.

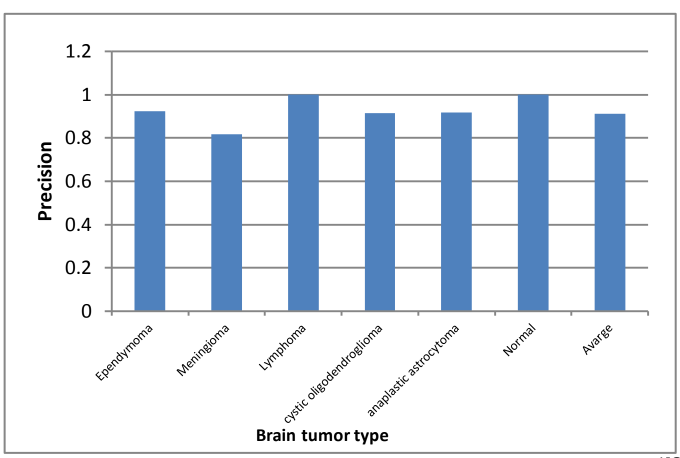


Fig. 5: Represents The Precision of Brain MR Image Type Used

As shown, in the table (2) that Multi-Layer Perceptron algorithm has the average TP rate of 0.949 and average FP rate of 0.009 while the precision was of about 95%.

TABLE 2 RESULT OF MULTI-LAYER PERCEPTRON ALGORITHM

Brain tumor type	TP Rate	FP Rate	Precision
Ependymoma	0.923	0.015	0.923
Meningioma	0.909	0.03	833
Lymphoma	1	0	1
cystic oligodendroglioma	1	0.015	0.909
anaplastic astrocytoma	0.846	0	1
Normal	1	0	1
Average	0.949	0.009	0.952

The graphical representation of the results obtained from Multi-Layer Perceptron algorithm is given in Fig. 6.

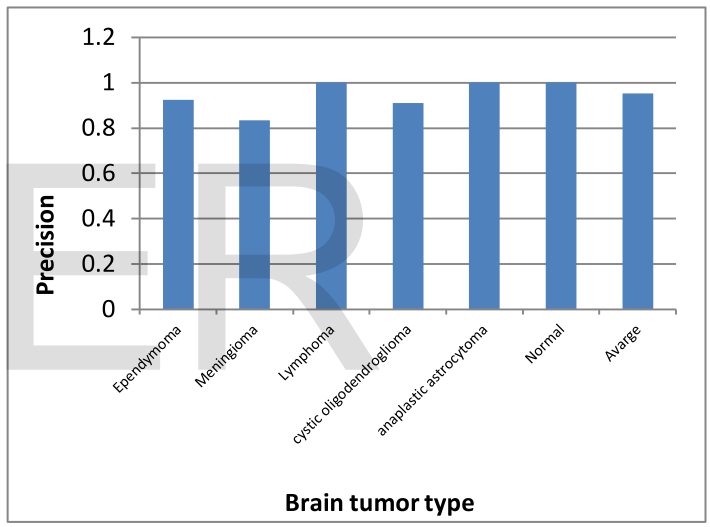


Fig.6: the precision of Brain MR Image type used MLP algorithm

It is seen from the table (3) the classified using the Multi-Layer Perceptron takes more time to build the model and gives more precision while the C4.5 gives less precision and takes more time. Because of different appearances and multifaceted nature of tumors, the result that obtained from the proposed work was satisfied precision. The precision of brain MR Images using C4.5 was of around 91% while the precision using MLP was of about 95%.

TABLE 3 COMPARISON OF CLASSIFICATION TECHNIQUES

ML Algorithm	Total instance	Model Build Time	Classification Rate(%)
MLP	173	1.22	95.2
C4.5	173	0.03	91.1

The graphical representation of the results obtained from Multi-Layer Perceptron algorithm is given in Fig. 7 and Fig. 8

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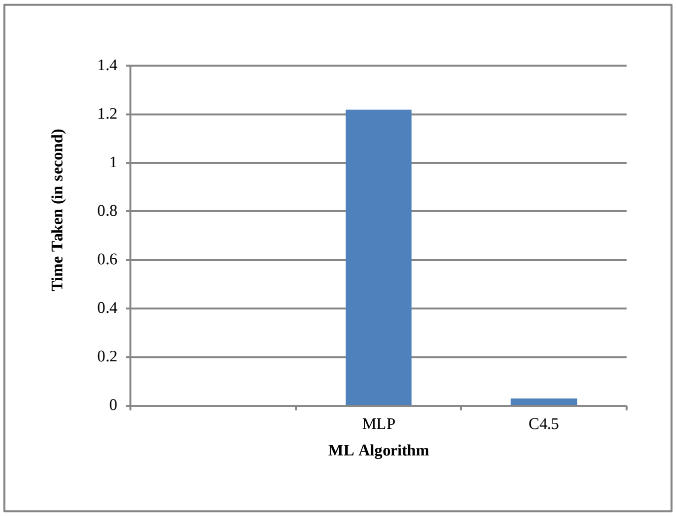

Fig. 7: Graphical Representation of Time Taken

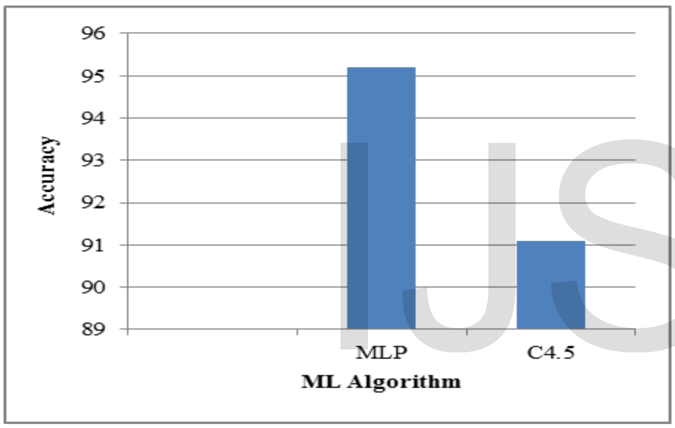

Fig. 8: Graphical Representation of Precession

5 Conclusion

This paper proposes two approaches for brain tumor classification depended on machine learning algorithms. Shape features are extracted and used for classification. Numbers of shape features are considered in this paper include Major axis length, Minor axis length, Euler Number, Solidity, Area and Circularity. For the purpose of classification, C4.5 and Multi-Layer Perceptron are used. The maximum precession of about 95% is achieved by considering 174 samples of brain MR Images and using MLP algorithm. To increase this precession can use a large dataset and add other features such as texture and intensity based features.

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