Tumor Detection and Classification using Decision Tree in Brain MRI

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Summary
The main focus of image mining is concerned with the classification of brain tumor in the CT scan brain images. The major steps involved in the system are: pre-processing, feature extraction, association rule mining and classification. Here, we present some experiments for tumor detection in MRI images. The pre-processing step has been done using the median filtering process and features have been extracted using texture feature extraction technique. The extracted features from the CT scan images are used to mine the association rules. The proposed method is used to classify the medical images for diagnosis. In this system we are going to use Decision Tree classification algorithm. The proposed method improves the efficiency than the traditional image mining methods. Here, results which we get are compared with Naive Bayesian classification algorithm.

Key words:
MRI, image mining, CT

1. Introduction

Brain tumor is a cluster of abnormal cells growing in the brain. It may occur in any person at almost any age. It may even change from one treatment session to the next but its effects may not be the same for each person. Brain tumors appear at any location, in different image intensities, can have a variety of shapes and sizes. Brain tumors can be malignant or benign. Benign brain tumors have a homogeneous structure and do not contain cancer cells. They may be either monitored radiologically or surgically destroyed completely, and they seldom grow back. Malignant brain tumors have a heterogeneous structure and contain cancer cells. In this system, we are going to implement a technique which can classify tumor and give more accurate result.
Tumor can be treated by radiotherapy, chemotherapy or a combination thereof, and they are life threatening. Therefore, diagnosing the brain tumors in an appropriate time is very essential for further treatments. In recent years, neurology and basic neuroscience have been significantly advanced by imaging tools that enable in vivo monitoring of the brain. Magnetic resonance imaging (MRI) has proven to be a powerful and versatile brain imaging modality that allows non-invasive longitudinal and 3D assessment of tissue morphology, metabolism, physiology, and function. The information MRI provides, has greatly increased the knowledge of normal and diseased anatomy for medical research, and is a important component in diagnosis and treatment planning. MR imaging is currently the method of choice for early detection of brain tumor in human brain. However, the interpretation of MRI is largely based on radiologist's opinion.
The conventional method in medicine for brain MR images classification and tumor detection is human inspection. Operator-assisted classification methods are impractical for large amounts of data and are also non-reproducible. MR images also contain a noise caused by operator performance which can lead to serious inaccuracies classification. The MR images data is by nature, a huge, complex and cognitive process. Accurate diagnosis of MR images data is not an easy task and is always time consuming. In some extreme scenario, diagnosis with wrong result and delay in delivery of a correct diagnosis decision could occur due to the complexity and cognitive process of which it is involved.
In this paper image mining concepts have been used. It deals with the implicit knowledge extraction, image data relationship and other patterns which are not explicitly stored in the images. This technique is an extension of data mining to image domain. It is an inter disciplinary field that combines techniques like computer vision, image processing, data mining, machine learning, data base and artificial intelligence [1]. The objective of the mining is to generate all significant patterns without prior knowledge of the patterns [2]. Rule mining has been applied to large image data bases [3]. Mining has been done based on the combined collections of images and it is associated data. The essential component in image mining is the identification of similar objects in different images [4].

2. System Description

There are mainly two phases in our system. Training phase and Testing phase. Overview of proposed system has been shown in Fig. 1. Initially to perform classification on MRI mages, we require image database. After gathering images we have to apply various image processing techniques in

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both training and testing phase. Techniques followed in these phases are, pre-processing, feature extraction, rule generation classification and Diagnosis. The pre-processing and feature extraction technique are common for both training and test phase.

Images are required to be preprossed for feature extraction process. Extracted features are used to mine association rules for classification.

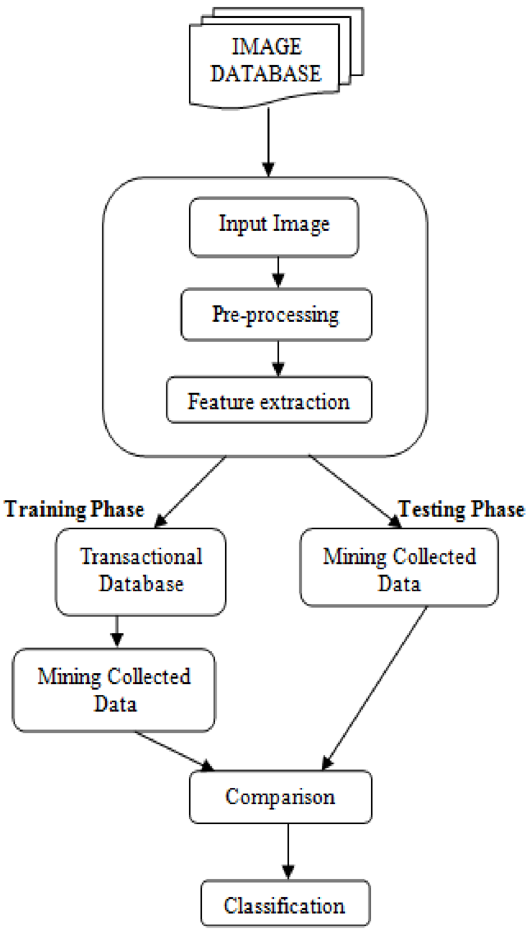

Fig. 1 Proposed system

2.1 Preprocessing

The prime objective of the pre-processing is to improve the image data quality by suppressing undesired distortions (or) enhancing the required image features for further processing. The irrelevant data present in the image has been eliminated using the pre-processing technique. The pre-processing technique eliminates the incomplete, noisy and inconsistent data from the image in the training and test phase. In order to improve the quality of images taken from the CT-scan brain images and to make the feature extraction phase more reliable, pre-processing is necessary. CT-Scan brain images into normal, benign and abnormal.

2.1.1. Median Filtering:

During the digitization process, noise could be introduced that needs to be reduced by applying median filtering techniques. Median filtering is a nonlinear process useful in reducing impulsive noise. It is also useful in preserving edges in an image while reducing random noise. Impulsive noise can occur due to a random bit error in a communication channel. In a median filter, a window slides along the image, and the median intensity value of the pixels within the window becomes the output intensity of the pixel being processed [5]. Here 3x3 median filter is used.

2.1.2. Morphological Opening:

An opening is erosion followed by dilation with the same structuring element:

$$A \circ B = (A \ominus B) \oplus B$$

Remember that erosion finds all the places where the structuring element fits inside the image, but it only marks these positions at the origin of the element. By following erosion by dilation, we “fill back in” the full structuring element at places where the element fits inside the object. So, an opening can be considered to be the union of all translated copies of the structuring element that can fit inside the object. Openings can be used to remove small objects, protrusions from objects, and connections between objects [5].

2.1.3. Power law Transformation:

Image enhancement is a very basic image processing task that defines us to have a better subjective judgment over the images. Image enhancement simply means, transforming an image f into image g using T. Where T is the transformation. The values of pixels in images f and g are denoted by rand s, respectively. As said, the pixel values r and s are related by the expression [5],

$$s = T(r)$$

Where T is a transformation that maps a pixel value r into a pixel value s.

The nth power and nth root curves shown in fig. A can be given by the expression,

$$s = cr^{\gamma}$$

This transformation function is also called as gamma correction. For various values of γ different levels of enhancements can be obtained. This technique is quite commonly called as Gamma Correction. Using the image negation formula given above, it is not necessary for the results to be mapped into the grey scale range [0, L-1]. Output of L-1-r automatically falls in the range of [0, L-1]. But for the Log and Power-Law transformations resulting values are often quite distinctive, depending upon control parameters like λ and logarithmic scales. So the results of these values should be mapped back to the grey scale range to get a meaningful output image.

2.2 Feature Extraction

In medical image diagnosis, the earliest phase of a CAD system demands to extract the main image features regarding a specific criterion [6].
Histogram based features are local in nature. These features do not consider spatial information into consideration. So for this purpose gray-level spatial cooccurance matrix hd(i,j) based features are defined. Texture features can be described using this co-occurrence matrix. Some of the most commonly used texture measures are derived from the Grey Level Co-occurrence Matrix (GLCM). The GLCM is a tabulation of how often different combinations of pixel brightness values (gray levels) occur in a pixel pair in an image. We extract feature called energy in our system. Energy provides the sum of squared elements in the co-occurrence matrix. It is also known as uniformity or the angular second moment.

2.3 Mining Association rules

Association rule mining has been extensively investigated in the data mining literature. Many efficient algorithms have been proposed, the most popular being apriori [7] and FP-Tree growth [8]. Association rule mining typically aims at discovering associations between items in a transactional database. Given a set of transactions $D = \{T_1,...,T_n\}$ and a set of items $I = \{i_1,...,i_n\}$ such that any transaction T in D is a set of items in I, an association rule is an implication A⇒B where the antecedent A and the consequent B are subsets of a transaction T in D, and A and B have no common items. For the association rule to be acceptable, the conditional probability of B given A has to be higher than a threshold called minimum confidence. Association rules mining is normally a two-step process, wherein the first step frequent item-sets are discovered and in the second step association rules are derived from the frequent item-sets. In our approach, we used the FP tree algorithm in order to discover association rules among the features extracted from the MRI database and the category to which each image belongs. In other words, a rule would describe frequent sets of features per category normal and abnormal (benign and malign) based on the association rule discovery algorithm. Once the association rules are found, they are used to construct a classification system that categorizes the brain tumor as normal, malignant or benign.

2.4 Classification

The most delicate part of the classification with association rule mining is the construction of the classifier itself. Although we have the knowledge extracted from the database by finding the existing association rules, the main

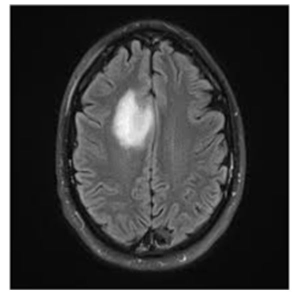

Figure 2. Brain MRI

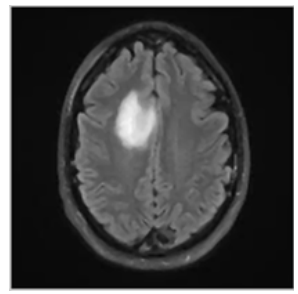

Figure 3. Median Filtering

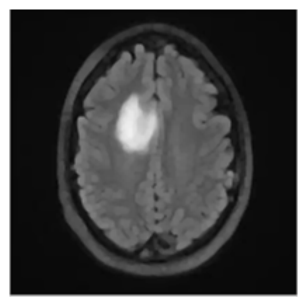

Figure 4. Morphological Opening

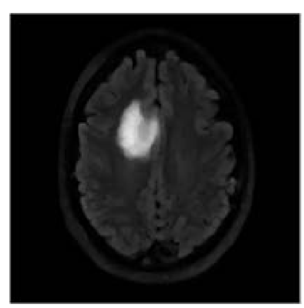

Figure 5. Power law Transformation

question is how to build a powerful classifier from these associations. The association rules that have been generated from the database in such a manner that they have as consequent a category from the classification classes. The association rules could imply either normal or abnormal. When a new image has to be classified, the categorization system returns the association rules that apply to that image. The first intuition in building the classification system is to categorize the image in the class that has the most rules that apply. This classification would work when the number of rules extracted for each class is balanced. In other cases, a further tuning of the classification system is required. The tuning of the classifier is mainly represented by finding some optimal intervals of the confidence such as both the overall recognition rate and the recognition rate of abnormal cases are at its maximum value. In dealing with medical images it is very important that the false negative rate be as low as possible. It is better to misclassify a normal image than an abnormal one. That is why in our tuning phase we take into consideration the recognition rate of abnormal images. It is not only important to recognize some images, but to be able to recognize those that are abnormal.

This classification algorithm is based on a decision tree. A decision tree is a set of simple rules. Decision trees [9] are also nonparametric because they do not require any assumptions about the distribution of the variables in each class. Every interior node contains a decision criterion depending only on one feature. For the first split into two parts, the feature with the highest relevance is used. This procedure is recursively repeated for each subset until no more splitting is possible. It followed from a root to a leaf node the decision tree corresponds to a rule-based classifier. An advantage of decision tree classifiers is their simple structure, which allows for interpretation (most important features are near the root node) and visualisation. A decision tree is built from a training set, which consists of objects, each of which is completely described by a set of attributes and a class label. The class that is associated with the leaf is the output of the tree. A tree misclassifies the image if the class label output by the tree does not match the class label. The proportion of images correctly classified by the tree is called accuracy.

3. Experimental Results

The confusion matrix can be used to determine the performance of the proposed method. Here, two classification algorithms, Naive Bayesian and Decision Tree, have been implemented. This matrix describes all possible outcomes of a prediction results in table structure. The possible outcomes of a two class prediction be represented as True positive (TP), True negative (TN), False Positive (FP) and False Negative (FN). The normal and abnormal images are correctly classified as True Positive and True Negative respectively. A False Positive is when the outcome is incorrectly classified as positive when it is a negative. False Positive is the False alarm in the classification process. A false negative is when the outcome is incorrectly predicted as negative when it should have been in fact positive.

In our system consider,
TP= Number of Abnormal images correctly classified
TN= Number of Normal images correctly classified
FP= Number of Normal images classified as Abnormal
FN= Number of Abnormal images classified as Normal.

Precision: The fraction of abnormal images with correct results.

$$\frac{TP}{TP+FP}$$

Sensitivity (Recall): The probability of the test finding the abnormal case among all abnormal cases.

$$\frac{TP}{TP+FN}$$

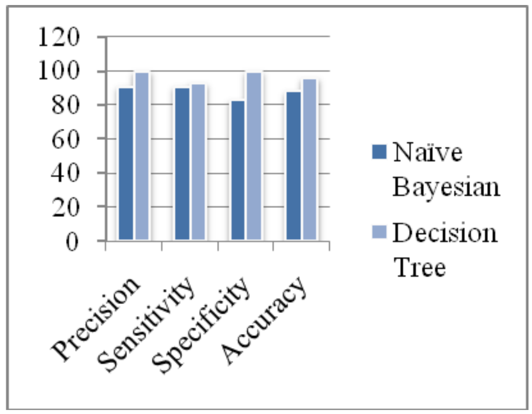

Fig. 6 Performance comparison of classifiers

Specificity: The probability of the test finding the normal case among all normal cases.

$$\frac{TN}{TN+FP}$$

Accuracy: The fraction of test results those are correct.

$$\frac{TP+TN}{TP+FN+TN+FP}$$

Using these equations, we can analyze which classification method gives better performance. In our system we have analyzed 124 MRI images. From 124 images, we have used 73 images for training phase and remaining 51 images for the testing phase.

Results using Naïve Bayesian classification:
Precision: 91%
Sensitivity: 91%

Specificity: 83%
Accuracy: 88.2%

Results using Decision Tree classification:
Precision: 100%
Sensitivity: 93%
Specificity: 100%
Accuracy: 96%

Fig.6 shows graphically representation of comparison of both classifiers. According to these results it is shown that Decision tree classifier gives better performance than Naïve Bayesian classifier.

4. Conclusion

"Tumor Detection and Classification using Decision Tree in Brain MRI" is used to get accurate and efficient result. Using Decision tree classification technique tumor has been found as well as classified in Normal or Abnormal class. Here we used two algorithms, Naïve Bayesian and Decision Tree, to compare performance. After evaluating performance we can say that the proposed algorithm has been found to be performing well compared to the existing classifiers. The accuracy of 96% and sensitivity of 93% were found in classification of brain tumor using decision tree classifier. This will produce result into normal or abnormal in efficient way. The developed brain tumor classification system is expected to provide valuable diagnosis techniques for the physicians.

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