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Brain Tumor Detection and Classification Using Histogram Equalization And Fuzzy Support Vector Machine Approach

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Abstract

There are a number of different quantitative models that can be used in a medical diagnostic decision support system. The complexity of the diagnostic task is thought to be one of the prime determinants of model selection. Using histogram equalisation the input image is pre-processed and segment the suspicious portion from the image based on markov random field algorithm for segmentation method. Features are extracted based on texture, fractal and histogram features, finally the classification is done by using the support vector machine approach.

Key words: Brain Tumor, Histogram Equalisation, Markov random field algorithm, Fractal, Texture, and Support vector machine.

I. Introduction

Every year nearly about 30,000 people in the UnitedStates are identified with primary brain tumors. Tumorsof the brain are the significance of abnormal progresses of cells in the brain. Not all primary brain tumors are cancerous;only malignant tumors are cancerous, they growfastly and destructively and occupyneighbouring tissue.Benign tumors are noncancerous, they are less aggressiveand normally do not spread the surrounding tissues.Any kind of brain tumor is fundamentallystern anddangerous because of its invasive and infiltrativecharacter in the limited space of the intracranial cavity.Early detection of malignant tumor and treatment willhelp to prolong the human life for many more years.

The risk of evolving brain cancer growths with age. Currently, imaging plays a very vital role in the diagnosis of brain tumors. Computed Tomography (CT) scan has become a commonly performed techniquewhich is an reasonable, safe and well-tolerated one. Usually, physiologists will be able to diagnose the abnormalities in the brain cells through CT scan brain images. Since radiologists are handling vast number of images every day, even experienced and well trained radiologists might be making mistakes in diagnosing the tumors [1]. Therefore, the Computer-Aided Diagnosis (CAD) systems are developed to help the radiologists as a second opinion for diagnosing the cancerous cells in the CT-scan images.

In this paper, we present a method based on Support Vector Machine (FSVM) to classify the brain images into two categories: benign and malignant. The results show high accuracy, sensitivity and specificity.

II. Related works

A. Fractal, and Fractional Brownian Motion (fBm) for tumor segmentation

A fractal is an unequalsymmetrical object with an infinite nesting of building at all scales. Fractal texture can be quantified with the non-integer fractal dimension (FD) FD estimation is proposed in brain MRI using piece-wise triangular-prism-surface-area (PTPSA) method.

B. Multifractal Process

Although fBm modeling has been shown useful for brain tumor texture analysis considering the irregular heterogeneous presence of tumor texture in brain MRI, fBm appears homogeneous, or mono fractal. In fBm Process, the local degree is unhurried the equal at all Spatial/time variations. However, like severalextra real world Signals, tumor texture in MRI may display multi-fractal structure, with fluctuating in space and/or time [7].

The multi fractal may be well proper to model processes wherein uniformity varies in planetary as in brain CTs. Takahashi et al. adventure multi fractal to illustrate micro structural variations of white matter in T2-weighted MRIs. Accordingly, this work recommends a model to estimate multi fractal dimension of tumor and non-tumor regions in MRI based on mBm analyses [9].

System model

The input image will be taken from the user, the image will pre-processed by histogram equalisation method. This process is used to enhance the quality of the image and remove the unwanted noise from the image.so the image quality will be increased. Next the affected portion is extracted from the image using markov random field algorithm. The suspicious portion will be extracted from the image for feature extraction and selection phase.

In the feature extraction and selection phase some of the image features such as texture, fractal and histogram features are extracted and selected for the further classification of the images. In the classification phase using support vector machine (SVM) the image will be classified according to the features that are selected. Finally it produce the result as benign or malignant.

The below system diagram shows the entire process as step by step:

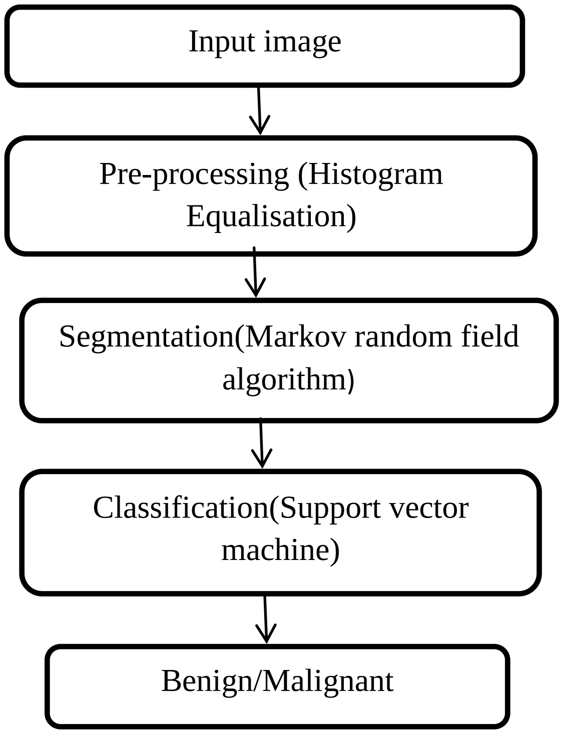


Fig 1., Architecture diagram

The proposed approach consist of the following process such as,

- Pre-processing
- Segmentation
- Feature extraction and selection
- Classification

The specified techniques are used in this step by step process and produce the decision support system. Finally the result will be as the input brain image is bening or malignant.

Pre-processing

CT scan brain images are collected from the documentationsof hospitals that habitually screen patients for tumor. Around 600 CT-scan brain images are taken for this research. For one patient one image is selected with the help of radiologist i.e. incomplete, inconsistent dataand eliminating the noisy. The histogram equalisation operation is achieved to remove the noise and to develop the quality of the images. The histogram equalization technique [17] is hands-on to upsurge the dissimilaritymaterial and to chequeredgeneralconcentrationcirculation within the soft tissue of the brain images.

Segmentation

Segmentation is the process of separating an image into non-overlapping regions, such that every region is standardized but the unification of any two neighbouring regions is inhomogeneous [4]. In this paper, the Markov random field segmentation algorithm is embraced to locate the mistrustfuldistrict from the pre-processed step conversed in [4].This process can detect substances whose limitations are not unavoidably defined by ramp or with very smooth boundaries. It can automatically detect interior contours starting with only one initial curve. The suspected area of the image is separated and can be used for further processing.

Feature extraction and selection

Feature extraction and selection: In the proposed CAD system, we analyze and extract three kinds of features (textural, fractal and histogram-based features) from the suspicious areas. Usually, a large amount of features are extracted and we need to select thesignificant ones from them. In this paper, we apply the stepwise regression method [9] to select an optimal subset of features.

2.2.1. Textural features

Textural features are based on co-occurrence matrices of the texture information [11]. All textural features are derived from the spatial gray-level dependence (SGLD) matrices, which are two-dimensional histograms. An element of the SGLDθmatrix P(i, j,d, θ) is defined as the joint probability of the gray levels i and j separated by distance d and along direction θ . In order to simplify the computational complexity, the values of θ are often given as $0°, 45°, 90°\ , and\ 135°$, and the distance d is often defined as the Manhattan or city block distance.

$$p(i,j,d,0°) = \left|\left|\{((x1,y1),(x2,y2)) where\ |x2-x1| = d, y_2 - y_1 = 0\}\right|\right|$$

$$p(i,j,d,45°) = \left|\left|\{((x1,y1),(x2,y2)) where\ |x2-x1| = d, y_2 - y_1 = d\}\right|\right|$$

$$p(i,j,d,90°) = \left|\left|\{((x1,y1),(x2,y2)) where\ |x2-x1| = 0, y_2 - y_1 = d\}\right|\right|$$

$$p(i,j,d,135°) = \left|\left|\{((x1,y1),(x2,y2)) where\ |x2-x1| = d, y_2 - y_1 = -d\}\right|\right|$$

$i = I(x1,y1), j = I(x2,y2), I(x,y)$ is the intensity value of pixel (x,y), and _S_ is the cardinality of set S.

Textural features can be extracted from SGLD matrices with different distances d’s and directions θ’s. In practice, given a distance d, four SGLD matrices can be calculated corresponding to 0◦, 45◦, 90◦, and 135◦, respectively, and produce a setof four values for each of the 14 measures listed in Appendix A. For each measure, we can compute the mean and range of the set of four values.

2.2.2. Fractal features

Fractal perception is useful to represent a arithmeticaleminence of roughness and self-similarity at changed scales of expectedsurfaces and/or curves. The fractal dimensions as symmetrical features have become popular in modeling image properties. Spontaneously, the degree of bumpiness of the image texture is comparative to the fractal measurement. In this work, five features are mined based on the fractal extents:

- $fp1\ =\ fractaldimension\ of\ the\ ROI.$
- $fp2\ =\ fractal\ dimension\ of\ the\ suspicious\ area.$

- $fp3 = fractal\ dimension\ of\ the\ ROI\ excluding\ the\ suspicious\ area.$
- $fp4 = fp2/fp1.$
- $fp5 = fractal\ dimension\ of\ the\ contour\ of\ the\ suspicious\ area.$

2.2.3. Histogram-based features

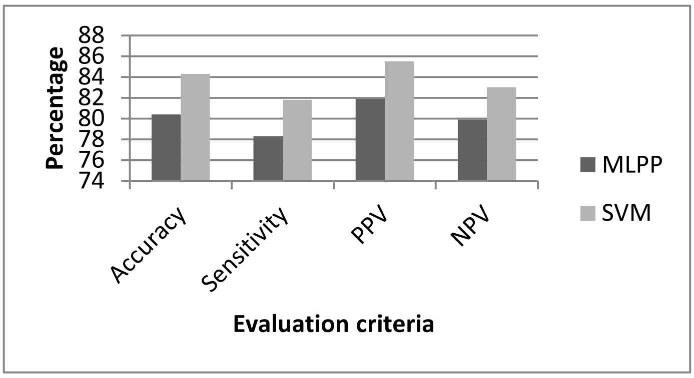
The shape of the histogram affords many clues to pronounce the appearances of the image. Six measurement features extracted from the histogram are mean, variance, skewness, kurtosis, energy, and entropy. The mean is the average intensity level whereas the variance infers the difference of concentrations around the mean. The skewness shows whether the histogram is symmetric about the mean. The histogram is symmetrical if the skewness is zero. Otherwise, it is skewed abovethe mean if the skewness is positive, and skewed below the mean if the skewness is negative. Data with high kurtosis tend to have a differentcrowningnear the mean, lessening rather rapidly, and having heavy tails.Entropy is a measure of how much disorder in a system.

2.2.4. Feature selection

Some of the above features are strongly correlated with each other. A feature collectiontechnique is applied to select a subset of the features in order to progress the performance of the system. Stepwise regression [8] is a statistical technique for picking an optimal subdivision of illustrative variables.

Classification using SVM

The cataloguing problem can be controlled to reflection of the two-class problemdeprived of loss of generalisation. In this problem the goal is to separate the two lessons by ameaning which is tempted from available examples. That it should produce the accurate result such as benign or malignant.



III. Experimental results

Totally, 120 features are derived from each of the US images: 160 texture features, 7 fractal dimensions, and 6 histogram-based features. The feature selection using stepwise regression

Figure 2.Performance analysis using line chart.

Produces an optimal subset of 13 features, including eight texture features, three fractal dimensions, and two histogram-based features.

Techniques	Accuracy	Sensitivity	PPV	NPV
MLPNN	80.4%	78.3%	81.7%	79.2%
SVM	84.3%	81.8%	84.5%	82.3%

Table 1.Fuzzy-SVM, SVM and MLPNN performances.

Conclusion

In this paper the FSVM which can yield a high accuracy rate of mass organisation. Using histogram equalization the pre-processing done with high quality of image. Morkov random field algorithm produced the efficient segmentation of the image and FSVM produce the accurate classification. The experimental result deals with the feature and produce an accuracy of classification. The proposed approach is improve the accuracy rate of the diagnosis of the classification of features.

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