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Research Article

COMPUTER-AIDED DIAGNOSIS AND CLASSIFICATION OF BRAIN TUMOR IDENTIFICATION USING PNN AND SVM

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Abstract

Brain Disease is one of the most important causes of non-accidental death in the individual. Early prediction of the disease allows the clinician to direct appropriate treatment and can recover the patient's survival rate. Due to the huge scale of the medical image data, this manual diagnosis is often difficult and can be very subjective due to inter-observer variability. Computer-aided detection/diagnosis (CAD) systems can increase the diagnostic capability of medical person and decrease the occasion essential for exact analysis. The main objective of this paper is segmentation and classification techniques and they're state-of-the-art for the human brain magnetic resonance images (MRI). The infectious part was automatically extracted from images by the proposed segmentation technique disease is represented by extracting its texture, shape, and boundary features. Then features are used to train the classifier with support vector machine and probabilistic neural network inputs into normal, abnormal. The experiments were carried out on 101 images consisting of 14 normal and 87 abnormal from a real human brain MRI dataset. The proposed technique shows its efficiency compared with the previous machine learning recently published techniques. The results exposed that the proposed hybrid approach is accurate and fast and robust. Finally, possible future directions are recommended. Experimental results showed that SVM classifier has better accuracy than PNN classifier.

Keywords: CAD, Segmentation, Brain Tumor, Classification, Feature Extraction.

1. Introduction

Brain Tumor has been one of the major threats to human life. It is likely to become the most important reason of death over the subsequently a small number of decades. Based on the statistics received from the WHO. Deaths caused by brain disease are predictable to rise in the future, with a predictable 11 million people dying in the year 2030 [1].

According to the statistics published by ASCO, The five-year relation survival rate of people with brain cancer is only 11% [2]. Hence, finding of this cancer in early stages becomes essential to cure a deadly disease. Brain tumors are classified into two types as benign tumors and malignant tumors it depends on the tumor growth pattern. Benign tumors are non-cancerous tumors which grow slowly and do not extend to the nearby tissue such as meningioma and schwannoma, whereas malignant tumors are cancerous tumors which grow fast, aggressive, and occupy nearby organs such as glioblastoma and medulloblastoma. Brain cancer can cure by chemotherapy, surgery and radiation therapy [3]. By choosing the best treatment for brain cancer depends on the doctor being able to accurately spot the tumor location, size, type, position, and borders.

At present needle biopsy is the only consistent for brain cancer, however, this is a persistent technique and generally not recommended by physicians [4]. MRI is most common technique using for brain image capturing around the world which uses radio waves and magnetic fields to acquire a set of cross-sectional images of the brain it is also a noninvasive method. Compare with CT images MRI images has many advantages particularly for brain disease due to its superior contrast properties [5]. MRI images encapsulate important information about numerous tissue parameters such as proton density (PD), spin–lattice (T1) and spin–spin (T2) relaxation times, flow velocity and chemical shift, which guide to more exact brain tissue characterization. These advantages have been characterized magnetic resonance imaging as the method of choice in brain tumor studies. It is often the medical imaging method of choice when soft tissue explanation is essential. This is particularly true for any effort to classify brain tissues. For visualizing the internal structure of the body radiologist using this method. It provides a wealth of information about human soft tissues anatomy.

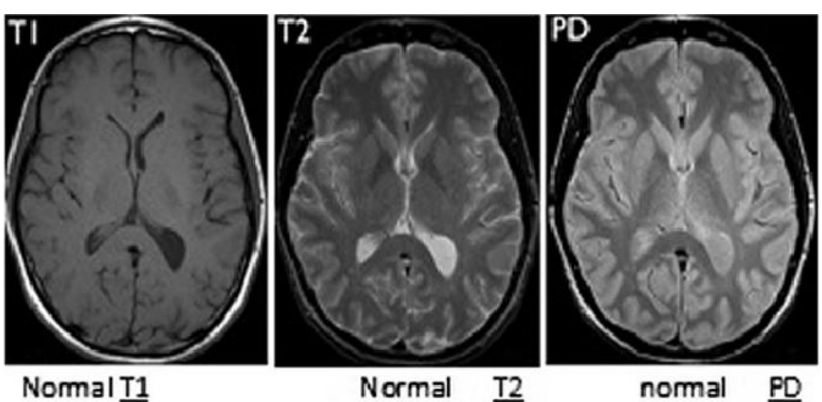

Fig.1: MRI Images for a Brain:

(a) T1-Weighted (b) T2-Weighted (c) PD-Proton Density.

This method is used for analyzing and studying the behavior of the human brain. MRI signal strength depends mainly on three molecules. Other two parameters are T1 and T2 relaxation, which reflect different features of the local environment of individual protons. The T2 scan is helpful for locating the lesioned region in the brain. The T1 scans regularly have the best scan resolution and are useful for localizing anatomical structures. The PD-scan shows generally hydrogen density per cubic mm [6].

2. Related Work

G. Evelin Sujji *et al.* proposed a comparative study on various threshold based segmentation which can distinguish the pathological tissues such as edema and tumor from the normal tissues such as WM, GM, and CSF. Thresholding techniques are simple and easy to implement. They have discussed global threshold method, Otsu method, iterative threshold method and manual selection of the threshold [7]. S. Roy *et al.* proposed a preprocessing technique to remove skull or non-brain tissues from brain MRI based on a global threshold and computational geometry like Convex Hull. They have used the standard deviation of the input image as a global threshold and based on that it is converted to a binary image. Then labeling is done on the binary image and calculating the area of each connected component authors have tried to extract the brain portion. To produce the final image Convex Hull of all one pixel is done on the binary image. Here Quick hull algorithm for Convex Hull is used [8]. Prof B. K. Saptalakar *et al* .proposed another tumor detection method based on watershed segmentation. Before segmentation preprocessing is done using high pass filter and median filter to remove impulsive noise. Watershed segmentation is done on the intensity base which is proposed by F. Meyer. Then some of the morphological operations are also done to separate the tumor region from the image [9]. S. Patil *et al.* proposed various techniques which need to consider during preprocessing of MRI and CT scan. Their techniques are based on preprocessing using a median filter and using morphological operations. The median filter produces a good result comparing to tracking algorithms, for a particular window size a median value is calculated and all the pixels under that window is replaced with the median value. For an even number of the data value, there is a possibility of more than one median values. Morphological operations such as erosion and dilation also produce efficient results in skull removing from brain MRI [10]. Anam Mustaqeem *et al.* proposed a tumor detection algorithm using watershed and thresholding based segmentation preprocessing of the image is done using filtering techniques such as median filter and Gaussian high pass filters. The preprocessed image is then segmented using threshold which is selected using some common methods like maximum entropy method. Watershed segmentation is also used as it is best to group pixels of an image on the basis of their intensities. Finally used morphological operations to extract the only tumor portions [11]. Marshkole Singh *et al.* proposed early detection of the brain tumor is very important and the motivation for further studies. In the brain magnetic resonance imaging (MRI), the tumor may appear clearly but for further treatment, the physician also needs the quantification of the tumor area [12]. Zöllner *et al.* proposed that feature selection techniques can improve the accuracy of the SVM classifier in predicting the glioma grade many algorithms have been proposed for feature selection. The most popular among them are principal component analysis, independent component analysis, and genetic algorithm [13]. Fazel Zarandi *et al.* proposed an automated system for diagnosing brain tumors using the framework of fuzzy rules to handle the ambiguous information about the set of symptoms, diagnosis, and phenomena of disease. They considered mass effect and age of the brain as vital features for identifying the benign and malignant tumor. But tumors also possess other important properties such as texture and shape which can help in better characterization of tumors [14].

Arizmendi *et al.* proposed a binary classification of brain tumors by extracting wavelet energy features and Bayesian neural network with an accuracy of 90%.However, the learning process of the neural network is very time-consuming and initial parameter dependent [15]. Corso *et al.* proposed a graph-based approach by used a Bayesian integration model to minimize the cost of graph cuts that segment tumor and edema. The classification techniques such as neural network and support vector machine (SVM) are also employed to segment brain tumor on MR images. These methods require manually selected data from various tissue types. Therefore, the accuracy of segmentation technique depends on the accuracy and repeatability of the necessary operator intervention [16].

3. Preprocessing of Images

Pre-processing is the first step of the process. The input image taken in this work is normal and ocular ultrasound images. The RGB input images are converting into grayscale images. Then Histogram equalization technique is applied on that image for getting smoothened surrounding image. Now smoothened image is applied for ROI extraction in this work focusing on Abnormal images if ROI applies directly on smoothened image cannot able to get the surface need to take the complement of the image then ROI processing is carried for that. The final process is the morphological operation applying on the processed image with the SVM training and testing data set.

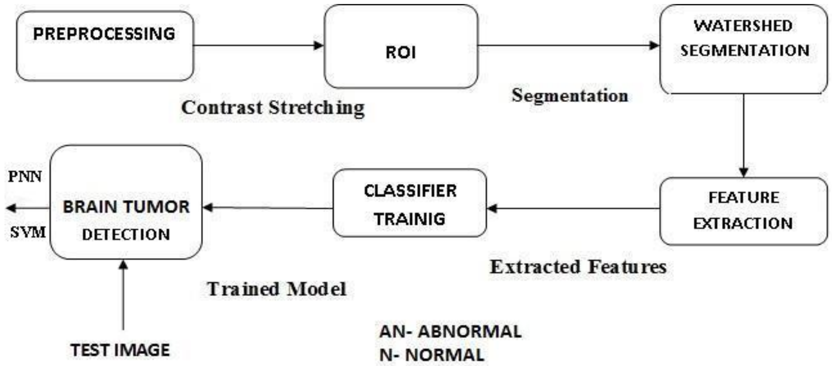

Fig. 2: Block Diagram of Proposed Method.

3.1 Histogram Equalization

Histogram equalization technique in image processing of contrast adjustment using the image's histogram. In this method trying to increase the contrast of the image by applying a gray level transform which tries to level the resulting histogram.

It turns out that the gray level transform that looking for is basically a scaled version of the input image's cumulative histogram. The technique is useful in images with backgrounds and foregrounds that are mutually bright and may be dark [17]. Histogram equalization provides more visually pleasing results across a wider range of images.

3.2 Region of Interest (ROI).

ROI may consist of one combined area and may have some unconnected areas. By creating combinations of several ROIs it can be manipulated. ROIs are used for the reason of dividing a volume data set into separate parts and agree to analyses to be constrained to specific areas of a data set. In this model, Watershed Segmentation is applied to the image. After getting the region maxima edge detection process is done to detect circumference of the disease.

3.3 Watershed Segmentation

Watershed segmentation technique which is commonly used in image segmentation. It is now being the familiar method used in image segmentation. It is classified as a region-based segmentation approach. Even when the target regions with a constant gray level constitute the flat zone of images. Watershed transformation can provide closed contours. When a landscape or topographic relief is flooded with water, the divide lines of the domains of rain falling over the regions forms the watersheds [18].

A drop of water falling on a topographic relief flows towards the "nearest" minimum. The "nearest" minimum is that minimum which lies at the end of the path of steepest descent. In terms of topography, this occurs if the point lies in the catchment basin of that minimum. If there are more minima in the image than the object of interest, the image will be over-segmented. The steps involved in segmentation algorithm are following below

3.3.1 STEPS:

• Read in an Image and convert it to grayscale

• Use the gradient magnitude as the segmentation function

• Mark the foreground objects

• Compute the Background markers

• Compute the watershed transform of the segmentation function

• Visualize the result.

The main problem of this algorithm is over-segmentation because all of edge and noise would appear in the image gradient, which makes the de-noising process necessary.

4. Feature Extraction

Feature extraction is the process of convert an image into a set of features. For the purpose of classification effective features are extracted from the image. It is a difficult task to extract a good feature set for classification. There are many methods for feature extraction e.g. texture Features [19, 20], features based on Gabor [21], wavelet transform features [22], principal component analysis, minimum noise fraction transform, discriminant analysis, decision boundary feature extraction, non-parametric weighted feature extraction and spectral mixture analysis [23]. In our proposed system texture based features are using.

4.1 Texture Features

Our Proposed system for extracting the texture features two methods are used. Method one belongs to first order histogram which is local in nature and another method is based on co-occurrence matrix which is called as second order texture feature.

4.2 First-Order Histogram Based Features

Histogram of the image provides the statistical knowledge about the image. We can obtain the first order statistical information of the image with the histogram of the image. Probability density of occurrence of the intensity levels can be obtained by dividing the value of intensity level histogram with a total number of pixels in the image appears in the image gradient, which makes the de-noising process necessary.

$$P(i) = \frac{h(i)}{NM}, \quad i = 0, 1, \ldots, G-1 \qquad (1)$$

$$\text{Mean}: \mu = \sum_{I=0}^{G-1} ip(i) \qquad (2)$$

$$\text{Variance}: \sigma^2 = \sum_{I=0}^{G-1} (i-\mu)^2 p(i) \qquad (3)$$

Where N is a number of the resolution cells in the horizontal spatial l domain and M is the number of resolution cells in the vertical spatial 1 domain. The total gray level of an image is represented by G. For significance describing the first order statistical features of the image, valuable features of the image can be gained from the histogram. The mean is the standard value of the intensity of the image. Variance let know about the intensity difference around the mean. Skewness is the measure which tells the symmetries of the histogram around the mean. Kurtosis is the flatness of the histogram. Uniformity of the histogram is represented by the entropy. Following is the list of features gained using a histogram of the image.

$$\text{Skewness}: \mu_3 = \sigma^{-3} \sum_{I=0}^{G-1} (i-\mu)^3 p(i) \qquad (4)$$

$$\text{Kurtosis}: \mu_4 = \sigma^{-4} \sum_{I=0}^{G-1} (i-\mu)^4 p(i) - 3 \qquad (5)$$

$$\text{Energy}: E = \sum_{I=0}^{G-1} [p(i)]^2 \qquad (6)$$

$$\text{Entropy}: H = -\sum_{I=0}^{G-1} p(i) \log_2 [p(i)] \qquad (7)$$

5. Classification

It is the process for classifying the input patterns into a set of categories. Classification classifies the unidentified data samples. Selection of a suitable classifier needs the attention of many things like computational resources it used, the exactness of the classifier for a few datasets, and completion of the algorithm. Classifiers can be classifying into two categories, first, one is supervised classifier [24] and another one is an unsupervised classifier. Supervised classifiers classify unknown data samples using the knowledge of the known dataset. Supervised classification needs complete information of the linked area.

Training data must be given with the labels for supervised classification. It is capable of spotting serious errors by examining training data to decide whether data have been properly classified. Unsupervised classification is the recognition of natural groups, structures, within multi-spectral data. Unsupervised classification does not need a wide knowledge of the region.

Most of the featured decisions needs for supervised classification are not required for unsupervised classification creating less chance for the operator to make faults. Unsupervised classification permits unique classes to be recognized as distinct units.

5.1 Support Vector Machine

SVM is one of the techniques used for the supervised classification purposes. It is machine learning for binary classification problems suppose a training dataset is a feature vector and d is the dimension of the input feature vector and is a class label it is used for classification and regression analysis.

Specified set of training examples, each marked as belonging to one of two categories, SVM training algorithm builds a representation that assigns original examples into one category, making it a non-probabilistic binary linear classifier [25]. More formally, a support vector machine constructs a hyperplane or set of hyperplanes in a high or infinite-dimensional space, which can be used for categorization, regression, and other purposes.

5.1.1 RBF Kernel

$$K(\mathbf{x}, \mathbf{x}') = \exp\left(-\frac{||\mathbf{x} - \mathbf{x}'||_2^2}{2\sigma^2}\right) \tag{8}$$

In this model given the extracted features as input to the classifier for training than from classifier output getting the training model, this training model is given as input for the testing purpose. In testing using the MRI images for testing purpose suppose if get the output with any abnormalities, it considers as affected image otherwise it considers as a normal image.

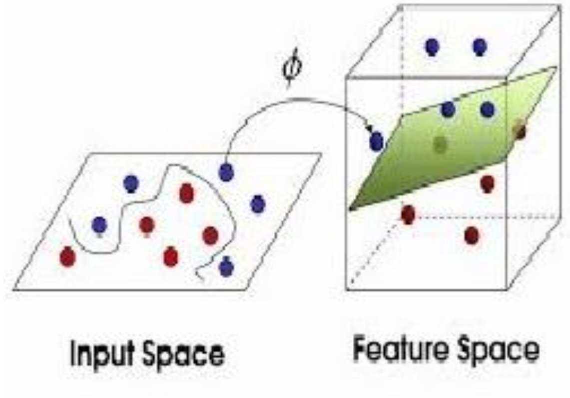

Fig. 3: SVM Architecture.

5.2 Probabilistic Neural Network

The PNN was first perspective in the architecture is arranged of many consistent processing units or neurons ordered in successive layers. The input layer unit does not execute any processing and basically distributes the input to the neurons in the pattern layer. On getting a pattern *x* from input layer *x*, the pattern layer computes its output [26].

$$\phi_{ij}(x) = \frac{1}{(2\pi)^{\frac{d}{2}}\sigma^d}\exp[-\frac{(x-x_{ij})^T(x-x_{ij})}{2\sigma^2}] \quad (9)$$

Where *d* stands for the measurement of the pattern vector x, σ is the regular parameter and x_{ij} is the neuron vector. The summation layer neurons calculate the maximum likelihood of pattern *x* being classified into c_i by sum up and averaging the output of all neurons that fit into the same class

$$P_i(x) = \frac{1}{(2\pi)^{\frac{d}{2}}\sigma^d}\frac{1}{N_i}\sum_{j=1}^{N_i}\exp\left[-\frac{(x-x_{ij})^T(x-x_{ij})}{2\sigma^2}\right] \quad (10)$$

Where, N_i denotes the total number of samples in class C_i. If the priority probabilities for each class are the identical, and the losses associated with creating an incorrect conclusion for each class are the same, the decision layer unit classifies the pattern in accordance with the Bayes's decision rule based on the output of all the summation layer neurons

$$\hat{C}(x) = \arg\max\{P_i(x)\}, \quad i = 1,2,\ldots\ldots n \quad (11)$$

The above formula denotes the expected class of the pattern *x* and m is the total number of classes in the training samples. Fig.4 shows the PNN configuration with four layers. There were six input features, which created a six-dimensional input vector *(x1, x2, x3,. . . ,x6)*. Each image had a grouping of exact values of the input vector which is called an input pattern that explain the use of features in the image.

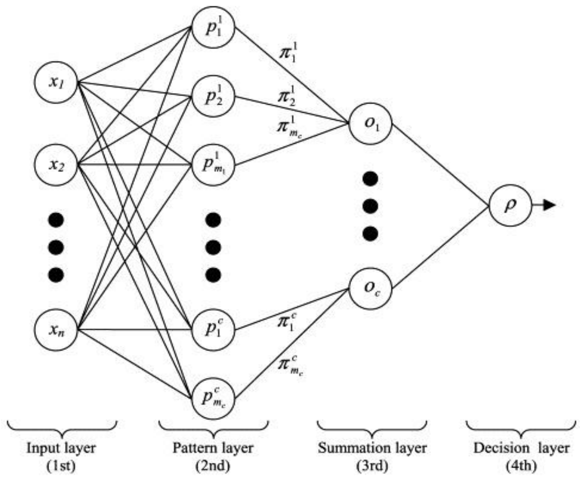

Fig. 4: PNN Architecture.

6. Experimental Results

The proposed method has been applied using the MATLAB environment on Core 2 Duo, processor speed 3 GHz. It has also been tested on a dataset of real-time brain MR images consisting of normal and abnormal brain images. The dataset consists of a record of 780 patients, 480 patients were diagnosed with begin tumor and 300 patients with malignant tumor based on histopathological analysis of samples.

6.1 Segmentation Results

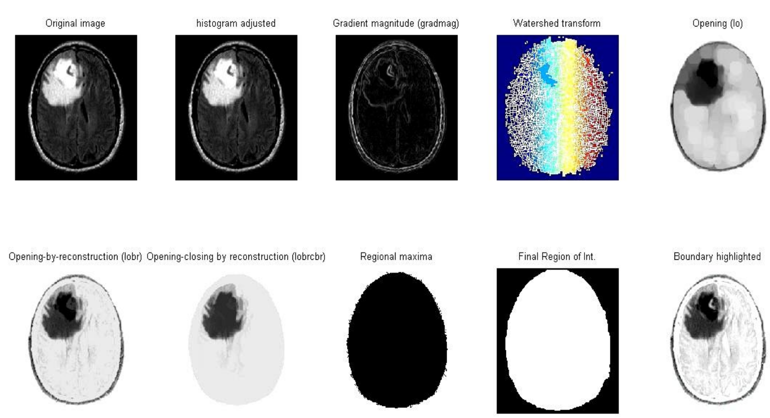

Fig. 5: Segmentation Output.

Table 1: Output of PNN and SVM Classification.

Technique	TP	TN	FP	FN
PNN	180	44	6	20
SVM	196	48	2	4

Table 2: Output of Sensitivity, Accuracy, Specificity.

Technique	Sensitivity	Accuracy	Specificity
PNN	90	88	89.6
SVM	98	96	97.6

7. Conclusions

The intention of this paper is to develop computer-aided diagnosis system for disease identification which can perfectly classify brain tumor as a normal stage or abnormal stage on MR images of the brain. Appropriately, the system was designed based on utilizing the watershed segmentation, feature extraction based on texture features in our proposed technique, feature selection, and classification technique based on support vector machine and probabilistic neural network. The experimental results indicated that proposed computer aided diagnosis system offers useful methods for differentiating between benign (normal image) and malignant tumors (abnormal image). The results show SVM is better sensitivity compare with PNN and the proposed system can be used as an analytical tool which can give a helpful second opinion for the physicians in the differential diagnosis of a brain tumor on MR images, thus improving the diagnostic exactness and reducing the needed validation time. Future work includes validation of the proposed brain tumor segmentation technique using watershed segmentation with ensemble classifiers. This would help in comparing the proposed segmentation technique with the existing brain tumor segmentation approaches.

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