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Original Research

Brain Tumor Classification And Diagnosis Using Multilayer Symmetry Technique In Image Processing

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Abstract

Accurate and timely detection of the brain tumor area has a very high impact on choosing the type of treatment, its success rate and following the course of the disease during the treatment. Existing algorithms for brain tumor diagnosis face problems in terms of good performance on various brain images with different qualities, low sensitivity of the results to the parameters introduced in the algorithm, and reliable diagnosis of tumors in the early stages of formation. For this purpose, digital image processing methods along with machine learning help to diagnose the tumor as quickly as possible, as well as treatment and type of surgery. These combined techniques in understanding medical images are an important tool for researchers to increase the accuracy of diagnosis. In this thesis, we intend to perform the classification methods related to the MRI images of the human brain with a tumor, with the aim of reviewing the glands containing astrocytoma. The methods used for brain tumor classification include pre-processing steps, windowing, and extraction of histological and statistical features of the tumor using two types of T1-w and Flair brain MRI images, as well as the method of reducing the dimensions of the extracted features and how to train them for classification. The results have shown that by using the combined technique of symmetry and multi-layer clustering, while increasing the accuracy, the processing time is also reduced.

Keywords: Brain tumor, MRI, Classification, Diagnosis, Image processing.

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Introduction

Brain tumor is a kind of solid neoplasm inside the brain and the central canal of the spinal cord. In simpler terms, a brain tumor is an abnormal mass in the brain that may be cancerous (malignant) or non-cancerous (benign). It depends. The brain is completely covered by the skull. This makes a quick and early diagnosis of a brain tumor possible only if there are preclinical tools and appropriate diagnostic tools to check the condition of the cavity inside the skull in the early stages of tumor formation. Existence With these tools, it is very difficult to accurately diagnose brain tumors due to the variety of their shape, size and appearance. In addition, in most cases, brain tumor is diagnosed in the advanced stages of the disease and when its presence causes unexplainable signs and symptoms to appear in patient [1-5]. It is possible to identify a brain tumor by image segmentation, in terms of the brightness intensity uniformity criterion. Manual separation of the tumor region in MRI images of the brain is a time-consuming and quite difficult process. Today, with the advancement of image segmentation algorithms, it is possible to diagnose brain tumor automatically. Despite the fact that automatic brain tumor diagnosis methods reduce the operator's work and human errors, they also provide the possibility of storing the state of tumor growth during the treatment [6]. Tumor is very difficult in a wide range of images. Also, the proper performance of many algorithms presented for the segmentation of magnetic resonance images of the brain depends on the appropriate selection of the input parameters of the algorithm, for example, the appropriate determination of the initial values of the number of clusters, the maximum repetition, and the termination parameter in Kernel fuzzy c-means clustering method, which is presented in [7]. It is important in the accurate segmentation of the tumor in the magnetic resonance images of the brain. In addition, to select the values of the input parameters, a large range of values cannot be selected by the user as an example in the reference [3], according to the wide range of images, to choose a suitable threshold value. A large range of values cannot be considered for the 2-phase connection segmentation algorithm, and the user may not have an idea of the appropriate value of the parameter used in the algorithm. In [8], an algorithm for the diagnosis of benign, malignant and normal tumors has been presented with the help of tissue characteristics and possible neural network. In this algorithm, wavelet conversion coefficients are used in different bands. In [9], classification of four tumors, astrocytoma, meningioma, carcinoma and sarcoma with the help of features based on gray level co-occurrence matrix 6 with the help of neural network and Levenberg–Marquardt nonlinear optimization algorithm has been investigated. In [10], classification of brain and bone cancer tumors was done using gray level co-occurrence matrix coefficients and back-propagation neural network and the results were reported for four levels of tumors. The classification of brain tumors in [11] has been done with the help of the coefficients of the gray level occurrence matrix and the fast discrete transform and with the classification based on the probabilistic neural network with radial basis functions. Classification is done on benign, malignant and normal types of tumors. In [12], by using the combination of image processing techniques and neural network, an attempt has been made to increase the speed and accuracy of finding brain tumors. Histogram-based features were extracted from the tumor areas and normal parts of the image, and then the neural network was used to detect the tumor area. In [13], the combination of features extracted from histogram, gray level co-occurrence matrix, gray level repetition length matrix 14 and support vector machine are used to identify benign and malignant tumors. In [14], a classification algorithm for brain tumors based on a probabilistic neural network trained with the help of gray level co-occurrence matrix features and morphological operators obtained from discrete wavelet transform coefficients is proposed. In [15], different algorithms presented in order to classify brain tumors based on different characteristics and categories were examined and the results of the diagnosis were compared with each other. In [16], an algorithm was introduced to detect the area and region of brain tumor. In this method, after image growth and noise removal, the effect of head rotation is removed, and by applying symmetry analysis, selected areas are recognized as tumor locations. In the following, the area of each of these areas is calculated and the area that has a certain area within the area of the areas of the tumor areas of the images is considered as the main area of the tumor. In [17], a method for identifying malignant and normal brain tumors is presented based on the features obtained from the co-occurrence matrix of the gray level and features based on the shape extracted from the connected areas of the image. For this purpose, in this paper an integrated symmetric image processing based on the multi-layer classification based on the PNN was proposed to reduce the processing time and improve the accuracy and precision in tumor detection.

Methods

Segmentation

Image clustering is done by different methods. In [18], a system based on combined clustering is presented, which includes three main stages of pre-processing, clustering and extraction and contouring. The image obtained from the pre-processing stage is extracted by the K-means clustering technique combined with the Fuzzy C-means algorithm. In the last step, the leveling algorithm is applied on the image and provides a more accurate segmentation. The dependence of the output on parameters such as the number of clusters, the maximum repetition and the termination parameter is one of the disadvantages of this method. In [19] have presented a method based on the improved fuzzy relation algorithm for brain tumor segmentation. In this study, the implementation stages of the proposed method include three main stages, data processing, brain mapping and neural network-wavelet transformation and correlation analysis.

Data preprocessing

The purpose of this stage is to reduce the dimensions of the input space and produce a well-defined input vector by deleting redundant and unimportant data that is appropriate for the intended application. Pre-processing of the raw EEG data recorded from the electroencephalogram device, including passing through a low-pass filter (0.5-60 Hz BPF) to remove unnecessary very high and low frequencies and a slit filter to remove city electricity noise, sampling with an appropriate frequency and finally Removal of pseudo-epileptic signals or artifacts (such as the movement of the eyeball and the contraction of the muscles that lead to the creation of a quasi-epileptic signal in the EEG and errors in the diagnosis of epilepsy).

In the second stage of pre-processing, after drawing the brain map, the dimensions of the data are further reduced by image thresholding and violet analysis, and finally, the violet coefficients are used as descriptive characteristics of the brain map for training the neural network [20] as a result of reducing the dimensions of the input patterns of the neural network [21].

Feature extraction

The classification of patterns based on the EEG signal leads to poor results in terms of classification performance, therefore, specific extraction of data and their conversion into two-dimensional mapping can increase the accuracy of classification to a great extent. Generally, the characteristics used for the EEG signal are divided into three groups, time domain characteristics, frequency domain characteristics, and entropy-based characteristics. In fact, in this study, feature extraction was done in 2 steps, feature extraction from the EEG signal of each electrode and Extraction of horizontal, vertical and diagonal Violet coefficients [22-24]. The characteristics that we have used for the EEG signals of each channel are the characteristics of energy in the time domain. This characteristic was first used by Alessandro et al. to predict epilepsy in convulsive patients. This equation is obtained:

$N(k) = x2\,(k) - x(k-1)x(k+1)$

Where X is equal to the amount of EEG signal in each K sample. Then its average is calculated as a characteristic in a cycle period.

The PNN classifier structure consists of 4 layers as seen in Figure 1. The input layer, pattern layer, aggregation layer and output layer are the constituent layers of PNN classification.

In the input layer, each feature vector is temporarily stored to feed the network. Therefore, in the input layer, there is a neural string for each dimension of the input feature vector.

The pattern layer, which is the second layer of the PNN classifier structure, has several layers, each layer consisting of several neural fibers. Each input feature vector in the input layer is mapped to a neural string in the model layer. The task of the pattern layer is to calculate the Euclidean distance between the input and training features.

As it is clear from Figure 1, the aggregation layer also has one neural string for each layer in the model layer. So that the neural strings that are in one layer of the pattern layer are mapped to a neural string in the summing layer. The output layer also consists of a neural string and the basis of this layer's work is that it assigns the input feature vector to a class using the classifier system.

In this article, PNN classifier with symmetric multilayer carpet is used. This stage also includes two parts. Training and testing are two parts that should be considered in classification. In the training part, the classifier is given a training matrix that contains the features of several brain MRI images as input to the classifier. In the testing part, the features of the images that are not used in the previous part are given to the classification predictor. The classification results are evaluated based on sensitivity, specificity and accuracy criteria. Below are the relationships between these three criteria:

$$sensitivity = \frac{n_{TP}}{n_{TP} + n_{FN}} 100\%$$

$$\text{Precision} = 2\frac{\text{n}_{\text{TN}}}{\text{n}_{\text{TN}} + \text{n}_{\text{FP}}} 100\%$$

$$accuracy = \frac{n_{TP} + n_{TN}}{n_{TP} + n_{TN} + n_{FP} + n_{FN}} 100\%$$

$$F1 = 2\frac{\text{Sensiticity. Precision}}{\text{Sensiticity} + \text{Precision}}$$

Results

A method for brain tumor segmentation is proposed from MR images, which is based on multi-layered PNN and also uses shape-oriented topological features to identify the exact region of the tumor.

The first row shows the original images, the second row shows the tumors with CSE. The third row shows the distributed tumors and the fourth row shows the tumors identified by the proposed method and manual segmentation [25, 26]. A packet-based k-means method is also implemented for skull banding (brain tissue extraction), as a pre-processing step. Learning mechanisms based on learning and classification are effectively used in the segmentation process with various uncertainties and noises, and increase the obtained results. Currently, it is suggested to use the automatic tumor segmentation method based on topological properties based on PNN and shape, in order to accurately determine the tumor area.

It is also implemented for skull blanking (brain tissue extraction) as a pre-processing step, which has the additional feature of element classification, depending on its neighborhood patterns. After removing the skull, the PNN is applied to the brain tissue and finally the brain tumors using shape-based topological properties.

The images used in this article include brain MIR images with tumors obtained from the NCI-MICCAI 2015 Multimodal Tumor Classification Challenge. These images are anonymized and obtained from the Center for Cancer Imaging

Archive. In this database, tumor-infected areas in brain MRI images are manually identified by experts. The proposed method has been performed for simulated and real magnetic resonance images. It should be noted that the target database also includes these images (simulated and real).

By using hierarchical learning and extracting high-level features, the proposed model achieves better performance than other methods. In order to implement the codes related to the proposed deep learning network, an NVIDIA 1060 computer, a Corei9-6700HQ graphics card with a processor, 8Gbyte with 12Gbyte DDR4 RAM and a 2TB hard drive have been used. Anaconda software version 3.7, and Matlab Image processing software have been used to run the program in the Windows environment.

This study presents a multi-class classification method of MRI images of brain tumors using a convolutional deep learning network. The proposed algorithm includes a main stage of classification using convolutional network. In the next step, a twelve-layer convolutional network is used, which includes three convolution layers, three layers, Max pooling, one layer, Flatten, two layers, and Dropout, three fully connected layers. For classification, Softmax activation function is used to classify three classes. The average accuracy in 4 times of implementation of the proposed method is 98.43%. The proposed method can be used as a practical software to diagnose brain tumors. In table 1, the average total accuracy and other parameters are shown for four times of program execution.

The proposed method was compared with several similar researches that mostly used the image zoning method and it was observed that the accuracy of the proposed method was much higher and the results of the comparison are shown in Table 2. One of the strengths of this study is the use of a deep convolutional network. Twelve layers pointed out that the accuracy of the network reached 68.98%, and the negative points include the lack of use of clinical MRI images with different classes in order to diagnose several brain diseases at the same time (multi-class diagnosis).

In the next step, to check the results with the methods proposed in previous researches, the results for two automatic and semi-automatic modes have been checked. As shown in table (2), the proposed model has been able to detect the tumor with more precision and accuracy by using two layers of image processing, the first stage of symmetrization and the second stage of exfoliation. Of course, it should be noted that the MRI images of two studies were different, but they had the same brain tumor.

Discussion

The tumor classification and diagnosis by image processing have been utized in this paper for the sample tumors brains. The results shows the efficacy of the proposed method which is an agreement with results of [3]. Nowadays, most brain tumor identification and diagnosis methods depend on the decision of neurologists and radiologists to evaluate the images, which is involved in human errors and takes time. The process and techniques used in brain tumor detection are reviewed and analyzed based on Magnetic Resonance Imaging (MRI) and Artificial Neural Network (ANN) techniques. Computer (CAD), after collecting image data is done [14].

The first step is to pre-process and post-process the MRI images to improve them and make them more suitable for analysis. A threshold is then used to segment the MRI images by applying the mean gray level method. In the second step, statistical feature analysis is applied to extract features from the images. The calculated features, based on the spatial gray level dependency matrix (SGLD), are calculated in the images. Then the best and most appropriate features are selected to identify the location of the tumor. In the third step, artificial neural networks are designed. Neural networks, through back-propagation, feed-forward and supervised learning, are applied as an automated method to classify the images under investigation as tumor or non-tumor. The performance of these networks was successfully evaluated and the best results were obtained with 99% accuracy and 97.9% sensitivity [2].

Brain tumor identification, in the early stages, motivates further studies and can be challenging. In the field of medical imaging, stroke injuries and brain tumors are challenging cases, because their accurate identification has a critical impact on clinical diagnosis [7]. A brain tumor is an abnormal cell that actually shows changes in brain structure and behavior that has grown in or around the brain itself. According to the National Brain Tumor Foundation (NBTF), for research reports, brain tumor is actually the leading cause of death in the world and has worsened in the last three decades. There are several types of brain tumors in the literature and they are divided into two categories: benign (non-cancerous) and malignant (cancerous).

The human brain is characterized by structural complexity, which makes it difficult to analyze. In addition, the analysis of these images is very limited compared to their high quality. Analyzing these images manually has several disadvantages (such as being time-consuming). In addition, balancing the level of focus during classification can lead to a reduction in false detection rates. Therefore, an automated system for analyzing MR images is needed, in which CAD can be a promising solution.

Various techniques have been proposed to classify MRI images. The results are compared with previous studies [13, 17] and show that this plan has the highest performance. All these methods require different image features that actually show the determining information that is the input vectors of the classifier. Feature extraction plays a vital role in identifying effective features and can provide higher accuracy rates. In general, we can divide classification techniques into two types: supervised and unsupervised. Supervised techniques require information layers and can advance the previous model based on the training set; While unsupervised methods do not require specific training data. These methods are fast and do not require training steps, but in some cases, they do not have the necessary efficiency. This study has two goals: on the one hand, different feature extraction techniques and some classifiers are investigated. On the other hand, a plan based on this review is developed that can classify the images according to the healthy and tumorousness of the patient's brain, using DWT and BoW resources [11].

Conclusion

Brain tumor refers to the uncontrolled growth of cells in the human brain. Tumors can lead to cancer, which is one of the leading causes of death in the world. The initial diagnosis of the tumor and the estimation of its progress based on the MRI image help doctors to save human lives. In this article, an automatic method based on multi-layer symmetry analysis in MRI images based on PNN is presented to find the exact range of the tumor area. In order to improve the accuracy of the system, an image processing system based on symmetry and a multilayer segmentation system has been used. The results show that at the same time as the input information is reduced, the accuracy and accuracy of the output can be increased and the time of information analysis and access to the output can be shortened, which is very important in today's medical affairs.

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Table & Figure:

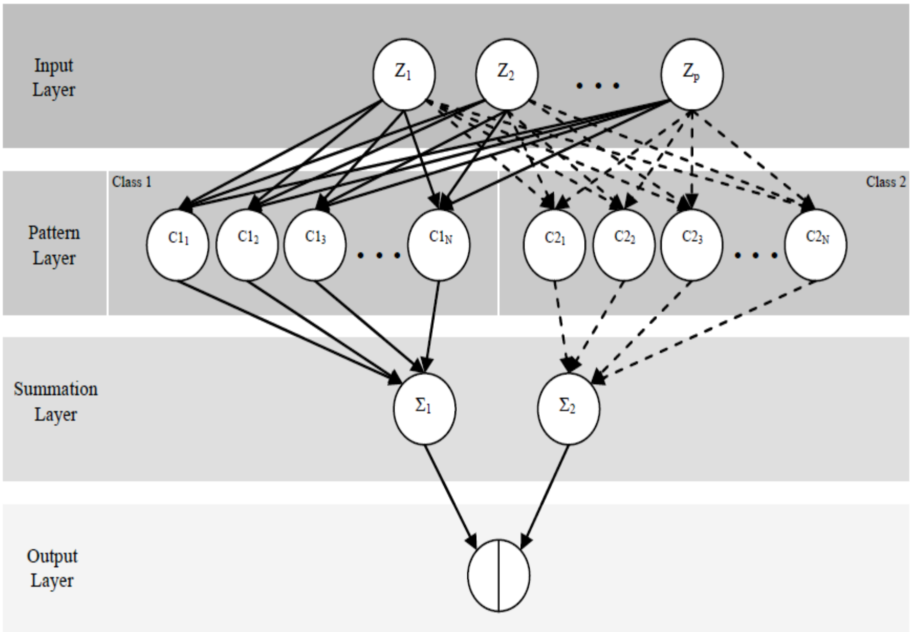

Figure 1. How the PNN classifier works

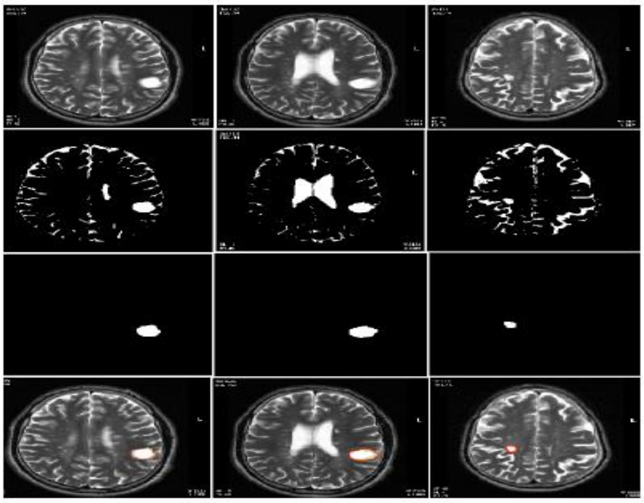

Figure 2- Tumor segmentation based on PNN on MRI data

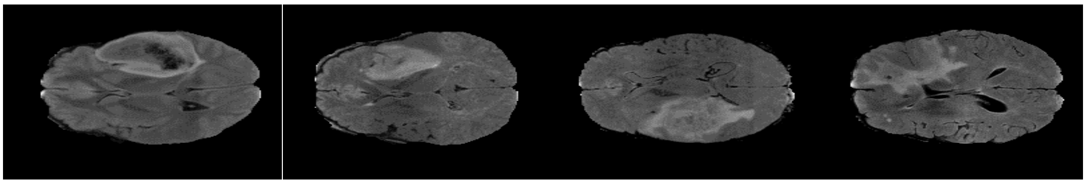

Figure 3. Real brain MRI images and T1W simulation

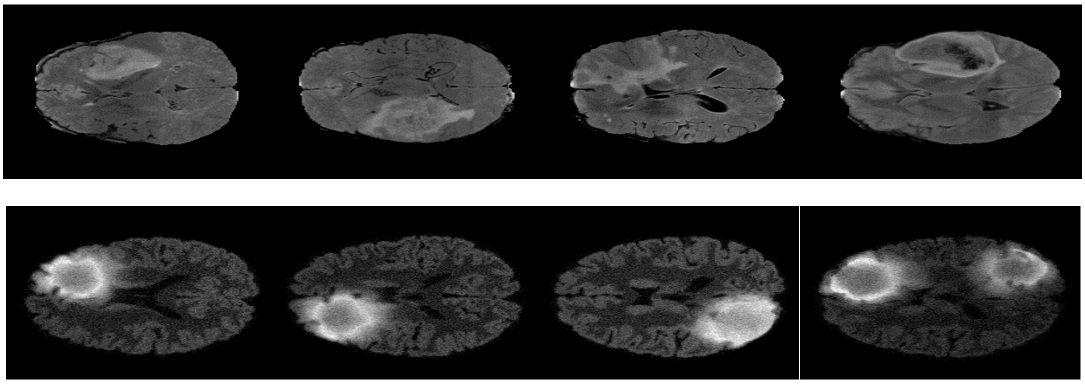

Figure 4. Real and simulated brain MRI images of Flair

Table 1: Results of parameters for clusters

No	**Precision**	**Sensitivity**	**Accuracy**	**F1**
1	99.14	95.32	92.96	97.17
2	98.26	96.01	94.33	97.12
3	97.31	98.11	96.55	97.70
4	99.01	94.98	94.55	96.95
Mean	98.43	96.11	94.96	96.75

Table2: Validation Results of parameters for clusters

No	**Precision**	**Sensitivity**	**Accuracy**	**F1**
Reference Automat [3]	96.55	96.01	90.25	96.27
Reference Semi-automat [25]	97.51	94.25	92.25	95.85
Proposed results	98.43	96.11	94.96	96.75