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Research Article

Brain Tumor Type Classification Using Deep Features of MRI Images and Optimized RBFNN

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RBFNN
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Abstract

The detection of Brain cancer is an essential process, which is based on the clinician's knowledge and experience. An automatic tumor classification model is important to handle radiologists to detect the brain tumors. However, the precision of present model should be enhanced for appropriate treatments. Numerous computer-aided diagnosis (CAD) models are offered in the literary works of medical imaging to help radiologists concerning their patients. This paper proposes an intelligent diagnostic method for early detection of brain tumor based on radial basis function neural network (RBFNN) and efficient deep features of magnetic resonance imaging (MRI) scans. The developed method includes four main modules including the segmentation, feature extraction, classification and learning modules. In the segmentation module, Grab cut method is applied for segmenting tumor region. In the feature extraction module, a convolutional neural network (ConvNet) is utilized for extraction of new deep features from segmented images. The extracted deep features are fed into RBFNN in the classification module. In the RBFNN, learning algorithm has a high impact on the network performance. Therefore, a new learning algorithm based on the bees algorithm (BA) has been used in the learning module. The developed method applied on Brain Tumor Segmentation (BraTS) 2015 datasets and the obtained results showed that the developed method is effective and can be used in computer-aided systems to detect brain tumor.

1. Introduction

The tumor is the uncontrolled growth of cancerous cells in any body part. The tumor is classified into different kinds according to the features and the conflicting treatments. From all types of tumors, the brain tumor is considered as the most hazardous and scrupulous disease, which requires clear analysis by the medical practioner, which could categorize the tumor precisely. Hence, intelligent digitalized image processing methods are widely utilized in the classification and detection phases of the tumor images. The segmentation and detection of brain tumor using magnetic resonance images (MRI) is significant part in medical treatment. This process offers information connected to anatomical structures for planning treatment. The tumor segmentation can be useful for modelling the brains and constructing the atlases of brain. In spite of many methods and their

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gifted results in the medical imaging, the precise description and segmentation of abnormalities are a major issue and complex task due to different location, intensities and shapes of tumors. MRI is an enhanced imaging modality which is utilized for analyzing the tumors present in brain images [1].

The brain tumor is treated in the later stages using MR images. The MRI represents a ubiquitous imaging modality that assist the medical practioner to diagnose and treat conditions of patient. MRI utilizes magnetic area, pulses and computer for visualizing the area of organs, bones and structures of bodies. Analysis of brain MRI is the process of identifying the disorders caused in the brain. The brain MRI offers comprehensible images with posterior brain brainstem that are complicated while viewing from CT scan. The segmentation plays a significant role in extracting malicious regions from the complicated medical images [1, 2].

Glioma is a primary brain tumor type and it has two classes such as benign or Low Grade Glioma (LGG) and malignant or High Grade Glioma (HGG). Generally, LGG cells do not attack neighboring normal cells whereas brain tumor cells at- tack on their adjacent cells in case of HGG [3]. Therefore, accurate glioma classification at an initial stage is a significant requirement.

Recently, magnetic resonance imaging (MRI) is widely used by radiologists to analyze brain tumors. This process offers information connected to anatomical structures for planning treatment [4]. Radiologists still find it challenging to distinguish between LGG and HGG cells. Unfortunately, with a visual inspection, this suffers from the unavoidable human mistake and malfunction, which can be further amplified by noisy MRI images. Furthermore, excellently-trained algorithms in machine learning (ML) can concentrate on points that are not perceptible to the doctor's unaided vision, and therefore can serve to change such a perception. In addition, providing expert clinicians to each and every clinic is a difficult challenge due to a limited number of radiologists, especially in remote areas. Accurate, quick and easy solutions focused on ML-based approaches could therefore be incredibly helpful in tackling this problem and providing patients with timely assistance [4].

Over the past few years, ML-based approaches have become one of the leading research topics in medical image computing as well as in clinical diagnosis [5]. Such intelligent technologies also have great benefits over radiologists. They are reproducible, and hence they identify the subtle changes that visual observation cannot identify. Over the past few years, several studies have been done on MR image processing using ML algorithms with the aim of providing a fast and accurate brain tumor classification method. Most of the developed methods have used convolutional neural networks (ConvNet) as the intelligent classifier.

Considering the importance of early and accurate detection of brain tumor, a simple, fast and accurate diagnostic method is proposed in this study. In the developed method, we used ConvNet for automatic feature extraction from MR image slices. In order to improve the generalization capability, we used radial basis function neural network (RBFNN) instead of fully connected layers (FCLs). Outstanding generalization capability of RBFNN makes it different from other classification algorithms. The RBFNN is one of the few ML algorithms to address the generalization problem. Moreover, bee's algorithm (BA) is applied to train the RBFNN. The BA is one of the most accurate and fast nature-based optimization algorithms that has been introduced recently [7]. In recent years optimization algorithm have applied in different engineering problems [8- 20].

The rest of the article is arranged as follows. Section two presents the basic concepts and section three presents the proposed method and provides details. In the fourth section, the results of numerical studies and simulations are presented. Section five summarizes and concludes the paper.

2. Basic tools

2.1. Classifier

RBFNN is one of the most important ANN paradigms in machine learning. It is a feed forward network with a single layer of hidden units, called radial basis functions (RBFs). RBF outputs show the maximum value at its center point and decrease its output value as the input leaves the center. Typically, the Gaussian function is used for the activation function. The RBF network is constructed with three layers: input layer, hidden layer and output layer as shown by Fig. 1.

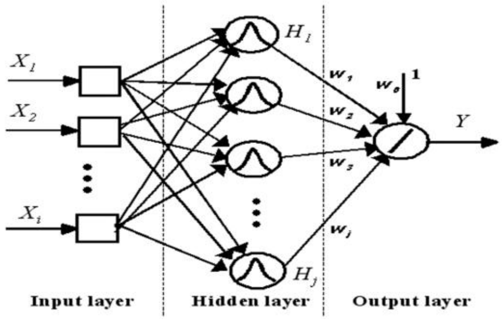

Fig 1. Structure of RBFNN [7]

In input layer, the number of neurons is the same with the number of input dimension. The neurons of input layer will transmit data to the hidden layer and calculates a value of the RBFs received from the input layer. These values will be transmitted to the output layer which calculates the values of linear sum of the hidden neuron. In this study, the Gaussian function is used as RBF. Let $h_j(.)$ be the j*th* radial basis function. The output of each radial basis function is:

$$H_j = h\left(\left\|x - c_j\right\|, \sigma_j\right) \quad , \quad j=1, 2, ..., m \tag{1}$$

Here, $x=\left(x_1, x_2, ..., x_d\right)^T$ is the input vector, $\|.\|$ is a norm, usually Euclidean, defined on the input space, $c_j=\left(c_{1j}, c_{2j}, ..., c_{dj}\right)^T$ and σ_j^2 are the j*th* center vector and the width parameter, respectively. The output of RBF network y which is the linear sum of radial basis function, is given as follows:

$$y = w_i^T H = \sum_{j=1}^{m} w_{ij} H_j \quad , \quad i=1, 2, ...,o \tag{2}$$

where y is the output of the RBF network, $w_i = [w_{i1}, w_{i2}, ..., w_{im}]^T$, $i = 1, 2, ..., o$ are the network weight vectors for each output neuron i, $H = [H_1, H_2, ..., H_m]^T$ is the vector of basis functions and o is the number of network output units [27].

To construct RBF network, the number of the hidden layer neuron *m* must be set. Moreover, the centers c_j, the widths σ_j and the weights w_j must be estimated. In RBF typical learning, the network structure will be determined based on prior knowledge or the experiences of experts. The parameters are estimated using either the clustering or the least mean squared method.

2.2. Bees-RBFNN

The RBF neural network training process can be divided in two steps. The first involves the determination of the radial basis functions features to be used in the hidden layer of the network and the second one involves determining the weights of the output neurons. Different learning strategies can be used in the design of an RBF network depending on how the centers of the radial basis functions network are specified, such as fixed centers selection and self-organized selection. A RBFNN uses radial basis as its activation function and presents some main free parameters to be adjusted during training:

1) The number and location of the basis functions in the hidden layer;

2) The widths or spreads of these basis functions;

3) The weights in the output layer of the network.

The performance of the RBFNN strongly depends upon the number and positions of the basis functions composing the network hidden layer. The traditional methods to determine the centers are: random selection of the input vectors from the training dataset; obtaining prototypes based on unsupervised learning algorithms, such as k-means clustering; or using the supervised learning to train the network. Using the fixed or self-organized centers in RBFNN have the main drawback of working with an arbitrary number of RBF centers whose positions and spreads are either chosen randomly or self-organized, respectively.

Many approaches have been proposed in the literature with the goal of overcoming these limitations. In [20], a new learning algorithm, named Bees-RBF is introduced that utilizes the bees algorithm (BA) inspired clustering algorithm to obtain the number and location of radial basis function centers (prototypes) automatically to be used in an RBFNN . Then, the spread of each RBF center found by algorithm is dynamically determined based on the distribution of the clustered input data. The goal of this method is to guarantee that each basis function is sufficiently spread so as to cover all the data points that lie within its radius. Using this approach, the most important parameter of RBFNN including RBF centers and spread of RBFs will be found automatically and optimally.

In the Bees-RBF method, the clustering performed in the first layer of the RBFNN is done by the bees algorithm. In this method, each bee represents the centers of the clusters, and the number of clusters is determined by the algorithm. If the number of m clusters is determined, a spread must be determined for each cluster center. To do so, each vector in the data set is grouped to the nearest cluster center based on the Euclidean distance. After dividing the data between the clusters, the distance from the farthest data is determined from the center of the same cluster. For example, for the jth cluster, the spread amount (σ_j) is calculated as follows:

$$\sigma_j = 1.1 \times d_{j\max} \tag{3}$$

where $d_{j\,max}$ is the farthest distance from the center of jth cluster (in the same cluster (cluster j)). After determining the cluster centers and spread of each cluster by the bee algorithm, the output of the first layer 1 is calculated by Eq. (1). Based on the output of the first layer, the final output of the network is obtained using the Eq. (2). More details regarding this algorithm can be found in [7].

3. Proposed method

This paper proposes an intelligent method based on ConvNet and RBFNN for MR image analysis and brain tumor classification. The proposed method includes four main modules including the segmentation, feature extraction, classification and learning algorithm. Initially, RGB image is converted into a single channel. Then the Grab cut method with morphological operations is applied in the first module to segment and refine tumor region more correctly. The Grab cut is a powerful extension of the graph cut technique for segmentation of color images. In the feature extraction module of the proposed method, we used a ConvNet for generating deep and abstract features from segmented images that cannot be seen or detected by a human expert. The automatically extracted features lead to more accurate classification. In the classifier module, we used RBFNN. The RBFNN seem to be powerful alternatives to FCL, which overcome some of the basic weakness related to FCL while retaining all strengths of FCL. In the proposed method, the learning algorithm introduced in the previous section is used to train the RBFNN.

One of the critical challenges in the optimization task is defining a suitable fitness function. Recognition accuracy (RA) which is calculated through confusion matrix has been utilized as the fitness function of the BA in our developed method. The confusion matrix consists of four entries, namely: True positive (TP), False positive (FP), True negative (TN) and False negative (FN). In this matrix, TP refers to the cases' number which has been classified accurately as HGG, FP refers to the cases' number which has been classified incorrectly when they are LGG, TN refers to the cases' number which has been classified correctly when they are LGG, and FN refers to the cases' number classified incorrectly when they are HGG. RA refers to a test's capability in differentiating between LGG and HGG cases in an accurate way. For estimating a test's RA, the proportion of TP and TN in all of the cases which have been evaluated need to be calculated. Mathematically, this can be formulated as below:

$$\text{Fitness function:} \quad RA=\frac{TP+TN}{TP+FN+FP+TN}\times 100 \tag{4}$$

An ideal medical test should show a positive result for all cases who have the target condition (in this study, HGG condition). Its capability to do this is stated by its sensitivity. Sensitivity is the proportion of all patients with the disease (TP + FN) who indeed have a positive test result (TP). However, a high sensitivity alone does not make a test a perfect medical test. The test also needs to be negative for all cases without the disease. This ability is described by the specificity of the test. The specificity is the proportion of all patients without the disease and a negative test result (TN) of all those without the disease (TN + FP). The BA should find optimal values of RBFNN parameters with the aim of increasing the RA. At the same time, the proposed method must have high sensitivity and specificity.

4. Results

In this section, the performance of the proposed method is evaluated. For this purpose, several experiments were performed and the obtained results are presented in the following subsections. The standard MRI benchmark datasets, Brain Tumor Segmentation (BraTS) 2015, is used to evaluate the performance of the developed brain tumor classification method. The BraTS 2015 Challenge dataset includes 384 cases such that 220 HGG and 54 LGG are in training and 110 of both (HGG, LGG) are in testing. The MRI cases have $(240 \times 240 \times 155 \times 4)$ dimension, where 155 shows the number of slices for each case and four shows the number of sequences. Therefore, we have 33480 LGG and 136400 HGG slices in the training phase. In the testing phase, we used 8500 LGG slices and 41000 HGG slices. All the obtained results are the average of 50 independent runs.

The obtained results using different architectures are shown by Figs. 3 and 4. In this figures, the performance of proposed method is shown in term of recognition accuracy (RA), sensitivity or true positive rate (TPR), specificity or true negative rate (TNR), precision or positive predictive value (PPV), and negative predictive value (NPV). For the first classifier (Fig 2), which uses the 4096 extracted deep features as the input of FCL, the value of RA is 98.8%. This values increase to 99.6% if replace the FCL by proposed RBFNN.

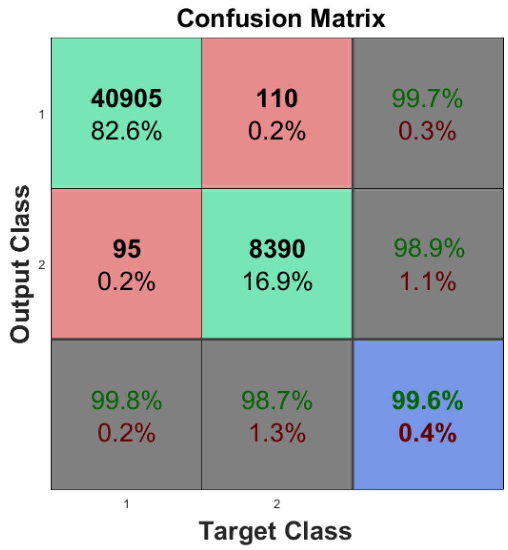

Fig 3. Performance of ConvNet - FCL

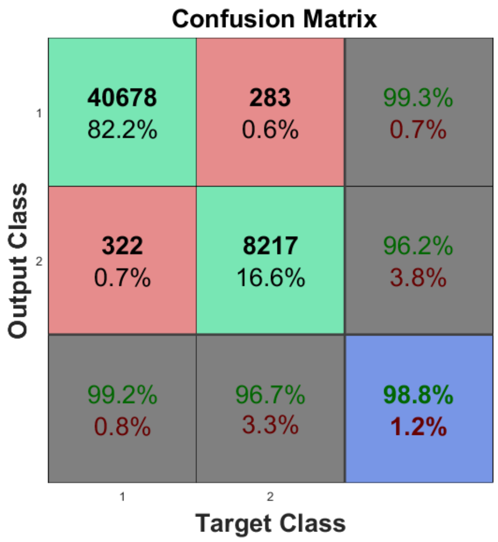

Fig 4. Performance of the proposed method

5. Conclusion

In this study, a new hybrid method proposed for brain tumor detection and classification, and applied on BraTS 2015 dataset. In order to evaluate the performance of the developed method, several experiment was performed. In the first experiment, ConvNet followed by FLC are implemented for classification, and 98.8% accuracy achieved. In the next experiment, we used optimized RBFNN as the classifier The obtained results showed that using efficient features and high performance classifier leads to highest accuracy, 99.6%. The obtained results showed that the developed method, ConvNet-BA-RBFNN, is effective and can be used in computer-aided systems to detect brain tumor.

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