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A Fully-Automated Detection of Brain Tumor in MRI Images using Input Cascaded CNN

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Abstract

In this paper, we propose a fully-automated tumor detection method based on Input cascaded Convolutional Neural Network (CNN). For this, each input image is convolved using two different kernels of 3 x 3 and 7 x 7 to produce a separate feature map. The average of these feature maps is cascaded with the input image and processed into an upcoming hierarchy of 3 convolutional and pooling layers. Finally, tumor and non tumor class labels are predicted using softmax and compared with ground truth for performing an evaluation. This proposed tumor detection system has tested with BRATS-2018 dataset and achieved 95% accuracy, 98% precision, 97% recall, 97% F1-score and 97% specificity. These simulation results show that this proposed method achieves 4% higher accuracy than the state-of-art detection methods.

1 Introduction

The Brain is the most complex organ in the human body. The brain tumor is an abnormal growth of cells forming inside or around the brain. Each patient image from low and high grade Gliomas tumor type having four image

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sequences: T1-weighted with Fluid Attenuated Inversion Recovery (FLAIR); T1-weighted (T1); T1-weighted with contrast-enhanced image (T1c) and T2-weighted (T2) image [6] [2]. Some of the existing semi-automatic techniques like Extreme Learning Machine, Discrete Wavelet Transformation (DWT), Fuzzy-C-Means, Discrete cosine transformation (DCT), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM) are used for the tumor identification process. These techniques are less accurate, time-consuming and radiologists dependent process.

Marco et al. [4] have used SVM for brain image classification. Anitha et al. [7] proposed KNN based method brain tumor detection in MRI images. Nowadays, Ensemble Classifier (EC) [6] and Extreme Learning Machine (ELM) [2] are used for the tumor detection process. These ELM and EC methods competitively provide lesser accuracy than the existing methods. To overcome these limitations, automated methods are used for tumor classification process [3]. Gladis et al. [5] and Kumar et al. [1] have used FFANN (Feed-Forward Artificial Neural Network) for identifying tumor images. FFANN and existing CNN based methods contain a single way of feature map, which has limited accuracy in poor illumination images. To avoid these drawbacks, an automated tumor detection method based on input cascaded Convolutional Neural Network (CNN) is proposed for handling multiple cascaded features to get more accuracy.

2 Proposed Methodology

This proposed network is based on Deep Neural Network (DNN) learning architecture for detecting brain tumors in MRI images. The block diagram of this proposed method is shown in Figure 1. The ultimate goal of this network is to learn tumoral features automatically from input MRI data. First, an input image is trained with dual streams using two different kernels namely, 3 x 3 and 7 x 7. Here, each input image is separately convolved using two different kernels to produce twin feature maps in Layer 1 and Layer 2. F1 and F2 are the feature maps from these convolutions produced by multiplying input X with weight W and added with bios B are illustrated in the following two equations.

$$F1 = f(\sum_{i=1}^{n}[X_i * W_i] + B)$$

$$F2 = f(\sum_{j=1}^{n}[X_j * W_j] + B),$$

where $i = 1, 2, 3, , n$ and $j = 1, 2, 3, , n$ are the intensity of an input image and f is the non-linear activation function for transforming the convolution

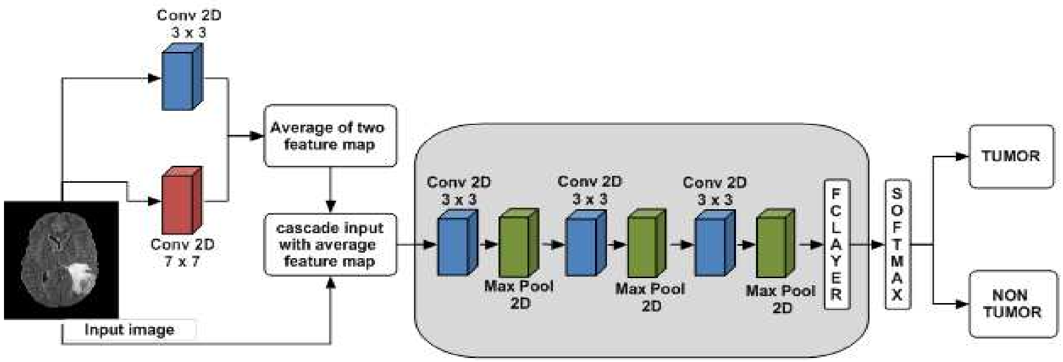

Figure 1: Input Cascaded Architecture

Rectifier Linear Unit (ReLU) is one of the most efficient activation functions with the ability to train faster in Convolutional Neural Network architecture is given by:

$$f(i, j) = max(0, (X))$$

The average of two feature maps F1 and F2 is calculated using the following equation:

$$Y_{avg} = mean(F1, F2)$$

The average output Yavg is cascaded with the input image to produce Yout is given as:

$$Y_{out} = Y_{avg} + X$$

The outcome Yout is processed with the series of convolutional layers intervene with max-pooling and ReLU. Layers 3 and 4 are the convolutional and pooling layers having the input dimension 64 x 240 x 240 and 128 x 240 x 240. After completion of convolution, the output feature maps are processed into the upcoming two convolution layers to intervene with max-pooling. Moreover, this final extracted feature having dimension 128 x 30 x 30 is converted into the dimension 1 x 115200 in Fully Connected (FC) layer. An FC layer is to take input from the previous layer and fed into softmax classification for predicting the tumor present in a particular slice or not. These classified labels have compared with ground truth for calculating performance using benchmark metrics namely: Accuracy, Precision, Recall, F1-score, and specificity.

3 Experimental Results and Discussion

The proposed network performance is tested with the imaging data from BRATS-2018 dataset. All images from this dataset are trained by the proposed architecture for extracting tumoral features automatically from input data. The extracted features are fed into softmax classification to predict whether the particular image shows a tumor or not. These classified labels compare with ground truth for calculating performance. The results of tumor detection using BRATS-2018 dataset are depicted in Table 1.

Table 1: Performance of Input Cascaded Architecture using BRATS-2018

BRATS 2018 Dataset						
Gliomas Type	**Gliomas Name**	**Accuracy**	**Precision**	**Recall**	**F1-score**	**Specificity**
HGG	FLAIR	0.92	0.97	0.96	0.96	0.90
	T1	0.92	0.99	0.99	0.99	0.98
	T1C	0.92	0.98	0.98	0.98	0.98
	T2	0.98	0.99	0.99	1.00	0.99
LGG	FLAIR	0.97	0.98	0.98	0.98	1.00
	T1	0.96	0.98	0.97	0.97	0.95
	T1C	0.95	0.97	0.96	0.96	1.00
	T2	0.96	0.97	0.97	0.97	0.98
Avg (HGG,LGG)		0.95	0.98	0.97	0.97	0.97

The tumor detection performance of input cascaded CNN architecture is evaluated by comparing state-of-the-art detection methods like Feed Forward Artificial Neural Network (FFANN) [1], Ensemble Classifier (EC) [6], Support Vector Machine (SVM) [4] and Extreme Learning Machine (ELM) [2]. Finally, the proposed detection method has 4% higher accuracy than those state-of-the-art detection methods.

4 Conclusion

An accurate and automated brain tumor detection algorithm from MRI is essential for medical analysis, clinical assessments, interpretation and treatment. In this paper we proposed a fully-automated tumor detection method based on Input cascaded Convolutional Neural Network (CNN). This network has convolved using two different kernels of 3 x 3 and 7 x 7 to produce a separate feature map. An average of these feature maps were cascaded with the input image and processed into the upcoming hierarchy of three convolutional, three pooling and softmax layers. These predicted class labels were compared with the ground truth for calculating performance using benchmark metrics namely, Accuracy, Precision, Recall, F1-score, Sensitivity and Specificity. The whole architecture was tested using BRATS-2018 dataset and achieved 4 % higher accuracy than the state-of-the-art detection methods.

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