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An Efficient Cascaded CNN Architecture for Brain Tumor Detection in MRI Images

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Abstract*: This research work proposed an automated tumor detection system based on cascaded Convolutional Neural Network (CNN) architecture. In this, each input has convolved separately with three kernels (3 x 3, 5 x 5 and 7 x 7) and their three output feature maps are cascaded to be processed into the hierarchy of two convolution and pooling layers followed by fully connected (FC) layer. In FC layer, the softmax classification technique has performed to find the pixel-wise classification and to detect whether the particular image consisting of tumor or not. This proposed work is tested with BRATS-2018 dataset of both Low-Grade Gliomas (LGG) and High-Grade Gliomas (HGG) brain images. Further, this work has evaluated using different metrics namely accuracy, precision, recall, F1-score, specificity and sensitivity. Thus, this method outperforms well with 96% accuracy, 98% precision, 98% F1-score and 99% sensitivity, demonstrating that the tumor identification has achieved 5% better accuracy than the existing tumor detection methods.

Keywords* : Brain tumor detection, deep learning, Cascaded Convolutional Neural Network, Magnetic Resonance Imaging (MRI).

I. INTRODUCTION

Automated detection of brain tumor in Magnetic Resonance Image (MRI) becomes challenging in medical research because size, shape and intensity variations among tumors are different from normal brain images [11]. Glioma is the most common and aggressive tumor type having a high mortality rate. There are two basic types of gliomas, namely HGG – High Grade Gliomas, LGG – Low Grade Gliomas [3]. Each Gliomas image consists of four different multi-modal contrast sequences namely, FLAIR - Fluid Attenuated Inversion Recovery, T1C - T1 Weighted with contrast-enhanced image, T1-Weighted image and T2-Weighted contrast image [2].

In this work, an automated tumor detection system based on cascaded Convolutional Neural Network (CNN) architecture is proposed for extracting tumoral features and identifying tumor images automatically from brain MRI images. This architecture is one of the deep learning models having the capability to learn image features automatically and to detect tumor images from brain images.

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In this, each input has convolved separately with three kernels (3 x 3, 5 x 5 and 7 x 7) and their three output feature maps are cascaded to be processed into the hierarchy of two convolution and pooling layers followed by FC layer. This outcome of feature map is converted into the single dimension in FC layer for predicting pixel-wise classification of labels.

In FC layer, the softmax classification technique has applied to find the pixel-wise classification and maps them using the class label for finding whether tumor cells present in a particular image or not. Pixel-wise classification of these labels to be compared with ground truth for finding performance using well-known metrics, namely Accuracy, Precision, Recall, Sensitivity, specificity and F1-score. This proposed work is tested with BRATS-2018 dataset. The performance of this proposed method is having 96% accuracy, 98% precision, 98% F1-score and 99% sensitivity, demonstrating that the tumor identification has achieved 5% better accuracy than the existing tumor detection methods. This article is structured into four main sections: The related kinds of literatures are discussed in Section 2; an experimental method of proposed cascaded CNN method has detailed in Section 3; results and comparison are depicted in Section 4; finally, these results have concluded in Section 5.

II. RELATED WORKS

Brain tumor detection from Magnetic Resonance Image (MRI) becomes challenging in medical research. In recent years, the diagnosis of tumor regions from brain images is made by the radiologists. It produces inaccurate results of having high rater variability. Then, semi-automatic detection methods like Extreme Learning Machine, K-Nearest Neighbor (KNN), Fuzzy-C-Means, Ensemble Classifier (EC) and Support Vector Machine (SVM) have used for the detection process. These methods are used for reducing manual interactions, but it has less accuracy and time-consuming. For this, a system based detection system is necessary to avoid these drawbacks. Here, an automated tumor detection system based on cascaded Convolutional Neural Network (CNN) architecture for extracting tumoral features and identifying tumor images automatically from brain MRI images [9]. Parveen et al [16] have proposed FCM algorithm for detecting brain images. This method needs developer interaction for defining cluster numbers. After the Gray Level Co-occurrence Matrix (GLCM) based features have been extracted from brain images [5] [7]. Sometimes DWT (Discrete Wavelet Transformation) based methodologies are also used for feature extraction [8].

The significant details of brain images are loss while using these feature extraction techniques. Marco et al and Sandhya et al have proposed SVM for tumor identification [12] [4]. Anitha et al have used KNN based tumor detection method. KNN and SVM are the semi-automatic methods and it requires developer's interaction from for parameter initialization. Then, Extreme Learning Machine and Ensemble Classifier (EC) based models have used for classifying tumor images [10] [13]. But these semi-automatic methods have less accuracy than the current automated tumor detection method. For these reasons, deep learning-based automated detection methods are used [1].

Feed-Forward Back propagation Network (FFBN) and Feed-Forward Artificial Neural Network (FFANN) has implemented for detecting tumor images [6] [14]. These methods consisting of performance on real patient brain images having diverse intensity variations. To avoid this, an automated tumor detection system based on cascaded Convolutional Neural Network (CNN) architecture is proposed for extracting tumoral features and identifying tumor images automatically from brain MRI images. This method achieved 5% better accuracy than the existing tumor detection methods.

III. PROPOSED METHODALOGY

The proposed brain tumor detection method is entirely automated. This process is based on CNN more precisely on 2-Dimensional Convolutional Neural Network and it aims to identify whether the brain images having a tumor or not. This detection method follows four main processes: feature extraction using cascaded CNN architecture, classification of the final extracted feature is done by softmax, the loss function is calculated and their performance is evaluated. The workflow of this proposed network is presented in Fig. 1.

A. Feature Extraction in Cascaded CNN Architecture

The cascaded CNN architecture is one of the deep learning models having the capability to learn image features automatically and to detect tumor images from brain images. The main building block of this network is the convolutional layer. Several layers are stacked to form the hierarchy of features and each layer has to extract features from the proceeding layer into upcoming layers in the hierarchy. First, three convolutional layers have designed using three different filters namely 3 x 3, 5 x 5 and 7 x 7. These three convolutional layers take input with the shape of 240 x 240 and convolve it separately with three kernels to produce three different outputs or feature maps having the same dimension. Here, the Rectified Linear Unit (ReLU) activation function applied for the non-linear transformation of input image into output image [17]. Three feature maps $F1_{3x3}$ and $F2_{5x5}$ and $F3_{7x7}$ are produced by convolving input (X) with weight (W) and concatenate with bios (B) are shown in (1) - (3).

$$F1_{3x3} = f\left(\sum_{i=1}^{n} [X_i * W_i] + B\right) \quad (1)$$

$$F2_{5x5} = f\left(\sum_{j=1}^{n} [X_j * W_j] + B\right) \quad (2)$$

$$F3_{7x7} = f\left(\sum_{k=1}^{n} [X_k * W_k] + B\right) \quad (3)$$

Where, i,j and k are the intensity values of each pixel present in the image. Further, three output feature maps are cascaded to form cascaded output Y is given in (4).

$$Y = F1_{3x3} + F2_{5x5} + F3_{7x7} \quad (4)$$

This cascaded feature map (Y) to be processed into convolution and max-pooling layer.

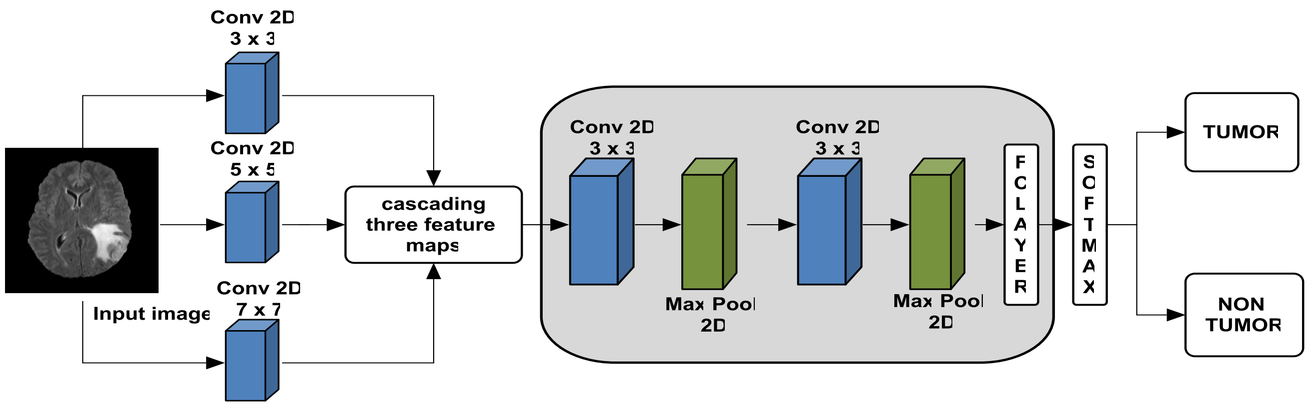

Fig. 1. Proposed Cascaded CNN Architecture.

Table- I: Layers Model of the proposed Architecture

Dual phase cascaded CNN								
Layers	**Type**	**Filter Size**	**Stride value**	**Filters**	**Normalization**	**Activation**	**FC units**	**Input**
Layer 1	Conv	3 x 3	1 x 1	64	B-N	ReLU		1 x 240 x 240
Layer 2	Conv	5 x 5	1 x 1	64	B-N	ReLU		1 x 240 x240
Layer 3	Conv	7 x 7	1 x 1	64	B-N	ReLU		1 x 240 x240
cascading output feature maps from first three convolution layers (Layer1, Layer 2, Layer 3)								
Layer 3	Conv	3 x 3	1 x 1	128	B-N	ReLU		64 x 240 x 240
Layer 4	Max-pool	3 x 3	2 x 2	-	B-N	-		128 x 240 x 240
Layer 5	Conv	3 x 3	1 x 1	128	B-N	ReLU		128 x 120 x 120
Layer 6	Max-pool	3 x 3	2 x 2	-	B-N	-		128 x 120 x 120
Layer 9	-	-	-	-	-	-	256	460800 (128x60x60)
Layer 10	-	-	-	-	-	-	256	256
Layer 11	-	-	-	-	-	-	2	256

This max-pooling layer has the capability to combine spatially nearby features for down sampling an input image to produce an output having a dimension of 120 x 120. After, this output is processed in to convolutional and pooling layer to form final output feature map with the dimension 60 x 60. Further, this outcome is converted into single dimension in FC layer for predicting pixel-wise classification of labels.

B. Softmax Classification

The FC layer output is processed using softmax for predicting labels at each pixel level and processed them individually throughout the brain image. For training, all brain images have split into two classes, namely normal images and tumor images. This softmax takes zero (0) value for the 1^{st} class and one (1) value for the 2^{nd} class. Softmax classification method takes each pixel value individually and maps them using the class label for finding whether tumor cells present in a particular image or not. The configuration details of each layer used in this architecture are mentioned in Table 1.

C. Loss Function

Loss function is widely used for finding errors between original labels (p(x)) and predicted labels (q(x)) are given in (5) and (6).

$$H(p,q) = -\sum_{j=1}^{n} p(x_j) \log\left(q(x_j)\right) \qquad (5)$$

D. Training and Evaluation

This internal fused CNN architecture is trained using BRATS-2018 dataset for extracting tumoral features. These final extracted features are labeled using softmax classification. Pixel-wise classification of these labels to be compared with ground truth for finding performance using well-known metrics, namely Accuracy, Precision, Recall, Sensitivity, specificity and F1-score are illustrated in (6) - (11).

$$Accuracy = (TP + TN) / (TP+FP+FN+TN) \qquad (6)$$
$$Precision = (TP) / (TP+FP) \qquad (7)$$
$$Recall = (TP) / (TP+FN) \qquad (8)$$
$$Sensitivity = (TP) / (TP+FN) \qquad (9)$$
$$Specificity = (TN) / (TN+FP) \qquad (10)$$
$$F1\text{-}score = (2TP) / (2TP+FP+FN) \qquad (11)$$

where, TP - True Positive and TN - True Negative are the total numbers of accurately identified positive and negative pixels. FP - False Positive and FN - False Negative are the falsely identified positive and negative pixels.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Database and workstation

This experiment has tested by BRATS-2018 dataset comprises of 65 images of LGG and 210 patient images of HGG. Each image from this dataset has four contrast multi-model MRI sequences, namely FLAIR, T1, T1c, and T2. These contrast sequences have skull-stripped and annotated by the radiologists. This dataset is acquired from different centers, namely Heidelberg University, Wang lab, Debrecen University, Massachusetts General Hospital, Bern University, Computational Biomarker Imaging Group (CBIG) and Center for Neuroimaging in Psychiatry (CNIP).

B. Effectiveness of Proposed Methodology

The efficiency of this proposed method is evaluated using BRATS-2018 dataset. Automated extraction of features in brain tumor images has done by the proposed cascaded CNN architecture. This outcome of the feature map is converted into single dimension in FC layer for predicting pixel-wise classification of labels. In FC layer, the softmax classification technique has performed to find the pixel-wise classification and processed them individually throughout the brain image.

Softmax classification method takes each pixel value individually and maps them using class label for finding whether tumor cells present in a particular image or not. This final outcome of classified labels to be compared with ground truth for finding performance using well-known metrics, namely Accuracy, Precision, Recall, Sensitivity, specificity and F1-score.

The tumor detection results of four multi-modal MRI sequences of both LGG and HGG images are detailed in Table 2 and some examples of detected tumor images are represented in Fig. 2.

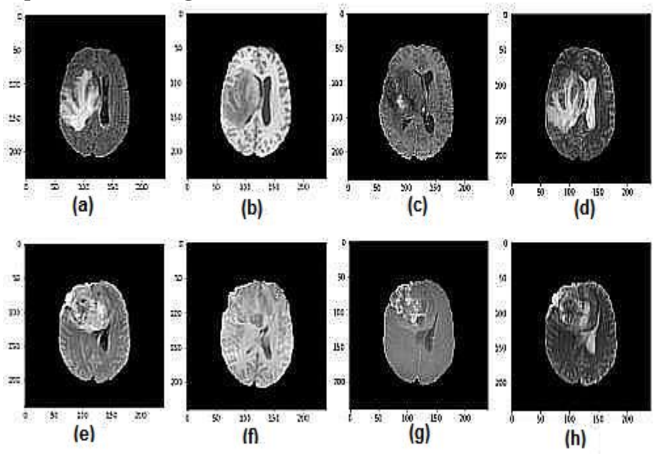

Fig. 2. Tumor detection results of four multi-modal MRI sequences using BRATS-2018 dataset a. HGG-FLAIR, b. HGG-T1, c. HGG-T1C, d. HGG-T2, e. LGG-FLAIR, f. LGG_T1, g. LGG-T1C, h. LGG-T2

Table- II: Performance of Cascaded CNN architecture using BRATS-2018.

BRATS-2018 Dataset							
Gliomas Type	**Sequence Name**	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**Sensitivity**	**Specificity**
HGG	Flair	0.95	0.99	0.99	0.99	1.00	1.00
	T1	0.96	0.97	0.96	0.96	1.00	0.94
	T1C	0.94	0.97	0.96	0.96	0.99	0.93
	T2	0.98	1.00	1.00	1.00	1.00	1.00
LGG	Flair	0.97	1.00	1.00	1.00	1.00	1.00
	T1	0.96	0.99	0.99	0.99	0.99	0.98
	T1C	0.96	0.99	0.99	0.99	1.00	0.98
	T2	0.94	0.99	0.99	0.99	1.00	0.97
Average (HGG, LGG)		**0.96**	**0.98**	**0.99**	**0.98**	**0.99**	**0.97**

Table- III: Comparing rusults of State-of-art detection methods with proposed methods.

Classification Technique	Accuracy (%)	Precision (%)	F1-Score (%)	Sensitivity (%)
FFANN	84.33	89.41	90.66	91.94
Extreme Learning Machine (ELM)	86.00	90.20	91.63	93.12
Support Vector Machine (SVM)	89.67	92.99	93.90	94.83
Ensemble Classifier (EC)	91.17	94.17	94.81	95.47
Proposed Method	**96.00**	**98.00**	**98.00**	**99.00**

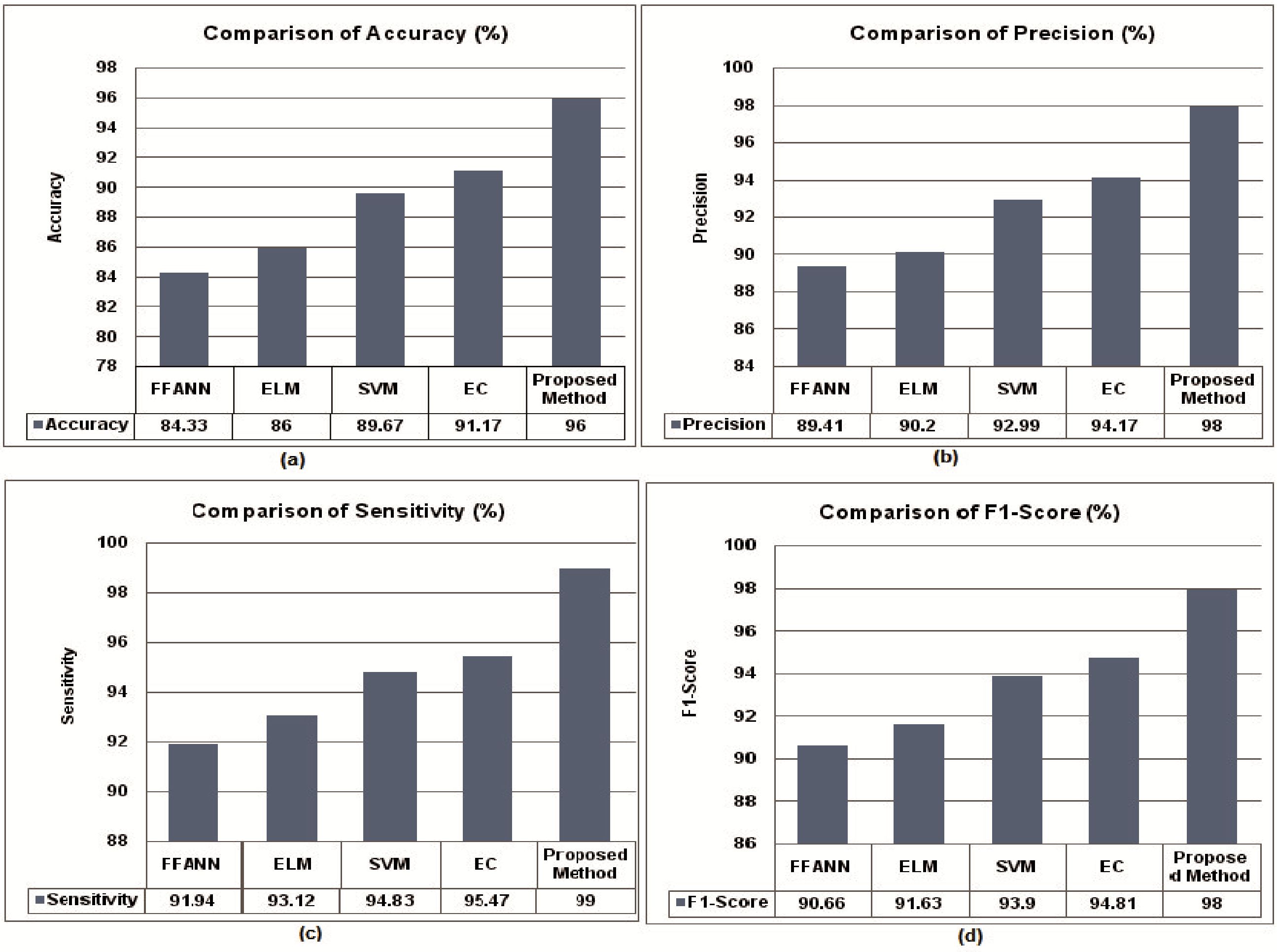

Fig. 3. Comparing results of various existing tumor detection methods with proposed results. a. Comparison using accuracy, b. Comparison using precision, c. Comparison using F1-score and d. Comparison using Sensitivity.

C. Performance Comparison of proposed Network.

The performance of the proposed detection system is evaluated in comparison with existing state-of-art detection methods like Extreme Learning Machine (ELM), Feed Forward Artificial Neural Network (FFANN) [15], Support Vector Machine (SVM) and Ensemble Classifier (EC). The performance of the proposed detection system is compared using statistical measures such as accuracy, precision, sensitivity and F1-score in comparison with various classification systems is depicted in Table 3 and shown in Fig. 3. Extreme Learning Machine and Support Vector Machine are the semi-automatic method for tumor detection; it requires user interactions in each step for some parameter initialization. Ensemble classifier and FFANN are the types of automated methods for tumor detection [16]. These methods are yielding very low performance on high-intensity deflections in real images. The performance of this proposed method is having 96% accuracy, 98% precision, 98% F1-score and 99% sensitivity, demonstrating that the tumor identification has achieved 5% better accuracy than the existing tumor detection methods.

V. CONCLUSION

Brain tumor detection from Magnetic Resonance Image (MRI) becomes challenging in medical research. In this research, an automated tumor detection system based on cascaded CNN architecture is proposed for extracting tumoral features and identifying tumor images automatically from brain MRI images. In this, each input has convolved separately with three kernels (3 x 3, 5 x 5 and 7 x 7) and their three output feature maps are cascaded to be processed into the hierarchy of two convolution and pooling layers followed by FC layer. In FC layer, the softmax classification technique has applied to find the pixel-wise classification and maps them with ground truth class labels for finding whether the tumor cells present in a particular image or not. This proposed work is tested with BRATS-2018 dataset. The performance of this proposed method is having 96% accuracy, 98% precision, 98% F1-score and 99% sensitivity, demonstrating that the tumor identification has achieved 5% better accuracy than the existing tumor detection methods.

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