Cascaded CNN with Haar Wavelet Feature based Brain Tumor Detection Technique

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ABSTRACT

Abnormal tumor image identification from brain Magnetic Resonance Images (MRI) is essential for medical diagnostics. In this research, Cascaded Convolutional Neural Network (CCNN) with Haar wavelet features based brain tumor detection technique has been proposed for automatic identification of tumor images. The significant LL sub-band features are first extracted in all image slices. These slices are further processed using CCNN architecture for brain tumor detection. In this architecture, each image slice is convolved with three different 7 x 7, 3 x 3 and 5 x 5 kernels to produce three separate feature maps. These feature maps are cascaded to be processed into the hierarchy of convolutional, pooling and softmax layers to predict whether an image is having a tumor or not. This proposed algorithm is implemented using the BRATS-2018 training dataset. It achieves 96% of Accuracy, 97 % of F1-score, 97 % of Precision, 97 % of Specificity and 96 % of Sensitivity values.

Keywords:
Tumor detection, Cascaded Convolutional Neural Network (CCNN), Deep Learning, Feature Extraction, Magnetic Resonance Imaging (MRI), Discrete Wavelet Transformation (DWT).

I. INTRODUCTION

The brain is the most complex organ in the human’s body that works with millions of cells [15]. An anomalous surge or intracranial solid neoplasm of cells presents in the brain nucleus is called brain tumor [4]. MRI is an efficient medical imaging tool used to provide high quality images and also to visualize the internal brain structure. Brain tumor is categorized into two types: benign or low-grade and malignant or high-grade. Recently, neuro radiologists predicted the most affected tumor type names as Gliomas. The Gliomas tumor is divided into benign or LGG (Low-Grade Gliomas) and malignant or HGG (High-Grade Gliomas) respectively [19]. Image from these Gliomas

Grades has four MRI sequences, i.e. T1c (T1 Weighted with contrast-enhanced), T1 (T1-Weightedimage), T2 (T2-Weighted contrast image) and FLAIR (T2 weighted Fluid Attenuated Inversion Recovery) [5].

Tumor and normal image identification from brain Magnetic Resonance Images (MRI) is essential for medical diagnostics. Brain tumor detection is performed using three kinds of techniques: manual; machine learning and deep learning methods. Traditionally, manual methods are used to detect brain tumor in MRI images. In this method, the detection task is performed by a neuroradiologist or doctor. The accuracy and rater variability of this task depends on the radiologist's knowledge. Machine learning methods are also having less accuracy, and time-consuming process, which contains hand-crafted features that needs programmer interaction to initialize the parameters. Most of the researchers have presented different semi-automated approaches like K-Means, K-Nearest Neighbor (KNN), Support Vector Machine and Fuzzy-C-Means methods for tumor detection in MRI images. These methods need interaction from the human observer for initializing some parameters. To avoid these drawbacks, deep learning methods have been used to extract and detect the image features automatically from input images [9].

Now a day, Feed Forward Artificial Neural Network (FFANN) becomes very popular for this brain tumor identification task. This network extracts image patches, which need larger computation than other methods [15]. For this purpose, CCNN with Haar wavelet features based brain tumor detection technique has been proposed for automatic identification of tumor images. Here, the Haar DWT feature extraction technique is first used to extract significant features from brain MRI images [6]. These features are classified by CCNN [17] to predict whether an image is having tumor or not. This cascaded method is performing better than the recent neural network and CNN based methods. Rest of the research paper is organized as follows: related tumor detection of brain tumor images are discussed in Section II,

II. RELATED WORKS

Efficient tumor detection from MRI is essential for clinical assessments and also treatment planning. Traditionally, manual methods are used in the brain tumor detection process [12]. In this method, the detection task is performed by a neuroradiologist or doctor. To avoid these limitations, machine learning methods have been used to address the solution of tumor detection [18]. Recently, most of the researchers have used different semi-automated approaches like K-Means, K-Nearest Neighbor (KNN), Support Vector Machine and Fuzzy-C-Means methods for tumor detection in MRI images [13]. Parveen et al proposed a novel FCM based method, which needs user interaction for selecting cluster numbers [3]. Marco et al implemented SVM and fast fourier transformation based tumor detection methods [10].

Sandhya et al used DWT and SVM model to predict whether tumor present or not in MRI brain images. Nilesh et al implemented Berkeley Wavelet Transformation and SVM based image analysis to detect tumors [14]. These methods need interaction from the human observer for initializing some parameters. In recent years, hierarchical methods, Conditional Random Field (CRF), Random Forest and

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Markov Random Field (MRF) are used for detecting complete, core and enhanced tumor. The CRF and MRF methods are having very poor erformance on volatile intensity variations in real MRI images.

To overwhelm these drawbacks, ensemble classifiers [16] and Extreme Learning Machine [ELM] [21] are effectively used for brain tumor detection. These methods are having less accuracy and hugely time-consuming. For this, automated detection method is required because it reduces the computational load of the human observer [11]. Hema Rajini has been implemented Convolutional Neural Network with Particle Swarm Optimization based brain tumor identification method [20]. These methods are using image patches for tumor detection, which has data reconstruction problem. To avoid these drawbacks, an automated wavelet feature based CCNN tumor identification method is proposed to detect abnormal tumor images. This proposed method achieves 96% of Accuracy, 97 % of F1-score, 97 % of Precision, 97 % of Specificity and 96 % of Sensitivity values

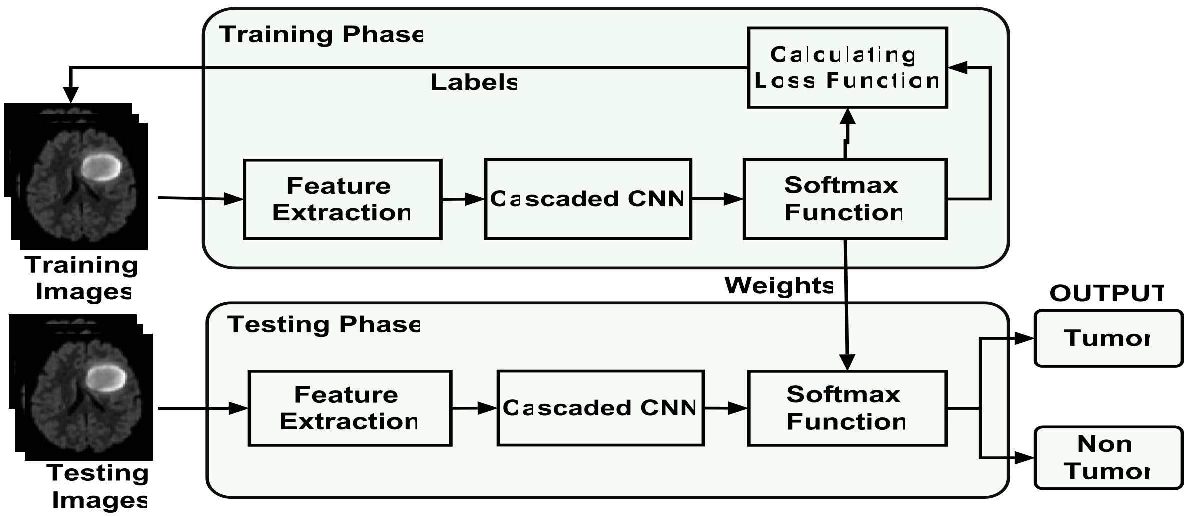

Fig. 1: Proposed architecture.

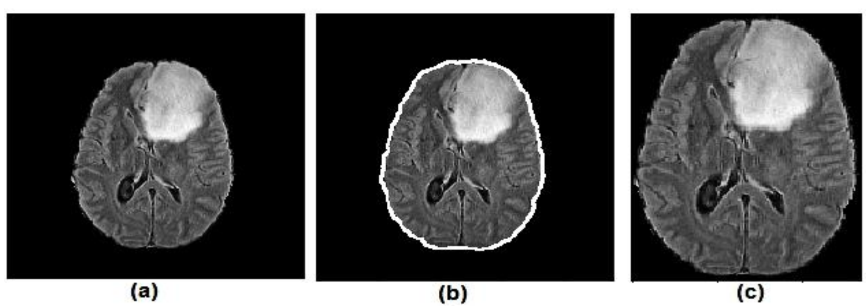

Fig. 2: Representation of brain extraction: (a) brain image; (b) contour curve; (c) Brain extraction using bounding rectangle.

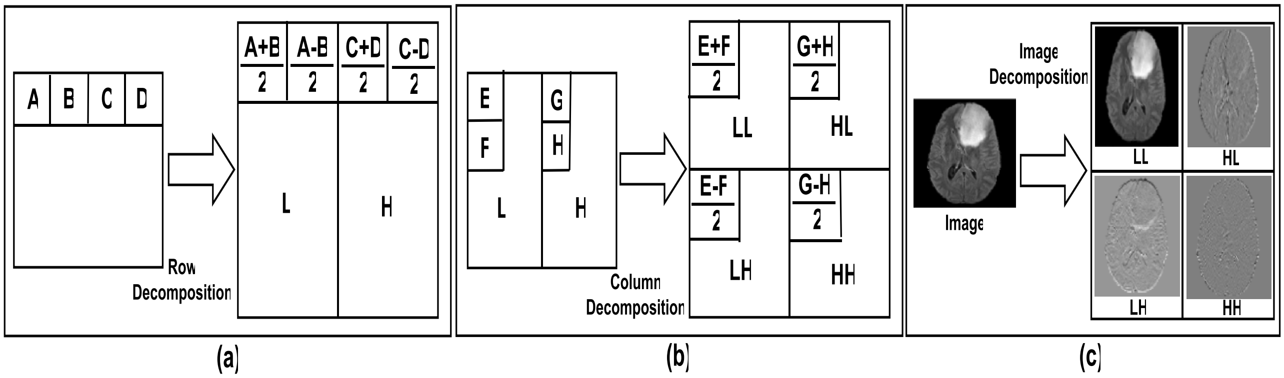

Fig. 3: Decomposition of image using Haar DWT: (a) row decomposition; (b) column decomposition; (c) 1st level 2D decomposition.

III. PROPOSED METHODOLOGY

In this proposed method, each image is processed in three steps: The cardinal and detailed tumoral features are extracted using Haar DWT; Feature classification is done by using CCNN and finally Performance is evaluated. The detailed workflow architecture of proposed method is illustrated in Fig. 1.

3.1. Brain Extraction

These image slices consist of two regions namely, background region having zero pixel intensity and foreground brain region having significant non-zero pixel intensity. Extracting cardinal intensity values of brain MRI slices plays an essential role to detect tumor regions effectively. For this, the contour curve is drawn over the boundary of the foreground brain region. Then, this region has extracted using a bounding rectangle. After extraction, all image slices have resized into 180 x 180. The Pictorial representation of brain region extraction is illustrated in Fig.2.

A. Haar DWT based image feature extraction

The transition of an image to a set of features is defined as feature extraction. Here, the Haar DWT feature extraction technique is used to extract the wavelet coefficient by localizing frequency information of signal function [8]. First, low and high frequencies are extracted by applying low and high pass filters. These frequencies are column wise decomposed by low and high pass filters to yields four frequencies like LL, HL, LH and HH. In this, the LL

subband is highly considered as an approximation coefficient and the remaining three LH, HL and HH subbands are the detailed coefficients of an image [7]. detailed representation of Haar DWT is visualized in Fig.3.

B. CCNN based tumor detection

Totally 32550 of HGG and 10075 of LGG image slices in each MRI sequence (FLAIR, T1, T1C and T2) are present in the dataset. These images are split for training (80%) and testing (20%) process. The significant LL sub band is extracted in all images slices. Extracted LL subband of image slices are processed using CCNN architecture for brain tumor detection. For training, each image x is convolved with weights w in three different 3 x 3, 5 x 5 and 7 x 7 kernel to produce an output feature maps F_{3x3}, F_{5x5} and F_{7x7} is mentioned in Eq. (1) – Eq. (3).

$$F_{3X3} = f\left(\sum_{i=1}^{n}[x_i * w_i] + b\right) \quad \ldots (1)$$

$$F_{5X5} = f\left(\sum_{j=1}^{n}[x_j * w_j] + b\right) \quad \ldots (2)$$

$$F_{7X7} = f\left(\sum_{k=1}^{n}[x_k * w_k] + b\right) \quad \ldots (3)$$

where, i, j and k are the pixel intensity values of the image slice. The ReLU activation function is used for non-linear transformation of all inputs in network layers.

The output feature maps F_{3x3}, F_{5x5} and F_{7x7} are cascaded to yield an output Y is given in Eq. (4).

$$Y = F_{3X3} + F_{5X5} + F_{7X7} \quad \ldots (4)$$

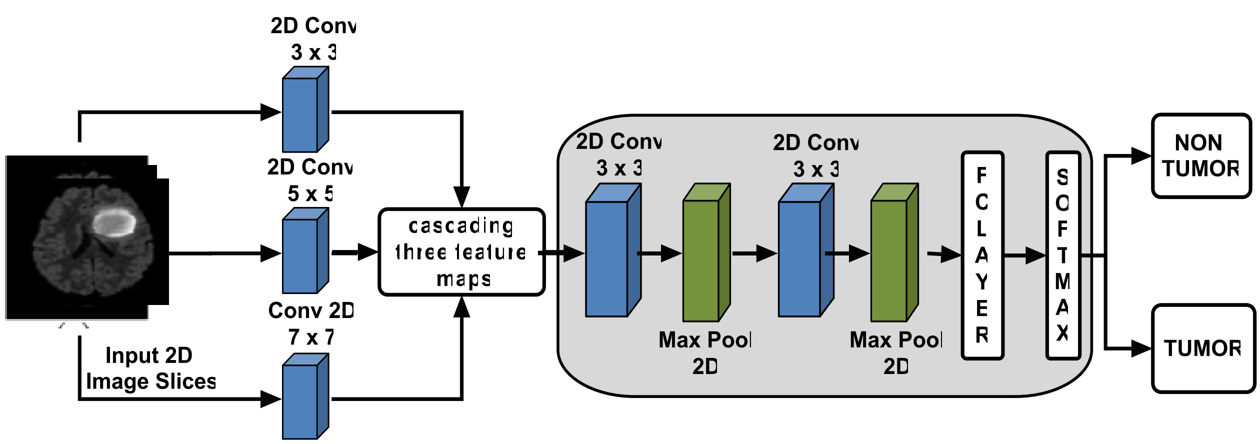

Fig. 4: CCNN architecture.

This cascaded output is processed in the hierarchy of two convolutional layers and pooling layers to extract tumoral features. These features are classified as tumor and non-tumor using softmax classification. Likewise, all training image slices have classified and their learnable parameters are stored in the form of weights. Then testing slices are classified using learned classifier weights to predict whether tumor present or not. The detailed architecture of CCNN is depicted in Fig. 4.

B. Performance Evaluation

The proposed brain tumor detection results are compared with ground truth results from the BRATS-2018 dataset for evaluation.

TABLE 1

Formula's for performance evaluation metrics.

Metrics	Formulas
Accuracy	$Acc = (t_p + t_n)/(t_p + f_p + f_n + t_n)$
F1-score	$F1 - score = (2t_p)/(2t_p + f_p + f_n)$
Precision	$Pre = (t_p)/(t_p + f_p)$
Specificity	$Spe = (t_n)/(t_n + f_p)$
Sensitivity	$Sen = (t_p)/(t_p + f_n)$

The performance of evaluation is calculated using Accuracy, F1-score, Precision, Specificity and Sensitivity values. Formulas for these metrics have mentioned in Table 1.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Database and workstation

The proposed method has tested using BRATS 2018 dataset contains 210 and 65 images of HGG and LGG respectively. Each patient image has four MRI sequences namely FLAIR, T1-weighted, T1C and T2. All MRI sequences have a skull-stripped image and annotated by the neuroradiologists. This dataset images have acquired from various vendors at different centers namely, Heidelberg University, Washington University School of Medicine in St. Louis, University of Debrecen, MD Anderson Cancer Center, University of Bern and the Center of Biomedical Image Computing and Analytics (CBICA).

B. Performance of Brain Tumor Detection

The proposed CCNN is used to detect brain tumor in MRI images. In this architecture, an LL feature of each image slice is processed using three different kernels to produce three separate feature maps. These feature maps have cascaded to be processed into the hierarchy of convolutional and pooling layer followed by softmax classification. Finally, this technique is to predict whether an image is having tumor or not.

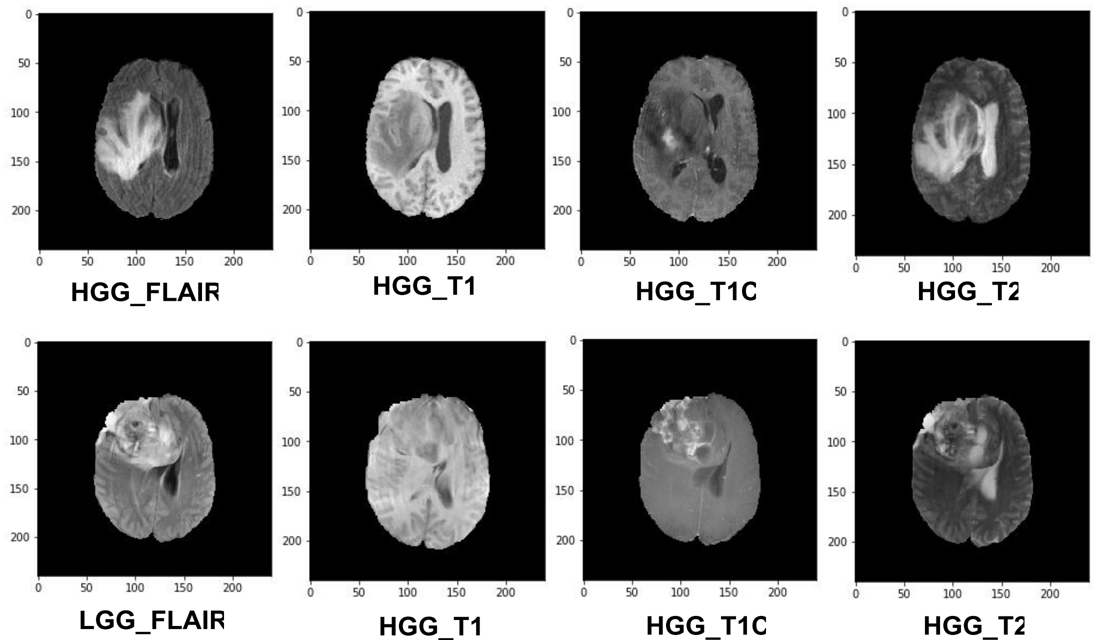

Fig. 5: Examples of tumor detected images using BRATS-2018 dataset having four multi-modal MRI sequences of HGG and LGG images.

TABLE 2
Detection performance of CCNN architecture.

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

Examples of tumor detected images using BRATS-2018 dataset having four multi-modal MRI sequences of HGG and LGG images are presented in Fig. 5. The evaluated performance of four multimodal MRI sequences of both LGG and HGG images are detailed in Table 2. Thus, the proposed method achieves 96% of Accuracy, 97 % of F1-score, 97 % of Precision, 97 % of Specificity and 96 % of Sensitivity values.

B. Performance Comparison of Brain Tumor Detection

Table 3 and Fig. 6 illustrate the performance comparison of CCNN architecture with state-of-art detection methods like CNN with Particle Swarm Optimization (PSO), Feed Forward Artificial Neural Network (FFANN), ELM and Ensemble Classifier (EC).

ELM achieves 86% of Accuracy, 91.63 % of F1- Score, 90.20% of Precision and 93.12 % of Sensitivity. FFANN achieves 84.33 % of Accuracy, 90.66 % of F1- Score, 89.41% of Precision and 91.94 % of Sensitivity In this, ELM and FFANN are the neural network-based methods which are having limited performance on higher intensity deflections in real patient images [1] [2]. The ensemble classifier method is combined with the neural network, extreme learning machine and SVM for detecting tumors effectively. EC achieves 91.17 % of Accuracy, 94.81 % of F1- Score, 94.17% of Precision and 95.47 % of Sensitivity values. But this method needs higher computing power than ELM and FFANN. CNN and PSO method achieves 95.60 % of Accuracy, 93.54 % of F1- Score, 94.07 % of Precision and 93.02 % of Sensitivity Now a day, CNN with PSO based methods are giving promising results in brain tumor detection. These methods handle a single way of feature maps using the same kernel size. But, the proposed method uses three different cascaded feature maps for tumor detection and it achieves higher performance compared to the existing automated detection methods.

TABLE 3

The detection Performance comparison of proposed method with state-of-art methods

Classification Technique	**Accuracy (%)**	**F1-score (%)**	**Precision (%)**	**Sensitivity (%)**
CNN and PSO	95.60	93.54	94.07	93.02
FFANN	84.33	90.66	89.41	91.94
Extreme Learning Machine (ELM)	86.00	91.63	90.20	93.12
Ensemble Classifier (EC)	91.17	94.81	94.17	95.47
Proposed Method	**96.00**	**97.00**	**97.00**	**96.00**

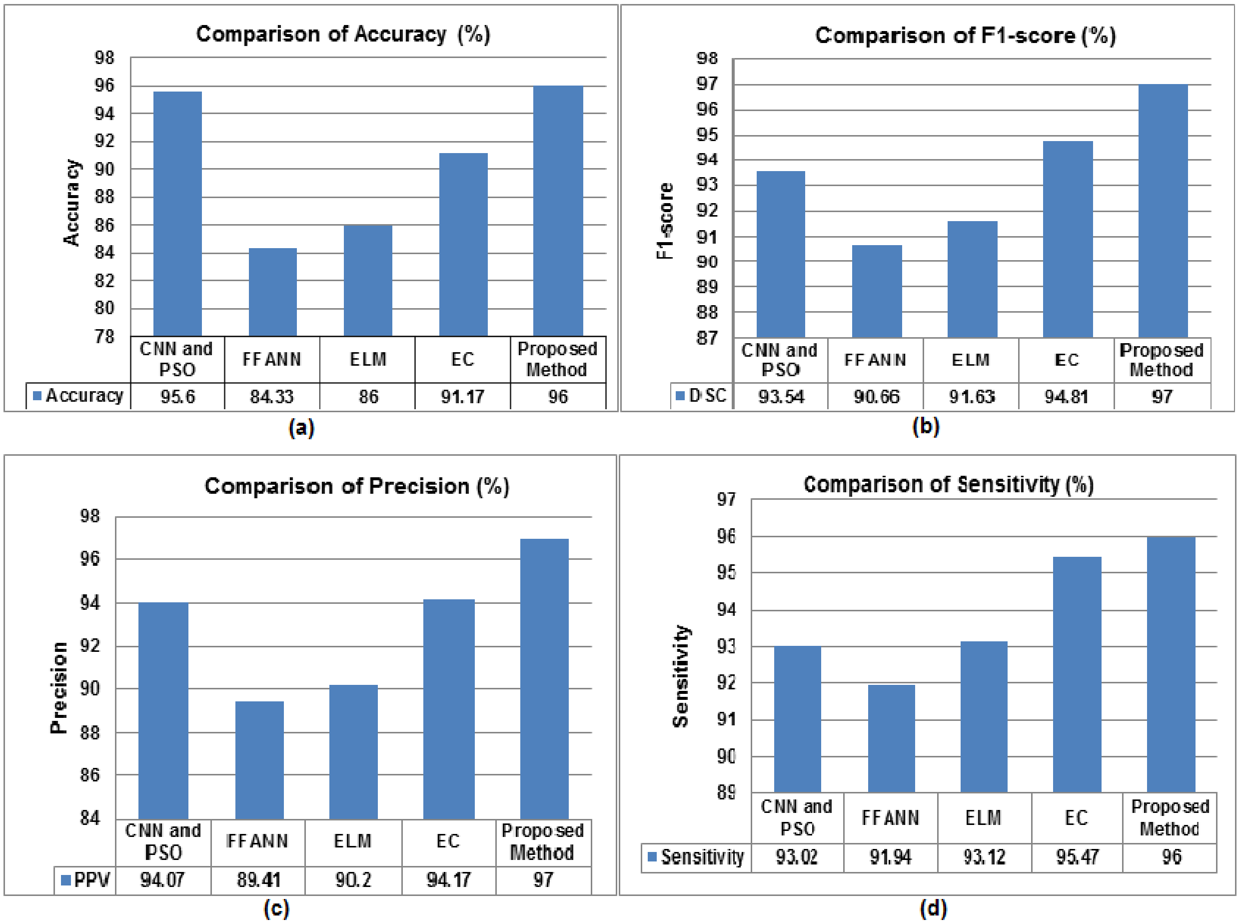

Fig. 5: The detection Performance comparison of the proposed method with state-of-art methods: (a) comparison using accuracy; (b) comparison using F1-score; (c) comparison using precision; (d) comparison using sensitivity.

V. CONCLUSION

Efficient tumor detection from MRI is essential for clinical assessments and also treatment planning. In this research, an automated wavelet feature based CCNN tumor identification method is proposed to detect abnormal tumor images. In this, extracted LL features of each image slice are processed using three different kernels to produce three separate feature maps. These feature maps have been cascaded to be processed into the hierarchy of convolutional and pooling layer followed by softmax classification. This proposed algorithm is implemented and tested using the BRATS-2018 training dataset. This proposed method achieves 96% of Accuracy, 97 % of F1-score, 97 % of Precision, 97 % of Specificity and 96 % of Sensitivity values, which is having higher performance compared to the existing automated detection methods.

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