Multiclass Brain Tumor Classification Using Convolutional Neural Network and Support Vector Machine.

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Abstract— **Brain tumor is caused by abnormal growth of cells inside the skull. It is a lethal disease, the diagnosis of which is a difficult task for radiologists. Most of the tumors are misdiagnosed due to the variability and complexity of lesions, which reduces the survival rate in patients. Diagnosis of brain tumors via computer vision algorithms is a challenging task. Traditional brain tumor identification techniques require manual segmentation or handcrafted feature extraction that is error-prone and time-consuming. This research explores multiclass brain tumor classification methods using Deep Learning (DL) and Machine Learning (ML) techniques. First, the brain MRI images are classified via end-to-end Convolutional Neural Network (CNN) models i.e. ResNet-18 and GoogLeNet. The deep features extracted from the CNN models are also classified using Support Vector Machine (SVM). The proposed method is trained and evaluated on 15,320 MRI images and achieved the highest accuracy of 98% via CNN-SVM based method. Our proposed method outperformed the existing brain tumor identification systems and can assist the doctors to detect brain tumors and make key decisions related to the patient's treatment.**

Keywords—**Deep Learning, Computer Vision, Brain Tumor**

I. INTRODUCTION

Brain is a vital organ that is responsible for controlling all voluntary and involuntary processes in the human body. The brain can be affected by many diseases including brain tumors that are usually caused by uncontrolled growth of cells inside the brain [1] These tumors are very hard to treat [2], so early diagnosis plays a vital role in the patient's health. WHO predicted that brain tumors will be increased by 5% every year all around the world [3].

The interpretation of tumor type by professionals before surgery is a complicated task because the lesions vary in intensity and shape. Misdiagnosis of tumor type can decrease the chance of a patient's survival. Traditional brain tumor detection approaches require manual lesion segmentation and handcrafted feature extraction before classification that is time-consuming and suffers from inter-observer variability. On the other hand, the CNNs can automatically extract deep features and perform classification [4, 5].

In recent years, DL and ML are dominating medical image diagnosis problems. DL and ML based medical image classification algorithms provide an opinion to medical professionals in making therapy-related decisions. CNNs are widely being applied to image analysis tasks i.e. deep feature extraction, segmentation and classification. An automated brain tumor classification system can help physicians decide upon successful treatment options [6].

Many researchers have developed automated brain tumor identification techniques. A detailed summary of some of the existing brain tumor classification techniques is provided in TABLE 1. The table discusses the DL techniques employed, the dataset used to conduct those experiments and the accuracy percentage obtained. The authors in [4, 7] presented a VGG based brain tumor classification system. [3, 8] proposed a Residual Network-based technique whereas, [4, 9] presented AlexNet based approach.

This paper presents an automated approach employing DL and ML algorithms to classify brain tumors in MRI images. The proposed method is evaluated on a publically available dataset [10] and can assist doctors in making decisions regarding the therapy of the patients. The remaining paper is arranged as follows: Section 2 discusses the proposed methodology. Section 3 describes the experimental setup. Section 4 presents the results. Finally, the conclusion is presented in Section 5.

TABLE 1. SUMMARY OF EXISTING BRAIN TUMOR IDENTIFICATION SYSTEMS

Reference	**Year**	**DL Technique**	**Dataset**	**ACC %**
Cinar et al. [3]	2020	ResNet-50	Kaggle	97
Swati et al. [4]	2019	VGG (16,19) , AlexNet	Figshare	94
Anarkari et al. [5]	2019	Custom CNN	Figshare	94
Naser et al. [7]	2020	U-Net, VGG-16	TCIA	92
Sharma et al. [8]	2020	ResNet	SICAS Local	93
Hashemzehi et al. [9]	2020	AlexNet, ConvNADE	Figshare	96

II. PROPOSED METHODOLOGY

In the proposed method, we employed DL and ML-based algorithms to identify and classify Pituitary, Meningioma and Glioma tumors in MRI images. The elaborate diagram of the proposed scheme is shown in Fig 1. Before feeding the images to the CNNs for classification, they are preprocessed and artificially augmented.

A. *Image Preprocessing*

During this phase, the images are normalized using the min-max normalization technique as discussed in equation (1).

$$f(x,y) = \frac{f(x,y) - Z_{min}}{Z_{max} - Z_{min}} \tag{1}$$

The brain image is denoted by f, whereas, Z_{max} and Z_{min} represent the maximum and minimum pixel values in the image. After the normalization process, the images are resized [224 224 3] to match the size of the input layer of the CNN architectures.

B. *Data Augmentation*

In the next step, we increased the data samples by artificially augmenting the data. Data augmentation reduces the problems of imbalanced classes so that the model is not biased towards classifying instances as majority class types [11]. We augmented images by adding salt and pepper noise, left/right mirroring, flipping around the x-axis and rotating the images to 45 degrees. These augmentation techniques increased the dataset by a factor of 5 from 3064 images to 15,320 images. TABLE II shows the number of images before and after augmentation. Fig 2. displays different image augmentation techniques applied to the MRI dataset.

C. *Convolutional Neural Network*

CNN is an efficient supervised learning method that has made remarkable improvements in the field of computer vision. In our proposed method we applied two deep transfer learned models i.e. GoogLeNet [12] ResNet-18 [13] to a three-class brain tumor classification problem. Transfer learning is a commonly used technique in DL that aims to improve learning in the target domain using the source domain and the learning task [14].

Training the DL models from scratch is computationally intensive as it requires a lot of resources, so the transfer learning frameworks aim to solve the resource problem [13, 15].

In this study, we fine-tuned the CNN models by changing the last three layers of the architecture according to our target domain. The Fully Connected (FC) layer from the original architecture was replaced by a new one. Similarly, we also replaced the Softmax layer and the classification layer from both architectures. Fig 3. presents the modifications made in the CNN architectures for this study.

We also classified the deep CNN features using an SVM classifier with an error-correcting output code (ECOC) model. SVM belongs to category of supervised learning algorithms. It has gained popularity due to promising results and is employed in various machine learning researches all over the world. It is memory efficient and effective in high-dimensional spaces [16].

III. EXPERIMENTAL SETUP

A. *Dataset*

To conduct this study, we used a publically available Figshare dataset that contains 3064 brain MRI images of 233 patients. It is composed of 708 samples of Meningioma, 930 samples of Pituitary and 1426 samples of Glioma. The final version of the dataset was uploaded in 2017 [10].

B. *Implementation Details*

For implementation, we used Matlab 2019a on Intel Core i5 6300 CPU with 8 GB RAM. The dataset was split randomly into a 70% training set for training the network and a 30% validation set to evaluate the trained model impartially.

TABLE II. NUMBER OF MRI SAMPLES BEFORE AND AFTER AUGMENTATION

Tumor Type	**MRI samples before Augmentation**	**MRI samples after Augmentation**
Glioma	708	3540
Meningioma	1426	7130
Pituitary	930	4650
Total	**3064**	**15,320**

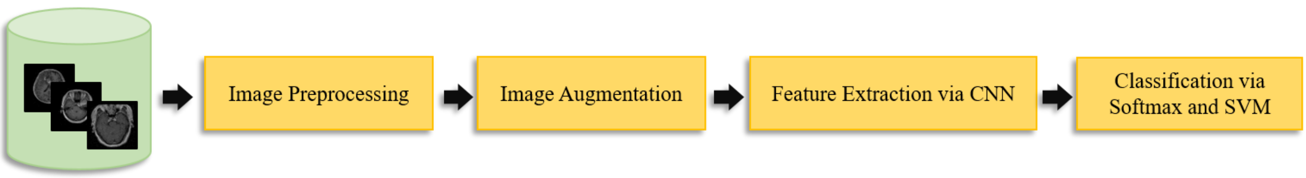

Fig 1. Proposed Method Design

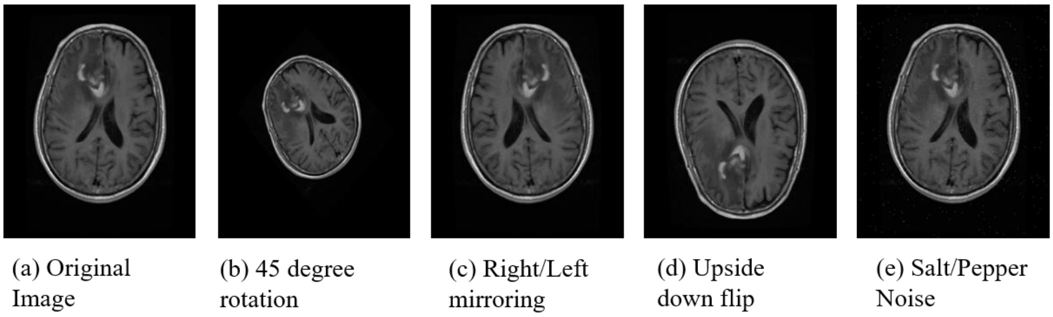

Fig 2. Image Augmentation Techniques

IV. RESULTS

A. Evaluation Parameters

The proposed method is evaluated via Precision (PRE), Recall (REC) and Accuracy (ACC). PRE is mentioned in Equation (2), REC in Equation (3), and ACC in Equation (4).

$$PRE = \frac{tp}{tp + fp} \quad (2)$$

$$REC = \frac{tp}{tp + fn} \quad (3)$$

$$ACC = \frac{tp + tn}{tp + tn + fp + fn} \quad (4)$$

where tp denotes true positives, tn represents true negatives, fp denotes false positives and fn represents false negatives.

B. Proposed method results

In this study, we trained and evaluated two end-to-end DL models to identify brain tumors in MRI images. We then supplied the deep feature vectors as input to SVM with an ECOC model for final output. End-to-end learning models i.e. GoogLeNet and ResNet-18 achieved an accuracy of 97.4% and 97.8% respectively. The detailed results of CNNs in terms of ACC, PRE and REC are presented in Fig 4. The graph indicates that ResNet-18 performed better than GoogLeNet to classify brain tumors.

SVM classified deep feature vector from ResNet-18 and GoogLeNet with an accuracy of 98% and 97.6% respectively It is observed that the proposed system's accuracy increased when SVM was used instead of the Softmax layer of the CNN. TABLE III discusses the classification results obtained via SVM in terms of ACC, PRE and REC.

C. Comparison with state-of-the-art

TABLE IV presents an elaborate result comparison of the proposed method with the existing brain tumor classification techniques. Our proposed method succeeded in achieving an accuracy of 97.8% via ResNet-18, and 97.4% via GoogLeNet. Whereas SVM obtained 98% accuracy to classify deep feature vector from ResNet-18 and 97.6% accuracy to classify feature vector from GoogLeNet. The results are proof that the proposed method provides better performance than the existing techniques.

TABLE III. RESULTS OBTAINED FROM SVM

Deep feature vector	ACC %	PRE %	REC %
GoogLeNet	97.6	97.3	97.3
ResNet-18	98.0	98.3	98.0

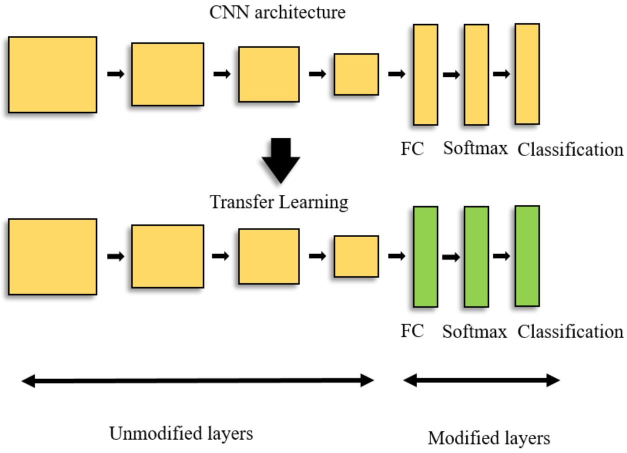

Fig 3. Modifying CNN for Application

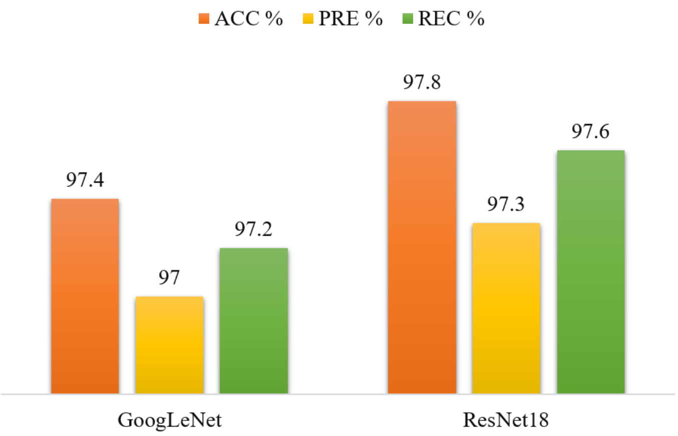

Fig 4. Results Obtained via End-to-End Classification Models

TABLE IV. COMPARISON OF PROPOSED METHOD WITH EXISTING TECHNIQUES

Ref.	Year	DL Technique	ACC %
Swati et al. [4]	2019	AlexNet	89.9
Hashemzehi et al. [9]	2020	Hybrid CNN-NADE	95.0
Cinar et al. [3]	2020	ResNet-50	97.2
Sharma et al. [8]	2020	ResNet	93.0
Pundir et al. [14]	2021	VGG-16	91.8
Sejuti et al. [17]	2021	CNN+SVM	97.1
Noreen et al. [18]	2021	Inception-v3-Ensemble	94.3
Proposed Method	**2021**	**ResNet-18**	**97.8**
		GoogLeNet	**97.4**
		ResNet-18 + SVM	**98.0**
		GoogLeNet + SVM	**97.6**

V. CONCLUSION

This paper introduces an automated brain tumor classification method using DL and ML based techniques. The MRI images are preprocessed, augmented and supplied to fine-tuned CNN models i.e. ResNet-18 and GoogLeNet for tumor classification. The deep feature vectors are also supplied to SVM classifier for final output. The proposed method is evaluated using ACC, SEN, and SPE. The highest performing CNN architecture i.e. ResNet-18 achieved 97.8% accuracy; whereas, the combination of ResNet-18 and SVM obtained 98% accuracy. From the results, it is evident that the proposed method is robust and efficient in classifying brain tumors from MRI images.

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