Brain Tumor Detection and Classification

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Abstract— Brain Tumor segmentation is one of the most crucial and arduous tasks in the terrain of medical image processing as a human-assisted manual classification can result in inaccurate prediction and diagnosis. Moreover, it is an aggravating task when there is a large amount of data present to be assisted. Brain tumors have high diversity in appearance and there is a similarity between tumor and normal tissues and thus the extraction of tumor regions from images becomes unyielding. In this paper, we proposed a method to extract brain tumor from 2D Magnetic Resonance brain Images (MRI) by Fuzzy C-Means clustering algorithm which was followed by traditional classifiers and convolutional neural network. The experimental study was carried on a real-time dataset with diverse tumor sizes, locations, shapes, and different image intensities. In traditional classifier part, we applied six traditional classifiers namely Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naïve Bayes and Random Forest which was implemented in scikit-learn. Afterward, we moved on to Convolutional Neural Network (CNN) which is implemented using Keras and Tensorflow because it yields to a better performance than the traditional ones. In our work, CNN gained an accuracy of 97.87%, which is very compelling. The main aim of this paper is to distinguish between normal and abnormal pixels, based on texture based and statistical based features.

Keywords— CNN, FCM, Medical Image, segmentation, SVM

I. Introduction

Medical imaging refers to a number of techniques that can be used as non-invasive methods of looking inside the body [1]. Medical image encompasses different image modalities and processes to image the human body for treatment and diagnostic purposes and hence plays a paramount and decisive role in taking actions for the betterment of the health of the people.

Image segmentation is a crucial and essential step in image processing which determines the success of a higher level of image processing [2]. The primary goal of image segmentation in medical image processing is mainly tumor or lesion detection, efficient machine vision and attaining satisfactory result for further diagnosis. Improving the sensitivity and specificity of tumor or lesion has become a core problem in medical images with the help of Computer Aided Diagnostic (CAD) systems.

According to [3], Brain and other nervous system cancer is the 10th leading cause of death, and the five-year survival rate for people with a cancerous brain is 34% for men and 36% for women. Moreover, the World Health Organization (WHO) states that around 400,000 people in the world are affected by the brain tumor and 120,000 people have died in the previous years [4]. Moreover, An estimated 86,970 new cases of primary malignant and nonmalignant brain and other Central Nervous System (CNS) tumors are expected to be diagnosed in the United States in 2019 [5].

A brain tumor occurs when abnormal cells form within the brain [6]. There are two main types of tumors- Malignant and Benign. Malignant brain tumors originate in the brain, grows faster and aggressively invades the surrounding tissues. It can spread to other parts of the brain and affect the central nervous system. Cancerous tumors can be divided into primary tumors, which start within the brain, and secondary tumors, which have spread from elsewhere, are known as brain metastasis tumors. On the other hand, a benign brain tumor is a mass of cells that grow relatively slowly in the brain.

Hence, early detection of brain tumors can play an indispensable role in improving the treatment possibilities, and a higher gain of survival possibility can be accomplished. But manual segmentation of tumors or lesions is a time consuming, challenging and burdensome task as a large number of MRI images are generated in medical routine. MRI, also known as Magnetic Resonance Imaging is mostly used for a brain tumor or lesion detection. Brain tumor segmentation from MRI is one of the most crucial tasks in medical image processing as it generally involves a considerable amount of data. Moreover, the tumors can be ill-defined with soft tissue boundaries. So it is a very extensive task to obtain the accurate segmentation of tumors from the human brain.

In this paper, we proposed an efficient and skillful method which helps in the segmentation and detection of the brain tumor without any human assistance based on both traditional classifiers and Convolutional Neural Network.

II. Literature Review

One of the most challenging as well as demanding task is to segment the region of interest from an object and segmenting the tumor from an MRI Brain image is an ambitious one. Researchers around the world are working on this field to get the best-segmented ROI and various disparate approaches simulated from a distinct perspective. Nowadays Neural Network based segmentation gives prominent outcomes, and the flow of employing this model is augmenting day by day.

Devkota et al. [7] established the whole segmentation process based on Mathematical Morphological Operations and spatial FCM algorithm which improves the computation time, but the proposed solution has not been tested up to the evaluation stage and outcomes as- Detects cancer with 92% and classifier has an accuracy of 86.6%. Yantao et al. [8] resembled Histogram based segmentation technique. Regarding the brain tumor segmentation task as a three-class (tumor including necrosis and tumor, edema and normal tissue) classification problem regarding two modalities FLAIR and T1. The abnormal regions were detected by using a region-based active contour model on FLAIR modality. The edema and tumor tissues were distinguished in the abnormal regions based on the contrast enhancement T1 modality by the k-means method and accomplished a Dice coefficient and sensitivity of 73.6% and 90.3% respectively.

Based on edge detection approaches, Badran et al. [9] adopted the canny edge detection model accumulated with Adaptive thresholding to extract the ROI. The dataset contained 102 images. Images were first preprocessed, then for two sets of a neural network, for the first set canny edge detection was applied, and for the second set, adaptive thresholding was applied. The segmented image is then represented by a level number and characteristics features are extracted by the Harris method. Then two neural network is employed, first for the detection of healthy or tumor containing the brain and the second one is for detecting tumor type. Depicting the outcomes and comparing these two models, the canny edge detection method showed better results in terms of accuracy. Pei et al. [10] proposed a technique which utilizes tumor growth patterns as novel features to improve texture based tumor segmentation in longitudinal MRI. Label maps are being used to obtain tumor growth modeling and predict cell density after extracting textures (e.g., fractal, and mBm) and intensity features. Performance of the model reflected as the Mean DSC with tumor cell density- LOO: 0.819302 and 3-Folder: 0.82122.

Dina et al. [11] introduced a model based on the Probabilistic Neural Network model related to Learning Vector Quantization. The model was evaluated on 64 MRI images, among which 18 MRI images were used as the test set, and the rest was used as a training set. The Gaussian filter smoothed the images. 79% of the processing time was reduced by the modified PNN method. A Probabilistic Neural Network based segmentation technique implemented by Othman et al. Principal Component Analysis (PCA) was used for feature extraction and also to reduce the large dimensionality of the data [12]. The MRI images are converted into matrices, and then Probabilistic Neural Network is used for classification. Finally, performance analysis is done. The training dataset contained 20 subjects, and the test dataset included 15 subjects. Based on the spread value, accuracy ranged from 73% to 100%.

Concentrating on Region based Fuzzy Clustering and deformable model, Rajendran et al. [13] accomplished 95.3% and 82.1% of ASM and Jaccard Index based on Enhanced Probabilistic Fuzzy C-Means model with some morphological operations. Zahra et al. [14] performed with LinkNet network for tumor segmentation. Initially, they used a single Linknet network and sent all training seven datasets to that network for segmentation. They did not consider the view angle of the images and introduced a method for CNN to automatically segment the most common types of a brain tumor which do not require preprocessing steps. Dice score of 0.73 is achieved for a single network, and 0.79 is obtained for multiple systems.

III. Proposed Methodology

In our proposed methodology, there are two distinct model for segmentation and detection of Brain tumor. First model segmented the tumor by FCM and classified by traditional machine learning algorithms and the second model focused on deep learning for tumor detection. Segmentation by FCM gives better result for noisy clustered data set [15]. Though it takes more execution time, it retains more information.

A. *Proposed Methodology of Tumor Segmentation and Classification Using Traditional Classifiers*

In our first prospective model, brain tumor segmentation and detection using machine learning algorithm had been done, and a comparison of the classifiers for our model is delineated. Our proposed Brain image segmentation system consists of seven stages: skull stripping, filtering and enhancement, segmentation by Fuzzy C Means algorithm, morphological operations, tumor contouring, feature extraction and classification by traditional classifiers. The results of our work accomplished satisfactory results. The main stages of our proposed model (Fig. 1) will be illustrated in the following sections.

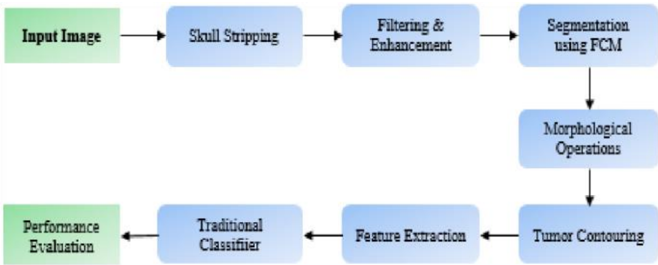


Fig. 1. Proposed methodology for classification using Traditional Classifiers

1) *Skull Stripping:* Skull stripping is a very important step in medical image processing because of the background of the MRI image not containing any useful information, and it only increases the processing time. In our work, we removed the skull portion from the MRI images in three steps. These three steps are:

a) *Otsu Thresholding:* For skull removal, at first we used Otsu's Thresholding method which automatically calculates the threshold value and segments the image into background and foreground. In this method, the threshold that is selected minimizes the intra-class variance, defined as a weighted sum of deviations of the two classes.

b) *Connected Component Analysis:* At the last stage of our skull stripping step, we used connected component analysis to extract only the brain region and as a consequence the skull part was removed.

2) *Filtering and Enhancement*: For better segmentation, we need to maximize the MRI image quality with minimized noise as brain MRI images are more sensitive to noise than any other medical image. Gaussian blur filter was used in our work for Gaussian noise reduction existing in Brain MRI which prevailed the performance of the segmentation.

3) *Segmentation using FCM:* Fuzzy C-Means clustering algorithm was used for segmentation, which allows one piece of data to belong to two or more clusters. We got the fuzzy clustered segmented image at this stage, which ensured a better segmentation.

4) Morphological Operation: To segment the tumor, we only need the brain part rather than the skull part. For this, we applied morphological operations in our images. At first, erosion was done to separate weakly connected regions of the MRI image. After erosion, we will get multiple disconnected regions in our images. Dilation was applied afterwards.

5) Tumor Contouring: Tumor cluster extraction was done by an intensity based approach which is thresholding. The output of this image is the highlighted tumor area with a dark background.

6) Feature Extaction: Two types of features were extracted for classification. Texture-based features such as- Dissimilarity, Homogeneity, Energy, Correlation, ASM and Statistical based features including- Mean, Entropy, Centroid, Standard Deviation, Skewness, Kurtosis were extracted from the segmented MRI Images.

7) Traditional Classifiers: We used six traditional machine learning classifiers which are K-Nearest Neighbor, Logistic Regression, Multilayer Perceptron, Naïve Bayes, Random Forest, and Support Vector Machine to get the accuracy of tumor detection of our proposed model.

8) Evaluation Stage: Implementing other region-based segmentation methods and comparing it to our proposed segmentation technique, our model segments the ROI and segregates the tumor portion most accurately. An illustration of the whole process is depicted in Fig. 5. After segmentation and feature extraction from the tumor, we applied six classification techniques. Among them, we got the best result from SVM and obtained an accuracy of 92.42%.

B. Proposed Methodology Using CNN

Convolutional Neural Network is broadly used in the field of Medical image processing. Over the years lots of researchers tried to build a model which can detect the tumor more efficiently. We tried to come up with an exemplary which can accurately classify the tumor from 2D Brain MRI images. A fully-connected neural network can detect the tumor, but because of parameter sharing and sparsity of connection, we adopted CNN for our model.

A Five-Layer Convolutional Neural Network is introduced and implemented for tumor detection. The aggregated model consisting of seven stages including the hidden layers provides us with the most prominent result for the apprehension of the tumor. Following is the proposed methodology with a brief narration-

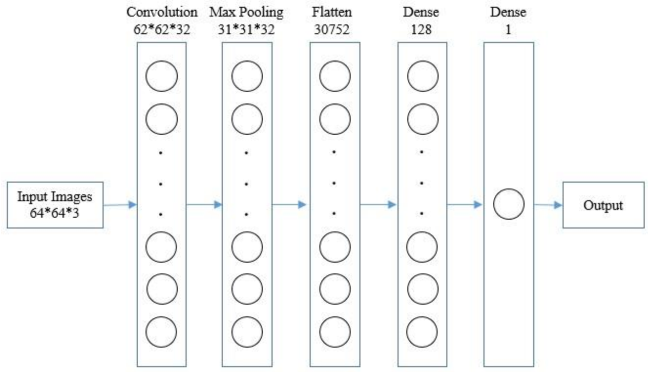


Fig. 2. Proposed Methodology for tumor detection using 5-Layer Convolutional Neural Network

Using convolutional layer as the beginner layer, an input shape of the MRI images is generated which is 64*64*3 converting all the images into a homogeneous dimension. After accumulating all the images in the same aspect, we created a convolutional kernel that is convoluted with the input layer — administering with 32 convolutional filters of size 3*3 each with the support of 3 channels tensors. ReLU is used as an activation function so that it's not corroborating with the output.

In this ConvNet architecture, progressively shorten the spatial size of the depiction for diminishing the chunk of parameters and computational time of the network. Working on the Brain MRI image can also cost the contamination of the overfitting and for this Max Pooling layer perfectly works for this perception. For spatial data which substantiate with our input image, we use MaxPooling2D for the model. This convolutional layer runs on 31*31*32 dimension. Because of divide the input images in both spatial dimensions, the pool size is (2, 2) which means a tuple of two integers by which to downscale by vertically and horizontally.

After the pooling layer, a pooled feature map is obtained. Flattening is one of the essential layers after the pooling because we've to transformed the whole matrix representing the input images into a single column vector and it's imperative for processing. It is then fed to the Neural Network for the processing.

Two fully connected layers were employed Dense-1 and Dense-2 represented the dense layer. The dense function is applied in Keras for the processing of the Neural Network, and the obtained vector is work as an input for this layer. There are 128 nodes in the hidden layer. Because the number of dimension or nodes proportional with the computing resources we need to fit our model we kept it as moderate as possible and for this perspective 128 nodes gives the most substantial result. ReLU is used as the activation function because of showing better convergence performance. After the first dense layer, the second fully connected layer was used as the final layer of the model. In this layer, we used sigmoid function as activation function where the total number of the node is one because we need to lower the uses of computing resources so that a more significant amount assuages the execution time. Though there is a chance of hampering the learning in deep networks for using of the sigmoid as the activation function, we scale the sigmoid function, and the number of the nodes is much lesser and easy to handle for this deep network. In a summary, Fig. 3 shown the working flow of the proposed CNN model.

Working Flow Devised for Proposed Methodology

1. Load the input dataset
2. Adding a Convolution Layer with 32 convolutional filter
3. Passing the Convolutional kernel into the Max Pooling layer
4. Pooled feature map is used to get the single column vector
5. Processing of the vector in dense layer with 128 nodes
6. Final dense layer applying Sigmoid as the Activation function
7. Validation stage and Performance evaluation

Fig. 3. Working flow of the proposed CNN Model.

Using Adam optimizer and binary cross-entropy as a loss function, we compiled the model and find the accuracy of detecting the tumor. An algorithm is depicted in Fig. 4 where we evaluated the performance of the model.

Algorithm 1: Evaluation process of CNN model

```
loadImage();
dataAugmentation();
splitData();
loadModel();
for each epoch in epochNumber do
    for each batch in batchSize do
        ŷ = model(features);
        loss = crossEntropy(y, ŷ);
        optimization(loss);
        accuracy();
        bestAccuracy = max(bestAccuracy, accuracy);
return
```

Fig. 4. Algorithm of the performance evaluation

All the hyper-parameters value are constituted in Table-I. Approximately 97.87% is achieved as the accuracy.

TABLE I. HYPERPARAMETER VALUE OF CNN MODEL

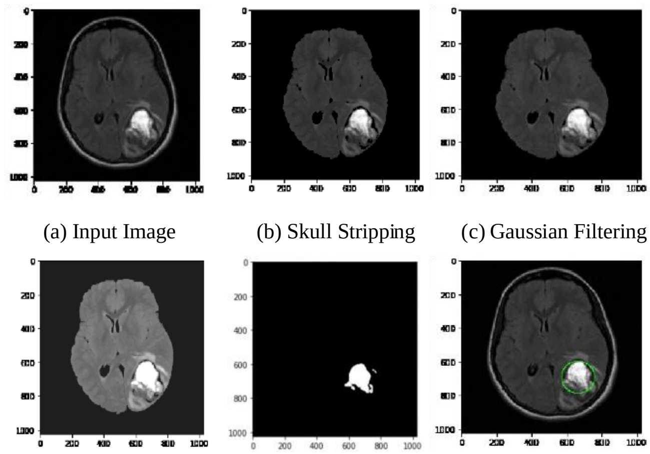
Stage	Hyper-parameter	Value
Initialization	bias	Zeros
	Weights	glorot_uniform
	Learning rate	0.001
	beta_1	0.9
	beta_2	0.999
	epsilon	None
Training	decay	0.0
	amsgrad	False
	epoch	10
Stage	**Hyper-parameter**	**Value**
	Batch_size	32
	steps_per_epoch	80

IV. EXPERIMENTAL RESULTS

To justify our proposed model, steps of segmenting the tumor from 2D Brain MRI is illustrated (Fig. 5) and a comparative analysis of our proposed models of classification using machine learning, and deep learning is shown. We got 92.42% of accuracy using SVM and 97.87% of accuracy is achieved using CNN.

A. Experimental Dataset

For Performance Evaluation of our proposed model, we used the benchmark dataset in the field of Brain Tumor Segmentation, and that is BRATS dataset [16], consisting two classes'— class-0 and class-1 represents the Non-Tumor and Tumor MRI images. 187 and 30 MRI Images containing tumor and non-tumor respectively classified as class-1 and class-0. All the images are MRI images from different modalities like- T1, T2, and FLAIR. For traditional machine learning classifiers, we obtained the superlative result splitting the dataset by 70 to 30 in terms of training to testing images, and for CNN, we divided the dataset in both 70 to 30 and 80 to 20 formation and compared the outcomes.



(a) Input Image (b) Skull Stripping (c) Gaussian Filtering

B. Segmentation using Image processing techniques

Based on our proposed methodology, we segmented the tumor without loss of any subtle information. We removed the skull because for tumor segmentation the role of skull is approximately null and ambiguous in this process.

(d) Image Enhancement (e) Segmentation (f) Tumor Contouring

Fig. 5. Segmentation processes of an MRI

TABLE II. EXTRACTED FEATURES FROM SEGMENTED TUMOR

Image No	Contrast	Dissimilarity	Homogeneity	Energy	Correlation	ASM	Label
1	281.18	1.37	0.97	0.90	0.97	0.81	1
2	97.36	0.53	0.98	0.98	0.94	0.96	1
3	337.39	1.68	0.98	0.97	0.82	0.95	1
4	357.59	2.34	0.94	0.92	0.90	0.86	1
5	149.37	0.82	0.98	0.96	0.96	0.93	0
6	357.59	2.34	0.95	0.93	0.90	0.86	0

TABLE III. CONFUSION METRICS OF THE CLASSIFIERS

Classifiers	Accuracy	Recall	Specificity	Precision	Dice Score	Jaccard Index
K-Nearest Neighbor	89.39	0.949	0.428	0.933	0. 941	0.889
Logistic Regression	87.88	0.949	0.286	0.918	0.933	0.875
Multilayer Perception	89.39	**1.000**	0	0.894	0.944	0.894
Naïve Bayes	78.79	0.797	**0.714**	**0.959**	0.870	0.770
Random Forest	89.39	0.983	0.167	0.903	0.943	0.892
SVM	**92.42**	0.983	0.428	0.935	**0.959**	**0.921**

From the dataset, a 2D MRI was taken as an input image, Skull stripping technique is performed on the input image (Fig. 1b) followed by image enhancement (Fig. 1c) for understanding the features of the MRI properly. After that, Gaussian filter (Fig. 1d) is used for noise removal and finally simulating the FCM segmentation technique (Fig. 1e) followed by tumor contouring (Fig. 1f) to find out the ROI which is the tumor for Brain MRI. After the segmentation of the tumor, we classified the tumor based on different traditional Machine learning Algorithms.

C. Classification Using Machine Learning

Texture and Statistical based features are more popular for detecting the Region of Interest (ROI). Based on these features we can segregate the tumorous and non-tumorous MRI. We used texture and statistical based features for classification. Texture-based features like- Dissimilarity, Homogeneity, Energy, Correlation, ASM and Statistical based features including- Mean, Entropy, Centroid, Standard Deviation, Skewness, Kurtosis were extracted from the segmented Brain tumor. Further, we extracted the Area, Convex Hull Area and Diameter of the tumor. Extrapolating these features from the segmented MRI, we classified the image as the existence of normal and abnormal tissue. TableII depicts the values of the features of some of the segmented MRI. After feature extraction, classification had been done. We adopt six classifiers which are- KNN, Logistic Regression, Multilayer Perception, Naïve Bayes, Random Forest, and SVM and achieved the best accuracy as the performance from SVM. Confusion Metrics' along with the performance of the classifiers is characterized in Table-III.

The following factor evaluates the performance-

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$Sensitivity(recall) = \frac{TP}{TP+FN} \quad (2)$$

$$Speficity = \frac{TN}{TN+FP} \quad (3)$$

$$Precision\ (PPV) = \frac{TP}{TP+FP} \quad (4)$$

From Table-III, we characterized that, among the six traditional machine learning classifiers, SVM gives the most prominent result and it is 92.42% in terms of accuracy. Though in terms of Precision and Specificity, Naïve Bayes gave the prominent outcome but the discrepancy with SVM was very subtle and also negligible considering the other performance metrics. From other performance metrics', it's also concluded that from SVM we obtained the pre-eminent result in terms of Jaccard Index, Dice Score, Precision, recall etc.

D. Classification Using CNN

The five-layer proposed methodology gives us the commendable result for the detection of the tumor. Convolution, Max Pooling, Flatten, and two dense layers are the proposed five layer CNN model. Data augmentation had been done before fitting the model as CNN is translation invariance. We evaluate the performance in two ways based on splitting the dataset. We accomplish 92.98% of accuracy for 70:30 splitting ratio where the training accuracy is 99.01%. Then at the second iteration, 80% of the images assigned for training and the rest of the images accredited for testing where we concluded 97.87% of accuracy and 98.47% of training accuracy. So our proposed model gives the best result when the division is 80:20. Table-IV represents the performance of the proposed methodology based on CNN.

We got 97.87% as accuracy which is remarkable in terms of using five-layer CNN. We analyzed with a different number of layers but the divergent of the outcomes were not very significant in terms of using this five-layer CNN model. Some of the aspects that we obtained when we increase the number of layers is- computation time, the complexity of the method batch size and steps per was immensely high. Further, we used 0.2 as the dropout value but did not commensurate the model as the accuracy flattened. As a result, this model provides the best accuracy without using dropout.

TABLE IV. PERFORMANCE OF THE PROPOSED CNN MODEL

No	Training Image	Testing Image	Splitting Ratio	Accuracy (%)
1	152	65	70 : 30	92.98
2	174	43	80 : 20	**97.87**

Fig. 6 depicts the training and validation accuracy of our model. It was calculated by the Keras callbacks function. Operating with the different number of epochs we observed the training and validation accuracy. We found that after 9 epochs model has the maximum accuracy for both training and validation.

Fig. 6. Accuracy of the proposed CNN model.

E. Performance Comparison

Finally, we carried out a comparison between our proposed methodologies which are classification using traditional machine learning classifiers and CNN. We also compared our result with some other research articles which worked on the same dataset. In Seetha et al. [17], researchers got 83.0% accuracy using SVM based classification and 97.5% accuracy using CNN. Our proposed methodology provided an improved result for both machine learning and CNN based classification. Mariam et al. [18] got approximately 95% of dice co-efficient where we have 96% as the Dice score.

TABLE V. PERFORMANCE COMPARISON

Methodology	Accuracy (%)
Seetha et al [17]	97.5
Proposed CNN Model	**97.87**

CONCLUSION AND FUTURE WORK

Image segmentation plays a significant role in medical image processing as medical images have different diversities. For brain tumor segmentation, we used MRI and CT scan images. MRI is most vastly used for brain tumor segmentation and classification. In our work, we used Fuzzy C-Means clustering for tumor segmentation which can predict tumor cells accurately. The segmentation process was followed by classification using traditional classifiers and Convolutional Neural Network. In the traditional classifier part, we applied and compared the results of different traditional classifiers such as K-Nearest Neighbor, Logistic Regression, Multilayer Perceptron, Naïve Bayes, Random Forest, and Support Vector Machine. Among these traditional ones, SVM gave us the highest accuracy of 92.42%.

Further, for better results, we implemented CNN which brought in the accuracy 97.87% with a split ratio of 80:20 of 217 images, i.e. 80% of training images and 20% of testing images. In the future, we plan to work with 3D brain images, achieve more efficient brain tumor segmentation. Working with a larger dataset will be more challenging in this aspect, and we want to build a dataset emphasizing the abstract with respect to our country which will accelerate the scope of our work.

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