Brain Tumor Detection Using Convolutional NeuralNetwork

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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 braintumor 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 wasimplemented 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

Introduction:

Medical imaging refers to several 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.

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 AidedDiagnostic (CAD) systems.

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.

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 andConvolutional Neural Network.

Literature Review:

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 computationtime, but the proposed solution has not been tested up to the evaluation stage and outcomes as- Detects cancer with 96 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 usinga region-based active contour model on FLAIR modality.

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.

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 morphologicaloperations. Zahra et al. [14] performed with LinkNet networkfor tumor segmentation

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 ondeep learning for tumor detection. Segmentation by FCM gives better result for noisy clustered data set [15]. Though ittakes more execution time, it retains more information.

A. *Proposed Methodology of Tumor Segmentation andClassification 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

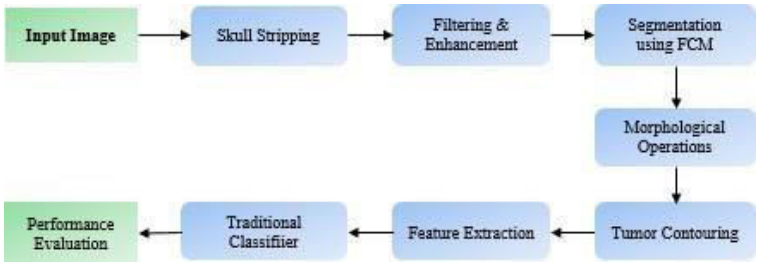


Fig. 1. Proposed methodology for classification using Traditional Classifiers

*1) **Skull Stripping:*** Skull stripping is a very important stepin medical image processing because of the background of the MRI image not containing any useful information, and itonly increases the processing time. In our work, we removedthe 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 thatis selected minimizes the intra-class variance, defined as a weighted sum ofdeviations of the two classes.

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

*2) **Filtering and Enhancement**:* For better segmentation, we need to maximize the MRI image quality with minimizednoise 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 MRIwhich prevailed the performance of the

segmentation.

*3) **Segmentation using FCM:*** Fuzzy C-Means clustering algorithm was used for segmentation, which allows one pieceof 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, weonly need the brain part rather than the skull part. For this, weapplied morphological operations in our images. At first, erosion was done to separate weakly connected regions of theMRI image. After erosion, we will get multiple disconnectedregions 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 darkbackground.

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 MRIImages.

7) ***Traditional Classifiers:*** We used six traditionalmachine learning classifiers which are K-Nearest Neighbor, Logistic Regression, Multilayer Perceptron, Naïve Bayes, Random Forest, and Support Vector Machine to get theaccuracy 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 resultfrom SVM and obtained an accuracy of 92.42%.

B. Proposed Methodology Using CNN

Convolutional Neural Network is broadly used in the fieldof Medical image processing. Over the years lots of researchers tried to build a model which can detect the tumormore efficiently. We tried to come up with an exemplary which can accurately classify the tumor from 2D Brain MRIimages. 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 forthe apprehension of the tumor.

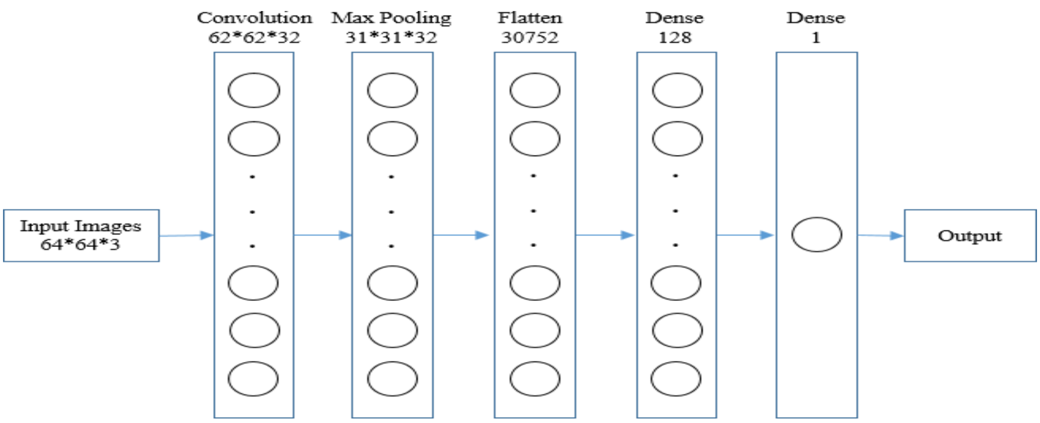


Fig. 2. Proposed Methodology for tumor detection using 5-LayerConvolutional Neural Network

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

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 lossfunction, we compiled the model and find the accuracy of detecting the tumor. An algorithm is depicted in Fig. 4 wherewe 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

Experimental Results:

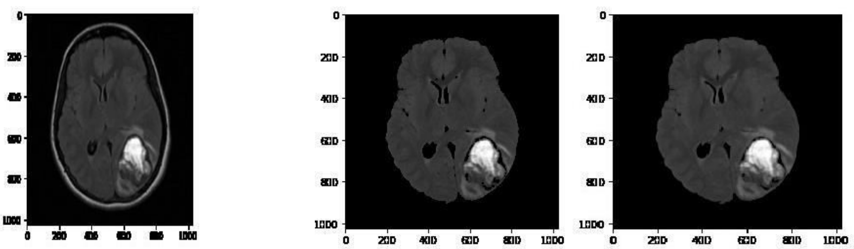
To justify our proposed model, steps of segmenting the tumor from 2D Brain MRI is illustrated (Fig. 5) and a comparative analysis of our proposed models of classificationusing machine learning, and deep learning is shown. We got92.42% of accuracy using SVM and 97.87% of accuracy is achieved usingCNN.

Experimental Dataset:

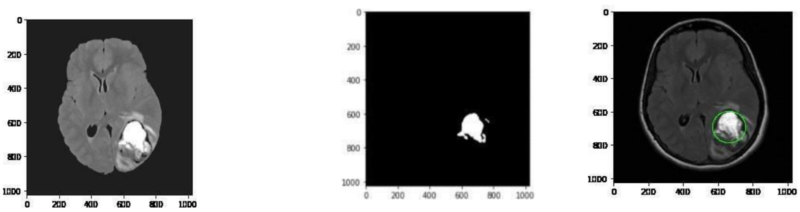
For Performance Evaluation of our proposed model, we used the benchmark dataset in the field of Brain Tumor Segmentation, and that is BRATS dataset [16], consisting two classes'— class-0 and class- 1 represents the Non-Tumorand Tumor MRI images. 187 and 30 MRI Images containingtumor and non- tumor respectively 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 testingimages, and for CNN, we divided the dataset in both 70 to 30and 80 to 20 formation and compared the outcomes.

A. *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.



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



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

Fig. 5. Segmentation processes of an MRI

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

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 I. EXTRACTED FEATURES FROM SEGMENTED TUMOR

Classifiers	**Accuracy**	**Recall**	**Specificity**	**Precision**	**Dice Score**	**Jaccard Index**
K-Nearest Neighnout	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**

TABLE II. CONFUSION METRICS OF THE CLASSIFIERS

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, recalletc.

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 arethe 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 fortesting where we concluded 97.87% of accuracy and 98.47%of training accuracy. So our proposed model gives the best the training and validation accuracy. We found that after 9 epochs model has the maximum accuracy for both training and validation.

and we want to build a dataset emphasizing the abstract withrespect to our country which will accelerate the scope of ourwork.

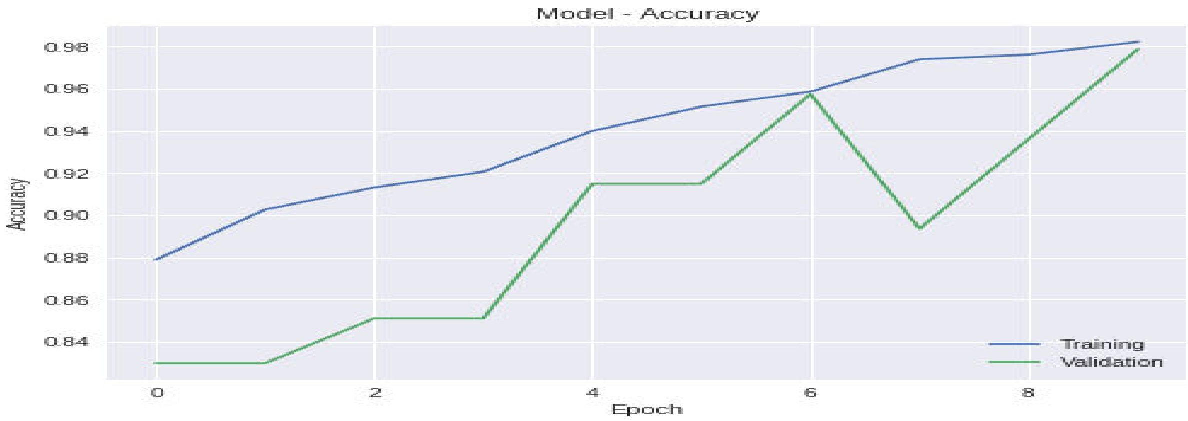


Fig. 6. Accuracy of the proposed CNN model.

We got 97.87% as accuracy which is remarkable in termsof using five-layer CNN. We analyzed with a different number of layers but the divergent of the outcomes were notvery 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 themethod 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.

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], researchersgot 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.

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

TABLE IV. PERFORMANCE COMPARISON

Conclusion and Future Works:

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 FuzzyC-Means clustering for tumor segmentation which can predict tumor cells accurately. The segmentation process wasfollowed 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 traditionalones, 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 of217 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,

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