Brain Tumor Detection Using Convolutional Neural Network

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Abstract

In the field of medical image processing, brain tumor segmentation is one of the most important and challenging problems since manual classification by a person can lead to incorrect diagnosis and prediction. Furthermore, it is a frustrating chore when there is a lot of data that needs to be helped. The extraction of tumor regions from images becomes hard because brain tumors show a great degree of visual diversity and resemble normal tissues. In this work, we suggested using the fuzzy C-Means clustering approach to extract brain tumors from 2D magnetic resonance imaging (MRI). Conventional classifiers and convolutional neural networks were then used. The experimental investigation was conducted using a real-time dataset that included a variety of tumor sizes, locations, forms, as well as various picture intensities. We used six conventional classifiers in the traditional classifier section, including Support Vector Machine(SVM), Scikit-learn was used to implement K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naïve Bayes, and Random Forest. Then, as it performs better than the conventional ones, we switched to Convolutional Neural Networks (CNNs), which are implemented using Keras and Tensorflow. CNN achieved a really impressive accuracy of 97.87% in our work. This paper's primary goal is to differentiate between normal and aberrant pixels using statistical and texture-based criteria.

INTRODUCTION

Medical imaging encompasses a variety of non-invasive procedures for examining the inside of the body [1]. Medical imaging, which includes many image modalities and procedures to picture the human body for diagnostic and therapeutic reasons, is crucial and essential in taking action to improve people's health.

The success of a higher degree of image processing is determined by the critical and necessary step of image segmentation [2]. The detection of tumors or lesions, effective machine vision, and obtaining satisfactory results for additional diagnosis are the key objectives of image segmentation in medical image processing. Using computer aided diagnostic (CAD) technologies to improve the sensitivity and specificity of tumors or lesions has become a major issue in medical imaging.

According to [3], the five-year survival rate for individuals with brain cancer is 34% for males and 36% for women. Brain and other nervous system cancer is the tenth largest cause of death. Additionally, according to the World Health Organization (WHO), approximately 400,000 individuals worldwide suffer from brain tumors 120,000 people have died in the previous years [4]. Moreover, An estimated 86,970 new cases of primary malignant and non- malignant 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.

LITERATURE REVIEW

Segmenting the region of interest from an object is one of the most difficult and demanding tasks, and it is an ambitious undertaking to segment the tumor from an MRI brain image. In order to replicate different divergent approaches from a unique perspective and obtain the best segmented ROI, researchers from all around the world are researching in this subject. Neural network-based segmentation produces notable results these days, and the use of this approach is growing daily.

The accuracy of the classifier is 86.6%. The segmentation method used by Yantao et al. [8] was similar to that of histograms. Considering the brain tumor segmentation task as a three-class classification problem using two modalities (FLAIR and T1) (tumor includes necrosis and tumor, edema, and normal tissue). Using a region-based active contour model on the FLAIR modality, the aberrant areas were identified. 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.

In order to extract the ROI, Badran et al. [9] used the clever edge detection model accumulated with adaptive thresholding, which is based on edge detection techniques. There were 102 photos in the dataset. After preprocessing the images, two neural network sets were used: adaptive thresholding was used for the second set while canny edge detection was used for the first. A level number is then assigned to the segmented image, and the Harris method is used to extract its distinctive features. Then, two neural networks are used: one to identify if the brain is healthy or contains tumors, and the other to identify the type of tumor. Depicting the outcomes and comparing these two models, the canny edge detection method showed better results in terms of accuracy. Pei et [10] suggested a method to enhance texture-based tumor segmentation in longitudinal MRI by using tumor development patterns as unique features. Following the extraction of textures (such as fractal and mBm) and intensity features, label maps are utilized to forecast cell density and achieve tumor growth models. The mean DSC with tumor cell density—LOO: 0.819302 and 3 Folder: 0.82122—reflects the model's performance.

A paradigm for Learning Vector Quantization based on the Probabilistic Neural Network model was presented by Dina et al. [11]. 64 MRI pictures were utilized to test the model; 18 of them served as the test set, and the remaining images served as the training set. The pictures were smoothed by the Gaussian filter. The updated PNN approach lowered the processing time by 79%. Othman et al. used a segmentation method based on probabilistic neural networks. Both feature extraction and reducing the high dimensionality of the data were accomplished using Principal Component Analysis (PCA) [12]. After converting the MRI images into matrices, a probabilistic neural network is employed to classify the pictures. Performance analysis is completed in the end. There were 20 participants in the training dataset, and There were fifteen participants in the test dataset. The accuracy ranged from 73% to 100% depending on the spread value.

Rajendran et al. [13] achieved 95.3% and 82.1% of the ASM and Jaccard Index based on the Enhanced Probabilistic Fuzzy C-Means model with certain morphological procedures, respectively, by focusing on Region based Fuzzy Clustering and the deformable model. For tumor segmentation, Zahra et al. [14] used the LinkNet network. In the beginning, they delivered all seven training datasets to a single Linknet network for segmentation. They presented a technique for CNN to automatically separate the most prevalent types of brain tumors, which do not take into account the view angle of the pictures. not need preprocessing procedures. For a single network, the dice score is 0.73, and for many systems, it is 0.79.

PROPOSED METHODOLOGY

There are two different models for brain tumor segmentation and detection in our suggested methodology. While the second model concentrated on deep learning for tumor identification, the first model identified the tumor using conventional machine learning methods and segmented it based on FCM. For noisy clustered data sets, FCM segmentation produces superior results [15]. It maintains more information even though it takes longer to execute.

A. Proposed Methodology of Tumor Segmentation and Classification Using Traditional Classifiers Our first prospective model used a machine learning algorithm to detect and segment brain tumors, and a comparison of our model's classifiers is shown. Skull stripping, filtering and enhancement, segmentation using the fuzzy C Means algorithm, morphological operations, tumor contouring, feature extraction, and classification using conventional classifiers are the seven steps of our suggested brain picture segmentation method. Our efforts produced outcomes that were satisfying. The subsequent sections will provide illustrations of the primary phases of our suggested model .

1) Skull Stripping: Because the MRI picture's background contains no relevant information and only lengthens processing time, skull stripping is a crucial step in medical image processing. Three stages were taken in our study to eliminate the skull part from the MRI pictures. These three actions 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 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.

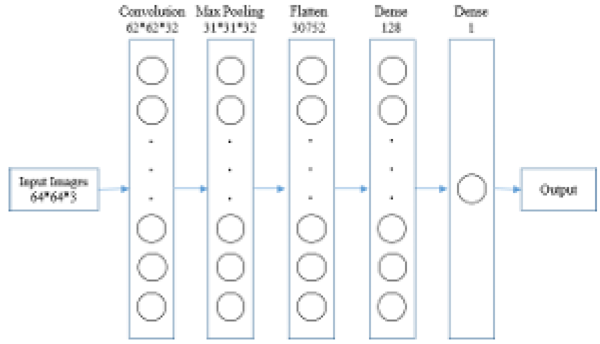


Fig. 2. Proposed Methodology for tumor detection using 5-Layer Convolutional Neural Network

The MRI pictures are converted into a homogenous dimension by generating an input shape of 64*64*3 using the convolutional layer as the starting layer. We developed a convolutional kernel that is convoluted with the input layer after gathering all the images in the same aspect. It administers 32 convolutional filters of size 3*3 each, supported by three channel tensors. To prevent it from interfering with the output, ReLU is employed as an activation function.

Reduce the chunk of parameters and network computation time by gradually reducing the spatial dimension of the representation in this ConvNet design. Working with the brain MRI image can also result in overfitting contamination, and the Max Pooling layer is ideal for this impression. We utilize MaxPooling2D for the model when dealing with spatial data that is consistent with our input image. The dimensions of this convolutional layer are 31*31*32. The pool size, which is a tuple of two integers by which to downscale by vertically and horizontally, is (2, 2) as a result of dividing the input images in both spatial dimensions.

A pooled feature map is produced following the pooling layer. One of the most important layers following pooling is flattening, which is necessary for processing as we must convert the entire matrix containing the input images into a single column vector. After that, it is supplied to the neural network for processing.

There were two fully connected layers used. The dense layer was represented by Dense-1 and Dense-2. The resultant vector is used as an input for this layer when the dense function is applied in Keras for the Neural Network processing. The hidden layer consists of 128 nodes. We kept it as reasonable as feasible because the number of dimensions or nodes corresponds with the computer resources required to fit our model, and from this angle, 128 nodes yields the most significant result. ReLU's superior convergence performance makes it the activation function of choice. The second fully connected layer served as the model's last layer after the first dense layer. We employed the sigmoid function as the activation function in this layer. 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.

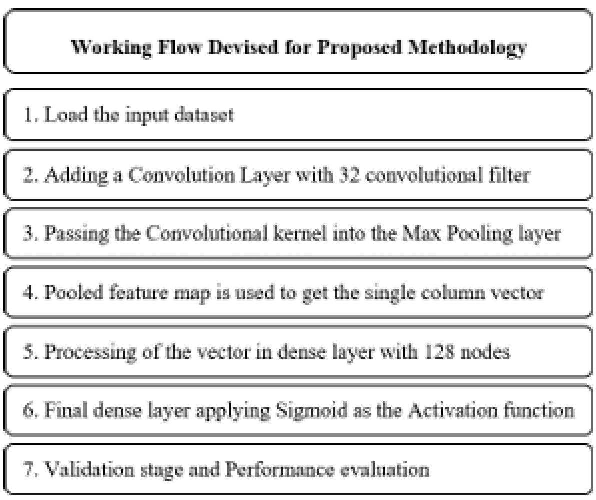


Fig. 3. Working flow of the proposed CNN Model.

We assembled the model and determined the tumor detection accuracy using the Adam optimizer and binary cross-entropy as a loss function. Fig. 4 shows a method that we used to assess the model's performance.

```
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

Table I has the values for all of the hyper-parameters. The accuracy is attained at about 97.87%.

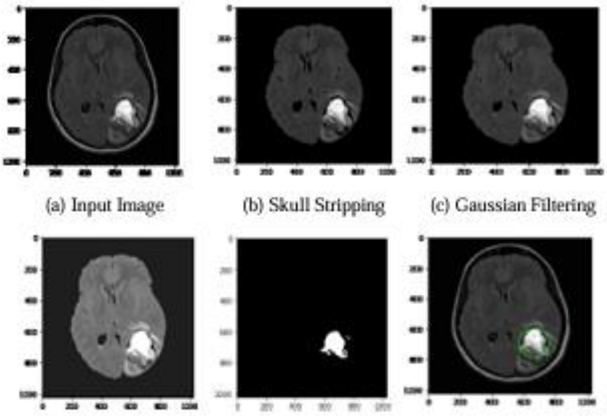
TABLE I. HYPERPARAMETER VALUE OF CNN MODEL

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

A comparison of our suggested models of categorization using machine learning and deep learning is presented, along with steps for segmenting the tumor from 2D brain MRI to support our model (Fig. 5). SVM yielded an accuracy of 92.42%, while CNN produced an accuracy of 97.87%.

A. Experimental Dataset We employed the BRATS dataset [16], a benchmark dataset in the field of brain tumor segmentation, to evaluate the performance of our suggested model. It is divided into two classes: class-0 and class-1, which stand for non-tumor and tumor MRI images, respectively. Thirty and 187 MRI images with and without tumors were categorized as class-0 and class-1, respectively. All of the pictures are MRI pictures taken with various modalities, such as FLAIR, T1, and T2. In terms of training to testing images, we split the dataset in both 70 to 30 and 80 to 20 formations for CNN and compared the results. For traditional machine learning classifiers, we achieved the best results by splitting the dataset by 70 to 30.

B. Segmentation using Image processing techniques We segmented the tumor using our suggested methods without losing any nuanced information. Since the skull's function in tumor segmentation is essentially null and ambiguous, we deleted it.



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

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

Fig. 5. Segmentation processes of an MRI

A 2D MRI was selected from the dataset as the input image. To adequately grasp the MRI's features, the input image was subjected to the skull stripping technique (Fig. 1b) and then image enhancement (Fig. 1c). The ROI that represents the tumor for the brain MRI is next determined by using the Gaussian filter (Fig. 1d) to remove noise, then mimicking the FCM segmentation technique (Fig. 1e), and finally, tumor contouring (Fig. 1f). Following tumor segmentation, we used various conventional machine learning algorithms to classify the tumor.

C. Classification Using Machine Learning For identifying the Region of Interest (ROI), texture and statistically based features are increasingly widely used. We can distinguish between tumorous and non-tumorous MRIs based on these characteristics. For classification, we employed statistically based characteristics and texture. Dissimilarity, homogeneity, energy, correlation, and ASM are examples of texture-based characteristics; mean, entropy, centroid, and standard are examples of statistical-based features.

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 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**

According to Table III, SVM produces the most notable outcome out of the six conventional machine learning classifiers, with an accuracy of 92.42%. Although Naïve Bayes produced the most notable results in terms of precision and specificity, the difference with SVM was extremely slight and insignificant when taking into account the other performance metrics. We also deduced from other performance metrics that SVM produced the best results in terms of precision, recall, dice score, Jaccard Index, and so forth.

D. Classification Using CNN Convolution, Max Pooling, Flatten, and two dense layers comprise the proposed five-layer CNN model. Since CNN is translation invariant, data augmentation was done prior to model fitting. We assess performance in two ways based on splitting the dataset: we achieve 92.98% accuracy for 70:30 splitting ratio at which the training accuracy is 99.01%, and at the second iteration, 80% of the images are assigned for training and the remaining images are accredited for testing, where we conclude 97.87% accuracy and 98.47% training accuracy.

This model provides the best accuracy without using dropout. We analyzed with a different number of layers, but the divergent outcomes were not very significant when using this five-layer CNN model. Some of the aspects that we obtained when we increased the number of layers were computation time, the complexity of the method batch size, and steps per. Additionally, we used 0.2 as the dropout value, but did not commensurate the model as the accuracy flattened. 97.87% is a remarkable accuracy when using a five-layer CNN the accuracy of training and validation. We discovered that the model's greatest accuracy for both training and validation occurs after 9 epochs.

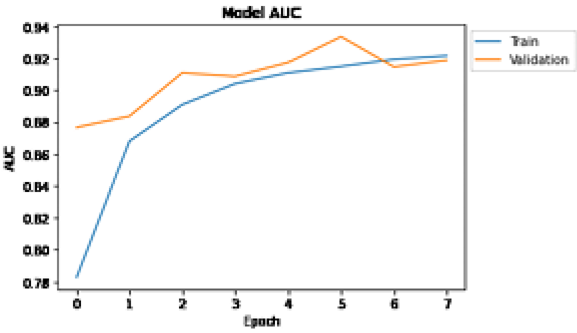


Fig. 6. Accuracy of the proposed CNN model.

E. Performance Comparison Lastly, we conducted a comparison between CNN and our suggested classification approaches, which use conventional machine learning classifiers. Additionally, we contrasted our findings with those of a few other studies that used the same dataset. Researchers in Seetha et al. [17] achieved 97.5% accuracy using CNN and 83.0% accuracy with SVM-based categorization. Our suggested approach produced better results for CNN-based categorization as well as machine learning. Mariam et al. [18] obtained a dice coefficient of almost 95%, but our dice score is 96%.

TABLE V. PERFORMANCE COMPARISON

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

CONCLUSION AND FUTURE WORK

We used MRI and CT scan images to segment brain tumors. The most common applications of MRI are in the segmentation and classification of brain tumors. Fuzzy C-Means clustering, which can precisely predict tumor cells, was employed in our work for tumor segmentation. Convolutional neural networks and conventional classifiers were used for classification after the segmentation phase. The findings of several classic classifiers, including K-Nearest Neighbor, Logistic Regression, Multilayer Perceptron, Naïve Bayes, Random Forest, and Support Vector Machine, were applied and compared in the traditional classifier section. SVM provided us with the highest accuracy of 92.42% among these conventional ones.

Additionally, to achieve better results, we used CNN, which resulted in an accuracy of 97.87% with a split ratio of 80:20 of 217 photos, meaning that 80% of the images were training and 20% were testing. We intend to work with 3D brain imaging in the future to segment brain tumors more effectively. In this regard, working with a larger dataset will be more difficult. and we wish to expand the scope of our work by creating a dataset that highlights the abstract in relation to our nation.

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