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Segmentation Using AI For Identifying Tumors in Brain MRI

Priya Prasad[1], Agya Mishra[2]
[1]*(Department of Electronics and Telecommunication, Jabalpur Engineering College, Jabalpur, India)*
[2]*(Department of Electronics and Telecommunication, Jabalpur Engineering College, Jabalpur, India)*
**Corresponding Author: Priya Prasad[1]*

ABSTRACT: Image segmentation is a part of image processing of MRI images. It plays a very important part in brain tumor segmentation. It is immensely helpful in abnormality check and is a matter of research. This paper reviews the different algorithms particularly used for brain tumor segmentation and proposes an intelligent model for abnormality detection in brain MRIs. Cascade CNN, Deep Wavelet Autoencoder, CNN, U-Net, HNF-Netv2 based on a combination of Distance wise attention (DWA), seeded region growing are discussed and compared based on their performance and concluded that seeded region growing along with Convolutional Neural Network (CNN) provide better result, so it will be good for the field of researchers. The results in this paper show that our technique gives a better sensitivity value than the previous models and can be effectively used to identify tumors in brain MRIs.

Keywords – Artificial Intelligence, Abnormality detection, Brain MRI Segmentation, Dice Similarity Coefficient, Intelligent Model

I. INTRODUCTION

Tumor is defined as an atypical and uncontrolled development of the tissues. An irregular tissue mass in which cells increase in an unbounded fashion, apparently unstopped by the mechanisms which supervise the usual growth of cells has been termed a brain tumor. Brain tumors are classified as primary or metastatic, and they can either be life-threatening or harmless.

Broadly, hundreds of MRI images are recorded by doctors from various angles and tumors aren't displayed in all of the brain MRIs. To cope up with the workload, doctors review three or four MRIs every second. So, a huge possibility of a tumorous MRI being left unnoticed exists. Also, manually segmenting and analyzing is very difficult and usually only done by doctors [1].

An automatic technique for segmentation of abnormality from brain MRI can support radiologists by providing important information about the position, and shape of tumors and make prognosis progress more effectively and meaningfully.

To solve this problem, a system to detect tumor in brain MRI is evolved. So, an automatic AI based algorithm is proposed which is an intelligent model and provides effective segmentation and automatically detects tumor and can provide assistance to radiologists.

Additionally, it helps in providing fast, dependable, and highly accurate analysis and helps physicians in their eventual conclusion. Moreover, neurological disorders can be timely detected which can help in the treatment of diseases such as Alzheimer's disease (AD), schizophrenia, and dementia.

Algorithms that show high value for sensitivity of segmentation are DWAE [3] and CNN [5] as they display good results which can be executed. As both of these algorithms perform better in juxtaposition with the algorithms that already exist, a combination algorithm is made in the paper to make an intelligence model that provides better sensitivity. The intelligent model is a combination of wavelet transform, convolutional neural network and seeded region growing algorithms.

1.1 CRITICAL REVIEW OF EXISTING TECHNIQUES

A qualitative comparison of image segmentation methodology is done for performance analysis.

Table-1 Comparison of various techniques for abnormality detection

S. No	Paper No.	Technique	Measurement Parameter	Advantages	Limitations
1.	[1]	Cascade CNN, Distance-wise Attention (DWA) mechanism	Dice Scores a) ET=0.9113 b) TC=0.8726 c) WT=0.9203	Less time needed for computation and overcomes overfitting problems in cascade deep learning model	1. Can't detect tumors with volume of more than $\frac{1}{3}^{rd}$ of the whole of the brain. 2. Increase in size of tumor's expected area leads to decrease in feature extraction performance.
2.	[3]	Seed growing approach for segmentation of brain tumor, Deep Wavelet Auto Encoder (DWAE) model for classification	Accuracy =99.3% Sensitivity=95.6% Specificity=96.9% Precision=97.04% Dice Similarity Coefficient (DSC)=96.55%	Can analyze large data from MRI with high accuracy	Seeded region growing technique can lead to a hole in the deduced shape
3.	[4]	HNF-Netv2	Dice Coefficients a) ET=0.878514 b) TC=0.872985 c) WT=0.924919	Provides better results as compared to HNF-Netv1	
4.	[5]	CNN	Dice Coefficients a) ET=0.812 b) TC=0.874 c) WT=0.916 Sensitivity a) ET=0.798 b) TC=0.864 c) WT=0.903 Specificity a) ET=0.823 b) TC=0.887 c) WT=0.929	Significantly better performance on smaller and more complex class in the dense multi-class segmentation task against data imbalance, global morphology of brain tumor is better recognized, tumor location and brain shape are well captured by making use of symmetric information from brain structures	Large training data required
5.	[6]	U-Net	Dice score a) BraTS 2012=0.94 b) BraTS 2019=0.87 c) BraTS 2020=0.88	Improves segmentation ability, provides high accuracy and low-cost segmentation	Learning may slow down in middle layers
6.	[9]	ANN	Precision = 92.14% Sensitivity = 89%	Filtered out non- ROI process in histogram investigation to select the correct object in brain MRI	Low precision and sensitivity

1.2 PROBLEM FORMULATION

Concluding Table 1 we find that Convolutional Neural Network is the most frequently used segmentation technique for MRI images. Wavelet transform helps in accurate feature extraction before segmentation. So, to increase the accuracy, Dice Similarity Coefficient and sensitivity of abnormality detection a combination of CNN and wavelet transform is used. Hence, the problem design of abnormality detection in MRI the intelligent model has been formulated.

1.3 TENTATIVE STEPS REQUIRED IN DESIGNING THE PROPOSED MODEL

- Retrieve input MRI images
- Design of Intelligent Model
- Performance and experimental analysis
- Comparison with existing techniques

II. SEGMENTATION USING INTELLIGENT TECHNIQUE

Grouping of pixels into segments of similar properties is image segmentation. Segmentation involves partitioning the image into its integral parts. Automatic segmentation is the most tedious task in digital image processing. A strong segmentation technique leads to efficient solutions of problems in imaging which need parts of an image to be individually identified. Frail segmentation leads to inaccuracy of the system.

Segmentation basically is the conclusion of what pixels in an image constitute the segment of interest in the image and the background.

Segmentation is basically of two types, semantic segmentation and instance segmentation. Semantic segmentation manages various objects in one particular category as one object. Contrarily, instance segmentation recognizes separate objects within the category. For segmentation of visual information, like in medical images, semantic segmentation can be very effectively applied.

The proposed intelligent model that is a modified form of CNN which has wavelet transform before the fully connected layer.

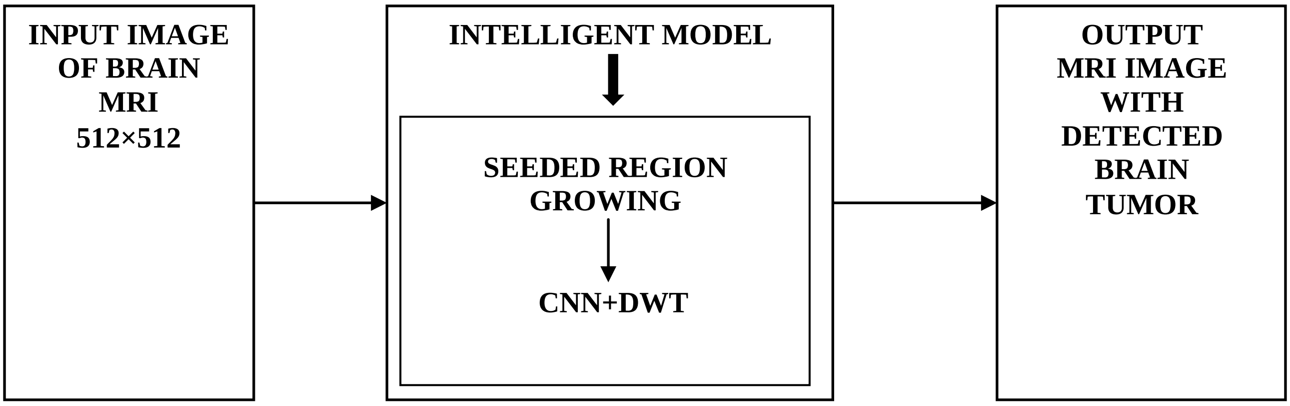


Figure 1. Block Diagram of Intelligent model

CNN extracts feature and calculates convolution and is a deep learning method that is very commonly used especially in the field of image processing. It is also used for classification as well as prediction. In image processing CNN minimizes the error between the actual label and the inference made by the model. CNN has many shortcomings such as the requirement of huge training data and the efficiency, precision and accuracy can also be improved.

So, to acquire better results CNN and wavelet transform are used. The local information of signals can be examined using wavelet transform and it also helps in better feature extraction which enhances the actual segmentation process. These are the major advantages of wavelet transform.

Scale is the guideline of wavelet function and its extension is controlled by this parameter. Upon changing the scale parameter, the information extraction ability of the wavelet transform, from the original signal can be manipulated. Adjusting translation and scale can lead to learning of various features using the wavelet transform.

So, learning of extra features can be done by the addition of wavelet transform in CNN. This intelligent model helps in improving the accuracy as well as sensitivity of the neural network.

The intelligent has three basic layers:

Input layer is the first layer where convolution is performed which is given by:

$$I[a,b] = (f * h)[a,b] = \sum_{j} \sum_{k} h[j,k] f[a-j, n-b] \qquad (1)$$

Fully connected layer is the second layer which is connected with all the neurons of the first layer. It is given by:

$$Z = W^T . I[a, b] + bias \quad (2)$$

Wavelet transform is applied before the fully connected layer for better feature extraction. It is given by:

$$\psi(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) * \varphi\left(\frac{t - b}{a}\right) \quad (3)$$

The third layer is the output layer which is given using softmax classification.

III. PROPOSED TECHNIQUE

Here the intelligent model-based system is used for effective segmentation of brain MRI images. First is the input layer. 512×512 are the dimensions of the input brain MRI. The output from the input layer is then passed onto a high pass filter with the cut-off frequency of 40Hz is used for extracting the edges and helps in reducing noise in the image. Next, the output of the HPF is segmented using seeded region growing technique. Seeded region growing helps in effective segmentation of those regions which have the same properties. Here, seeded region growing is applied using four connected regions. The output of the seeded region growing is sent into the intelligent model (CNN + wavelet transform). Then, softmax classification is used to identify if the brain MRI is tumorous or not. In case of tumorous MRI, the tumorous region is highlighted.

Algorithm for proposed system (implemented on MATLAB)

1. BraTs database is loaded
2. The database images are read using the imread function and image features are obtained using extract LBP Features
3. The features obtained from the database are stored in a variable ‘f’ which will further be used for training the intelligent model.
4. The database images are resized to 240×240 by using imresize function
5. Input MRI image is taken
6. MRI image is resized to 240×240 pixels.
7. Input image is passed through High Pass Filter.
8. Image is segmented using seeded region growing
9. Wavelet transform is applied before the fully connected layer of CNN. This is the intelligent model
10. The intelligent model is trained with the database by using trainNetwork function.
11. Output of seeded region growing is passed through intelligent model
12. Softmax classification is done to identify the presence of tumor in MRI
13. In case of tumorous MRI, the tumor is highlighted with a rectangle using ObjectAnnotation function
14. The sensitivity, DSC and accuracy are calculated.
15. The input MRI, segmented image and output image are displayed using imshow function.

IV. EXPERIMENTAL RESULTS

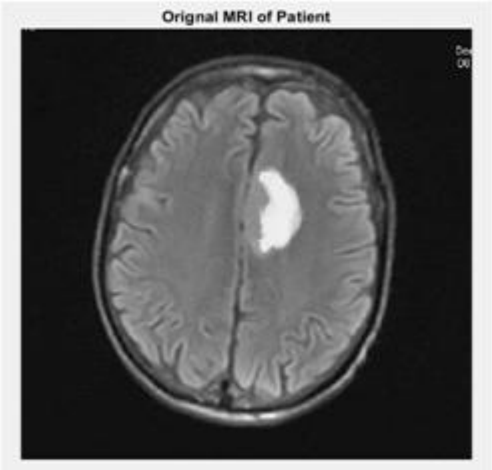
In this section the proposed intelligent model is evaluated by a couple of case studies. These case studies consider two brain MRIs.

A. Case Study I:

1) Input Image: The input brain MRI image has been resized to a standard of 512×512 pixels. The input image is shown in figure 2.

2) Segmentation Image: After passing from the HPF the image is segmented through seeded region growing algorithm which uses four connected regions. The output is then processed through the intelligent model. The segmented image, which is resized to 240×240, is shown in figure 3.

3) Softmax classification: Tumour identification in the MRI image is done using softmax classification.



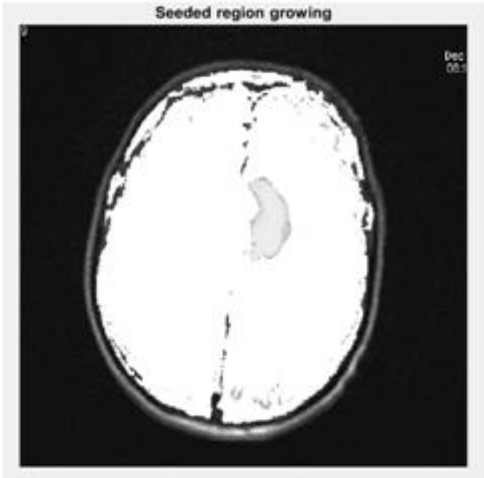


Figure 2. Image of input MRI **Figure 3. (a)Output of seeded region growing**

Figure 3. (b) Output of Intelligent Model **Figure 4. Image of detected abnormality**

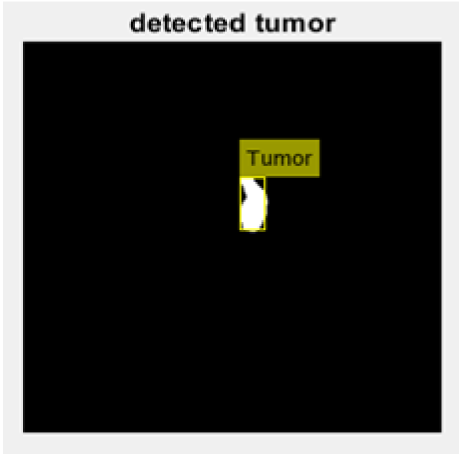


Figure 3. Segmented image

B. Case Study II:

1) Input Image: A second MRI image is taken as the input in this case. To maintain the standard, this image is also resized the same as the first image, i.e., 512×512 pixels.

2) Segmented Image: After resizing the image is sent to the HPF, the output of which is segmented using seeded region growing. Then the image is sent to the intelligent model. The segmented image is shown in Figure 6.

3) Softmax Classification: Softmax classification output which shows the detected tumor is shown in figure 7.

Figure 5. Image of input MRI **Figure 6. (a) Output of seeded region growing**

Figure 6. (b) Output of Intelligent Model

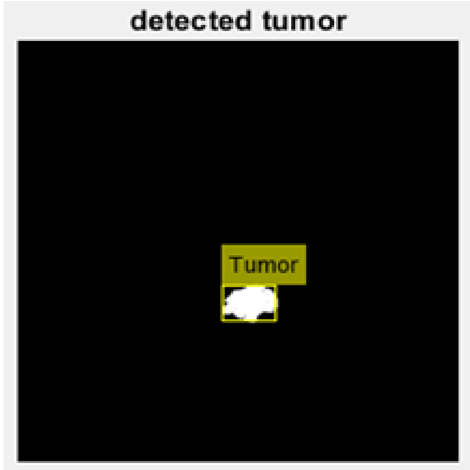


Figure 7. Image of detected abnormality

Figure 6. Segmented image

C. Comparison:

Table 2 compares the sensitivity values which are obtained with various state of the art techniques and the proposed method. Table 2 displays the results acquired which clearly indicates that the proposed model has a superior sensitivity.

Table II. Comparison with existing techniques

S. No.	Technique	Sensitivity
1.	DWA[1]	97.12%
2.	DWAE [3]	95.6%
3.	CNN[5]	90.3%
4.	Proposed Technique	98.98%

D. Measuring Parameters

Measuring parameters are sensitivity, dice similarity coefficient and accuracy. This model has achieved an accuracy of 99.44%, a dice similarity coefficient of 96.6% and a sensitivity of 99.44% which are all better than the pre-existing models.

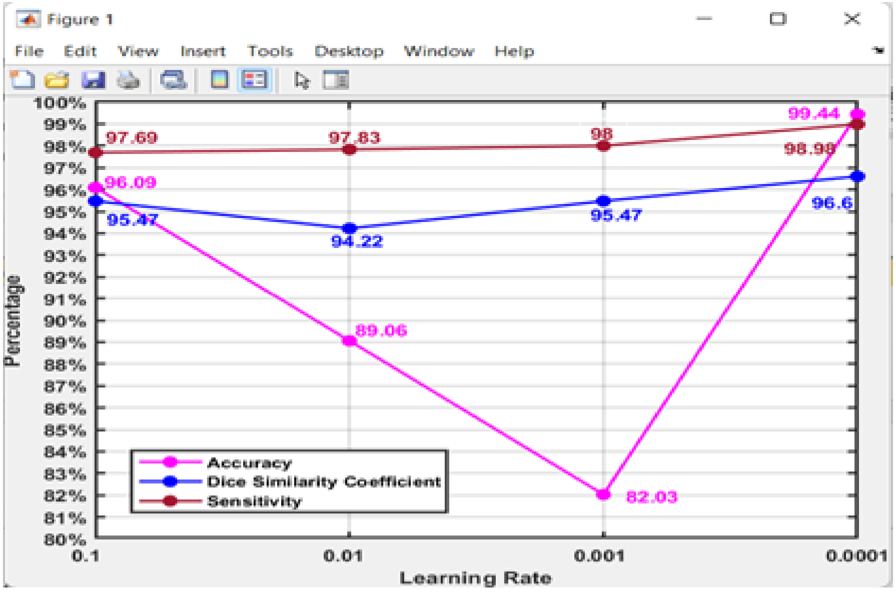


Figure 9. Learning rate vs Accuracy, DSC and Sensitivity

V. CONCLUSION

This paper concludes with the successful development of the intelligent model. The intelligent model has achieved high accuracy, sensitivity and dice similarity coefficient values. It also successfully identifies tumors in brain MRI with an accuracy of 99.44%, which indicates its fitness for practical usage. Experimental results have shown the accuracy to be 99.44%, the sensitivity to be 98.98%, the DSC to be 96.6%, which is higher than the CNN[5], seeded region growing and DWAE model[3] and hence can be successfully implemented.

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Corresponding Author: Priya Prasad[1]
[1](Department of Electronics and Telecommunication, Jabalpur Engineering College, Jabalpur, India)