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A HYBRID SEGMENTATION APPROACH FOR DETECTION OF TUMOR CELLS

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Abstract
Chronic Stress is one of the impacts of tumor formation in the human body. Radiation exposure and some family background of brain tumors are also harmful factors for tumor formation. There is no such correct explanation of what risk factors the primary tumor formation is possible. The Brain tumor is the most crucial and painful disease in the current generation. People even face difficulty in detecting the risk factors of the brain tumor. When people find a brain tumor at a starting stage, and then treating the tumor will be much easier. Before treating the tumor, they must know about every detail of the tumor, like the tumor's size, shape, and soon. They have three different ways: Machine Learning, Deep learning, and computer vision techniques. Image segmentation in computer vision is the method chosen in our proposed model. The image segmentation separates the tumor tissues from the normal tissues. A combination of Region-Growing Segmentation and threshold segmentation is used in the proposed model. Firstly, the input is taken as an MRI image of a brain tumor, and for the pre-processing, the wavelet-transform and an unsharp filter are used. Those images are used for image segmentation using the combination of region-growing Segmentation and threshold segmentation. Now, finally, do classification using CNN. Finding the accuracy, F1 score, precision, and recall for the ranking of the model. This proves that best outcome is achieved for MRI image segmentation of brain tumors.
Keywords: Region-growing, Threshold, Wavelet transform, CNN, Unsharp filter.

1. Introduction

A brain tumor is a seriously accustomed illness in mortals of all eras. The foremost cause of brain tumors is the defective development of normal cells in the brain, leading to increased production of abnormal cells. The tumor is nothing but the growth of unwanted cells in the brain. Brain tumors have two types of low-grade and high-grade tumors. Low-grade tumors are like normal cells & the maturation rate is slow. The growth rate of high-grade tumors is very high. There are several symptoms of brain tumors Frequent headaches, changes in patterns of headache, Vomiting, Vision problems, Confusion, Seizures, Hearing problems, and Getting tired. The previous papers used different techniques of image segmentation. The disadvantages are time-consuming. The selection of seed points needs to be improved in region-growing Segmentation [4]. Using the random seed points will be the problem in the seed point selection. Filters like the Gabour filter [1] are also time-consuming, and the Unsharp filter combination will reduce the time. This Unsharp filter can also increase the quality of images by reducing noise. Extracting of tumor region from the scanned image of MRI, then the severity of the disease can be defined. The BRATS 2021 dataset is the updated version of the BRATS 2020. It has more clinically checked mpMRI(multi-parametric MRI) images of glioma.

1.1. Image segmentation

Image segmentation has two types, Semantic and other is Instance Segmentation. Semantic Segmentation is used to classify the background with the objects, but in Instance Segmentation,
the division of every object and background is classified. There are different methods for doing image segmentation; they are given in below Fig 1.

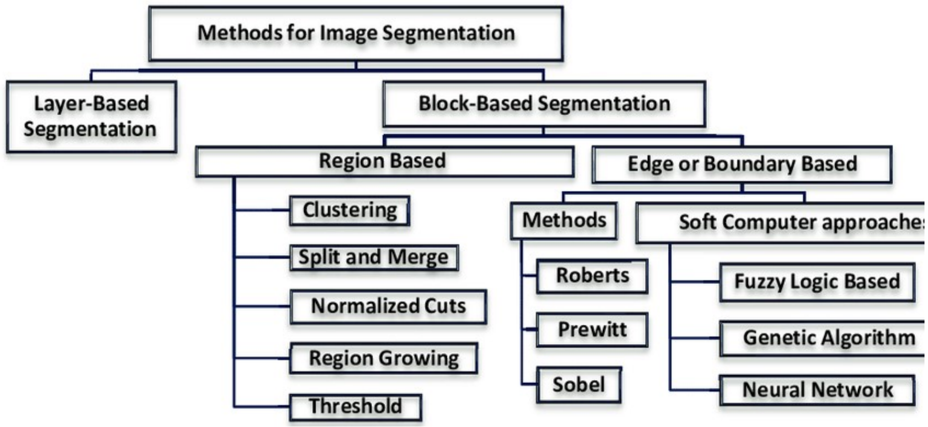

Figure 1: Methods for Image Segmentation

1.2. Layer-Based Segmentation

Layer based segmentation is a technique of image segmentation where the image partition is done based on certain criteria like colour, texture, features. The layer-based segmentation consists of colour-based segmentation, texture-based segmentation, motion-based segmentation, depth-based segmentation, semantic segmentation, Instance segmentation. It can be used in different fields like object detection etc.

1.3. Block-Based Segmentation

Block based segmentation is a technique of dividing the image into blocks and then analyse these blocks individually to find the area of interest in those blocks. This is mostly used in the computer vision applications and detection of tumour cells is about the block-based segmentation. Firstly, the image is divided into blocks and then feature extraction takes place based on the texture, intensity or based on other characteristics. Now, the segmentation algorithm will put in every block according to extracted features and post preprocessing steps can be applied to get more clear segmentation results. The region-based and edge or boundary based are the two types in block-based segmentation.

1.4. Region Based Segmentation

Region Based Segmentation is mainly divided into different classes. The division of classes are based on similarities between pixels. The segmentation will first choose one seed pixel and then grow the region based on similarity between pixels. After growing one region then it will choose another seed pixel and grow another region. This will continue until the whole image is classified into different classes.

1.5. Edge or Boundary Based

Edge or Boundary Based is used to detect edges and boundaries to divide the pixels into individual classes. This is applied using the special filters which will produce the edges in the image. Mostly used edge-based segmentation technique is Canny edge detection as it reduces the data which is to be processed.

1.6. Region Growing Segmentation

Region growing means combining pixels or small regions into larger regions. The logic behind this algorithm is the Principle of Similarity. The major drawbacks of the thresholding algorithm are that they produce isolated regions. Also, they produce isolated regions, which means processing that segmented image is required to produce a coherent region. And that is the concept of a region-growing algorithm. The similarity criteria are the Principle of similarity states that a region is coherent if all the pixels of that region are correlative. Homogeneity of regions is used as the main segmentation criterion in region growth. The choice of criteria that affects segmentation results dramatically is grey level, intensity, color, models, texture, shape, model, and soon. The steps required in this algorithm are

- Choosing of starting pixel.
- Seed growing norm.
- Termination of the segmentation process.

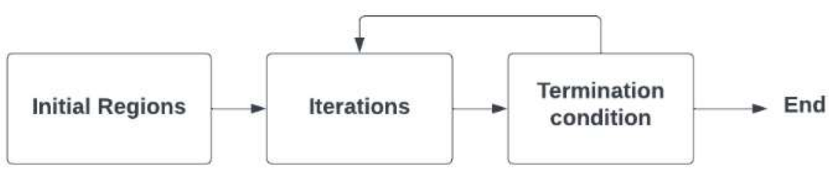

Figure 2: Major Steps in Region Growing Algorithm

The above Fig 2 tells the initial regions; pixel grouping begins with a seed region and expands by combining nearby pixels. See how to begin, how to iterate, and when to stop in an iterative process. There are two methods for growing in this area. Top-down and bottom-up approaches are both used. In the top-down approach, the predefined seed pixel must first be defined. Either way, all pixels can be designated as seed pixels or randomly selected pixels. Grow regions until they contain all of the image's pixels. Choose the seed for the bottom-up approach only from the interesting objects. Grow regions only if the similarities requirements are met. Different textures and other spatial properties, intensity differences within the region, or other factors can be used to compare grey-scale images.

While combing the pixels, consider the similarity measures which can decide whether the pixel belongs to which region and how to classify it.

1.7. Threshold Segmentation

Threshold Segmentation is a process of generating a binary image where the values of pixels either 0 or 1. Each pixel only required only one bit to store the image. In threshold segmentation, the threshold value is given according to the requirement and then if pixel intensity is more than the given threshold then it is considered as 1 or it will be considered as 0. It can only perform the threshold segmentation on grayscale images. The white colour is used for binary value 1 and black colour represents the 0 binary value.

2. Discussion

Sunil L. Bangare et al. [1] found a way the classification of normal and pathological tissues. For the classification process, they applied the following methodology: fuzzy min-max neural network. Eliminated noise from brain MRI images using the Gabor filtering technique. They also used a region-growing technique for image segmentation. They also found accuracy in the evaluation of the model. The only limitation is the Gabor filter they used takes too high time.

Bobbillapati Suneetha et al. [2] proposed a methodology to detect brain tumor in an effective manner from the segmented image. And it will also detect the tumor in the starting stage with high accuracy. They used the (OKPCM) Optimized kernel possibilistic C-means algorithm for pre-processing of MRI images. Also, they used the DW-MTM filtering technique to denoise the image. For image segmentation, they used the region-growing algorithm. They used MRI images that produced more high-quality images than other imaging modalities. They found the accuracy of the OKPCM and the region-growing algorithm to evaluate the techniques.

K.S. Angel Viji et al. [3] proposed a methodology using K-NN Classifier. The working platform of MATLAB contains the suggested MRI tissue segmentation and abnormality detection method (version 7.12). Ground truth, LBP, RGW segmentation, and ORGW images were among the inputs many images required work to be done. The automatic recognition of brain tumors using MRI technology can offer a valuable outlook and increase the precision of previous brain tumor recognition.

A.R. Kavitha et al. [4] proposed using modified region growth and neural networks to detect brain tumors in scanned images of MRI. Their process includes pre-processing, modified region growth, feature extraction from the region, and classification at the end. Our suggested image segmentation technique was applied to a dataset of MRI images that were obtained from freely available resources. The improved region-expanding technique had a higher quantity rate for all feed images. The disadvantage of this approach is the time and effort required to manually separate brain tumors from MRI images.

Neeraj Shrivastava et al. [5] reviewed the region-growing image segmentation methods in a detailed explanation. And image segmentation is the primary step for all image processing strategies. In Region-growing, we have 3 different techniques. They are split and merge, fast scanning, seeded region-growing. This review paper tells that the Seeded Region-growing is used chiefly for medical image segmentation because of its robustness and fastness. The main limitations for the region-growing are seed point selection, threshold value detection, and boundary detection.

Anjali Wadhwa et al. [6] have reviewed the different papers for brain tumor segmentation on scanned images of MRI. They also watched the combined CRF and FCNN, and CRF with the deep medic is a more practical method for Segmentation. But the only limitation is that they need to get better results for the evaluation parameters.

Table 1: Existing Techniques Analysis

S.No	Author	Algorithm Used	Demerits/Future Work	Accuracy
1.	Sunil L. Bangare	Region-growing, Gabor filtering, and fuzzy min-max neural networks	Gabour filter is a time-consuming process, having long dimensions for the feature vector.	95%
2.	Bobbillapati Suneetha, A. Jhansi Rani	k-NN classifier, genetic algorithm (GA), and optimized region growing (ORGW) segmentation optimization	OKFCM has moderate elapsed processing time.	94.5%
3.	K.S. Angel Viji, J. Jayakumari	optimized using genetic algorithm (GA), Segmentation using the k-NN classifier with optimized region growing (ORGW)	It is a time-consuming process.	93%
4.	A R Kavitha, C Chellamuthu	Region-growing, feature extraction, neural network, and Gaussian filter.	Tumors from MRI images must be manually segmented, which is difficult and time-consuming.	80%
5.	Neeraj Shrivastava, Jyoti Bharti	Seeded Region-growing	Seed point selection, Threshold value detection.	94%

3. Dataset Used for this Proposed Model

Firstly, collect the MRI (Magnetic Resonance Images) scans of brain tumors. Then use those images as our input data for training and testing our created model for the Segmentation of tumors. The BRATS 2021 has a .nii file extension used for neuroimaging. .nii is used to store large amounts of data. Clinically checked Multi-parametric MRI images of Glioma scans are there in BRATS 2021. It is the updated version of the BRATS '20.

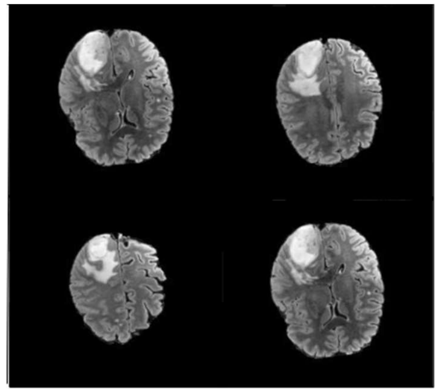

Figure 3: Dataset Images

4. Methods

The Segmentation of MRI images of brain tumors is the focus of model. For the Segmentation of scanned images of MRI, the region-growing and threshold methods are combined. To determine the extent of the tumor, it is necessary to segment the images. Then follows integrated pre-processing steps before segmenting images to remove noisy and unwanted data from the images. Then segment the images using hybrid Segmentation and then classify images. Finally, the generation of the classification report is done.

The BRATS data set is used. The data set contains brain MRI images. Before performing the Segmentation, performed pre-processing on the images. Then remove noise in the data and perform some enhancement methods to increase the clarity of images.

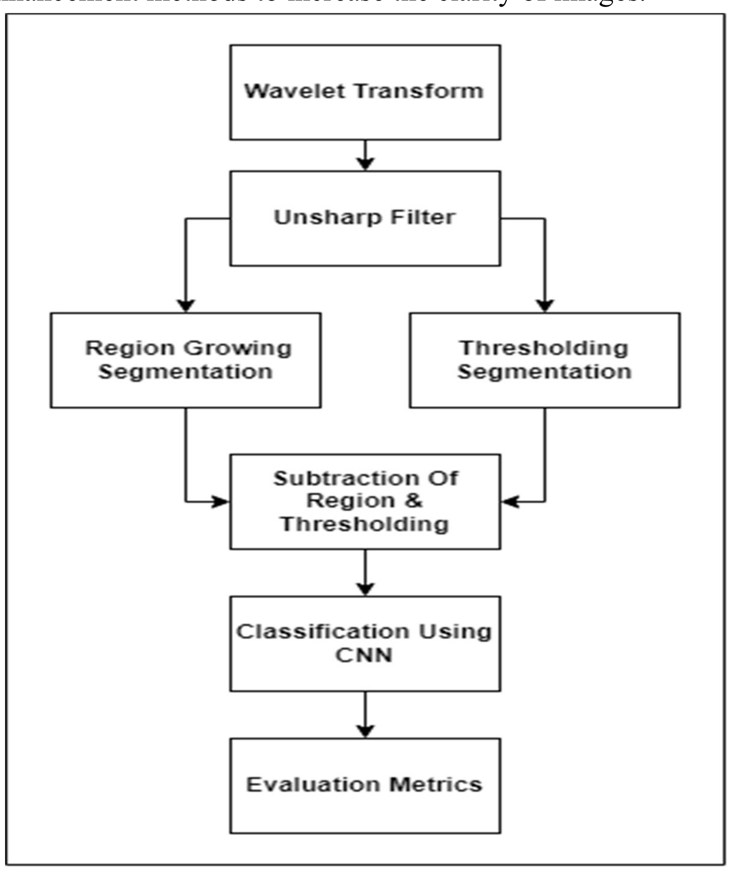

Figure 4: Proposed Model

4.1. Discrete Wavelet Transform (DWT)

Discrete Wavelet Transform (DWT) is used for the first step of pre-processing. The wavelets from the images are sampled at discrete levels. Decimation, low pass filters, and high pass filters were combined to create DWT. Low-pass filters are used to store an image's precise information, and high-pass filters are used to store the image's edges. From the two 1D transforms, get the 2D transform. The 2D transform divides the image into 4 different ways (cA, cV, cH, cD). After dividing images into subbands, use the below equation (1).

$I = I_a^1 + \{I_h^1 + I_V^1 + I_d^1\} \ - Eq(1)$

Where I_a^1 means input image. I_h^1 means horizontal details of the image. I_V^1 means vertical details of the image. I_d^1 means diagonal details of the image. Here power represents the level of decomposition.

4.2. Unsharp Filter

In unsharp filter, the output of wavelet transform is taken as input. An unsharp filter is the best filtering method for the removal of noisy data in the images. It can produce more accurate results in the segmentation method. It increases the contrast of the image. It also detects the edges and sharpens them in the output of the image.

$$\text{Unsharp image} = \text{Real image} + \text{Amount} \times (\text{Real image} - \text{Blurred image}) - \text{Eq}(2)$$

4.3. Region growing and Thresholding Segmentation

Image segmentation used the new technique by subtracting the results of two different image segmentation techniques. The techniques used are Region Growing and then Thresholding segmentation. Region growing is used to grow the pixels with similar features and give some color to that region. The output is the different regions along with the tumor region for region growing and using the results of threshold then got the region of brain tumor.

Input: Pre-processed Images are given as input.

Output: Segmented Images of brain tumor.

Algorithm for Hybrid Image Segmentation:

```
Begin
Create Stack
If Stack is full
        Return
End if
Else
        Increment top
        Stack[top] assign Pixels of Pre-processed images
End else
X ← Random.randint(0, length (Stack))
Seed Pixel ← Stack[x] and Set as Visited
While Top = -1
        Pop (Stack[X])
        For Initialize i from 0 to length (Stack)
```

Point $\leftarrow$ Stack[i]
Euclidean Measure $\leftarrow$ $((c_1 - c_2)^2 + (d1 - d2)^2)^{1/2}$
Where Point = (c_1, d_1)
Seed Pixel = (c_2, d_2) are pixels of the image.
If Euclidean Measure < Threshold:
Add that point to the region
End if
Increment i value
End For
Add the Neighboring Unvisited Pixels Stack

End While
New image $\leftarrow$ Blurred (Pre-processed Image) < 0.8
Load the Region List Image and New Image
Return Subtract (Region List Image, New Image)
End

4.4. Classification Using CNN

Classification is done using CNN (Convolutional Neural Networks) and used to classify using the segments of images. CNN, pass the image into multiple layers and find the similarity between images. This CNN used the 3 layers. Fully connected layers, Relu layers, Convolutional layers, and pooling layers. Then follow some steps first to upload the dataset. Then split the dataset into train & test datasets. Then send it into layers of the CNN. This used mainly 5 layers of CNN. Conv2D, MaxPool2D, Dropout, Flatten, and Dense layers can be observed in below Fig 5. From the multi-colored image, the Conv2D will convert into a single-colored image by extracting the necessary features and leaving the remaining ones. Using MaxPool2D, the extraction of maxing value from the feature map, sharpens the edges more than the previous image. While sending the image to the next layer, only some necessary things are sent, which makes the unnecessary things null. Flatten layer is used to convert the long 2D dimensional array into one prolonged continuous linear array. The last layer used is the dense layer for converting the images based on the output of convolutional layers. The Relu activation function is used, often applied function and default one in CNN. Another activation function used is softmax [11].

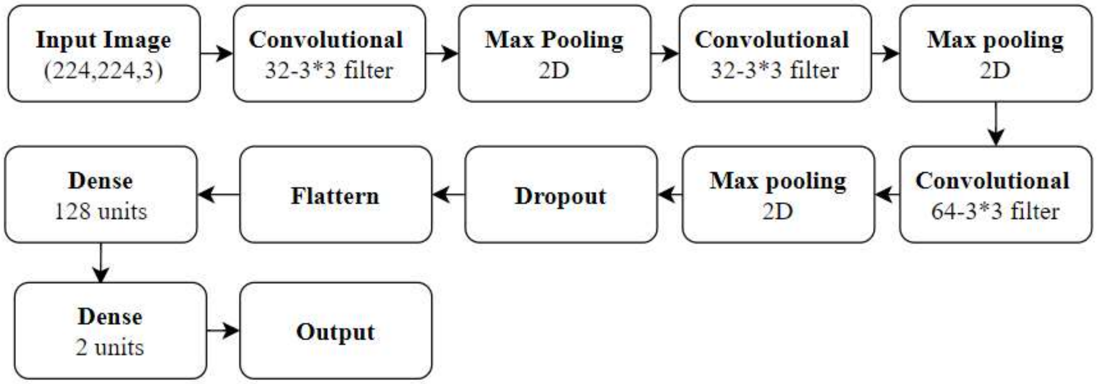

Figure 5: Classification using CNN

The above image consists of different layers of CNN. The first layer is Convolutional layer which is used to extract the features of input image. In that 3*3 filter is used to perform convolution operation, the dot product is taken for some parts of input image and filter used. The output extracted is a feature map which will tell us about the image features. The next layer is Pooling layer, main aim is to reduce the size of feature map which is produced in convolutional layer which leads to reduce the cost of computation. It reduces the features produced by convolutional layer. Pooling has 2 types max pooling and average pooling. The max pooling layer takes the maximum element in the feature map. In Dropout layer helps to remove neurons which can cause the problems of overfitting during training. Flatten layer is an important component as it makes model to learn the complex patterns and do the predictions from that. Dense layer is the simplest layer in the CNN as it is used to classify the image based on output.

5. Results & Discussion

After performing pre-processing, got the images with sharp edges and without noise in the images. The difference is observed between the previous images and pre-processed images in the below Fig a and Fig b in Pre-processing images of Fig 6. The clarity is there in the pre-processed images compared to the original images. Sharpening the edges of images will give more clarity to separate the regions. By removing the noise image increases in terms of quality.

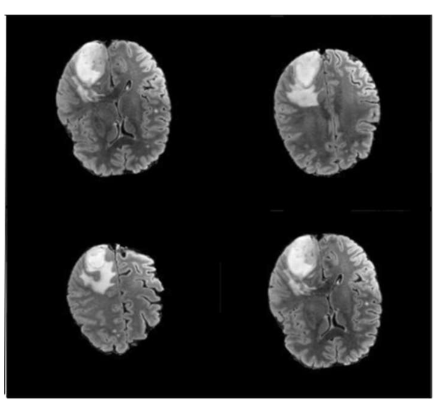

Fig a: Before Pre-processing

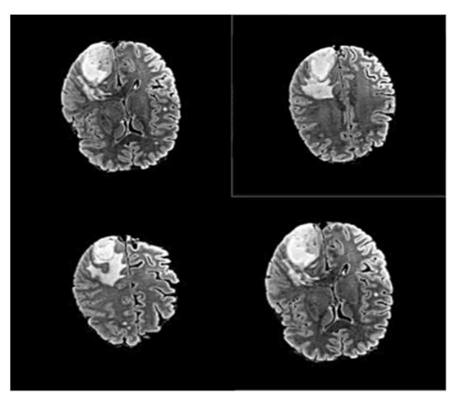

Fig b: After Pre-processing

Figure 6: Pre-processing Images

The below figures can tell the difference between before segmentation Fig a and after segmentation Fig b in Segmented Images Fig 6. Now, proposed a new technique in image-segmentation of tumors in brain. Used subtraction operation on the results of the Threshold from the region growing. And then saved those images for the classification process. The black of the images represents the tumor in Fig 9. At present, only extraction of the tumor is done. With this extraction, the estimation of severity will become easy. In the future, expansion of this technique can be used to classify the types of tumors and find at which stage the tumor is there. The pixel similarity calculation can also be improved.

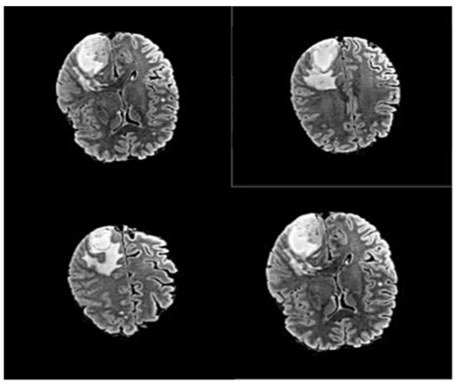

Fig a: Before Segmentation

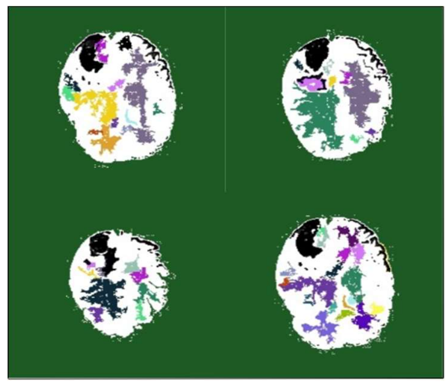

Fig b: After Segmentation

Figure 7: Segmented Images

The layers used in CNN model is showed in the Fig 8 below. In those the convolutional, pooling, dense, flatten, dropout layers are used. It shows the output shape and the parameters used.

```
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_24 (Conv2D)          (None, 224, 224, 32)      896

 max_pooling2d_24 (MaxPoolin  (None, 112, 112, 32)     0
 g2D)

 conv2d_25 (Conv2D)          (None, 112, 112, 32)      9248

 max_pooling2d_25 (MaxPoolin  (None, 56, 56, 32)       0
 g2D)

 conv2d_26 (Conv2D)          (None, 56, 56, 64)        18496

 max_pooling2d_26 (MaxPoolin  (None, 28, 28, 64)       0
 g2D)

 dropout_8 (Dropout)         (None, 28, 28, 64)        0

 flatten_8 (Flatten)         (None, 50176)             0

 dense_16 (Dense)            (None, 128)               6422656

 dense_17 (Dense)            (None, 2)                 258

=================================================================
Total params: 6,451,554
Trainable params: 6,451,554
Non-trainable params: 0
_________________________________________________________________
```

Figure 8: Model Summary

Evaluation metrics such as accuracy, F1 score, recall, and precision were used in the model evaluation process. Accuracy is calculated as the ratio of correctly predicted observations to all observations. The percentage of correctly predicted positive cases out of the total number of predicted positive cases determines how precision is calculated. The percentage of correctly predicted positive cases among all cases is used to calculate the recall. The result F1 is the harmonic mean of precision and recall. These metrics can be calculated using a confusion matrix that has four characteristics. True positive (TP), true negative (TN), false negative (FN), and false positive (FP). These four items can help you measure by calculating the evaluation metrics, which show the results in Table 2 below and uses the following formulas to calculate the values in the Table 2 below.

$$Precision = \frac{TP}{TP + FP} - \text{Eq}(3)$$

$$Recall = \frac{TP}{TP + FN} - \text{Eq}(4)$$

$$F1\ score = \frac{2 * precision * recall}{precision + recall} - \text{Eq}(5)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} - \text{Eq}(6)$$

Table 2: Classification Report

Classification Report	Precision	Recall	F1-score	Support
Tumor (class 0)	98.0	0.99	0.84	32
Non-Tumor (class 1)	2.00	0.01	0.16	12
Accuracy			0.73	44
Macro avg	0.36	0.50	0.42	44
Weighted avg	0.53	0.73	0.61	44

Different Techniques are previously used in the existing models. In those techniques, some valuable techniques are chosen in our technique. But there are some difficulties they faced, like low accuracy, and this difficulty can be achieved by this Hybrid Segmentation. This model aims to escalate the accuracy of the segmented region. Finally, this is achieved by our technique, and it is observed in the following Table 3 and Fig 8 below.

Table 3: Comparison of the Existing Model with Our Model

S.No	Author	Accuracy	Precision	Recall	F1-score
1	Region Growing with Fuzzy min-max Neural Network	95%	94	93	83
2	Region Growing with DW-MTM	94.5%	95	92	75
3	Optimized Region Growing	93%	93	90	79
4	Modified Region Growing	80%	90	89	82
5	Automated Region Growing	94%	92	91	77
6	Hybrid Segmentation	98%	98	99	84

In Fig 9, it shows the precision comparison. In Fig 10, It shows the Recall comparison. In Fig 11, It shows the F1-score comparison. In Fig 12, the Hybrid Segmentation achieved greater accuracy than other existing techniques. The x-axis is the representative of Methodology, and the y-axis is the representative of accuracy. This bar graph can explain the benefits of our model.

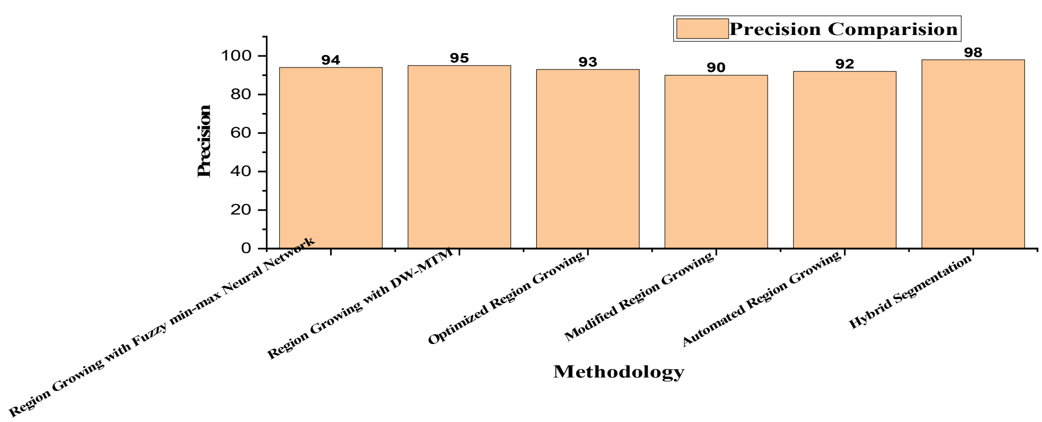

Figure 9: Graph for precision comparison of existing systems and proposed system

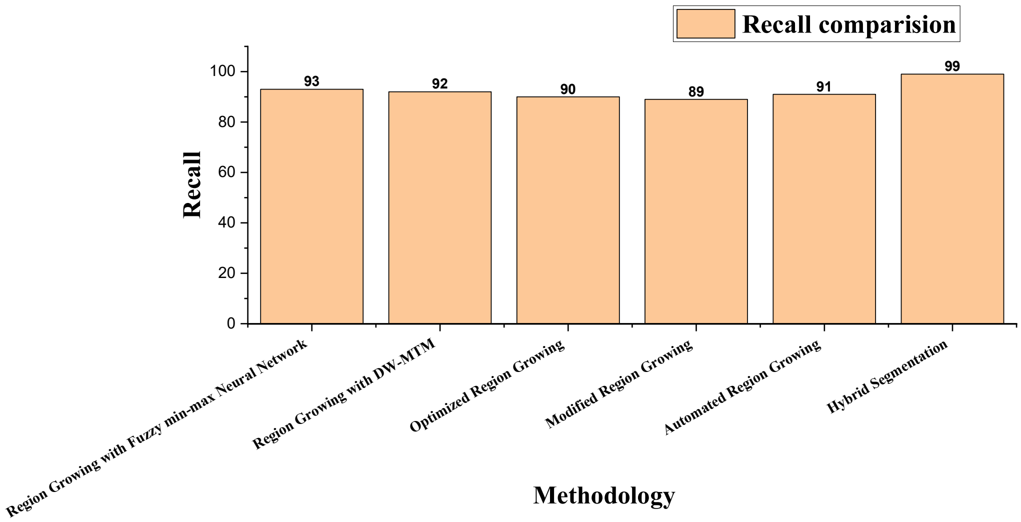

Figure 10: Graph for recall comparison of existing systems and proposed system

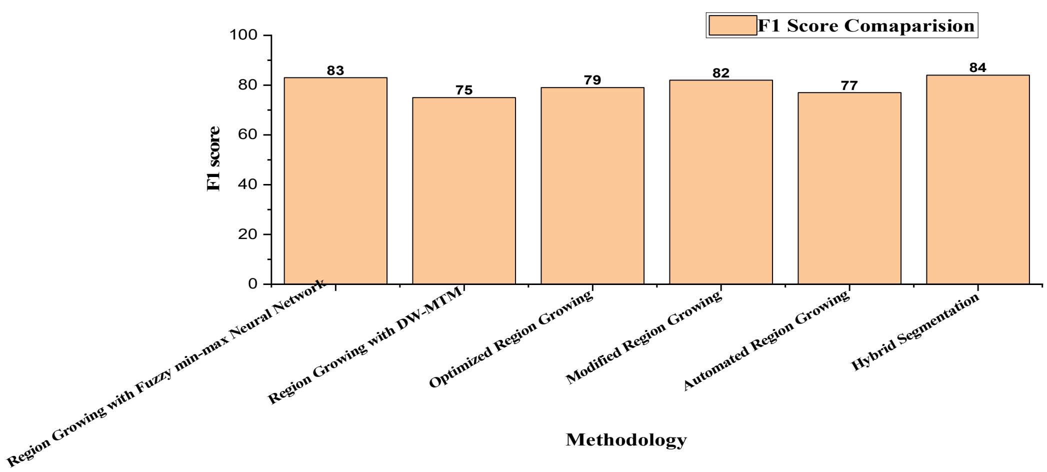

Figure 11: Graph for f1-score comparison of existing systems and proposed system

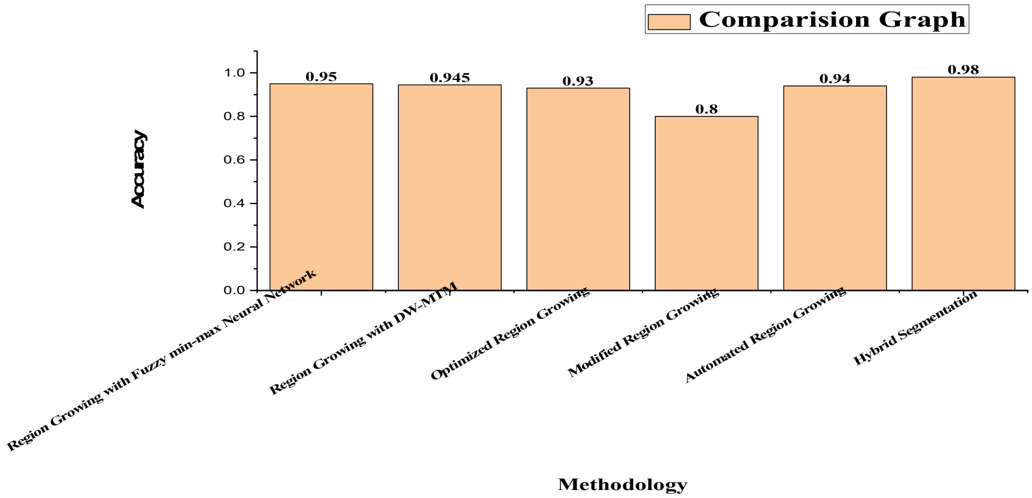

Figure 12: Graph for accuracy comparison of existing systems and proposed system

6. Conclusion

The focus of the paper is the Segmentation of images of brain tumors. They used a dataset of brain tumor MRI images and various operations to separate the tumor from the images. For the pre-processing, the wavelet-transform and unsharp filter were used to remove noise. Combining the region-growing and threshold segmentation techniques is a novel approach to image segmentation. Following that, CNN is used to classify the segmented images and used 300 epochs to run the algorithm on the dataset. Finally, the model's accuracy after construction is 98%. Find a more precise method for the Segmentation of images of brain tumors in the future.

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