# A Novel Brain Tumor Detection Method using DWT and Clustering Techniques from T2-Weighted Brain MRI Images

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***Abstract***

*Manual segmentation is time consuming process and increases the false finding rate thereby the segmentation becomes inefficient and accuracy of the detection method becomes poor. Automatic tumor detection methods can overcome such problems. This paper describes a novel method for brain tumor detection from MRI images using hybrid DWT and fuzzy C means technique and support vector machine classifier. Our proposed system consists of four stages. Stage 1 is preprocessing, stage 2 is segmentation, stage 3 is feature extraction and stage 4 is classification. In the first stage the images are acquired and enhanced the quality by removing the noise by median filtering technique and in the second stage the discrete wavelet transform ad fuzzy c means techniques partitioned the images to identify the abnormal part. The identified tumor part is extracted and classified in stage three and four respectively. And at final, calculated the performance parameters of the brain MRI images and compared with existing techniques. The proposed method is robust, efficient and fast computing technique comparing with existing methods.*

***Keywords:*** *Brain tumor, T2-Weighted MRI images, Segmentation, GLCM, Classification, SVM*

## 1. Introduction

Now-a-days people thought-out the world affected with one or other types of cancer. One of the major causes of increment in mortality is brain tumor, in all over the world. Brain tumor is an uncontrollable growth of abnormal tissues. Brain tumor is classified as benign and malignant. The benign is noncancerous but malignant is cancerous, rapid growing of active cancer cells [1]. However, the World Health Organization (WHO) categorization is chosen as standard classification in the medical field. According to WHO, there are 120 types of tumors in brain and 20 major categories and sub categories .WHO has allocate grades to each tumor type based on tumor growth rate. The four grades as per classification of WHO for brain tumor is listed below: Grade I: This type of brain tumor has been growing very slowly; Grade II: This type of tumor in the brain has been fast in growth rate, Grade III- has been faster growing, it means growth rate of abnormal cells is greater than grade II, and Grade IV - fastest growing of abnormal cells [2]. This more aggressive in nature, sometimes it causes to sudden dismissal of human or leads to unconscious state.

Early recognition of brain tumor increases the lifespan of patients as possible in terms of quality. There are different screening modalities to imprison the tumor in brain such as magnetic resonance imaging (MRI) and computed tomography (CT) are popularly used modalities [3]. Comparing to CT, the MRI provides exceptional contrast for different tissues in brain. And also MRI is very less radiation effect and harmless to the highly sensible parts of brain and other parts in brain. MRI imaging produces different pulse sequences of brain images such as T1-weighted (T1-W), T2-weighted (T2-W) and proton density (PD) based on contrast levels. Among these, T2-W pulse sequences of brain MRI images having good contrast levels to clear visualization of the different tissues such as white matter (WM), gray matter (GM), cerebrospinal fluid (CSF) and tumor which are lodged in brain tumor images of normal and abnormal category [4]. So we are focusing and working on T2-W MRI images of brain tumor. Currently there are many segmentation techniques available to make partition and identify the tumor from brain T2-W MRI images such as thresholding based methods, histogram based methods, edge detection based methods, cluster based methods and hybrid methods (combining more than one technique)[5-6].

Anam and Ali [7] proposed brain tumor detection by using thresholding and watershed algorithm based segmentation methods. Those methods detect tumor from MRI images but the performance characteristics has not determined. P.Sharma et al [8] proposed watershed and morphological methods to segment the brain tumor and compared with edge detection method. The main problem of watershed method is resulting over segmentation. So this makes unnecessary portion as tumor leads misclassification. Region growing method proposed by H.Hooda et al [9] can correctly separate the regions, and its performance is excellent with respect to noise. But the region growing technique requires seed point which can be selected manually and removes all the pixels which are connected to the seed point, it is very much sensitive to noise. S.T.Kamble et al [10] and A.A.Wankhade [11] presents K-means clustering technique for detection of tumor from human brain MRI images. The common drawback of the above existing methods is less accuracy and not much efficient. In this research work, we proposed a hybrid method using discrete wavelet transform and fuzzy c means.

The steps in this work are: 1) initially read the input MR images, 2) to enhance the contrast of brain MR images the median filter technique is used to adjust intensity levels and eliminate high frequencies and improve the visual quality of input image, 3) DWT algorithm to segment the image and reduce the computational complexity, 4) Fuzzy c-means clustering and can improve the segmented results in less time consumption and with high accuracy, 5) the GLCM and extracts the features, 6) SVM classifier decides the tumor is cancerous or not. The structure of this article has arranged as follows. In section II, the methods and materials are presented. The hybrid DWT and FCM techniques used for segmentation of brain image are explained in section III. In section IV the results are presented and discussed. Finally, the conclusion and scope for future are presented in section V.

## 2. METHODS AND MATERIALS

In this section, we present the materials and the methodology which is used to detect brain tumor from T2-W brain MRI images using DWT and fuzzy clustering. The block diagram as shown in figure 1 gives the process flow and different stages of identification and extraction of tumor from brain MRI images. The steps and various algorithms involved in the proposed methodology have been discussed in the following subsections.

### 2.1 Image Acquisition and Preprocessing

The proposed work used T2-weighted brain MR images. These images acquired from websites which having publically available datasets such as BrainWeb [12], Harvard Medical School [13] and real patient images. To improve the signal-to-noise ratio, we applied median filter to the images as a preprocessing step. This nonlinear filter smoothes the internal part of the regions and preserve the edges and degrades the noise. The median filtering is widely used denoising technique used to improve the quality of a brain MRI image by removing high frequency components without disturbing the edges. T2-weighted MR image is chosen as the reference image.

### 2.2 Segmentation

Once the image is pre-processed by filtering, the noise is removed. This will be helpful to extract the pixels which are connected. Partition the image into segments is called segmentation. It is the most important task in medical imaging. Here the DWT and fuzzy C means are the segmentation techniques used to segment the MRI images of human brain. The details of the segmentation using these DWT and FCM are explained in section III.

### 2.3 Feature Extraction

The useful features of the segmented images are extracted for classification purpose and analyse the characteristics of the extracted tumor. This is becomes a challenging task to extract good feature set for classification. In this study, the feature extraction of T2-W brain MRI images is obtained using gray level co-occurrence matrix (GLCM). The GLCM has used to determine the spatial information and distribution of neighbour pixels. The GLCM has powerful features, though time consuming. Contrast, correlation, homogeneity, entropy and energy are the features determined by using this GLCM technique. Other features also determine in this study such as PSNR, MSE, segmentation accuracy, sensitivity, specificity, tumor size in terms of pixels and area and time required to classify the tumor.

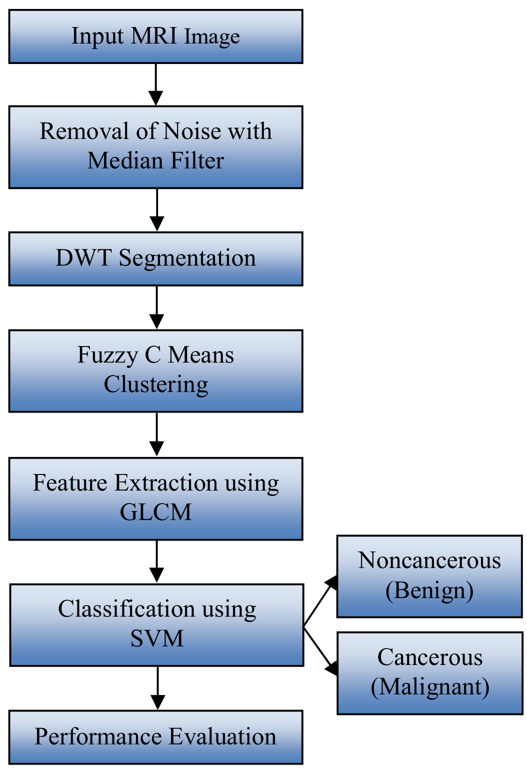


Fig.1. Block diagram of hybrid DWT and FCM segmentation

### 2.4 Classification

Classification is a technique which is used to classify the output obtained from the feature extraction stage. The classification classifies the features into the proper class. The support vector machine (SVM) is the best binary classifier for brain tumor detection. SVM did not depend on any dimension or feature set. It changes the higher dimensional information into nonlinear map function by conducting the new hyper plane with maximum margin from training dataset.

Steps occupied in the development of the proposed work:

1. Read the input T2-weighted brain MRI image.
2. Resize the input image into 256x256 sizes.
3. If the image is in color, then convert it to gray scale.
4. The image has filtered by using Median filter which is used to eliminate the noise from the gray scale image so as to make image is smoother and preserve the edges.
5. Discrete wavelet transform segment the image into different levels. Various levels in the wavelets produced various resolution which is matched to their scale and analyzed at various levels.
6. Apply LL sub-image as input to next step.
7. Fuzzy C means technique makes partition and divided into different sub images using number of predefined initial parameters like number of iterations and number of cluster levels etc.
8. Apply the gray level co-occurrence matrix to find different features which are used for the performance evaluation.
9. Classifies the image is having tumor or not.
10. Calculate the area (size) of the tumor in terms of $mm^2$ and number of pixels occupied by tumor. And specified the tumor is benign (noncancerous) or malignant (cancerous).
11. Compared the different performance parameters of the different brain tumor images.

## 3. DWT AND FCM TECHNIQUES

### 3.1 Discrete Wavelet Transform: Haar DWT

The discrete wavelet transform (DWT) is an incredibly helpful implementation for analysis of signal processing and image processing. The DWT is essentially useful in multi-resolution illustration. This can be capable of decompose the signal or data into various components. This process occurs in the domain of frequency. One-dimensional DWT (1-D DWT) decompose an input series of data (here the enhanced image by median filter is taken as input to the DWT). There are two components in the 1D DWT, one is average component, and other one is detail component. These can be the calculations obtained by a LPF (low pass filter) and a HPF (high-pass filter). Two dimensional DWT (2-D DWT) makes the decomposing by taking input image data (here also the enhanced image by median filter is taken as input to the DWT) and converts it into four sub-bands such as one average component (LL) and three detail components (LH, HL, HH) as shown in Figure 2.

| | |
|---|---|
| LL | HL |
| LH | HH |

Fig.2 Two-Dimensional DWT decomposition results

In the image processing applications, the multi-resolution of 2-D DWT has been utilized to identify the edges of the original image. The conventional edge recognition filters can offer the similar result as well. The 2-D DWT can identify three varieties of edges at a time but the traditional edge recognition filters cannot. The processing times of the 2-D DWT is greater than conventional edge detection filters.

Three types of edges are present in the detail component sub-bands but look unobvious (very small coefficients). Specifically, the DWT filters which made by Haar DWT, the edges are detected in very less period. It means that the computational complexity using Harr transform is very less. The operations in the Haar DWT are very simpler than that of any other wavelets. This transform can be applied in many of the image processing applications, for example; multi-resolution representation.

The Haar DWT components of an image, we can find various characteristics regarding the image as follows:

1) LL sub-band: it has detected the average components;
2) HL sub-band: it has detected the vertical edges;
3) LH sub-band: it has detected the horizontal edges;
4) HH sub-band: it has detected the diagonal edges.

*Some of the significant features of Harr DWT are as following:*

a. Haar wavelets are real, symmetric, and orthogonal.
b. They have simple boundary conditions while compare with other wavelet based techniques.
c. The arbitrary spatial grid intervals are allowed by minimum support property.
d. They used for analyzing the texture and identify the edges of the characters.
e. The two coefficients of high-pass and the low-pass filters are simple. They are either 1 or –1.

**3.2 Fuzzy C Means Clustering**

Clustering means it organizes the items into -group in this criteria, Fuzzy c-means algorithm clusters more than one group, it does not cluster absolute member of point where us it calculate degree of membership(like hood) which belongs the point that gathered cluster and the number of iteration complete by FCM algorithm. Accuracy calculated by degree of membership from iteration to next with all data points with thresholding parameter.

$u_{ij}$:$x_i$'s degree of membership in $j^{th}$ cluster,: $x_i$ it is the $i^{th}$ data, $c_j$: it is the $j^{th}$ center of the cluster, $m$: fuzziness exponent; it is any real number than 1. For any data point, summation of membership for all clusters should be equal to 1.

The cluster center can be selected in randomly.

i. $U = \left[u_{ij}\right]$ matrix, $U^{(0)}$ is initialized by the following equation

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_k\right\|}\right)^{\frac{2}{m-1}}} \tag{1}$$

ii. Calculate $C(k)=\left[c_j\right]$, centers vectors at $k^{th}$ step.

iii. Update $U^{(k)}$, now $U^{(k+1)}$

$$u_{ij}=\frac{1}{\sum_{k=1}^{c}\left(\frac{\left\|x_i-c_j\right\|}{\left\|x_i-c_k\right\|}\right)^{\frac{2}{m-1}}} \tag{2}$$

iv. End when minimum $j$ is accomplished or $\left\|U^{(k+1)}-U^{(k)}\right\|<\varepsilon$ ; otherwise go to step 3.

At final, the membership matrix has taken and each pixel will move about to the cluster for which has the highest probability of belonging. And the clustered or segmented image has obtained.

## 4. Results and Discussion

The proposed research work is performed and trained on MATLAB R2016a using the image processing toolboxes and running under Windows 8.1 on Intel Core i3-5005U processor with speed of 2.00 GHz and installed memory (RAM) is 4GB. The proposed approach has applied to the dataset which contains T2-W MR images. The performance of the proposed system is evaluated by various performance metrics and the results obtained at each step are discussed in this section.

All the images were in gray color with intensity ranging from 0 to 255. The input images are acquired from publically available datasets which are Harvard and BrainWeb datasets. It contains different pulse sequences of MRI images of human brain such as T1-W, T2-W and PD with different noise levels. The figure 3(a) shows some of the T2-weighted input MRI images acquired from databases and figure 3(b) shows the pre-processed by median filter which enhanced the input images by removing the noise and preserve the edges of the brain images by restricting the high frequency components. The figure 3(c) shows the decomposition using Haar DWT (2-D). The wavelet decomposed sub-band LL is segmented by using the application of FCM clustering on the images shown in figure 3(d). The brain image is partitioned into four clusters such as white matter, gray matter, cerebrospinal fluid and last cluster represents brain tumor as shown in figure 3(e).

In this work we determined different performance evaluation parameters which makes the proposed technique is efficient to detect brain tumor. And they are tabulated as shown in table 1.

Table 1: Comparison of statistical parameters.

| Image Name | Specificity | Accuracy | MSE | PSNR | No of defected cells | Tumor Area | Elapsed Time (sec) |
|---|---|---|---|---|---|---|---|
| 1 | 73.8554 | 73.846 | 12.9975 | 36.9922 | 1824 | 11.275 | 125 |
| 2 | 73.3664 | 75.330 | 11.0271 | 37.7062 | 1598 | 10.553 | 118 |
| 3 | 77.3228 | 77.279 | 11.7665 | 37.4243 | 1111 | 8.7696 | 132 |
| 4 | 78.6517 | 78.022 | 13.8654 | 36.7115 | 658 | 6.7720 | 106 |

The performance measure use four techniques such as 1) true positive (TP), specifies perfect classification of tumor; 2) false positive (FP), indicates normal portion of the tissue as tumor; 3) false negative (FN), represents tumor part as normal; and 4) true negative (TN), provides perfect classification of normal part in brain. Using the above four values, determined the various parameters as presented in below equations:

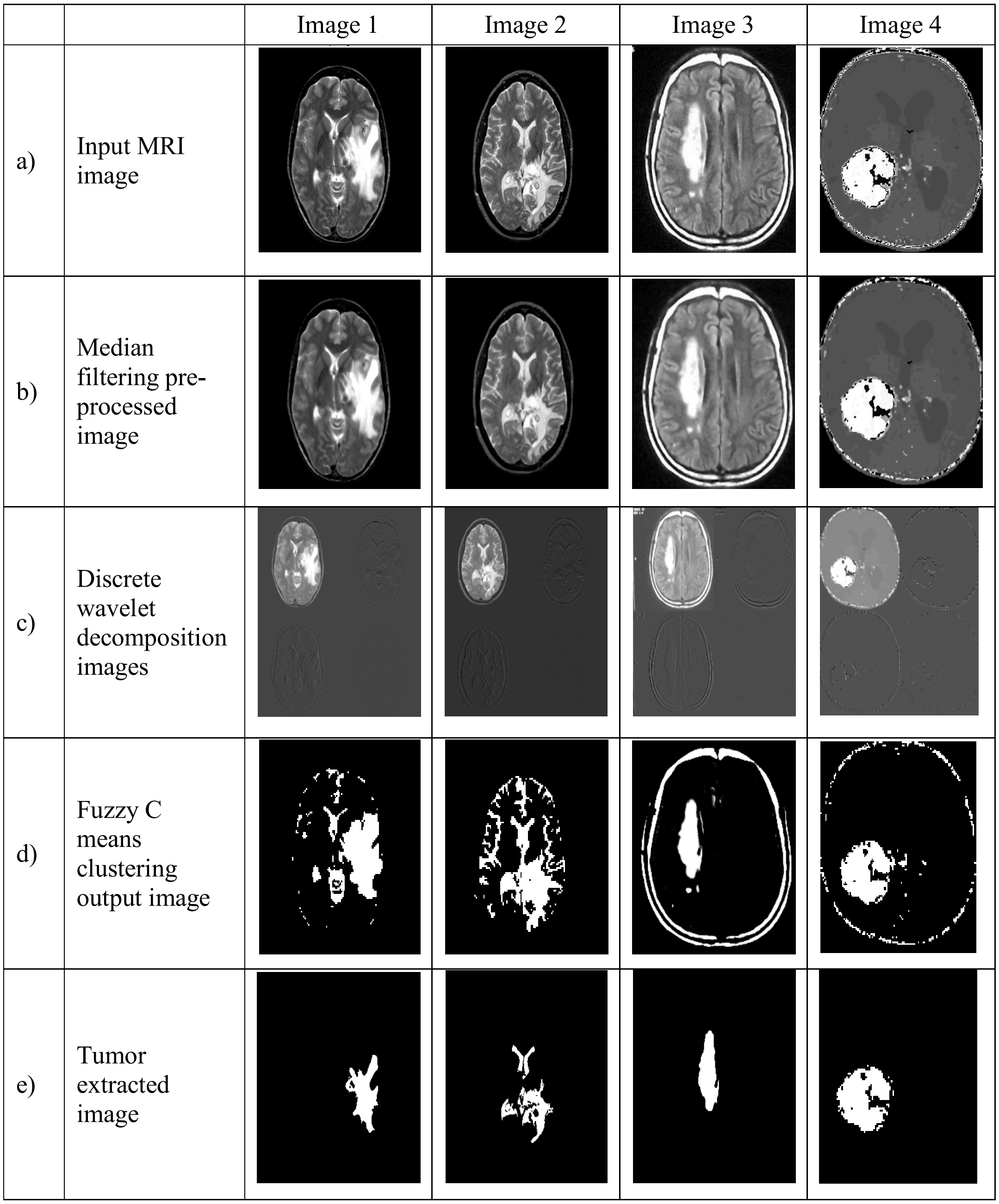


Fig.3. Different stages in brain tumor detection.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{4}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$\text{MSE} = \frac{1}{P \times Q} \sum \sum \left[ f(i,j) - f^{R}(i,j) \right]^2 \tag{6}$$

$$\text{PSNR} = 10\log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 20\log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \quad (7)$$

Table 2 gives the comparison with the existing segmentation techniques. It shows that the proposed method is efficient to detect the tumor by concerning the performance parameters. The PSNR value and accuracy of our proposed method is greater than the existing techniques while the MSE is lesser than other techniques. The efficiency of the method is confined when the PSNR and accuracy is more and MSE is lesser. So our method is efficient to extract tumor from brain MRI image.

Table 2: Comparison of existing and proposed methods.

| Technique | MSE | PSNR | Accuracy |
|---|---|---|---|
| Watershed [7] | 108.53 | 27.7974 | 53.1593 |
| Region growing[10] | 87.052 | 28.7332 | 56.5403 |
| K-Means[9] | 50.575 | 31.1218 | 62.3695 |
| Proposed method | 12.132 | 37.2925 | 78.0220 |

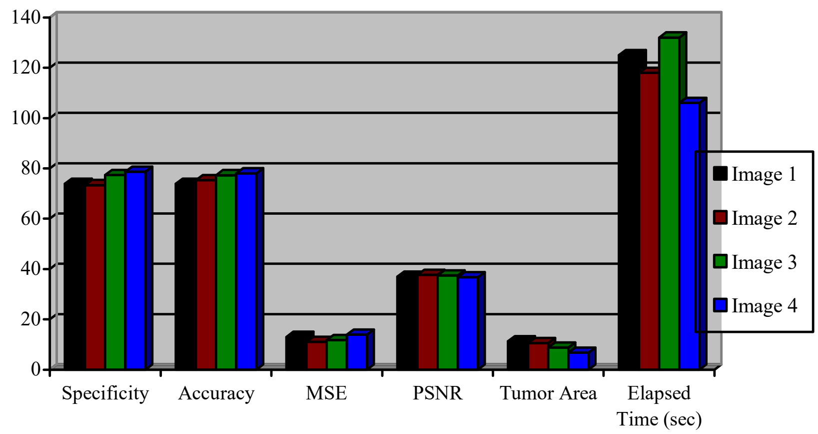


Fig.4. Graphical comparison of different statistical values for four images

Table 3: Comparison of existing and proposed methods.

| | MSE | PSNR | Accuracy |
|---|---|---|---|
| Watershed [7] | 108.53 | 27.7974 | 53.1593 |
| Region growing[10] | 87.052 | 28.7332 | 56.5403 |
| K-Means[9] | 50.575 | 31.1218 | 62.3695 |
| Proposed method | 12.132 | 37.2925 | 78.0220 |

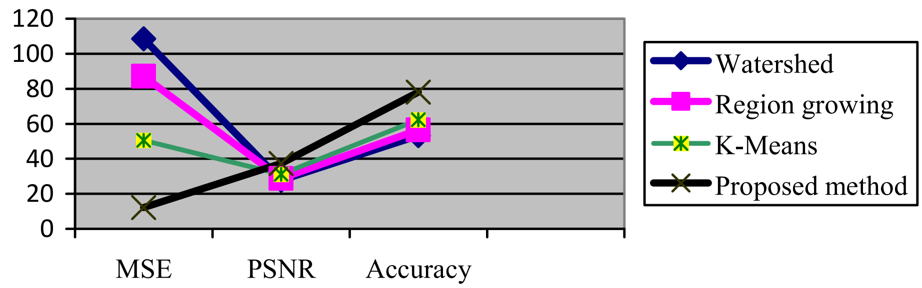


Fig.5. Graphical comparison of proposed technique with existing techniques

## 5. Conclusion and Feature work

In this letter, discussed the preprocessing and post processing steps in brain tumor detection using wavelet and clustering based technique. In preprocessing the image acquisition and enhancement has been discussed. In these stages the MRI brain image has been obtained and reduced the noise using median filter which is helpful for further post processing steps. In the post processing the segmentation has been performed by Haar DWT and FCM clustering, which partition the image and separate the tissues in the brain. The feature extraction and classification has been employed by GLCM algorithm and SVM classifier respectively. The binary classifier classified the tumor kind and finally the characteristics and the features are determined and tabulated. Also the parameters such as accuracy, sensitivity, specificity are compared with existing segmentations. This methodology is also gives fast segmentation results as the false finding rate is less and accuracy is more. Thus the proposed approach of detection of tumor from brain MRI images is efficient, accurate, fast and robust. The future works focus on increase the segmentation accuracy and reduce the false rate. The optimization techniques may reduce the false rate and increase the accuracy.

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