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REGRESSIVE NONLINEAR TEAGER FILTER BASED MAP ESTIMATED RELEVANCE VECTOR SEGMENTATION FOR BRAIN MRI IMAGE PROCESSING

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ABSTRACT

Magnetic resonance images (MRI) is significant in medical diagnosis as it provides detailed information related to anatomical structures as well as abnormal tissues of the body for treatment planning. The current medical imaging research is still a very difficult task to diagnosis the disease perfectly. Since the developed imaging system has more error for exact analysis. In order to overcome such issues, Regressive Nonlinear Teager Filter based MAP Estimated Relevance Vector Image Segmentation (RNTF-MAPRVIS) Method is developed for processing the brain MRI images with higher accuracy and minimum time. The numbers of brain MRI images are collected from the database. The RNTF-MAPRVIS method performs two major processes with medical images, namely preprocessing and segmentation. Initially, the Regressive Nonlinear Teager Filter process is used to remove the noisy pixels from the image. The designed filter analyzes the relationship of an image pixel to obtain super-resolution brain MR image through the warping and interpolation. After preprocessing, MAP estimated

Relevance Vector Machine based image segmentation process is carried out to segment the input preprocessed image for finding as normal or abnormal. In RNTF-RVIS Method, Relevance Vector Machine constructs the hyperplane uses Maximum a Posteriori that segments the images based on the similarity between the extracted features and testing features. After performing the segmentation, the input image is said as normal or abnormal. Experimental evaluation is carried out on factors such as PSNR, segmentation accuracy, segmentation time and false positive rate with respect to a number of MRI images. The observed results prove that the presented RNTF-MAPRVIS method improves the segmentation accuracy, PSNR and minimize time as well as the false positive rate than the state-of-the-art methods.

Keywords: Magnetic resonance images (MRI), preprocessing, Regressive Nonlinear Teager Filter, Maximum a Posteriori, Relevance Vector Machine Image Segmentation.

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1. INTRODUCTION

Magnetic resonance imaging (MRI) is a more efficient imaging method and efficient diagnostic tool in medical applications to analyze the information of internal body parts. MRI images are affected by the noise during collection and it minimizes the quality of the images. The removal of the noisy image without corrupting the original images is essential for exact analysis. Therefore, the noise reduction technique is essential for the medical image in the medical field. In addition, image segmentation plays a major role in image processing in order to represent an image in a simply analyzable way without difficulty. Several image processing techniques have been introduced for filtering and segmentation. However, accurate analysis was not performed. In order to improve performance, machine learning techniques are used in the proposed work.

A small kernels two-path convolutional neural network and random forests (SK-TPCNN+RF) was introduced in [1] for processing the MRI images to segment the brain tumors. But, the performance of peak to signal ratio was not improved. A modified level set method was developed in [2] for brain tumor segmentation and removing the noise. Though the PSNR was improved, it failed to improve the segmentation accuracy of the abnormal brain and normal MRI brain images.

A clustering algorithm integrated with morphological operations was developed in [3] to segment the brain tumors images. But the performance of segmentation time was not minimized. A multicascaded convolutional neural network (MCCNN) was introduced in [4] for segmenting the brain tumor images. Though the model has less computation time, the performance of the peak signal to noise ratio remained unsolved. In [5], a multi-modality aggregation network (MMAN) was presented to extract multi-scale features of the brain for improving the segmentation accuracy. But it failed to use the accurate filtering technique for noise removal.

A fully convolutional neural network was developed in [6] for segmenting the brain tumors images. Though the designed model improves the segmentation, the time consumption was not minimized. A Markov multiple feature random fields (MMFRF) method was designed in [7] to segment the brain MR image. The method failed to minimize the artifacts of the images.

A Wiener filtering technique was introduced in [8] for noise reduction to classify the brain images using random subspace ensemble classifier. The designed technique failed to analyze the performance of the image quality through the peak signal to noise ratio.

A texture feature and kernel sparse coding method was developed in [9] for automatic brain tumor segmentation with minimum computation cost. The developed method failed to improve the segmentation performance. Random forests combined with an active contour model was introduced in [10] for the automated segmentation of the MR images. The feature learning was not improved to obtain higher segmentation accuracy.

Proposal contribution

The major issues reviewed by the above-said literature are overcome by introducing a novel method called RNTF-MAPRVIS. The overall contribution of the proposed RNTF-MAPRVIS method is summarized as follows,

To improve the peak signal to noise ratio**,** RNTF-MAPRVIS uses the regressive nonlinear Teager filtering technique. The machine learning technique called regression is used for analyzing the adjacent pixels. Followed by, the warping and interpolation of the image sequence are measured for digitally manipulating an image and correcting the image distortion. Finally, the median denoising is performed to remove the noisy pixels. To improve the segmentation accuracy**,** MAP estimated relevance vector machine is applied in the RNTF-MAPRVIS method.

The relevance vector machine constructs the hyperplane to segment the input preprocessed images into the normal or abnormal by measuring the similarity between the features. The extracted features are highly correlated with the disease testing feature, and then the images have a higher probability for classified into an abnormal. This in turn minimizes the false positive rate.

To minimize segmentation time, the RNTF-MAPRVIS method performs image denoising as well as feature extraction. Based on these two processes, relevance vector machine accurately segmenting the image with minimum time consumption.

The outline of the paper is organized into five different sections. Section 2 discusses the literature review using MRI imaging techniques. Section 3 briefly describes the proposed RNTF-MAPRVIS method for MRI image processing. Section 4 provides the information on the experimental setup with the MRI image database. In section 5, the test outcomes and comparative analysis are presented using various parameters. Finally, section 6 concludes the paper.

2. LITERATURE REVIEW

A Berkeley wavelet transformation (BWT) based tumor segmentation was introduced in [11] to enhance the performance and minimize the complexity. But it failed to improve the accuracy of the classification of the tumor as normal or abnormal. **A** deep convolutional neural network (CNN) was developed in [12] to classify the brain tumors from the MRIs. But the designed model failed to perform the denoising to enhance the image contrast. An adaptive differential evolution algorithm was designed in [13] for MRI brain image segmentation. However, the algorithm failed to make it less sensitive to noise.

A fully convolutional neural network (CNNs) was developed in [14] to improve the accurate brain tissue segmentation. The segmentation time was minimized but the model failed to analyze the pixels for improving the image contrast by removing the noisy pixels. A 3D super voxel based learning model was designed in [15] for segmentation of tumor from the multimodal MRI brain images. But the more detailed segmentation of tumor tissue was not performed.

A possibilistic fuzzy c-means (FCM) method was introduced in [16] Based on a similarity to enhance the segmentation performance for MRI brain images. The method minimizes the error rate but the performance of segmentation time was not minimized. A Bayesian theory-based 3D MRI image denoising was performed in [17]. But the computational efficiency of the filter was not improved.

A modified particle swarm optimization technique was introduced in [18] for effective 3D brain tumor segmentation with minimum time. The technique failed to consider the image denoising for improving the image quality. A Hyper Densely connected convolutional neural network was developed in [19] for segmenting the multi-modal image. The performance of false-positive rate in the segmentation was not minimized.

Deep learning with a convolutional neural network was introduced in [20] for image segmentation with higher accuracy. The designed method preprocessing the images but the peak signal to noise ratio was not improved.

The major issues of the existing reviews are overcome by introducing a new technique called CWFE-BAC technique. The description of RNTF-MAPRVIS Method with the neat diagram is explained in the next section.

3. METHODOLOGY

In medical image processing, the MRI image produces high-quality representations of the parts in the human body. The MRI image analysis is a very important process for providing the proper treatment at the right stage for the infected individual. In general, there are various imaging modalities utilized for capturing the images of the organs in the body such as Ultrasound imaging, computed tomography (CT) and X-RAY radiography, magnetic resonance imaging (MRI), and so on. Among them, MRI is an accurate medical diagnostic instrument to provide accurate images for diagnosing the illness. In addition, the various image processing techniques with MRI is very hard for accurate diagnostic. Therefore, an efficient machine learning technique based segmentation is required to improve the MRI image processing. The new machine learning-based segmentation method called RNTF-MAPRVIS is introduced with two processing steps such as preprocessing and segmentation. The architecture with these two processes of the RNTF-MAPRVIS method is shown in figure 1.

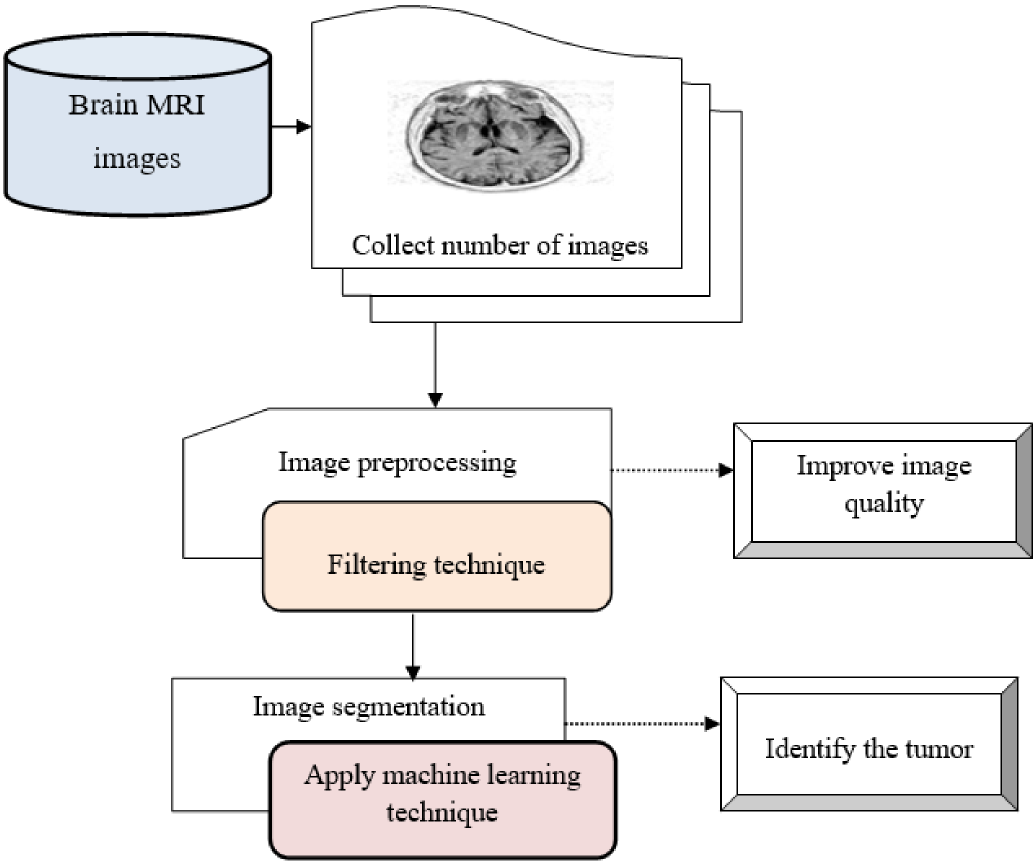

Figure 1 Architecture diagram of proposed RNTF-MAPRVIS method

Figure 1 shows the architecture diagram of proposed RNTF-MAPRVIS method is to automatically detect the tumor from the MRI images. Initially, image acquisition is carried out where the number of brain images $bi_1, bi_2, bi_3, \ldots . bi_n$ are collected from the MRI image database. Followed by, preprocessing is done by applying the Regressive Nonlinear Teager Filter to remove the noise artifacts from the images resulting in the quality of image gets improved and minimize the tumor detection time. Finally, the machine learning technique called MAP estimated Relevance Vector Machine is applied to segment the images based on the pixel based feature extraction. The segmentation results are used for identifying the given input images as normal or malignant. The machine learning technique effectively identifies the tumor in the brain MRI images with higher accuracy. The detailed explanation of the above said two processes are described in the following subsections.

3.1. Regressive Nonlinear Teager Filter based image preprocessing

In the proposed RNTF-MAPRVIS method, initially, the input MRI brain images are pre-processed in order to remove the noise artifacts before the segmentation. The MRI image generally comprises distortion and artifacts. For computer-aided segmentation, the distortion and artifacts must be removed. Therefore, the RNTF-MAPRVIS method uses the regressive nonlinear Teager filtering technique to enhance image quality. The regression is the machine learning technique used for analyzing the pixels in the given input MRI images and removing the noisy pixels using Nonlinear Teager filter. The Nonlinear Teager filter is a denoising technique used to obtain the super-resolution image and suppress the noise. The block diagram of the Regressive Nonlinear Teager Filtering is shown in figure 2.

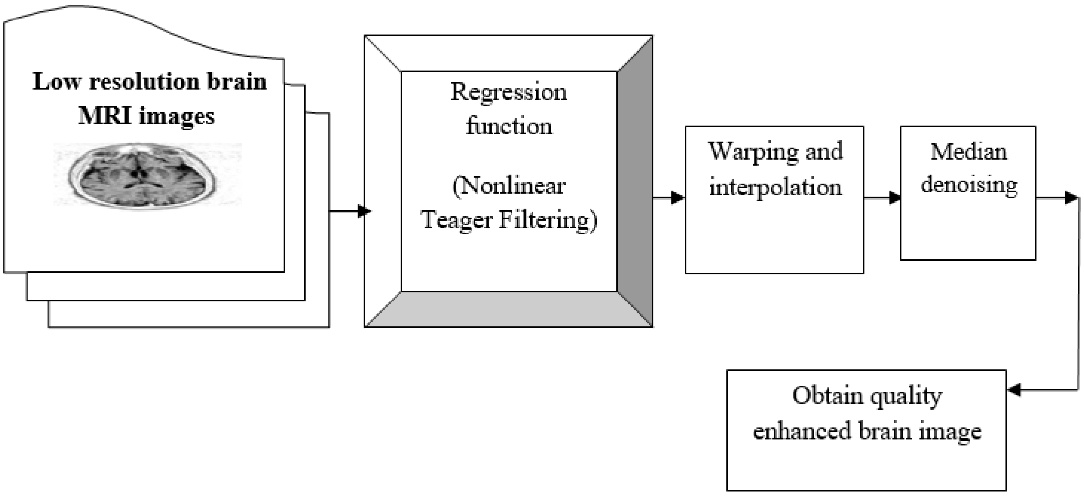

Figure 2 block diagram of the Regressive Nonlinear Teager Filter

Figure 2 shows the block diagram of the regression-based filtering technique to evaluate the pixels from the input MRI images. Let us consider the number of MRI images collected from the brain database.

$$bi_1, bi_2, bi_3, \ldots . bi_n \in DB \qquad (1)$$

From (1),$bi_1, bi_2, bi_3, \ldots . bi_n$ denotes a number of Brain MRI images collected from the databaseDB. After collecting the images, the pixels analysis is done by applying the regression function and Improve the image quality using Nonlinear Teager Filter. For any brain MRI image, the Teager filter is applied to measure the pixel relationship as follows,

$$p_{ij} = 3\, p^2\,(i,j) - 0.5 * p\,(i+1, j+1)\, p(i-1, j-1) - 0.5\, p\,(i+1, j-1) p(i-1, j+1) - p(i+1, j) p(i-1, j) - p(i, j+1)\, p\,(i, j-1) \qquad (2)$$

Where,p_{ij} denotes a pixel of the input images, (i,j) denotes a horizontal (i.e. row) and vertical (i.e. column) translation. Each image pixels are represented in the 3x3 windows with the rows and columns. $i+1, j+1, i-1, j-1$ represents the neighboring pixels in the window. Then the filter highlights the edges and suppresses the noise. Then the images are warped and interpolated as follows,

$$w\ (i,j) = I\left(\sum_{i=1}^{n}\sum_{j=1}^{m} A_b\ p_{ij}\right) \tag{3}$$

Where, $w\ (i,j)$ denotes a output of the warping and interpolation with the pixels, I denotes a non linear interpolation function used to make a images into smooth, A_b is the warp matrix for each low resolution image, p_{ij} is the pixels of the image. Image warping is used for digitally manipulating the image and correcting the image distortion. Then the normalization is applied for ordering the range of pixel intensity values from minimum to maximum.

$$w_{ij} = \frac{w\ (i,j) - \min(w\ (i,j))}{\max(w\ (i,j)) - \min(w\ (i,j))} \tag{4}$$

Where, w_{ij} is the normalized output of the pixels (i,j) using warped and interpolation, $min\ and\ max$ denotes a minimum and maximum value of output of the warped and interpolation with pixel intensity $w\ (i,j)$. After the normalization, images are then applied to median denoising for smoothing the artifacts due to the reconstruction process and obtaining the final super resolutions image. The mathematical formula for median denoising are explained as follows,

$$f\ (x) = med\left\{w_{ij}\right\} \tag{5}$$

In the above equation (5), $'f\ (x)'$ denotes an output of the median denoising and Med denotes a median, w_{ij} denotes a normalized value of the pixels (i,j) using warped and interpolation. The median process is applied in the entire pixel and accordingly , the median value removes the noisy pixels in the window. This helps to improve the image quality for identifying the brain tumor in the given images.

3.2.MAP estimated Relevance Vector Machine based Image Segmentation

After preprocessing, the RNTF-MAPRVIS method performs the image segmentation to identify the tumor as normal or abnormal using MAP estimated Relevance Vector Machine. The image segmentation is considered as a classification task. A Relevance Vector Machine (RVM) is a machine learning technique that uses Maximum a Posteriori (MAP) for probabilistic classification. Maximum a Posteriori is used for identifying the maximum correlation between the features. Initially, the MR parameters (i.e. pixel-level features) such as size, shape, texture, color, area, length are extracted from the preprocessed images. Then the tumor is characterized as normal (having no tumor) or abnormal (having tumor) with the extracted feature from the Region of Interest (ROI).

The MAP estimated Relevance Vector Machine considered as a set of training samples '$\{(x_1, y_1), (x_2, y_2), \ldots\ (x_n\ , y_n)\}$' where '$x_i$ indicates an input preprocessed images and 'y_i' refers to the output (classification result $y_i \in \{0,1\}$. Relevance Vector Machine uses optimal hyperplane for classifying the images. The hyperplane is a decision boundary between the two classes. The Relevance Vector classifies the images on either side of the decision boundary.

$$D_b \rightarrow \vartheta . br_i + d = 0 \qquad (6)$$

Where, D_b represents a decision boundary, ϑ is the normal weight vector to training samples (i.e. images), $d$denotes a bias. The two marginal hyperplanes are selected as lower and upper side of the decision boundary.

$$M_1 \rightarrow \vartheta . br_i + d > 0 \quad i.e \quad '+1' \qquad (7)$$

$$M_2 \rightarrow \vartheta . br_i + d < 0 \quad i.e \quad ' - 1' \qquad (8)$$

Where, M_1, M_2 are the lower and upper marginal hyperplanes to classify the brain images into above and below the boundary. The relevance vector machine uses the kernel function to obtain the final classification.

$$y = sign\ \sum \vartheta_i\ k\ (f_i, f_t) \qquad (9)$$

In (9) y denotes a predicted classification results, ϑ_i denotes a weights of the training images, k denotes a kernel function that measures the similarity between any pair of features i.e. extracted features (f_i) and testing features (f_t), '$sign$' determines whether the classification output either positive (+1) or negative (-1). The hyperplane measures the similarity between extracted features and testing features using maximum probability for classifying the images into any of the two classes.

$$\mu_{map}(y_i|br_1, br_2, br_3, \dots br_n) = arg\,max \;\; p\,(br_i|y_i) \tag{10}$$

$$p\,(br_i|y_i) = \;\; exp\left(-\frac{\|f_i - f_t\|^2}{2\sigma^2}\right) \tag{11}$$

In (10), (11), μ_{map} is the maximum probability function, $arg\,max$ represents an argument of a maximum function using MAP rule, $p\,(br_i|y_i)$ is the classification probability. Gaussian kernel function is used for measuring the similarity between the features, f denotes a extracted features, f_t denotes a testing disease features, $\|f_i - f_t\|^2$ denotes a squared distance between the extracted features and testing disease features, σ denotes a deviation. The squared distance is used to measure the similarity of the features. If the distance is minimized, the two features are highly correlated. Based on the MAP estimated relevance vector, the features with higher similarity have a maximum probability belongs to the class '-1' i.e. images are classified as malignant. Otherwise, it has a maximum probability belongs to the classes '+1' i.e. image is classified as normal.

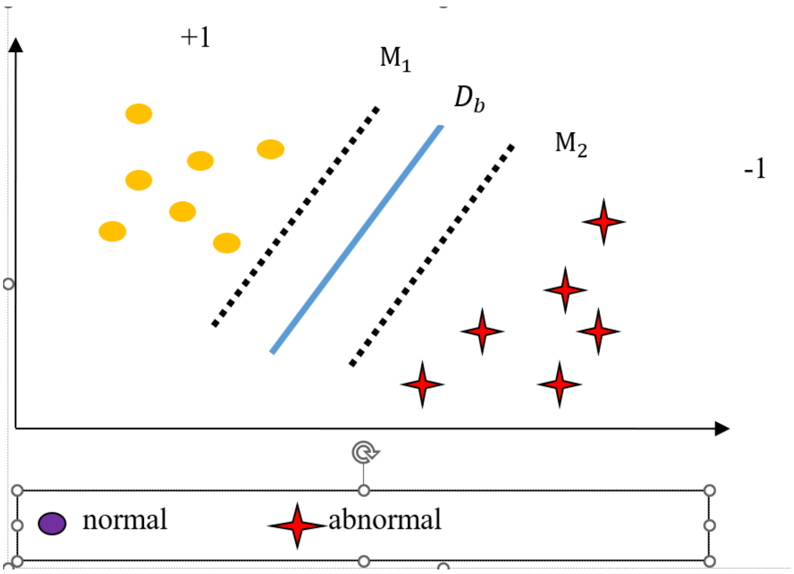

Figure 3 Map estimated relevance vector machine

Figure 3 shows the Map estimated relevance vector machine to classify the brain MRI images into the normal or abnormal. As shown in figure 3, the input preprocessed images are segmented and the upper sides of the hyperplane are called as normal images whereas the lower labeled samples are abnormal images.

4. SIMULATION SETUP AND PARAMETER SETTINGS

In this section, the simulation of proposed RNTF-MAPRVIS Method, SK-TPCNN + RF [1] and modified level set segmentation method [2] are implemented using MATLAB coding for processing the MRI brain images to find the abnormality with minimum time. The number of brain MRI Images are collected from the brain tumor database called Radiopaedia taken from https://radiopaedia.org/cases/anaplastic-astrocytoma-8?lang=us. This database comprises different brain MRI images for the various patients. The dataset comprises more than the 25,500 patients MRI images. Totally 100 images are taken for preprocessing the brain MRI images and performing the segmentation.

The performance of technique and existing methods are conducted on different parameters such as

- Peak signal to noise ratio
- Segmentation accuracy
- False-positive rate
- Segmentation time

5. PERFORMANCE ANALYSIS

In this section, the performance results of proposed RNTF-MAPRVIS Method, SK-TPCNN + RF [1] and modified level set segmentation method [2] are discussed with the certain parameters such as peak signal to noise ratio, segmentation accuracy, false-positive rate, and segmentation time with respect to a number of MRI brain images. The effectiveness and efficiency of the proposed and existing methods are discussed with the help of tables and graphical representation.

5.1 Performance analysis of peak signal to noise ratio

Peak Signal to Noise Ratio is measured based on a mean square error which is defined as the difference between preprocessed image and noisy image. The mathematical formula for calculating the mean square error and peak signal to noise ratio is given below,

$$E_{MS} = \left(br_i - br_p\right)^2 \quad (12)$$

$$PSNR = 10 * \log_{10}\left(\frac{R^2}{E_{MS}}\right) \quad (13)$$

Where, E_{MS} denotes a mean square error, br_i represents the original image and br_p is a preprocessed images, $PSNR$ represents Peak Signal to Noise Ratio, R denotes a Maximum possible pixel value of the brain images (R) (with size 255). Here the input image is considered as brain MRI image. The PSNR is measured in the unit of decibel (dB).

Table 1 peak signal to noise ratio

Brain Image size (KB)	Peak signal to noise ratio (dB)		
	RNTF-MAPRVIS	SK-TPCNN + RF	Modified level set segmentation method
13.4	49.04	45.20	43.02
12.5	51.22	44.60	42.11
14.3	52.56	47.30	44.60
11.9	50.06	45.85	43.02
18.3	54.15	50.06	48.13
19.7	46.54	44.04	42.11
17.8	49.04	43.52	42.55
23.4	47.30	45.20	43.02
26.2	52.56	48.13	45.20
29.3	49.04	46.54	44.04

Table 1 reports the experimental results of peak signal to noise ratio of three methods namely RNTF-MAPRVIS Method, SK-TPCNN + RF [1] and modified level set segmentation method [2]. For the experimental consideration, the ten various sizes of the MRI images are taken from the database. The above mathematical results and table values show that the mean square error of the RNTF-MAPRVIS Method is reduced as compared to the other two existing methods. Then the peak signal to noise ratio is also improved using RNTF-MAPRVIS Method. The results are shown in the graphical representation.

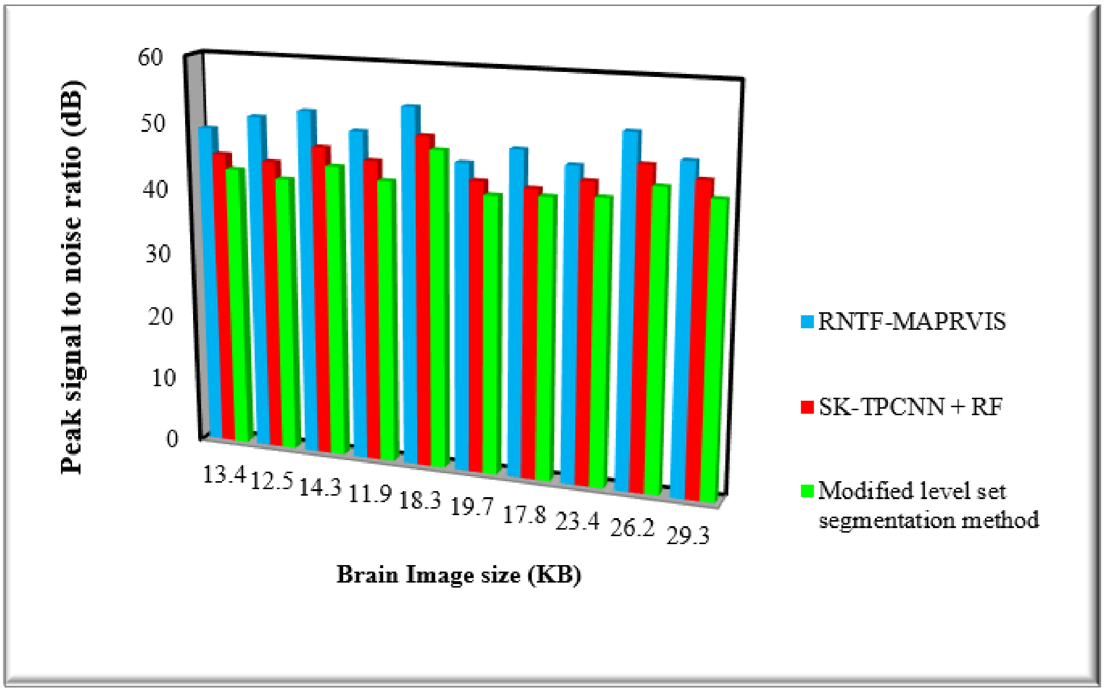

Figure 4 Comparatives analysis of peak signal to noise ratio

Figure 4 illustrates the comparatives analysis of peak signal to noise ratio using three different methods. As shown in the figure, the horizontal axis represents the size of the MRI brain images taken from the database. The vertical axis represents the outcomes of the peak signal to noise ratio. The results of three methods RNTF-MAPRVIS Method, SK-TPCNN + RF [1] and modified level set segmentation method [2] are represented in the three different colors such as blue, red and green respectively. The peak signal to noise ratio of RNTF-MAPRVIS Method is found to be improved than the existing methods. This is due to the application of the Regressive Nonlinear Teager Filtering technique. The proposed filtering technique uses machine learning for analyzing the relationship of the adjacent pixel and performing the warping and interpolation for smoothing the images. Finally, the median denoising is carried out to remove the noisy pixels from the images. Thus the image quality gets improved. The ten different results of RNTF-MAPRVIS method is compared to the existing results. Then the average of comparison results evident that the peak signal to noise ratio is found to be increased using RNTF-MAPRVIS Method by 9% compared to SK-TPCNN + RF [1] and 15% compared to modified level set segmentation method [2].

5.2. Performance analysis of segmentation accuracy

Segmentation accuracy is measured as the numbers of input brain images are correctly classified as normal or abnormal. The formula for calculating the segmentation accuracy is expressed as follows,

$$SA = \left(\frac{Number\ of\ images\ correctly\ classified}{n}\right) * 100 \qquad (14)$$

Where SA represents the segmentation accuracy, n is the number of input images. Segmentation accuracy is measured in terms of percentage (%).

Let us consider, the segmentation accuracy of three methods is mathematically calculated using 10 MRI brain images. Assuming the ten images, the 8 images are correctly classified as normal or malignant using RNTF-MAPRVIS method and their accuracy is 80%. Whereas, the 7 and 6 images are classified and the accuracy is 70% and 60% using SK-TPCNN + RF [1] and modified level set segmentation method [2]. From the above discussion, it is clear that segmentation accuracy using RNTF-MAPRVIS method is higher than the other conventional works. The various results of segmentation accuracy are demonstrated in Table 2

Table 2 Segmentation accuracy

Brain MRI images (Numbers)	Segmentation accuracy (%)		
	RNTF-MAPRVIS	SK-TPCNN + RF	Modified level set segmentation method
10	80	70	60
20	85	75	70
30	83	77	73
40	85	78	75
50	86	82	78
60	90	85	82
70	93	87	84
80	91	86	81
90	93	87	83
100	90	85	82

Table 2 shows the various results of segmentation accuracy with respect to a number of brain MRI images taken in the range from 10 to 100. The above result shows that the numbers of brain MRI images are correctly classified. This is the significant metric for identifying the disease at an earlier stage for providing the correct treatments to the patient. The table value shows that the segmentation accuracy is increased using RNTF-MAPRVIS method. The results are shown in the below graph.

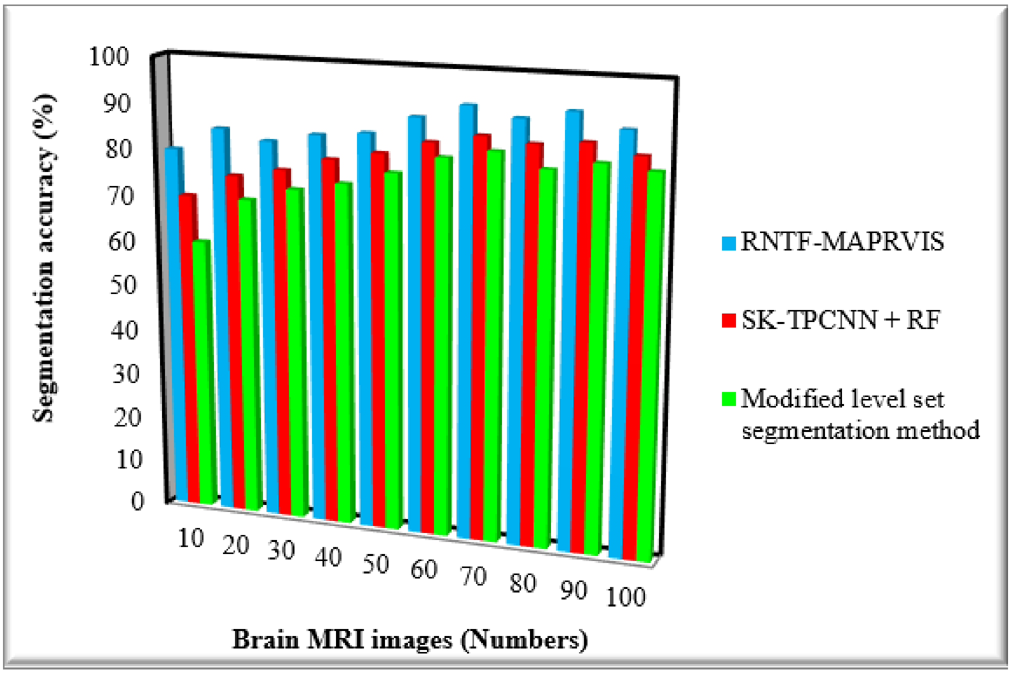

Figure 5 Comparatives analysis of segmentation accuracy

Figure 5 given above shows the results of segmentation accuracy with respect to 100 brain MRI images and three different methods are considered. From the figure, it is inferred that the segmentation accuracy of RNTF-MAPRVIS method is improved using the MAP estimated relevance vector-based image segmentation. By using the segmentation algorithm, the preprocessed images are given as input. Then the pixel level features of the images are extracted and it correlated with the testing disease features. If these two features are highly correlated, the hyperplane classifies the images as i.e abnormal with higher probability. Otherwise, the hyperplane classifies the image as normal. This is evident from the sample mathematical calculation. The comparison of ten various results shows that the brain tumor segmentation accuracy of RNTF-MAPRVIS method is considerably improved by 8% and 15% when compared to SK-TPCNN + RF [1] and modified level set segmentation method [2] respectively.

5.3. Performance analysis of false-positive rate

The false-positive rate is measured as the numbers of input brain images are misclassified as normal or abnormal. The false-positive rate is calculated mathematically as follows,

$$FPR = \left(\frac{Number\ of\ images\ misclassified}{n}\right) * 100 \qquad (15)$$

Where FPR represents the false positive rate, n is the number of input brain MRI images. The false positive rate is measured in percentage (%).

Table 3 False positive rate

Brain MRI images (Numbers)	False positive rate (%)		
	RNTF-MAPRVIS	SK-TPCNN + RF	Modified level set segmentation method
10	20	30	40
20	15	25	30
30	17	23	27
40	15	20	25
50	14	18	22
60	10	15	18
70	7	13	16
80	9	14	19
90	7	13	17
100	10	15	18

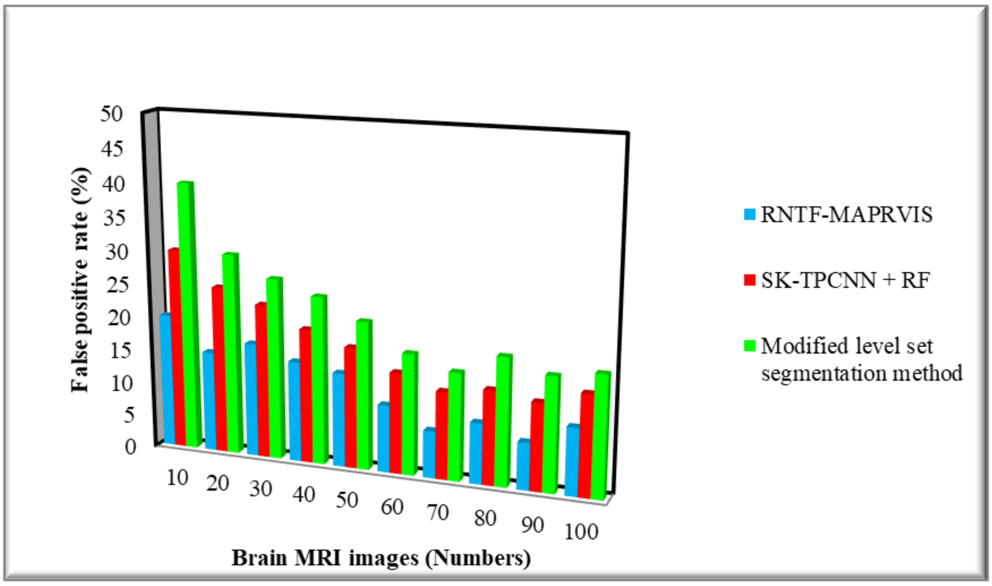

Figure 6 Comparative analysis of false-positive rate

Figure 6 depicts the false positive rate with respect to 200 Brain MRI images. As shown in the above figure, the false positive rate is minimal using proposed RNTF-MAPRVIS method using MRI image database. This improvement is achieved by applying the MAP estimation in the relevance vector-based image segmentation. The MAP function measures the posterior probability with the Gaussian function. The Gaussian function measures the similarity between the features using squared distance. This helps to minimize the misclassification of the images as normal or abnormal. In addition, preprocessing of the images also improves the image quality for correctly segmenting the input mages and minimizes the misclassification. This is evident from the sample mathematical calculation. With '10' MRI image is considered for experimentation and '2' images are misclassified using RNTF-MAPRVIS method. Similarly, with '3' images, '4' images are misclassified using SK-TPCNN + RF [1] and modified level set segmentation method [2]. Therefore, the overall false-positive rate was found to be '20%', 30% and '40%' respectively. The comparison results show that the false positive rate of RNTF-MAPRVIS method is minimized by 34% compared to SK-TPCNN + RF [1] and 47% compared to the modified level set segmentation method [2].

5.4. Performance analysis of segmentation time

Segmentation time is measured as the amount of time taken by an algorithm to classify the brain images as normal or malignant. The segmentation time is calculated as follows,

$$ST = n * time\ (classifying\ single\ brain\ image\ ) \qquad (16)$$

Where ST represents the segmentation time, n is the number of input brain MRI images. The segmentation time is measured as milliseconds (ms). Lesser the time, the method is said to be a more efficient.

Sample calculation:

- **Proposed RNTF-MAPRVIS**: Number of MRI brain images are 10 and time for classifying one brain image is $1.6ms$. Therefore, the overall segmentation time is computed as,

$$ST = (10 * 1.6ms) = 16ms$$

- **Existing SK-TPCNN + RF**: Number of MRI brain images are 10 and time for classifying one brain image is $1.8ms$. Therefore, the overall segmentation time is computed as,

$$ST = (10 * 1.8ms) = 18ms$$

- **Existing Modified level set segmentation method**: Number of MRI brain images are 10 and time for classifying one brain image is $2.1ms$. Therefore, the overall segmentation time is computed as,

$$ST = (10 * 2.1ms) = 21ms$$

Table 4 segmentation time

Brain MRI images (Numbers)	Segmentation time (ms)		
	RNTF-MAPRVIS	SK-TPCNN + RF	Modified level set segmentation method
10	16	18	21
20	24	28	32
30	30	33	39
40	32	36	40
50	35	40	45
60	41	45	48
70	46	49	53
80	50	52	54
90	52	54	57
100	54	56	59

To evaluate the segmentation of MRI brain images, proposed RNTF-MAPRVIS method and existing methods are implemented in MATLAB with a number of brain images taken in the range of 10-100. From the results, it is cleared that the segmentation time using proposed RNTF-MAPRVIS is minimized when compared to existing methods. The result of the segmentation time is shown in figure 7.

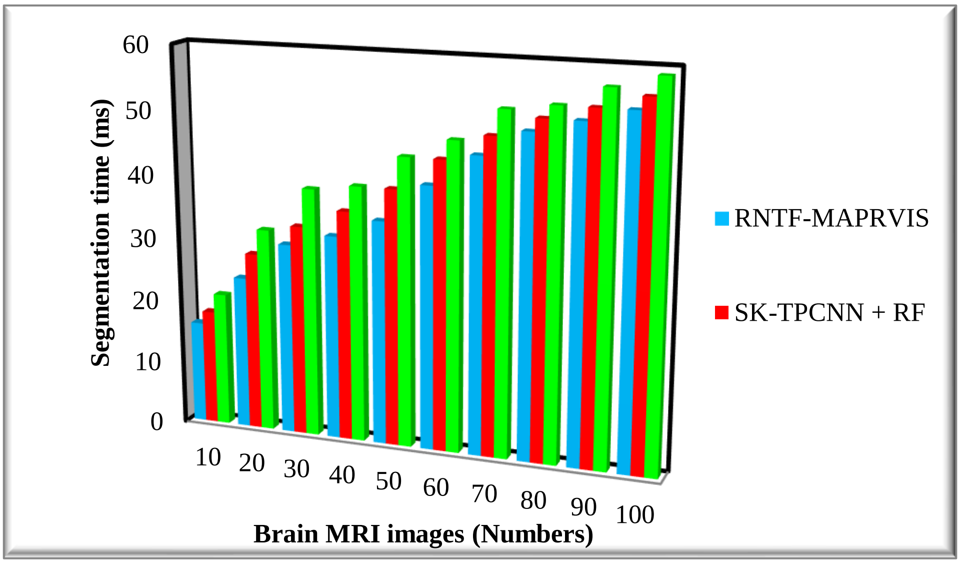

Figure 7 Comparatives analysis of segmentation time

Figure 7 portrays the segmentation time of three different methods with numbers of the brain images in the range of 10-100 taken from the database. By increasing the number of data images, the various segmentation time results are obtained. The time of segmenting the input images are minimized using RNTF-MAPRVIS method. The segmentation time minimization is achieved by performing the preprocessing as well as the feature extraction. Because the noisy images are taken more time to identify the brain tumor in the given MRI image. In the case of preprocessing, the clear image is obtained and used for segmenting the images with lesser time consumption. The RNTF-MAPRVIS method also extracts the features in the preprocessed images and correlated with the testing features. This helps to minimize the time for image segmentation.

Let us taken 10 images for the first iteration, the segmentation time of RNTF-MAPRVIS method is $16ms$ whereas the segmentation time of SK-TPCNN + RF [1] and Modified level set segmentation method [2] are $18\ ms$ and $21ms$ respectively. Similarly, the nine various iterations are done with a number of brain MRI images. The results of the proposed method are compared to the results of existing methods. The average of comparison results shows that the segmentation time is minimized by 8% and 17% using RNTF-MAPRVIS method as compared to the two state of the art methods.

The discussed result of the parameters proves that the RNTF-MAPRVIS method efficiently processing the brain images and accurately detects the tumor with higher accuracy and minimum time.

6. CONCLUSION

A novel method called RNTF-MAPRVIS is designed for processing the MRI brain images through the segmentation algorithm. The main goal of the RNTF-MAPRVIS method is to perform the preprocessing and segmentation for isolating the region of interest from its background. The regressive pixel analysis based filtering is applied to remove the noisy pixels and enhance the image contrast for further processing. After preprocessing, the image is segmented by the classification. In this segmentation module, the preprocessed brain MRIs obtained, which is to be classified as a normal or abnormal through the separating the hyperplane. The relevance vector-based segmentation method is robust and precise. The experimental is conducted with the MRI brain image database. The proposed algorithm is compared with state-of-the-art approaches using different parameters such as peak signal to noise ratio, segmentation accuracy, false positive rate and segmentation time. From the results obtained, it is clearly noted that the proposed RNTF-MAPRVIS method offers better performance in the peak signal to noise ratio, segmentation accuracy, false positive rate and minimum time than the state-of-the-art methods.

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