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A Novel Denoising and Segmentation of Brain Tumors in MRI Images

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Abstract

Objectives: The objective of this work is to study denoising and segmentation methods to extract brain tumor area from the MRI image, implemented using MATLAB2013b and to examine its performance metrics. **Methods/Statistical Analysis:** As preprocessing stage is essential for better segmentation as it removes noise that makes images having similar qualities so that tumor area can be shown and extracted with great accuracy. An anisotropic diffusion filter with 8-connected neighborhood is employed for noise removal and Fast Bounding Box (FBB) for exactly showing tumor area on MRI images. Finally Support vector machine classifies the boundary and extracts the tumor from the MRI image. **Findings:** Brain tumor is the major cause of cancer deaths in human which is due to uncontrollable cells growth in brain portion. Prior detection, diagnosis and accurate healing of brain tumor are the primary work to prevent human death. Image segmentation can also be done in several approaches like thresholding, region growing, watersheds and contours. Specialists with their basic knowledge do manual segmentation, which is time consuming process, where this limitation can be overcome by our fully automatic proposed method. Employing of an isotropic diffusion filter with 8-connected neighborhood compare to 4-connected neighborhood results in considerable improvements in terms of lower identical error rates. Our proposed Fast Bounding Box (FBB) method is applied that exactly shows tumor area on MRI images and its central region is selected judiciously to have sample points required for functionality of one class SVM classifier training. To achieve optimal classification level there is necessity of SVM with optimum efficiency, so that we adapted Support vector machine that immediately stops its operation once all the points are separated. **Application/Improvements:** Segmented tumor obtained with precision are very useful for radiologists and specialists to had good idea of estimating tumor position and size with great dealt with ease and without any prior information.

Keywords: Brain Tumor, Feature Extraction, Fast Bounding Box, MRI, Support Vector Machine, Tumor Extraction

1. Introduction

Brain has a very difficult structure and is viewed as a kernel section in the body. Nature has tightly preserved the brain within a skull that hinders the study of its function as well as makes the analysis of its diseases more complex. Brain tumors either include in the significant spinal canal or throughout the skull. Computerized defect detection in MRI is really priceless in several diagnostic and therapeutic usages like CT images, MRI images, are two imaging modalities that assist researchers and medical practitioners to gain knowledge about the brain through watching noninvasively. Noise elimination or denoising is an essential task in image processing applications. As per image enhancement we define it as a gathering of events that emphasize the acceptable study for the specified image which makes targeted elements of the image less complicated to peer or lowering the noise.

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Regularly, noise removal is having resilient influence on the major elements of the image processing system. In present days major constraint in biomedical field is noise, which is termed as a random signal produced by electronic instruments. But today's electronic equipment is designed to reduce the noise certain extent. Regularly in order to study the noise we require prior knowledge for judging the characteristics of a desired signal and undesired noise present in the MRI images.

Recent MRI imaging technique can provide complete information about human body internal view. It is completely secured and free from any kind of injury due to radiation, since there is no drug injecting into the human body[1]. Likewise Positron Emission Tomography (PET)[1,20], Computer Tomography (CT) is the other techniques available for medical imaging applications. In traditional methods even experienced doctors also taking more time to identify the diseases. So for this reason inevitability of clear-cut and fully automatic process that can make available detailed evidence to the doctor is imperative[2,20].

Similar works previously undertaken by authors mainly rely on the manual and automatic natured segmentation on MRI brain tumors, that are broadly categorized into two types non-intelligent and intelligent based. In[3] the author presented image denoising using Haar and Daubechies Transforms. It is found to be Daubechies3 (db3) wavelet seems to be more efficient than Haar wavelet for reducing a certain level of speckle noise in the medical images and also it enhances the visual quality of the medical image a lot. In[4] the author states that there are numerous noise reduction techniques had been developed for removing noise and conserving edge details in images. Each technique has its own suppositions, benefits and restrictions. Finally the idea behind these techniques is to acquire better results in terms of quality and in removal of different type of noises.

In[5] the author presented a technique to improve the image quality with the help of denoising and resolution enhancement. Here the paper concentrates on the average, median type of filter and Wiener type filtering for image denoising purpose and an interpolation based Discrete Wavelet Transform (DWT) method for resolution enhancement. In[6] the author presented work where it improves Signal to Noise Ratio (SNR) of CT images utilizing wavelet transforms. It analyzed signals and the entire set of wavelet share some common properties but each wavelet has a certain unique properties of Image decomposition, denoising and reconstruction which provide difference in PSNR. In[7] the author proposed Symlets wavelet technique using 2-D DWT in image processing. The scope of the effort comprises compression and denoising, image clarity and being in quench of the decomposition and phases of threshold and to discover energy retained (image recovery) and misplaced.

In spite having major constraints and challenges in case brain tumor segmentation in terms of irregular shape and location, among those one severe challenge is how to inspect the real data nonlinear distribution. Likewise the main job of one class classification in[8] is to pick the data that belongs to target class or not. Additionally one-class Support Vector Machines (SVMs) is employed in such cases of brain tumor segmentation in[9] that have learning nonlinear distribution of real data is considered without prior knowledge.

As we summarized the rest of this paper as follows: Section 2 describes the methods and materials used in the algorithms. Section 3 elucidates the simulation results and its discussion. Finally, conclusions in the last section.

2. Proposed Method and Materials

Our main intension in current work is brain image denoising and segmentation algorithms using FBB and SVM for improved performance. Brain tumor segmentation on brain MRI images which is unconditionally automatic and thus no requirement of human involvement. Figure 1 shows the block diagram of the proposed approach explained as follows below.

2.1 Pre-Processing

The pre-processing phase has two folds:

- During the first step useless parts of skull present outside are to be eliminated, for doing this boundary of skull is identified with the aid of automatic global thresholding technique[10], which can generate binary mask image thus it is becomes very easy to eliminate the useless parts of the skull that present outside to it. Therefore by following likewise required calculations in further steps and segmentation computation can greatly reduce.
- In this step noise in brain MRI images are removed where these noises are present in random nature in

image to be eliminated before segmentation process without disturbing the edges and reduce the image clarity. So therefore an anisotropic diffusion filter with 8-connceted neighborhood is used in order to eliminate the noise with ease.

$$I(x,y,t) = I_0(x,y) * G(x,y,t) \quad (1)$$

$I(x,y,t)$ is filtered image
$I_0(x,y)$ is original image
$G(x,y,t)$ is Gaussian kernel with different scale parameter t

In this filtering technique treated to be iterative process of heat diffusion equalization method where $I(x,y,t) = I_0(x,y)$is the initial condition, and it is alike to time 't'. Here the authors Perona and Malik presented a determination for the prior indicated problem that documents space variant (anisotropic) obscuring appropriate to trace edges with more accuracy. In[11] authors employed the 4-connected neighborhood for calculation purpose where here we used for calculations 8-connected neighborhood[19,20].

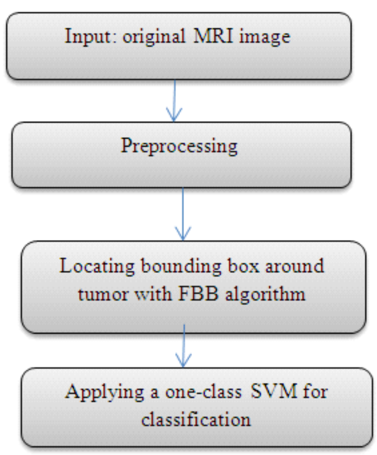


Figure 1. Block diagram of the proposed approach.

2.1.1 FBB Procedure

Basically presence of tumor in brain contains right and left symmetry which is in dissimilar symmetry. Here FBB technique is applied to know the similarity of gray scale intensity histograms, then by using Bhattacharya coefficient calculation the tumor portion is marked by rectangle bounding box automatically.

2.1.2 SVM Classification

In one class SVM classifier the tumor pixels are considered as training set. When we detect tumor of different shapes in MRI image those parts are extracted with bounding box without affecting healthy part in brain image and to overcome this type of catastrophe, only the central part is considered as sample points. Moreover to simplify the job kernel RBF with SVM is taken into consideration thus feature extraction process also completes during training step of SVM only, thus results in elimination of feature extraction process in this technique.

As extension work our proposed technique embedded with the algorithm having capability of finding the tumor at different locations of the brain, by this means the output comprises of oblong pack around the brain tumors. Further symmetrical axis line isolates brain into two equilibrium regions one being test image and other being reference.

The output for the input image it takes the input as MRI image then finds the boundary of the brain and axis of symmetry In order to detect the tumor precisely horizontal and vertical score values must plotted contrary to the number of days and growth rate, when the plots shows dissimilar it indicates presence of tumor. The similarity among two normalized intensity histograms can be obtained by coefficient of Bhattacharya by considering horizontal and vertical score function. By using the centroids of the border marker method the unsupervised mean shift clustering is instigated to catch the prevalent cluster successive in MR slices. MR images are taken as input for the simulation.

2.2 Pre-processing

By reducing noise and enhances some of the image features for further processing stages. It is evident that every MRI images contains noise and must be removed without affecting the useful portion like weak edges of image. It is the initial stage of every image processing application where its main job is to improve the image data and diminishes the quality of MRI images. For reducing this type of noise several methods are employed like Gaussian filtering technique[12], thresholding technique[13], medial filtering, wavelet transforms and also anisotropic diffusion filtering.

As mentioned earlier an anisotropic diffusion filtering technique that greatly removes noise present in MRI images by smoothing out images without affecting valuable date in edges and structures of image. Here to regulate level of smoothing in particular areas on edge structure in local is to be motivated. Finally enormously smoothing on homogenous areas and barely smoothing on strong edge areas to hold the structure in MRI images.

2.2.1 Fast Bounding Box Algorithm

Here the input brain MRI slice (axial view) have axis of symmetry that segments brain in to two halves one half treated as test image and other as reference image. Now in order to know the dissimilarity that is necessary for locating the tumor region, novel score function is employed that can search rapidly in two directions of brain region one along horizontal and other in vertical direction. This novel score function Bhattacharya Coefficient (BC) which is similarity measurement to detect rectangle between two normal histograms of grey scale intensity. It is evident that two grey scale intensity normalized histograms seems to be same the BC between them is 1and if not BC value is 0.[14,20]

2.2.2 Support Vector Machine based Algorithm

As SVM is widely used technique in several fields of image processing like classification, segmentation to yield optimized results. Since it is capable of treating linear and nonlinear separation it is well-intentioned to apply for classification in the confined space. So the separation operation field f(x) is formulated as

$$f(x) = \sum_{x_j \in S} a_j y_j K(x_j, x) + b \tag{2}$$

Where, x_i designates the trainings, $y_j \in \{+1,-1\}$ embodies class label with S as a set of support vectors.

The dual formulation of the above is formulation (2) is prearranged as;

$$\min_{0 \le a_i \le C} W = \frac{1}{2} \sum_{i,j} a_i Q_{ij} a_j - \sum_i a_i + b \sum_i y_i a_i \tag{3}$$

where the term a_i are supposed to be the coefficients of vector and whereas b treated to be offset value.

$Q_{ij} = y_i y_j$ K (x_j, x): Designates symmetric kernel matrix and C embodies parameters of error points.

As well-known Karush-Kuhn-Tucker (KKT) is employed to achieve an optimal point in this work as it possesses to solve constrained problems with great ease which is formulated as:

$$g_i = \frac{\delta W}{\delta_{a_i}} = \sum_i Q_{ij} a_j + y_j b - 1 = y_i f(x_i) - 1 \tag{4}$$

$$\frac{\delta W}{\delta_b} = \sum_j y_j a_j = 0$$

As stated above to there is necessity of speed up the processing , so revised kernel function with SVM converges rapidly as it having great ability of storing complete vector sets at once also starts initialization from reverse classes . In addition this method having the iterative style of summing up all the given candidates by means of feature violation either misclassified or else left unclassified and immediately stops its operation once all the points are separated. The further support vectors are delivered to C for the present or initialized help vector S. If no present SV block is incorporated in C to S, then all of the S vectors are support vectors. If the value of α_p is not up to zero, then the classification of C to S is just not needed. The violator is the pixel which is categorized incorrectly or not regarded as part of segment the place it's supposed to be**.** To achieve optimal classification level there is necessity of SVM with optimum efficiency[15].

2.2.3 Performance Metrics

Peak Signal to Noise Ratio (PSNR) is generally utilized for the quality measure of recovery of image. The signal in this case is the original data, and the noise is the error introduced by segmentation[16-19]. When comparing segmentation, PSNR is an approximation to human perception of reconstruction quality. By having higher PSNR values shows higher quality reconstruction. Also PSNR in most cases defined via the MSE (Mean Squared Error).

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \tag{5}$$

2.2.3.1 Mean square error

$$PSNR = 10.\log_{10}\left(\frac{MAX_I^2}{MSE}\right) \tag{6}$$

Here, MAX_I is the maximum possible pixel value of the image. Generally as image pixels are denoted with 8 bits per sample, this is 255 and if it were denoted with linear PCM with B bits per sample, MAX_I is 2^B-1.

2.2.3.2 Structural content

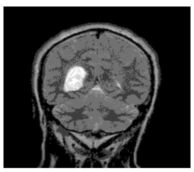
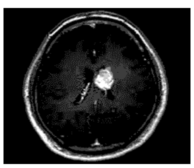
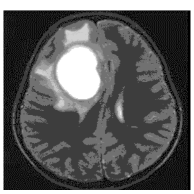
It is coined to be correlation based measures. It means the closeness between two images which can be quantified in terms of correlation function.

$$SC = \frac{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}(K(i,j))^2}{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}(I(i,j))^2} \quad (7)$$

3. Simulation Results

In order to examine the proposed work of denoising and segmentation algorithms, we use the MRI database that contains images with different noise factors are performed and results corresponding to techniques are shown in Figures 2, 3 and 4. Also to quantitatively evaluate the denoising algorithm, the performance metrics like Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE) and Structural Content (SC) are used. Table 1 delineates the simulation results for the proposed algorithm.

Table 1. Performance metrics of proposed algorithm on the MRI database

IMAGE	PSNR In (dB)	MSE In (dB)	SC
	12.42	3.71	0.58
	11.50	4.59	0.94
	11.35	4.75	0.96

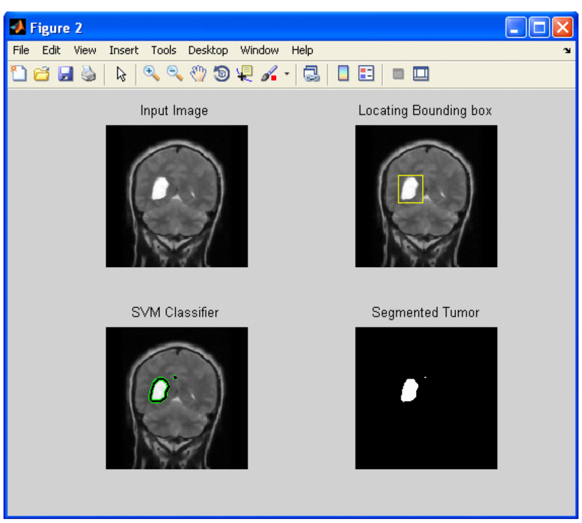


Figure 2. Pre-processing, Fast Bounding Box (FBB) and proposed one class SVM classification of the first MRI image.

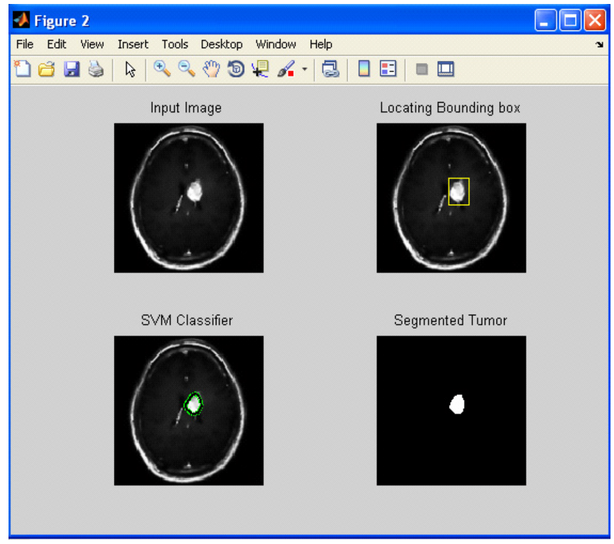


Figure 3. Pre-processing stage, Fast Bounding Box (FBB) and one class SVM classifier of second image.

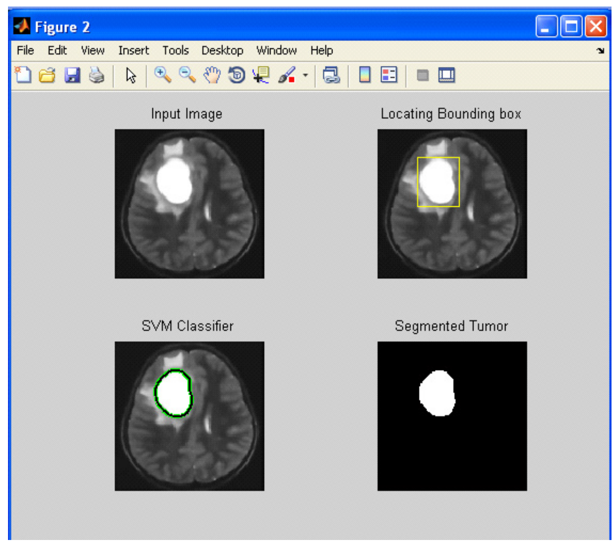
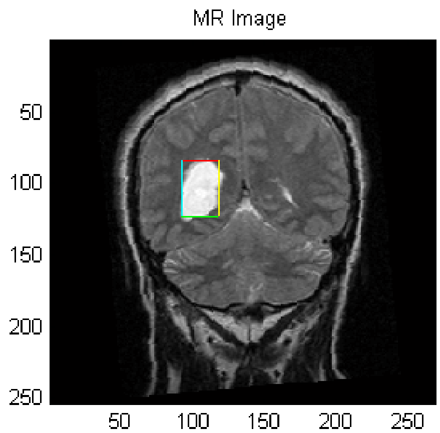


Figure 4. Pre-processing, Fast Bounding Box (FBB) and one class SVM classification of third image.

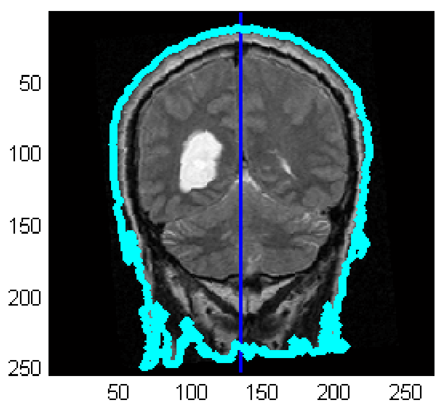
Since the brain skull mask image shown in Figure 5(a),(b) is divided into two regions one is left and other is right considered to be test image and reference in order to examine Approximate Line Of Symmetry (ALOS).

Figure 6(a) and 6(b) depicts the vertical and the horizontal score function plots contrary to the distances from the top and left of the image, correspondingly.

As depicted in Figure 6(a) and 6(b) we notice the rising and falling situation of score plots that are supportive us to know the severity of intensity levels in the bounding box of brain image.



(a)



(b)

Figure 5. (a)Tumor on the left side of the brain on a T1C (enhanced T1) MR slice. (b) Skull boundary detected by automatic global thresholding and subsequent post-processing.

From Figure 7 we aim to know the presence of tumor location on the image by examining the average intensity levels of bounding boxes on either sides of image and tumor existence can be known easily having mean intensity level at higher value at tumor location inside bounding box.

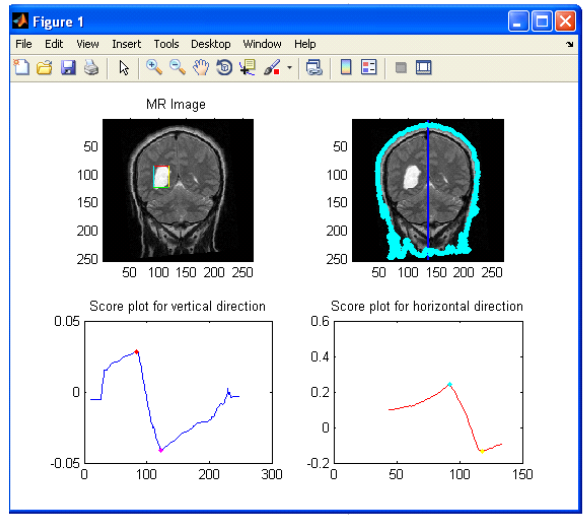
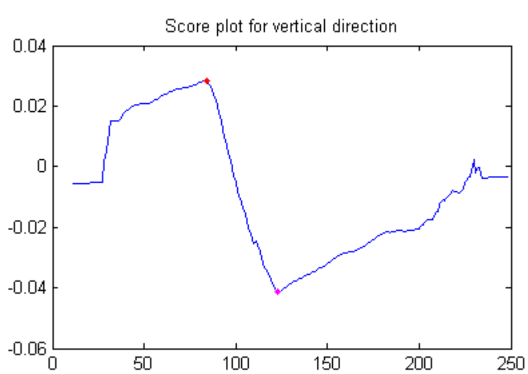


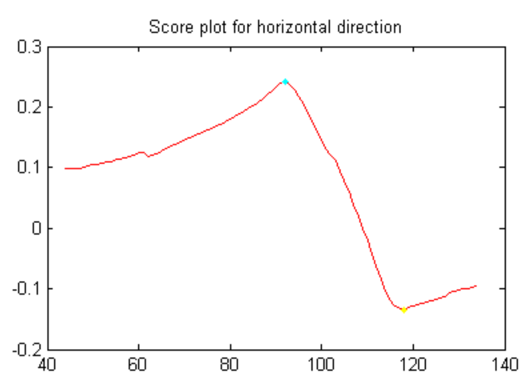
Figure 7. Segmentation with score plots.

5. Conclusion

In current work a fully automatic method for brain tumor segmentation of MRI images that has three folds, first phase is a pre-processing stage in which unusable parts of human brain are detached and anisotropic diffusion filter is applied to remove noise present in MRI images by embedding 8-connected neighborhood. In the second phase to know the tumor location we used FBB (Fast Bounding Box) process, and one class SVM is opted for substantial training sample set usage. Finally by opting the one class SVM classifier involving the Radial Basis Function (RBF) kernel is employed for locating exact



(a)



(b)

Figure 6. Vertical and the horizontal score function plots contrary to the distances from the top and left of the image, correspondingly.

tumor portion and isolates it from useful healthy texture region in MRI images.

5. References

1. Zhang N. Feature selection based segmentation of multi-source images: application to brain tumor segmentation in multi sequence MRI [PhD Thesis]. Lyon: L'Institut National des Sciences Appliquees; 2011.
2. Harati V, Khayati R, Farzan A. Fully automated tumor segmentation based on improved fuzzy connectedness algorithm in brain MR images. Computers in Biology and Medicine. 2011 Jul; 41(7):483-92.
3. Singh SK, Singh KB, Singh V. Medical image de noising in the wavelet domain using Haar and Db3 filtering. IRJES. 2012 Sep; 1(1):001-8.
4. Rupinderpal K, Rajneet K. Survey of de-noising methods using filters and fast wavelet transform. International Journal of Advanced Research in Computer Science and Software Engineering. 2013 Feb; 3(2):134-6.
5. Rajeshwari S, Sree ST. Efficient quality analysis of MRI image using preprocessing techniques. Proceedings of IEEE Conference on Information and Communication Technologies (ICT); Chennai. 2013. p. 391-6.
6. Anand C, Piyush C, Cheeran AN, Yashant A. Improving signal to noise ratio of low dose CT image using wavelet transform. JCSE. 2012 May; 4(5):779-87.
7. Kumar BBS, Satyanarayana PS. Compression and de noising analysis from still images using symlets wavelet technique. IJARS. 2013 Aug; 2(8):1-11.
8. Guo L, Zhao L, Wu Y, Li Y, Xu G, Yan Q. Tumor detection in mr images using one-class immune feature weighted SVMs. IEEE Transactions on Magnetics. 2011 Oct; 47(10):3849-52.
9. Zhou1 J, Chan KL, Chong VFH, Krishnan SM. Extraction of brain tumor from MR images using one-class support vector machine. IEEE Proceedings of 27th Annual Conference on Engineering in Medicine and Biology; Singapore. 2005. p. 6411-4.
10. Otsu N. A threshold selection method from gray level histogram. IEEE Transactions on Systems, Man and Cybernetics SMC. 1979 Jan; 9(1):62–6.
11. Perona P, Malik J. Scale-space and edge detection using anisotropic diffusion. IEEE Trans on Pattern Analysis and Machine Intelligence. 1990 Jul; 12(7):629–39.
12. Diaz I, Boulanger P, Greiner R, Murtha A. A critical review of the effect of de-noising algorithms on MRI brain tumor segmentation. IEEE Annual International Conference on Engineering in Medicine and Biology Society (EMBC); 2011 Sep. p. 3934-7.
13. Rajalakshmi N, Prabha VL. Brain tumor detection of MR images based on color-converted hybrid PSO+K-means clustering segmentation. European Journal of Scientific Research. 2012 Apr; 70(1):5-14.
14. Saha BN, Ray N, Greiner R, Murtha A, Zhang H. Quick detection of brain tumors and edemas: A bounding box method using symmetry. Elsevier Computerized Medical Imaging and Graphics. 2012 Mar; 36(2):95–107.
15. Bian ZQ, Zhang XG. Pattern Recognition [M]. Beijing: Tsinghua University Press; 2000.
16. Prabhu C, Narayana Moorthy S. An improved method to overcome existing problems in brain tumor segmentation. Indian Journal of Science and Technology. 2016 Jan; 9(1). Doi no:10.17485/ijst/2016/v9i1/71374
17. Baraiya N, Modi H. Comparative study of different methods for brain tumor extraction from MRI images using image processing. Indian Journal of Science and Technology. 2016 Jan; 9(4). Doi no:10.17485/ijst/2016/v9i4/85624
18. Jayasri T, Hemalatha M. Categorization of respiratory signal using ANN and SVM based on feature extraction algorithm. Indian Journal of Science and Technology. 2013 Sep; 6(9). Doi no:10.17485/ijst/2013/v6i9/37144
19. Mahalakshmi S, Velmurugan T. Detection of brain tumor by particle swarm optimization using image segmentation. Indian Journal of Science and Technology. 2015 Sep; 8(22). Doi no:10.17485/ ijst/2015/v8i22/79092
20. Fazli S, Nadirkhanlou P. A novel method for automatic segmentation of brain tumors in MRI images. IJASCSE. 2013; 2(6).