ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 2, February 2017

Analysis of Segmentation in MRI Images Using FCM Segmentation and Optimization Techniques

N.Arulmozhi Vijaya Banu

Lecturer, Department of ECE, IRT Polytechnic College, Chennai, India

ABSTRACT: In the acquisition of images of the human body, medical imaging devices play an important role. Tissue abnormalities and tumors in the human body are detected using the Medical Resonance Imaging (MRI) systems. MRI images are subject to degradation by the various kinds of noise during the formation process.

The removal of such kind noises followed by the segmentation of images for the classification of abnormalities is challenging research work. Segmentation of MRI images is done to identify the suspicious regions in an MRI image. It is a very complex process. The identification of suspicious regions has to be done with higher accuracy. Here a bio-inspired optimization tool is introduced to identify the suspicious regions in an MRI brain image to detect the brain tumor.

Classification is a decision-making process that occurs when an object or a thing is classified into a particular predefined group based on the parameters measured from it. A neural network is the most widely used tool for the classification process. These adaptive methods, universal functional approximation, and nonlinear modeling of neural networks make them very useful in the field of classification. Back Propagation Network (BPN) classifier is utilized for classification purposes.

KEYWORDS: Brain MRI, optimization, Segmentation.

I. INTRODUCTION

1.1 PROLOGUE

Brain image Segmentation and classification is a demanding task, since the images are very complex, and no anatomy models are capturing all potential deformations within each structure. Brain tissues are especially complex and their segmentation is a significant step in deriving computerized anatomic atlases and for clinical intervention pre and intra-operational guidance. For a variety of clinical investigations of varying scope, segmentation and classification of MRI were suggested. In clinical terms, medical image processing is typically equated with a radiology-based examination or clinical imaging analysis, and the image is interpreted by medical practitioners or radiologists. The technical part of medical imaging, and especially the acquisition or achievement of medical images through a specific system, is assigned by diagnosis radiography or medical practitioners.

1.2 HUMAN BRAIN

A human brain is a fragile, elastic, non-replaceable, and spongy tissue mass. It incorporates static equilibrium and autonomous roles in the body and controls them. The brain generates several hormones and controls their emotionally-related thought process, recognition, comprehension, and integration. The human brain samples are shown in figure 1.1.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 2, February 2017

Figure 1.1 Human Brains

1.3 STAGES OF BRAIN TUMOR

The names of the tumor depend on the origin of the tumor, the growth pattern of the tumor, and whether or not it is cancerous. Classification is one way to tell the tumor how bad it is. How the cells are interpreted by a pathologist with a microscope depends on the stage of the tumor. Higher-quality tumors typically look less like specialized cells. Such cells are described as anaplastic, and thus tumors often are more significant than those not described as anaplastic.

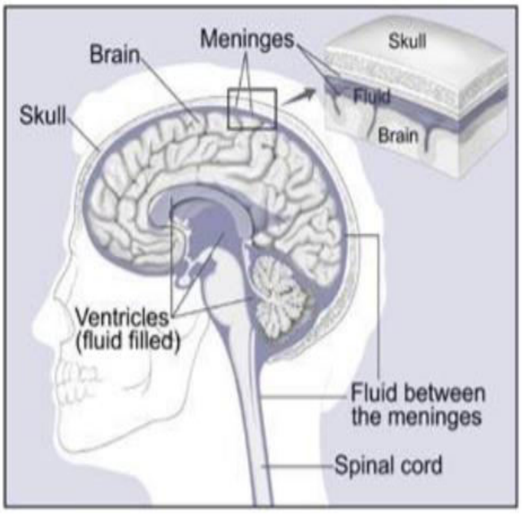

Figure 1.2 The structure of the brain

The brain structure is shown in figure 1.2. During the disease, many patients have significant changes in a tumor. There are two reasons why these changes happen. The tumors grow and become more aggressive than they were in the initial stage. Secondly, the grading is solely dependent on the biopsy portion of the tumor. Tumors also are heterogeneous, so that one section of a tumor may have different grades. The pathologist typically gives the highest rating to a tumor he or she has, but higher degrees of cells may lurk elsewhere, especially in the case of a small biopsy. Although it is an art as well as a science that rules to determine tumor form and grade, it is therefore critical that a neuropathologist who sees a large number of brain tumors analyze your biopsy samples.

II. LITERATURE REVIEW

2.1 INTRODUCTION

Noise removal is a challenging task of researchers and it has a significant impact on various applications including image restoration, visual monitoring, image registration, image segmentation, and image classification are important for superior performance to get real image information. The extraction and examination of brain tumors pose difficulties in medical imaging as the picture and function of the brain are complex and can only be examined by

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 2, February 2017

professional radiologists. Various algorithms have been published and every technique has its assumptions, benefits, and drawbacks.

2.2 Review of literature

Manuel González-Hidalgo et al. (2017) stated the use of fuzzy mathematical operators in removing the noise from an image corrupted by Salt and Pepper Noise. They demonstrated an improved angry open-closure mathematical moral morphology, an improved version of an open-closure furrow mathematical morphology. Mathematical operators used here are designated to reconstruct the noisy pixels without considering noisy pixels in a processing window.

Tian Bai et al. (2014) presented a novel continued fractions interpolation filter which emphasized the use of median filters. The noise-free pixels in an image are kept as it is. The noisy pixels are reconstructed using the directional method. Four directional continued fractional interpolations are calculated. The weighted mean is the reconstruction of the noisy pixel by four directional interpolations.

Deivalakshmi et al. (2016) implemented an effective tolerance-based selective arithmetic mean filtering technique. This proposed technique utilizes the wavelet thresholding method to restore the highly corrupted image. The noisy pixels are detected using the difference between the processing pixel and the arithmetic mean of the processing window. If a noisy pixel is found, it is replaced by the arithmetic mean. All the noisy pixels are reconstructed using the arithmetic mean.

Xiangyu Deng et al. (2016) presented a denoising method that is based on the Multi-Layered Pulse Coupled Neural Network (MLPCNN). An improved multi-layered pulse coupled neural network is used to detect the noisy pixels in an image. Noise detection is done by setting the parameters of a multi-layered pulse coupled neural network adaptively. This adaptation is based on mathematics firing.

SayanKahali et al. (2017) presented a two-stage fuzzy multi-objective framework for MRI image segmentation. The soft tissue regions of the MRI images are blurred and make it difficult to segment due to the limitations of the image capturing systems and issues related to it. In the first stage, local membership functions and global membership functions are assigned by using spatial information along with the spatial Fuzzy C Means (FCM) algorithm.

III. PROPOSED METHODOLOGY

This thesis introduces and explores the algorithms to be proposed. The experimental results are then usually obtained by the use of different synthetic images with well-known features to demonstrate the exactness and efficacy of the algorithm proposed. The real picture and views of the various patients also showed the broad application of the approaches suggested. In contrast to well-known methods like BOA, FFOA, the effects of state-of-the-art algorithms were also seen when they were used in the same test images. For brain tumor detection the attempts have been made to find the best values for the FFOA parameters. Due to the nature of the proposed algorithms, all the presented results are averaged and the MRI image of more than 20 sequences is used. We consider the basic sequence of T1, T2. Flur image brain tumors are detected and the result is compared and evaluated.

3.1 MRI image segmentation using boa with fuzzy c means (boa-cm) clustering

3.1.1 INTRODUCTION

In medical diagnosis, Magnetic Resonance Image (MRI) segmentation is a significant image analysis task. MRI offers complete information regarding brain tumor anatomy, cellular structure as well as vascular supply. The segmentation of brain tumors from MRIs is significant and on the other hand time-consuming task carried out with the help of medical experts. In recent times numerous segmentation techniques were presented for resolving the MRI brain tumor segmentation problem. Numerous research was carried out in the field of image segmentation by utilizing clustering. The distrustful area of tumors is segmented with the help of Fuzzy C means (FCM) with Bat Optimization Algorithm (BOA) for MRI images.

3.2 SEGMENTATION OF MRI IMAGES

MRI image segmentation is an important task in numerous medical applications. For post-surgical assessment, surgical planning, and abnormality detection. Precise segmentation is extremely significant for identifying tumors as well as cancer-affected tissues.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 2, February 2017

3.3 BOA with fuzzy c means (boa-cm) based segmentation

Fuzzy C-means (FCMs) Homogeneity and/or weighted bias strength algorithm, and T1-T2 segmented MRI brain images of the same patient. A distance table is generated to indicate the distance between the elements of each category. The maximum distance between groups is determined as well as a mean value. For that query, the objective function J was thus changed:

$$J_m = \sum_{i=1}^{C}\sum_{k=1}^{n} \mu_{ik}^{m}[\alpha d_{ik}^{2} + \delta(d_{ik}^{*})^{2}] + \frac{n}{c}\left[1 - \sum_{i=1}^{C} \mu_{ik}^{m}\right] \quad \textbf{(1)}$$

Here

$$d_{ik}^{2} = ||x_k - v_i|| \text{ and } d_{ik}^{*} = ||x_k + \varepsilon - b_k - v_i||^2$$

$$\varepsilon\epsilon(0,1) \text{ and } \alpha, \delta > 0$$

3.4 BAT OPTIMIZATION ALGORITHM (BOA)

Algorithm 1: BOA with FCM segmentation

Step 1: The optimal value BOA is used to select the initial cluster point.
Step 2: Calculate the cluster centers.
Step 3: Compute the Euclidean distances edij
Step 4: Update the fuzzy membership matrix is by equation (below)

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left[\frac{||x_j - v_i||}{||x_j - v_i||}\right]^{2/(m-1)}} \quad \textbf{(2)}$$

Step 5:Repeat step 4 until it reaches the lesser error
Step 6: Calculate the average clustering points by the sum of all results in equation (1)
Step 7: Compute the adaptive threshold =max (Adaptive threshold, ci)i=1...n
In the MRI image, the pixels containing fewer intensity values compared to the adaptive threshold value are altered to zero. The complete process is repetitive any number of times for getting the more estimated value.

IV. RESULTS AND DISCUSSION

The efficiency of the research method is identified using taking out the distrustful region from the MRI image with the help of BOA.

Rand Index (RI)

RI counts the fraction of pixel pairs whose labeling is reliable, both in measured segmentation and in the ground reality that averages multiple segmentation of ground facts.

$$R = \frac{a+b}{a+b+c+d}$$

Variation of Information (VOI)

The information variation (VOI) metric defines the distance between two segments as the average conditional entropy of one segment given by another, which makes the randomness sum in one segment which cannot be represented by the other measured.

$$VI(X, Y) = H(X) + H(Y) - 2I(X, Y)$$

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 2, February 2017

Boundary Displacement Error (BDE)

BDE measures both the average one-boundary pixels displacement error and the nearest boundary pixels in the other segment.

$$\mu_{LA}(u,v) = \begin{cases} \frac{u-v}{L-1} & 0 < u < L_1 \\ 0 & u - v < 0 \end{cases}$$

Table 4.1 Performance comparison metrics vs. segmentation methods

Metrics	K means	Improved K means (IKM)	FCM	BOA with FCM
RI	0.9012	0.9125	0.9356	0.9548
VOI	0.5053	0.4056	0.2596	0.1058
BDE	0.2818	0.2348	0.1893	0.0752
Error	0.0988	0.0875	0.0644	0.0452

The experimentation is carried out over a lot of images utilizing the algorithms k means, improved k means, FCM, presented BOA with FCM segmentation and their outcomes are shown in Figure 4.1-4.4 with essential statistical parameters as well as their outcomes are given in Table 4.1.

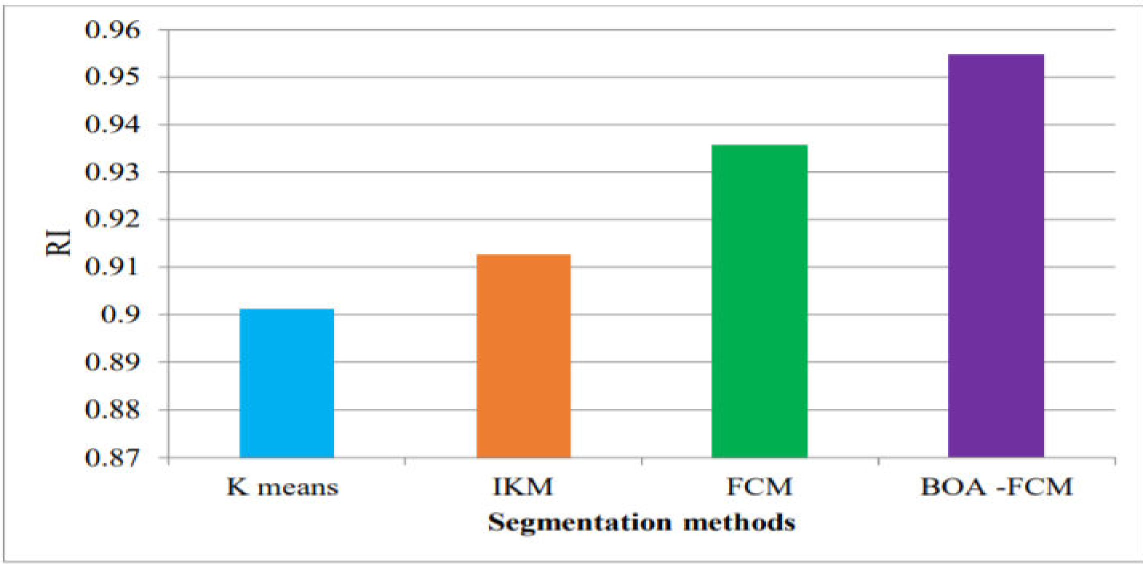

Figure 4.1 RI vs. Segmentation methods

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 2, February 2017

Figure 4.1 shows the performance analysis outcome that indicates that the rand index of BOA with FCM segmentation is greater (0.9548) compared to other techniques. It is as well exposes that the error, variation of information, and boundary displacement error are lesser compared to others are shown in figure 4.2, figure 4.3, and figure 4.4. Figure 4.2 displays the performance analysis outcomes indicating that the error of presented BOA with FCM segmentation is lesser (0.0452) that is 0.0536, 0.0423, and 0.0192 lower while matched up with k means, IKM, and FCM approach correspondingly.

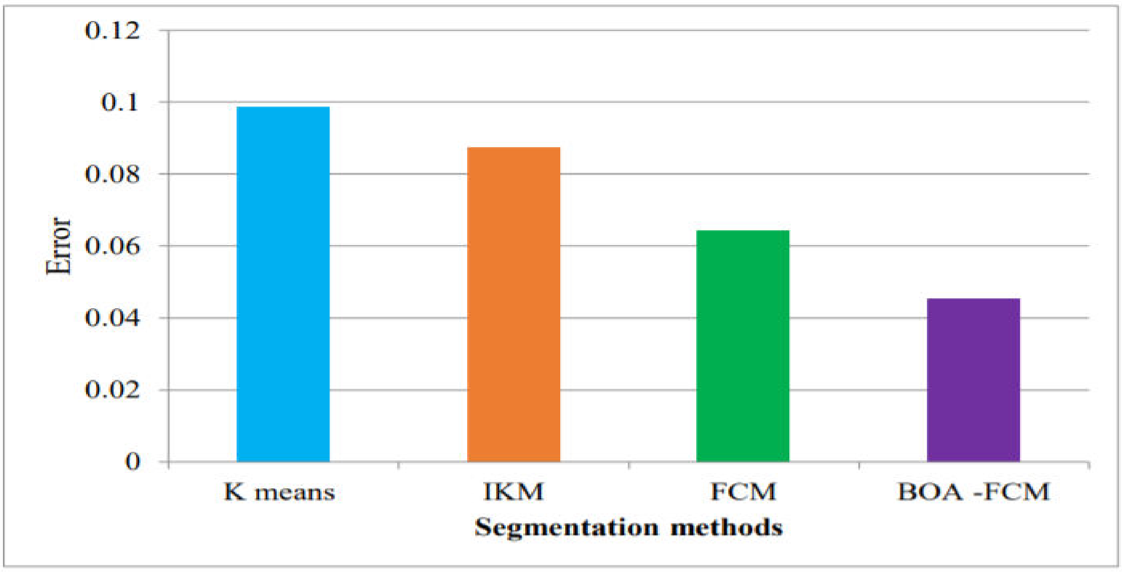

Figure 4.2 Error vs. Segmentation methods

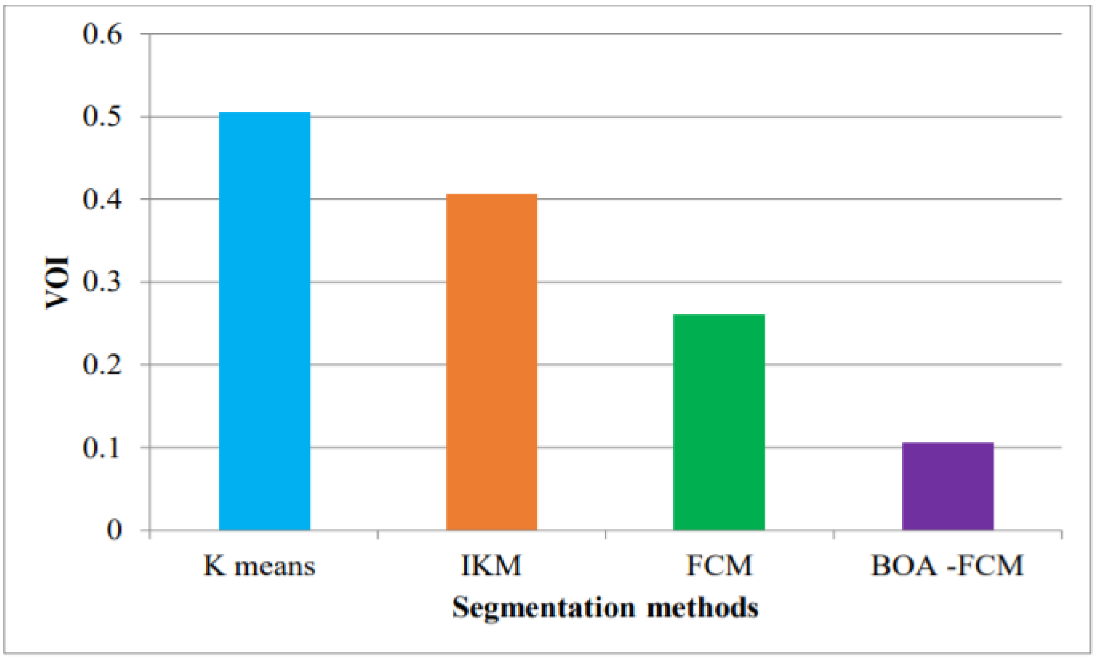

Figure 4.3 VOI vs. Segmentation methods

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 2, February 2017

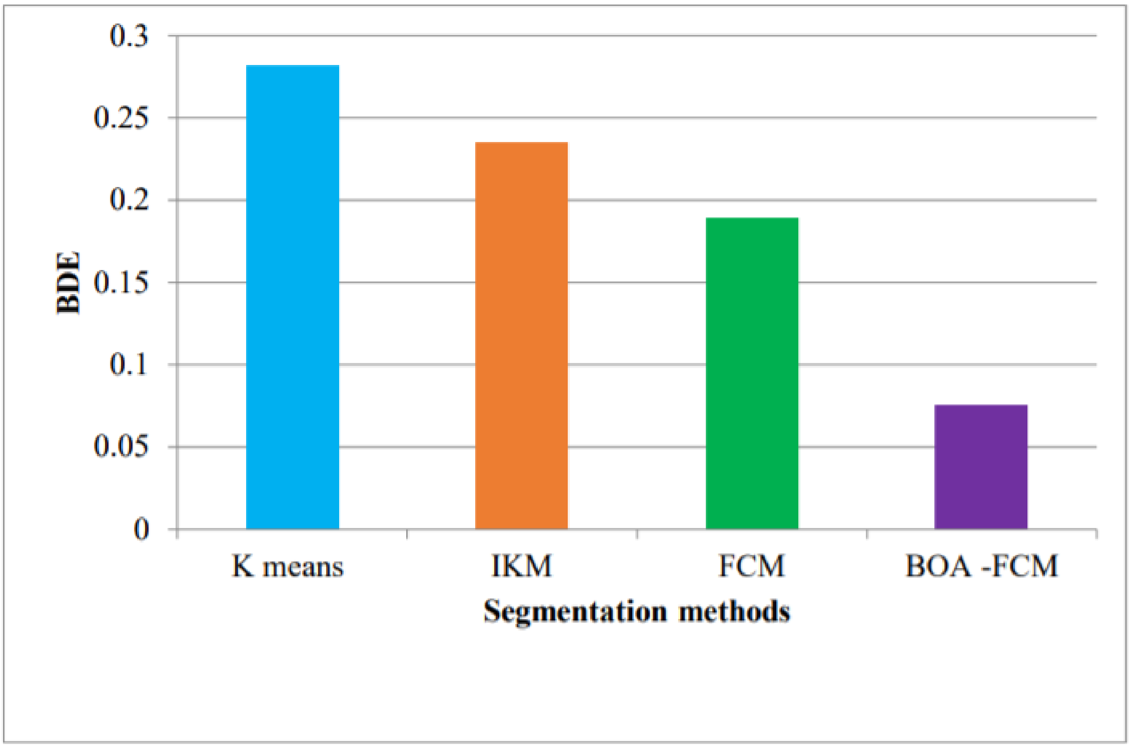

Figure 4.4 BDE vs. Segmentation methods

V. CONCLUSION

The analyzed data of MRI utilizing the Bat Optimization Algorithm (BOA) was presented in this paper. The numerous kinds of segmentation in MRI images utilizing diverse clustering techniques were examined. The presented BOA-FCM algorithm provides improved outcomes while matched up with the existing method. The traditional FCM gives lesser outcomes while matched up with the presented BOA-FCM algorithm.

REFERENCES

1. Ching-Ta Lu, Mu-Yen Chen, Jun-Hong Shen, Ling-Ling Wang &Chih-Chan Hsu, 2017, ‗ Removal of salt-and-pepper noise for X-ray bio-images using pixel-variation gain factors', Computers and Electrical Engineering an International journal.
2. Ching-Ta lu, Yung-Yue Chen, Ling-Ling Wang & Chun-Fan Chang, 2016, ‗Removal of salt and pepper noise in the corrupted image using three values weighted approach with variable window size', Pattern recognition letters
3. Chithambaram, T. and Perumal, K., 2017. Brain Tumor Detection and Segmentation in MRI Images Using Neural Network in International Journal, 7(3).
4. Despotović, I., Goossens, B. and Philips, W., 2015. MRI segmentation of the human brain: challenges, methods, and applications in Computational and mathematical methods in medicine.
5. Ganesh M., Naresh M. & C. Arvind, 2017, ‗MRI Brain Image Segmentation Using Enhanced Adaptive Fuzzy K-Means Algorithm', Intelligent Automation & Soft Computing an International journal, vol 23, no . 2, pp.325–330.
6. Ganesh M., Naresh M. & C. Arvind, 2017, ―MRI Brain Image Segmentation Using Enhanced Adaptive Fuzzy K-Means Algorithm‖, Intelligent Automation & Soft Computing an International journal, Vol.23, No.2, pp.325–330.
7. Hanafy M. Ali, 2017, ‗MRI Medical Image Denoising by Fundamental Filters', SCIREA Journal of Computer, vol.2, no.1, pp. 12-26

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 2, February 2017

8. Hinge, M.M., Matkar, M.S.B., Mane, M.A.B. and Shirsat, M.A.M., 2015. Classification of MRI brain image using an SVM classifier. LISTE Int. J. Sci. Technol. Eng, 1(9), pp.24-28.
9. Kumar, S., Dabas, C. and Godara, S., 2017. Classification of Brain MRI Tumor Images: A Hybrid Approach in Procedia Computer Science, 122, pp.510-517.
10. Kumari, R., 2013. SVM classification an approach on detecting abnormality in brain MRI images in International Journal of Engineering Research and Applications, 3(4), pp.1686-1690.