

Classification and Segmentation of MRI Brain Images using Support Vector Machine and Fuzzy C-means Clustering

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Abstract- An early diagnosis of brain disorders is very important for timely treatment of such diseases. Several imaging modalities are used to capture the anomalies by obtaining either the physiological or morphological information. The scans obtained using imaging modalities such as magnetic resonance imaging (MRI) are investigated by the radiologists in order to diagnose the diseases. However such investigations are time consuming and might involve errors. In this paper, a fuzzy c-means clustering method is used for brain MRI image segmentation. The GLCM features are obtained from the segmented images and are subsequently mapped in to a PCA space. A support vector machine (SVM) classifier is used to classify brain MRI images taken from BRATS-13 images. The method is evaluated by employing various performance measures such as Jaccard index, Dice index, mean square error (MSE), peak signal to noise ratio (PSNR). The results show that the method outperforms the existing methods.

Keywords- Segmentation, magnetic resonance imaging, Mean Square Error, Computer-Aided Diagnosis, Support vector machines.

1. Introduction

Several types of brain disorder such as Alzheimer's disease, dementias, brain cancer, epilepsy, and Parkinson's, etc. can be diagnosed using one imaging modality or the other [Gahukar, Sayali D., and S. S. Salankar, 2014]. Among many such imaging modalities, positron emission tomography (PET), computerized tomography (CT), and magnetic resonance imaging (MRI) are used by neurologists [Thankam, T. Akhila, and KS Angel Viji, 2013]. While CT scan of the brain can provide a detailed information about the brain structure with high resolution, it is incapable of providing the physiological information which is very much needed in the diagnosis of many brain disorders [Pham, Thuy Xuan, Patrick Siarry, and Hamouche Oulhadj, 2018]. PET scans help the neurologist to assess the changes in the metabolism caused by the neurological disorders, however, the method is not a recommended imaging modality for a group of patients suffering from some other diseases. MRI has been proved to be a preferred imaging modality for the diagnosis of many brain disorders due to its capability of detecting brain tumours, capturing different anomalies, and hence helping the doctors to diagnose various types of brain disorders [Kanmani, P., and P. Marikkannu, 2018].

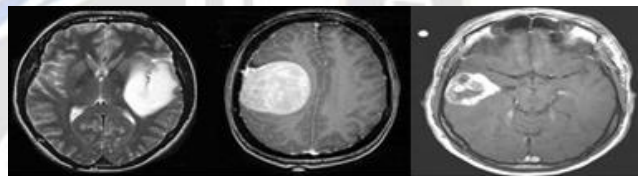


Figure 1. Brain MRI Images

The MRI is a painless and known non-invasive imaging modality that creates images of the brain using radio waves. The instrument used for taking MRI images employs a strong magnet producing high intensity magnetic field making the protons present in the body to align in one direction [Myint, Hla, and Soe Lin Aung, 2020]. These protons orient themselves against the magnetic field on the application of radio frequency current in the target tissue of the patient. The sample brain MRI images are shown in Fig.1. The MRI image so obtained is evaluated by a radiologist to diagnose the brain diseases and subsequently decide the type of treatment to be given to the patient [Hua, Lei, et al. 2021]. The manual inspection of MRI images by the radiologists is not only time consuming but also is prone to errors [Alsmadi, Mutasem K., 2014]. With the advancement in information technology, several automated methods have been developed by the researchers during the past few decades.

To effectively diagnose the disease from the MRI images, several pre-processing tasks such as denoising, extraction of region of interest, contrast enhancement, and segmentation, etc. are applied [Ahmed, Mohamed N., et al., 2002]. In this paper, the classification of brain tumours is done with machine learning methods after performing the segmentation of brain MRI images using C means clustering algorithm. The method has been tested on BRATS-2013 dataset which contains MRI images of 25 patients, each image divided into high grade gliomas (HG) and low-grade gliomas (LG). The results validate the performance of the proposed method. The rest of the paper is organized as follows. Section 2 gives the details of the dataset and the methods used. Section 3 gives a discussion on the results obtained. The conclusion of the work is given in section 4.

2. Methods and Materials

The dataset used in this paper is the BRATS-2013 dataset [Naz, Samina, Hammad Majeed, and Humayun Irshad,2010]. The dataset contains synthetic as well as real MRI images along with images sequences viz. T1 weighted scan, T2 weighted scan, and post gadolinium scan taken from a total of 25 patients. The images are segmented using C means clustering algorithm prior to classification. The flowchart for the C means clustering is shown in Fig. 2. The segmented image is used to extract the features to give them to a classifier. Extraction of features is accomplished in the wavelet domain by converting the segmented brain MRI image in the spatial domain to the wavelet domain [Forouzanfar, Mohamad, Nosratallah Forghani, and Mohammad Teshnehlal,2010]. For this, discrete wavelet transform (DWT) is applied on the two-dimensional images by taking each dimension separately [Forouzanfar, Mohamad, Nosratallah Forghani, and Mohammad Teshnehlal,2010]. To reduce the complexity of computation, the images after DWT are mapped on another domain using principle component analysis (PCA). The features in the PCA domain are used to extract the first order and second order statistical performance metrics. [Birgani, Parmida Moradi, Meghdad Ashtiyani, and Saeed Asadi,2008]. Among the first order statistical performance metrics, mean, variance, and skewness are calculated [Chen, Aiguo, and Haoyuan Yan, 2021]. For mapping the correspondence of pixels with same grey levels, grey level co-occurrence matrix (GLCM) is obtained which provides features viz. energy, entropy, contrast, homogeneity, inverse differences moment, angular second moment, etc.

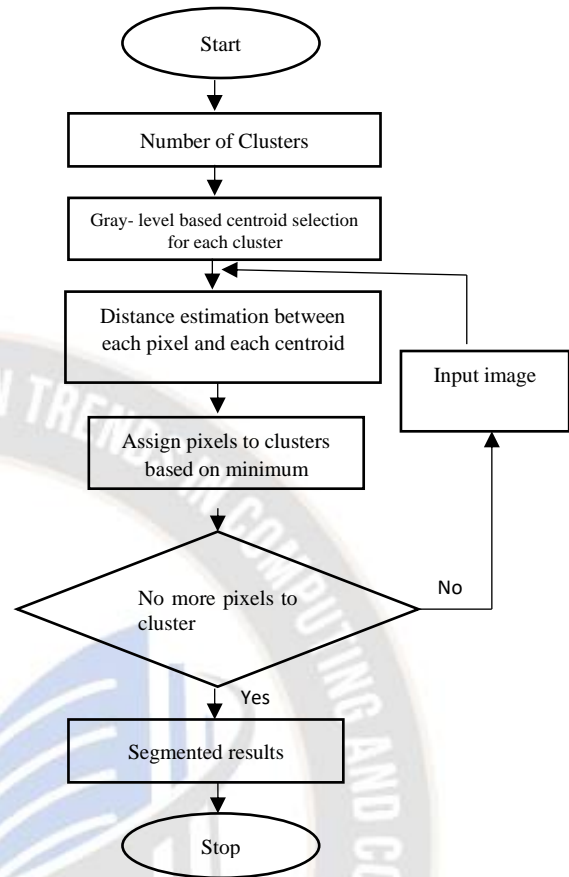


Fig. 2. Flowchart for C-means with Initialised Centroids for Clusters

The classifier is trained with the parameters obtained from the brain images taken from the BRATS- 2013 dataset. The training is done on malignant and benign tumour images using linear, quadratic, polygonal, and radial basis function kernels. The RBF kernel has the kernel function defined as given in equation (1).

$$k(x, y) = \exp \left[-\sqrt{(x^2 - y^2) \div \sigma} \right] \quad (1)$$

The quadratic kernel has the transformation function defined as given in equation (2).

$$k(x, y) = [1 + xy]^2 \quad (2)$$

As the images are prone to noise during MRI scanning, a noise removal framework as shown in Fig. 3 is used.

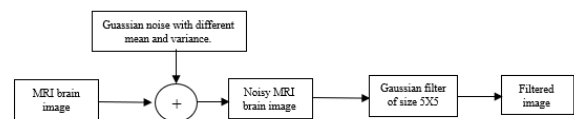


Fig. 3. Block diagram for noise removal process.

The filtered image is obtained from the noisy MRI brain image by convolving it with a gaussian filter of size 5x5.

3. Results and Discussion

The Jaccard index is calculated and the results are shown in Fig. 4. Similarly, Dice index, PSNR, MSE are shown in Fig. 5, Fig. 6, Fig. 7, respectively. The Jaccard index is a metric to

evaluate the similarity between the two images, which is calculated from two images a and b as given in equation (3).

$$Jaccard\ index = \frac{(a \cap b)}{[a + b - (a \cap b)]} \quad (3)$$

where a and b are the two images to determine the similarity. A comparison of Jaccard indices for five different images is shown in Fig. 4.

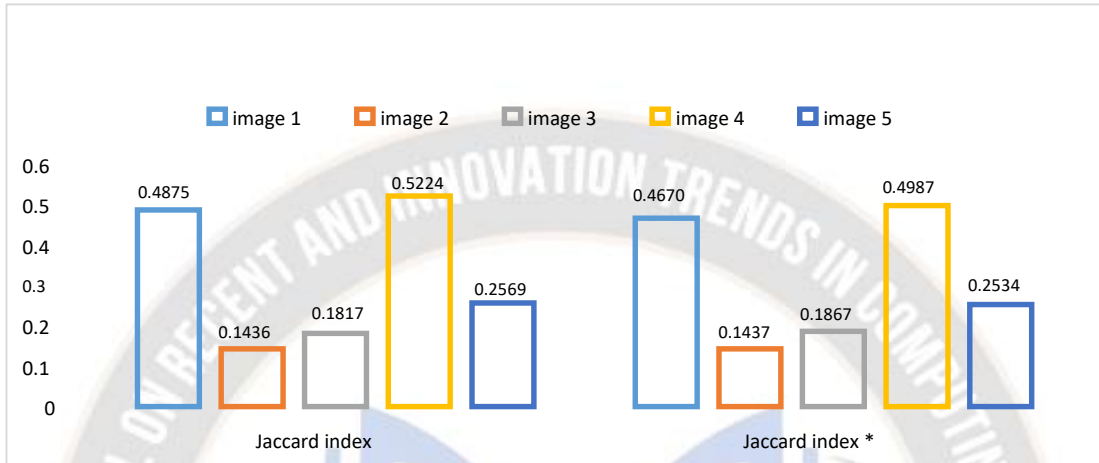


Fig. 4. Comparison of Jaccard Index

The Dice index also gives the similarity between the two images and is given in equation (4).

$$Dice\ index = \frac{2 \times |a \cap b|}{(|a| + |b|)} \quad (4)$$

where a and b are the two images whose similarity is to be determined. Fig. 5 gives a comparison of dice indices for 5 different images.

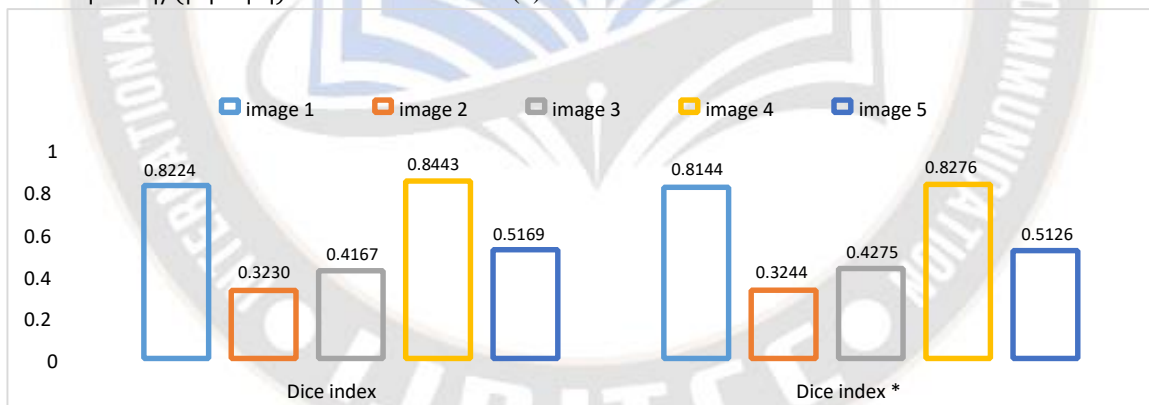


Fig. 5. Comparison of Dice Index

The MSE and PSNR are given in equation (5) and (6), respectively.

$$MSE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (S(i,j) - G(i,j))^2 \quad (5)$$

where S(i,j) and G(i,j) are the segmented and ground truth images respectively. Fig.(7) gives a comparison of MSE for 5 different images.

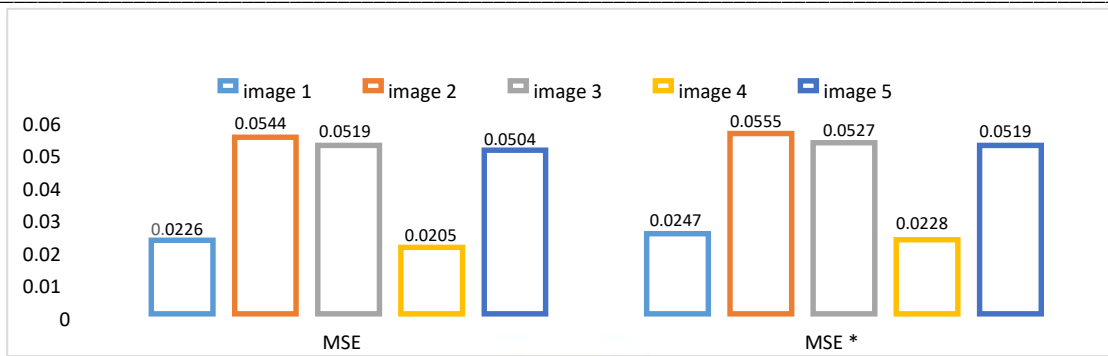


Figure 7. Comparison of MSE

$$PSNR = 10 \log_{10}[\max S(i, j) / MSE] \quad (6)$$

where MSE used in equation (7) is given in equation (6). A comparison of PSNR for 5 different images is shown in Fig. (8).

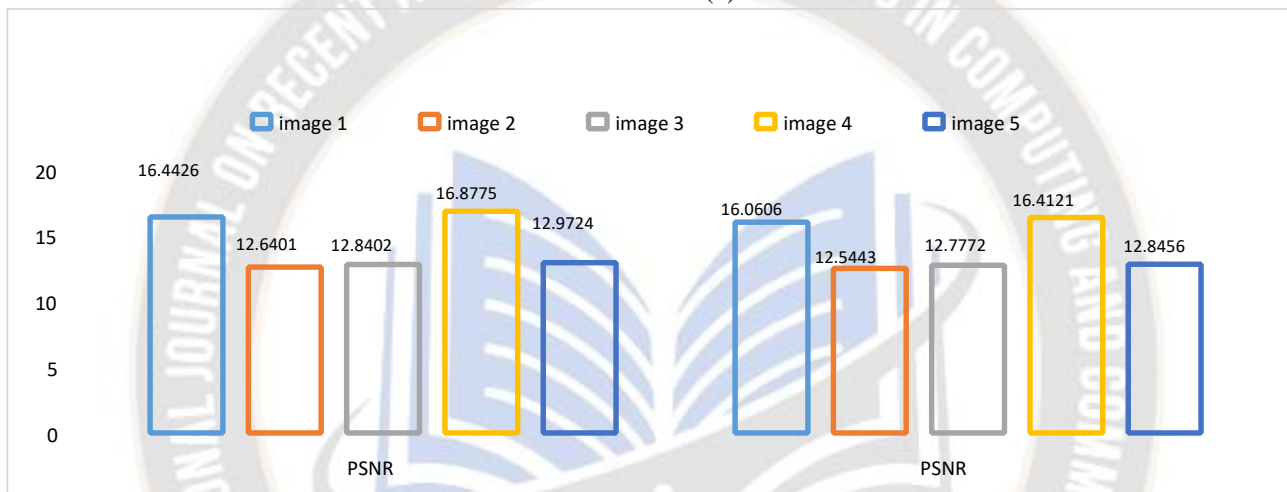


Figure 8. Comparison of PSNR

Table 1 and 2 give the performance metrics for k-means clustering and FCM clustering respectively.

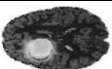
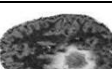
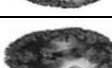
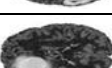

Image	Dice Index	Jaccard Index	MSE	PSNR
	0.8144	0.467	0.0247	16.0606
	0.3244	0.14335	0.05556	12.5443
	0.4275	0.18674	0.0527	12.777
	0.82765	0.4987	0.0228	16.410
	0.5126	0.25341	0.0519	12.8456

Table 1: Performance metrics for k-means Clustering

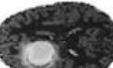

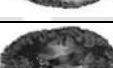
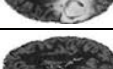
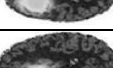
Image	Dice Index	Jaccard Index	MSE	PSNR
	0.8224	0.4875	0.02264	16.44
	0.3230	0.14364	0.0544	12.6401
	0.4167	0.18175	0.0519	12.8402
	0.84431	0.52244	0.0205	16.8775
	0.5169	0.25699	0.05044	12.970

Table 2: Performance metrics for FCM Clustering
It has been observed that in images where the boundaries are clear, the FCM outperforms the k-means clustering technique in terms of Jaccard index, Dice index, MSE, and PSNR performance metrics. The classifier is trained with

GLCM features extracted from the training images with equal no. of malignant and benign tumour images. A 10-fold cross validation is employed to assess the prediction accuracy of the classifier.



Figure 9. Confusion Matrix of Training Dataset

The scatter plots for the standard deviation vs mean and RMS vs entropy are shown in Fig. (10)

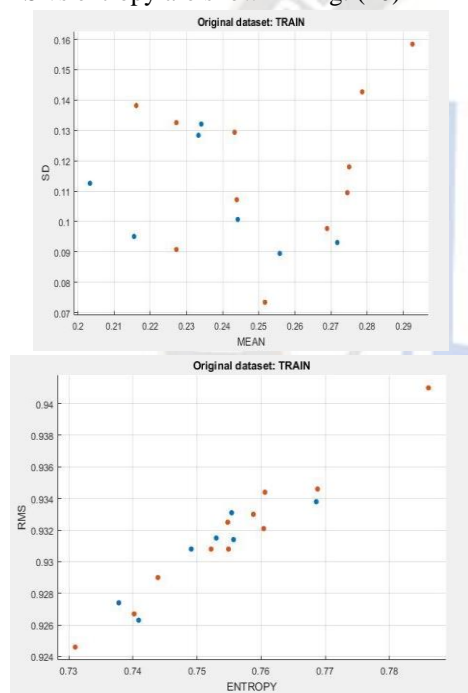


Figure 10. Scatter Plot of Input Data and training data
The ROC curve for the classifier is shown in Figure 11.

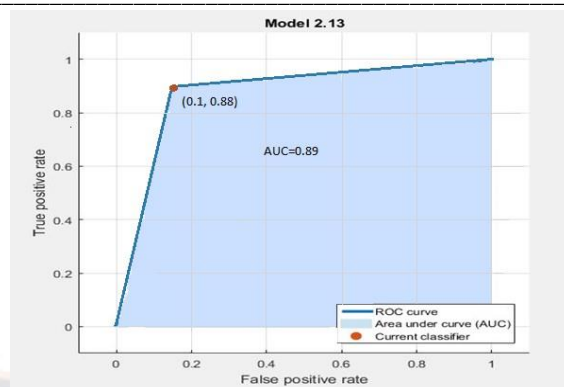


Figure 11. ROC Curve of Trained Model

Table 3 gives the accuracy of SVM classifier used with linear, quadratic, polygonal, RBF kernels.

Image	Predicted tumor type	RBF kernel accuracy (%)	Linear kernel accuracy (%)	Polygonal kernel accuracy (%)	Quadratic kernel accuracy (%)
	Malignant	70	90	80	80
	Malignant	80	80	80	80
	Benign	70	90	80	80
	Malignant	70	90	80	80
	Benign	80	80	80	80

Table 3. Accuracy of SVM with different Kernel

4. Conclusion

The Fuzzy c-means clustering algorithm for brain MRI image segmentation improves the prediction accuracy of support vector machine classifier. The gaussian filter used to denoise the brain MRI images enhances the segmentation results of Fuzzy c- means clustering. The GLCM features mapped on to a PCA space reduce the computational complexity of the method. The results obtained in terms of confusion matrix, ROC, Jaccard index, Dice index, MSE, and PSNR using brain MRI images taken from BRATS -13 dataset validate the method.

References

[1]. Gahukar, Sayali D., and S. S. Salankar. "Segmentation of MRI brain image using fuzzy c means for brain tumor

- diagnosis." *International Journal of Engineering Research and Applications* 4.4 (2014): 107-111.
- [2]. Thankam, T. Akhila, and KS Angel Viji. "Abnormality Segmentation of MRI Brain Images using Fuzzy Nearest Neighbour Approach." *International Journal of Computer Applications* 67.19 (2013).
- [3]. Pham, Thuy Xuan, Patrick Siarry, and Hamouche Oulhadj. "Integrating fuzzy entropy clustering with an improved PSO for MRI brain image segmentation." *Applied Soft Computing* 65 (2018): 230-242.
- [4]. Kanmani, P., and P. Marikkannu. "MRI brain images classification: a multi-level threshold-based region optimization technique." *Journal of medical systems* 42.4 (2018): 1-12.
- [5]. Myint, Hla, and Soe Lin Aung. "An efficient tumor segmentation of MRI brain images using thresholding and morphology operation." *Proceedings of the eighteenth international conference on computer applications (ICCA 2020)*. 2020.
- [6]. Hua, Lei, et al. "A novel brain MRI image segmentation method using an improved multi-view fuzzy c-means clustering algorithm." *Frontiers in Neuroscience* 15 (2021): 245.
- [7]. Alsmadi, Mutasem K. "A hybrid firefly algorithm with fuzzy-C mean algorithm for MRI brain segmentation." *American Journal of Applied Sciences* 11.9 (2014): 1676-1691.
- [8]. Ahmed, Mohamed N., et al. "A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data." *IEEE transactions on medical imaging* 21.3 (2002): 193-199.
- [9]. Naz, Samina, Hammad Majeed, and Humayun Irshad. "Image segmentation using fuzzy clustering: A survey." *2010 6th international conference on emerging technologies (ICET)*. IEEE, 2010.
- [10]. Forouzanfar, Mohamad, Nosratallah Forghani, and Mohammad Teshnehlab. "Parameter optimization of improved fuzzy c-means clustering algorithm for brain MR image segmentation." *Engineering Applications of Artificial Intelligence* 23.2 (2010): 160-168.
- [11]. Birgani, Parmida Moradi, Meghdad Ashtiyani, and Saeed Asadi. "MRI segmentation using fuzzy c-means clustering algorithm basis neural network." *2008 3rd International Conference on Information and Communication Technologies: From Theory to Applications*. IEEE, 2008.
- [12]. Chen, Aiguo, and Haoyuan Yan. "An improved fuzzy C-means clustering for brain MRI images segmentation." *Journal of Medical Imaging and Health Informatics* 11.2 (2021): 386-390.