ISSN: 0975-8585

Research Journal of Pharmaceutical, Biological and Chemical Sciences

Semantic Segmentation of Brain Tumour Images Using Support Vector Machine Classification.

Meryl B Asha C, Nandhini J, and K Srilatha*

Department of Electronics and Communication Engineering, Sathyabama University, Chennai, Tamilnadu, India

ABSTRACT

Segmentation and Classification are the two common tasks performed in order to analyze the image digitally .The goal of semantic image segmentation is to divide the images into semantically meaningful parts and classifying each part into one of the predefined class. Image classification plays an important role in digital image analysis. The feature extracted from the image is further used for the classification process. This proposed method represents both image segmentation and classification technique. The images are first segmented using semantic segmentation and after that images are classified with the help of support vector machine (SVM). Input image segmentation and feature extracted from segmented image finally features classified our database using SVM classifier. The goal of Classification is to find Object from input ones. At the end the image is classified as normal and abnormal image and various parameters are obtained from this method. The best results can be achieved by this proposed image segmentation and classification technique.
Keywords: Semantic Segmentation, SVM, Tumour, Classification, NSCT

Corresponding author

ISSN: 0975-8585

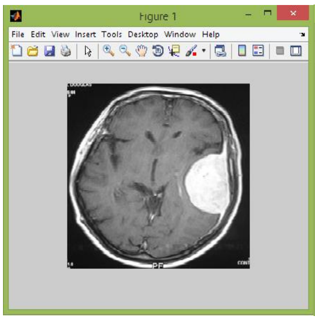
INTRODUCTION

Image segmentation is considered as a basic low-level vision problem in digital image analysis. The main goal of the segmentation process is to divide the image into non-overlapping regions corresponding to structural units or objects of interest. In spite of the efforts devoted in the last two decades, it still remains a challenging problem. Two fundamental tasks that are often built upon segmentation results are object detection and semantic image segmentation. Most approaches use object detection in order to detect prominent objects in the image foreground, while semantic image segmentation assigns a predefined label to each pixel. These are the three problems (image segmentation, object detection, and semantic image segmentation) that are essentially interdependent as pixel labels in semantic segmentation that benefit from the segmentation and discriminative object detectors. This work proposes an approach for semantic image segmentation, by jointly considering classification and image segmentation.

Picture element, or pixel is the term used for representing the brightness value of the image at a particular location. A typical digitized image may have 512 × 512 or 250,000 pixels, although much larger images are becoming common. There are three basic operations that can be performed on it in the computer once the image has been digitalised. For a point operation, a pixel value in the output image completely depends on a single pixel value in the input imageSiva Kumar. B, Srilatha.K et al [3]. For local operations, the output value can be determined with the help of several neighbouring pixels in the input image.

Existing Method

This approach uses an OBSIS technique (Ontology Based Semantic Image Segmentation). The contributions of this paper can be summarized as follows. A semi-semantic segmentation technique is proposed firstly, that detects effectively the object parts. Secondly, a technique is introduced inorder to altar the visual space into a higher level space with numerical values as intermediate labels (using Dirichlet process mixture models and multiple CRFs). Here, each visual feature in the transformed space is individually weighed, and then allocated to super pixels F. S. Khan et al [7]. Thirdly, ontology-based inference is introduced for the final semantic labelling.



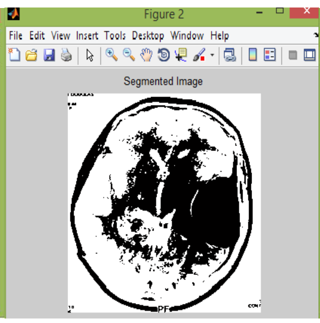


Fig 1: Input image **Fig 2: Segmented Image** **Fig 3: Thershold image**

In semi-semantic segmentation, the visual features from segmented super pixelsare utilized and learned individually in the new feature space using Dirichlet mixture models and CRFs. In this step, the acquired object parts along with their image objects, intermediate labels, and relationships at various levels are incorporated into the semantic ontology. Finally the semantic segmentation is achieved by induced labels of the semantic ontology. This ontology formally represents, models, and induces relations and object structures. Their overall proposed ontology-based semantic image segmentation approach is called OBSIS.

A three-layered ontology-based approach is proposed to allow the most comprehensive semantic description of the image content. The first layer consists of the ontology that helps in capturing the contextual relationships between image objects. Object decomposition into object subparts is designed in the second layer. The third layer combines the visual content into the ontology by describing the visual features of the object parts in terms of intermediate semantic labels. The overall goal is to make the use of this ontology to previously unseen images that would reason out the uniformity of the labels of segmented objects Mohsenz et al [1].

Proposed Method

This main objective of this proposed method is to segment the tumour image using semantic segmentation and to classify the tumour image using support vector machine classification. Semantic segmentation is also known as pixel classification. It associates one of the pre-defined class labels to each pixel. In the simplest case pixels are classified w.r.t. their local features, such as colour and/or texture features. The transform used in this method is non subsampled counterlet transformNSCT decomposition is to figure out the multi scale and different direction components of the discrete images K.Srilatha, S.Kaviyarasu et al [9].The feature extraction is done with the help of Gray Level Co-Occurrence matrix(GLCM).Gray-level co-occurrence matrix (GLCM) is the statistical method of examining the textures that considers the spatial relationship of the pixels.

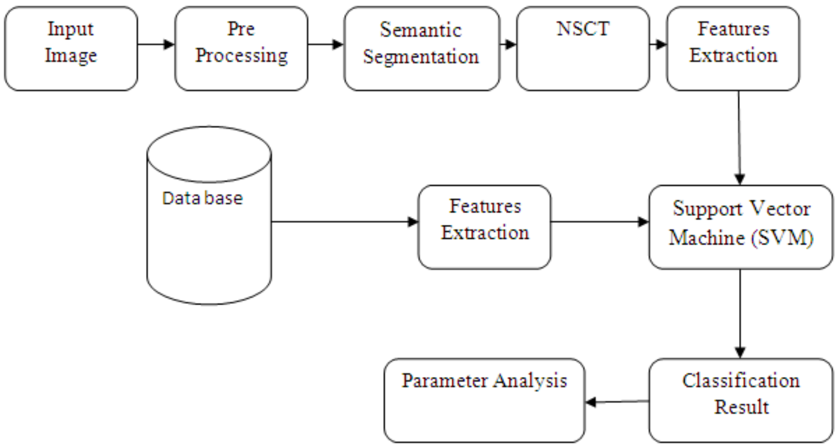


Fig 5: Block diagram using support vector machine

The GLCM functions describes the texture of an image by calculating pairs of pixel with specific values. The database consists of both normal and abnormal images of brainL. Zhu et al [11] .The abnormal images refers to the tumour image and the normal image refers to the tumourless images. The work of SVM classifier is to classify each row of the data in Sample, a matrix of data, with the help of the information in a support vector machine classifier structure SVMStruct. When the input image is given the svm classifier helps to know whether the input image is normal or abnormal image and in the abnormal case i.e., the image with tumour the svm classifier helps us to know the type of tumour Y.Yang et al [2].

There are two types of tumour benign tumour and malignant tumour. With the help of SVM classifier the tumour stages can be detected. Benign tumour refers to the starting stage of tumour and malignant tumour refers to the serious stage of tumour. Once the classification is done the result is obtained. Various parameter such as accuracy, PSNR (Peak Signal to Noise Ratio), MSE (Mean Square Error), sensitivity and specificity are obtained from the classification result.

RESULTS AND DISCUSSION

This paper proposes semantic image segmentation of brain tumour images using support vector machine classification which efficiently employs different types of information at the proper levels. GLCM (Gray Level Co-Occurrence Matrix) is one of the best feature extraction method which is used to calculate various textural features such as contrast and entropy. The classification technique used here is support vector machine classification through which the image can be classified as normal and abnormal images. Further the abnormal image is classified as benign and malignant tumour images. With the help of the classification results various parameters are obtained. The parameters such as accuracy, specificity, sensitivity peak signal to noise ratio (psnr) is increased and the value of mean square error is decreased when compared to the existing method.

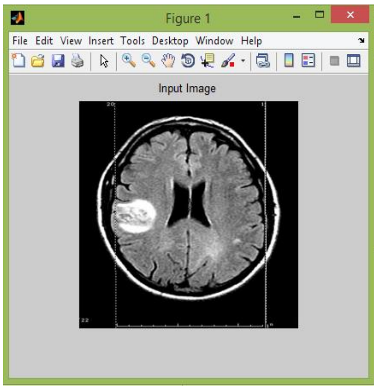


Fig 6: Input image

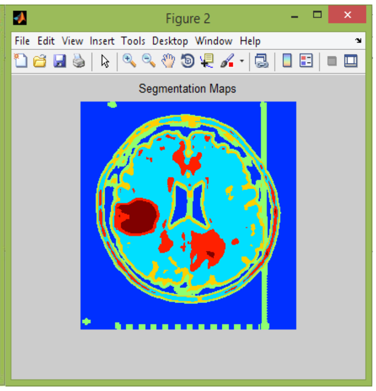


Fig 7: Segmented Image

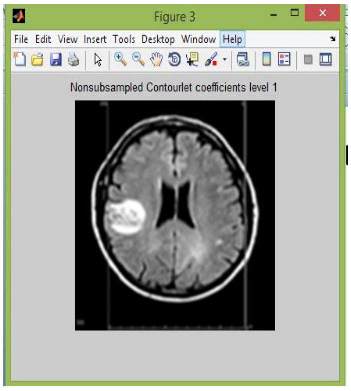


Fig 8: NSCPcoefficient level 1

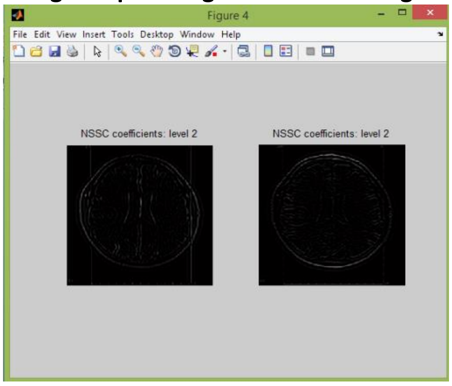


Fig 9: NSCP coefficient level 2

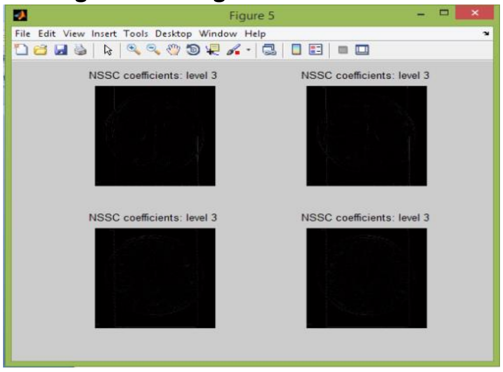


Fig 10: NSCP Coefficient level 3

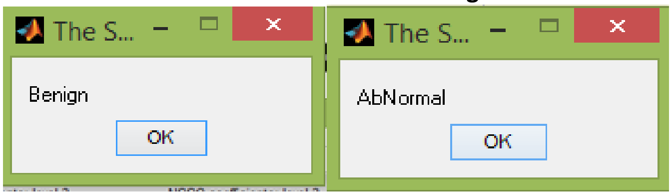


Fig 11: Classification Results

Table 1: Parameters of Proposed Method and Existing Method

Parameters	Proposed Method	Existing Method
Sensitivity	50	40
Specificity	99.823	93.2659
Accuracy	98.6934	86.3698
PSNR	30.7598	23.5698
MSE	2.36	5.36

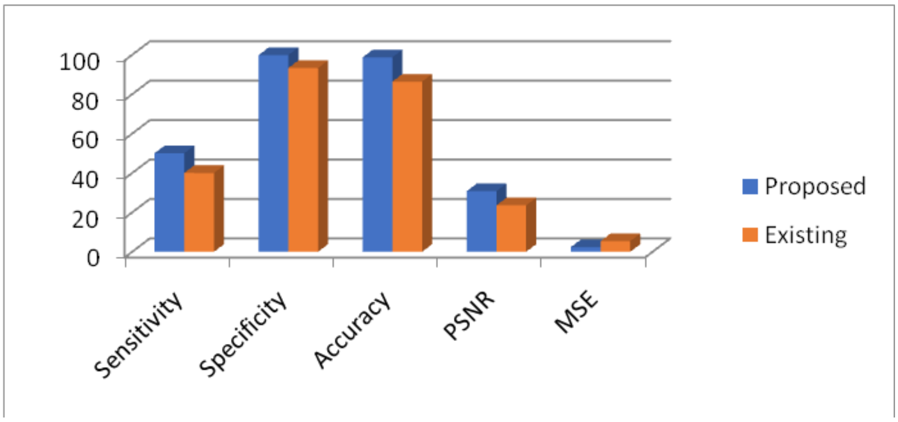


Fig 11: Parameters of Proposed Method and Existing Method

CONCLUSION

The proposed method is used in the medical field. Various medical application such as image guided surgery, measuring and visualizing the brain anatomical structure and analyzing the brain changes is possible. The time consumption and the noise level is less when compared to the previous approach. A greater percent of accuracy is obtained.

REFERENCES

[1] Mohsenz and, ShyamalaDoraisamyAlfian Abdul Halin and Mas RinaMustaffa, "Ontology Based Semantic Image Segmentation Using Mixture Models and Multiple CRF'S", IEEE Trans.Image Processing.,vol.25,No.7, july 2016.

[2] Y.Yang, S.Hallman, D.Ramanan, and C.C.Fowlkes, "Layered object models for image segmentation," IEEE Trans. Pattern Anal. Mach.Intell., vol. 34, no. 9, pp. 1731–1743, Sep. 2012. [3] Z.Li, X. M. Wu, and S. F. Chang, "Segmentation using superpixels:A bipartite graph partitioning approach," in Proc. IEEE Conf. Comput.Vis.PatternRecognit. (CVPR), Jun. 2012, pp. 789–796.

[3] Siva Kumar, B., Srilatha, K, "A novel method to segment blood vessels and optic disc in the fundus retinal images", Research Journal of Pharmaceutical, Biological and Chemical Sciences, VOL 7/ISSUE 3/MAY 2016/PP 365-373.

[4] D.Comaniciu and P. Meer, "Mean shift: A robust approach towardfeature space analysis," IEEE Trans. Pattern Anal. Mach. Intell., vol. 24,no. 5, pp. 603–619, May 2002.

[5] C.Cheng, A.Koschan, C.-H. Chen, D. L. Page, and M. A. Abidi,"Outdoor scene image segmentation based on background recognition and perceptual organization," IEEE Trans. Image Process., vol.21,no.3,pp.10071019,Mar.2012

[6] Z. Tu and X. Bai, "Auto-context and its application to high-level vision tasks and 3D brain image segmentation," IEEE Trans. Pattern Anal.Mach. Intell., vol. 32, no. 10, pp. 1744–1757, Oct. 2010.

[7] F. S. Khan, J. van de Weijer, and M. Vanrell, "Top-down colorattention for object recognition," in Proc. IEEE 12th Int. Conf.Comput. Vis., Sep./Oct. 2009, pp. 979–986.

[8] P. Gehler and S. Nowozin, "On feature combination for multiclass objectclassification," in Proc. IEEE 12th Int. Conf. Comput. Vis., Sep. 2009,pp.221-228.

[9] K.Srilatha, S.Kaviyarasu,"An efficient directive contrast based multi modal medical image fusion under improved NSCT domain",Research Journal ofPharmaceutical, Biological and ChemicalSciences,ISSN NO:0975-8585,September - October 2015 RJPBCS 6(5) Page No.775-789.

[10] C. Cheng, A. Koschan, C.-H. Chen, D. L. Page, and M. A. Abidi,"Outdoor scene image segmentation based on background recognition and perceptual organization," IEEE Trans. Image Process.,vol. 21, no. 3, pp. 1007–1019, Mar. 2012.

[11] L. Zhu, Y. Chen, Y. Lin, C. Lin, and A. Yuille, "Recursive segmentationand recognition templates for image parsing," IEEE Trans. Pattern Anal.Mach. Intell., vol. 34, no. 2, pp. 359–371, Feb. 2012.

[12] J. Han, D. Zhang, G. Cheng, L. Guo, and J. Ren, "Object detection in optical remote sensing images based on weakly supervised learning andhigh-level feature learning," IEEE Trans. Geosci. Remote Sens., vol. 53,no. 6, pp. 3325–3337, Jun. 2015.

[13] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Imagequality assessment: From error visibility to structural similarity," IEEETrans. Image Process., vol. 13, no. 4, pp. 600–612, Apr. 2004.

[14] M.Bertalmío and S. Levine, "Denoising an image by denoising itscurvature image," SIAM J. Imag. Sci., vol. 7, no. 2, pp. 187–201, 2014.

[15] D.R. Martin, C. C. Fowlkes, and J. Malik, "Learning to detect natural image boundaries using local brightness, color, and texture cues," IEEE Trans. Pattern Anal. Mach. Intell., vol. 26, no. 5, pp. 530–549, May 2004.