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EFFICIENT NEURON SEGMENTATION AND MORPHOLOGICAL ANALYSIS USING SVM-KNN CLASSIFIER

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Abstract: A novel method of neuron segmentation in image volumes attained by microscopy is a proposed model. Like agglomerative or correlation clustering, existing methods relay solely on boundary signs and have problems where such a piece of evidence is lacking (e.g., incomplete staining) or ambiguous (e.g., co-located cell and mitochondria membranes). This paper investigates these complications through sparse region appearance cues distinguish between pre-and postsynaptic neuron segments in neural tissue. In this proposed paper, for pre-processing stage, an adaptive histogram equalization technique and wiener filters employed. Efficient segmentation performed by Morphological processing and Otsu's threshold. Using support vector machine (SVM) classifier to classify tumours (Neuroblastoma) and the results compare with the prevailing-nearest neighbour (KNN) model. SVM classifier achieves higher accuracy, sensitivity, specificity, precision, Recall, gmean than the existing KNNmodel.

Keywords: Neuroblastoma; Morphological; Support vector machine (SVM); Otsu's threshold; k-nearest neighbour (KNN).

1. Introduction

There are several methods for the segmentation and classification of tumours. Here the proposed model presents the detection of one different rare cancer, typically Neuroblastoma. Efficient segmentation of neurons in ssTEM (Transmission electron microscopy) image is a complicated assignment. It is essential to recognize the neuronal cancer primary stage is a need in medical application. The use of genetic algorithms with SVM classifiers to detect tumours was attempted by Kavitha et al. (2016).

To improve the accuracy of prevailing-nearest neighbour (KNN), Srinivas & Rao (2019) proposes the hybrid convolutional neural network (CNN)-KNN model. The proposed methods Otsu's method and gradient vector flow (GVF) for segmentation uses similar approaches to (Sharma et al., 2019; Bauer et al., 2009). The dynamic thresholding for further improvement of result using unsupervised learning algorithm learned from (Jones et al., 2013). The proposed paper presented a feature extraction such as discrete cosine transform (DCT) and Texture feature approaches (Logeshwaran et al., 2015; John, 2012). Used the morphological processing of Erosion and Dilation (Vanitha et al., 2015) to improve the result of segmentation. The segmentation of neuronal structures depicted in stacks of ssTEM image addressed in literature (Ciresan et al., 2012) this paper efficiently segments neuronal structures.

The tumour classification proposed is a type found in the literature (Zhang et al., 2011). The edge pattern feature for efficient analysis of brain tumour done in literature (Kamal & Ruchi, 2013). Gaussian filter for noise removal in pre-processing steps utilized in (Kavitha et al., 2015). The problems in segmenting some of the most prominent neuronal structures such as mitochondria and synapses and the membrane and lack of boundary evidence can be overcome by GVF (Xu & Prince, 1998), representing a core component of the approach. The proposed model SVM is considered as a good classifier for efficient neuron segmentation compared with artificial neural network (ANN) and KNN by evaluating its accuracy (Chithambaram & Perumal, 2017).A novel colour image segmentation technique based on multilevel threshold and Otsu-optimization approach were introduced (Harrabi & Braiek, 2012).The proposed model extracts discrete wavelet transform (DWT)feature, DCT feature similar in literature (Ghazali et al., 2007; Dabbaghchian et al., 2007).

SVM based pixel classifier for segmentation and classification of neuronal ssTEM image introduced in (Iftikhar & Godil, 2013). The entire stack of electron microscopy (EM) slices for neuronal structure segmentation from the literature (Jain & Seung, 2012). Region of interest (ROI) identification, feature extraction, feature selection, and classification (Zacharaki et al., 2009). Segmentation is the principal stage for investigating images accurately since it deviates the precision of consequent stages. But the proper segmentation is complex due to the good realities of the lesion shapes, sizes, and colours alongside different neuron types and textures. Additionally, some lesions have uneven boundaries, and in some category, there's an even transition among the lesion and thus the neuron. This paper discussed the following methods of segmentation. They are • Otsu's threshold method •Morphological method •SVM-KNN algorithm.

2. Methodology

Efficient neuron segmentation is proposed using SVM and KNN classification approaches for segmenting neuronal structure. The proposed model utilized (a) Pre-processing (b)Morphological operation (c) Channel separation (d) Otsu's threshold for segmentation (e) Feature extraction (f) SVM and KNN for classification. **Figure 1** exhibits the functional diagram of the proposed work.

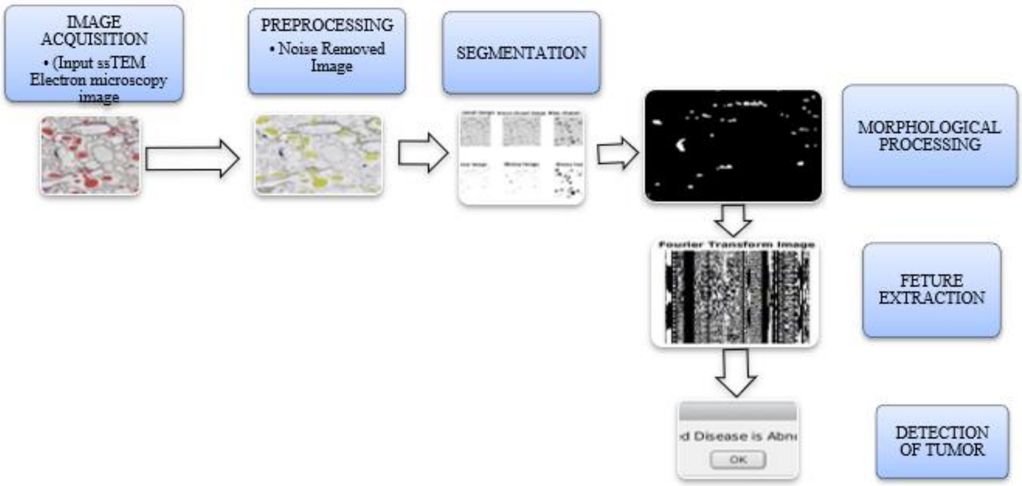

Figure 1. Functional diagram

2.1. Input ssTEM image

The input for the proposed model is Transmission Electron Microscopy(ssTEM) of the Drosophila melanogaster's third instar larva ventral nerve cord with approx. 4.7*4.7*1 micron with a resolution of 4.6*4.6nm/pixel and with 45-50 nm.

2.2. Noise Removal

For noise removal, "Bottom-hat Filter" is used. The Bottom-hat block executes bottom-hat filtering on an input image employing a predefined structuring element. Bottom-hat filtering stays the equivalent of decreasing the input image from making a morphological closing operation on the input image. The Noise region alone extracted from the original input ssTEM electron Microscopy image of drosophila melanogaster's third nerve cord and shown in **Figure 2.** The Noise removal done by the Bottom hat filter which improves the dark points in a white background and will close the holes and join nearby objects and shown in **Figure 3.**

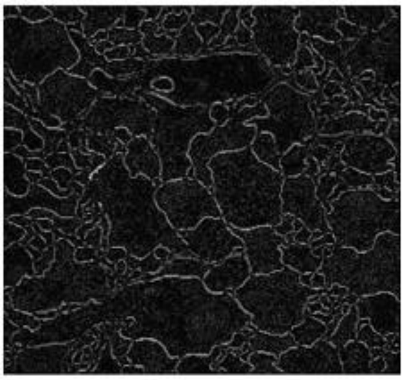

Figure 2. Noise region image

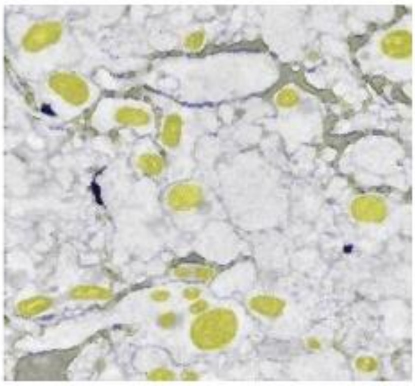

Figure 3. Noise removed image

2.3. Filtering

This paper used a Gaussian filter technique to execute the filtering process whose impulse response is a Gaussian function. Gaussian filters have the characterises of getting no overshoot to a step function input while minimalizing the rise and fall time periods.

2.4. Images Resize

Image resizing is a process of changing pixel information, resizing an image involves changing the size of the pixels without cutting anything out. Image resizing to regulate ideas to a fixed scale (512×512) supports the classification with clear and accurate highlights. The conversion of images from RGB to the grey level where the elements are depends on the grey level co-occurrence matrix.

3. Segmentation

Segmentation is done by Morphological processing. The proposed data flow diagram shown in **Figure 4.**

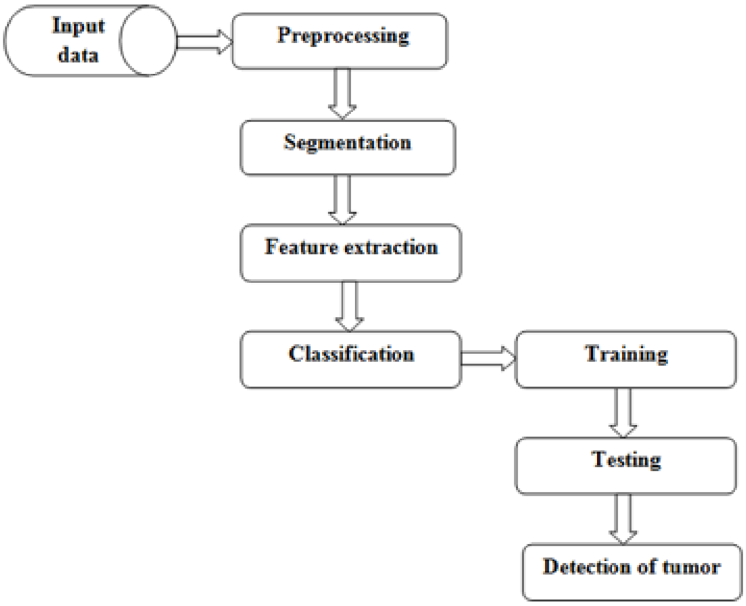

Figure 4. Data flow diagram

3.1. Otsu's Threshold

Otsu's image segmentation refers to algorithms that divider the image into dissimilar segments or groups of pixels. There is a sense; image thresholding is the only image segmentation since it partitions the image into two groups of pixels - white for the foreground and Black for background. Image thresholding is a future again sectioned into the local and global image thresholding algorithms. In global thresholding, one threshold is focused globally for the entire image. In few regional areas could use some characteristics (the local contrast) to select a particular point for various image parts in local thresholding. Otsu's method may be a global image thresholding algorithm. In **Figure 5**, three-channel such as Red, Green, and Blue can be separated individually, and the outcome of a binary image with the optimum threshold value.

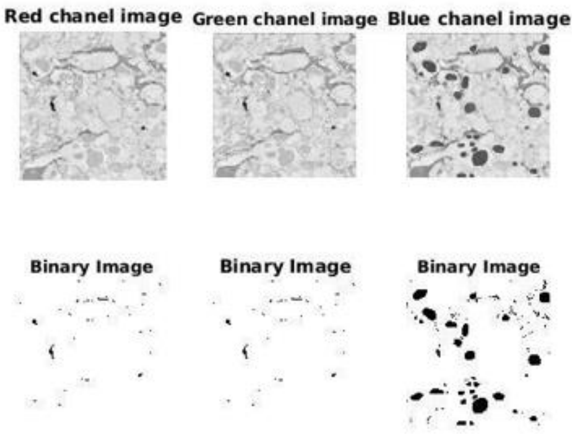

Figure 5. Channel separation

The classification technique processes image histogram, segmenting the items by minimization of the variance. Otsu's method is adaptive thresholding for the binarization of images. Otsu's threshold value 0.760784 is obtained from the global threshold of the histogram graph. The histogram graph is displayed in **Figure 6.**

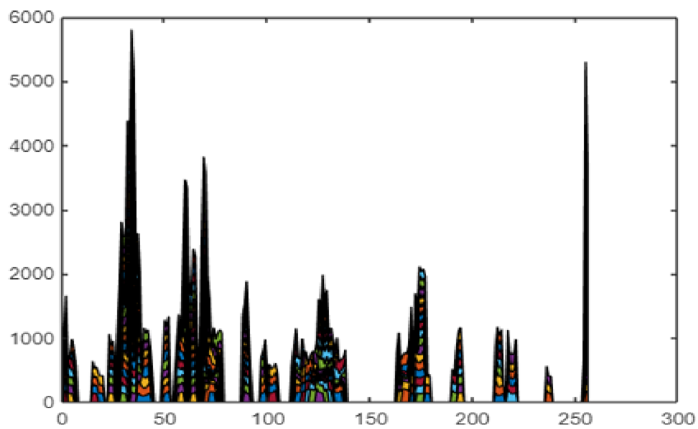

Figure 6. Histogram graph

The common algorithm's pipeline for the between-class variance maximization option is used inside the following way, calculate the histogram and intensity level probabilities initialize iterate over probable thresholds: update the values of, where is a likelihood. It is a mean of class calculate the between-class variance value the closing point is the maximum value.

4. Morphological Processing

Morphology is a wide-ranging set of image processing processes based on shapes. In morphological operations apply a structuring portion to an input image, creating an output image of the same size. The morphological operations of the proposed method are displayed in **Figure 7.**

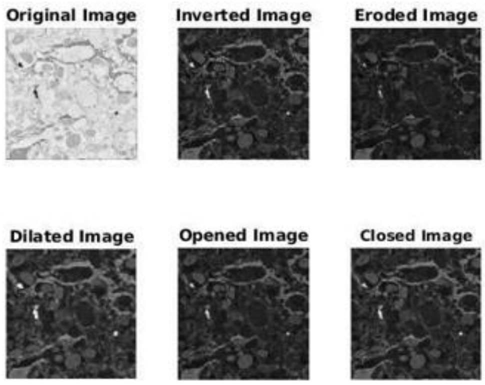

Figure 7. Morphological operations

Segmentation is done after morphological processing (Figure 10), such as inversion, erosion, Dilation, opening, and closing. The final segmented image consists of abnormal cells. The segmentation output displayed in **Figure 8**.

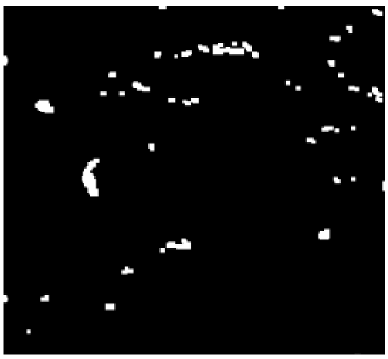

Figure 8. Segmented image

5. Feature Extraction

The feature extraction increases the accuracy by extracting features from the input data. It can produce a more concise description of the data. The proposed model removed ten parts from the original image for better analysis.

They are 1. FFT feature, 2. DCT feature, 3. Combinational element, 4. Colour feature, 5. Pigment feature, 6. Shape feature, 7. Orientation feature, 8. Lesion margin, 9. Lesion intensity, 10. Lesion variation, 11.DWT feature.

Fourier transform feature extracted from the background image which calculates various frequency of an image. The FFT output shown in **Figure 9.**

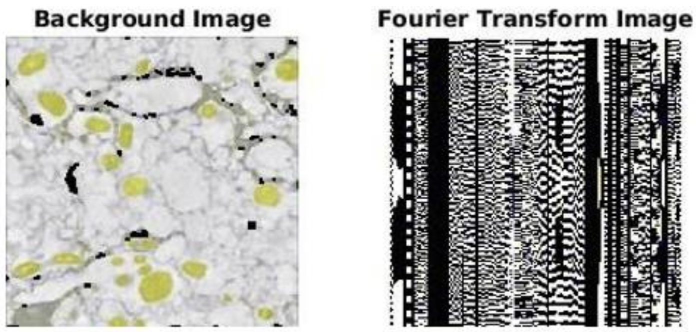

Figure 9. FFT image

Figure 10 shows DCT feature and orientation feature extracted from the centroid value of the segmented output which is 128.5.

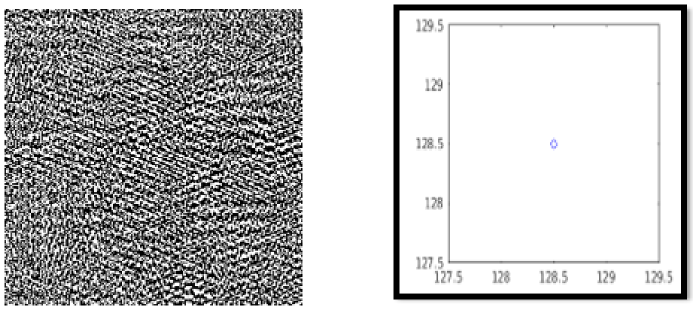

Figure 10. DCT feature and orientation feature

6. Results and Discussion

Feature extracted shown in **Table1**. The final values of KNN and SVM were compared shown in **Table 2** in which SVM performs efficiently than KNN.

Table 1. Features extracted

Combinational Feature	**Mean**	**STD**	**MS**	
	1.6578	0.6769	[1.65780.6769]	
DCT feature	-84.4461			
Color Feature	194211			
Pigment Feature	**F2**	**F3**	**F4**	**F5**
	7.714844	1.000000	0.05156	1.000000
Orientation feature	128.5			
Lesion margin	DXP=171.702164			
Lesion intensity	LIP=0.000957			
Lesion variation	GR1=183.142021			
Discrete Wavelet Feature extraction	**D1**	**D2**	**D3**	**D4**
	415.4937	0.0387	-0.0070	-0.0070

Table 2. Performance metrics

	KNN	**SVM**
Accuracy	98.7900	99.4900
Sensitivity	98.6000	99.1000
Specificity	98.2000	99.2000
Precision	99.8481	99.8992
Recall	98.6000	99.1000
Gmean	98.3998	99.1500

7. Classification

SVM and KNN are proposed here for the classification of the tumor. SVM has several advantages over the more classical classifiers such as decision trees and neural networks. The k- Nearest Neighbours algorithm is a non-parametric method used for classification. A main vote of its neighbours classifies an image. The idea is assigned to the class most common among its k nearest neighbours (k is a positive integer, characteristically small. If k = 1, then the image is allotted to the class of that single adjacent neighbour. The KNN algorithm is the simple and efficient model among all the machine learning algorithms. The Classification output displayed in **Figure 11**. In the proposed model, SVM performed better than KNN and gave a high accuracy rate. The comparison chart of prediction value of KNN and SVM classifier illustrated in **Figure 12.**

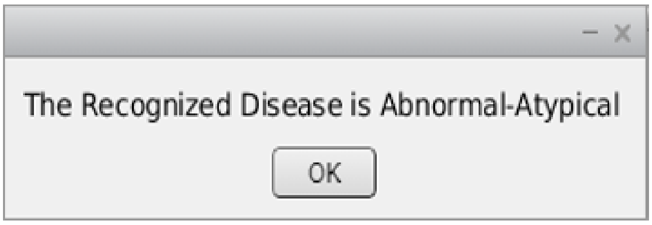

Figure 11. Classification output

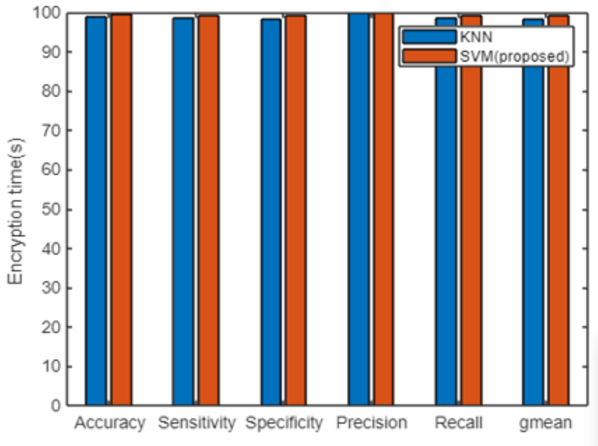

Figure 12. Prediction values of SVM and KNN

8. Conclusion

The proposed technique, segments and classifies the ssTEM (Transmission electron microscopy) brain tumor images accurately. Suppose the doctor found the tumor at earlier curable stages, and the noise of the input data was removed in the pre-processing step. The segmentation will be following by Otsu's threshold value and Morphological processing. For better classification, extracted eleven features from the segmented output, which consists of abnormal cells. The recognized disease of the production is strange. The experimental result reveals high accuracy, sensitivity, specificity, recall rate than the KNN model.

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