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Incorporating K-Means Clustering, DWT and Neural Network for Image Segmentation

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Abstract: ***In the field of image segmentation, hybrid image segmentation techniques have always been a favorite way of researchers in past decades. In this paper we are going to propose a unique hybrid approach to image segmentation problem. Various images has been taken into this experiment to evaluate the proposed method. Features are extracted from the given image by using Discrete Wavelet Transformation (DWT) and Image gradient. Then the K-Means Clustering algorithm is fed with the features extracted which are unsupervised clustering method. Then the K-Means membership function is fed to the back propagating neural network as target value. Taking the features as input, Back propagation Neural network (BPNN) trained. Thus, to achieve a better solution to image segmentation problem, combination of K-Means Clustering and BPNN has been proposed in this paper. We have taken free images available in UCI Machine Learning repository.***

Keywords: Image Segmentation, K-Means Clustering, Back Propagation Neural Network (BPNN), Discrete Wavelet Transformation (DWT)

1. Introduction

Image segmentation is one of the critical problems in the field of image processing. So, it's always been an interesting topic for researchers. In simple words, Segmentation is a process of dividing the color space of an entire image to sub groups having meaningful and homogeneous regions on image pixel parameters like quality, sharpness, color etc [4]. It is quite applicable and helpful to medical fields like retina scan, face recognition and various types of tumor detection. All image segmentation procedures are mainly classified into two classes. In first method, texture of an image and in second method, grey level of pixel taken into consideration. According to first method, the given image is divided into many areas with reference to different homogeneous pixel textures [10]. In second method, the entire segmentation of the target image is guided by some predefined threshold value in grey scale of pixel in any band. Now, for this selection of threshold value is divided into five major categories such as entropy method, preserving method, quad tree method, statistic method and class variance method. Other than these there are several methods like Similarity based method, Graph based method, Intensity based method, Clustering based method, Pixel based method, Discontinuity based method and hybrid methods [1]. Each of these methods will work well for certain cases, but not for every case. For example, in intensity based image segmentations, the method will not work for homogeneous distribution of intensity of grey scale. It will only work for hetero generous distribution of intensity. To overcome this type of problems, we have to adopt learning methods accompanied by other clustering techniques, so that it will adapt to the case of image and give a better segmentation. We are going to propose hybrid method of image segmentation comprising of K-means clustering and Back propagation based neural network for various images. In our proposed method, we have used Discrete Wavelet Transform (DWT) and Image gradient to extract features from the given images. Already several learning methods have been adopted in past decades by many researchers and a brief description given in the next section.

2. Background History

We are going to discuss some related work regarding this topic. We are basically concentrating in three major topics such as K-Means clustering, DWT and BPNN. In 2018, Manami proposed a neuro-computing structure where clustering algorithms are integrated with neural network architecture. The network used in this experiment is a Multi Layer Perceptron (MLP) [1]. The entire experiment is conducted with varying no. of hidden layes in the network. In 2017, Baozhong proposed an algorithm to detect glassware crack defects based on wavelet transformation method. In this experiment, first image segmentation is carried out on the test images [8]. After that, the segmented images are undergo wavelet decomposition method and the results are accompanied by wavelet fusion methods to extract the crack defects. In 2017, Meena proposed an segmentation method to detect breast cancer in thermal infrared images using K-Means clustering, FCM and EM algorithms [4].

3. Theoretical Background

Now, we are going to discuss about some theoretical back ground of the methodology.

3.1 K – Means Clustering

K-Means clustering is a basic unsupervised learning procedures to solve clustering problems. The concept is to define K no. of centroids for each available cluster. For effective results each clusters are placed large distance from each other. Then all the data points are associated with its near centroids [21]. After this step, new cluster centers are calculated from each clusters resulting K new cluster centers. Then these two steps are repeated until cluster centers don not move anymore [22].

Minimizing an objective function is the aim of this algorithm. The objective function can be defined as

$$T = \sum_{t=1}^{k}\sum_{i=1}^{n}\left\|X_i^{(t)} - C_t\right\|^2 \quad \text{..........Eq.1}$$

Where $\left\|X_i^{(t)} - C_t\right\|^2$ is distance measure between any data point at any given point $X_i^{(t)}$ and the cluster center C_t and n is no. of data points.

3.2 Discrete Wavelet Transformation (DWT)

Primary aim of a wavelet transform is to divide signal or image in this case into a set of basic functions i.e. wavelets. Wavelets are derived by dilations and shifting from one mother wavelet represented as $\Psi_{a,b}(t)$[11, 12, 13]:

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) \quad \text{................Eq.2}$$

Where a =scaling parameter
b = shifting parameter

The wavelet function and scaling function can be represented as two variable function as $\Psi_{a,b}(t)$ and $\Phi_{a,b}(t)$. The three different wavelet functions are $\Psi^H(x,y)$, $\Psi^V(x,y)$ and $\Psi^D(x,y)$ [2]. Actually, the scaling function is a low frequency component of the previously defined scaling function in two dimensions [16,18,19]. These functions can be represented as:

$$\Phi(x,y) = \Phi(x)\Phi(y),$$
$$\Psi^H(x,y) = \Psi(x)\Phi(y),$$
$$\Psi^V(x,y) = \Phi(x)\Psi(y),$$
$$\Psi^D(x,y) = \Psi(x)\Psi(y).$$

After filtering, each image resulting to a co-efficient image of half of size in each dimension. Hence, four wavelet coefficient (LL, LH, HL, HH) are generated [10]. The approximation co-efficient matrix CA and detail co-efficient matrix along horizontal, vertical and diagonal can be represented as CH, CV and CD respectfully.

3.3 Back Propagation Neural Network

Back propagation is a form of supervised learning for multi-layer networks. It is commonly known as generalized delta rule for the input data. Error, that is calculated in the end of output layer, is "back propagated" to the start of the network or we can say the input layer [6,7]. It provides incoming weights to all the previous layers of the network. The whole operation can be distinctly classified in two phases. The first phase propagates the input from input layer to output layer and in the second phase, it updates the weights by moving from output layer to input layer [9,15,17]. The back propagation algorithm switches between these phases multiple times in a single epoch or we can say a single simulation process. The entire simulation completes, when the algorithm scans the entire dataset.

3.3.1 Weight Adjustments with Sigmoid Activation Function:

The weight of network is updated by error but by it's a fix amount of proportional to the product of error value 'δ', in a measurement unit 'k' which receives the input signal and the output signal in a measurement unit 'j' and then sending this calculated signal throughout the entire connection [14,20].

$$\Delta_p w_{jk} = \gamma \delta_k^p y_j^p \quad \text{..........Eq.3}$$

If the given unit that is to be calculated is an output unit, the error calculation is given by

$$\delta_o^p = (d_o^p - y_o^p)F(s_o^p) \quad \text{.......Eq.4}$$

Take as the activation function F the 'sigmoid' function as defined

$$y^p = F(s^p) = \frac{1}{1+e^{-s^p}}$$

In this case the derivative is equal to

$$F(s^p) = \frac{\partial}{\partial s^p}\frac{1}{1+e^{-s^p}}$$
$$= \frac{1}{(1+e^{-s^p})^2}(-e^{-s^p})$$
$$= \frac{1}{(1+e^{-s^p})}\frac{e^{-s^p}}{(1+e^{-s^p})}$$
$$= y^p(1-y^p)$$

Such that the error signal calculated for a given output neuron unit can be represented as:

$$\delta_o^p = (d_o^p - y_o^p)y_o^p(1-y_o^p) \text{..........Eq.5}$$

The error signal value for a hidden neuron unit is calculated repeatedly in terms of error signals of the neuron units to which it directly connects and the weights of those connections. For the sigmoidal activation function the general expression is given as below:

$$\delta_h^p = F(s_h^p)\sum_{0=1}^{N_o}\delta_o^p w_{ho} = y_h^p(1-y_h^p)\sum_{0=1}^{N_o}\delta_o^p w_{ho} \text{.....Eq.6}$$

3.2.2 Learning rate and momentum

The learning procedure requires that the change in weight is proportional to

$$\partial E^p/\partial w$$

True gradient descent requires that in finite simal steps are taken. The constant of proportionality is the learning rate. For real life experiment purposes, a learning rate is chosen that is as big as possible which will not lead to oscillation in the learning process [3, 5]. One way to avoid oscillation at large scale is to update weights according to the dependency of the past weight change by adding a momentum term factor which can be represented as below:

$$\Delta w_{jk}(t+1) = \gamma\delta_k^p y_j^p + \alpha\Delta w_{jk}(t), \text{ ....Eq.7}$$

Where 't' indexes the presentation number and 'F' is a constant which determines the effect of the previous weight change.

Although, theoretically, the back-propagation algorithm based neural network works on gradient descent on the total error only if the weight adjustment is calculated after the full dataset of the given learning patterns has been presented earlier, more often than not the learning rule is applied to each pattern separately, i.e., a pattern p is applied, Ep is calculated, and the weights are adapted (p = 1, 2,..... P).

3.4 Image Gradient

Image gradient can be defined as directional change in intensity in an image. For each image pixel, the gradient vectors directs towards largest possible increase in intensity and the rate of change in that direction can be represented as length of gradient vector. Gradients of an image in X and Y direction can be used to extract addition features from an image.

It can be represented by below formula:

$$\Delta g = \frac{\partial g}{\partial x}\hat{x} + \frac{\partial g}{\partial y}\hat{y} \quad \text{..............Eq.8}$$

Where $\frac{\partial g}{\partial x}$ = Gradient in X-direction (GX)

$\frac{\partial g}{\partial y}$ = Gradient in Y-direction (GY)

4. Proposed Methodology

In this section, proposed algorithm is introduced and explained.

Step A:

First, histogram of the entire image plotted to know the no. of clusters available in the image.

Step B:

Feature extraction done using DWT (refer section 3.2) to get CA, CH, CV and CD. Two extra features are added that are extracted by image gradient method (refer section 3.4).

Step C:

The next step deals with clustering by K-Means Algorithm. It is used to calculate index label for each image pixel by dividing each pixel to a specific centroids (refer section 3.1)

Step D:.

Next step is to prepare a random dataset out of all the pixel available in the image. After the random no. of pixels are chosen, CA, CH, CV, CD, GX and GY value of those corresponding pixel are collected to make the input for the network and corresponding index label of those pixel obtained in previous step to make the output target value of the network.

Step E:

This step involves a segmentation through learning using Back Propagation Neural Network by the input and output obtained in previous step. The network architecture is given below:

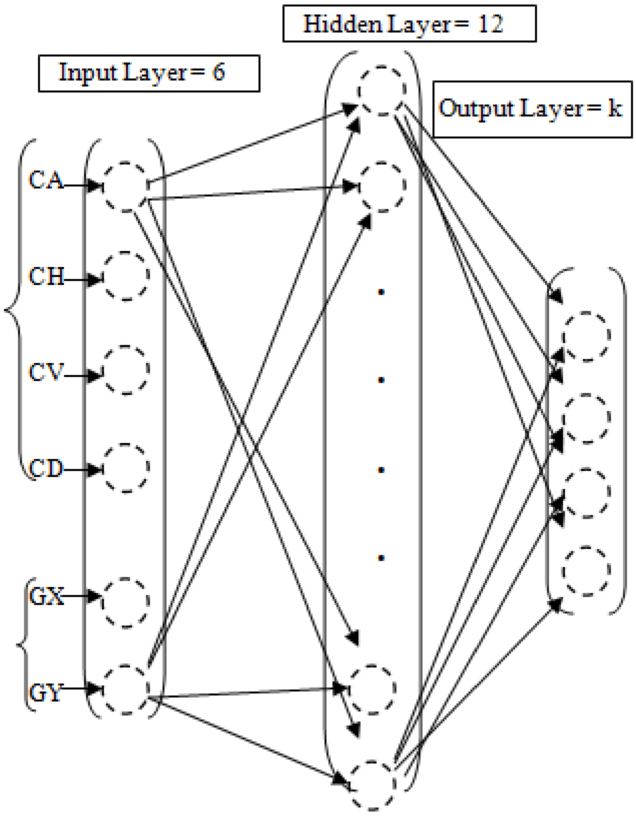


Figure 1: Back propagation neural network architecture

Algorithm for Back Propagation Algorithm is as follows:

Step 1: Initialisation

Set all the weights and threshold levels of the network to random numbers uniformly distributed inside a small range.

Step 2: Activation

Activate the back-propagation neural network by applying inputs $x_1(p)$, $x_2(p)$,…, $x_n(p)$ and desired outputs $y_{d,1}(p)$, $y_{d,2}(p)$,…, $y_{d,n}(p)$.Calculate the actual outputs of the neurons in the hidden layer[2]:

$$y_j(p) = sigmoid\left[\sum_{i=1}^{n} x_i(p)\cdot w_{ij}(p) - \theta_j\right] \text{....Eq. 9}$$

Where n is the number of inputs of neuron j in the hidden layer, and *sigmoid* is the *sigmoid* activation function.

(a)Calculate the actual outputs of the neurons in the output layer**:**

$$y_k(p) = sigmoid\left[\sum_{j=1}^{m} x_{jk}(p)\cdot w_{jk}(p) - \theta_k\right] \text{....Eq.10}$$

Where m is the number of inputs of neuron k in the output layer.

Step 3: Weight training

Update the weights in the back-propagation network propagating backward the errors associated with output neurons. Calculate the error gradient for the neurons in the output layer:

$$\delta_k(p) = y_k(p)\cdot[1 - y_k(p)]\cdot e_k(p) \text{......Eq. 11}$$

Where $e_k(p) = y_{d,k}(p) - y_k(p)$

Calculate the weight corrections:

$$\Delta w_{jk}(p) = \alpha \cdot y_j(p) \cdot \delta_k(p) \text{ ....Eq. 12}$$

Update the weights at the output neurons:

$$w_{jk}(p+1) = w_{jk}(p) + \Delta w_{jk}(p) \text{ ....Eq. 13}$$

(*b*) Calculate the error gradient for the neurons in the hidden layer:

$$\delta_j(p) = y_j(p) \cdot [1 - y_j(p)] \cdot \sum_{k=1}^{l} \delta_k(p)\, w_{jk}(p) \text{...Eq. 14}$$

Calculate the weight corrections:

$$\Delta w_{ij}(p) = \alpha \cdot x_i(p) \cdot \delta_j(p) \text{.........Eq. 15}$$

Update the weights at the hidden neurons [1]:

$$w_{ij}(p+1) = w_{ij}(p) + \Delta w_{ij}(p) \text{ .....Eq. 16}$$

Step 4: Iteration

Increase iteration *p* by one, go back to *Step 2* and repeat the process until the selected error criterion is satisfied.

Step F:

After the network is trained, all the pixels of image is passed through the network and resulting index label is plotted to get the final segmented image.

Step G:

In this step accuracy assessment of image segmentation is done to in terms of Sensitivity, Specificity, Segmentation Accuracy, Neural Network Root Mean Square Error (RMSE) and Time Of Completion (TOC).

These can be calculated by:

$$\text{Sensitivity} = \frac{TP}{TP + FN} * 100\ \%$$

$$\text{Sensitivity} = \frac{TN}{TN + FP} * 100\ \%$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} * 100\ \% \text{ ....Eq.17}$$

Where

True positive(TP) : pixels correctly segmented as foreground
False positive (FP) : pixels falsely segmented as foreground
True negative (TN) : pixels correctly detected as background
False negative (FN) : pixels falsely detected as background

The entire methodology is given by below flow chart:

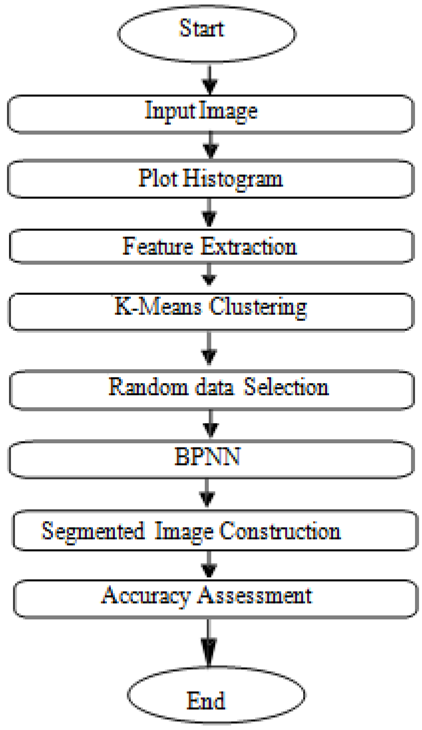


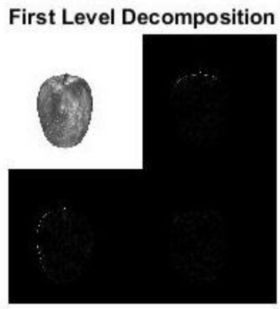
Figure 2: Flow chart of proposed methodology

5. Result Analysis and Discussion

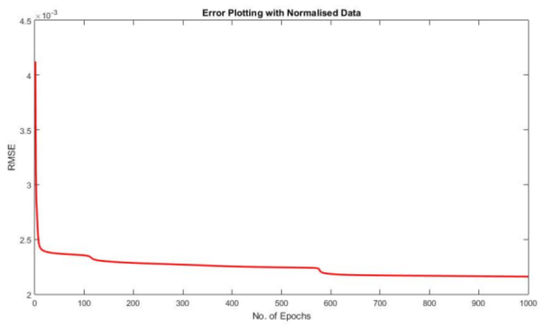
Image segmentation based on the above mentioned methods has been applied in 3 different type of images and there ground truths are also been defined. All these simulations are carried out in MATLAB R2015a software and in a windows system with 16 GB RAM and 2.8GHz Intel core-i5 processor.

Below figures show the result of segmentation of different images.

(a)



(b)

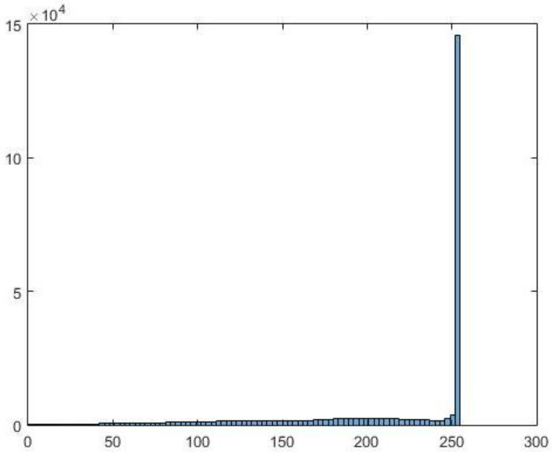


(c)
(d)

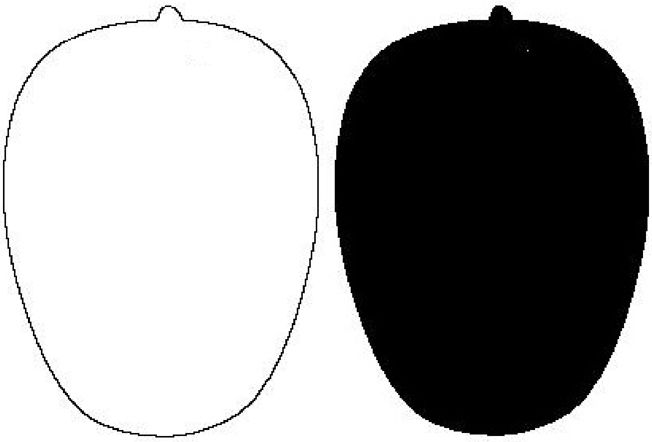
Figure 3: Result of Apple image segmentation (a) Input Image (b) DWT decomposition (c) Image histogram plot (d) No. of epochs vs. RMSE of BPN (e) Ground truth (f) Final Segmented Image

(a)

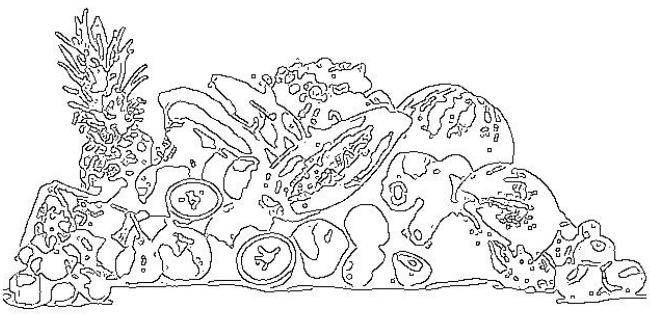
(b)



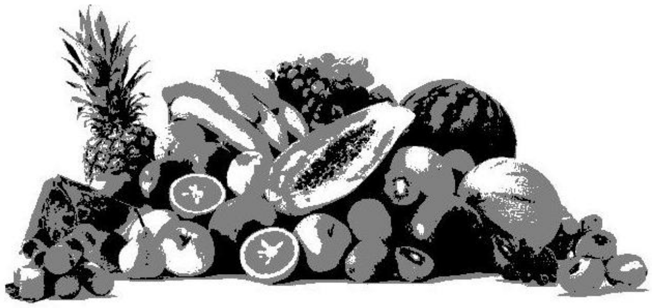
(c)



(d)

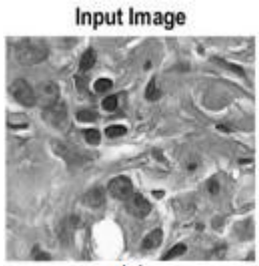


(e)

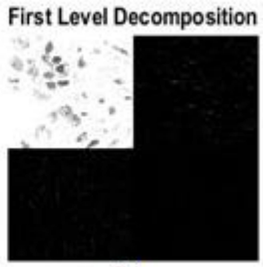


(f)

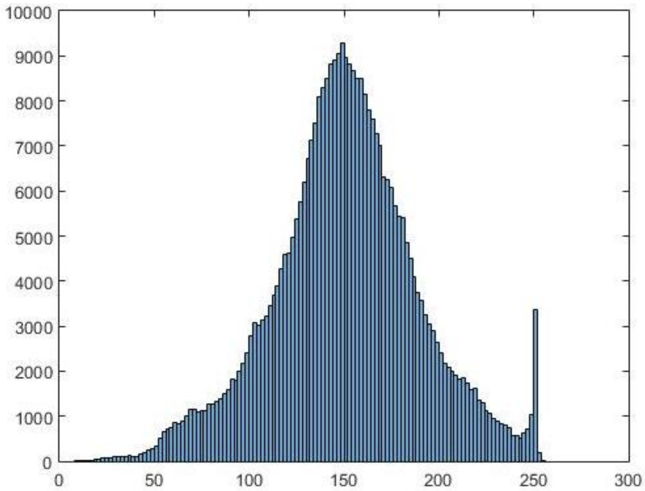
Figure 4: Result of Mix fruit image segmentation (a) Input Image (b) DWT decomposition (c) Image histogram plot (d) No. of epochs vs. RMSE of BPN (e) Ground truth (f) Final Segmented Image



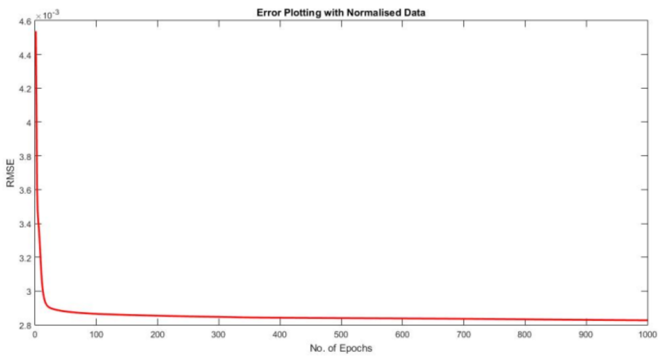
(a)



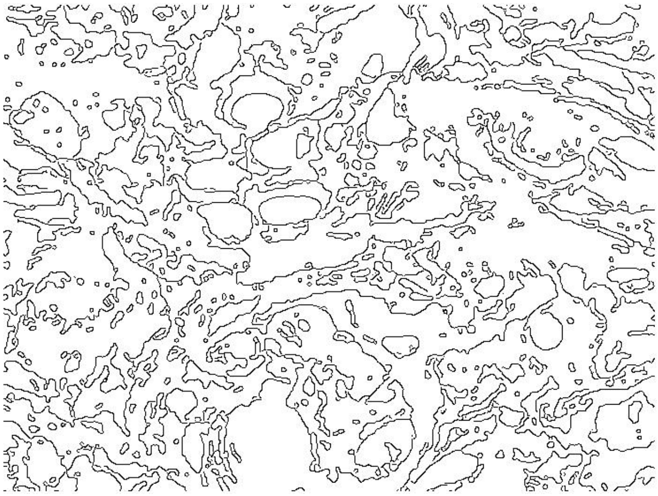
(b)



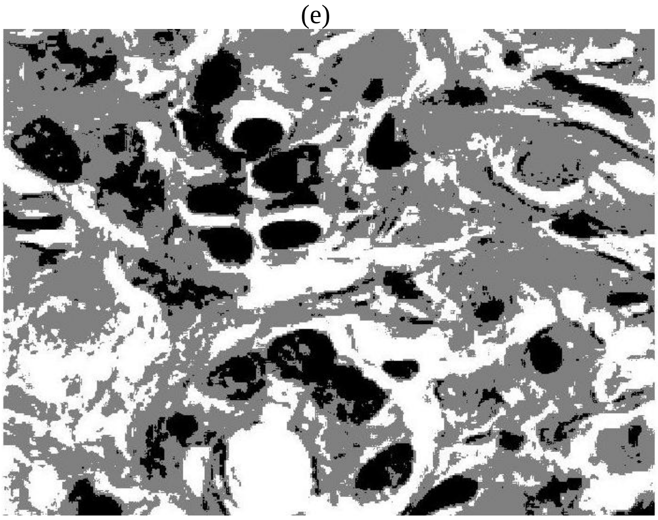
(c)



(d)



(e)



(f)

Figure 5: Result of Nuclei image segmentation (a) Input Image (b) DWT decomposition (c) Image histogram plot (d) No. of epochs vs. RMSE of BPN (e) Ground truth (f) Final Segmented Image

Table 1 represents all the results of image segmentation and comparison between the three different type of images. As the histogram shows, no. of classes chosen as the no. of peaks available in the plotted histogram. Here, the condition for ideal image segmentation is 100% for Sensitivity, Specificity and Segmentation Accuracy and zero for RMSE of neural network.

Table 1: Image Segmentation Results

S. No.	Apple Image	Mix Fruit Image	Nuclei Image
No. Of Classes	2	3	3
Time of Calculation (in Sec.)	80.087208	79.868912	80.28330
RMSE (1000 iterations)	0.0012	0.0022	0.0028
Sensitivity (in %)	97.6592	95.3285	91.2373
Specificity (in %)	98.6619	96.5388	93.9647
Segmentation Accuracy (in %)	98.4766	95.6572	92.1188

6. Conclusion

To get higher accuracy, we have combined dwt, K-Means clustering and back propagation based neural network to solve image segmentation in this proposed method. We have extracted feature using DWT and image gradient in this approach. We have used these extracted features as input for our proposed neural network and K-Means cluster index of each pixel is used as a target value in the neural network. We have seen that we do not have to take the entire image for learning. So, it reduces the time of calculation. We have validated the results with the ground truth to calculate Sensitivity, Specificity and Segmentation Accuracy. We have found that by applying this approach, we can get more accurate and effective solution to image segmentation problem.

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