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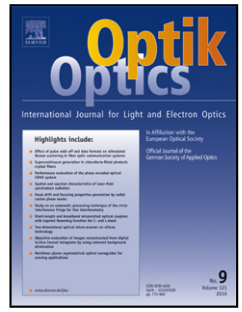

Title: WOOD SPECIES CLASSIFICATION BASED ON LOCAL EDGE DISTRIBUTIONS

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WOOD SPECIES CLASSIFICATION BASED ON LOCAL EDGE DISTRIBUTIONS

ABSTRACT

The wood species classification system is developed in order to give fair service to the wood industry. An image is characterized mostly by the low level features such as color, shape and texture. Among them texture features play a major role in characterizing the image and the statistical features are found to be efficient for classification. For a better classification result, wood image first has to be preprocessed in order to get meaningful feature extraction. Among various preprocessing techniques, Contrast Limited Adaptive Histogram Equalization is found to be an appropriate method for wood image enhancement. The edges in an image reveals spectral discontinuity, contrast, directional information, and structure pattern. In this paper , in addition to ten statistical features , Saliency index is another significant parameter used for texture classification of different wood species. Edges are used as the main source of information to compute the saliency in the local window of every pixel. The computation of saliency index is simple and it is more powerful for recognizing the wood species. The back propagation neural network is used for classification of wood species.100 number of wood images are used for training the neural network and 50 number of images are used for testing which are taken from prospect data base available for wood images. The percentage of classification accuracy in this work is more encouraging and the classification accuracy is 90%.

Key words—*wood species recognition, texture classification, saliency index, edge detection.*

1. INTRODUCTION

The identification of wood types becomes very important when related to illegal logging, taxes, and the suitability of the product. The experts in identification of wood are very limited in terms of amount, power, and time. And also every type of wood has different strength, durability and density. This makes the industrial price of the wood is different from one another. It is important to differentiate these woods correctly to have them for their appropriate uses. This is because wrongly identified wood could cause huge impact. Because, some woods are being used as important structure of buildings in the construction field.

Wood species classification using computer vision is still a new area of study. Wood species classification requires well-trained experts to study the characteristic seen on the cross-section surfaces of the wood samples obtained under macroscopic view, and when required to, the microscopic view will be studied as well. Today, wood species classification is still mainly conducted by well-trained wood identification experts. It takes a long period of time to train a wood identification expert until he is qualified to identify wood species with a high accuracy. There is a great demand in the industry involving the identification of wood species but the number of wood identification experts is not sufficient to meet the market need.

Computer vision techniques have been used to solve a number of problems that involve the study of patterns, such as text detection, face classification, signature verification and etc. Since each species of wood has a type of pattern observable on the cross section surfaces, computer vision algorithms can be used to create an automated means to solve the problem.

Computer vision techniques such as texture classification are useful algorithms that can be used to solve problem involving patterns that can be perceived as textures, such as the wood species classification problem where the cross-section surface can be viewed as different textures for different wood species.

The wood species classification system developed by Jordan [1], based on analysis of ultrasonic signals. Many species of wood have subtly different elastic responses due to its own cellular structural characteristics. Thus the recipient waveform that propagates through the tangential, radial and longitudinal surfaces of the wood is used to identify the species of the wood according to this technique. The artificial neural network is used to identify the received waveform in terms of species. However, this research involved classification of only four different major species of temperate woods in United States of America, i.e. Oak, Alder, Maple and Pine. The accuracy rate of this system is about 97 % using 20 samples for training and 10 samples for testing. Chen Guang-Sheng and Zhao Peng used microscopic images of wood samples for wood cell recognition [2]. First, a novel 2-D cell image collection system is devised, and the wood cell images are segmented by using a dual threshold segmentation algorithm. Second, a geodesic active contour (GAC) is applied in the segmented binary image to extract the edge contours of multiple cells simultaneously. Third, wood cell recognition is performed based on the Mahalanobis distances calculated by using the principal component analysis (PCA) algorithm.

In the previous research, authors used 20 types of wood, using seven characteristics of RGB image, and the six characteristics of image edge detection [3]. This research provide 85% classification rate. Then Adaptive Neuro Fuzzy Inference System (ANFIS) is used and it is based on the textural features [4]. Five types of wood can be classified using the system. Harjoko and et.al. [5] developed a classification method using 15 types of wood and it is based on texture analysis of microscopic wood images using Artificial Neural Network Back Propagation

Algorithm (ANNBP), and gives the classification accuracy of 95% It requires magnification of wood images using powerful microscopes. Peng Zhao, Gang Dou, Guang-Sheng Chen [6] developed a method that integrates the color, texture and spectral features so as to identify the wood species. Then a fuzzy Back Propagation neural network is used to perform the classification work, which consists of 4 sub-networks based on the color feature, texture feature and spectral feature. The recognition accuracy is approximately 90% for 5 wood species.

There has not been much development in automatic wood classification system due to the difficulty in obtaining a wide range of wood database, lack of availability of proven techniques for wood classification, current research makes use of expensive devices, availability of human inspectors especially in developing countries. Furthermore, manual examination of the wood sample can be very subjective. These problems motivated us to develop such a system to identify the species of wood without any difficulty.

In this paper, saliency index [7] is used for the texture classification of different wood species. Edges are used as the main source of information to compute the saliency in the local window of every pixel. The edge in an image reveals spectral discontinuity, contrast, directional information, and structure pattern. The work presented in this project can be used to classify the wood species based on its texture.

2 MATERIALS AND METHODS

In this paper wood images are recognized based on the distribution of the edge pixels. Edges are used as the main source of information to compute the saliency in the local window of every pixel. The pre-processing is performed so that the edges in the wood images can be distinguished easily. The pre-processing methods used are histogram equalization, bi-histogram equalization, histogram equalization with Bin Underflow and Bin Overflow (BUBO) method, integral mask filtering approach and Contrast Limited Adaptive Histogram Equalization (CLAHE) method. Among these CLAHE is found to be appropriate for wood images. Then the edges are obtained from the pre-processed image and finally saliency index is obtained from the binary edge image.

2.1 PRE-PROCESSING METHODS

2.1.1 Histogram Equalization

Image Histogram plots the number of pixels for each intensity value. Histogram manipulation can be used effectively for image enhancement. The intensities can be better distributed on the histogram using histogram equalization. This allows the areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. Let 'r' denote the intensities of an image to be processed and 'r' is in the range [0, L-1]. Then the transformations (intensity mapping) is of the form s=T(r), where's' is the output intensity level for every pixel in the input image having intensity 'r'.

2.1.2 Bi-Histogram Equalization(BHE)

The BHE firstly decomposes an input image into two sub-images based on the mean of the input image. One of the sub-images is the set of samples less than or equal to the mean whereas the other one is the set of samples greater than the mean. Then the BHE equalizes the sub-images independently based on their respective histograms with the constraint that the samples in the formal set are mapped into the range from the minimum gray level to the input mean and the samples in the latter set are mapped into the range from the mean to the maximum gray level. In other words, one of the sub-images is equalized over the range up to the mean and the other sub-image is equalized over the range from the mean based on the respective histograms. Thus, the resulting equalized sub-images are bounded by each other around the input mean, which has an effect of preserving mean brightness.

Let X_m denote the mean of the image X and assume that $X_m \in \{X_0, X_1, \ldots, X_{L-1}\}$. Based on the mean, the input image is decomposed into two sub-images X_L and X_U as given in Equation (1).

$$X = X_L \cup X_U$$

where $X_L = \{ X(i,j) \mid X(i,j) \leq X_m , X(i,j) \in X\}$ (1-a)

$X_U = \{ X(i,j) \mid X(i,j) \geq X_m , X(i,j) \in X\}$ (1-b)

Note that the sub-image X_L is composed of $\{X_0, X_1, \ldots, X_m\}$ and the other sub-image X_U is composed of $\{X_m, X_{m+1}, \ldots, X_{L-1}\}$. The decomposed sub-images are equalized independently and the composition of the resulting equalized sub-images constitutes the output of the BHE. That is, the output image of the BHE, **Y,** is finally expressed as in Equation

$$Y = f_L(X_L) \cup f_U(X_U) \quad (2)$$

where f_L and f_U are the cumulative distribution function of the sub-images X_L and X_U respectively.

2.1.3 Histogram Equalization with BUBO method

BUBO is a simple enhancement rate control mechanism for the Histogram Equalization [8]. Fill the bin for the PDF estimation up to a point when the bin has underflow, and throw away the surplus over another point when the bin has overflow as given in Equation (3).

$$pdf'[k] = \begin{cases} C_{BO}, \text{ if } pdf[k] > C_{BO} \\ pdf[k], \text{ if } C_{BU} < pdf[k] < C_{BO} \\ C_{BU}, \text{ if } pdf[k] < C_{BU} \end{cases} \quad (3)$$

C_{BU} , C_{BO} the bin underflow (BU) and bin overflow (BO) thresholds respectively. One way to set the BU and BO thresholds is by Equation (4) and (5).

$$C_{BU} = (1-\alpha)/(MN) \quad (4)$$

$$C_{BO} = (1+\alpha)/(MN) \quad (5)$$

where α value ranges from 0 to 1 and MN is the size of the image.

A modified Clipped Histogram Equalization is [9] for dynamic range adjustment. Assuming that the noise is nearly white, i.e., the noise is distributed in roughly equal amounts in different histogram bins. Then, the bins with large/small values most likely represent useful information/high frequency noise. Based on this concept, the purpose of histogram modification is to reveal the details in both dark and bright regions of the input image by detecting useful information as follows. For regions in the input image with a narrow dynamic range, large values are assigned in the output histogram bins because more details are there to be emphasized. In contrast, for regions with a wide dynamic range, small values are assigned in the output histogram bins because a less enhancement is desirable in this case to avoid amplifying high frequency noise.

2.1.4 Integral Mask Filtereing Approach

The mask-filtering approach is widely used to sharpen an image owing to its simplicity by means of the second derivative. The illumination adjusting mask filtering approach is used to brighten the dark area in an image[10]. This is a local approach which involves a target pixel and its eight nearberhood pixels. We had proved the merits of the modified mask-filtering by employing some nonlinear transfer functions. In this, the cubic root of a sinusoidal function is selected as the transfer function. The larger inputs are expected to gradually saturate after the transferring, while the smaller ones could derive larger outputs. Hopefully, the processed image would be with less overshooting as well as clearer fine characteristics.

The sharpened new image g(m,n) of the original image f(m,n) is given in Equation (6), where A is the co-efficient.

$$g(m,n)=f(m,n)+A.\ \Delta f(m,n) \tag{6}$$

$$\Delta f\,(m,n) = \sum_{i=-1}^{1}\sum_{j=-1}^{1} sin^{1/3}\left[\frac{\pi}{2}.\frac{\left(f\,(m,n)-f\,(m+i,n+j)\right)}{255}\right] \tag{7}$$

where 2≤ m,n ≤255.

2.1.5 CLAHE based on Entropy

Histogram equalization is to get an image with uniformly distributed intensity levels over the whole intensity scale. This means that it does not adapt to local contrast requirement; minor contrast differences can be entirely missed when the number of pixels falling in a particular gray range is relatively small.

An adaptive method to avoid this drawback is block-based processing of histogram equalization. In this method [11], image is divided into sub-images or blocks, and histogram equalization is performed to each sub-images or blocks. The CLAHE introduced clip limit to overcome the noise problem. The CLAHE limits the amplification by clipping the histogram at a predefined value before computing the Cumulative Distribution Function. The redistribution will push some bins over the clip limit again, resulting in an effective clip limit that is larger than the prescribed limit and the exact value of which depends on the image.

Image entropy becomes relatively low when histogram is distributed on narrow intensity region while image entropy becomes high when histogram is uniformly distributed. Therefore, the entropy of the histogram equalized image becomes higher than that of the original input image. The discrete entropy is given by Equation (8).

$$H = -\sum_x \sum_y p(x,y)\log_2 p(x,y) \tag{8}$$

where p(x,y) is the normalized joint probability distribution of the gray levels x,y. The clip limit which corresponds to the maximum entropy is considered for further processing. Experimental results show that the method enhances images with very low contrast.

2.2 EDGE DETECTION

2.2.1 GRADIENT BASED METHOD

The salient texture or objects usually are in the regions where there are spectral differences and discontinuities in an image. The edge pixels in an image can be obtained by the following method. If magnitude of the gradient function is larger than the magnitude of the two neighbors in the direction of the gradient it is labelled as edge pixel. An edge image is created by setting the edge pixel as its magnitude of the gradient, whereas the non-edge pixels are set as 0. The gradient of an image f can be given as Equation (9).

$$\nabla f = \frac{\partial f}{\partial x}\hat{x} + \frac{\partial f}{\partial y}\hat{y} \tag{9}$$

where $\frac{\partial f}{\partial x}$ is the gradient in the x-direction and $\frac{\partial f}{\partial y}$ is the gradient in the y-direction.

The magnitude of the gradient is given by Equation (10).

$$\mathrm{Mag}(\nabla f)=\sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2} \tag{10}$$

The direction of the gradient is given by Equation (11).

$$\theta(\nabla f) = \tan^{-1}\left(\frac{\frac{\partial f}{\partial y}}{\frac{\partial f}{\partial x}}\right) \tag{11}$$

The Otsu method [12] is then used for thresholding the edge image, by which the between-class variance of the non-edge and edge classes is minimized. The Otsu method is an effective bi-class segmentation method. Assuming that there are weaker edges and stronger edges measured by gradient magnitude in an image, in order to detect “salient” structures, as the stronger edges are more “salient” than the weaker ones.

2.2.2 CORTX METHOD

For accurate edge extraction, Cortx filter[13] is used. Cortx filter is the neural architecture that detects, regularizes and completes sharp image boundaries in up to 50% noise, while simultaneously suppressing the noise. The network nodes that constitute the architecture are simple cells, complex cells, hyper complex cells un-oriented and oriented cooperative cells. The neural architecture involves feed forward operations hence simple to implement in analog chip versions.

The first stage is an oriented contrast detector that is sensitive to the orientation, amount direction and spatial scale of image contrast at a given image location. This type of cells may be compared to the simple cells present in the primate visual cortex. The output is modeled as given in Equation (12).

$$\text{Max}\,[L_s(x,k)-\alpha_s\, R_s(x,k)-\beta_s\,,0] \tag{12}$$

where x is the position of the receptive field center: k is the receptive field orientation ranging as 0°, 90°,135° and 45°, and the masking field is given by Equation (13).

$$L_s(x,k)=\int_{(\text{left half})} I(y)\, dy / \int_{(\text{right half})} I(y)dy \tag{13}$$

The steps involved in the Cortx edge detection algorithm is given below.

1. The image is transformed compatible to the mask (3 x 3 or 7 x 7).
2. The pixel orientation in the image is changed for every mask and it forms the simple cell.
3. The simple cells are added to form the complex cell.
4. Then the hyper complex cell (z1) is obtained from the complex cell (c1).
5. z1=c1(i-1,j-1)+c1(i,j-1)+c1(i+1,j-1)+c1(i-1,j+1)+c1(i+1,j+1)-c1(i,j+1).
6. Like step 5 , z2, z3 and z4 are calculated and z is calculated as follows

   z=z1+z2+z3+z4;

   z'=0.3*z;
7. If z' is greater than the neighboring two pixels and greater than zero it is named as edge pixel.

2.3 SELECTION OF FEATURES FOR WOOD IMAGES

The unique features that can identify wood a particular species are its strength, density, hardness, odor, texture and color. Reliable wood identification usually requires the ability to recognize basic differences in cellular structure and wood anatomy. In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. In this paper we have considered eleven features for wood classification. They are Hue, Saturation and Intensity Components, Kurtosis, Skewness, Standard Deviation, energy, contrast, correlation, and homogeneity and saliency index.

Energy=$\sum_x \sum_y p(x,y)^2$

Contrast = $\sum_i \sum_j (x_i - y_j)^2 \, p(x_i, y_j)$

Correlation = $\sum_i \sum_j \frac{(x_i - m1)(y_j - m2)p(x_i, y_j)}{\sigma^2}$

Homogeneity=$\sum_i \sum_j \frac{p(x_i, y_j)}{1+(x-y)^2}$

Standard Deviation= $\frac{\sum_{i=1}^{N} \sum_{j=1}^{N} (x_i - \bar{x})^2 (y_j - \bar{y})^2}{(N-1)}$

Kurtosis = $\frac{\sum_i \sum_j (x_i - \bar{x})^4 (y_j - \bar{y})^4}{\sum_i \sum_j (x_i - \bar{x})^2 (y_j - \bar{y})^2} - 3$

Skewness = $\frac{\sum_{i=1}^{N} \sum_{j=1}^{N} (x_i - \bar{x})^4 (y_j - \bar{y})^4}{(N-1)\, s^3}$ where ‘s’ is standard deviation.

Saliency Index

For each pixel in the binary edge image, a texture saliency index is computed within a local window based on the edge density and the distribution evenness of the edge pixels. Given that de denotes the edge density and ds denotes the distribution evenness, the saliency index is given by Equation (14).

$$I = d_e \cdot d_s \quad (14)$$

$$d_e = n_e / n_w \quad (15)$$

$$d_s = \min(n_i)/\mathrm{Mean}(n_i) \qquad i=1,2,3,4 \quad (16)$$

In Equation (15), n_e and n_w are the number of the edge pixels and all pixels in the local rectangular window respectively. d_e measures the local edge density. In Equation (16), n_i is the number of edge pixels in each of the four quadrants of the local window, and ds measures how evenly the edge pixels are distributed in the four quadrants as shown in Figure 2.

If there are no edge pixels in any of the quadrants, then d_s is 0. This ensures that only locations mainly within the texture area output nonzero values for d_s. This property improves the accuracy for the extraction of the texture regions. The saliency index I tends to be large only if the edge density and evenness of spatial distribution are also large.

2.4 CLASSIFICATION TOOL

For the classification of the wood species artificial neural networks are used. The multilayer perceptron is trained using the back propagation algorithm. The back propagation learning algorithm can be divided into two phases: propagation and weight update.

Phase 1: Propagation

Each propagation involves the following steps:

1. Forward propagation of a training pattern's input through the neural network in order to generate the propagation's output activations.
2. Backward propagation of the propagation's output activations through the neural network using the training pattern target in order to generate the deltas of all output and hidden neurons.

Phase 2: Weight update

For each weight-synapse follow the following steps:

1. Multiply its output delta and input activation to get the gradient of the weight.
2. Subtract a ratio (percentage) of the gradient from the weight.

This ratio (percentage) influences the speed and quality of learning; it is called the *learning rate*. The greater the ratio, the faster the neuron trains; the lower the ratio, the more accurate the training is. The sign of the gradient of a weight indicates where the error is increasing, this is why the weight must be updated in the opposite direction. Repeat phase 1 and 2 until the performance of the network is satisfactory.

3. EXPERIMENTAL RESULTS AND DISCUSSION

The experiment has been done using ten different wood species and five sample images from the Prospect Wood Database are tested for each species and the image size is 256*256. The images are pre-processed using three different methods before the feature extraction phase.

3.1 PRE-PROCESSING RESULTS

The original images and their corresponding preprocessed images are given. Figure 3 shows the results obtained using bi-histogram equalization (BHE), Histogram Equalization with Bin Underflow Bin Overflow (BUBO) method and Contrast Limited Adaptive Histogram Equalization (CLAHE) based on entropy techniques.

From Figure 3 it is evident that CLAHE gives the best result. Hence it is used for further processing. The CLAHE is performed with the block size of 64x64 and clip limit used is 0.06 as it gives maximum entropy. Figure 4 shows the graph between clip limit and entropy.

3.2 FEATURE EXTRACTION RESULTS

The original image and the binary edge image before pre-processing, the corresponding binary edge image after pre-processing and the corresponding saliency map is shown in Figure 5.

From the results it is shown that some edge points are missing in the binary edge image before pre-processing. The method used for pre-processing is CLAHE based on entropy. The experimental results show that the edges are more prominent after preprocessing. Saliency map gives the strength and distribution of the edge points in an image. The local window size used for obtaining saliency map is 5x5 and from this saliency index is obtained.

3.2.1 STATISTICAL FEATURES OF WOOD IMAGES

The values of statistical features for each wood species are presented in Table 1. Among these features, contrast and correlation can be used for the classification as its values are unique for various wood species. Based on the range of the feature values the wood images are recognized using the back propagation network.

3.2.2 SALIENCY INDEX MEASURE OF WOOD IMAGES

The saliency index values of the wood images for various pre-processing methods are shown in Table 2. The pre-processing methods used are bi-histogram equalization, histogram equalization with Bin Underflow and Bin Overflow method and Contrast Limited Adaptive Histogram Equalization (CLAHE) based on entropy. The variations in the saliency index values for various wood images can be obtained by using CLAHE. From Table 2 it is clear that the wood images mulberry, rosewood and tamarind yields the same range of saliency index values (nearly 3) when bi-histogram equalization and BUBO pre-processing methods are used. Hence CLAHE is taken as the enhancement method for this work..

The saliency Index comparison based on various edge detection methods is shown in Table 3. Compared to the Sobel operator, gradient method and Cortx method gives better results. The saliency indices of various wood species for the latter two methods are distinguishable.

The saliency index values for the three samples of each species are given in Table 4. The saliency index values for each species falls into a range and based on this a dataset is collected for classification. If the value of the saliency index is between 2.0 and 2.5 it is recognized as rosewood timber.

3.3 CLASSIFICATION

In this paper, artificial neural networks (ANN) are used for classifying wood species. The features of each image for each type of wood are stored in the form of the ANN weights. Weights in the ANN will experience changes during the training period, up to the value of parameter goal is reached. To achieve the expected goal, recognizing 100% trained image, and the highest test images (90%), the ANN architecture must be the best. To get the best architecture, it was trial and error on some architecture, i.e. the number of hidden layers and number of neurons of each hidden layer. We used 3 hidden layers, and each hidden layer has 73 neurons, while the number of input neurons is 40. The sigmoid function is used as the activation function. For each wood species 10 images are used for training and 5 images for testing. The classification rates for various features are shown in Figure 6. The classification rate is found to be 90% when all the 12 features are used for training the neural network. When the neural network is trained with the saliency index the classification rate is 80%.

4. CONCLUSION

In this paper an effective method called Saliency Map was utilized to extract Saliency Index with the purpose of identifying the wood species based on their edges. Edges are used as the main source of information to compute the saliency in the local window of every pixel. The edge in an image reveals spectral discontinuity, contrast, directional information, and structure pattern. Along with the saliency index ten statistical features are also used for the classification. In this work ten different wood species are used for the species recognition and the accuracy is validated by using five different samples for each species. Compared to other wood recognition methods, the advantages of the proposed method is the timber images acquired using digital cameras can directly be used for recognition of species i.e., the images need not be magnified. The experimental results show that the proposed method is sufficiently powerful for recognizing the wood species .The proposed method is simple to implement and the classification accuracy is 90%. The further progress of this work can be done using real-time database of wood images.

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Figure Captions

Figure.1 Workflow for the classification of wood species.

Figure 2 Local window to calculate Saliency index.

Figure 3 Pre-processing Results

Column 1: Input wood images (From top to bottom- Teak, Pine, Mulberry and Cedar-Elm);

Column 2: Enhancement Results for BHE; Column 3: Enhancement Results for BUBO;

Column 4: Enhancement Results for CLAHE.

Figure 4 Clip limit vs. Entropy.

Figure 5 Experimental Results for Edge Detection.

Column 1: Input Wood Images (From top to bottom- Teak, Pine, Mulberry, Cedar-Elm and Mango); Column 2: Edge Detection results before pre-processing; Column 3: Edge Detection results after pre-processing; Column 4: Saliency Map.

Figure 6: Comparison of Classification Rate for various features.

Table 1 Statistical Features of Wood images

Species Name	Contrast	Correlation	Energy	Homogeneity	H Component	S Component	I Component	Kurtosis	Skewness	S.D
Teak	0.3142	0.1772	0.4094	0.8443	0.4470	0.0101	0.0954	7.6054	0.1240	0.1240
Pine	0.2242	0.6813	0.4334	0.8908	0.0773	0.0093	0.1376	39.369	0.6012	0.6012
Mulberry	0.1445	0.5005	0.5872	0.9278	0.1042	0.0138	0.1132	12.623	1.0891	1.0891
Cedar-elm	0.1861	0.4040	0.5587	0.9073	0.0908	0.0114	0.1928	4.8616	0.5980	0.5980
Mango	0.0818	0.3676	0.8024	0.9591	0.2274	0.0183	0.1312	24.806	0.8754	0.8754
Rose wood	0.1211	0.7081	0.4787	0.9394	0.1318	0.0143	0.1174	7.1608	0.0581	0.0581
White Oak	0.1891	0.1298	0.6302	0.9055	0.0372	0.0050	0.1059	34.988	0.3574	0.3574
Padauk	0.0085	0.0557	0.9826	0.9957	0.3115	0.0509	0.1482	24.841	2.4237	2.4237
Fir	0.2268	0.5157	0.3603	0.8867	0.8443	0.0140	0.1891	72.679	2.4292	2.4292
Tamarind	0.5693	0.5468	0.2315	0.8081	0.6743	0.0321	0.1240	45.398	0.5849	0.5849

Table 2 Saliency Index values of wood images for various pre-processing methods

Species Name	Saliency Index		
	Bi-Histogram Equalization	BUBO	CLAHE based on Entropy
Teak	1.3281	1.1245	0.973
Pine	4.3859	4.2987	4.021
Mulberry	3.0455	3.1702	1.728
Rosewood	3.3825	3.0586	2.001
Tamarind	3.3128	3.5204	4.870

Table 3 Saliency Index Comparison for various edge detection methods

Species Name	Sobel	Gradient Method	Cortx Method
Teak	0.0001	1.021	2.91
Fir	0.07326	4.134	5.47
Pine	0.02	4.089	5.21
Tamarind	0.0092	4.870	4.07
Rosewood	0.0436	2.078	4.03

Table 4 Saliency Index values of wood images

Species Name	Saliency Index		
	Sample 1	Sample 2	Sample 3
Teak	1.021	0.973	1.095
Pine	4.089	4.021	4.15
Mulberry	1.845	1.728	1.802
Cedar-elm	1.433	1.502	1.485
Mango	1.102	1.198	1.212
Rosewood	2.078	2.001	2.105
White Oak	3.566	3.502	3.483

Padauk	3.833	3.952	3.894
Fir	4.134	4.037	4.093
Tamarind	4.870	4.870	4.870

WOOD SPECIES CLASSIFICATION BASED ON LOCAL EDGE DISTRIBUTIONS

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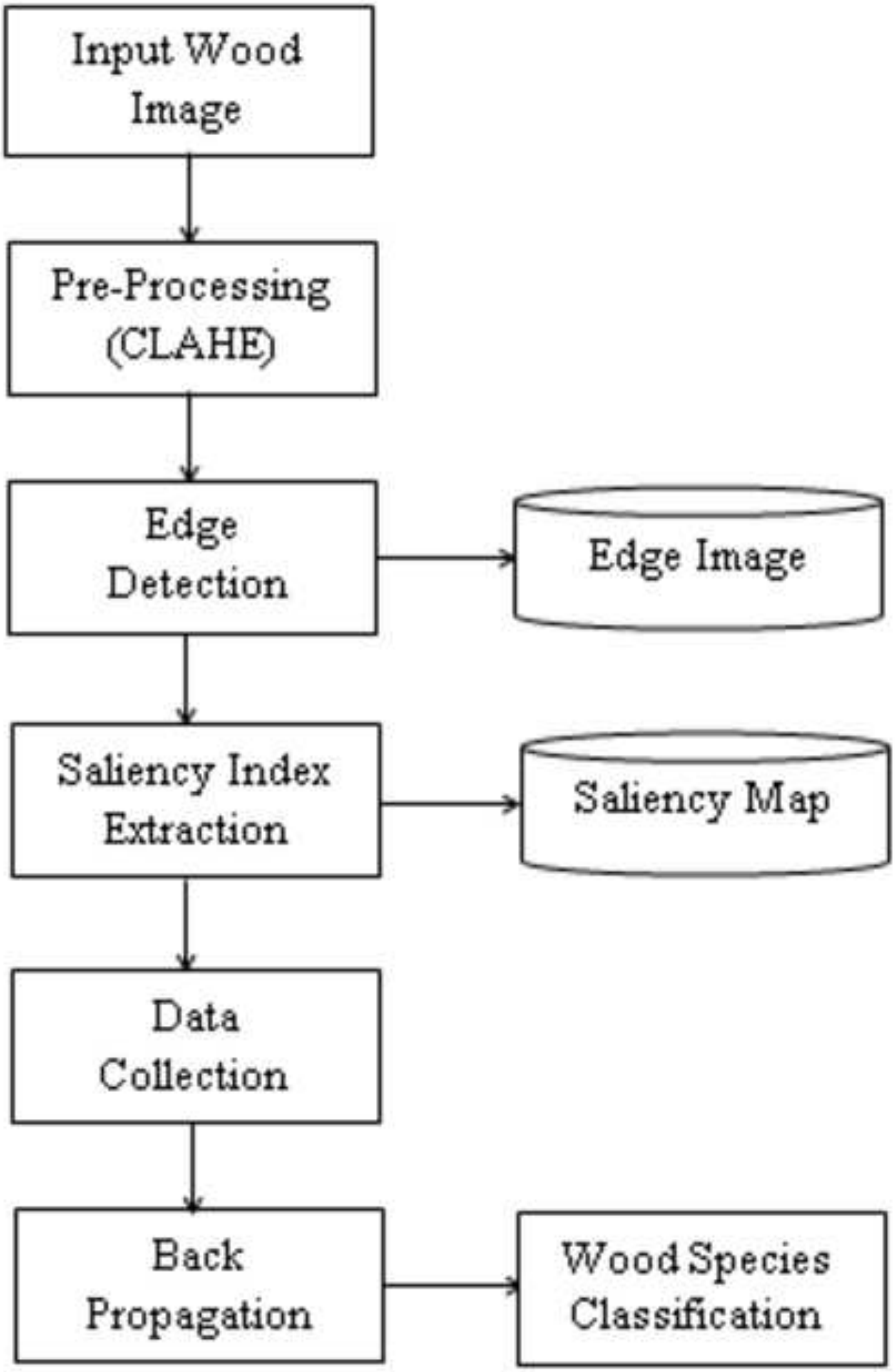
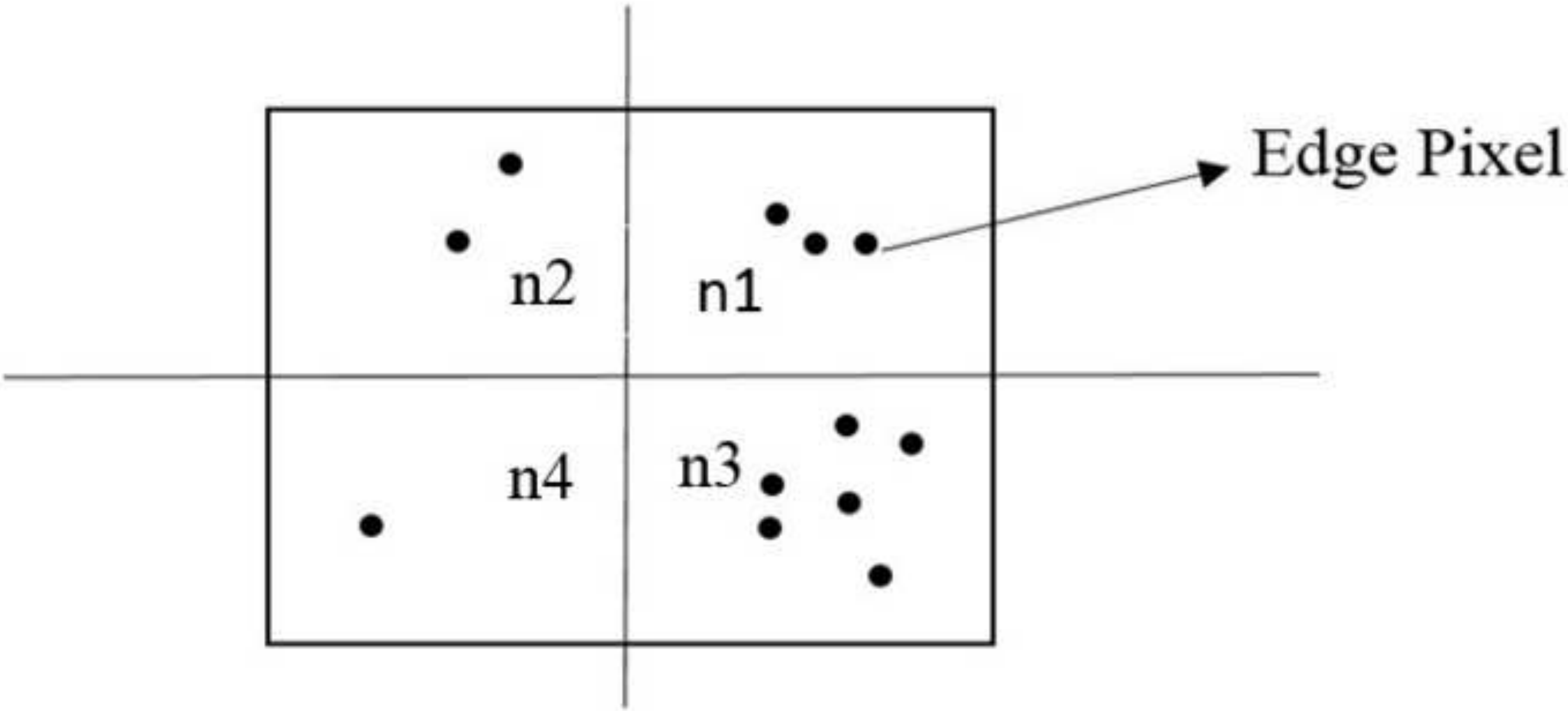

Input Wood Image
Pre-Processing (CLAHE)
Edge Detection
Edge Image
Saliency Index Extraction
Saliency Map
Data Collection
Back Propagation
Wood Species Classification

Figure-2



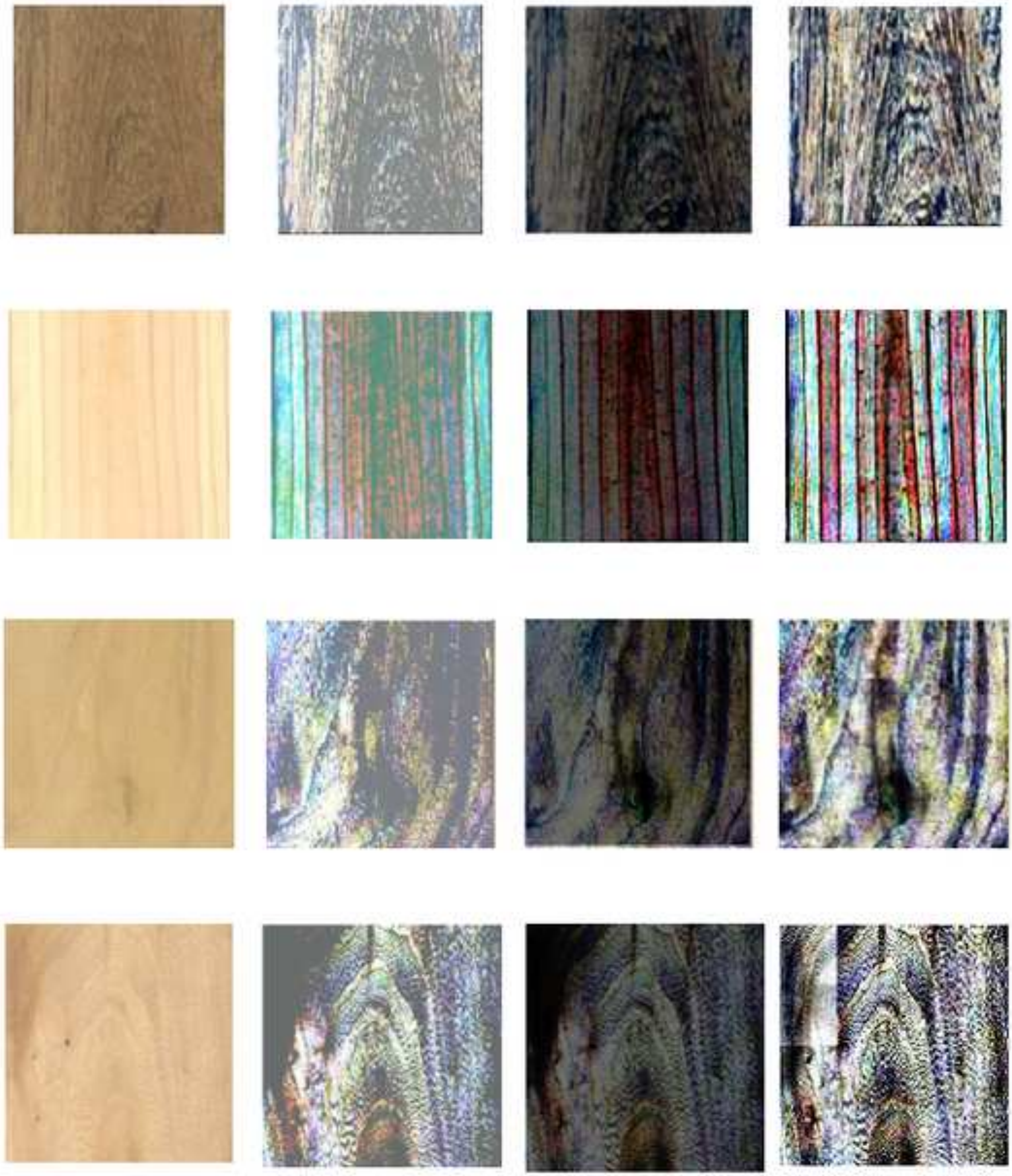
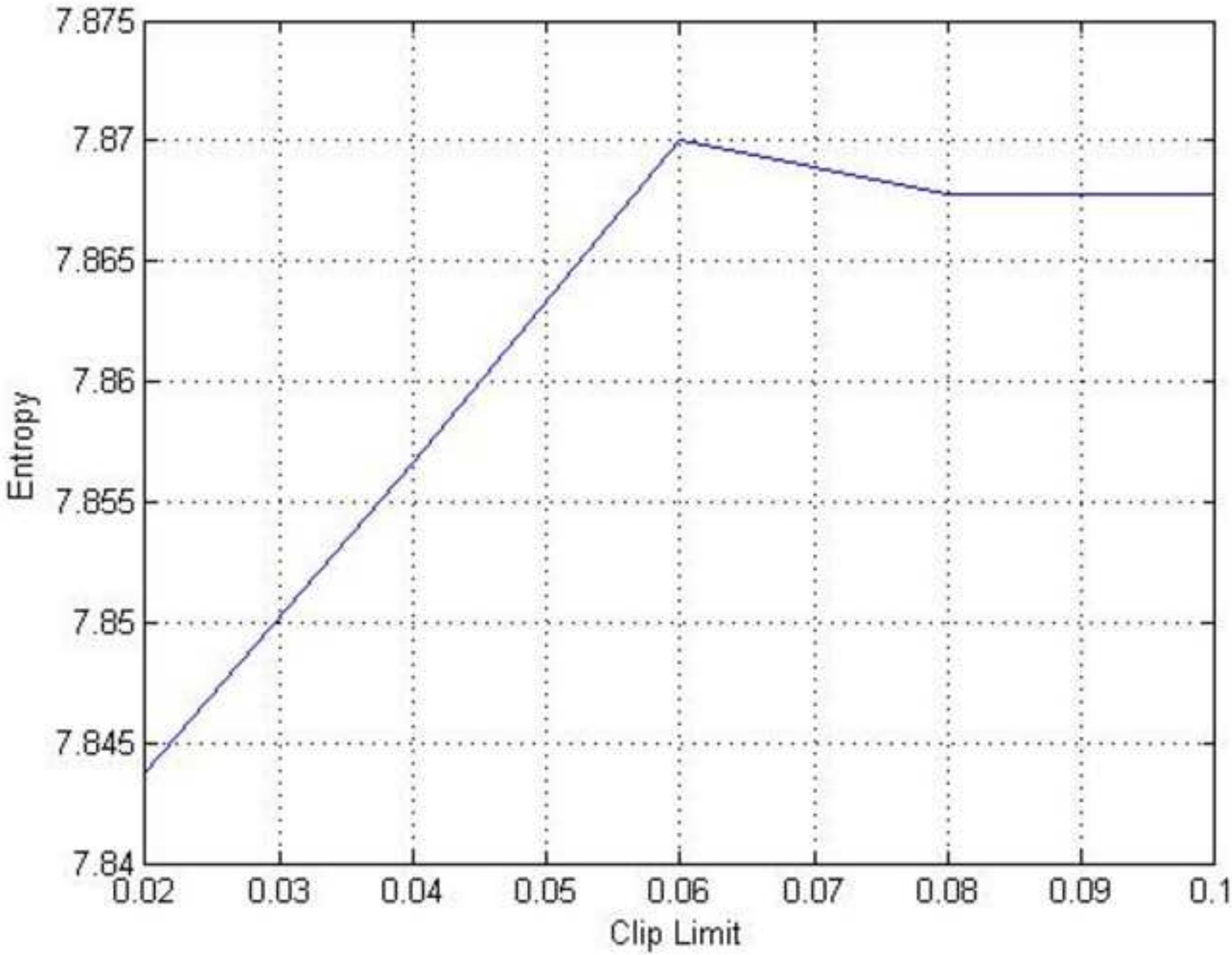


Figure-4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7.87
7.865
7.86
7.855
7.85
7.845
7.84
Entropy
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0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
Clip Limit

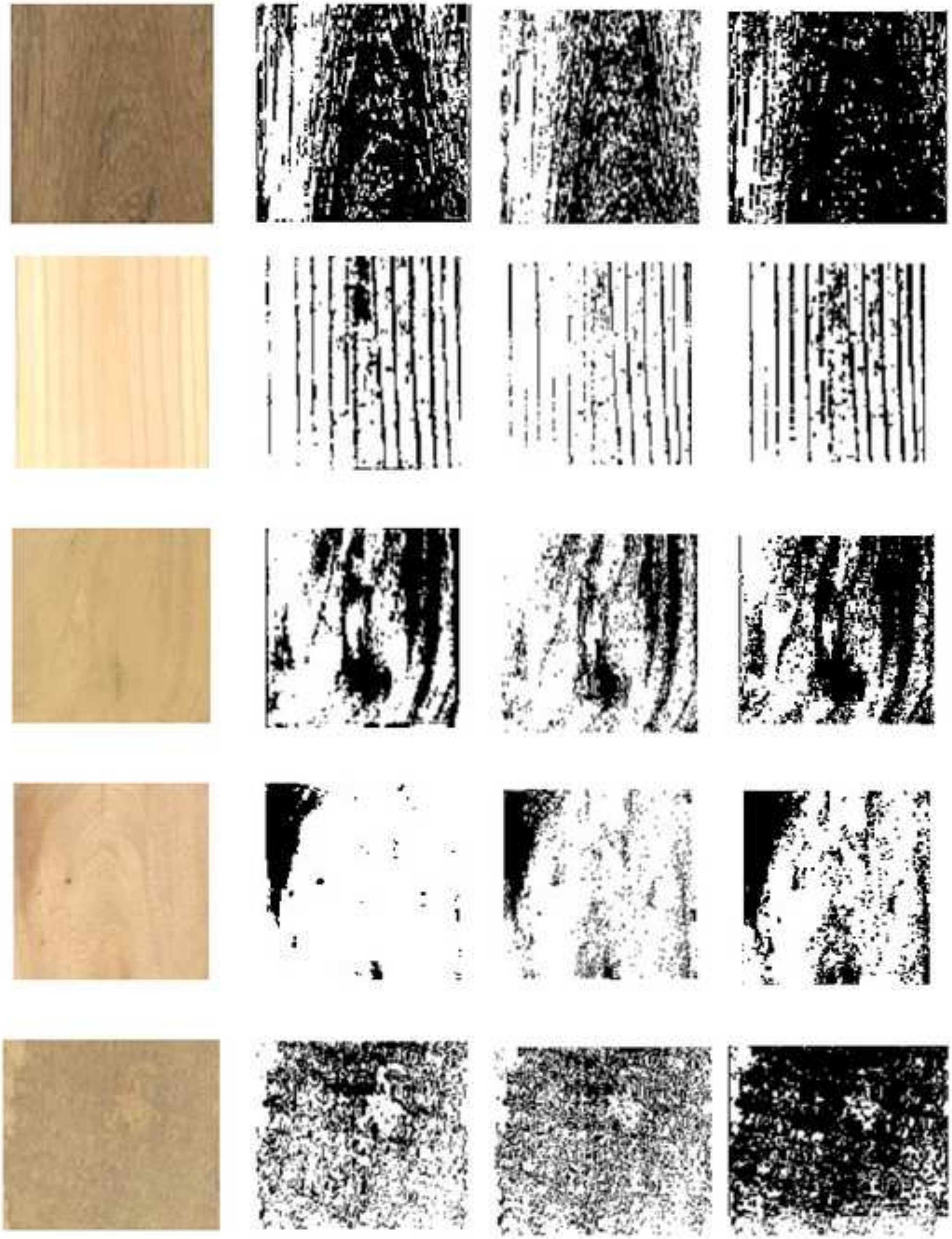
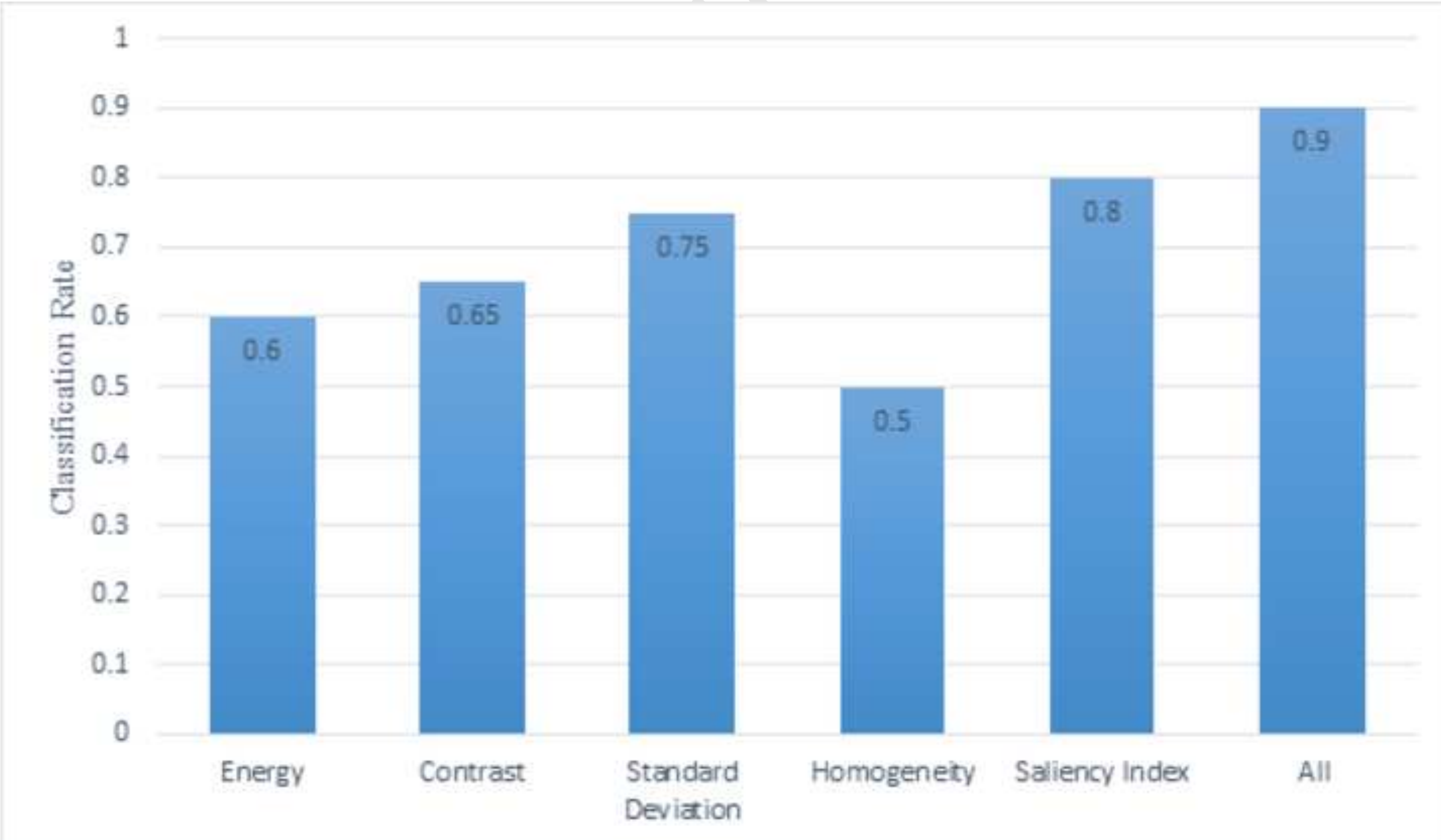


Figure-6


Classification Rate
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0.6
0.65
0.75
0.5
0.8
0.9
Energy
Contrast
Standard Deviation
Homogeneity
Saliency Index
All