A Hybrid of Extreme Learning Machine and Cellular Neural Network Segmentation in Mangrove Fruit Classification

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***Abstract*—Mangroves are a collection of plants that inhabit the intertidal zone, namely the area between the lowest and highest points reached by the tide. Overall, mangroves provide a range of advantages, including the prevention of coastal erosion, the inhibition of seawater intrusion onto land leading to brackish groundwater, and serving as habitats and food sources for diverse animal species. In addition, many types of mangrove fruit have been used as sustenance for humans and as ingredients in processed food products. Mangrove fruit has a considerable variety of species, each characterized by distinct forms. At now, farmers and the general public rely only on visual observation to identify mangrove fruit species. Consequently, their ability to accurately detect the correct species is not guaranteed. In order to address this issue, this study employs digital image processing using the Extreme Learning Machine technique to facilitate the identification of various kinds and varieties of mangrove fruit by the general public and farmers. The study utilizes gray-scaling and Contrast Enhancement as image processing methods, while segmentation is performed by the use of the Cellular Neural Network approach. Following extensive testing in this study, it was determined that the used methodology effectively identified several species of mangrove fruit. The results yielded an accuracy rate of 94.11% for extracting shape, texture, and color elements, and accuracy rate of 99.63% for extracting texture and color features.**

Keywords—Mangroves; mangrove conservation; image processing; ecological informatics; cellular neural network; extreme learning machine

I. Introduction

Mangroves are highly productive and distinctive ecosystems due to their exclusive ability to grow and endure in the transitional area between the ocean and land, where no other plants can live [1]. Indonesia has over 60% of the whole mangrove population in Southeast Asia, establishing it as the nation with the highest number of mangroves in the region. Indonesia is home to a minimum of 48 out of the 52 known mangrove species. Indonesia has the highest level of mangrove population diversity globally [2]. Mangroves are a kind of arboreal flora that often thrives in aquatic habitats with high salinity, such as marine and brackish waters. Mangroves often thrive in the intertidal zone, including the stretch of shoreline between the lowest ebb tide and the highest water level. Nevertheless, mangroves only thrive in regions characterized by tropical and sub-tropical climates [2].

Mangroves are very productive ecosystems that often serve as an economic resource, particularly for those living in coastal areas. Due to their significant impact on marine ecosystems, particularly fisheries, mangroves play a crucial role [2], [3]. Approximately 77% of all mangroves provide utilitarian value, with the most prevalent uses being medicinal, building, culinary (including vegetables, spices, and fruit), decorative, and as a source of fuel) [4]. Overall, mangroves provide a range of advantages, including the prevention of coastal erosion, the inhibition of seawater intrusion that may lead to the salinization of groundwater, and the provision of habitat and sustenance for several animal species. In addition, some mangrove fruit species have been used as a source of sustenance for humans and as ingredients in processed food products. The desirability of mangrove fruit as an economic resource is high among the community. Mangroves play a crucial role in the economics of coastal settlements due to the market value of goods derived from them and their contribution to sustaining coastal fisheries [2].

Several previous studies related to this research include those studied by Naskar & Bhattacharya [5] who examined the introduction of several types of fruit. There were six types of fruit studied, namely apples, bananas, lychees, oranges, pineapples and pomegranates. This research uses the Artificial Neural Network method, and achieves accuracy above 90%. However, the data used is still small. For the six types of fruit processed, they only used 150 data. The fruit features used are also only texture, color and shape. If other features are added to image processing, accuracy may be higher.

In research conducted by Ji et al. [6] carried out fruit classification by combining biogeography-based optimization (BBO) and feedforward neural network (FNN) methods. The data is processed more efficiently with four stages of preprocessing, then feature extraction (color, texture and shape) is carried out. In the third stage, unnecessary features are removed using component analysis. Finally, fruit classification was carried out using the biogeography-based optimization (BBO) and feedforward neural network (FNN) methods. This research used data from 1653 images from 18 fruit categories, but the accuracy was less high than research

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using other methods, namely 89.11%. Similar with research in [5], if researchers add features and processed data, the accuracy achieved can be even higher.

The study conducted by Lu et al. [7] examines the categorization of fruits for industrial purposes. They used a Convolutional Neural Network consisting of six layers and utilized a dataset of 200 samples for each fruit species. The accuracy achieved by this study was 91.44%. Nevertheless, comprehending the weights of a Convolutional Neural Network using this approach is challenging. Enhancing the classification performance of Convolutional Neural Network requires the use of a more effective approach for parameter configuration. This would enable better handling of bigger datasets including diverse fruit kinds. Rouhi et al. [8] performed research on the categorization of benign and malignant breast cancers using the Cellular Neural Network segmentation approach. The accuracy gained in this study was very high, exceeding 95%. Nevertheless, the dataset used in this work remains quite small, consisting of just 93 photos depicting malignant tumors and 170 images depicting benign tumors. While the suggested approach is really strong, its varying outcomes on the DDSM and MIAS databases are seen as a shortcoming. An in-depth analysis of preprocessing procedures may be conducted to ensure consistent outcomes. The study done by Ghoneim, Muhammad, and Hossain [9] examines the categorization of cervical cancer via the use of Convolutional Neural Network and Extreme Learning Machine classification techniques. The acquired accuracy is quite high, namely 99.7% for 2 class classification and 97.2% for seven class classification. Nevertheless, the dataset used remains quite small, consisting of just 917 data points distributed over seven distinct categorization groups. The use of additional data is very likely to enhance accuracy.

The aforementioned studies conducted Rouhi et al. [8] and Ghoneim, Muhammad, and Hossain [9] demonstrate that Cellular Neural Network is effective for segmentation, while Extreme Learning Machine is effective for classification and image detection. These methods yield higher accuracy when accompanied by preprocessing techniques and a substantial amount of data.

Until now, there has not been much research on the classification of mangrove fruit, we have carried out several studies related to mangroves and machine learning. Among them is research related to the classification of mangrove shoots based on measurements of their morphology. This research uses a Multi-Layer Perceptron to carry out a basic classification of the types of mangroves shoots to be planted. The results obtained were not satisfactory, namely 91.9% using 3000 data [4]. Another research related to mangroves is the classification of maturity levels of mangrove fruit using deep convolutional neural networks. Where in this research the accuracy rate reached 99.1% [3]. From previous research conducted [3], it is deemed necessary to classify fruit types. This is because the level of ripeness and type of fruit are closely related. Apart from that, using the Extreme Learning Machine method with Cellular Neural Network also needs to be tested for its level of accuracy. Apart from that, mangrove fruit has quite a lot of species with different shapes. Currently, farmers or the public generally see and recognize mangrove fruit species only with the naked eye, so the introduction of mangrove fruit species does not necessarily match the species they are looking for. Therefore, an approach was taken to this problem in order to classify mangrove fruit species. Thus, we can form our research gap, which state that mangrove identification with machine learning technique is a must considering the concern of ecological urgency around the world. We also state that the novelty of our data and mangrove fruit classification system is a new field of ecological research in the world.

In this study, we imposed several constraints to restrict the extent of the issue from proliferating. The specific limitations of this problem include the focus on studying mangrove fruit species found in the North Sumatra region, specifically Rhizophora stylosa and Rhizophora mucronata. Additionally, only images with the file extensions .jpg or .jpeg will be processed, and the image size must be 720×84 pixels. The research provides several benefits. Firstly, it serves as a valuable reference for future studies on the classification of mangrove fruits. Secondly, it facilitates the identification of different mangrove species based on their fruits, benefiting both the general public and farmers. Thirdly, it aids in the recognition of specific mangrove fruit species, assisting individuals in replanting according to their desired species. Lastly, it simplifies the process for new farmers who wish to propagate mangrove plants by helping them identify different mangrove species, particularly through their fruits.

The content of paper is arranged as follows; in the Section II, we describe the methodology and algorithm used in this study. While in Section III we analyze the experimental results. Section IV is the summarization and future research of this paper.

II. METHODOLOGY

The research in this study included many stages: image acquisition, image preprocessing, image segmentation, feature extraction, and classification using the Extreme Learning Machine. The overall structure illustrating the sequential steps undertaken may be shown in Fig. 1.

A. Image Acquisition

This phase involves gathering visual data of mangrove fruit, which serves as the system's first input. Two sets of data are utilized to classify the mangrove fruit images: training data and testing data. Without utilizing a light, the image was obtained using a DSLR camera equipped with 18 megapixels of resolution. It is imperative that the captured image be situated on a backdrop of black. The information utilized in this investigation was gathered from numerous mangrove forests situated in North Sumatra. Three specific locations in the North Sumatra region provided the information utilized in this study: Percut Sei Tuan, Kampung Nipah Mangrove Beach, and Mangrove Ecotourism, Sicanang Belawan. Seven distinct occasions were utilized to collect the data, spaced at varying intervals.

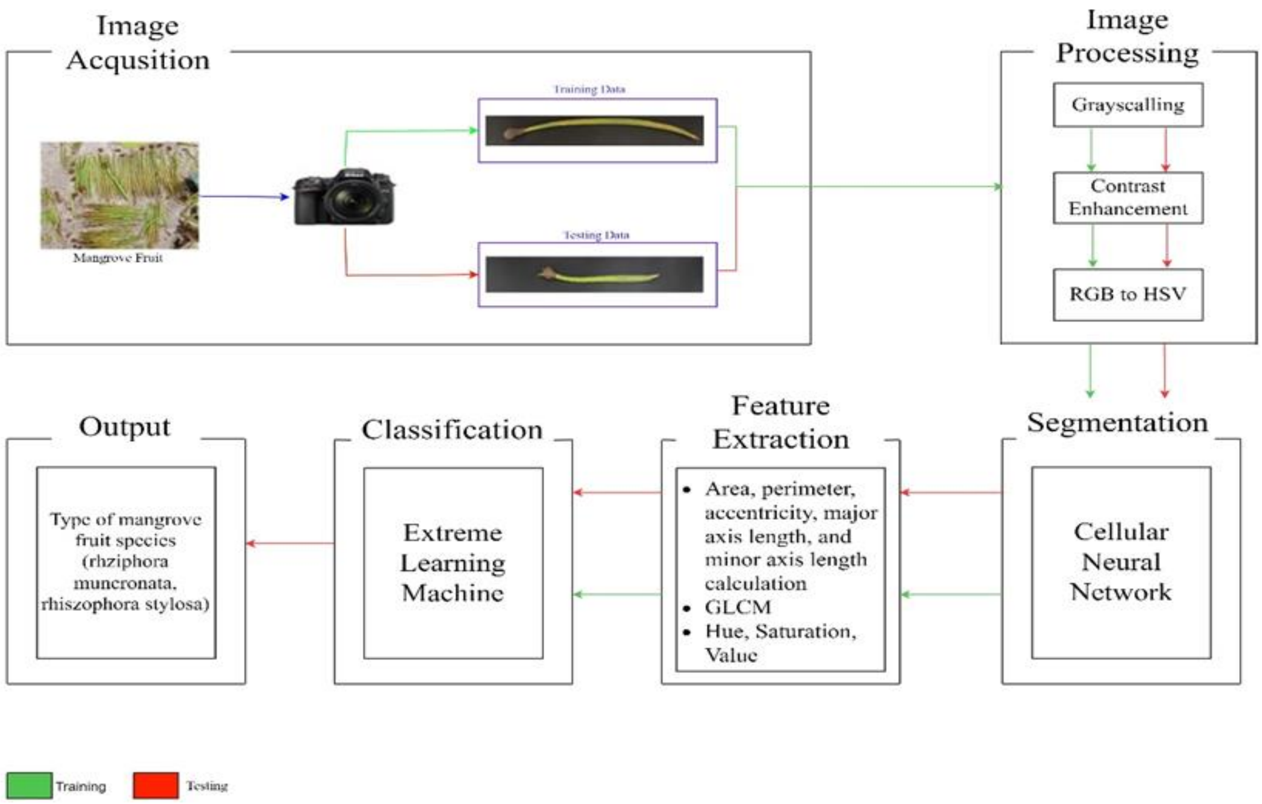

Fig. 1. General architecture.

The study utilizes an image with the file extension .JPG or .JPEG, measuring 720 × 84 pixels in size. Fig. 2 and Fig. 3 provide visual data of mangrove fruit.

Fig. 2. Image of Rhizophora mucronata.

Fig. 3. Image of mangrove fruit Rhizophora stylosa.

B. *Image Processing*

The phase of preprocessing involves altering of the acquired image to enhance its quality and facilitate further processing. The preprocessing phase includes three steps: grayscaling, contrast enhancement, and conversion of the RGB picture to HSV.

1) Grayscaling: Grayscaling is the first step in the preprocessing phase. At this point, the initial RGB picture is transformed into a grayscale image. The objective of grayscaling is to facilitate the identification of different mangrove fruit species in images. The grayscaling technique used in this study is the luminosity approach. The luminosity technique of grayscaling involves multiplying each value of the red (R), green (G), and blue (B) channels by a certain constant value that has been predetermined. The process of converting RGB photos to grayscale is performed on both training and testing images. The conversion of an RGB picture to a gray image using the luminosity approach can be achieved by using the Eq. (1).

$$GI = 0.2989R + 0.5870G + 0.1140B \qquad (1)$$

Images of mangrove fruits after the grayscalling process can be seen in Fig. 4 and Fig. 5.

Fig. 4. Image of Rhizophora mucronate mangrove fruit after the grayscalling process.

Fig. 5. Image of mangrove fruit Rhizophora stylosa after the grayscalling process.

2) Contrast enhancement: Following the completion of the grayscaling procedure, the subsequent step involves enhancing the contrast. Contrast enhancement is performed to augment the contrast value of the captured picture of the mangrove fruit. This process aims to make the image more distinct, increase the visibility of its characteristics, and minimize the presence of noise [10]. The use of contrast enhancement in this study can be achieved utilizing the Eq. (2)

$$f_{0(x,y)} = G\left(f_{i(x,y)} - P\right) + P \qquad (2)$$

The image of mangrove fruit that has had contrast enhancement applied can be seen in Fig. 6 and Fig. 7.

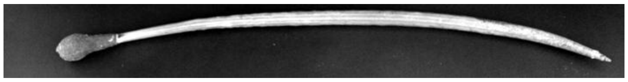

Fig. 6. Image of Rhizophora mucronate mangrove fruit after contrast enhancement.

Fig. 7. Image of mangrove fruit Rhizophora stylosa after contrast enhancement.

3) RGB to HSV conversion: At this stage, the RGB image of the mangrove fruit is converted from the RGB color model to the HSV color model. To get the HSV value, we must first know the RGB value of a pixel. In this research, RGB values were taken and conversion of RGB values to HSV. The results of converting RGB images of mangrove fruit to HSV images can be seen in Fig. 8 and Fig. 9.

Fig. 8. HSV image of Rhizophora mucronata mangrove fruit.

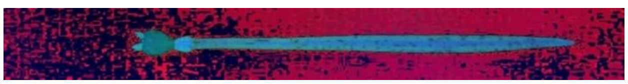

Fig. 9. HSV image of mangrove fruit Rhizophora stylosa.

C. *Image Segmentation*

Image segmentation follows the preprocessing phase. Image segmentation is used to distinguish the image of mangrove fruit from the surrounding background. This study uses the Cellular Neural Network approach for segmentation.

1) Cellular Neural Network: A Cellular Neural Network (CNN) is a network consisting of linked cells arranged in a MxN matrix, where M represents the number of rows and N represents the number of columns [11]. The architecture of a Cellular Neural Network has resemblance to that of cellular automata, whereby neighboring cells in the network may engage in direct interactions. Cells that lack direct connections may have indirect impact on neighboring cells via the propagation of continuous effects [12].

CNNs have shown efficacy in detecting malignancies and challenging objects, as evidenced by the studies conducted by Döhler et al. [13] and Abdullah et al. [14]. In order to do segmentation, three parameters need to be configured with appropriate values. The inputs consist of the template matrices A and B, as well as a bias value. The approach used in this study to ascertain the suitable values for template matrix A, template matrix B, and bias values was a process of trial and error. Following the completion of many trials, the values for template matrix A, template matrix B, and their respective bias values were acquired, such as:

$$\text{Template A} = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 2 & 1 \\ 0 & 0 & 0 \end{bmatrix} \quad \text{Template B} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\mathrm{B\iota\alpha\sigma} = 0.8$$

Cellular Neural/Nonlinear Networks are complex circuits that exhibit nonlinear dynamical behavior on a vast scale. These networks are comprised of cells, which are analog processing components that are locally coupled. They are characterized by study [12]:

$$\dot{x}_{ij}(t) = -x_{ij}(t) + \sum_{kl \in N_{\bar{r}}} A_{ij,kl} y_{kl}(t) + \sum_{kl \in N_{\bar{r}}} B_{ij,kl} u_{kl}(t) + I_{ij} \tag{3}$$

Where $x_{ij}(t)$ is the state, $y_{ij}(t)$ is the output, $u_{ij}(t)$ is the input, I_{ij} is the cell current, $A_{ij,kl}$ and $B_{ij,kl}$ are the parameters forming the feedback template A and the control template B, respectively, whereas $kl \in \overline{N_r}$ is a grid point in the neighborhood within the radius $\bar{r}$ of the cell ij [12], [15].

Assign template A as feedback, template B as control, and interpret bias as a threshold value. The input image to this Cellular Neural Network (CNN) is a preprocessed image. The segmentation process utilizing Cellular Neural Networks (CNN) involves the following steps [16]:

- Determine the image that will be used as input.
- Determine the values of template A, template B, and bias.
- Convert the input image to double class.
- If $t < 1$, calculate the output value in vector column form.
- Calculate the state value of the CNN
- Resize the output to its original size

The segmentation result image can be seen in Fig. 10.

Fig. 10. The segmentation result image.

D. *Feature Extraction*

Following the segmentation process, feature extraction is performed to acquire values from the features present in the picture of the mangrove fruit. The characteristics that are considered include form, texture, and color.

1) Area feature extraction calculation: In order to derive form characteristics from mangrove fruit, a method of feature extraction is conducted, using the object's shape as a basis, resulting in distinct feature values. The feature extraction method involves the computation of several measurements, such as area, perimeter, eccentricity, major axis length, and minor axis length, on the segmented picture. Subsequently, these values will serve as input parameters during the classification phase. Here we describe area, perimeter and major minor axis length.

$$Area = Number\ of\ White\ Pixel \tag{4}$$

Thus, perimeter calculated by.

$$PR = \sum_{i=1}^{N-1} d_i = \sum_{i=1}^{N-1} |x_i - x_{i+1}| \tag{5}$$

And major axis length.

$$MaAL = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{6}$$

2) Gray Level Co-Occurrence Matrix (GLCM): Various methods may be used to extract texture characteristics from grayscale photos, including local binary patterns, gray level co-occurrence matrices, and scale invariant feature transform [17]—[19]. Once the form characteristic values of the image have been obtained, the subsequent step involves extracting the texture characteristic value using the Gray Level Co-Occurrence Matrix (GLCM) approach. The input for this GLCM procedure is a grayscale image. This study employs four Gray-Level Co-occurrence Matrix (GLCM) matrices to extract texture features from images of mangrove fruits. Specifically, the GLCM matrices are computed with a spatial distance of 1 and angles of 0°, 45°, 90°, and 135°. The extracted features include entropy, contrast, correlation, energy, and homogeneity. Here we describe the equation of every features.

Entropy is a stochastic metric that quantifies the amount of information related to characterization of image's texture. The entropy value is maximized when all pixel value for grey is equal or exhibits greatest randomness. If the entropy value increase it means the complexity of the image will increase too, which entropy also measure the level of complexity of grey distribution in the image.

$$ENT = \sum_{i,j=0}^{N-1} P_{ij} \left(-In\ P_{ij}\right) \tag{7}$$

Contrast is used to quantify the variations in intensity between neighboring pixels over the whole image. Contrast is indicative of both the sharpness of the picture and the intricacy of the texture's ridges. The more distinct the texture, the higher the contrast.

$$CNT = \sum_{i,j=0}^{N-1} P_{i,j} \, (i-j)^2 \tag{8}$$

Correlation is used to measure the degree of resemblance between the gray levels of an image in either the horizontal or vertical orientation. The size of the value represents the extent of local gray level correlation. The values of -1 and 1 represent the existence of negative and positive correlation in the image, respectively.

$$Corr = \sum_{i,j=0}^{N-1} \frac{(i-\mu)(j-\sigma)}{\sigma^2} \tag{9}$$

Energy also called as angular second moment, where the homogeneity of gray distribution and the level of texture. A finer texture correspondent to a higher component value in the GLCM matrix which will resulting smaller energy. The energy value will experience a substantial increase when the pixels exhibit a strong correlation, suggesting that the current texture exhibits reasonably consistent and predictable variations. The formula for energy is:

$$EGY = \sum_{i,j=0}^{N-1} (P_{ij})^2 \tag{10}$$

Homogeneity also called deficit moment, is a degree of texture clarity and regularity, refers to a big number indicating a clear image texture with great regularity.

$$HMY = \sum_{i,j=0}^{N-1} \frac{P(i,j)}{1+(i-j)^2} \tag{11}$$

Each value obtained from the process of feature extraction will generate four Grey-Level Co-occurrence Matrices (GLCMs), and each matrix will provide five distinct texture characteristics. Therefore, the total number of features produced is twenty. Nevertheless, the GLCM matrix just captures statistical values for each feature. Consequently, five characteristics will be retrieved and used as input for ELM.

3) Hue Saturation, Value (HSV): During this step, the process of extracting color features is performed, namely by capturing the hue, saturation, and value values. Once the RGB picture is transformed into an HSV image, the HSV value of the image will be extracted.

E. Extreme Learning Machine - Classification

Extreme Learning Machine was the approach that was used in this research project for the purpose of classification. Extreme Learning Machine, often known as ELM, is a learning algorithm that is based on the idea of single hidden-layer feedforward neural networks. (SLFN) [20]. When compared with other algorithms which also have the concept of single hidden-layer feedforward neural networks (SLFN), ELM provides better speed and performance [21], [22]. Because ELM can provide better speed and performance, it is believed that ELM can overcome the learning speed problem that has occurred in other feedforward neural networks algorithms [23], [24]. The learning speed of feedforward neural networks is generally much slower than other algorithms. This is because feedforward neural networks use a slow gradient-based learning algorithm in the training process, and all parameters in the neural networks are determined repeatedly [25].

Let's assume that there are N distinct sets of learning samples. $(x_i, y_i), 1 \leq i \leq N, X_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T \in R^n, y = [y_{i1}, y_{i2}, \ldots, y_{im}]^T \in R^m$, The expression for a neural network with a single hidden layer and L hidden nodes is as follows:

$$\sum_{i=1}^{L} \beta_i g(W_i \cdot X_i + b_i) = O_i, i = 1, \dots, N \tag{12}$$

$W_i = [w_{i1}, w_{i2}, , w_{in}]^T$ is the input weight vector, β_i is the output weight, $g(x)$ is the activation function, b_i is the bias of the ith hidden layer node, $W_i \cdot X_i$ is the inner product of W_i and $X_i, O_i = [o_{i1}, o_{i2}, \dots, o_{in}]^T$ denotes the network output value. The objective of the single hidden layer neural network is to reduce the inaccuracy in the output. Thus, it may be formulated as

$$\sum_{j=1}^{N} \| o_j - t_j \| \tag{13}$$

Exist β_i, W_i and b_i, and make

$$\sum_{i=1}^{L} \beta_i g\left(W_i \cdot X_j + b_i\right) = t_j, j = 1, \dots, N \tag{14}$$

It can be matrix expressed as

$$H\beta = Y \tag{15}$$

H is the vector that represents the output of the hidden layer of the neural network is denoted by the symbol β, while the output weight is denoted by the symbol T. The specific way of expressing it is Eq. (15).

$$\begin{aligned} &H(W_1, \dots, W_L, b_1, \dots, b_L, X_i, \dots, X_L) \\ &= \begin{bmatrix} g(W_1X_1 + b_1) & \cdots & g(W_LX_1 + b_L) \\ \vdots & \ddots & \vdots \\ g(W_1X_N + b_1) & \cdots & g(W_LX_N + b_N) \end{bmatrix}_{NxL} \end{aligned} \tag{16}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{Lxm}, T = \begin{bmatrix} T_1^T \\ \vdots \\ T_N^T \end{bmatrix}_{Nxm}$$

In order to train a single hidden layer neural network, we need to get $\widehat{W}_i$, $\hat{b}_i$, and $\hat{\beta}_i$, such that

$$\begin{aligned} &\left\| H\left(\widehat{W}_i, \hat{b}_i\right) \hat{\beta}_i - T \right\| \\ &\quad = min_{W,b,\beta} \| H(W_i, b_i)\beta_i - T \| \end{aligned} \tag{17}$$

$i = 1, \dots, L$, that's equivalent to minimizing the loss function

$$E = \sum_{j=1}^{N} \left(\sum_{i=1}^{L} \beta_i g\left(W_i \cdot X_j + b_i\right) = t_i \right)^2 \tag{18}$$

In solving such issues, the Extreme Learning Machine (ELM) outperforms other conventional methods that rely on gradient descent algorithms. Unlike classic learning algorithms that require adjusting all parameters throughout each iteration phase, the algorithm employed by the ELM only requires to alter the input weights W_i and hidden bias b_i is determined, the output of the hidden layer matrix H is stochastically determined, resulting in significant savings in human labor and material resources. Consequently, the process of training a neural network with a single hidden layer may be simplified to solving a linear equation. $H\beta = T$ which Simultaneously, the output weight may also be ascertained.

$$\hat{\beta} = \overline{H}T \tag{19}$$

$\overline{H}$ is the generalized inverse of the matrix that Moore and Penrose have developed, and the norm of the solution that has been produced is the lowest and most unique.

The features obtained in the previous stage of feature extraction will be used in this stage as input. This stage is comprised of two distinct phases, namely the training phase and the testing phase. The training phase is conducted to determine the most optimum weights and biases that will subsequently be used during the testing phase. The testing step corresponds to the stage when data validation takes place. The ELM architecture for training has three layers: the input layer, hidden layer, and output layer. The input nodes consist of 13 nodes that include shape, GLCM, and HSV feature extraction. Additionally, there is an input node with 8 nodes that only use GLCM and HSV feature extraction. The following procedures will be executed.

1) Determining the number of nodes in the hidden layer: The values of the nodes in the artificial neural network, particularly in the hidden layer, play a crucial role in processing the training data. The hidden layer is responsible for computing the final outcomes of the artificial neural network. Insufficient hidden layers lead to underfitting, causing suboptimal performance of the accessible nodes in detecting signals from the input layer. An overfitting issue occurs when the hidden layer has an excessive number of node values. This happens because the network's processing capacity is too big to effectively handle the quantity of information acquired from the training data.

2) Determination of the activation function: The choice of the activation function is determined by the process of determining the number of hidden layers. The purpose of selecting this activation function is to use it for neurons throughout both the training and testing stages. The research utilizes the sigmoid function as its activation function. The sigmoid function is a kind of activation function often used in backpropagation algorithms, which aim to decrease computing time.

3) Training process: The first phase conducted by the extreme learning machine involves the training procedure for categorizing mangrove fruit. The training procedure involves configuring an artificial neural network to provide the desired output by using a certain dataset. The ultimate outcome of this procedure is an artificial neural network that has undergone training to provide outcomes that align with the data used in the training phase. The training procedure is conducted in three distinct phases, namely:

a) Randomization of input weight and bias: The first phase of the training procedure included assigning input weight and bias values. The number of neurons in the input layer is adapted to match the number of parameters obtained from the used dataset. The weight and bias values used in this investigation were assigned randomly.

b) Calculation of hidden layer output matrix: Following the completion of the phases that came before it, the calculation of the hidden layer output matrix will be carried out. The hidden layer output matrix is the result of the input processing that neurons in the hidden layer receive from neurons in the input layer. This processing is received by neurons and then processed. The processing has been carried out by using the activation function that was constructed in the phase that came before it, namely the sigmoid function.

c) Calculation of output weight: And last but not least, the computation of the output weight is carried out once the procedure of calculating the hidden layer output matrix has been finished. Following the completion of this procedure, a matrix is produced that is a representation of the weight of each neuron in the output layer.

4) Testing process: The artificial neural network generated after the training phase will undergo testing in the evaluation phase. The testing procedure was conducted to assess the efficacy of the extreme learning machine technique in categorizing mangrove fruit photos according to their species.

5) Output calculation: The calculation process is carried out using an artificial neural network that has been trained in the previous training process. The results of the calculation process will be a classification of mangrove fruit images based on species.

III. Result and Analysis

The tests conducted on mangrove fruit images included two forms of classification: one based on shape, texture, and color features, and another based solely on texture and color features. Here we describe feature extraction result from shape, texture and color feature extraction depicted in Table I, while feature extraction for texture and color depicted in Table II below.

Experimentation was conducted with varying quantities of concealed neurons, commencing with 30, 50, 80, and 100. Conducting experiments with varying numbers of hidden neurons seeks to determine the optimal number of hidden neurons required to accurately distinguish various types of mangrove fruit. The confusion matrix is shown in the Table III.

The accuracy presentation of the system with various hidden neurons is as follows:

$$Accuracy = \frac{Correct\ Testing\ Data}{Sum\ of\ all\ Testing\ Data} \times 100\%$$

TABLE I. Feature Extraction from Shape, Texture, and Color

Area	PR	ECC	MaAL	MiAL	ENT	CNT	Corr	EGY	HMY	H	S	V
609	306.16	0.9998	303.90	6.526	0.559	0.325	0.949	0.271	0.916	-0.1635	-0.0469	-0.1471
673	128.92	0.9998	353.11	6.491	0.558	0.317	0.952	0.274	0.920	-0.1687	-0.0468	-0.1448
697	128.28	0.999	380.65	6.298	0.556	0.321	0.952	0.268	0.919	-0.1685	-0.0464	-0.1461
608	126.69	0.999	387.81	6.132	0.556	0.322	0.951	0.275	0.919	-0.1709	-0.0463	-0.1461
613	127.45	0.999	368.62	6.215	0.556	0.330	0.950	0.270	0.915	-0.1702	-0.0460	-0.1484
…	…	…	…	…	…	…	…	…	…	…	…	…
668	3.556	0.9992	423.26	17.10	0.420	0.207	0.958	0.554	0.955	-0.0948	-0.0363	-0.0590

TABLE II. Feature Extraction from Texture and Color

ENT	CNT	Corr	EGY	HMY	H	S	V
0.5592	0.3254	0.9499	0.2717	0.9163	-0.1635	-0.0469	-0.1471
0.5581	0.3176	0.9520	0.2740	0.9201	-0.1687	-0.0468	-0.1448
0.5565	0.3211	0.9521	0.2684	0.9198	-0.1685	-0.0464	-0.1461
0.5562	0.3220	0.9516	0.2755	0.9195	-0.1709	-0.0463	-0.1461
0.5564	0.3304	0.9502	0.2705	0.9154	-0.1702	-0.0460	-0.1484
…	…	…	…	…	…	…	…
0.4207	0.2071	0.9584	0.5543	0.9555	-0.0948	-0.0363	-0.0590

TABLE III. Confusion Matrix (Shape, Texture, and Color Extraction Feature)

	Shape, Texture, and Color Extraction Features		**Texture, and Color Extraction Features**		**Total**
	Rhizopora mucronate	***Rhizopora stylosa***	***Rhizopora mucrotae***	***Rhizopora stylosa***	
Rhizopora mucronate	61	11	72	0	72
Rhizopora stylosa	5	195	1	199	200
Total	66	206	73	199	272

TABLE IV. SYSTEM ACCURACY

Shape, Texture, and Color Extraction Features				**Texture, and Color Extraction Features**			
Correct amount of test data	***Number of incorrect test data***	***Number of hidden neurons***	***Accuracy***	***Correct amount of test data***	***Number of incorrect test data***	***Number of hidden neurons***	***Accuracy***
253	19	30	93,01%	264	8	30	97,05%
253	19	50	93,01%	268	4	50	98,52%
254	19	80	93,38%	271	1	80	99,63%
256	16	100	94,11%	271	1	100	99,63%

The accuracy presentation of the system with various hidden neurons can be seen in Table IV. From the calculations above, demonstrate that the experiment that achieved a level of accuracy of 94.11% for shape, texture, and color extraction features using 100 hidden neurons. Additionally, the accuracy reached 99.63% for texture and color extraction features with the same number of hidden neurons. While these results indicate a relatively high level of accuracy, they are not perfect. The accuracy achieved in classification using form, texture, and color characteristics is inferior than that achieved using just texture and color features. When observing with the naked eye, one of the most noticeable distinctions between the Rhizophora mucronata and Rhizophora stylosa species is the form characteristics, particularly the size of their mangrove fruit. Rhizophora mucronata often exhibits greater dimensions in comparison to Rhizophora stylosa. The decrease in system accuracy observed when incorporating additional shape features is likely attributed to the limited variation in data from the Rhizophora mucronata species. Consequently, the classification performance of ELM diminishes slightly compared to when only texture and color feature extraction are employed.

The imperfection of this system may be attributed to many variables, primarily the influence of ambient light that results in incorrect image segmentation. Consequently, the accuracy of the Extreme Learning Machine in identifying mangrove fruit species is compromised. Fig. 11 displays an instance of an image that was not successfully categorized. The image in Fig. 11 was not successfully categorized due to the deteriorated state of the mangrove fruit, which was found to be in worse condition compared to the fruit of other Rhizophora mucronata species. Rhizophora mucronata often has a more vibrant green coloration in its fruit and possesses a more uniform appearance, lacking the intricate textural features shown in Fig. 11.

Fig. 11. Example of image that failed to classified.

In our previous study [3], we implemented Deep Convolutional Neural Network in order to classify mangrove fruit ripeness. While it is not relevant to be compared in this study, we see a chance to implement deep-learning based technique in mangrove fruit classification as our foresight research. There are several deep learning techniques that can implement such as deep neural network, Faster-RCNN, AlexNet, RestNet, YOLO or even ensemble learning.

IV. CONCLUSION

The study successfully used the Extreme Learning Machine (ELM) approach to accurately identify mangrove fruit based on species. The system achieved an accuracy of 94.11% when shape, texture, and color features were extracted, and an accuracy of 99.63% when just texture and color features were extracted. Nonetheless, the act of capturing images with a DSLR camera significantly impacts the resulting image. Inadequate suitability of the captured imagine and insufficient brightness of the surrounding light will result in noise and a dark image, so preventing the image features from being prominent. This will interfere with the process of segmenting and classifying. The determination of the value in the segmentation process, particularly the bias value, is very crucial in achieving effective image segmentation. Excessive bias values will result in the segmentation of the image's background as well. Conversely, if the bias value is too low, the segmentation of the mangrove fruit in the image will not be complete.

Several limitations and suggestion have been arising during our study such as, the mobility of our system can be improved using deep learning based mobile application includes its accuracy-concern. While other deep learning methodology can be implemented for our future research in classifying mangrove species. Thus, other limitation including mangrove zone plantation decision system is still open for research which will determine which area is suitable for certain kind of mangrove to increase the life chance of mangrove.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

AUTHORS' CONTRIBUTION

Conceptualization, RFR and SAC; methodology, RFR; software, SAC; validation, OSL, MSL, and F; formal analysis, RS; investigation, PIN; resources, RS; data curation, F; writing—original draft preparation, RFR; writing—review and editing, OSS, MSL, SAC, RFR; visualization, PIN; supervision, OSS, RS; project administration, OSL, MSL, F, RS; funding acquisition, RFR.

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