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Adaptive Neuro-Fuzzy Inference System for Non-linear Classification Problem of *Theobroma cacao* Image

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Abstract. Fine-flavor cacao is one of the cacao varieties with superior characters, especially the flavor quality. In this research, we develop a rapid and non-destructive method to evaluate cacao seed. Normally, it takes several years to identify whether a cacao seed is among the fine-flavor or bulk varieties. However, since it was known that the colors of the leaves can distinguish fine-flavor cacao from bulk cacao, the image classification method can serve as an alternative means of rapid identification. Furthermore, an Adaptive Neuro-Fuzzy Inference System (ANFIS) is applied to provide an intelligence agent that can automatically learn and identify cacao seed as fine-flavor or bulk. The ANFIS is used because designing a robust non-linear mathematical classification model on color image data is not an easy task. Therefore, the soft computing approach is used to resolve the difficulties. Other soft computing classification methods, i.e. Artificial Neural Network (ANN) and Fuzzy Multilayer Perceptron (Fuzzy-MLP), are also applied in order to evaluate the performance of ANFIS. Our experiment demonstrate that ANFIS model is more robust than the other two methods and could classify the cacao leaves at accuracy rate up to 94% for in-sample and 84% for-out sample prediction.

Key-words: Adaptive Neuro Fuzzy Inference System (ANFIS); cacao; image classification; non-linear classification .

1. Introduction

Cacao (*Theobroma cacao*) is among the top export products from Indonesia. It also establishes Indonesia as one of the top ten cacao producers in the world. This commodity has a wide variety of uses, from foods, cosmetics to coloring agents. It also has a global implication on food and sweet producers, the retail business as well as cacao importers and exporters. Unfortunately, the quality of Indonesian cacao is below other major countries in the trade. In 2009, Indonesian government launched a program to strengthen cacao trees by providing fertilizers and better seeds. Furthermore, the Indonesian Coffee and Cacao Research Institute (ICCR) has also improved their research on fine-flavor cacao to produce more cacao varieties with superior characters and high value in the market.

It is proven that the bulk cacao variety contains more anthocyanin pigment than fine-flavor cacao variety [1]. Anthocyanin is responsible for cacao's purplish color. It is also known that bulk cacao flush (young leaf) tended to visualize purplish color rather than greenish color since its early developmental stages. This fact has led some researcher to develop a system that can rapidly identify the fine-flavor cacao tree via color analysis [2]. Using such system, the amount of time taken to identify fine-flavor cacao, which is several years normally, could be reduced significantly. Formerly, the researcher will wait until the cacao tree produced flowers and fruits to determine whether the tree under observation shows superior characteristics. Now, using colorimetry method, the identification process could be done earlier because anthocyanin could be measured from the seed plant leaves [3]. Moreover, taking the advantage of the non-destructive techniques, e.g. digital imaging and spectroscopy, the identification process is more cost-efficient.

In this research, the measurement of anthocyanin is done by non-destructive measurements on the image of a cacao leaf. Moreover, after the digital measurements is gathered, the soft computing method is applied to automatically classify the seed under observation whether it is bulk or fine-flavor cacao. This soft computing approach is taken due to classification problem. In the preliminary study, it was revealed that color components of the cacao leaves' image cannot well be classified by a linear model. Thus, this task is among the non-linear classification problems. Furthermore, as a result of cross plant breeding effort, some varieties could have intermediate characteristics between fine-flavor and bulk [4]. This fact has been increasing the difficulties of the classification task.

Non-linear classification problems are common in agricultural studies. The influence of nature on the behavior of plant growth is highly complex [5] and very difficult to be controlled by the researcher. Therefore, the development of a powerful non-linear classification methods becomes very important. Some popular non-linear classification methods are Support Vector Machine (SVM) [6, 7], k-Nearest Neighbor (KNN) [8, 9] and Artificial Neural Network (ANN) [10–12]. Those methods have indeed proven to be successful in solving non-linear classification problems in plants, but if there are overlapping properties between classes, those methods will decrease in performance [13]. The solution is to implement a soft decision strategy rather than the crisp decision strategy [14]. So, the implementation of Fuzzy logic is very promising to be integrated.

Adaptive Neuro-Fuzzy Inference System (ANFIS) is known to be able to integrate the learning ability of ANN and the ability of Fuzzy logic to model complex dynamic systems in a more intuitive way [15]. Using Fuzzy logic, the only requirement is a well-defined set of rules for the system to work in a rather straightforward way. Indeed, ANFIS could handle non-linear classification problems and also help define overlapping class boundaries through its fuzzy sets [16]. Abirami et al. [17] had implement ANFIS to classify aquatic plants based on images. It has been reported that ANFIS performance is significantly better than Generalized Regression Neural Network (GRNN). It has also been reported that ANFIS is significantly better than Proximal Support Vector Machine (PSVM) [18]. Tias [19] demonstrated that ANFIS could well classify healthy and unhealthy soybean leaves using digital color data. Therefore, in this research ANFIS was used as the main classification method to deal with non-linear classification and overlapping characteristics between classes on the image of cacao leaves.

2. Material and Methods

2.1. Sample Preparation

As much as 480 leaves from 16 varieties of cacao plant were collected from ICCR plantation in Jember, East Java. Among them, 8 varieties were fine-flavor cacao and the remaining were bulk cacao. For each variety, 30 leaf samples were prepared. The leaves were selected with the consideration of data variation adequacy. Age, color gradation, and position from the terminal bud were carefully determined to ensure the sample quality. This task was important as the ANFIS performance would depend on it. Afterward, samples underwent image acquisition.

2.1.1. Image Acquisition

Canon EOS 750 D digital camera was used as the acquisition tool. Each leaf was taken to the laboratory to proceed with the camerawork. To control the surrounding environment, a plain white paper was used as the background. The white paper was also used as the reference to ensure that the data was purely the color which is produced by the leaf pigments not influenced by the light illumination. Figure 1 depicts the leaves' image, Figure 1a is an example of common fine-flavor cacao leaf and Figure 1b is an example of common bulk cacao leaf. However, there are some fine-flavor varieties that have a similar color to the common bulk varieties and vice versa. Figure 1c is an example of fine-flavor cacao leaf that the color resembles the bulk cacao color and Figure 1d is an example of bulk cacao leaf that the color resembles the fine-flavor cacao color. This fact leads to the non-linear classification problem.

(a) (b) (c) (d)

Fig. 1. Images of cacao leaves, (a) fine-flavor cacao; (b) bulk cacao; (c) fine-flavor cacao resembling bulk cacao; (d) bulk cacao resembling fine-flavor cacao.

2.1.2. Image Preprocessing

The main feature being studied in this research is leaf colors. In previous research, it was known that the anthocyanin content in cacao leaves (especially young leaves) is the main distinctive feature to differentiate fine-flavor cacao from bulk cacao [3]. In general, fine-flavor cacao leaves contain less anthocyanin than the leaves of bulk cacao. This condition makes fine-flavor cacao leaves tend to be greenish whereas bulk cacao leaves tend to be purplish. Therefore, those colors were set as the main consideration in developing the ANFIS architecture. Three preprocessing methods were applied to set up the input data i.e. color adjustment, color model transformation and segmentation. The purpose of color adjustment is to deal with the white balance issue. This is due to the fact that different sources of light give different 'colors' (or temperatures) to the same object. Human eyes don't generally notice this difference because human brain automatically adjusts to the changes. Except if the temperature of the light is exceptionally brilliant, a white sheet of paper will be look white to human eyes. Unfortunately, a digital camera doesn't have the capacity to make such automatic adjustment. Moreover, only RGB raw data format can be the output from common image sensor in camera [20] and it is known that RGB is not the best color model since its inability to ensure color constancy. However, using the algorithm developed by Garud et al. [21] white balance issue was solved. In this research, another color model, i.e. hue-saturation-intensity (HSI), was also used. HSI color model is characterized by how it resembles the way humans view colors, which makes it better than RGB to represents how humans identify colors. A color model transformation was applied to convert the RGB format (the output of digital camera) to HSI format. Segmentation process was also done to automatically separate the leaf from the background. And finally, some pixels of the segmented image that best represent the samples were taken by mode operation and then stored in the database. Other less representative pixels are not used. For example, pixels with high intensity due to the effects of excessive reflection (as the presence of a waxy substance on the surface of the leaf).

2.1.3. Data Collection

There are 480 records with 7 variables. The first six variables are RGB and HSI components and the last variable is cacao class (1 = fine-flavor, 2 = bulk). Samples were then randomly divided into two sets, the training set and the test set. Four hundred of them are reserved as training data and the remaining are reserved as test data. The training set was used to provide supervised learning for the ANFIS whereas the test set was used to provide the performance evaluation of the model. Table 1 shows the data arrangement of the experiment. The HSI components (H, S, I) are obtained by converting the RGB components (R, G, B) [22].

Table 1. Data arrangement

Sample No.	RGB			HSI			Class
	Red	Green	Blue	Hue	Saturation	Intensity	
1	127.10	114.48	14.44	36.35	235.64	75.39 7	1
2	132.30	81.48	42.24	10.56	222.41	103.62	1
:	:	:	:	:	:	:	:
479	135.53	71.22	49.25	10.18	217.11	91.60	2
480	133.86	88.50	33.64	18.03	216.28	97.67	2

Note: Each cell contain the average intensity value (0-255) for each color component.

Figure 2 depicts the scatter plot of the fine-flavor (green circles) and bulk class cacao (blue circles) based on its digital color components. Figure 2a depicts the scatter plot for RGB components and Figure 2b depicts the scatter plot for HSI components. Those figures show that it is not possible to separate the two classes by a linear classifier. Therefore, we choose the non-linear approach in this classification problem.

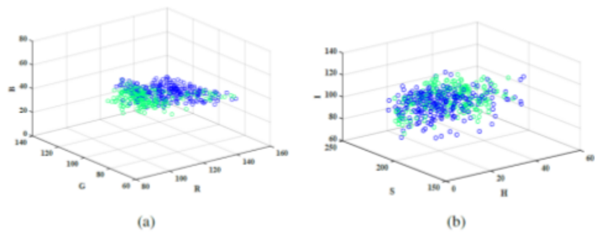

Fig. 2. Scatter plot of the raw data, (a) RGB data; (b) HSI data.

2.1.4. ANFIS Architecture

The first task in ANFIS development is fuzzification. This procedure transforms all the quantitative input variables into fuzzy variables. Six input variables are taken from the RGB and HSI color components, i.e. red, green, blue, hue, saturation, and intensity. For each variable, there are several fuzzy sets (e.g. low, medium, and high) with Generalized Bell-Shaped membership function. Figure 3 depicts the general form of the fuzzy variable used for each input variable. In our experiment, the number of fuzzy sets will be varied to find the best architecture. Initially, the parameter for each membership function is determined. The backpropagation then adjusts those parameters by using error information from the network. The output variable is a cacao class (fine-flavor or bulk).

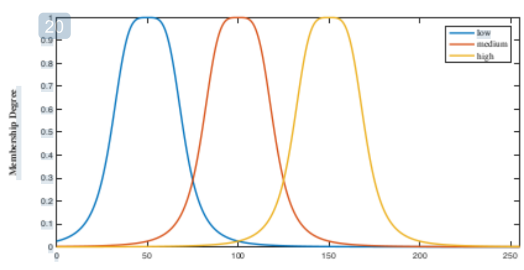

Fig. 3. Generalized Bell-Shaped membership function with 3 fuzzy sets.

The ANFIS architecture developed in this research is composed of 5 layers. Figure 4 depicts the example of ANFIS architecture with RGB input and 3 fuzzy sets for each RGB component. Layer 1 calculates the input membership degrees for each fuzzy set using (1). This equation refers to the Generalized Bell-Shaped model with parameters a (standard deviation), b (usually a positive constant to controls the slopes at crossover points), and c (mean). Those parameters are called premise parameters, altering those parameters will change the Gaussian curve shape. During the backpropagation process, the values of a, b, and c will be updated automatically based on the error information obtained from the last layer. So the values a, b and c will change continuously until the backpropagation process is ended.

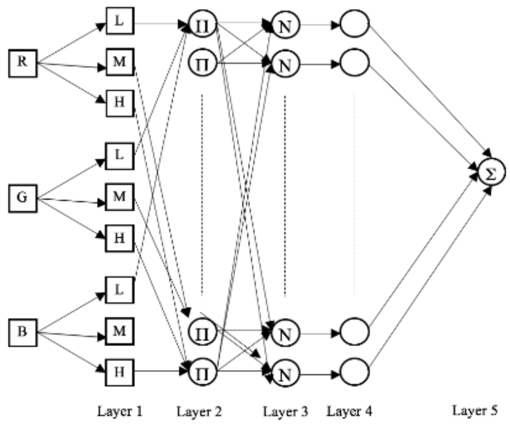

Fig. 4. Example of ANFIS architecture for RGB input.

$$\mu(x) = \frac{1}{1 + |\frac{x-c}{a}|^{2b}} \tag{1}$$

Layer 2 represents the rules used in the fuzzy inference. Generally, these rules are determined by an expert. But, in the absence of an expert, all possible rules could be inserted here. There are in total 27 (3^3) rules that could be generated from 3 input variables and 3 fuzzy sets for each variable. Each node in this layer will calculates a fire strength which measures the degree to which the rule matches the inputs. Layer 3 calculates the normalized fire strength ($\bar{w}_i$) using (2). This is the ratio of the fire strength of a rule (w_i) with the total fire strength from all rules.

$$\bar{w}_i = \frac{w_i}{\Sigma_{n=1}^{27} w_i} \tag{2}$$

Layer 4 calculates the output (y) for each rule based on Sugeno model using (3), where x represent the inputs (x_1 for R, x_2 for G and x_3 for B) and c is consequent parameters. The consequent parameters is identified by the forward pass algorithm using least-squares method.

$$\bar{w}_i y_i = \bar{w}_i(c_{i1}x_1 + ... + c_{i6}x_6 + c_{i0}) \tag{3}$$

Layer 5 runs the aggregation process as a summation of all outputs from the previous layer using (4). The value of O ranges from 0 to 1. Next, O is rounded up so that there will be only two possible integer values, i.e. 0 and 1. Zero represents the fine-flavor class, and 1 represents the bulk class.

$$O = \Sigma_i \bar{w}_i y_i \tag{4}$$

2.1.5. Performance Indicators

The performance indicators used in this research are calculated from the confusion matrix for binary data classification evaluation (Table 2). Those indicators evaluate the generalization ability of the trained classifier. Four indicators, i.e. sensitivity (5), specificity (6), accuracy (7), and precision (8) summarize the performance of ANFIS architectures [23]. Sensitivity measures the fraction of fine-flavor class that are correctly classified. Specificity measures the fraction of bulk class that are correctly classified. Accuracy measures the ratio of correct predictions over the total number of instances evaluated. Precision measures the fine-flavor class that are correctly predicted from the total predicted patterns in a fine-flavor class.

Table 2. The Confusion matrix for binary classification

		Actual	
		Fine-flavor	Bulk
Predicted	Fine-flavor	True Positive (tp)	False Negative (fn)
	Bulk	False Positive (fp)	True Negative (tn)

$$Sensitivity = \frac{tp}{tp + fn} \tag{5}$$

$$Specificity = \frac{tn}{tp + fn} \tag{6}$$

$$Accuracy = \frac{tp + tn}{tp + fp + tn + fn} \tag{7}$$

$$Precision = \frac{tp}{tp + fp} \tag{8}$$

3. Result and Discussion

We designed 8 different ANFIS architectures for every kind of input data (RGB, HSI, and RGBHSI) and evaluate them to find the best architecture. Table 3 represent the input of ANFIS architectures that are used in the experiment. Each cell contains the number of fuzzy sets created for each color component. There are 24 different architectures being analyzed in the experiment. The difference between those architectures lies in the number of the fuzzy set for each color component. For each architecture, the training and testing processes were repeated 10 times and the best 5 results were taken. The performance indicator metrics are determined by calculating the average of those best results (Table 4). The best ANFIS architecture for RGB input is when there are 6, 5 and 3 fuzzy sets for each R, G and B component respectively (architecture no. 7). Both R and G components are known to have a high correlation with leaves color, especially colors related to main photosynthetic pigments i.e. chlorophyll, carotenoid and anthocyanin [24]. Therefore, more number of fuzzy sets are needed to represent the R and G components to explain the color gradation in cacao leaves. On the other hand, the number of the fuzzy sets for the B component does not significantly affect the performance of ANFIS architecture. The best ANFIS architecture for HSI input is the one using 5 fuzzy sets for all component (architecture no. 11) and the best architecture for RGBHSI input is the one using 3 fuzzy sets for R and G component and 4 fuzzy sets for H and S component (architecture no. 23). The experiment reveals that using RGB and HSI components simultaneously did not improve the accuracy. Instead, removing the B and I components gave a better result.

Table 3. The input of ANFIS architectures used in the experiment

Architecture	RGB			Architecture	HSI			Architecture	RGBHSI					
No.	R	G	B	No.	H	S	I	No.	R	G	B	H	S	I
1	3	3	3	9	3	3	3	17	2	2	2	2	2	2
2	4	4	4	10	4	4	4	18	2	2	-	2	2	-
3	5	5	5	**11**	**5**	**5**	**5**	19	2	2	-	3	3	-
4	6	6	6	12	6	6	6	20	3	3	-	3	3	-
5	7	7	7	13	7	7	7	21	3	3	-	2	2	-
6	5	5	3	14	5	5	3	22	4	4	-	3	3	-
7	**6**	**5**	**3**	15	6	5	3	**23**	**3**	**3**	-	**4**	**4**	-
8	6	4	3	16	6	4	3	24	4	4	-	4	4	-

Table 4. Performance comparison of the best ANFIS architecture for RGB, HSI, and RGBHSI inputs

Metric	Input					
	RGB		HSI		RGBHSI	
	In Sample	Out Sample	In Sample	Out Sample	In Sample	Out Sample
Sensitivity	0.84	0.74	0.94	0.83	0.9	0.77
Specificity	0.88	0.82	0.95	0.84	0.94	0.81
Accuracy	0.86	0.78	0.94	0.84	0.92	0.79
Precision	0.89	0.85	0.95	0.85	0.94	0.83

Table 4 summarizes the performance indicators of the best ANFIS architecture in Table 3 (architecture no. 7, 11 and 23). In general, using HSI gave a better result than using RGB or RGBHSI components as an input. All of the performance indicators of HSI-based architecture show that they outperform the RGB's, for either in sample or out sample. This result agrees with the fact that HSI color model could overcome the color constancy problem in RGB [25] and provides a better estimation of the actual color. Therefore, using the RGB and HSI components simultaneously as the input did not improve the ANFIS performance either. The out sample performance for all kinds of input is slightly lower than those of in sample. However, there is no evidence that the overfitting problem has been occurring. Since sensitivity value is relatively the same as the specificity value, it can be inferred that ANFIS with HSI input could identify the fine-flavor varieties as good as the bulk one. On the contrary, the ANFIS with RGB input shows a different result. The specificity value is higher than the sensitivity value, indicating that the ANFIS with RGB input identifies the bulk varieties better than the fine-flavor varieties.

In order to provide a better understanding of ANFIS performance, we compare two other soft computing-based classification methods, i.e. Artificial Neural Network (ANN) and Fuzzy Multi-layer Perceptron (Fuzzy-MLP). The comparison aims to investigate whether the implementation of fuzzy theory could reveal the particular pattern on cacao digital color data in such a way that the classifier performance could be improved. The input of ANN and Fuzzy-MLP are the value of color components being analyzed. The main difference between the two methods lies in the output. In ANN architecture, there are 2 output nodes with a binary value (0 or 1) representing the class (fine-flavor or bulk). There are also 2 output nodes in Fuzzy-MLP architecture. But, instead of a binary value, it contains the membership degree of a data for each class. We designed 33 different ANN and Fuzzy-MLP architectures and trained them to discover the best one. The best architecture for both methods is shown in Table 5.

Table 5. The best architecture of ANN and Fuzzy-MLP

Method	Input	Σ Node		Activation Function		Learning Rate	Optimization Method
		Hidden Layer 1	Hidden Layer 2	Hidden Layer	Output Layer		
ANN	RGB	3	-	Logistic Sigmoid	Linear	0.3	Scaled conjugate gradient
	HSI	4	-			0.3	
	RGBHSI	2	-			0.5	
Fuzzy-MLP	RGB	2	2	Logistic Sigmoid	Linear	0.5	Scaled conjugate gradient
	HSI	4	-			0.1	
	RGBHSI	3	3			0.1	

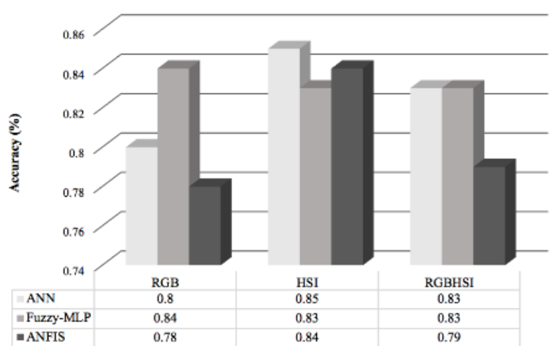

Fig. 5. The out sample accuracy comparison of ANN, Fuzzy-MLP and ANFIS based on RGB, HSI and RGBHSI input.

Figure 5 shows that either ANN or Fuzzy-MLP perform better out sample accuracy when using the HSI components as an input. Among the three methods, the accuracy of ANFIS tends to be more sensitive to color model preferences for the input. On the other hand, the accuracy of Fuzzy-MLP tends to be more stable when handling various color model inputs. The overall comparison reveals that in term of out sample classification, ANFIS did not significantly outperform the other two methods. However, ANFIS performance for in sample prediction significantly outperforms the other two methods (Figure 6). This fact is an indication that ANFIS architecture is possibly more robust than ANN or Fuzzy-MLP architecture when handling another new data set. The next discussion based on Figure 7 will explain one of the evidence.

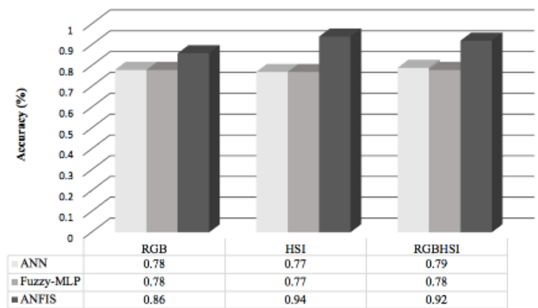

Fig. 6. The in sample accuracy comparison of ANN, Fuzzy-MLP and ANFIS based on RGB, HSI and RGBHSI input.

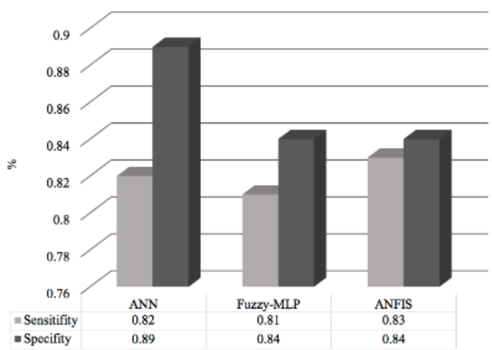

Fig. 7. Sensitivity and specificity comparison among ANN, Fuzzy-MLP and ANFIS.

Figure 7 compares the sensitivity and specificity values of the three methods. It shows that ANFIS could well recognize both fine-flavor or bulk varieties since the two values are relatively the same. On the contrary, ANN and Fuzzy-MLP have difference performances. Both methods better in recognizing the bulk varieties since its specificity value higher than its sensitivity value. In case of the new data set being analyzed is composed of more fine-flavor varieties, the out sample accuracy could decrease significantly. The addition of fuzzy concept is also proven could decrease such problem. It is shown in 7 that the sensitivity and specificity difference is larger in ANN than in Fuzzy-MLP. The fuzzy concept could well facilitate the representation of intermediate colors which commonly lead to misclassification.

4. Conclusion

We demonstrated that by the implementation of soft computing methods with self-learning superiority, the non-linear classification task on cacao leaves image could be done rapidly. Using MATLAB Fuzzy Logic and Neural Network Toolbox, we developed ANFIS, ANN, and Fuzzy-MLP model and run them on the 1.6 GHz Intel Core i5 CPU with 8 GB Memory 1600 MHz DDR3. The ANFIS model could classify cacao leaves into two classes (fine-flavor and bulk) with in-sample and out-sample accuracy rate up to 94% and 84% respectively. Compared with ANN and Fuzzy-MLP, ANFIS provided better classification results in term of robustness. While ANN and Fuzzy-MLP are better in recognizing the bulk varieties, ANFIS could recognize fine-flavor and bulk varieties equally. This research also reveals that using fuzzy approach, the classification difficulties with some cacao varieties that have intermediate characteristics between fine-flavor and bulk cacao could be solved. Hence, the classification accuracy is successfully increased. Next, it is necessary to test the implementation of ANFIS model in a microcontroller or microcomputer-based device. The future goal is to invent a portable device that could be used to classify cacao seeds outdoors in the plantation in real time.

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References

[1] ANITA-SARI, I., YUSIANTO, WARDANI, S. 2012. Characterization and Determination of Bean Color of Some Fine-Cocoa (*Theobroma cacao L*) Genotypes for Criteria of Selection. *Coffee Cocoa Res. J.*, 28(3): 136-144.

[2] ADHIWIBAWA, M.A.S., ANITA-SARI, I., PRILIANTI, K.R., SITEPU, R., SUSILO, A.W., LIMANTARA, L., BROTOSUDARMO, T.H.P. 2015. Rapid Determination of Anthocyanin in Cacao (*Theobroma cacao L.*) Leaves Using Digital Image Processing for Finest Cacao Clone Selection. In: "Proc. IOP", *International Symposium on Modern Optics and Its Applications (ISMOA 2015)*, Indonesia. pp. 108-109.

[3] ANITA-SARI, I., SETYAWAN, B., ADHIWIBAWA, M.A.S., SUSILO, A.W. 2016. Chromatographic Identification of Leaf Color Characteristics on Fine-Flavor and Bulk Cacao as Selection Indicator. *Coffee Cocoa Res. J.*, 32(1): 1-9. doi: 10.22302/iccri. jur.pelitaperkebunan.v32i1.210

[4] PAUWELS, A,. 2016. Review of The Quality Potential of Cocoa in Sauthern Vietnam. Master Thesis, Ghent University, Belgium.

[5] DANIEL, J., ANDRES, P., HECTOR, S., MIGUEL, B., PATRICK V.D., MARCO, T. A Survey of Artificial Neural Network-Based Modeling in Agroecology, in Soft Computing Applications in Industry, Prasad, B. (eds.), Springer-Verlag, pp. 247-269, 2008.

[6] RUBERTO, C.D., PUTZU, L., 2014. A Fast Leaf Recognition Algorithm Based on SVM Classifier and High Dimensional Feature Vector. In: "Proc. IEEE", *9th International Conference on Computer Vision Theory and Applications (VISAPP 2014)*, Portugal. pp. 601-609.

[7] AKBARZADEH, S., PAAP, A., AHDEROM, S., APOPEI, B., ALAMEH, K. 2018. Plant Discrimination by Support Vector Machine Classifier Based on Specral Reflectance. *Comput. Electron. Agr.*, 148: 250-258. doi: 10.1016/j.compag.2018.03.026

[8] BALAKRISHNA, K., RAO, M. 2019. Tomato Plant Leaves Classification Using KNN and PNN. *Int. J. Comput. Vis. Image Process.* 9(1): 1-13. doi: 10.4018/IJCVIP.2019010104

[9] BUTTREY, S.E., KARO, C. 2002. Using K-Nearest-Neighbor Classification in The Leaves of a Tree. *Comput. Stat. Data Anal.* 40(1): 27-37. doi: 10.1016/S0167-9473(01)00098-6

[10] KHO, S.J., MANICKAM, S., MALEK, S., MOSLEH, M., DHILLON, S.K. 2018. Automated Plant Identification Using Artificial Neural Network and Support Vector Machine. *Front. Life Sci.* 10(1): 98-107. doi: 10.1080/21553769.2017.1412361

[11] INGOLE, A. 2015. Detection and Classification of Leaf Diseases Using Artificial Neural Network. *Int. J. Tech. Res. Appl.* 3(3): 331-333.

[12] SHARMA N., KULSHRESTHA, A., BHOJWANI, H. 2016. An Overview on Detection and Classification of Plant Diseases Using Image Processing. *Int. J. Eng. Manag, Sci.* 3(8): 2348-3733.

[13] PRATI, R.C., BATISTA, G.E.A.P.A., MONARD, M.C. 2004. Class Imbalances versus Class Overlapping: An Analysis of A Learning System Behavior. In: *Mexican International Conference on Artificial Intelligence, Mexico.* pp. 312-321.

[14] MAO, K., MAK, L.O., NG G.W. 2010. Classification for Overlapping Classes Using Optimized Overlapping Region Detection and Soft Detection. In: "Proc. IEEE", *13th International Conference on Information Fusion, United Kingdom.* doi: 10.1109/ICIF.2010.571.2008

[15] HUANG. Y., LAN, Y., THOMSON, S.J., FANG, A., Hoffmann, W.C., and Lacey, R.E. 2010. Review: Development of Soft Computing and Applications in Agricultural and Biological Engineering. *Comput. Electron. Agric.*, 71: 107-127. doi: 10.1016/j.compag.2010.01.001

[16] ORTIZ, M.P., FERNANDEZ, S.J., GUTIERREZ, P.A., ALEXANDRE, E., MARTINEZ, C.H., SANZ, S.S. 2016. A Review of Classification Problems and Algorithms in Renewable Energy Applications. *Energies*, 9(607): 1-27. doi: 10.3390/en9080607

[17] ABIRAMI, S., RAMALINGAM, V., PALANIVEL, S. 2012. Species Classification of Aquatic Plants using GRNN and ANFIS. *Int. J. Comput. Appl.*, 47(4): 47-52. doi: 10.1007/s00146-012-0433-z

[18] ABIRAMI, S., RAMALINGAM, V., PALANIVEL, S. 2013. Species Classification of Aquatic Plants using PSVM and ANFIS. *Pattern. Recognit. Image. Anal.*, 23(2): 278-286. doi: 10.1134/S1054661813020028

[19] TIAS, R.F. 2016. Identification of Nutrient Nitrogen in The Leaves of Soybean Plant using ANFIS Based on Soybean Leaves' Color. *J. Electr. Engineering Comput. Sci.*, 1(2): 119-123.

[20] CHIU, L., FUH, C. 2010. Calibration-Based Auto White Balanced Method for Digital Still Camera. *J. Inf. Sci. Eng.*, 26: 713-723. doi: 10.6688%2fJISE.2010.26.2.24

[21] Garud, H., Ray, A.K., Mahadevappa, M., Chatterjee, J., Mandal, S. 2014. A Fast Auto White Balance Scheme for Digital Pathology. In: "Proc. IEEE", *International Conference on Biomedical and Health Informatics (BHI 2014), Spain.* pp. 153-156. doi: 10.1109/BHI.2014.6864327

[22] GONZALEZ, R.C., WOODS, R.E., EDDINS, S.L. 2018. Color Image Processing. In Digital Image Processing using MATLAB. 2nd ed. New Jersey, USA: Prentice Hall.

[23] HOSSIN, M., SULAIMAN, M.N. 2015. A Review on Evaluation Metrics for Data Classification Evaluations. *Int. J. Data Min. Knowl. Manage. Process*, 15(2): 1-11. doi: 10.5121/ijdkp.2015.5201

[24] HU, H., ZHANG, J., SUN, X., ZHANG, X. 2013. Estimation of Leaf Chlorophyll Content of Rice Using Image Color Analysis. *Can. J. Remote Sens.*, 39(2): 185-190. doi: 10.5589/m13-026

[25] YING, Z., LI, G., WEN, S., TAN, G. 2017. ORGB: Offset Correction in RGB Color Space for Illumination-Robust Image Processing. In: *International Conference on Acoustics, Speech, and Signal Processing (ICASSP 2017), USA.* pp. 1-5. doi: 10.1109/ICASSP.2017.7952418

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