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Extreme learning machine with feature extraction using GLCM for phosphorus deficiency identification of cocoa plants

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Abstract

This study aims to analyze the implementation of the Extreme Learning Machine (ELM) Algorithm with Gray Level Co-Occurrence Matrix (GLCM) as an Image Feature Extraction method in identifying phosphorus deficiency in cocoa plants based on leaf characteristics. Characteristic images of cocoa leaves were placed under normal conditions and phosphorus deficiency, each with 250 datasets. The feature extraction process by GLCM was analyzed using the ELM parameter approach in the form of Network Node_Hidden variations and several Activation Functions. The method of this case study was conducted with data collection, algorithm development to validation, and measurement using ROC. It was found that the best accuracy when testing the dataset was 95.14% on the node_hidden 50 networks using the Multiquadric Activation Function. These results indicate that the feature extraction model with GLCM using Contrast, Correlation, Angular Second Moment, and Inverse Difference Momentum properties can be maximized on Multiquadric Activation Function.

Keywords: Extreme Learning Machine; GLCM feature extraction; Phosphorus deficiency; Cocoa.

Introduction

Indonesia is one of the largest cocoa-growing countries and is the third-largest cocoa-producing country after the Ivory Coast and Ghana, with a production value of 1,315,800 tons/year. In the last five years, the plantation area of cocoa has increased rapidly with an average growth rate of 8%/year, and it currently reaches 1,262,000 ha. Nearly 90% of the area is community plantations [1]. The implementation of image processing on various problems in the agricultural sector has been widely applied, including supporting cocoa cultivation. Previously, research has been carried out in the examination of the potential for image processing on the characteristics of pest attacks on cocoa pods [2], even further the development leading to more mobile-based applications [3]. The development of image processing research on cocoa cultivation continues to be carried out. This study aims to analyze the implementation of the Extreme Learning Machine with the C Algorithm as the method used for Feature Extraction in identifying phosphorus deficiency in cocoa plants based on leaf characteristics. The GLCM method is a method analyzing a pixel in the image and finds out the level of gray that often occurs. This method also tabulates the frequency of pixel value combinations that appear in an image. Also, GLCM is one way of extracting second-order statistical texture features [4].

Meanwhile, the ELM classification technique is used as a single-layer feedforward neural network technique or is usually abbreviated as SLFNs. There are many types of popular feedforward neural networks. This method consists of single or multi-hidden layers such as gradient-based learning, for example, the backpropagation method for multi-layer feedforward neural networks. However, its learning is slower than expected because all the given parameters must be determined manually, and iterative tuning is required for each parameter. The ELM method has almost the same structure as SLFNs but has a different computational model [5].

The case study of phosphorus deficiency is important because it is a factor that influences the quantity and quality of cocoa production. This nutrient deficiency causes leaf spots with a spreading pattern almost throughout the leaf body but more towards the middle body of the leaf so that the ribs (sticks) on the leaves are more visible [6]. According to experts, one of the leaf characteristics observed based on phosphorus deficiency is shown in the following figure.

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Figure 1. Leaf Characteristics Observed

Several related studies implementing image processing in the case of leaf features include Zikra et al. in 2021, who conducted research on Chili Disease Detection based on Leaf Images. That study used the Gray Level Co-Occurrence Matrix and Support Vector Machine methods with healthy classifications, yellow virus, curly shapes, and leaf spots. In addition, the system can provide information to farmers for countermeasures and prevention of diseases detected by the system. The research results show that this system's data sharing process in the dataset has a good accuracy rate, 95%, for detecting chili plant diseases through smartphone camera-based leaf images using the gray level co-occurrence matrix method and support vector machine. In testing the effect of the type of kernel and multiclass on the support vector machine classification, the accuracy was 95% on the polynomial kernel type with one-against-one multiclass. This system used three parameters, including contrast, energy, and four features, including contrast, correlation, energy, and homogeneity, in a computation time of 3 to 3.7 seconds [7].

The current study used the same method, namely the GLCM (Gray Level Co-Occurrence Matrix) method. However, the later has a different purpose, it aims to identify phosphorus deficiency elements through leaf imagery using GLCM and Extreme Learning Classification. Meanwhile, using the K-Nearest Neighbor (K-NN) classification technique on the same extraction technique, Paturrahman 2020 Conducted research on leaf pattern recognition analysis based on the Canny Edge Detection feature and the GLCM feature. The data used was 350 leaf images with seven different species obtained from previous research data. The leaf image feature extraction results will be input data for the Support Vector Machine (SVM) classification system [8]. In another different classification with the K-Means classification technique in the same extraction technique, Lihawa M. et al., 2018, conducted a study on the extraction of pathogenic spores features of disease images on corn plants and obtained maximum results with the parameters used for chromatic values 0.9 (maximum) on the entropy feature blight, spotting on the IDM feature, and finally on the ASM feature of blight and rust.

Meanwhile, the lowest minimum intensity value was 0.1 for rust disease, entropy feature, and IDM [9]. The combination of the GLCM and ELM methods in image processing-based research has been carried out in another study by Rahmat Fitriansyah et al. 2019 who concluded that the GLCM and ELM methods were able to detect the level of fatty liver in ultrasound images well. The same combination in the case of gingivitis identification [10], classification for COVID-19 detection [11], [12], and fast grading of mangosteen skin defect identification [13], research showed that this method was more accurate and sensitive. These results indicate that these two methods can be implemented in image processing cases [14].

Research on leaf pattern recognition can be done by recognizing leaf structural characteristics such as the shape and texture of a leaf [15]. The method for processing the input images by utilizing digital image processing techniques is carried out to analyze the structural characteristics of the leaf. Based on digital image processing techniques, one of the conveniences is to help humans interpret objects caught on camera using image quality binding techniques. This development allows performing digital image processing in real-time, storing images with smaller memory capacities without compromising quality and sending images quickly to distant places [16]. The development of technology for image processing techniques is also growing rapidly. Various methods have been developed to facilitate human work as image processors, image analysts, and image users for various purposes. Often the images used are not in ideal conditions due to many disturbances such as shadows, photos, or blurry images, and the lack of object clarity, it can cause problems and affect the interpellation results and this will affect the analysis and planning to be carried out, therefore it is necessary to make various image processing techniques to obtain the ideal image [17].

For this reason, this study identified phosphorus deficiencies based on the characteristics of the cocoa leaves using the GLCM (Gray Level Co-occurrence Matrix) method, which presented the uniqueness of each leaf and then used it as input in the classification process using the Extreme Learning Machine (ELM) method. The dataset was used to identify phosphorus deficiency in cocoa plants through leaf imagery. This project were expected to be a basic study to identify the deficiency of phosphorus elements using color and texture feature extraction in leaf images. Future implementation can help farmers prevent leaf diseases by taking an anticipative treatment [18].

Method

Based on the model developed using the GLCM and ELM methods, a system framework flow was designed and run by using the Python 3.10 programming language. The following is a systematic framework to identify Phosphorus deficiency in cocoa plants through leaf images.

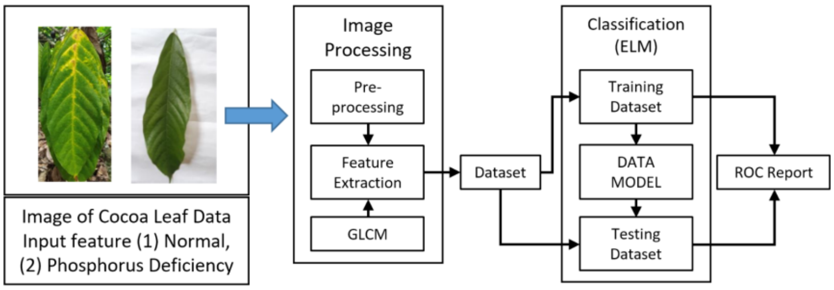


Figure 2. Research Method

The system framework above indicated that the user firstly input an image dataset identified according to expert analysis. The image contained a phosphorus nutrient deficiency and normal leaf conditions. Dataset training and Dataset Testing was then carried out. Previously, the image processing and feature extraction were carried out with GLCM and then classified using the Extreme Learning Machine (ELM) for further identification, and accuracy reports were generated during training and testing. Data retrieval using a standard smartphone camera of at least 10 Megapixels at a resolution of 3000x4000 pixels per data image. In the case of this study, it was conditioned on a white background to avoid image data noise at the research location. The number of datasets used on normal leaves (label 0) and leaves with identification of phosphorus deficiency (label 1) was 250 image data each. The data was then divided into 100 data for training with *train_tes_split=0.3* (30%) and 150 data for testing.

A. GLCM Feature Extraction Process

The stage of this extract process was to load the dataset, which contained a list of image files. It displayed a table containing the image filenames stored in the CSV dataset, which extracted GLCM features using grecomatrix from one image file that was read and changed the color space (color) to greyscale (gray) by converting the resolution to 256x256 (I_gray=I_gray.resize((256,256)). In calculating the value of the properties of GLCM, this research employed the predetermined formula (Contrast, Correlation, Angular Second Moment, and Inverse Difference Momentum), other than that, an empty list variable to store GLCM data and a table that were used to combine all properties into one variable then the GLCM data and Label data were stored into a dictionary variable, then the dictionary variable was stored in the form of a GLCM dataset with CSV format. Stages in the feature extraction process with GLCM as shown in Figure 3.

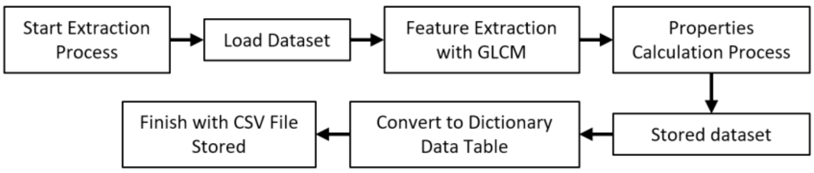


Figure 3. GLCM Feature Extraction Process

B. ELM Classification Process

The stages of the classification process started from the dataset load, then displaying the contents of the GLCM dataset format that has been saved in CSV form (dataset.csv) through the feature extract process and determine the X and Y values in loc_dataset. After that, a test_split train process was conducted to display the data_train and data_test sizes, so that it can carry out a training process that had some activation function (af). The ELM instrumentation applied in this study was tested on several Node Networks [10, 25, 50, 100, 150], with five activation functions used in the ELM implementation (*sigmoid, tanh, multiquadric, softlim, sine*) to compare the results later. . The classification report display was then displaying the values of accuracy training and accuracy testing in the form of a confusion matrix. The stages in the classification process with ELM are shown in Figure 4.

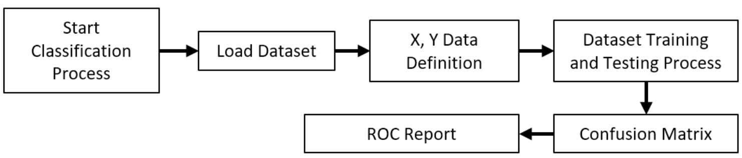


Figure 4. ELM Classification process

C. Data Validation with Receiver Operating Characteristics (ROC)

Receiver Operating Characteristics (ROC) used to determine the desired model parameters must be under the characteristics of the desired model classifier. The wider ROC system had many models that can be measured from data analysis, such as True Positive Rate (TPR)/sensitivity, False Negative Rate (FNR)/Specificity, Miss Rate/False Positive Rate (FPR)/ Fall-out, Specificity (SPC)/ True Negative Rate (TNR), Prevalence, Positive Predictive Value (PPV)/precision, False Omission Rate (FOR), Accuracy (ACC), False Discovery Rate (FDR), and Negative Predictive Value (NPV), however this study employed the following accuracy formula [19].

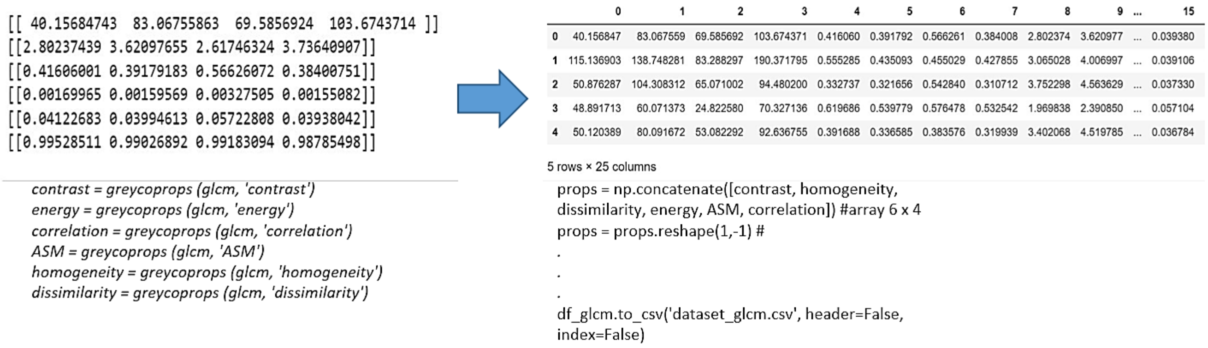
$$Accuracy\ (ACC) = \frac{\sum True\ positif + \sum True\ negative}{\sum Total\ population} \quad (1)$$

Results and Discussion

Based on the program execution results, as shown in Figure 4, in the GLCM process, image data with RGB color was converted to Grayscale I_gray = ImageOps.grayscale(I), then produced an image as shown in Figure 5.

Figure 5. RGB converted to grayscale

Furthermore, with the GLCM property values, the vector values were obtained to be stored in the dataset.



```
[[ 40.15684743  83.06755863  69.5856924  103.6743714 ]]
[[2.80237439 3.62097655 2.61746324 3.73640907]]
[[0.41606001 0.39179183 0.56626072 0.38400751]]
[[0.00169965 0.00159569 0.00327505 0.00155082]]
[[0.04122683 0.03994613 0.05722808 0.03938042]]
[[0.99528511 0.99026892 0.99183094 0.98785498]]
```

```
contrast = greycoprops (glcm, 'contrast')
energy = greycoprops (glcm, 'energy')
correlation = greycoprops (glcm, 'correlation')
ASM = greycoprops (glcm, 'ASM')
homogeneity = greycoprops (glcm, 'homogeneity')
dissimilarity = greycoprops (glcm, 'dissimilarity')
```

	0	1	2	3	4	5	6	7	8	9	...	15
0	40.156847	83.067559	69.585692	103.674371	0.416060	0.391792	0.566261	0.384008	2.802374	3.620977	...	0.039380
1	115.136903	138.748281	83.288297	190.371795	0.555285	0.435093	0.455029	0.427855	3.065028	4.006997	...	0.039106
2	50.876287	104.308312	65.071002	94.480200	0.332737	0.321656	0.542840	0.310712	3.752298	4.563629	...	0.037330
3	48.891713	60.071373	24.822580	70.327136	0.619686	0.539779	0.576478	0.532542	1.969838	2.390850	...	0.057104
4	50.120389	80.091672	53.082292	92.636755	0.391688	0.336585	0.383576	0.319939	3.402068	4.519785	...	0.036784

5 rows × 25 columns

```
props = np.concatenate([contrast, homogeneity,
dissimilarity, energy, ASM, correlation]) #array 6 x 4
props = props.reshape(1,-1) #
.
.
.
df_glcm.to_csv('dataset_glcm.csv', header=False,
index=False)
```

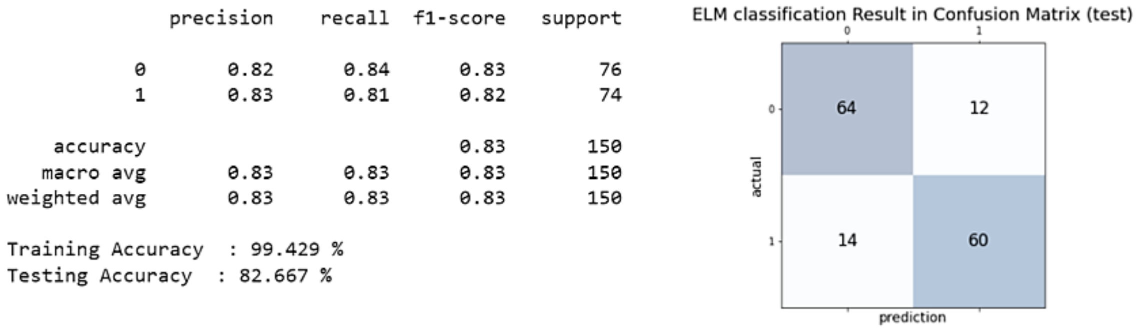
Figure 6. Storage of Extracted Dataset Feature

The classification process with ELM as described in Figure 4, each network Node_hidden and Activation Function was tested on each GLCM dataset, to be further validated with ROC.

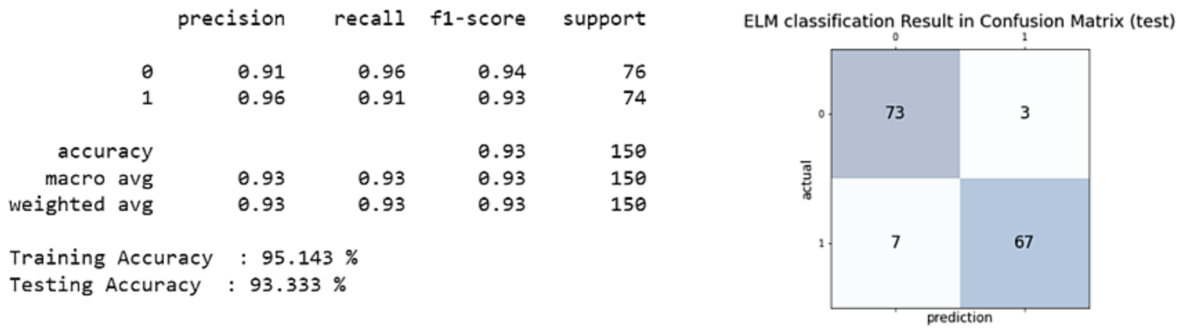
$$confusionMatrix = confusion_{matrix}(y_{test}, y_{pred}) \quad (2)$$

$$fig, ax = plt.subplots(figsize = (5{,}5)) \quad (3)$$

The function above displays training and testing accuracy and a confusion matrix, as the sample classification results in Figure 7 below. The sample was taken from running the program on the multiquadric activation function with two samples, namely on network *node_hidden* 150 and network *node_hidden* 50. The Confusion Matrix was only displayed in getting the Accuracy value in the testing section.



(a) Output Sample of ELM classification *node_hidden* network =150



(b) Output Sample of ELM classification *node_hidden* network =50

Figure 7. Sample Classification Results on Program

Based on Figure 6, it can be seen in the Confusion Matrix between Actual and Prediction of the two types of classification of Normal leaf characteristics (0) and Phosphorus deficiency (1), the ROC parameter value can be calculated, but in this study, only the accuracy value was taken as formula (1).

Table 1. Sample of Confusion Matrix *node_hidden* network=150 (testing)

Detection	**Actual**	
	Normal	***Phosphorus Deficiency***
Normal	64	12
Phosphorus Deficiency	14	60

$$Accuracy\ (ACC) = \frac{\sum True\ positif + \sum True\ negative}{\sum Total\ population} = \frac{64+60}{64+12+14+60} = \frac{124}{150} = 82{,}667 \tag{4}$$

Table 2. Sample of Confusion Matrix *node_hidden* network=50 (testing)

Detection	**Actual**	
	Normal	***Phosphorus Deficiency***
Normal	73	3
Phosphorus Deficiency	7	67

$$Accuracy\ (ACC) = \frac{\sum True\ positif + \sum True\ negative}{\sum Total\ population} = \frac{73+67}{73+3+7+67} = \frac{140}{150} = 93{,}333 \tag{5}$$

Table 3. ELM Classification Results

Node	Accuracy	Activation Function				
		sigmoid	***Tanh***	***multiquadric***	***softlim***	***sine***
10	Training	56.857%	52.857%	83.429%	69.143%	54.000%
	Testing	56.667%	43.333%	83.333%	64.667%	47.333%
25	Training	57.429%	69.714%	90.000%	69.429%	62.571%
	Testing	64.000%	62.000%	92.000%	66.667%	48.000%
50	Training	73.429%	78.571%	95.143%	69.429%	70.286%
	Testing	68.667%	76.667%	93.333%	62.000%	49.333%
100	Training	80.286%	76.000%	96.857%	70.000%	76.286%
	Testing	75.333%	70.667%	90.667%	68.000%	58.000%
150	Training	80.286%	77.429%	99.429%	78.857%	80.857%
	Testing	74.000%	70.667%	82.667%	78.000%	58.667%

Furthermore, as full instrumentation, the accuracy results obtained from both testing and training models on the classification data, with several ELM parameters used, are presented in Table 3. The results of the system test as in Table 3 was to display the Training Accuracy and Testing values so that the accuracy values can be compared to the GLCM test dataset results, which had two types of datasets, namely leaf data in the Normal category and leaf data in the category of phosphorus deficiency. The accuracy measurement in Table 3 showed that the lowest accuracy value in the training process was obtained at network *node_hidden*=10 with *tanh* Activation Function of 52.86%, and the highest was at network *node_hidden*=150 with *multiquadric* Activation Function of 99.43%. While in the Testing process, the lowest accuracy was obtained at network *node_hidden*=10 with a *tanh* activation function of 43.33%, and the highest at network *node_hidden*=50 with a *multiquadric* Activation Function of 93.33%. On average, the change in *node_hidden* of the ELM network used, the *multiquadric* Activation Function had a better accuracy value than other Activation Functions of 88.40%, followed by *soflim* at 67.87%, *sigmoid* at 67.73%, *tanh* 64.67%, and finally *sine* at 52.27%. Graphically, the change in network *node_hidden* in the *multiquadric* Activation Function can be seen as shown in Figure 8, while visually depicting the performance of the Activation Function against the overall dataset test shown in Figure 9.

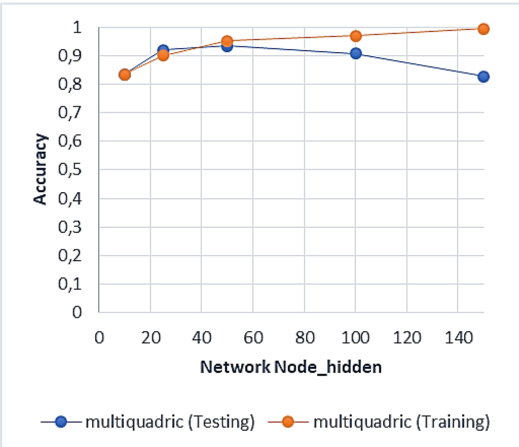


Figure 8. Graph of Changes in the network *node_hidden* in the *multiquadric* Activation Function

Figure 9. Result Chart (Training and Testing)

The graph in Figure 9 showed that the Activation Function, which had the best accuracy value, was *multiquadratic* in both training and testing. Suppose we refer to the best accuracy results on the multiquadric activation function in the training process. In that case, we obtained the best network node_hidden at a value of 150 with an accuracy of 99.43%, while in the testing process on network node_hidden 50 with an accuracy of 93.33%. These results indicated that in the case of identification of phosphorus deficiency in cultivated cocoa plants based on leaf characteristics, in a case study of 250 datasets, using the GLCM extraction algorithm with the properties of Contrast, Correlation, Angular Second Moment, and Inverse Difference Momentum, the maximum in the testing process at node_hidden network 50 even though during training it only got 95.14% accuracy. This result was also in line with the research conducted by W. Rahmawati in 2020 with different cases with different activation function tests. ROC parameters were obtained for the values of accuracy, recall, specificity, and precision, and the best f1-score was in the multiquadric activation function, but with 1000 neurons hidden layer ELM neurons [20].

Conclusion

Based on the results of the algorithm development as well as the research flow, it was found that the implementation of the Extreme Learning Machine (ELM) Algorithm with the Gray Level Co-Occurance Matrix (GLCM) Algorithm and the Feature Extraction method can identify phosphorus deficiency varied acuracy in cocoa plants based on leaf characteristics. The accuracy is depending on the Activation Function and the Network Node_Neuron used. In the conducted case study and the methodology applied from data collection, algorithm development to validation, and measurement using ROC, it was found that the best accuracy when testing the dataset was 95.14% on node_hidden network 50 using the multiquadric Activation Function. This shows a successful incorporation of the feature extraction process using GLCM with the properties of Contrast, Correlation, Angular Second Moment, and Inverse Difference Momentum, with a case study of Phosphorus nutrient deficiency in cacao plants on average maximum on the multiquadric Activation Function. This result is also recommended for developing an Applicative system in the future if it will be applied in a more mobile direction in early identification systems, especially in cacao cultivation.

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