Comparison of Image Extraction Model for Cocoa Disease Fruits Attack in Support Vector Machine Classification

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***Abstract*— This study aims to compare the results of four feature extraction models in the case of early recognition of disease attacks on cocoa fruits. The image extraction models used in this study are Local Binary Pattern (LBP), Gray Level Co-occurrence Matrix (GLCM), Hue Saturation Value (HSV), and Gray-level Co-occurrence Histograms (GLCH). In addition, the Support Vector Machine (SVM) model was used for the classification technique to evaluate the extraction results from the cocoa image dataset. The classification results using SVM showed the best performance on feature extraction HSV in all types of Kernel SVM used (Linear, RBF, and Polynomial), with the highest accuracy of 80.95% on RBF Kernel. Furthermore, the HSV performance in recognizing disease attacks on cocoa fruits, based on Precision, Recall, and F1-Score values, showed that, on average, HSV had a better value than other feature extraction methods.**

Keywords—cocoa, disease, image extraction, svm

I. Introduction

Image processing techniques have become a multimedia field that has been quite developed recently [1]. The implementation of image processing with feature extraction techniques has been widely applied in various cases, including in the agricultural sector. The integration of image processing in agriculture can even analyze and interpret various features of crops. For example, image processing is useful in identifying fruit ripeness and size [2]. Several reviews of research results that implement image processing techniques in agriculture, such as to detect plant diseases [3],[4],[5], even to predicting chili yields [6], and count cacao pods on trees using a 4K resolution drone [7].

In addition, like previous research, image processing can detect pests and plant diseases only by analyzing the texture features on the fruit skin but with the Gabor filtering method [8]. The research was then continued by integrating mobile-based applications with Deep Learning techniques to facilitate field research. The results show that the implementation of Deep Learning can be used but with development that still needs strengthening in image optimization [9]. Image optimization with a feature extraction approach is not carried out with an analysis tested for reliability. Several feature extraction approaches are very influential in classifying data objects, especially for real-time data objects [10]. The object of agricultural research, especially in the case of pest and disease attacks, requires a real-time system to provide early information. Relying on the human eye to monitor large agricultural lands with many plant objects is difficult, so an efficient system is needed [11].

The determination of the feature extraction technique is an essential concern because the disclosure of the characteristics of an object can be seen from the color pattern that is processed and then converted into vector values. There are various processes for revealing an object feature [12]. After a vector value, the computational system's feature is reprocessed to be classified using various classification techniques. Various classification techniques can be applied, but it is only studied to optimize the type of feature extraction from an image processing object in this research. As previously mentioned, the case study of image processing carried out in this study is a continuation of research from the roadmap developed for an early identification system of pests and diseases on cocoa fruits on an industrial scale. The development of the object of this research is based on the importance of machine learning research in cocoa cultivation, especially if it is to be managed in a modern way. Further development will be advantageous when the optimization of image processing begins to maximize so those cocoa problems such as pests and diseases, which are the most common problems, can be solved [13], [14].

The development of image processing models with various optimization techniques will be applied to various lines. The implementation of image processing with various methods can later be applied to surveillance techniques connected to drones in the Cocoa Cultivation Upstream Industry. Likewise, quality control by

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implementing image processing with machine learning techniques will be very much needed in the Downstream Industry. An illustration of the development of a potential research model is presented in Fig. 1. This depiction makes an image processing study with feature extraction analysis an essential first step before entering the classification and optimization stages.

Fig. 1 depicts in macro the research potential that researchers are developing. Still, in the current study, the focus is on evaluating the performance of several feature extraction models using Local Binary Pattern (LBP), Gray Level Co-occurrence Matrix (GLCM), Hue Saturation Value (HSV), and Gray-level Co-occurrence Histograms (GLCH). The feature extraction will then be analyzed for reliability and strengthen the characteristics of the classification combination using the Support Vector Machine (SVM), one of the popular Machine Learning methods implemented. The long-term development of this study will further become the potential for optimization of machine learning parameters and the basis for developing object feature extraction research.

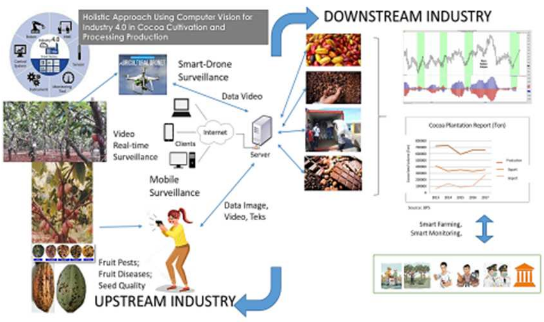


Fig. 1. Holistic Approach Using Computer Vision in Cocoa Upstream and Downstream Industry

II. Related Works

A. Local Binary Pattern (LBP)

The standard Local Binary Pattern (LBP) method calculates the difference in gray levels by encoding the relationship between the referenced pixels and the neighboring pixels. The LBP operator uses a comparison of the gray values of neighboring pixels. This algorithm has been widely implemented as a feature extraction technique and is considered capable of providing maximum results. Research [15] uses LBP modeling for Arabic letter recognition with an accuracy percentage of 99.72%. So the research concludes that LBP was easy to implement with maximum results and was a reasonably fast feature extraction method with low computational processes. Evaluation of implementation with LBP as in [16] shows that this method was much better when used as feature extraction than combined with other feature extractions, even when it gets additional feature reduction after classification.

B. Gray Level Co-occurrence Matrix (GLCM)

Gray Level Co-occurrence Matrix (GLCM) is a method for analyzing textures or extractions that produce textural features of an image [17]. Previous studies regarding GLCM only used 4 degrees of 0, 45, 90, and 135 degrees [18]. GLCM also describes the frequency with the concept of a matrix producing two pairs of pixels whose intensity is in distance and direction [19]. The implementation of GLCM as a feature extraction method has been widely applied. One of them is related to leaf characteristic research as in [20], which detects chili plant diseases through leaf imagery with implementation on a smartphone. The study also used SVM as a classification technique. It achieved an accuracy of 95% using four characteristic parameters, including contrast, correlation, energy, and homogeneity, in a computation time of 3 to 3.7 seconds. In addition to implementing fruit characteristics, as in [21], which uses GLCM for fruit feature extraction, further classified by the K-Nearest Neighbor (KNN) technique. The study results were maximally able to identify and classify the unique Parijoto fruit with an accuracy of 80%.

C. Hue Saturation Value (HSV)

Hue, Saturation, and Value are part of color image processing that represents the color seen, abbreviated as HSV, where Hue is the density or characteristic possessed by color so that it can be recognized. Saturation is the color intensity or purity of a color so that in some cases it given a better accuracy value [22]. Saturation is the density of a color / weak or strong color. A simple example is that a perfect bright red color means high intensity. If the intensity is low, the color is dark gray, while Value is a color value to determine a color's brightness or lightness. The feature extraction with HSV is also widely implemented in classification techniques, for example, identifying fruit maturity with eight types of fruit classification. The research was then classified using SVM. The feature extraction results with HSV Color get the best

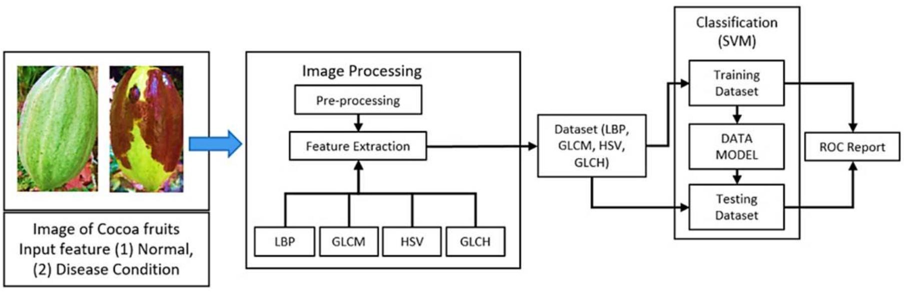


Fig. 2. System Framework

performance with accuracy, precision, recall, and F-Measures are 0.76, 0.80, 0.76, and 0.78, respectively [23].

D. Gray-level Co-occurrence Histograms (GLCH)

Gray-level Co-occurrence Histograms (GLCH) method runs the same as the Gray Level Co-occurrence Matrix (GLCM). The difference is in the grayscale function used. GLCM is a symmetric gray-level function, so GLCH is an asymmetric gray-level function [24]. This implementation is similar to the approach used in the new approach to breast tumor identification with the Neutrosophic Score feature. The GLCH approach is based on the GLCM function, but it is considered that in some instances, it can be more leverage [25]. Including in cases that identify breast tumors at normal, benign, and malignant levels and GLCH, a more maximal extraction process is obtained [26].

From several related studies, this study present evaluates the performance of each feature extraction method in the case of the cocoa fruit dataset with two types of conditions, namely normal fruit conditions and diseased fruit conditions. The feature extraction results were then analyzed by the SVM classification method for further comparison of the results. A study evaluates the performance of different feature extraction on a textured surface by applying a synthetically generated noise pattern using Structure From Motion Coupled With Multi-View Stereo (SFM-MVS). However, with a different feature extraction from what will be reached in this study [27]. The use of SVM is intended that SVM optimization research is still wide open because it has weaknesses in multiclass [28].

III. METHODOLOGY

The evaluation model development carried out in this study is shown in Fig 2. The classification process is carried out for two object classes: objects in normal condition (class 0) and diseased (class 1). These two classes are then pre-processed from the results of the image capture. The data were obtained using a 10 Megapixel smartphone camera with a resolution of *3000x4000* pixels per image. Then pre-processing is carried out to focus on the cocoa fruits, with an average pixel size of *400x600* pixels. The two types of data classes are then processed using the feature extraction algorithm described in the previous section. The feature extraction process from each class is then stored in a dataset (*dataset_feature.csv*), with 244 image data for the normal class and 173 for the diseased fruit condition class. The dataset is then extracted using the LPB, GLCM, HSV, and GLCH algorithms.

The results of the datasets that have been stored are then used respectively in the classification process using SVM. This section divides the dataset for the training and testing process, comparing 75% of the dataset for training and 25% for testing. The SVM algorithm's parameter is a cross-validation value of $C = 10$. This selection ensures that the results of the classification evaluation by SVM significantly affect the accuracy achieved. This study examines three types of Kernel, namely Linear Functions, Radial Basis Function (RBF) with *gamma=1*, and Polynomial with *degree=3,* so that the results obtained can be used as a comparison of the performance of each Feature Extraction [29]. Hyperplane classification of each SVM kernel through the following formula [30].

$$(Linear):\ k(x_i, x_j) = x_i^T x_j \tag{1}$$

$$(RBF):\ k(x_i, x_j) = exp\left\{\frac{||x_i,x_j||^2}{2\sigma^2}\right\} \tag{2}$$

$$(Polynomial):\ k(x_i, x_j) = (\Upsilon x_i^T x_j + r)^d, \text{ where } \gamma > 0 \tag{3}$$

Where x_i = training data set and y_i = class label of x_i. The best hyperplane is to find a hyperplane that lies in the middle between the two class boundaries. To get the best hyperplane is the same as maximizing the distance between two sets of objects of different classes. An overview of the SVM modeling is shown in Fig. 3.

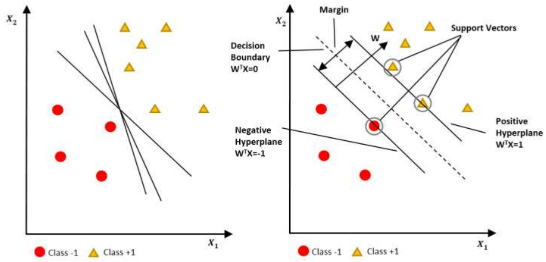


Fig. 3. Hyperlane by separating classes (–) and (+)

IV. RESULTS AND DISCUSSION

A. Implementation of Feature Extraction Model

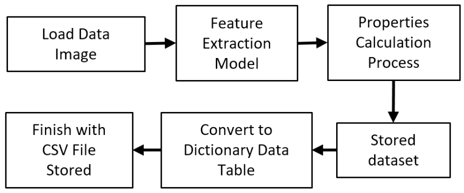


Fig. 4. Feature Extraction Process

The feature extraction process of each applied model is shown in Figure 4. In the initial stage, random labeling is carried out after going through the image data loading process based on the stored image data loaded, as shown in Figure. 5. The label data in the next process differed for each Feature Extraction model.

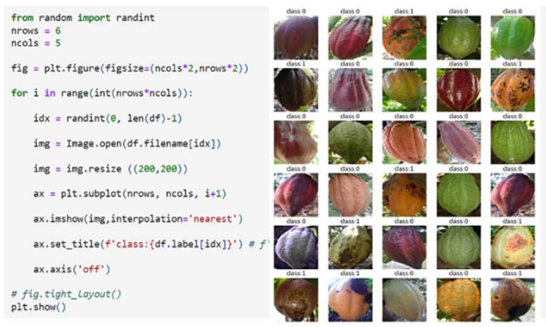


Fig. 5. Data Label

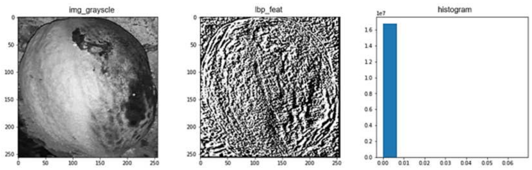


Fig. 6. LBP Extraction Image

The image in the feature extraction process was resized at *256x256* pixels. The resulting object from the initial LBP process is shown in Fig. 6, with a radius function value of three with a neighboring value of eight. While in the GLCM process, feature extraction uses a Grecomatrix from one image file that was read and

changed the color space (color) to grayscale (gray) with a resolution conversion to *256x256 (I_gray=I_gray.resize((256,256)*. Function properties of GLCM using a predetermined formula (Contrast, Correlation, Angular Second Moment, and Inverse Difference Momentum), and providing the extracted vector value through the GLCM property function, then stored into the dataset as shown in Fig. 7. For the HSV process, the implemented programming uses a value of *0* for Hue, *1* for Saturation, and *2* for Value, thus giving the output color as shown in Fig. 8. Whereas the process in GLCH has the same algorithm as the GLCM function, only the difference is in the symmetric and asymmetric functions, whose results are as in Fig. 9.

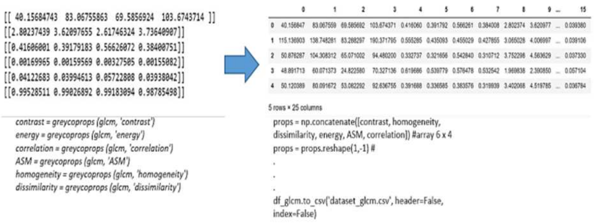
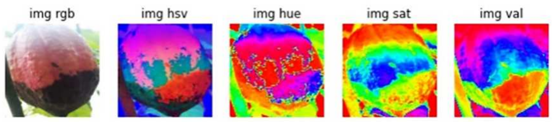


Fig. 7. Storage of GLCM Feature Extracted Dataset



Datasets are prepared before processing using SVM and uniformized using the CSV file mentioned in the Methodology section (dataset_feature.csv). The amount of data in each feature extraction adjusts the algorithm model used, where LPB is 257 attribute, GLCM is 25, HSV is 16, and GLCH is 25, with the last column being the definition of data class (1 or 0). The output dataset consists of 417 data lines, according to the amount of image data.

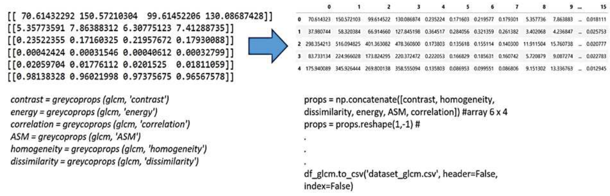


Fig. 9. Storage of GLCH Feature Extracted Dataset

B. SVM Classification Results

Based on the process in Fig. 2, the extraction results were analyzed using the SVM model as the parameters mentioned in the research methodology. The algorithm function used to process based on the CSV model of the feature extraction dataset, which in this case is defined as a variable x for input data and y for output.

$$x = dataset.loc[:, 0:x] \\ y = dataset.loc[:,y] \\ x.head,\ y.head \tag{1}$$

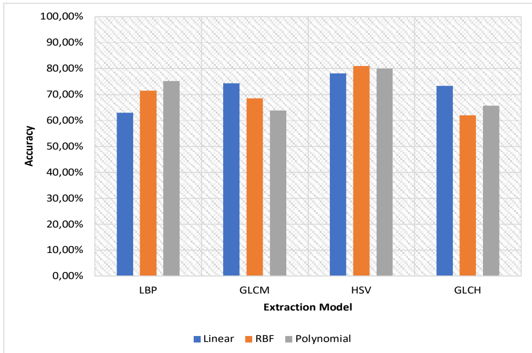


Fig. 10. Feature Extraction Performance in Accuration

The system output results are based on the accuracy of the Confusion Matrix Receiver operating characteristic (ROC) formula [31]. In Fig. 10, the classification results with SVM as described in the algorithm flow, each parameter that remains in the SVM is tested on each feature extraction dataset, to be further validated with ROC.

$$confusionMatrix = confusion\_matrix(y\_test, y\_pred) \\ fig, ax = plt.subplots(figsize=(5,5)) \tag{2}$$

The function above displays training and testing accuracy and a confusion matrix and classification results by displaying Precision, Recall, and F1-Score as presented in the table. 1. The sample is taken from running the program on each dataset resulting from feature extraction.

Based on the results of the SVM classification on all types of Feature Extraction models, as shown in Figure 10, it was found that HSV is better than other types of feature extraction. The accuracy value reaches 80.95% in the RBF kernel, following HSV in the Polynomial Kernel at 80% and HSV in the Linear Kernel at 78.09%. If analyzed based on the average of each feature extraction in all types of SVM kernels, HSV is still better with an average accuracy of 79.68% for all kernels, then LBP is 69.89%, GLCM is 68.89%, and finally, GLCH is 66.98%. These results indicate that the classification of cocoa pods in a diseased condition has a wide color distribution and is not so spread over several surfaces. Hence, it is very easy to classify by SVM when using HSV.

TABLE I. CLASSIFICATION PERFORMANCE

Liner Kernel							
ROC	Precision		Recall		F1-Score		Acc (%)
Class	0	1	0	1	0	1	
LBP	0,63	0,00	1	0,00	0,77	0,00	63,00
GLCM	0,74	**0,75**	**0,85**	0,60	0,79	0,67	74,29
HSV	**0,84**	0,69	0,8	**0,74**	**0,82**	**0,72**	78,09
GLCH	0,79	0,63	0,79	0,63	0,79	0,63	73,33
RBF Kernel							
ROC	Precision		Recall		F1-Score		Acc (%)
Class	0	1	0	1	0	1	
LBP	0,63	0,00	1	0,00	0,77	0,00	71,43
GLCM	0,67	**0,73**	**0,88**	0,42	0,76	0,54	68,57
HSV	**0,84**	0,69	0,8	**0,74**	**0,82**	**0,72**	80,95
GLCH	0,66	0,50	0,8	0,33	0,72	0,39	61,90
Polynomial Kernel							
ROC	Precision		Recall		F1-Score		Acc (%)
Class	0	1	0	1	0	1	
LBP	0,83	0,64	0,76	0,74	0,79	0,69	75,24
GLCM	0,62	**0,73**	**0,93**	0,24	0,75	0,37	63,81
HSV	**0,87**	0,70	0,80	**0,79**	**0,83**	**0,75**	80,00
GLCH	0,66	0,62	0,91	0,25	0,77	0,36	65,71

Based on Table I, the performance of SVM in classifying normal cocoa fruits (class 0) and diseased cocoa fruits (class 1) showed mixed results with average Precision, Recall, and F1-Score. However, the pattern of values obtained shows that HSV feature extraction was dominantly higher, except for class 1 precision and class 0 recall, which were all high using GLCM extraction. Still, based on table I, the average value of Precision, Recall, and F1-Score reaches the highest average value on HSV. Precision, Recall, and F1-Score on Linear Kernels are 77%, as well as on RBF Kernel. However, it differs slightly in Polynomial Kernel, although it is still on HSV with an average precision of 79%, recall of 80%, and F1-Score of 79%. Although it does not reach 100% on average, the performance evaluation of Feature Extraction reviewed in this paper showed that HSV had a better performance.

These results showed that features on the surface of cocoa fruits for identification with color parameters were much better than other extraction approaches. This results also indicates that HSV colors more stable and more suitable for color segmentation fot this case study. the HSV color space has the advantage that the basic color description is not only red, green and blue. Color descriptions such as orange, bluish green in HSV still enter the dominant color without having to hold on to red, green, blue. The use of SVM Classification with Kernel variants used in the research case shows that of the three types of SVM Kernels, RBF and Polynomials are sequentially better than Linear Kernels. Due to the surface classification pattern of diseased cocoa fruits, the extracted vector value is a data point value that cannot be separated linearly. The default implementation of the SVM kernel in non-linear cases generally uses RBF. A case study on the surface of cocoa pods on the identification of disease attacks, with pixel color patterns forming a collection of several colors that tend to be on one or two sides, making the RBF Kernel better than other types of kernels. The selection of *gamma=1* makes the classification process closer to the pixel pattern on disease attacks seen in cocoa pods. Meanwhile, in the selection of parameter *C=10*, it can be seen that the classifier model was tolerant of diseased cocoa pod image data points, so this value also provides better classification support.

V. CONCLUSION

Based on the instrumentation results using Feature Extraction with LBP, GLCM, HSV, and GLCH, SVM classification can provide the performance of the four feature extraction methods. Performance evaluation of each feature extraction method is then presented using ROC analysis. The results of the classification with SVM showed the best performance on Feature Extraction HSV in all types of Kernel SVM used (Linear, RBF, and Polynomial) with the highest value in RBF Kernel with an accuracy of 80.95%, followed by Polynomial Kernel 80%, and Linear Kernel 78.09%. Furthermore, the HSV performance in this case study is also presented with Precision, Recall, and F1-Score results on the Confusion Matrix of ROC. The evaluation results also show that, on average, HSV has a better value than other Feature Extraction methods. Therefore, it can be concluded that the surface characteristics of diseased cocoa objects are much easier to identify with feature extraction based on color analysis using HSV. For this reason, further research can undoubtedly be developed in a more implementable direction, including a better combination of pre-processing.

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