Pixel quantification and color feature extraction on leaf images for oil palm disease identification

Anindita Septiarini
Department of Informatics
Faculty of Engineering
Mulawarman University
Samarinda, Indonesia
anindita@unmul.ac.id

Hamdani Hamdani
Department of Informatics
Faculty of Engineering
Mulawarman University
Samarinda, Indonesia
hamdani@unmul.ac.id

Tiya Hardianti
Department of Informatics
Faculty of Engineering
Mulawarman University
Samarinda, Indonesia
tiyahardiyanti48@gmail.com

Edy Winarno
Faculty of Information Technology
Universitas Stikubank
Semarang, Indonesia
edywin@edu.unisbank.ac.id

Suyanto Suyanto
School of Computing
Telkom University
Bandung, Indonesia
suyanto@telkomuniversity.ac.id

Edy Irwansyah
School of Computer Science
Bina Nusantara University
Jakarta, Indonesia
eirwansyah@binus.edu

2021 7th International Conference on Electrical, Electronics and Information Engineering (ICEEIE) | 978-1-6654-3232-0/21/$31.00 ©2021 IEEE | DOI: 10.1109/ICEEIE52663.2021.9616645

***Abstract*— Oil palm disease can be identified by the appearance of yellowish spots on the leaf area. It causes a decrease in the quality and quantity of palm oil. Therefore, this work has developed a method for leaf disease identification using image processing to quantify the infected area's pixels and extract the color features. The region of interest (ROI) detection was initially performed by applying Otsu thresholding based on L*a*b color space to obtain the sub-image called ROI image. Afterward, pre-processing was performed by converting RGB to several color spaces and using contrast stretching. The features extracted the mean value intensity of each channel on five color spaces and counting the pixel number of the infected area. Those features were reduced using correlation-based feature selection (CFS) followed by k-nearest neighbors (KNN) classification. The dataset used consists of 100 leaf images (50 healthy and 50 unhealthy). The method performance achieved accuracy, precision, and recall of 99%, 98%, and 100%.**

Keywords*— *oil palm; Otsu method; thresholding; feature extraction; CFS; KNN

I. Introduction

Currently, image processing techniques in the computer field have been widely applied in several areas. In Agriculture field has been developed for various purposes, including land control [1] – [3], fruit maturity classification [4], fruit quality sorting [5], diseases control, and disease detection [6],[7]. Palm oil is a highly demanded plantation product. This plant has to planted on suitable land since it may cause a destructive impact on the surrounding environment [8]. Palm oil can be processed into various types of products, such as soap, shampoo, detergent, cosmetics, chocolate, oil, noodles, and fuel [9]. Therefore, palm oil is required in large quantities and even continues to increase every year. In order to produce large quantities of palm oil, the plant must be protected from disease. Oil palm disease mainly occurs on the leaves of the plant. The common illness on oil palm leaves is curvularia leaf spot [10]. The emergence of disease in plants should be immediately identified; hence, prevention and eradication are directly carried out to produce good quality palm oil.

Leaf disease identification using image processing has been successfully applied to differentiate healthy and unhealthy leaves. It developed to identified diseases in various plants, consisting of wheat [11], tea [12], and oil palm [9], [13]. In the previous works, supervised learning using several classifiers was applied to detect leaf disease [2], [14] – [18]. Generally, the main process required to develop it consists of pre-processing, segmentation, feature extraction, and classification [19]–[21]. In pre-processing, the tasks that were usually performed include resizing [13], [20], converting color spaces [9], [22], and Gaussian filtering [15]. Subsequently, popular segmentation methods were applied, i.e., edge detection [15], [23], clustering [9], [24], [25], thresholding [26], [27], and deep learning [28]. The features extracted for the leaf object consist of color [16], [27], shape [16], [20], and texture [9], [29]. Furthermore, in the classification process, methods that are often implemented include KNN [20], artificial neural network (ANN) [30], and support vector machine (SVM) [9], [13], [15].

Several previous works successfully detecting leaf disease. Cucumber disease was detected using a sparse representation classifier based on color and shape features. Those features extracted in the leaf area were segmented by K-means clustering. The accuracy value achieved is 85.7% for 420 images [25]. Meanwhile, wheat leaf rust successfully recognized by implementing Sobel edge detection in G channel of RGB color space followed by noise reduction using a flood filling algorithm. The experiment result obtained an accuracy value of 96.2% [11]. In another work, Chimaera and anthracnose diseases were detected using SVM classifier and K-means clustering that performed to segment the leaf area. The average accuracy achieved is 95% and 97% for anthracnose and chimaera, respectively [13]. Furthermore, leaf disease detection using local binary patterns as the texture feature combine with one class SVM as classifier was developed and achieved an accuracy value of 95% [29].

This work focuses on developing the identification methods of oil palm disease to differentiate the plants into two classes: healthy and unhealthy. The plant disease was indicated by the appearance of yellowish spots on the leaf area. The proposed method was developed by extracting the color features and quantifying pixels of the infected area on the leaf area that segmented using the K-means algorithm. Furthermore, feature reduction was applied using CFS, followed by implementing KNN classifier.

II. Materials And Methods

The proposed method developed consists of several main processes, including image acquisition, ROI detection, pre-

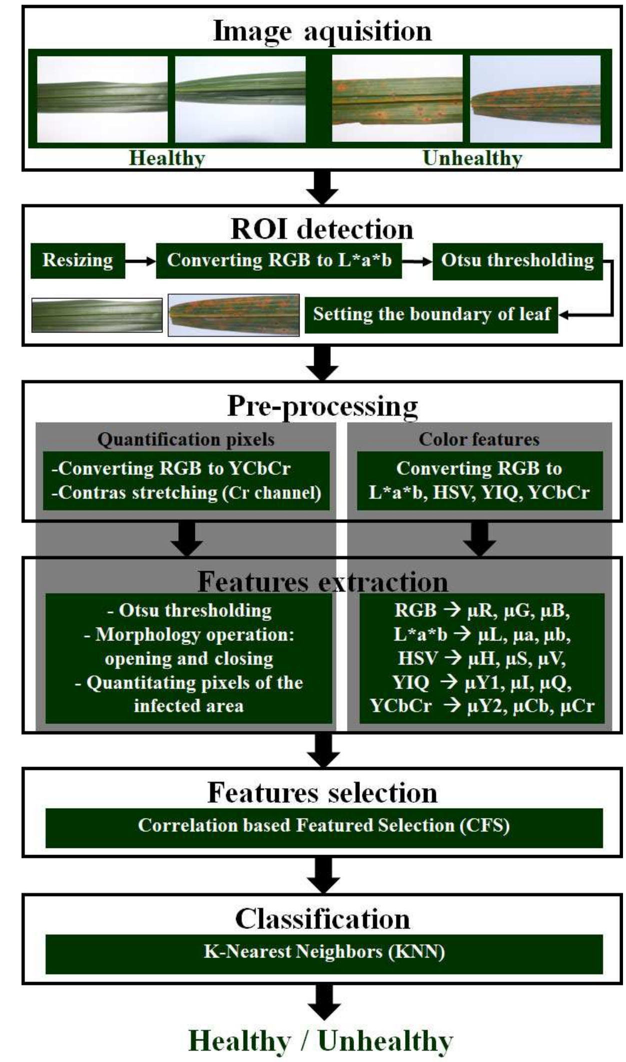

Fig. 1. An overview of the main process sequences in the proposed method

processing, features extraction, features selection, and classification. The sequence of these processes is shown in Fig. 1. Meanwhile, the details of each main process are described in the following sub-section.

A. *Image Acquisition*

This process was carried out to collect a dataset consisting of palm leaf images divided into two classes: healthy and unhealthy. The disease that often appears on oil palm leaves is curvularia leaf spot [10]. Therefore, the unhealthy class in this work was limited to curvularia leaf spot disease. This disease often appears during the growth period that indicated by the appearance of yellow spots. The resulting leaf image is 100 images consisting of 50 healthy and 50 unhealthy. The resolution of these images is 5184 × 3456 pixels saved in JPEG format. The leaves were acquired with a white artificial background. These were captured using a smartphone camera with an 18MP lens. The distance between the object and the camera of ± 20 cm with even lighting.

B. *ROI detection*

Initially, this process resized the original image of 5184 × 3456 pixels into 640 × 480 pixels as in [23], [31] to reduced the computation time of the subsequent process. Furthermore, the following process was implemented to form a sub image that focuses on containing the leaf area as a region of interest (ROI) called the ROI image. The conversion of the RGB to L*a*b color space is carried out on the resized image followed by thresholding using the Otsu method as in [32] on b channel of L*a*b color space. Converting RGB to L*a*b color space is computed based on (1) [32]:

$$L = 0.2126R + 0.7152G + 0.0722$$

$$a = 1.4749\,(0.2213R - 0.339G + 0.1177B) + 128 \qquad (1)$$
$$b = 0.6245\,(0.1949R + 0.6057G - 0.8006B) + 128$$

Afterward, the boundary of leaf area was set based on the binary image resulting from the thresholding. Hence the leaves have various widths; consequently, the size of the resulting ROI image become varies as shown in Fig. 2(a).

C. *Pre-processing*

This work proposed the result of quantification pixel and color as the features. Regarding the quantification pixel, this process aims to make the infected area more visible clearly. Therefore, converting RGB to YCbCr color space was implemented, followed by applying contrast stretching on the Cr channel. Meanwhile, related to color features, converting RGB to four color spaces including L*a*b, HSV, YIQ, and YCbCr were carried out due to the features extracted from each channel of those color spaces, including RGB. Convert RGB to L*a* b using (1), while converting RGB to other color spaces presented as follow.

- Convert RGB to HSV color space using (2):

$$H = \begin{cases} \theta, & B \le G \\ 360 - \theta, & B > G \end{cases} \qquad (2)$$
$$\theta = cos^{-1}\left\{\frac{\frac{1}{2}[(R-G)+(R-B)]}{[x(R-G)^2+(R-B)(G-B]^{1/2}}\right\}$$

$$S = \begin{cases} 0, & \max(R,G,B) = 0 \\ 1 - \dfrac{\min(R,G,B)}{\max(R,G,B)}, & otherwise \end{cases}$$
$$V = \max(R,G,B)$$

- Convert RGB to YIQ color space using (3) [30]:

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.274 & -0.322 \\ 0.211 & -0.523 & 0.312 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \qquad (3)$$

- Convert RGB to YCbCr color space using (4) [30]:

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 5 \\ 15 \\ 15 \end{bmatrix} + \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112.00 \\ 112.00 & -93.786 & -18.214 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \qquad (4)$$

D. *Features extraction*

In order to yield the pixel number of the infected area, the ROI image (Fig 2(a)) in RGB convert into YCbCr color space as shown in Fig 2(b). Subsequently, thresholding based on Cr channel (Fig 2(c)) of YCbCr color space was applied using the Otsu method. The aim of thresholding to formed the binary image containing the white pixels that indicate an infected area. Afterward, morphology operation, including opening and closing, was implemented to discard the healthy area classified as an infected area (Fig 2(d)). Furthermore, the quantification pixels of the infected area where applied. The resulting feature is called the QP feature, representing the number of white pixels that indicate the infected area. The image of the results of each process to obtain the infected area

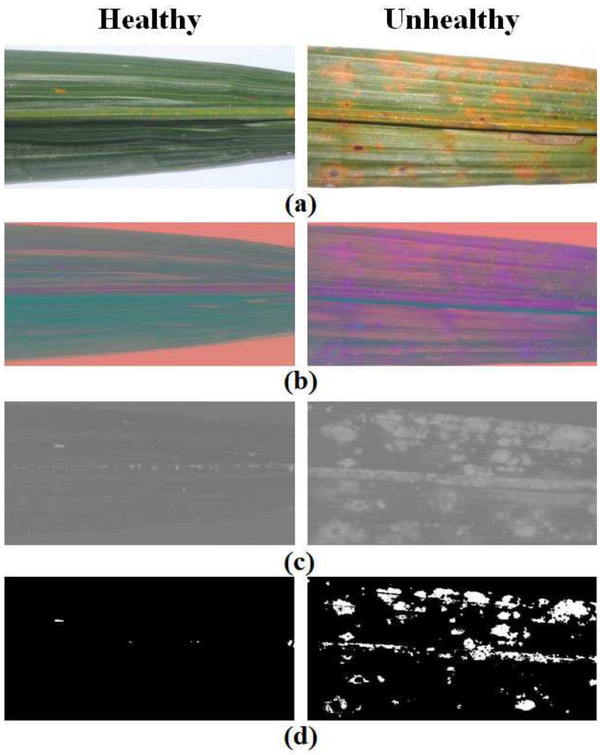

Fig. 2 The resulting images of each process: (a) ROI image; (b) YCbCr color space; (c) Cr channel; (d) thresholding and morphology operation

is presented in Fig 2. Furthermore, the color features obtained based on the mean (μ) value of each channel from RGB, L*a*b, HSV, YIQ, and YCbCr color spaces. The μ of M × N pixels image was generated using (5):

$$\mu = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} P_{ij}, \quad (5)$$

where P_{ij} is the value of intensity on row j and column i. Therefore, the total number of features produced was 16 features. The example of feature extraction results in a healthy and unhealthy leaf image, depicted in Fig 3.

E. Features selection

In this work, two feature selection methods, namely CFS and principal component analysis (PCA) were performed as in [35]. These methods have been widely used and successfully applied in various fields: CFS [34], [35] and PCA [14], [20]. The comparison of resulting features without and with applying the feature selection method (CFS and PCA) is summarized in Table 1. Table 1 shows that CFS is able to reduce features by more than 50%. The number of features produced using CFS and PCA is 7 and 11, respectively. The result of feature selection shows that not all channels in each color space are selected. It indicates that unselected color channel was not a discriminatory feature; therefore, it was not considered an essential role in the classification process.

TABLE I. THE RESULTS OF FEATURE SELECTION WITHOUT AND WITH FEATURE SELECTION METHOD CFS AND PCA

Feature selection method	Number of features	Features
Without	16	QP, μR, μG, μB, μL, μa, μb, μH, μS, μV, μY1, μI, μQ, μY2, μCb, μCr
CFS	7	QP, μR, μA, μH, μS, μI, μCr
PCA	11	μI, μCr, μR, QP, μB, μQ, μY1, μY2, μG, μA, μL

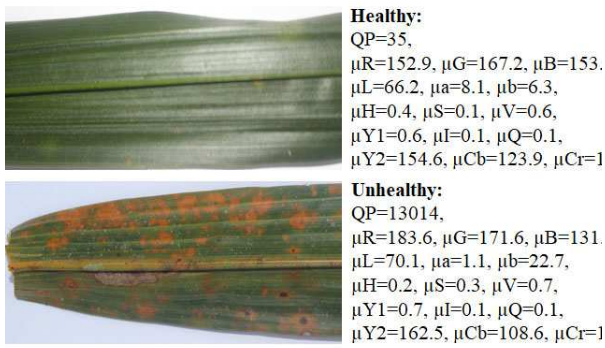

Fig. 3 The example of the features extraction result

F. Classification

The final process applied four classifiers to determine the resultant feature sets according to the class they belong to, including healthy or unhealthy. In this work, the four classifiers employed were KNN, Naive Bayes, decision tree, and SVM as in [15], [20] because these classifiers have been successfully implemented in various cases.

- K-Nearest Neighbor

K-Nearest Neighbor (KNN) is a practical classification method. In order to determine the predicted class of test data, the calculation of the distance between the feature set from the training data and the testing data has to perform. According to the class from the training data (x), the predicted class is obtained, which has a minimum distance against the testing data (y). In this work, the Euclidean distance (d) applied using (6) [15]:

$$d = \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}(x_i - y_i)^2} \quad (6)$$

where m is the number of training data and n is the number of features.

- Naïve Bayes

Naïve Bayes is an algorithm that is considered simple because it assumes that the feature value of a class does not depend on the feature value of another class which is called a conditionally independent class. The principle of the Bayes theorem is defined in (7) [20]:

$$P(H|X) = \frac{P(X|H)P(H)}{P(X)} \quad (7)$$

where P(H) is the prior probability of class (target) and P(X) is the prior probability of predictor. Meanwhile, P(H|X) and P(X|H) are the posterior and the likelihood, respectively.

- Decision tree

In this method, the construction of a classification model based on the tree structure divides all feature sets into minor feature sets, and then the tree is gradually developed. The final result is a tree with a decision node having the features extracted from the leaf nodes, and the class determines based on these leaf nodes. The decision tree construction aims to obtain the feature that returns the highest information gain. Information gain is defined using (8) [20]:

$$Gain(A,B) = Entropy(A) - Entropy(A,B) \quad (8)$$

- Support Vector Machine

Support Vector Machine (SVM) is one of the popular supervised learning methods. It works in the non-linear transformation to form the optimal hyperplane by separating negative and positive classes based on the maximum margins. The utilization of a kernel function is intended for the data transformation into higher dimension space. It operates on the points which lie nearest to separating hyperplane points. A non-linear support classifier is formed by replacing the product (x, y) with $K(x, y)$. The membership of x was determined using (9) [20]:

$$f(x) = sign\left(\sum_{i=1}^{j} a_i y_i K(x_i x) + b\right) \tag{9}$$

III. Result And Discussion

In this work, the method performance of oil palm disease identification was evaluated using three parameters: accuracy, precision, and recall. These parameters indicate the robustness of the method against the dataset used. All the parameters were computed as follow (10) [20]:

$$Accuracy = \frac{Number\ of\ correctly\ identified\ images}{Total\ number\ of\ images} \times 100$$
$$Precision = \frac{\sum True\ Positive}{\sum Predicted\ Condition\ Positive} \times 100 \tag{10}$$
$$Recall = \frac{\sum True\ Positive}{\sum Condition\ Positive} \times 100$$

The method evaluation is carried out by implemented several testing scenarios. Four classifiers, including Naïve Bayes, SVM, KNN, and the decision tree, were tested using different feature sets produced without the feature selection method, also using feature selection (PCA and CFS) shown in Table 1. Classification is done using k-fold cross-validation with k = 5 as in [20]. This method was implemented using 100 images (50 healthy and 50 Unhealthy). The evaluation results based on the value of accuracy, precision, and recall was depicted in Fig. 4 (a), (b), and (c). Fig 4 shows the highest accuracy generated using the KNN classifier, achieving 99% with 11 and 7 features produced using PCA and CFS. Conversely, the lowest accuracy is 92% produced by a decision tree using 16 features without applying the feature selection method. Based on these results, the appropriate method to applied in this work is the combination of CFS and KNN. Since these methods were able to produce the optimal accuracy values using a small number of features than implementing the PCA and KNN methods.

Meanwhile, the resulting precision value achieves 98%, as shown in Fig 4(b). It indicates that there is a misclassification, where the healthy image is classified as unhealthy. There are 50 unhealthy images, but the classification results obtained 51 unhealthy images. This condition is known as a false positive error. Furthermore, the achievement of the recall value is 100% which is shown in Fig 4(c). It shows that all the unhealthy images (50 images) are classified correctly. Based on the resulting precision and recall values, it shows the number of images that were misclassified.

IV. Conclusion

Oil palm disease usually appears on the leaves. It causes the quality and quantity of palm oil produced to decrease. Therefore, the disease needs to be identified early; hence its preventing can be carried out. The aim of this work is to develop methods for disease identification of oil palm leaves. This method applies ROI detection using Otsu thresholding on b channel of L*a*b color space, followed by pre-processing, which implemented the conversion of RGB to L*a*b, HSV, YIQ, and YCbCr color space. Afterward, Feature extraction by quantitating the pixel number of the infected area and computing the mean value of each channel from five (RGB, L*a*b, HSV, YIQ, and YCbCr) color spaces were applied. Subsequently, the CFS was implemented in feature selection, followed by performing the classification using KNN. This work achieved the highest accuracy value of 99%, indicating the method performance based on 100 images (50 healthy and 50 unhealthy). For future work, the identification method of leaf disease still has the possibility to be developed widely to improve the achievement of the accuracy value or carry out the disease grading.

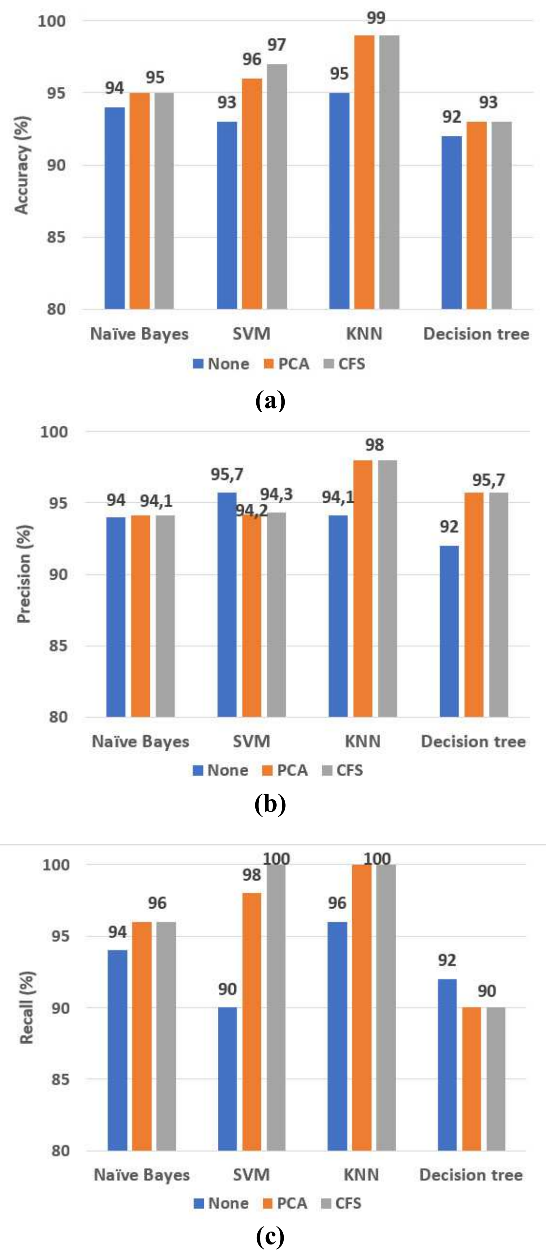

Fig. 4. The identification results of oil palm leaf disease based on the value of: (a) accuracy; (b) precision; (c) recall

ACKNOWLEDGMENT

This work was funded and supported by KEMENDIKBUD RISTEK Indonesia in 2021 (Grant no. 596/UN17.11/PG/2021).

REFERENCES

[1] V. Tewari, C. Pareek, G. Lal, L. Dhruw, and N. Singh, "Image processing based real-time variable-rate chemical spraying system for disease control in paddy crop," Artificial Intelligence in Agriculture, vol. 4, pp. 21–30, 2020.

[2] J. Zhang, Y. Huang, R. Pu, P. Gonzalez-Moreno, L. Yuan, K. Wu, and W. Huang, "Monitoring plant diseases and pests through remote sensing technology: A review," Computers and Electronics in Agriculture, vol. 165, pp. 104943, 2019.

[3] A. Khattab, S. E. Habib, H. Ismail, S. Zayan, Y. Fahmy, and M. M. Khairy, "An iot-based cognitive monitoring system for early plant disease forecast," Computers and Electronics in Agriculture, vol. 166, pp. 105028, 2019.

[4] A. Septiarini, H. R. Hatta, H. Hamdani, A. Oktavia, A. A. Kasim, and S. Suyanto, "Maturity grading of oil palm fresh fruit bunches based on a machine learning approach," in *2020 Fifth International Conference on Informatics and Computing (ICIC)*, 2020, pp. 1–4.

[5] M. Bhange and H. Hingoliwala, "Smart farming: Pomegranate disease detection using image processing," Procedia Computer Science, vol. 58, pp. 280–288, 2015.

[6] A. Rani, N. Donovan, and N. Mantri, "Review: The future of plant pathogen diagnostics in a nursery production system," Biosensors and Bioelectronics, vol. 145, pp. 111631, 2019.

[7] J.L. Xu, A. Gobrecht, D. H´eran, N. Gorretta, M. Coque, A. A. Gowen, R. Bendoula, and D. Sun, "A polarized hyperspectral imaging system for in vivo detection: Multiple applications in sunflower leaf analysis," Computers and Electronics in Agriculture, vol. 158, pp. 258–270, 2019.

[8] Hamdani, A. Septiarini, and D. M. Khairina, "Model assessment of land suitability decision making for oil palm plantation," in *2016 2nd International Conference on Science in Information Technology (ICSITech)*, 2016, pp. 109–113.

[9] A. N. I. Masazhar and M. M. Kamal, M.M, "Digital image processing technique for palm oil leaf disease detection using multiclass svm classifier," in *2017 IEEE 4th International Conference on Smart Instrumentation, Measurement and Application (ICSIMA)*, 2017, pp. 1–6.

[10] C. Pornsuriya, A. Sunpapao, N. Srihanant, K. Worapattamasri, J. Kittimorakul, S. Phithakkit, S., and V. Petcharat, "A survey of diseases and disorders in oil palms of southern Thailand," Plant Pathology Journal, vol. 12, pp. 169–175, 2013.

[11] P. Xu, G. Wu, Y. Guo, X. Chen, H. Yang, and R. Zhang, "Automatic wheat leaf rust detection and grading diagnosis via embedded image processing system," Procedia Computer Science, vol. 107, pp. 836–841, 2017.

[12] L. Yuan, P. Yan, W. Han, Y. Huang, B. Wang, J. Zhang, H. Zhang, and Z. Bao, "Detection of anthracnose in tea plants based on hyperspectral imaging," Computers and Electronics in Agriculture, vol. 167, pp. 105039, 2019.

[13] M. M. Kamal, A. N. I. Masazhar, and F. A. Rahman, "Classification of leaf disease from image processing technique," Indonesian Journal of Electrical Engineering and Computer Science, vol. 10(1), pp. 191–200, 2018.

[14] H. Hamdani, A. Septiarini, A. Sunyoto, S. Suyanto, and F. Utaminingrum, "Detection of oil palm leaf disease based on color histogram and supervised classifier," Optik, vol. 245, pp. 167753, 2021.

[15] P. Varalakshmi and S. Aravindkumar, "Plant disorder precognition by image based pattern recognition," Procedia Computer Science, vol. 165, pp. 502–510, 2019.

[16] A. Adeel, M. A. Khan, M. Sharif, F. Azam, J. H. Shah, T. Umer, and S. Wan, "Diagnosis and recognition of grape leaf diseases: An automated system based on a novel saliency approach and canonical correlation analysis based multiple features fusion," Sustainable Computing: Informatics and Systems, vol. 24, pp. 100349, 2019.

[17] S. Kumar, B. Sharma, V. K. Sharma, H. Sharma, and J. C. Bansal, "Plant leaf disease identification using exponential spider monkey optimization," Sustainable Computing: Informatics and Systems, vol. 28, pp. 100283, 2020.

[18] K. Karada˘g, M. E. Tenekeci, R. Tasaltın, and A. Bilgili, "Detection of pepper fusarium disease using machine learning algorithms based on spectral reflectance," Sustainable Computing: Informatics and Systems, vol. 28, pp. 100299, 2020.

[19] R. Sujatha, Y. S. Kumar, and G. U. Akhil, "Leaf disease detection using image processing," Journal of Chemical and Pharmaceutical Sciences, vol. 10(1), pp. 670–672, 2017.

[20] G. Saleem, M. Akhtar, N. Ahmed, and W. Qureshi, "Automated analysis of visual leaf shape features for plant classification," Computers and Electronics in Agriculture, vol. 157, pp. 270–280, 2019.

[21] V. Singh and A. Misra, "Detection of plant leaf diseases using image segmentation and soft computing techniques," Information Processing in Agriculture, vol. 4(1), pp. 41–49, 2017.

[22] A. K. Dey, M. Sharma, and M. Meshram, "Image processing based leaf rot disease, detection of betel vine (piper betlel.)," Procedia Computer Science, vol. 85, pp. 748–754, 2016.

[23] A. Septiarini, H. Hamdani, H. R. Hatta, and K. Anwar, "Automatic image segmentation of oil palm fruits by applying the contour-based approach," Scientia Horticulturae, vol. 261, pp. 108939, 2020.

[24] N. M. Al-Shakarji, Y. M. Kassim, and K. Palaniappan, "Unsupervised learning method for plant and leaf segmentation," in *2017 IEEE Applied Imagery Pattern Recognition Workshop (AIPR)*, 2017, pp. 1–4.

[25] S. Zhang, X. Wu, Z. You, and L. Zhang, "Leaf image based cucumber disease recognition using sparse representation classification," Computers and Electronics in Agriculture, vol. 134, pp.135–141, 2017.

[26] C. Mattihalli, E. Gedefaye, F. Endalamaw, and A. Necho, "Plant leaf diseases detection and auto-medicine," Internet of Things, vol. 1–2, pp. 67–73, 2018.

[27] A. Septiarini, H. Hamdani, H. R. Hatta, and A. A. Kasim, "Image-based processing for ripeness classification of oil palm fruit," in *2019 5th International Conference on Science in Information Technology (ICSITech)*, 2019, pp. 23–26.

[28] L. Xu, Y. Li, Y. Sun, L. Song, and S. Jin, "Leaf instance segmentation and counting based on deep object detection and segmentation networks," in *2018 Joint 10th International Conference on Soft Computing and Intelligent Systems (SCIS) and 19th International Symposium on Advanced Intelligent Systems (ISIS)*, 2018, pp. 180–185.

[29] X. Pantazi, D. Moshou, and A. Tamouridou, "Automated leaf disease detection in different crop species through image features analysis and one class classifiers," Computers and Electronics in Agriculture, vol. 156, pp. 96–104, 2019.

[30] S. Sabzi, Y. Abbaspour-Gilandeh, and H. Javadikia, "Machine vision system for the automatic segmentation of plants under different lighting conditions," Biosystems Engineering, vol. 161, pp. 157–173, 2017.

[31] J. Zhuang, S. Luo, C. Hou, Y. Tang, Y. He, and X. Xue, "Detection of orchard citrus fruits using a monocular machine vision-based method for automatic fruit picking applications," Computers and Electronics in Agriculture, vol. 152, pp. 64–73, 2018.

[32] L. Jidong, Z. De-An, J. Wei, and D. Shihong, "Recognition of apple fruit in natural environment," Optik , vol. 127(3), pp. 1354–1362, 2016.

[33] K. Kavitha, and A. Kangaiammal, "Correlation-based high distinction feature selection in digital mammogram," Materials Today: Proceedings, *In Press,* 2020.

[34] S. A., Mireei, S. Amini-Pozveh, and M. Nazeri, "Selecting optimal wavelengths for detection of insect infested tomatoes based on simca-aided cfs algorithm," Postharvest Biology and Technology, vol. 123, pp. 22–32, 2017.

[35] A. Septiarini, A. Harjoko, R. Pulungan, and R. Ekantini, "Automated detection of retinal nerve fiber layer by texture-based analysis for glaucoma evaluation," Healthcare Informatics Research, vol. 24(4), pp. 22–32, 2018.