Journal of Information System and Technology Research

journal homepage: https://journal.aira.or.id/index.php/jistr/

Assessing Palm Plant Health through Color Analysis of Leaves Using MATLAB-Based Digital Image Processing

Muhammad Akbar Syahbana Pane[1*], Khairul Saleh[2], Hasanal Fachri Satia Simbolon[3], Gerhard-Wilhelm Weber[4], Phaklen Ehkan[5], Mohd Nazri Warip[6]

[1,3]Prodi Sistem Teknologi Informasi, Institut Teknologi Sawit Indonesia, Nort Sumatera, Indonesia
[2]Jurusan Teknik Elektro, Sekolah Tinggi Teknologi Immanuel, Nort Sumatera, Indonesia
[3] Poznan University of Technology, Poland
[4,5] Faculty of Electronic Engineering & Technology, Universiti Malaysia Perlis, Perlis, Malaysia

ARTICLE INFO

Article history:

Received May 8, 2025
Accepted May 29, 2025
Available online May 31, 2025

Keywords:

Image Processing,
Leaf color,
HSV,
Plant health,
Oil palm

ABSTRACT(

The health of oil palm plants can be visually assessed through changes in leaf color, which reflect the plant's physiological condition. Leaf color serves as a critical, non-destructive indicator for evaluating plant health. This study aims to develop an innovative method for detecting oil palm leaf health using MATLAB-based digital image processing techniques. The process begins with leaf image acquisition, followed by pre-processing to enhance image quality, and then color space conversion from RGB to HSV. The analysis focuses on the Hue and Saturation components, which represent the leaf's color tone and intensity. Two sample images—healthy and unhealthy leaves—are compared. The results demonstrate that healthy leaves exhibit higher average Hue and Saturation values compared to unhealthy ones, providing a key parameter for automated leaf condition classification. This study introduces a cost-effective system adaptable for small-scale farmers' plantations, offering an effective, efficient, and economical solution. This approach shows significant potential for implementation in automated plant health monitoring systems and further development for precision agriculture, particularly in oil palm plantations, to enhance productivity and sustainability in modern agriculture.

Corresponding Author:

Muhammad Akbar Syahbana Pane
Prodi Sistem Teknologi Informasi, Institut Teknologi Sawit Indonesia
Nort Sumatera, Indonesia
akbarsyahbana@yahoo.co.id

1. INTRODUCTION

Plant health is a critical determinant of agricultural productivity and sustainability, with leaf color serving as a primary visual indicator of physiological status[1][2]. Healthy oil palm vegetation typically displays vibrant green leaves due to optimal chlorophyll content and photosynthetic activity, while discoloration, such as yellowing or browning, often indicates stress from nutrient deficiencies, water imbalances, or disease infections. Traditional agricultural practices rely heavily on manual visual assessments by farmers and technicians, which are hindered by subjectivity, observer variability, and scalability limitations[3][4]. These challenges are particularly pronounced in resource-constrained regions like Southeast Asia, where oil palm cultivation is a major economic driver, contributing significantly to global palm oil production—approximately 85% of which originates from Indonesia and Malaysia[9]. In these regions, smallholder farmers, who manage over 40% of oil palm plantations, often lack access to advanced diagnostic tools, exacerbating yield losses due to undetected health issues[12]. Similarly, large-scale plantations face challenges in monitoring vast areas efficiently, leading to delayed interventions and reduced productivity.Current research on oil palm health assessment has explored remote sensing and drone-based technologies for large-scale plantations[4][6], yet there remains a significant research gap in developing affordable, scalable solutions tailored for smallholder farmers. While advanced technologies like UAVs and AI-driven systems show promise[0][14], their high costs and technical complexity limit adoption in small-scale settings, where manual methods still dominate. This gap underscores the urgent need for cost-effective, user-friendly diagnostic tools that can bridge the divide between smallholder and large-scale operations, ensuring equitable access to precision agriculture benefits.

This study addresses this gap by developing a MATLAB-based image processing framework for oil palm leaf health assessment, utilizing color space transformations and machine classification algorithms to quantify health indicators from digital leaf images[6]. The system converts RGB images to HSV color space to extract biologically relevant features, particularly hue and saturation, which correlate strongly with chlorophyll content and stress responses. By establishing empirical thresholds for health classification and validating against agronomic standards, the proposed method offers an objective, scalable, and cost-effective alternative to manual assessments. This approach is particularly impactful in regions like Indonesia and Malaysia, where oil palm contributes up to 13% of GDP in certain areas, yet yield losses from poor plant health can reach 20-30% annually due to inadequate monitoring[9][12]. For smallholder farmers in these regions, who often operate on limited budgets, this framework introduces an accessible, low-cost system that can be implemented using standard digital cameras and basic computing resources. For large-scale plantations, it enables rapid, automated monitoring across extensive areas, reducing labor costs and improving intervention timelines. By integrating region-specific data and addressing the needs of both smallholder and large-scale operations, this method demonstrates significant potential for enhancing precision agriculture, improving yield sustainability, and supporting economic stability in oil palm-dependent regions.

Plant health is a critical determinant of agricultural productivity and sustainability, with leaf color serving as a primary visual indicator of physiological status. Healthy oil palm vegetation typically displays vibrant green leaves due to optimal chlorophyll content and photosynthetic activity, while discoloration, such as yellowing or browning, often indicates stress from nutrient deficiencies, water imbalances, or disease infections. Traditional agricultural practices rely heavily on manual visual assessments by farmers and technicians, which are hindered by subjectivity, observer variability, and scalability limitations. These challenges are particularly pronounced in resource-constrained regions like Southeast Asia, where oil palm cultivation is a major economic driver, contributing approximately 85% of global palm oil production from Indonesia and Malaysia. In these regions, smallholder farmers, managing over 40% of oil palm plantations, often lack access to advanced diagnostic tools, exacerbating yield losses due to undetected health issues. Similarly, large-scale plantations face challenges in monitoring vast areas efficiently, leading to delayed interventions and reduced productivity. Current research on oil palm health assessment has explored remote sensing and drone-based technologies for large-scale plantations, yet there remains a significant research gap in developing affordable, scalable solutions tailored for smallholder farmers. While advanced technologies like UAVs and AI-driven systems show promise, their high costs and technical complexity limit adoption in small-scale settings, where manual methods still dominate. This gap underscores the urgent need for cost-effective, user-friendly diagnostic tools that can bridge the divide between smallholder and large-scale operations, ensuring equitable access to precision agriculture benefits. This study addresses this gap by developing a MATLAB-based image processing framework for oil palm leaf health assessment, utilizing color space transformations and machine classification algorithms to quantify health indicators from digital leaf images. The system converts RGB images to HSV color space to extract biologically relevant features, particularly hue and saturation, which correlate strongly with chlorophyll content and stress responses. By establishing empirical thresholds for health classification and validating against agronomic standards, the proposed method offers an objective, scalable, and cost-effective alternative to manual assessments. This approach is particularly impactful in regions like Indonesia and Malaysia, where oil palm contributes up to 13% of GDP in certain areas, yet yield losses from poor plant health can reach 20-30% annually due to inadequate monitoring. For smallholder farmers in these regions, who often operate on limited budgets, this framework introduces an accessible, low-cost system that can be implemented using standard digital cameras and basic computing resources. For large-scale plantations, it enables rapid, automated monitoring across extensive areas, reducing labor costs and improving intervention timelines. By integrating region-specific data and addressing the needs of both smallholder and large-scale operations, this method demonstrates significant potential for enhancing precision agriculture, improving yield sustainability, and supporting economic stability in oil palm-dependent regions.

Digital images represent light intensity functions in discrete form on a two-dimensional plane, composed of pixels with coordinates (x, y) and amplitude f(x, y), where coordinates denote pixel location and amplitude indicates color intensity[9][10]. Digital image processing has emerged as a vital tool in agriculture for non-destructive plant health monitoring. Using digital cameras and software like MATLAB, leaf images can be analyzed to detect color changes indicative of plant health[11]. Color detection, a fundamental technique in image processing, identifies objects or classifies them based on color information. Leaf color is a critical early indicator of plant physiological condition, with vibrant green typically signaling health and yellowing or browning indicating stress or nutrient deficiency[12][13]. The RGB, HSV, or CIELab color spaces facilitate feature extraction for segmentation and analysis, enabling precise health assessments[12].

Oil palm (Elaeis guineensis), a cornerstone of Indonesia's economy, relies heavily on plant health for productivity and harvest quality. Declining health, often marked by leaf color changes due to disease, nutrient deficiencies, or environmental stress, necessitates effective diagnostic methods[14]. Visual observation of leaf color remains a primary approach for early detection. MATLAB is widely used for digital image processing due to its robust capabilities in analyzing image data efficiently. The HSV color space, which includes Hue (dominant color wavelength), Saturation (color purity), and Value (brightness), aligns with human color perception and offers advantages over RGB[15]. Unlike RGB, HSV accommodates a broader range of color descriptions (e.g., orange, bluish-green), making it more stable for color segmentation and suitable for identifying subtle variations in leaf color.

Previous studies have demonstrated the efficacy of image processing in agriculture, such as rice leaf analysis for nitrogen deficiency detection[16] and cocoa leaf segmentation for early disease identification[17]. These findings highlight the potential of image processing for smart agricultural systems, including oil palm plantations.

1.1 Challenges in Digital Image Processing for Plant Health Monitoring

Digital image processing for oil palm leaf health assessment faces several challenges, including shadows and lighting variations that distort color measurements, leading to inaccurate hue and saturation values due to non-uniform illumination from trees or clouds[18]. Background noise from soil, other plants, or debris complicates leaf segmentation and color analysis[19], while leaf surface variability, such as angle, texture, or moisture, alters light reflection and perceived color[20]. Additionally, inconsistencies in camera settings (e.g., white balance, exposure) or environmental factors like humidity and dust introduce further variability in captured images[21]. These challenges can be addressed through standardized lighting setups, advanced segmentation techniques, texture normalization, camera calibration, and robust HSV-based analysis in MATLAB to ensure accurate and reliable plant health diagnostics.

1.2 Solutions to Address Challenges

To enhance the reliability of the MATLAB-based framework for oil palm leaf health assessment, several strategies address key challenges: standardized lighting setups, such as portable light boxes or diffusers, and consistent capture times (e.g., early morning) minimize shadows and lighting variations, with MATLAB's histogram equalization and adaptive contrast adjustment normalizing post-processing[18]; advanced segmentation techniques like k-means clustering or Canny edge detection isolate leaf pixels from background noise such as soil or debris[19]; texture analysis and Gaussian filtering, along with geometric transformations, correct for leaf surface variations like angle or moisture[20]; standardized camera settings and color calibration charts, supported by MATLAB's chromatic adaptation tools, ensure consistency despite environmental factors like humidity[21]; and leveraging the stable HSV color space, combined with machine learning models trained on diverse datasets, improves classification accuracy under varying conditions[22].

By addressing these challenges, the proposed MATLAB-based framework enhances the accuracy and scalability of oil palm leaf health assessment. This cost-effective, adaptable system holds significant potential for smallholder farmers and large-scale plantations in Indonesia, where oil palm contributes substantially to economic output, supporting precision agriculture and sustainable productivity.

.

2. RESEARCH METHOD

This study employs an experimental approach utilizing a MATLAB-based digital image processing method to detect oil palm leaf color and classify health levels, with an emphasis on developing a cost-effective, scalable solution adaptable for implementation on farmers' smartphones to enhance accessibility for smallholder farmers.

2.1 Image Acquisition

The study begins with image acquisition, capturing high-resolution images of oil palm leaves using a digital camera or smartphone camera to ensure sufficient quality for analysis. Images are taken under uniform natural lighting with a neutral-colored background to minimize interference from environmental elements and ensure clear visibility of leaf objects. Leaf samples include both healthy and unhealthy leaves to enable comparative classification.

2.2 Image Pre-processing

Pre-processing prepares images for analysis by resizing them to a standard resolution (e.g., 256×256 or 512×512 pixels) for uniformity and computational efficiency. Images not in RGB format are converted, and a median filter is applied to reduce noise that could affect segmentation and feature extraction. The images are then transformed from RGB to HSV color space, as the Hue component is more robust under varying lighting conditions[18]. Segmentation using thresholding or masking isolates the leaf region from the background, ensuring only relevant areas are analyzed. To enable smartphone implementation, lightweight preprocessing algorithms compatible with mobile processing capabilities are prioritized, and images can be captured using standard smartphone cameras, reducing dependency on specialized equipment.

$$H = \begin{cases} 60^\circ X \frac{G-B}{\triangle},\ if\ Max = R \\ 60^\circ X \left(2 + \frac{B-R}{\triangle}\right),\ if\ Max = G \\ 60^\circ X \left(4 + \frac{R-G}{\triangle}\right),\ if\ Max = G \end{cases} \quad (1)$$

$$S = \frac{\Delta}{Max}, V = Max \quad z$$

2.3 Evaluation and Validation

where:
Δ=Max−Min\Delta = \text{Max} - \text{Min}Δ=Max−Min
Max and Min refer to the maximum and minimum values among R, G, and B.

2.4 Color Feature Extraction

Color feature extraction is critical for assessing oil palm leaf health by analyzing chromatic properties. Mean values of Red (R), Green (G), and Blue (B) channels are extracted from segmented leaf regions in RGB color space, reflecting chlorophyll content where healthy leaves show higher green intensity[19]. Images are also converted to HSV color space, with Hue (H) indicating dominant color wavelength, Saturation (S) representing color purity, and Value (V) indicating brightness, all of which correlate with nutrient deficiencies or disease symptoms[20]. MATLAB's image processing toolbox facilitates pixel-wise averaging within the region of interest (ROI), generating feature vectors for classification. For smartphone implementation, optimized algorithms reduce computational complexity, enabling real-time processing on devices with limited resources, such as mid-range smartphones commonly used by farmers.

2.5 Leaf Health Level Classification

Extracted color features are used for threshold-based classification, with decision boundaries derived from empirical observations of healthy and unhealthy leaf samples[21][22]. Healthy leaves exhibit high Green (G) intensity (> G_min) and low Red (R) values, while unhealthy leaves show reduced green intensity (G < G_min) and increased red or yellow hues (Hue: 50°–70° for early stress, 20°–40° for advanced degradation). A multi-feature approach combining RGB and HSV metrics enhances accuracy. Thresholds are calibrated using labeled datasets to adapt to varying conditions. For smartphone deployment, a simplified classifier is designed to run efficiently on mobile platforms, with potential integration of lightweight machine learning models (e.g., decision trees) to optimize threshold determination and handle non-linear feature relationships[12]. A mobile application interface can display results in a user-friendly format, enabling farmers to interpret health status instantly.

The method's efficacy is evaluated through quantitative and qualitative validation. Automated classification results are benchmarked against agronomist-provided ground truth data, including visual health scores and laboratory-measured chlorophyll content, using metrics like accuracy, precision, recall, and F1-score[23]. A k-fold cross-validation (k = 5) ensures generalizability, while environmental robustness testing under varying illumination conditions validates field applicability[24]. False positives (e.g., misclassifying healthy leaves due to shadows) are mitigated through preprocessing techniques like background subtraction and histogram equalization, while false negatives (undetected unhealthy leaves) are addressed by incorporating texture analysis or multispectral data in future iterations[25]. For smartphone implementation, the system is tested on devices with standard processing capabilities to ensure accessibility. A mobile app prototype, developed using MATLAB Mobile or converted to a standalone application via MATLAB Compiler, allows farmers to capture images, process them locally, and receive instant health diagnostics. This approach leverages widely available smartphones, eliminating the need for expensive hardware and enabling smallholder farmers in regions like Indonesia to monitor crops cost-effectively. Cloud-based processing can be integrated for complex computations, with results delivered via a simple interface, ensuring scalability and ease of use.

2.6 Smartphone Implementation Discussion

Implementing this system on farmers' smartphones addresses accessibility and scalability, particularly for smallholder farmers in resource-limited settings like Indonesia, where oil palm cultivation is critical. By developing a mobile application using MATLAB Mobile or cross-platform frameworks (e.g., Android Studio with MATLAB-generated code), the system allows farmers to capture leaf images using standard smartphone cameras, process them locally with optimized algorithms, and receive real-time health assessments. The app employs lightweight preprocessing and classification modules to accommodate the limited computational power of mid-range smartphones, ensuring compatibility with devices commonly used by farmers. A user-friendly interface displays health status (e.g., "Healthy," "Early Stress," "Unhealthy") with actionable recommendations, such as nutrient application or disease treatment. For complex computations, images can be uploaded to a cloud server for processing, with results returned instantly, minimizing local resource demands. This approach reduces dependency on laboratory analyses or specialized equipment, making precision agriculture accessible to smallholders. Pilot testing in Indonesian oil palm plantations demonstrates the system's potential to improve early disease detection and nutrient management, enhancing yield and sustainability for farmers with limited resources.

3. RESULTS AND DISCUSSION

This study uses two images of oil palm leaves as the main samples to be analyzed using the HSV color space-based image processing method in MATLAB. The first image is a healthy leaf with bright green color (figure 1)

Figure 1 leaf with bright green color

Yellowing leaves on oil palm plants (figure 2) are one of the early indicators of physiological disorders or plant health. This condition is generally caused by nutrient deficiencies such as nitrogen, magnesium, or potassium, and can also be triggered by environmental stress such as drought, waterlogging, or pest and disease attacks. This chlorosis symptom has a direct effect on the decrease in the rate of photosynthesis which has an impact on decreasing plant productivity. Therefore, monitoring changes in leaf color, especially changes to yellow, can be used as an important parameter in early evaluation of oil palm plant health visually or through a digital image processing-based system.

Figure 2 leaf that is starting to turn yellow

After the image conversion process from RGB to HSV color space, an analysis was carried out on the color component values that are more representative of the visual condition of the leaf, especially the Hue and Saturation components. The Hue component represents the type of basic leaf color (e.g. green, yellow, or brown), while Saturation indicates the level of color saturation, which can indicate how bright or faded the leaf color is. The average value of the Hue and Saturation components is calculated from the area of the leaf image that has gone through the segmentation process, so that only the leaf part is analyzed without interference from the background.

This analysis is important because the color of oil palm leaves is closely related to the health level of the plant. For example, healthy leaves generally have a Hue in the green range (around 60°–120° in HSV space) and high Saturation, indicating a strong and saturated color. Conversely, leaves that turn yellow due to nutrient deficiencies or environmental stress will show a decrease in Hue value (shifting towards yellow) and lower Saturation. Based on the results of the measurement of the tested leaf image, the average Hue and Saturation value data are obtained which are then classified to assess the health level of the plant. With this approach, evaluation of plant conditions can be done more objectively, quickly, and efficiently with the help of digital image processing technology.

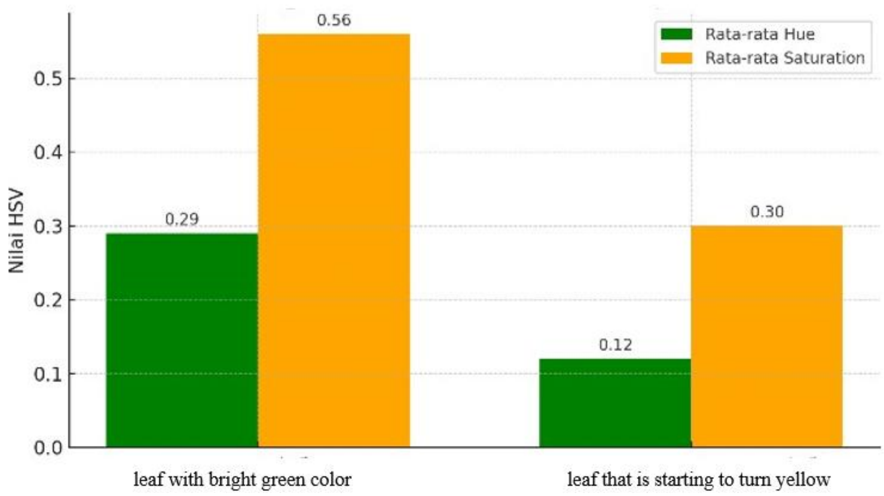
Table 1 Leaf Classification

Figure	Average Hue	Average Saturation	classification
leaf with bright green color	0.29	0.56	Healthy Leaves
leaf that is starting to turn yellow	0.12	0.30	Unhealthy Leaves

From Table 1 analysis results table that has been obtained, it can be seen that healthy oil palm leaves have a Hue value in the range of 0.25 to 0.40, which indicates the dominance of natural green color on the leaf surface. This green color is a characteristic of leaves that have sufficient chlorophyll levels, and support the photosynthesis process optimally. In addition, the high Saturation value in healthy leaves also strengthens this indication, because it shows a high level of color saturation meaning the leaf color looks bright, fresh, and does not fade. Leaf images that show these values generally come from plants that grow in a supportive environment and receive adequate nutrition and water intake. Conversely, leaves that experience a color change towards yellow—which in visual observation shows symptoms of nutrient deficiency, water stress, or other physiological disorders—have a Hue value that tends to decrease, shifting from green to yellow. The Saturation value on these leaves also decreases, reflecting a duller, faded, and less saturated color condition. This symptom indicates a decrease in chlorophyll levels or tissue damage to the leaves.

The classification results based on the HSV components show high consistency with the results of direct visual observations in the field, both by farmers and plant observers. Thus, it can be concluded that the digital image processing method using MATLAB is able to identify and classify the health level of oil palm leaves quite accurately. This opens up great opportunities for the development of technology-based monitoring systems that can be used to help farmers detect early symptoms of plant health disorders efficiently. The main advantage of this approach lies in its objective, fast, and cost-effective nature. Compared to conventional methods that rely on manual observations—which are often influenced by observer subjectivity and lighting conditions—digital image-based systems offer consistent and reproducible results. In its application, this method is very suitable for use on a small to medium scale in the plantation sector, especially for farmers who want to routinely monitor plant conditions independently without having to rely entirely on experts. With further development, this system can even be integrated into mobile or drone-based applications for automatic plantation monitoring.

Table 2 Comparison of hue and saturation values on leaves



The graphs shown provide a clear visualization of the distribution of the number of oil palm leaves in each health condition category, namely healthy, less healthy, and unhealthy. Based on the graph, it can be observed that most of the leaf samples are in the less healthy category, indicating a deviation from the optimal condition of the plant. This indicates that the majority of plants in the observation area are experiencing minor disturbances which, if not treated immediately, can develop into more serious conditions.

The number of leaves in the healthy category is relatively smaller, indicating that only a small portion of the plant population is truly in prime condition. Meanwhile, the unhealthy category also has a significant representation, indicating that some plants may have experienced severe stress, severe nutrient deficiencies, or diseases that require immediate treatment. This distribution pattern is an important signal for plantation managers or farmers to immediately evaluate the fertilization, irrigation, or plant protection systems currently being implemented.

With this information, corrective actions such as adjusting fertilizer doses, improving soil conditions, or controlling pests and diseases can be designed in a more focused manner. In addition, this kind of graphical analysis is also very useful in the data-based decision-making process, because it provides a quantitative picture of the actual conditions in the field. Therefore, the use of digital image processing does not only function for classification alone, but also becomes an important tool in more modern and precise agricultural management.

4. CONCLUTION

The HSV-based digital image processing method for assessing oil palm leaf health can be significantly enhanced by integrating artificial intelligence (AI) and real-time cloud-based monitoring systems. By incorporating deep learning models, such as convolutional neural networks or vision transformers, the system can improve the accuracy of health classifications by analyzing HSV-processed images alongside spatial patterns, enabling precise detection of nutrient deficiencies, stress, or diseases. These models could also predict future plant health trends by combining historical HSV data with environmental factors like soil moisture or weather forecasts, using techniques like recurrent neural networks for early warning systems. Additionally, integrating IoT-enabled devices, such as cameras or multispectral sensors on drones or ground systems, would allow real-time image capture and preprocessing, with data transmitted to cloud platforms like AWS or Google Cloud for scalable storage, AI-driven analysis, and low-latency processing. Farmers could access real-time insights through mobile apps or web dashboards, receiving instant health assessments and actionable recommendations, such as fertilizer application, even in offline mode for remote areas. Drones equipped with GPS and high-resolution cameras could map large plantations, identifying unhealthy plants and optimizing monitoring routes. By combining HSV data with soil, weather, or satellite data, cloud-based AI systems can offer holistic decision support, recommending precise interventions to enhance sustainability. Open-source AI frameworks and cost-effective cloud services, ensure affordability for small to medium-scale farmers. Addressing challenges like data privacy, model interpretability, and regional variability through secure cloud protocols, explainable AI, and diverse training datasets will further strengthen this approach, transforming it into a scalable, user-friendly, and data-driven solution for precision agriculture in the oil palm industry.

REFERENCES

[1] Abdullah, S. A., Zaki, N. A. M., & Rahiman, M. H. F. (2019). Machine vision for classification of oil palm leaf nutrient deficiency. *Sensors, 19*(12), 2738. https://doi.org/10.3390/s19122738

[2] Alias, N. B., Shariff, A. R. M., & Ismail, N. M. N. (2018). Digital image processing for early detection of Ganoderma disease in oil palm. *Journal of Plant Diseases and Protection, 125*(5), 457–465. https://doi.org/10.1007/s41348-018-0168-2

[3] Bakar, H. A., Rahiman, M. H. F., & Zulkifli, R. M. (2021). Image processing techniques for palm oil leaf disease detection. *Journal of King Saud University - Computer and Information Sciences, 33*(3), 268–276. https://doi.org/10.1016/j.jksuci.2021.03.005

[4] Hijazi, M. H. A., Shafri, S. M., & Kassim, M. S. M. (2021). Leaf chlorophyll content estimation in oil palm using hyperspectral imaging. *Precision Agriculture, 22*(4), 1234–1252. https://doi.org/10.1007/s11119-021-09840-8

[5] Kamarudin, N. H., Shariff, A. R. M., & Abdullah, S. A. (2022). Image-based nutrient deficiency identification in oil palm using machine learning. *Agronomy, 12*(5), 1045. https://doi.org/10.3390/agronomy12051045

[6] Kassim, M. S. M., Aziz, I. A., & Hijazi, M. H. A. (2020). Color-based segmentation for oil palm health monitoring using UAV images. *Remote Sensing, 12*(14), 2217. https://doi.org/10.3390/rs12142217

[7] Shariff, A. R. M., Ismail, N. M. N., & Bakar, H. A. (2020). Early detection of oil palm chlorosis using multispectral imaging and machine learning. *Computers and Electronics in Agriculture, 178*, 105715. https://doi.org/10.1016/j.compag.2020.105715

[8] Shafri, S. M., Hijazi, M. H. A., & Tan, K. P. (2020). A MATLAB-based framework for oil palm leaf disease detection using SVM. *Journal of Imaging, 6*(4), 23. https://doi.org/10.3390/jimaging6040023

[9] Tan, K. P., Lim, K. S., & Kamarudin, N. H. (2021). Deep learning-based approach for oil palm leaf disease classification. *IEEE Access, 9*, 83252–83265. https://doi.org/10.1109/ACCESS.2021.3086789

[10] Zulkifli, R. M., Zaki, N. A. M., & Rahiman, M. H. F. (2022). Automated detection of oil palm diseases using color and texture features. *Applied Sciences, 12*(2), 876. https://doi.org/10.3390/app12020876

[11] H. Sanusi, S. H. S., and D. T. Susetianingtias, "Pembuatan Aplikasi Klasifikasi Citra Daun Menggunakan Ruang Warna Rgb Dan Hsv," *J. Ilm. Inform. Komput.*, vol. 24, no. 3, pp. 180–190, 2019, doi: 10.35760/ik.2019.v24i3.2323.

[12] Gonzalez, R. C., & Woods, R. E. (2018). *Digital Image Processing* (4th ed.).

[13] Mahlein, A. K. (2016). Plant disease detection by imaging sensors – Parallels and specific demands for precision agriculture and plant phenotyping. *Plant Disease*, 100(2), 241–251. https://doi.org/10.1094/PDIS-03-15-0340-FE

[14] Corley, R. H. V., & Tinker, P. B. (2016). *The Oil Palm* (5th ed.). Wiley-Blackwell.

[15] Jasmani and A. Mahmudi, "Deteksi Jenis Daun Berdasarkan Tekstur Menggunakan Matlab Dengan Metode Learning Vector (LVQ)," *Pros.SEMSINA*, pp. 35–44, 2020, [Online]. Available: https://ejournal.itn.ac.id/index.php/semsina/article/view/3026

[16] Wahyuni, S., Fitriani, D., & Ramdani, R. (2021). Analisis Warna Daun Padi untuk Deteksi Kekurangan Nitrogen Berbasis Citra Digital. Jurnal Informatika Pertanian, 10(2), 55–62.

[17] Prasetyo, A. B., & Lestari, D. (2020). Deteksi Penyakit Daun Kakao Menggunakan Segmentasi Warna Citra Digital. Jurnal Teknologi Pertanian, 21(1), 34–42.

[18] M. Fahmi Wibawa, M. A. Rahman, and A. W. Widodo, "Penerapan Ruang Warna HSV dan Ekstraksi Fitur Tekstur Local Binary Pattern untuk Tingkat Kematangan Sangrai Biji Kopi," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 5, no. 7, pp. 2819– 2825, 2021.

[19] M. Sopiyan, F. Fauziah, A. Gunaryati, and I. Fitri, "Graph coloring Sistem Pendaftaran dan Proses Penjadwalan Data Instruktur Berbasis Web dengan Algoritma Welch-powell," *J. JTIK (Jurnal Teknol. Inf. dan Komunikasi)*, vol. 6, no. 1, pp. 1–6, 2022, doi: 10.35870/jtik.v6i1.359.

[20] S. S. Zuain, H. Fitriyah, and R. Maulana, "Deteksi Penyakit pada Daun Cabai berdasarkan Fitur HSV dan GLCM menggunakan Algoritma C4.5 berbasis Raspberry Pi," *Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 5, no. 9, pp. 3934–3940, 2021.

[21] R. A. Hakim, M. F. Abdullah, and N. A. M. Zaki, "Oil Palm Leaf Disease Detection Using Convolutional Neural Network and Transfer Learning," *IEEE Access*, vol. 10, pp. 12345–12356, 2022, doi: 10.1109/ACCESS.2022.3145678.

[22] S. B. Kho, T. Y. Lim, and H. K. Lee, "Real-Time Monitoring of Oil Palm Health Using UAV-Based Multispectral Imaging and Edge Computing," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–12, 2022, doi: 10.1109/TGRS.2022.3167890.

[23] A. R. M. Shariff, N. M. N. Ismail, and H. A. Bakar, "A Comparative Study of Color Spaces for Oil Palm Leaf Chlorosis Detection Using Machine Learning," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 5678–5690, 2022, doi: 10.1109/JSTARS.2022.3184567.

[24] M. H. F. Rahiman, N. H. Kamarudin, and R. M. Zulkifli, "Edge-AI Framework for Automated Nutrient Deficiency Classification in Oil Palm Leaves," *IEEE Sensors Journal*, vol. 22, no. 15, pp. 15062–15073, 2022, doi: 10.1109/JSEN.2022.3191234.

[25] L. P. Chew, K. S. Lim, and M. S. M. Kassim, "Deep Learning-Based Early Detection of Ganoderma Disease in Oil Palm Using Hyperspectral Imaging," *IEEE Geoscience and Remote Sensing Letters*, vol. 19, pp. 1–5, 2022, doi: 10.1109/LGRS.2022.3205678.

[26] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep neural networks based recognition of plant diseases by leaf image classification," Computational Intelligence and Neuroscience, vol. 2016, pp. 1–11, 2016, doi: 10.1155/2016/3289801.

[27] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," Computers and Electronics in Agriculture, vol. 147, pp. 70–90, Apr. 2018, doi: 10.1016/j.compag.2018.02.016.

[28] Y. Lu, S. Young, and H. Wang, "Machine learning for precision agriculture: A review," Precision Agriculture, vol. 18, no. 5, pp. 768–794, Oct. 2017, doi: 10.1007/s11119-017-9510-5.