Characteristics of Spectral Values and Spatial Distribution of Oil Palm Health in Relation to Productivity at PT Kayung Agro Lestari Plantation

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Abstract *Oil palm plantations support the non-oil and gas economy in Indonesia, but in business practice oil palm plantations still face challenges in maintaining the health of oil palm plants. Currently, one of the main problems is the large number of unhealthy trees that can directly affect neighboring trees. If an overview of the plantation area can be identified quickly and in detail, this information can be integrated into advanced planning in oil palm planta-tion management. To address this problem, this research presents a system for detecting the health of oil palm plants by utilizing deep learning tech-niques in collaboration with UAV orthophotos and descriptive analysis to see the relationship to the productivity of the oil palm fruit produced. The appli-cation of semantic segmentation using the U-net algorithm aims to identify the palm tree canopy, eliminate the bias between the tree canopy and the ob-jects below it and facilitate the classification of plant health. In the next stage, the algorithm used is a support vector machine (SVM) for accurate plant health classification with a fairly high value. The evaluation results of the classification of oil palm plant health gave satisfactory results with F1-score values in blocks D52 and D53 of 71.4% and in blocks E58 and E59 reaching 81.3%. It is known that the difference in the value of the F1-score results is influenced by the quality of the multispectral aerial photographs used. In multispectral aerial photographs in blocks D52 and D53 there is some noise that makes the difference in the value obtained. The relationship between oil palm plant health conditions and oil palm fruit productivity is carried out using productivity data in oil palm plant blocks with vulnerable months from January to June in 2024. The relationship between oil palm health conditions and productivity shows a tendency that the number of un-healthy trees correlates with decreased productivity, as seen in blocks D52 and E58. Conversely, blocks with fewer unhealthy trees, such as D53, show increased productivity. Although pests and diseases have been shown to have a significant impact, productivity is also influenced by other factors, such as land characteristics, climate, and harvest management, so a holistic approach is needed for optimal management.*

Keywords: Health Mapping, Oil Palm Plants, Productivity, Semantic Segmentation.

Introduction

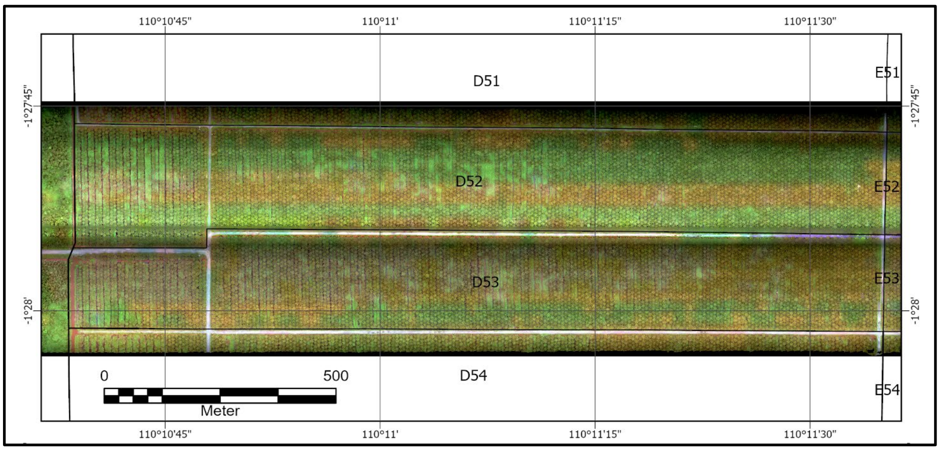
West Kalimantan Province ranks second in terms of the region with the largest oil palm plantation area in Indonesia. In 2023, the province recorded an increase in area of 128,135 hectares compared to the previous year (BPS, 2024). Despite having a huge plantation area, West Kalimantan's productivity is still lower than that of Cen-tral Kalimantan, which has a smaller area (BPS, 2024). One of the factors affecting the low productivity is the health of oil palm plants. Healthy plants are needed to achieve maximum genetic potential in production (Pangestu et al., 2023). Plant damage is the main indicator of compromised health, which can be caused by dis-ease, nutrient deficiencies, or pest attacks (Pertiwi et al., 2019). Nutrient deficien-cies are usually addressed through fertilization based on the results of leaf and soil content analysis (Afifudin et al, 2023), while attacks by leaf-eating pests such as caterpillars and leaf diseases can reduce leaf surface area and reduce photosynthetic rates (Corley & Tinker, 2003).

The economic viability of plantation agriculture is intrinsically linked to tree health, where each specimen represents a significant asset. A critical operational challenge is the absence of detailed monitoring, which leads to suboptimal fertilizer management, financial deficits, and depressed yields. Evidence suggests that ad-vanced technologies are underutilized in addressing these issues. For instance, Khan et al. (2021) highlight that the deployment of UAVs and machine learning for crucial applications in oil palm mapping, such as disease detection and yield monitoring, is still in its nascent stages.

Consequently, an integrated approach leveraging semantic segmentation, spectral analysis, and Support Vector Machine (SVM) classification is required to enhance the accuracy and efficiency of crop health assessment. Such a methodology facili-tates the extraction of pure pixel values, mitigating bias within the mapping process.

Methodology

This research was conducted on four blocks of PT Kayung Agro Lestari planta-tions, namely blocks D52, D53, E58, and E59. Block selection was based on differ-ences in external and internal factors. External factors refer to land characteristics, while internal factors relate to the management team of each block. Blocks D52 and D53 have two soil types with a peat land type, while blocks E58 and E59 have three soil types with a sandy land type. In addition, there are differences in technical cul-ture management between the two groups of blocks. This variation was chosen to observe the diversity of oil palm crop conditions at the study site.



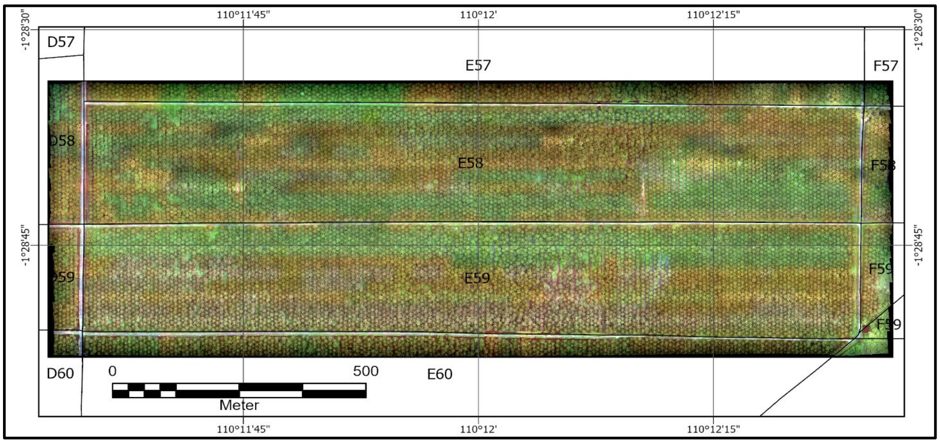


Figure 1 : Aerial Photo of Block D52, D53, E58 and E59 PT Kayung Agro Lestari

To improve the precision and efficiency of oil palm plant health assessment, this research integrates two spatial analysis techniques. A deep learning-based object detection method was selected for its innovative capacity and potential to address multi-class classification challenges in oil palm (Kipli et al, 2023). Complementing this, Support Vector Machines (SVM) were employed for pixel classification, lever-aging established plant health class labels (Widyaningsih et al., 2023).

The research followed a systematic progression through preparation, data collec-tion, processing, accuracy testing, and analysis. During data collection, we conduct-ed field surveys to acquire primary data, including multispectral aerial imagery from UAVs, spectral values via handheld spectrometers, and plant health location points. These aerial images were then processed using Agisoft Metashape software to gen-erate high-resolution orthomosaic images. Subsequently, canopy labeling and spec-tral value extraction were performed in Visual Studio Code, with validation against the spectrometer data.

Subsequent processing utilized semantic segmentation, employing a U-Net archi-tecture with an EfficientNetB7 backbone. Data preparation involved labeling 30% of the dataset, which was then augmented to form the training, validation, and test sets. Segmentation accuracy was quantified using the Intersection over Union (IoU) met-ric. After segmentation, plant health data underwent classification via an SVM algo-rithm, informed by field survey results and defined healthy and unhealthy tree cate-gories. Accuracy evaluation was conducted using the coefficient matrix method in Visual Studio Code. The concluding phase involved spatial and descriptive analysis to determine how plant health distribution impacts plantation productivity at PT KAL, including analyzing canopy spread and the correlation between plant health and harvest outcomes.

a. Data Collection and Sampling

The investigation into oil palm plant health was supported by a suite of tools and materials for both primary and secondary data collection. For primary field data, an Unmanned Aerial Vehicle (UAV) was instrumental, capturing 7 cm resolution mul-tispectral aerial photographs in March 2024. Concurrently, a handheld spectrometer was employed on the same day to directly acquire spectral values from oil palm leaves, providing crucial ground-truth data.

To complement our primary data collection, visual field surveys were conducted for ground truthing, documenting and pinpointing the locations of healthy and dis-eased oil palm plants. Secondary data included Cultivation Rights Title (HGU) maps, detailing block specifics, and palm fruit production data from 2019 to 2024, obtained from PT Austindo Nusantara Jaya (PT ANJ). Our research utilized three primary variable types: (1) oil palm plant health, classified into healthy and sick states; (2) spectral value characteristics, represented by statistical measures of leaf spectral properties; and (3) plantation productivity, expressed as fresh fruit bunch (FFB) yield in tonnes per hectare. These variables were fundamental to the subse-quent data processing and plant health classification.

Random sampling was utilized for sample selection in this research, with the sample size determined by Slovin's formula using a 10% margin of error. Our target population consisted of 20,265 trees spread across four distinct blocks, categorized by their respective soil types. The calculation yielded a sample size of 110 points, deemed adequate to represent the overall population effectively. This approach was adopted to guarantee both the efficiency and accuracy of data collection within the defined study region.

b. Spectral Characteristics

The concept of spectral characteristics is based on the principle that objects re-flect or absorb light differently across specific wavelength ranges. These differences are influenced by an object's chemical properties and surface morphology (Zhang & Kovacs, 1998 in Xue & Su, 2017). In this study, we utilized spectral characteristics to differentiate between healthy and unhealthy oil palm trees by analyzing the light reflectance values of their canopies.

Reflectance data was obtained from two main sources: a handheld spectrometer and multispectral aerial imagery from UAV mapping. Tree canopy segmentation, implemented with a U-Net architecture, enabled the extraction of individual pixel reflectance values from leaf areas within the imagery. We then analyzed these val-ues by calculating the average reflectance, margin of error, and confidence interval for each tree class. To ensure the representativeness of spectral reflectance, a leaf area masking technique was applied. The rasterio function played a critical role in accurately defining the wavelength for each band in both the UAV and handheld spectrometer datasets. Ultimately, a comparative analysis of the derived spectral response values facilitated the identification of characteristic differences between healthy and unhealthy oil palms.

c. Semantic Segmentation

Semantic segmentation is crucial for providing detailed spatial data and presents an ongoing challenge in image-based object separation, particularly in oil palm plan-tations (Widyaningsih et al., 2023). Unlike object detection, which merely provides bounding box locations, semantic segmentation precisely labels each image pixel according to its class, offering more detailed object boundaries and areas (Abramov, 2024). Studies by Herlawati et al. (2022) demonstrate that semantic segmentation models can achieve rapid and accurate classification, with reported accuracy rates up to 95%. This contrasts with object detection methods, which typically average around 85% accuracy (Ye et al., 2018), thereby demonstrating the superior precision of pixel-based classification.

Developed for detailed feature recognition, reduced training time, and efficacy with imperfect image annotations (Yu et al., 2015), semantic segmentation architec-tures have seen various algorithmic approaches, including texton forest and random forest-based classifiers (Sinan, 2022). Nevertheless, challenges persist, especially in segmenting vegetation images like oil palm, which feature irregular shapes and di-verse patterns and colors. The high dimensionality of input data further compounds this complexity, making segmentation more intricate (Sinaga & Kamal, 2019). Thus, despite the continuous evolution of machine learning technology, ongoing efforts to develop more robust algorithms are essential for achieving optimal segmentation.

d. Support Vector Machine

The application of the Support Vector Machine (SVM) algorithm in remote sens-ing exhibits performance variations contingent on data type, application, spatial resolution, and feature extraction methods (Sheykhmousa et al., 2020). Prior re-search indicates SVM's strong classification accuracy, reaching up to 93.75%, a notable improvement over discriminant analysis (90%) and decision tree algorithms (90.31%) (Foody & Mathur, 2004). Moreover, Liu's (2017) study, "SVM or Deep Learning?", revealed SVM's capability to surpass Stacked Autoencoder (SAE) in remote sensing image classification. A significant benefit of SVM is its inherent ability to model complex non-linear boundaries, making it exceptionally effective for spectral classification, particularly in the near-infrared spectrum (Devos et al, 2009).

In this study, oil palm plant health classification followed a two-class approach, distinguishing between healthy and unhealthy plants, as developed by Yarak et al. (2021). Class determination was based on field observations with expert involve-ment to ensure sample point accuracy. The Head of the Research and Development (RnD) Team at PT Kayung Agro Lestari, competent in assessing plant physiological conditions, provided crucial assistance.

Support Vector Machine (SVM) was selected as the classification method due to its ability to separate data classes with optimal margins. The algorithm functions by identifying the best hyperplane that maximizes the distance between classes, with support vectors (nearby data points) determining the dividing line's position and orientation (Talib et al., 2024).

SVM's effectiveness in managing non-linear data makes it well-suited for classifying plant health conditions based on remote sensing spectral data.

Results and Discussion

a. Spectral Reflectance Characteristics

The concept of spectral characteristics posits that each object uniquely reflects or absorbs light across specific wavelength ranges, influenced by its physical and chemical composition. Figure 2 exemplifies this principle by presenting the spectral reflectance response of healthy and unhealthy oil palm plants, data collected using both UAV multispectral imagery and a handheld spectrometer, both operating within the 450 nm to 800 nm wavelength range.

Analysis of the UAV multispectral data revealed that while both healthy and un-healthy trees exhibited their lowest reflectance between 450 nm and 650 nm, a sig-nificant divergence emerged in the 700–800 nm range. In this region, healthy trees consistently showed higher reflectance values compared to their unhealthy counter-parts. This finding underscores the strong sensitivity of the 700–800 nm wavelength range in distinguishing between different oil palm health conditions.

In contrast, the handheld spectrometer data showed pronounced differences in re-flectance values within the 500-550 nm and 650-700 nm ranges, where healthy plants once again exhibited greater reflectance than unhealthy plants. Such varia-tions in oil palm spectral values can stem from several factors, including water con-tent in leaf tissue, chemical composition, and other inherent properties of the oil palm. While reflectance values differed between healthy and unhealthy classes, their overall spectral patterns displayed similarities, implying that visual differentiation between the classes was not particularly striking.

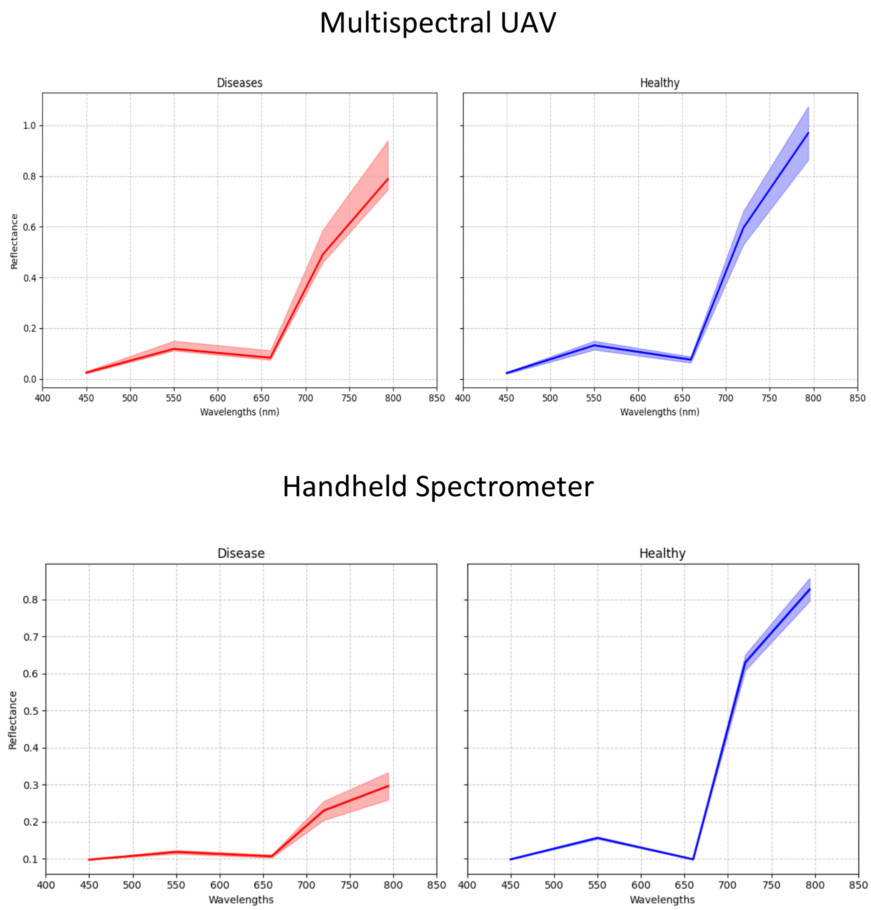


Figure 2 : Spectral Value Response in Healthy and Unhealthy Tree Classes.

The results of comparing spectral reflectance values between healthy and un-healthy oil palm trees across UAV multispectral bands are detailed in Figure 3. Spe-cifically, in the blue band, unhealthy trees demonstrated a slightly increased reflec-tance compared to healthy trees. For the green band, healthy trees did show higher reflectance, but the magnitude of this difference was minor and not particularly sig-nificant. A similar trend was observed in the red band, where unhealthy trees again displayed higher reflectance values, albeit with a greater intensity than seen in the blue band.

The red edge and near-infrared (NIR) bands revealed more pronounced differ-ences, with healthy trees consistently exhibiting higher spectral reflectance than unhealthy ones. These bands displayed the largest reflectance gap among all visual bands, indicating enhanced sensitivity for distinguishing plant health conditions. However, due to the relatively small inter-class reflectance difference, particularly when considering measurement error, careful interpretation of these results is essen-tial.

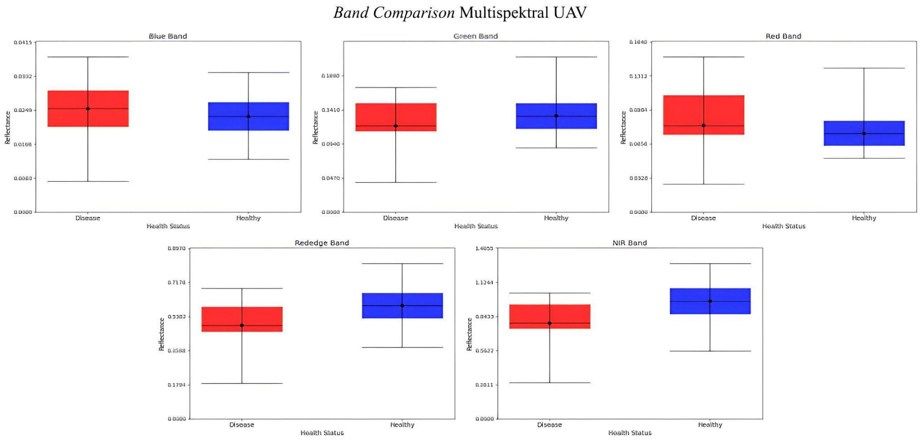


Figure 3 : Comparison of Spectral Band Values in UAV Multispectral on Healthy and Unhealthy Tree Classes.

Figure 4 illustrates the comparative spectral values of healthy and unhealthy trees based on handheld spectrometer data. In the blue band, the reflectance difference between the two classes was not significant. However, the green band showed a clearer distinction, with healthy trees reaching approximately 0.15 reflectance while unhealthy trees were around 0.125. The red band indicated slightly higher reflec-tance for unhealthy trees, though the values remained close.

The most striking differences were observed in the red edge and NIR bands. Healthy trees in the red edge band exhibited a reflectance of 0.6, compared to 0.2 for unhealthy trees. A similar pattern was seen in the NIR band, with healthy trees at 0.8 reflectance and unhealthy trees at 0.2. These findings suggest a high potential for the green, red edge, and NIR bands in early plant health detection, aligning with Shafri et al (2009) and M.A. (2020) who emphasize these regions' effectiveness for identi-fying healthy vegetation and assessing its condition.

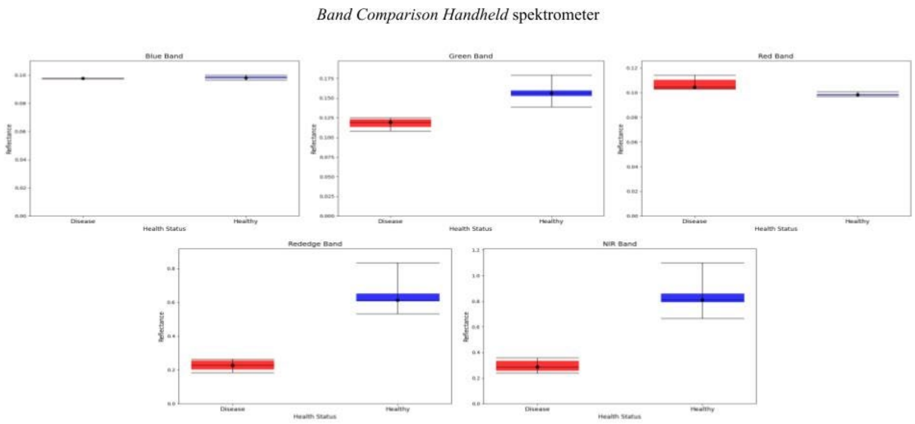


Figure 4 : Comparison of Spectral Band Values on Handheld Spectrometer for Healthy and Unhealthy Tree Classes.

Significant disparities emerged from the spectral value data processing between the UAV multispectral imagery and the handheld spectrometer. The UAV data dis-played a relatively homogenous spectral reflectance pattern across all wavelengths, lacking substantial variation between bands. In contrast, the handheld spectrometer data provided more distinct differences, particularly in the 450-550 nm and 650-800 nm wavelength ranges, highlighting its greater sensitivity for distinguishing plant conditions.

Collectively, the results from spectral response analysis and reflectance value comparisons suggest that UAV multispectral imagery currently lacks the full capa-bility to accurately classify oil palm plant health. Therefore, incorporating addition-al data support, such as field observations, is necessary for robust classification, or transitioning to technologies with superior spectral resolution, like hyperspectral UAVs, could improve the precision of plant health detection.

b. Oil Palm Canopy Segmentation

Semantic segmentation of aerial images using a U-Net architecture necessitates the strategic division of labeled data into training, validation, and test sets. This approach is fundamental to cultivate a model that genuinely understands object characteristics, moving beyond rote memorization of patterns. The training data (70%) is employed to enable the model to learn underlying patterns and iteratively refine its weights and biases to minimize prediction errors. A 15% validation set is dedicated to real-time performance monitoring during training, a critical step to mitigate overfitting. The final 15% test set then provides an unbiased evaluation of the model's generalization capability on novel data. To ensure consistent and accu-rate model input, pixel value adjustments were also meticulously performed between the label data and aerial imagery.

Our semantic segmentation model was built using multispectral images captured by a UAV. It utilizes the U-Net architecture as its deep learning core, with Effi-cientNetB7 serving as the backbone for feature extraction. TensorFlow was the pri-mary platform for model development and training. This architecture was chosen for its capability to identify objects with complex pixel structures, such as oil palm canopies, within imagery.

The model's segmentation accuracy was evaluated using the Intersection over Un-ion (IoU) metric. The training IoU value reached 0.92, which is considered excellent in assessing the model's learning capability. The validation IoU value was 0.63, sur-passing the 0.5 threshold referenced in Prasvita et al (2024) study. Across 50 train-ing runs, the model demonstrated reliable performance in distinguishing between oil palm and non-oil palm plant objects.

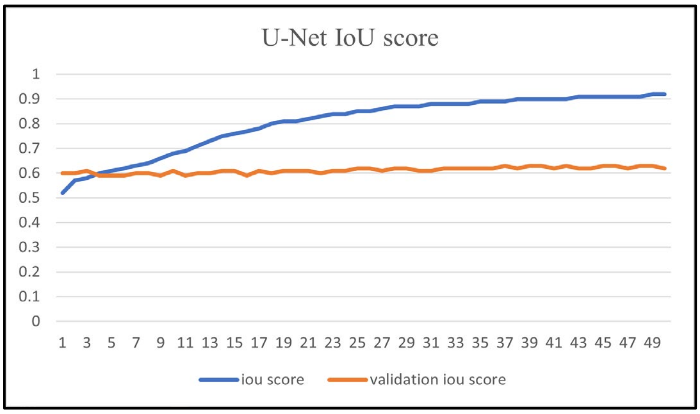


Figure 5 : Intersection over Union (IoU) Performance – Oil Palm Canopy Semantic Segmentation.

c. Oil Palm Health Classification Performance

Our classification of oil palm plant health in Block D52 indicated a significant dominance of healthy conditions, with 77% of plants categorized as healthy and primarily situated in the northern and southern sections. The 23% of unhealthy plants were notably concentrated in the block's central region, forming a clustered distribution suggestive of an uneven, localized disturbance. This overall healthy plant population in D52 signifies a promising potential for high fruit production. For Block D53, the classification also highlighted a strong prevalence of healthy plants at 79%, distributed from the eastern to central areas.

The 21% of unhealthy plants were predominantly found in the western part, exhibiting both a clustered pattern on the immediate western side and a more random spread towards the central-western areas. These findings from both blocks consistently reflect a majority of healthy conditions, signaling a positive outlook for palm fruit production.

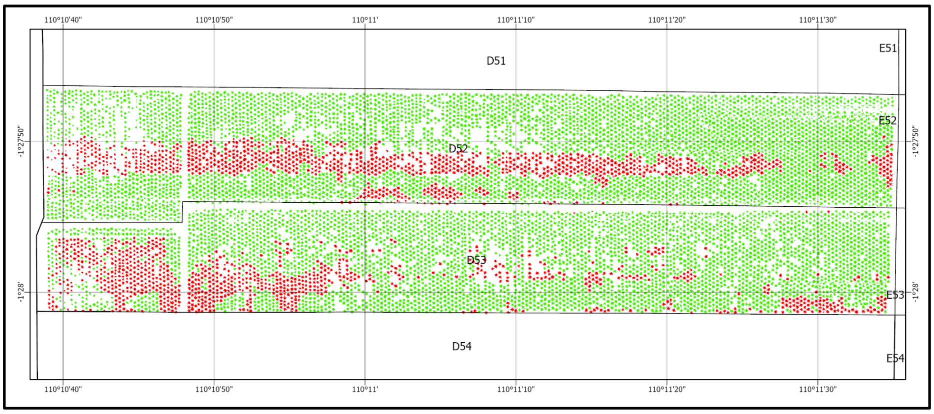


Figure 6 : Spatial Distribution of Oil Palm Health in Blocks D52 and D53.

Block E58 presented a similar health profile to the previously discussed areas, with 76% of its oil palm plants classified as healthy and dispersed across the north-ern and southern regions. The remaining 24% of unhealthy plants were scattered in the western and northeastern parts, predominantly exhibiting a clumped distribution, though some random scattering was also observed. Overall, the health status of plants in this block suggests sustained good productivity. In contrast, classification results for Block E59 revealed a significant dominance of unhealthy conditions at 55%, particularly concentrated in the southern area. Healthy plants constituted only 45% of the block and were scattered in the northern part. The distribution of un-healthy plants in this block largely showed a clustered pattern. This prevailing un-healthy condition suggests a decline in overall plant health, with the potential to negatively impact oil palm fruit production.

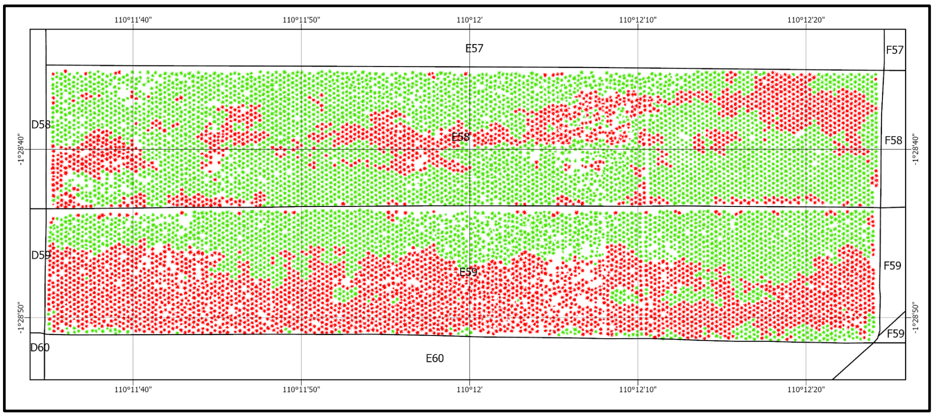


Figure 7 : Spatial Distribution of Oil Palm Health in Blocks E58 and E59.

The results of accuracy testing for blocks D52 and D53, derived from a confusion matrix, showed an accuracy value of 60%, which signifies a reasonably good align-ment between the model's predictions and the ground truth. A precision of 100% was achieved, confirming that every instance predicted as a healthy plant was indeed from the healthy class, thus eliminating false positives. However, recall was record-ed at 56.2%, indicating that the model successfully identified approximately half of all truly healthy plants. The resulting F1-score of 71.4% reflects a balanced perfor-mance between precision and recall, suggesting the classification model's overall effectiveness.

Table 1 : Accuracy Metrics of Oil Palm Health Classification in Blocks D52 and D53.

	Accuracy	*Precision*	*Recall*	**F1-***score*
Nilai	0.60	1.00	0.56	0.71

Accuracy testing conducted on blocks E58 and E59 using a confusion matrix re-vealed an accuracy of 78.7%, which reflects a good level of agreement between the model's predictions and the actual data. A particularly strong aspect was the preci-sion, reaching 94.1%, indicating that nearly all positive identifications of healthy plants were correct. Furthermore, a recall of 70.6% means the model successfully captured over two-thirds of all truly healthy plants. The F1-score, at 81.3%, under-scores an optimal balance between these metrics, thereby signifying the classifica-tion model's excellent overall performance.

Table 2 : Accuracy Metrics of Oil Palm Health Classification in Blocks E58 and E59.

	Accuracy	*Precision*	*Recall*	**F1-***score*
Nilai	0.78	0.94	0.70	0.81

d. Oil Palm Health Spatial Distribution and its Relationship with Plantation Productivity

The profound impact of diseases on oil palm plantation production is well-documented. Saipol et al (2022), in "Significant Oil Palm Diseases Impeding Global Industry," and Chung (2012), in "Effect of Pests and Diseases on Oil Palm Yield," both assert that pest and disease attacks can lead to substantial yield reductions. This consensus highlights the critical need for effective plant health management to op-timize per-hectare production. Our findings align with these studies, strongly indi-cating a direct correlation between the prevalence of unhealthy trees and diminished oil palm productivity.

During March, Block D52 led in productivity at 2.41 tonnes/ha, while Block D53 showed the lowest at 0.94 tonnes/ha. By April, a general trend of decline emerged across three blocks: D52 experienced a significant 49.9% reduction (coinciding with 1,263 unhealthy trees), E58 saw a 30.6% decrease (1,035 unhealthy trees), and E59 declined by 10.5% despite having the highest count of unhealthy trees (2,746). In contrast, Block D53 was the sole block to exhibit an increase in April, soaring by 114.8%, notably possessing the fewest unhealthy trees at 982. By June 2024, D52 and E58 continued their downward trend since March (down 47% and 22% respec-tively), while D53 recorded the highest surge of 57%, trailed by E59 with a 9% in-crease. This pattern consistently supports an inverse relationship between the num-ber of unhealthy trees and oil palm plantation product.

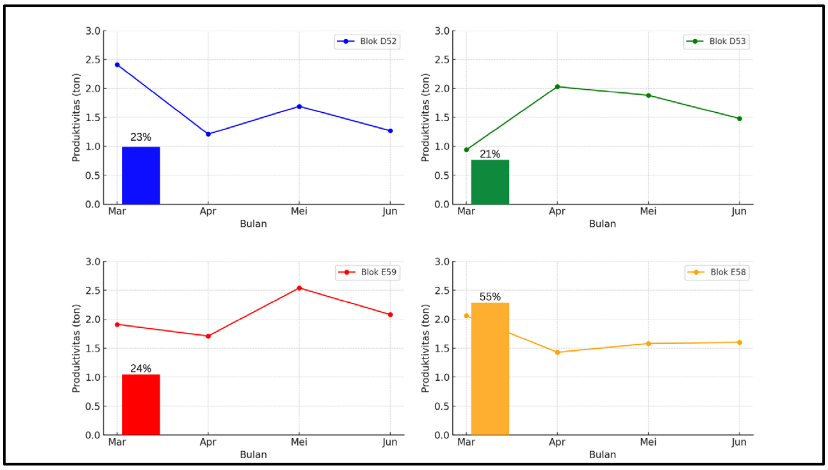


Figure 8 : Oil Palm Fruit Productivity (Tonnes/Ha) vs. Percentage of Unhealthy Trees.

Our analysis of oil palm plant health distribution and its effect on productivity across four blocks at PT Kayung Agro Lestari plantation reveals distinct patterns. Block E59, despite having nearly 55% unhealthy oil palm plants, surprisingly rec-orded the highest average productivity of 2.06 tonnes/ha. This appears to contradict observations in blocks E58, D53, and D52, which possess a higher proportion of healthy plants yet only achieved average productivity values between 1.58-1.67 tonnes/ha. Nevertheless, an examination of productivity trends over the three months following data collection provides a clearer picture: a strong inverse correlation between the number of unhealthy trees and oil palm productivity becomes apparent. Specifically, blocks D52 and E58 experienced notable productivity declines concur-rent with a high count of unhealthy trees, whereas Block D53, with the lowest num-ber of unhealthy trees, demonstrated a consistent increase in productivity.

Conclusion and Recommendation

Canopy-based mapping of oil palm health can be achieved using multispectral aerial photography validated with a handheld spectrometer. While the resulting spectral characteristics show differences in reflectance between healthy and un-healthy trees, particularly in the 650 nm - 800 nm wavelength range (red edge and NIR bands), these differences are not yet highly significant. This suggests that mul-tispectral UAVs alone are not fully capable of early detection of oil palm plant health conditions. Therefore, higher technology or supporting models such as U-Net for canopy segmentation and SVM for health classification are needed. The perfor-mance of the integrated U-Net and SVM models demonstrates good results in ana-lyzing oil palm plant health, and further development with larger datasets is recom-mended.

Our analysis of oil palm plant health's spatial distribution revealed a clustered pattern, suggesting a contagious effect among unhealthy plants. Paradoxically, Block E59, with nearly 55% unhealthy plants, yielded the highest productivity at 2.06 tonnes/ha. This stands in contrast to blocks E58, D53, and D52, which, despite hav-ing healthier plant populations, reported lower productivity values (1.58-1.67 tonnes/ha). This finding underscores that productivity is influenced by more than just plant health, encompassing other critical factors such as agronomic management and land adaptation. Furthermore, soil type emerged as a significant determinant: peat soils supported healthier plants, while sandy soils were associated with higher productivity. This confirms that plant health and productivity result from intricate interactions among environmental conditions, soil characteristics, and land man-agement practices.

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