YOLOv11n-Based Oil Palm Health Classification Using Orthomosaic Drone Imagery

Maudy Hellena Harlyn[1*], Ritna Wahyuni[2], Andi Prayogi[3]

[1,2,3]Department of Information Systems and Technology, Faculty of Science and Technology, Institut Teknologi Sawit Indonesia, Medan, North Sumatra, Indonesia
E-mail: [1*]maudyhellena@gmail.com, [2]ritnawahyuni@itsi.ac.id, [3]andiprayogi@gmail.com,

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Abstract

Monitoring oil palm plantation conditions across large-scale areas remains challenging because manual inspection is time-consuming, costly, and prone to observational errors. This study aims to develop a GIS-based monitoring system for oil palm health detection using the YOLOv11n algorithm and orthomosaic imagery acquired from UAV mapping. The study employed the Software Development Life Cycle (SDLC) Waterfall model and Unified Modeling Language (UML) for system development and design. The research stages included orthomosaic image acquisition, image tiling, dataset annotation, data augmentation, YOLOv11n model training, system implementation, and functional testing. The dataset was collected from oil palm plantation areas owned by PT Bakrie Sumatera Plantations and classified into three categories: healthy, unhealthy, and dead trees. The evaluation results demonstrated high detection performance with 0.99 precision, 0.99 recall, 0.99 mAP50, and 0.88 mAP50-95. The developed GEOPALM system was capable of generating centroid-based visualizations, plantation condition distribution graphs, and spatial outputs for plantation monitoring purposes. Overall, the proposed system can support faster, more efficient, and spatially structured oil palm plantation monitoring.

Keywords: Deep Learning, Object Detection, Oil Palm, Orthomosaic Imagery, YOLOv11n

I. INTRODUCTION

Oil palm (*Elaeis guineensis* Jacq.) is one of the most strategic plantation commodities and plays a significant role in the Indonesian economy [1]. Indonesia is currently the world's largest producer of palm oil, with plantation areas exceeding 16 million hectares and annual production surpassing 47 million tons. This highlights the importance of sustainable plantation management and monitoring systems [2]. The continuously expanding oil palm plantation area has increased the complexity of plantation monitoring, particularly in identifying plant health conditions across large-scale plantation areas. Effective management of plantation resources requires accurate and timely information to support sustainable agricultural practices and improve decision-making processes [3].

Plant health is one of the key factors affecting oil palm productivity because nutrient deficiencies, pest attacks, and diseases can significantly reduce crop yield and plantation performance [4]. However, manual monitoring methods are still widely implemented in plantation environments; these approaches are time-consuming, require high operational costs, and are prone to observational errors caused by human limitations [5], [6]. In addition, conventional field inspection methods are considered inefficient for supporting rapid and structured decision-making processes in large plantation areas.

Advances in Artificial Intelligence (AI), particularly in computer vision and deep learning, have created new opportunities for the development of image-based plantation monitoring systems [1], [7]. In agriculture, AI and computer vision have been increasingly applied to improve efficiency and accuracy in monitoring processes, including the identification, localization, and classification of crops, pests, diseases, and plant growth stages from image and video data [8]. Computer vision enables computers to automatically analyze visual information from digital images and videos, making it suitable for agricultural monitoring and object detection applications [8], [9]. One of the most widely used object detection methods is YOLO (You Only Look Once) due to its capability to perform real-time object detection with high accuracy and computational efficiency, making it widely adopted in agricultural monitoring applications [10], [11]. The original YOLO architecture introduced a single-stage object detection framework capable of performing object localization and classification simultaneously in real time [12]. The latest version, YOLOv11, offers improved performance in detecting

small and complex objects while providing better computational efficiency compared to previous generations [13].

UAV technology has become an important tool in precision agriculture because it enables the acquisition of high-resolution imagery for crop monitoring, health assessment, and spatial analysis. Previous studies have shown that UAV-based remote sensing can improve monitoring efficiency and provide detailed spatial information for agricultural management [14]. In the plantation sector, this technology can be utilized to identify plant health conditions using orthomosaic aerial imagery acquired through Unmanned Aerial Vehicle (UAV) mapping [6].

Several previous studies have implemented YOLO algorithms in oil palm plantations, primarily for tree detection and counting using drone imagery [15], [16]. Other studies have demonstrated that aerial imagery combined with deep learning techniques can improve the efficiency of automated plantation monitoring systems [17]. However, most existing studies mainly focus on object detection and tree counting, while research related to oil palm health classification based on orthomosaic imagery remains limited. Furthermore, the implementation of detection systems integrated with spatial desktop applications for direct plantation monitoring is still rarely explored. Spatial data analysis can provide valuable geographic information to support plantation monitoring and location-based decision-making processes [18].

Table 1. Research Gap Analysis of Previous Oil Palm Monitoring Studies

Study	Main Focus	Dataset/ Data Source	Method	Main Result	Gap Compared with This Study
Thapa et al., 2025	Oil palm tree condition classification	UAV imagery	YOLO Object Detector	Successfully classified oil palm tree conditions from UAV imagery	Did not integrate detection results into a GIS-based monitoring application and did not generate spatial outputs for plantation management
Syabana et al., 2025	Oil palm tree detection and counting	UAV imagery	YOLOv11	Precision 94.5%, recall 97.3% for oil palm detection	Focused on tree detection and counting rather than health classification
Rodi & Daliman, 2024	Oil palm inventory monitoring	Drone imagery	Image recognition techniques	Detection accuracy above 83%	Did not perform oil palm health classification and lacked GIS integration
Proposed study	Oil palm health classification and spatial monitoring	UAV orthomosaic imagery	YOLOv11n + GEOPALM	Precision, recall, mAP50 = 0.99; mAP50-95 = 0.88	Integrates health classification, centroid visualization, condition distribution analysis, and shapefile export for GIS-based monitoring

Table 1 summarizes previous studies related to oil palm monitoring and highlights the research gaps addressed by the proposed study. However, most existing studies focused on tree detection, counting, and plantation inventory management, while limited attention has been given to oil palm health classification integrated with GIS-based monitoring systems. Furthermore, the generation of spatial outputs for operational plantation monitoring remains relatively unexplored. Therefore, this study addresses these gaps by combining YOLOv11n-based health classification, orthomosaic UAV imagery, and the GEOPALM desktop application to support automated and spatially structured plantation monitoring.

Based on these limitations, this study aims to develop an oil palm health classification system using orthomosaic imagery and the YOLOv11n algorithm. The research dataset was acquired from three plantation blocks using DJI Air 2S and DJI Air 3S drones. The developed model was integrated into a spatial desktop application called GEOPALM, which is capable of displaying detection results, plant centroid visualization, oil palm health condition distribution, and output generation in shapefile (SHP) format. The proposed system is expected to support faster, more efficient, and spatially structured monitoring of oil palm plantation health conditions.

The novelty of this study lies in the integration of YOLOv11n-based oil palm health classification with UAV-derived orthomosaic imagery and a GIS-based desktop monitoring system. Unlike previous studies that mainly focused on oil palm tree detection or counting, this study classifies oil palm conditions into healthy, unhealthy, and dead categories and converts the detection results into centroid-based spatial outputs. In addition, the proposed GEOPALM system provides detection visualization, oil palm health distribution graphs, and shapefile export to support further spatial analysis in GIS software. Therefore, the main contribution of this study is not only the implementation of YOLOv11n, but also the development of an integrated workflow for automated and spatially structured oil palm health monitoring.

II. RESEARCH METHODOLOGY

This study was conducted through several stages, including problem identification, data collection, dataset

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preparation, YOLOv11n model training, desktop application development, system integration, and system testing and evaluation. The research workflow used in this study is presented in Figure 1.

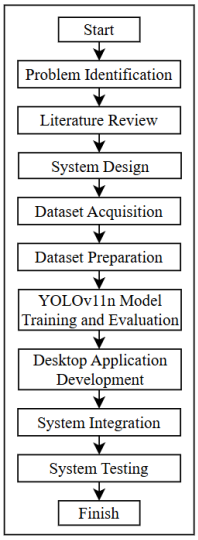


Figure 1. Research Workflow of the Proposed System

A. System Development Approach

The system development method applied in this study was the SDLC Waterfall model due to its structured development stages, including requirement analysis, system design, implementation, and system testing [19]. This approach was used in the development process of the GEOPALM desktop application integrated with the YOLOv11n deep learning model. The Waterfall model is suitable for software development projects with clearly defined requirements because each development phase is completed sequentially before proceeding to the next stage, enabling better project control and documentation [19].

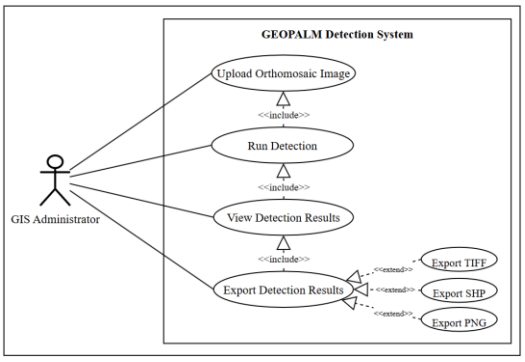


Figure 2. Use Case Diagram of the GEOPALM System

System design was conducted using Unified Modeling Language (UML) to represent system requirements and user interactions [20], while system design activities play an important role in defining software structure, functionality, and interactions before implementation begins [21]. The use case diagram of the system is shown in Figure 2. The UML used in this study consisted of a use case diagram illustrating the primary functions of the application, including orthomosaic image input, object detection, detection result visualization, and spatial data storage [20].

B. Study Area and Data Collection

The research data were acquired using DJI Air 2S and DJI Air 3S drones to produce orthomosaic aerial imagery in TIFF format. Orthomosaic imagery was selected because it provides geometrically corrected aerial images that can be used for accurate mapping and spatial analysis [22]. Data acquisition was carried out using Unmanned Aerial Vehicles (UAV) while considering image quality and plantation area coverage.

Data collection techniques included field observation, drone image documentation, and literature review. Field observation was conducted to obtain information regarding plantation conditions and monitoring activities within the plantation area. Documentation was performed by collecting orthomosaic imagery used as the research dataset, while the literature review involved examining scientific journals and previous studies related to *deep learning*, *computer vision*, and object detection.

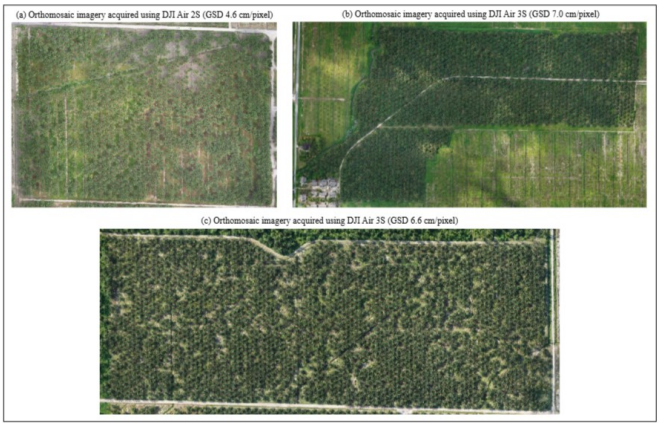


Figure 3. Orthomosaic Imagery Used as Research Dataset

Figure 3 presents the orthomosaic imagery used as the primary dataset in this study. The image represents a plantation area captured using UAV mapping and processed into a geometrically corrected aerial image. This orthomosaic format enables the observation of oil palm tree distribution from a top-down perspective and provides sufficient spatial detail for identifying tree crown patterns. The use of orthomosaic imagery is important because it allows large plantation areas to be analyzed more efficiently than manual field observation. In this study, the orthomosaic image served as the input source for the tiling, annotation, and YOLOv11n training processes.

C. Dataset Preparation

The research dataset originated from orthomosaic imagery collected from three plantation blocks and processed using a tiling method. The tiling process was conducted to facilitate object annotation and YOLOv11n model training on high-resolution orthomosaic imagery. The tiling process generated 1,200 image tiles, which were used as the initial dataset for this study. The orthomosaic tiling process is illustrated in Figure 4.

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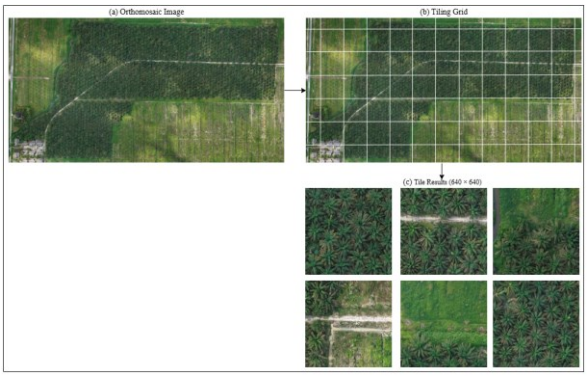


Figure 4. Orthomosaic Tiling Process

Following the tiling process, object annotation was performed using the YOLO annotation format with the bounding box method. The annotation process was conducted using the Roboflow platform, which provides tools for image labeling, dataset management, and preparation for object detection model development [23]. The annotation process was conducted to identify oil palm tree conditions based on three classes: healthy, unhealthy, and dead. This stage aimed to produce an annotated dataset for the model training process. An example of the bounding box annotation result is shown in Figure 5.

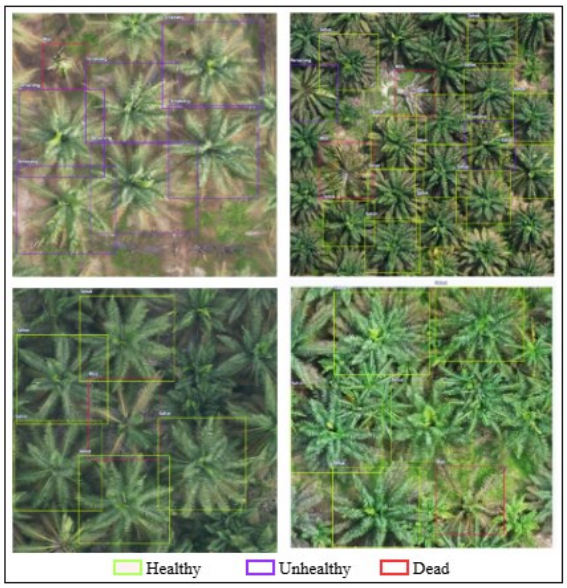


Figure 5. Bounding Box Annotation Result

The next stage involved data augmentation to increase dataset variation and reduce the risk of *overfitting* during the model training process. The augmentation process was conducted by applying several image transformations to the annotated dataset. After augmentation, the total dataset consisted of 7,025 images, including 4,917 *training* data, 1,405 *validation* data, and 703 *testing* data with a dataset split ratio of 70:20:10. An example of the dataset augmentation result is presented in Figure 6.

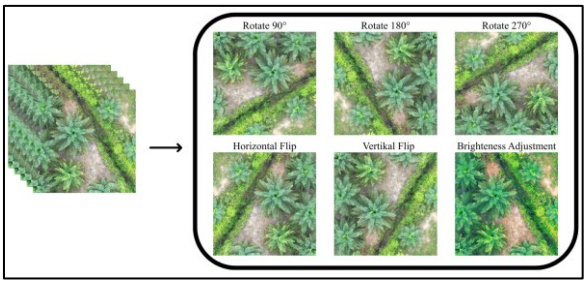


Figure 6. Dataset Augmentation Results

D. YOLOv11n Model Training

The YOLOv11n model was trained in a GPU-enabled Google Colab environment. Google Colab provides cloud-based computational resources with GPU acceleration that can significantly improve deep learning model training performance [24]. The training stage included dataset loading, training parameter configuration, training execution, and model evaluation. Python was used as the primary programming language because it provides extensive support for machine learning and deep learning libraries commonly applied in computer vision research [25]. The model was trained using the prepared dataset to classify oil palm tree conditions based on orthomosaic imagery.

Model evaluation was performed using *precision*, *recall*, *mean Average Precision* (*mAP50*), and *mAP50-95* metrics. The *precision* metric was used to measure the accuracy of the model in detecting objects, while *recall* was used to measure the model's ability to identify relevant objects within the testing dataset. The formulas for *precision* and *recall* are presented in Equation (1) and Equation (2).

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

TP (True Positive) represents correctly detected objects, FP (False Positive) represents incorrectly detected objects, and FN (False Negative) represents undetected objects.

In addition, model evaluation was also conducted using *mean Average Precision* (*mAP*) to measure object detection performance based on prediction accuracy and *bounding box* localization quality. The *mAP50* value was calculated at an *Intersection over Union* (IoU) threshold of 0.50, while *mAP50-95* was calculated using IoU thresholds ranging from 0.50 to 0.95 with an interval of 0.05.

E. System Development

The trained YOLOv11n model was integrated into the GEOPALM desktop application developed using C#. The selection of C# was based on its capability to support object-oriented programming and desktop application development through the .NET framework, which provides a reliable environment for implementing graphical user interfaces and system integration [26]. The application was developed to perform orthomosaic image input, oil palm condition

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detection, detection result visualization, and spatial data storage in TIFF, PNG, and shapefile (SHP) formats. A well-designed user interface is essential for enabling users to interact effectively with application features and improving overall usability during system operation [27].

The integration between the YOLOv11n model in Python and the C#-based desktop application was conducted through a data exchange mechanism between the detection process and the desktop application interface.

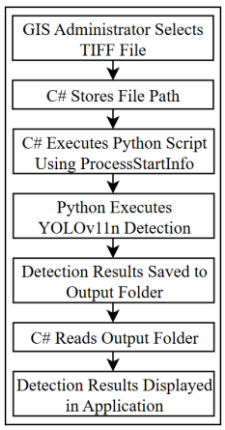


Figure 7. Integration Workflow Between YOLOv11n and the GEOPALM Application

Figure 7 illustrates the integration workflow between the trained YOLOv11n model and the GEOPALM desktop application. The process begins with orthomosaic image input in TIFF format, followed by image processing and object detection using the trained YOLOv11n model. The detection results are then converted into visual outputs, including bounding boxes, centroid points, and oil palm health classification labels. These outputs are displayed in the GEOPALM interface and can be exported into TIFF, PNG, and shapefile (SHP) formats. This workflow shows how the deep learning model is connected with the spatial monitoring application to support automated oil palm health detection and further GIS-based analysis.

F. System Testing

System testing was conducted using the *Black Box Testing* method to evaluate the primary functions of the application based on system inputs and outputs [28]. Testing was performed on orthomosaic image input, object detection, detection result visualization, and spatial data storage features.

III. RESULTS AND DISCUSSION

This section presents the results of YOLOv11n model training and evaluation for oil palm health classification using orthomosaic imagery. The discussion includes training performance analysis, object detection evaluation, detection error analysis, desktop application implementation, and system testing results. Model performance was evaluated using *precision*, *recall*, *mAP50*, and *mAP50-95* metrics to measure the effectiveness of the proposed system in detecting healthy, unhealthy, and dead oil palm trees.

A. YOLOv11 Training and Evaluation Results

The YOLOv11n model was trained using the prepared orthomosaic dataset that had undergone augmentation and dataset splitting processes. The training process was conducted using a GPU-based Google Colab environment with T4 GPU support. The training configuration used in this study is presented in Table 2.

Table 2. YOLOv11n Training Configuration

Parameter	Value
Model	YOLOv11n
Epochs	200
Batch Size	8
Image Size	640 x 640
Optimizer	SGD
GPU	T4
Dataset Format	YOLO

Based on the training results, both *training loss* and *validation loss* gradually decreased throughout the training process. At the same time, the *precision*, *recall*, *mAP50*, and *mAP50-95* values consistently increased until the final training epoch. These results indicate that the model was able to learn the visual characteristics of oil palm tree conditions effectively and maintain stable performance during the training process. The training performance of the YOLOv11n model is presented in Figure 8.

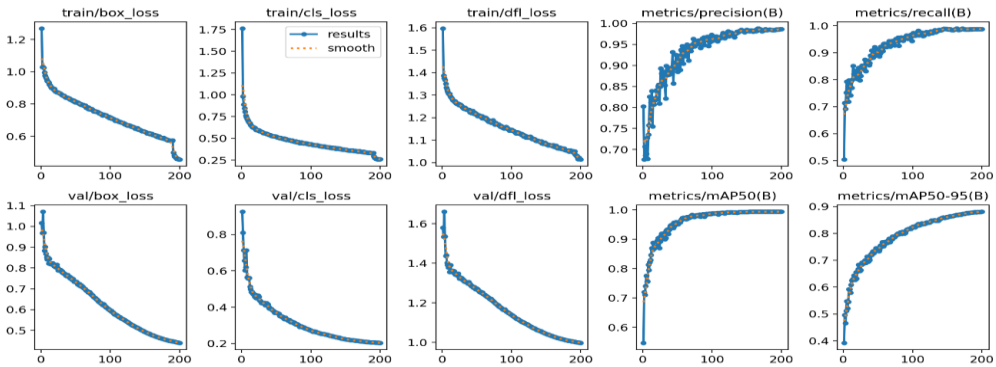


Figure 8. YOLOv11n Training Results

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Model evaluation was performed using a *confusion matrix* to analyze the classification accuracy for each oil palm condition class. The evaluation results show that most objects were correctly classified into the *healthy*, *unhealthy*, and *dead* classes. However, several misclassifications and undetected objects categorized as *background* were still observed, particularly in areas with lower image quality or objects located near tile boundaries. The *confusion matrix* results are shown in Figure 9.

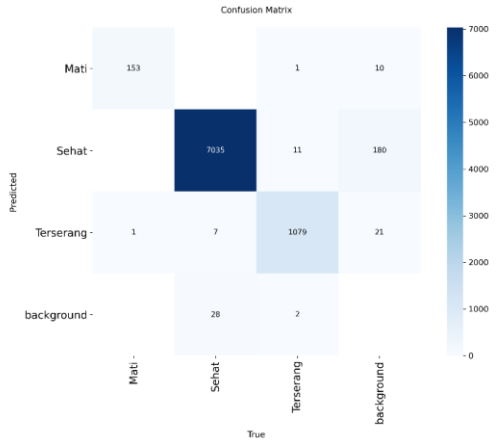


Figure 9. Confusion Matrix of the YOLOv11n Model

The evaluation results using *precision*, *recall*, *mAP50*, and *mAP50-95* metrics are presented in Table 3.

Table 3. YOLOv11n Evaluation Results

Class	Number of Labels	Precision	Recall	mAP 50	mAP 50-95
Healthy	5,997	0.99	0.99	0.99	0.90
Unhealthy	980	0.99	0.98	0.99	0.92
Dead	108	0.98	0.99	0.99	0.83
Overall	**7,028**	**0.99**	**0.99**	**0.99**	**0.88**

Based on the evaluation results, the YOLOv11n model achieved overall precision, recall, and mAP50 values of 0.99, while the mAP50-95 value reached 0.88. These results indicate that the model effectively detected oil palm tree conditions using high-resolution orthomosaic imagery.

At the class level, the healthy and unhealthy classes showed stable detection performance, with mAP50-95 values of 0.90 and 0.92, respectively. However, the dead class obtained a lower mAP50-95 value of 0.83. This result indicates that the model was still able to detect dead oil palm trees, but its bounding box localization consistency was lower under stricter IoU thresholds.

The lower mAP50-95 value in the dead class was influenced by the imbalanced class distribution in the dataset. The healthy class had the highest number of labels, followed by the unhealthy class, while the dead class had the smallest number of samples. This distribution reflects actual field conditions, where dead oil palm trees were encountered less frequently than healthy and unhealthy trees. In addition, visual similarities between dead trees and certain background areas in the orthomosaic imagery also contributed to classification and localization challenges. Therefore, dataset imbalance should be considered as one of the main factors influencing class-level performance. Future improvements may include increasing dead-class samples, applying targeted augmentation, and evaluating class-balancing strategies to improve the robustness of minority-class detection.

Similar findings have been reported in previous studies on UAV-based oil palm monitoring. Syabana et al. [16] reported that YOLOv11 achieved a precision of 94.5% and recall of 97.3% for oil palm tree detection, while Rodi & Daliman [17] demonstrated that drone-based image recognition techniques could achieve detection accuracies exceeding 83%. Compared to these studies, the proposed YOLOv11n model achieved higher overall precision, recall, and mAP values, indicating its effectiveness for oil palm health classification using orthomosaic imagery.

B. Detection Result and Error Analysis

The trained YOLOv11n model was tested on orthomosaic imagery to detect oil palm tree conditions classified into *healthy*, *unhealthy*, and *dead* classes. The detection results demonstrated that the model was capable of identifying most oil palm objects accurately across different plantation areas. Detection outputs were visualized using centroid points on orthomosaic imagery to support spatial monitoring and object distribution analysis. Examples of detection results are presented in Figure 10.

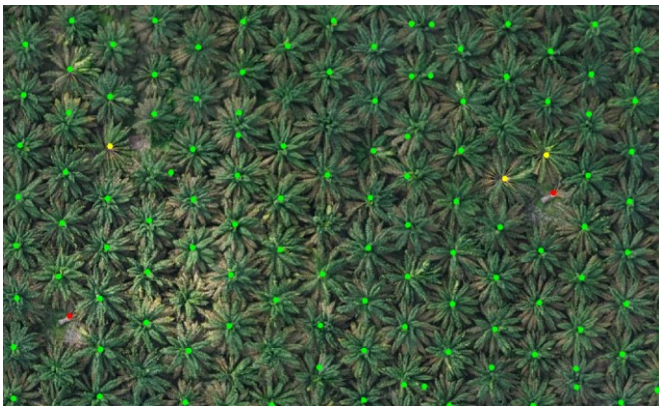


Figure 10. YOLOv11n Detection Results on Orthomosaic Imagery

Several types of detection errors were observed during the testing process, including false detections, missed detections, and duplicate detections. False detections occurred when background objects or vegetation patterns with visual characteristics similar to oil palm crowns were incorrectly identified as target objects. Missed detections were primarily found in areas with overlapping canopies, reduced image contrast, or partial crown visibility, which made object boundaries more difficult to distinguish. Duplicate detections were occasionally observed when individual trees were located near tile boundaries generated during the orthomosaic

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tiling process. Examples of these detection errors are presented in Figure 11.

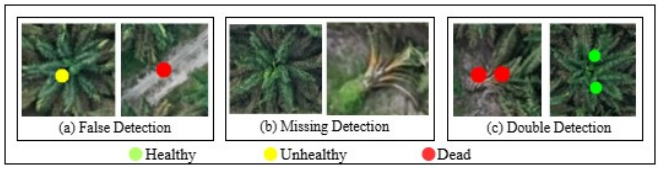


Figure 11. Examples of Detection Errors

These errors affected both classification accuracy and localization consistency, particularly under stricter IoU thresholds used in the mAP50-95 evaluation metric. The impact was more noticeable in the dead class, which contained substantially fewer training samples than the healthy and unhealthy classes. As a result, the model had fewer examples from which to learn the visual variability of dead oil palm trees, reducing its ability to generalize across different field conditions.

Although the overall performance remained high, the findings indicate that canopy overlap, image quality variation, tile-boundary effects, and class imbalance remain important challenges for orthomosaic-based oil palm health detection. Future improvements may include increasing minority-class samples, implementing advanced tile-merging strategies, and applying additional post-processing techniques to reduce duplicate and missed detections.

C. GEOPALM Desktop Application Implementation

The trained YOLOv11n model was subsequently integrated into the GEOPALM desktop application developed using the C# programming language. The application was designed to support automated oil palm health detection using orthomosaic imagery within a desktop-based environment.

The GEOPALM application is capable of processing orthomosaic imagery in TIFF format and displaying detection results through centroid visualization on aerial imagery. In addition, the system provides graphical visualization of oil palm health condition distribution to support plantation monitoring activities. An example of the GEOPALM application implementation is shown in Figure 12.

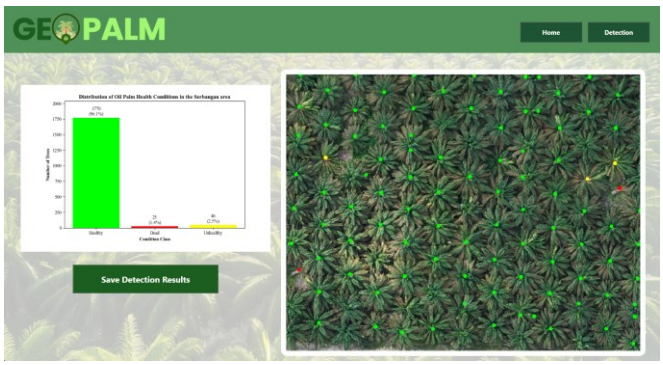


Figure 12. Detection Result Visualization in the GEOPALM Application

The detection results generated by the application can be exported in TIFF, PNG, and *shapefile* (SHP) formats. The TIFF format is used to store detection visualization results on orthomosaic imagery, while the PNG format is used to save graphical summaries of detection results. Furthermore, the SHP format enables the detection outputs to be reused in Geographic Information System (GIS) software for further spatial analysis.

Overall, the implementation results demonstrate that the YOLOv11n model can be effectively applied to a GIS-based monitoring system to support more efficient and structured oil palm health detection processes.

D. System Testing and Discussion

System testing was conducted to evaluate the capability of the GEOPALM application in performing oil palm health detection using orthomosaic imagery. The testing process focused on several main application functions, including image upload, object detection, detection result visualization, and export of detection outputs in TIFF, PNG, and SHP formats. The functional testing results indicate that all primary application features operated successfully according to the designed system functions. The functional testing results are presented in Table 4.

Table 4. Functional Testing Results of the GEOPALM Application

No	Tested Function	Result
1	TIFF Image Upload	Successful
2	Oil Palm Health Detection Process	Successful
3	Centroid Visualization of Detection Result	Successful
4	Export of Detection Results (TIFF, PNG, SHP)	Successful
5	Detection Result Visualization in the Application	Successful

In addition to functional testing, detection time evaluation was performed using orthomosaic imagery from multiple plantation blocks with different file sizes, spatial resolutions, and object densities. The detection time evaluation results are presented in Table 5.

Table 5. Detection Time Evaluation Results

Aerial Image Block	Spatial Resolution (cm/pixel)	File Size (MB)	Number of Detected Trees	Detection Time
A	3.8	1,797.16	5,083	4 min 28 s
B	3.5	2,469.57	5,131	4 min 20 s
C	4.6	1,841.50	3,611	3 min 6 s
D	6.9	720.67	3,761	1 min 35 s
E	6.6	637.63	2,238	1 min 15 s
F	7	467.71	1,841	57 s
G	6.9	1,059.89	6,566	2 min 40 s

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Based on the evaluation results, the detection time was influenced by image file size, spatial resolution, and the number of detected oil palm trees. Orthomosaic imagery with larger file sizes and higher object densities required longer processing times. In addition, higher spatial resolution imagery increased computational load during the detection process.

Overall, the testing results demonstrate that the GEOPALM application was capable of performing automatic oil palm health detection on orthomosaic imagery while generating spatial outputs that can be further utilized in Geographic Information System (GIS) software. To better position the proposed system within current research, a comparison with several related studies is presented.

Similar findings have been reported in previous studies involving UAV-based oil palm monitoring. Thapa et al. [6] demonstrated the effectiveness of YOLO-based approaches for oil palm condition classification using UAV imagery, while Syabana et al. [16] reported precision and recall values of 94.5% and 97.3% for oil palm tree detection. Rodi and Daliman [17] also showed that drone-based image recognition can support plantation monitoring with detection accuracies exceeding 83%. Compared with these studies, the proposed system not only achieved high detection performance but also extended the application of UAV-based oil palm monitoring through health classification and GIS integration. The GEOPALM application provides centroid visualization, oil palm health distribution analysis, and shapefile export, enabling the detection results to be utilized for spatially structured plantation monitoring and decision support. Nevertheless, the comparison should be interpreted as a contextual comparison because differences in datasets, object categories, plantation conditions, and evaluation protocols may influence the reported performance.

IV. CONCLUSION

This study successfully developed and implemented an oil palm health classification system using UAV-derived orthomosaic imagery and the YOLOv11n object detection model. The proposed approach classified oil palm trees into healthy, unhealthy, and dead categories with overall precision, recall, and mAP50 values of 0.99, while achieving an mAP50-95 value of 0.88, indicating strong detection performance on high-resolution orthomosaic imagery. The trained model was successfully integrated into the GEOPALM desktop application, enabling automatic detection, centroid-based visualization, oil palm health distribution analysis, and spatial data export in TIFF, PNG, and shapefile (SHP) formats. The results demonstrate that the integration of deep learning and GIS-based monitoring can support faster, more efficient, and spatially structured plantation management compared with conventional monitoring approaches. Although several challenges related to class imbalance, canopy overlap, and tile-boundary effects were identified, the developed system showed promising performance for practical plantation monitoring applications. Therefore, the proposed framework can serve as a useful decision-support tool for oil palm health assessment and provides a foundation for future research involving larger datasets, additional health categories, and comparative evaluation with other object detection models.

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