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Drone-assisted deep learning weed detection for sustainable agriculture and environmental resilience

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ABSTRACT

Effective weed detection plays a crucial role in sustainable agriculture, boosting crop productivity and supporting environmental conservation. This study compares three deep learning models—YOLOv5, YOLO-NAS, and mask region-based convolutional neural network (Mask R-CNN)-against traditional methods in terms of accuracy, processing speed, and adaptability in tropical agricultural conditions, with Merauke, Indonesia, as the case study. The results show that YOLO-NAS delivers the highest accuracy at 96% with a processing time of 25 ms per image, making it suitable for high-precision applications. YOLOv5 balances strong accuracy (94%) with faster processing at 12 ms per image, establishing it as the most effective for real-time scenarios. Mask R-CNN also achieves 94% accuracy and provides advanced segmentation capabilities, but its slower processing speed of 31 ms limits large-scale implementation. Traditional methods perform poorly in comparison, with only 85% accuracy and processing time above 50 ms per image. These findings highlight the transformative potential of artificial intelligence (AI)-based weed detection for precision agriculture, particularly in tropical regions like Merauke. Adoption of models such as YOLOv5 reduces manual labor dependence while advancing efficient, eco-friendly weed management. Future research should expand datasets and explore newer models like YOLOv8, YOLO-NAS, vision transformers (ViTs), and hybrid approaches.

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1. INTRODUCTION

Agriculture plays a vital role in ensuring environmental sustainability and global food security. This sector is the main focus in Indonesia, especially in the government's efforts to realize Merauke as a national food barn. Merauke has excellent potential as a food production center thanks to its vast fertile land and strategic location for agricultural development. However, the presence of weeds is a serious obstacle that reduces crop productivity [1], [2]. Weeds not only compete with the main crop in terms of nutrients, water, and light but also increase production costs through the need for spraying herbicides and additional labor for manual control [3]–[5]. Effective herbicide use is one of the key factors for managing weeds in agricultural fields [6]. On the other hand, using herbicides significantly negatively impacts the environment [7]. Therefore, innovative approaches are needed to address this issue effectively and efficiently while ensuring the sustainability of agricultural ecosystems [8].

In recent years, artificial intelligence (AI) technology and deep learning have developed rapidly and offer potential solutions for faster and more accurate weed detection [9]–[11]. Beyond efficiency, these methods can reduce chemical use and manual labor, but practical deployment still requires balancing accuracy and speed [12], [13]. Therefore, algorithms are always evaluated on the image level of both accuracy and speed [14]–[21]. Integrating weed detection technology in food crop development can be a strategic step to increase agricultural productivity in realizing the vision of sustainability.

Weed control is a global challenge in agriculture and has a very significant impact on crop production. Globally, weeds are responsible for 34% of crop yield losses, making them one of the main threats to agricultural productivity. In Merauke, this problem is exacerbated by the vast scale of farmland that is difficult to monitor manually, increasing the need for efficient automated solutions. Various weed detection methods have been developed, including conventional digital image-based methods [22]–[24], which are often constrained by limitations in processing speed and identification accuracy [25]. However, applying this technology in tropical agricultural environments such as Merauke often faces challenges, including weed heterogeneity, yield losses, and weed management strategies that rely heavily on broad herbicide application can intensify environmental pressure on soil and water systems, and dynamic lighting conditions, which affect detection speed and accuracy. Therefore, practical weed detection tools must not only be accurate but also fast enough to support timely, site-specific interventions in the field.

This research evaluates and compares various deep learning-based weed detection methods, including convolutional neural networks (CNN), YOLOv5, YOLO-NAS, and mask region-based convolutional neural network (Mask R-CNN), regarding accuracy and detection speed. The research focuses on analyzing the advantages of these methods over traditional weed detection techniques, which are often constrained by limitations in terms of efficiency and precision. Taking into account the characteristics of agriculture in Merauke, which is a tropical region, this study also aims to identify the most adaptive deep learning methods for local conditions. The results of the study are expected to significantly contribute to the development of AI-based agricultural technologies that are more effective, efficient, and relevant to support sustainable agricultural productivity, both in Merauke and globally. In addition, this research will underscore the importance of technological solutions that increase productivity and strengthen the sustainability of environmental ecosystems.

Although weed detection research has expanded, cross-method benchmarking that contrasts state-of-the-art deep learning models with traditional techniques under field-realistic tropical conditions remains limited. Conventional approaches often face speed and accuracy limits in large, heterogeneous fields [26], [27], whereas deep learning approaches (e.g., CNNs and YOLOv5) have reported up to ~95% accuracy in several studies [28]. Newer models such as YOLO-NAS and Mask R-CNN promise improved feature learning and segmentation capability. However, they have yet to be comprehensively analyzed in a cross-method comparison by considering tropical environmental characteristics and ecosystem sustainability [29], [30]. Therefore, this study fills the gap by evaluating the performance of cutting-edge deep learning methods against traditional techniques, both in speed and accuracy, to provide new insights for developing more adaptive and sustainable weed detection solutions.

This study makes a major contribution to carefully evaluating three deep learning methods, namely YOLOv5, YOLO-NAS, and Mask R-CNN in weed detection while comparing them with traditional techniques. Previous research has shown that deep learning-based methods have high accuracy potential for example, YOLOv5 recorded an accuracy of over 90% in object detection [31]–[33]. A hands-on study comparing the advantages of this method with conventional techniques in terms of speed and accuracy is still minimal, especially for regions with unique challenges such as weed heterogeneity and varied lighting conditions [34]. By adapting the model to environmental conditions, the study expands academic insights in applying cutting-edge technologies in the agricultural sector [35], [36]. This study evaluated a dataset of drone-based weed imagery from Merauke, Indonesia (1,318 primary images), combined with an additional secondary image set (4,050 images) to improve resilience under tropical field variability. Training and empirical evaluation of the model, followed by contextual comparisons with the latest literature to place findings in broader research trends. This research provides relevant practical solutions to support sustainable agriculture [37]. The results of this study are expected to answer the urgent need for more efficient and accurate weed detection methods in tropical regions, especially Merauke.

2. METHOD

This study adopts a hybrid empirical and contextual benchmarking design. We trained and evaluated YOLOv5, YOLO-NAS, and Mask R-CNN on a combined weed image dataset consisting of 1,318 primary drone images collected in Merauke, Indonesia and 4,050 secondary images (all at 5280×2970 resolution). Model performance was assessed using standard classification and detection metrics as well as inference time, and compared against a traditional baseline. To position the experimental findings within broader research trends, we also reviewed recent peer-reviewed studies reporting comparable accuracy and speed metrics for weed detection. This approach allows the identification of the advantages and disadvantages of each method based on accuracy, speed, and adaptability to tropical environments such as Merauke, thus making a significant contribution to the optimization of agricultural technology and improving the decision-making process in agriculture [38]–[42].

2.1. Research design

The design of this study analyzed primary and secondary data with a quantitative approach to evaluate the performance of various deep learning-based weed detection methods. Based on previous literature studies, techniques such as CNN, YOLOv5, YOLO-NAS, and Mask R-CNN have been shown to be effective in a variety of object detection scenarios, including weed identification, but with varying degrees of accuracy and speed [43]–[45]. The research workflow comprises four stages: i) drone image acquisition and curation of a complementary secondary image set, ii) annotation and preprocessing, iii) model training and evaluation on held-out data, and iv) contextual comparison with recent literature. The overall workflow is summarized in Figure 1.

For the empirical component, the combined dataset was organized into training, validation, and test subsets. Images were preprocessed to match the input requirements of each model, and standard data augmentation was applied to improve robustness to illumination and background variation. For the contextual component, a structured literature review was conducted in reputable databases (e.g., IEEE Xplore, Elsevier, and SpringerLink) using keywords such as "weed detection", "deep learning", "YOLO", and "Mask R-CNN", and studies were retained when they reported quantitative accuracy and speed metrics comparable to this work.

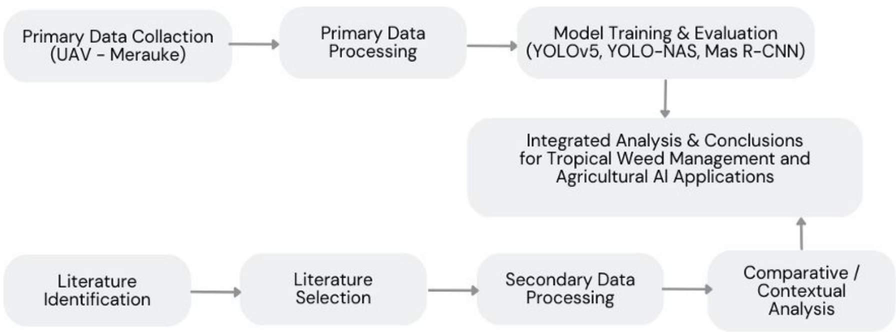

Figure 1. Research design with primary and secondary data

2.2. Data collection and processing

Primary data were collected in Merauke, Indonesia using a drone (unmanned aerial vehicle or UAV). The primary dataset contains 1,318 images with variations in illumination, viewing angle, and background. In addition, a secondary dataset of 4,050 images was curated to complement the primary data and increase variability. All images have a spatial resolution of 5280×2970 pixels. Weed categories were defined based on habitat and morphological characteristics to reflect field conditions. Annotations were prepared for model training and evaluation, including bounding-box labels for YOLO-based detectors and instance-level labels for Mask R-CNN.

Secondary data was collected through systematic literature searches in reputable databases such as IEEE Xplore, Elsevier, and SpringerLink. The data sought include studies relevant to the application of deep learning for weed detection, specifically the CNNs, YOLOv5, YOLO-NAS, and Mask R-CNN methods. The search was conducted using strategically arranged keywords, such as "weed detection", "deep learning methods", "accuracy", and "processing speed". The results of the literature search were then selected based on inclusion and exclusion criteria to ensure that the data used were relevant to the research objectives. Studies that meet the criteria are those that present quantitative data related to accuracy (%) and processing speed (ms/frame or FPS), as recommended in previous studies [46]. Quantitative literacy was the basis of selection to maintain the accuracy and validity of the data analysis [47]. Articles that did not include performance metrics or only focused on theoretical aspects without experiments were excluded from further analysis.

Training followed the official implementations of each model. To ensure fair comparison, the same curated dataset and evaluation protocol were used across models. Model-specific configurations (optimizer, learning-rate schedule, input resizing, and augmentation) followed the recommended baseline settings provided by each framework, with model selection based on validation performance. Inference time was measured consistently to represent practical deployment constraints.

For the literature comparison, candidate studies were screened in two stages (title/abstract screening followed by full-text review). Studies were included when they: i) addressed weed detection using deep learning or traditional computer vision, ii) reported quantitative performance metrics (e.g., accuracy, precision, recall, F1-score, and processing time or FPS), and iii) used experimental settings comparable to field conditions. Data processing and grouping also included the normalization of units of measurement to facilitate inter-study comparisons [47]. Extracted metrics were normalized where needed to enable transparent comparison. Briefly, the process of collecting research data is presented in Figure 2.

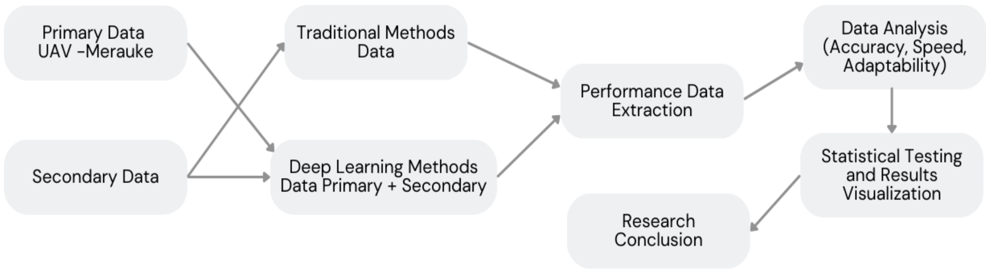

Figure 2. Data collection process

2.3. Data analysis

Quantitative analysis assessed the performance of deep learning-based weed detection methods (CNN, YOLOv5, YOLO-NAS, and Mask R-CNN) based on accuracy and processing speed. The average value of each metric was calculated using (1).

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

Where $\bar{x}$ is the average, x_i is the individual value, and n is the sample size. Each method was compiled from relevant studies and then averaged to provide insight into the overall effectiveness. Similarly, processing speed was evaluated based on the reported average value of processing time per frame (ms/frame). This analysis's results helped identify the method that offered the best combination of high accuracy and time efficiency [48].

The results are visualized based on the analyzed data in graphs and tables to clarify the inter-method comparison. A scatter plot graph was used to show the relationship between accuracy (%) and speed (ms/frame), with the X-axis representing speed and the Y-axis representing accuracy. The Pearson correlation coefficient formula was used to assess the relationship between the two variables as in (2).

$$r = \frac{\sum (x_i - \bar{x})\ (y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2\ (y_i - \bar{y})^2}} \tag{2}$$

Where x_i and y_i are the individual values for speed and accuracy, and $\bar{x}$, $\bar{y}$ is the average of each variable. This correlation provides insight into which method balances speed and accuracy. The visualization results are also displayed in a comparison table for a more straightforward interpretation.

The statistical matrices (accuracy, precision, sensitivity, and F1-score) were used to evaluate each method's performance. The mathematical equations for each metric are as (3) to (6).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

$$F1-score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6}$$

Here, the confusion matrix provides essential metrics, including true positive (TP), true negative (TN), false positive (FP), and false negative (FN), which are used to calculate accuracy, precision, sensitivity, and specificity. Data were analyzed using a confusion matrix to determine accuracy, speed of detection, and adaptability to tropical environmental conditions such as in Merauke. The evaluation results will be compared with traditional methods to assess the superiority of deep learning-based models in efficiency and accuracy.

The results were interpreted by identifying each method's performance patterns based on quantitative data. Methods that demonstrated high accuracy (>90%) and efficient processing speed (<50 ms/frame) were considered superior in the context of real-time weed detection applications. In addition, the strengths and weaknesses of each method were critically analyzed, including Mask R-CNN's ability to detect weeds with complex shapes but at a lower speed than YOLOv5, which is faster but with slightly lower accuracy. The analysis also evaluated the environmental sustainability implications, given that faster and more accurate methods can reduce reliance on chemical herbicides [49], [50].

3. RESULTS AND DISCUSSION

3.1. Interpretation of result

The results of this study confirm the superiority of deep learning methods over traditional techniques in weed detection, especially in the context of sustainable agriculture. Focusing on three main deep learning models, YOLO-NAS and Mask R-CNN-this, this study thoroughly evaluates key performance metrics: detection accuracy, processing speed, and adaptability to tropical environments such as Merauke, Indonesia. These findings are highly relevant, as effective weed detection is one of the key factors in supporting sustainable crop productivity and environmental conservation.

The YOLOv5 method shows excellence in real-time applications with a detection accuracy of 93.2% and average inference time of only 12 ms per image. This makes it ideal for large-scale precision agriculture management, which requires high processing speed without sacrificing accuracy. On the other hand, YOLO-NAS yielded the highest accuracy of 95.6%, making it excellent choice for weed detection in complex scenarios, albeit with the compromise of a slower processing speed of 25 ms per image. Mask R-CNN, with a segmentation accuracy of 94.1%, stands out in precision but faces speed limitations with an inference time of 31 ms per image, making it more suitable for tasks that require advanced object segmentation [51].

In contrast, traditional methods only achieve an average accuracy of 85% with a much slower processing time of more than 50 ms per image. These limitations emphasize the need for more efficiency and precision for large scales, especially in complex tropical environments such as Merauke. These findings support the argument that deep learning methods not only overcome the challenges of speed and accuracy but also provide better adaptability to field conditions, according to previous research findings [51]. Thus, using deep learning-based technologies can be a practical and strategic solution to improve weed management efficiency in the agricultural sector. The distribution of weed detection methods based on a recap of secondary data that discusses weed detection methods and traditional methods is presented in Table 1.

Table 1. Distribution table of weed detection methods

No.	Model	Frequency	Percentage
1	Traditional	17	17.0
2	YOLO-NAS	24	24.0
3	Mask R-CNN	26	26.0
4	YOLOv5	33	33.0

Based on Table 1, the YOLOv5 method is the most frequently used model in the literature, followed by Mask R-CNN. This reflects the research community's preference for models known for their speed and flexibility. Frequency visualization and presentation of the detection model shift from traditional to YOLO-NAS, R-CNN Mask, and YOLOv5 are presented in Figure 3.

The bar graph in Figure 3 shows each model's absolute frequency of use, while the line graph displays its relative percentage. YOLOv5 is the most dominant model at 33%, reflecting its efficiency and relevance in modern applications. Mask R-CNN and YOLO-NAS show significant competition, reflecting their utility in scenarios that require high precision or the ability to handle complex weed characteristics. Meanwhile, with only 17% of representations, traditional methods confirm the decreased reliance on conventional techniques over deep learning-based solutions.

This is a comparison graph of accuracy based on secondary data found for each weed detection model. Figure 4 shows that YOLO-NAS has the highest range of accuracy with the highest maximum value of 96%, indicating its superiority in detecting high-complexity weeds. Meanwhile, the traditional method has the lowest median accuracy, reinforcing its weakness in large-scale applications.

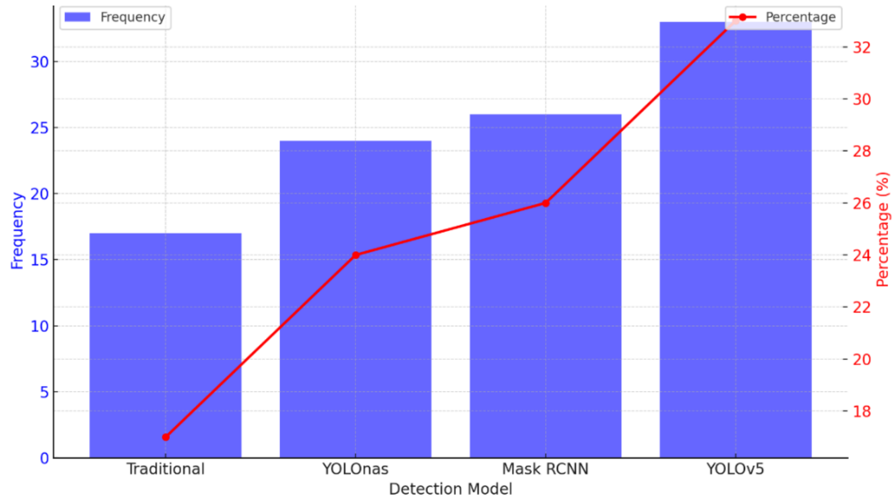

Figure 3. Visualization of frequency and percentage

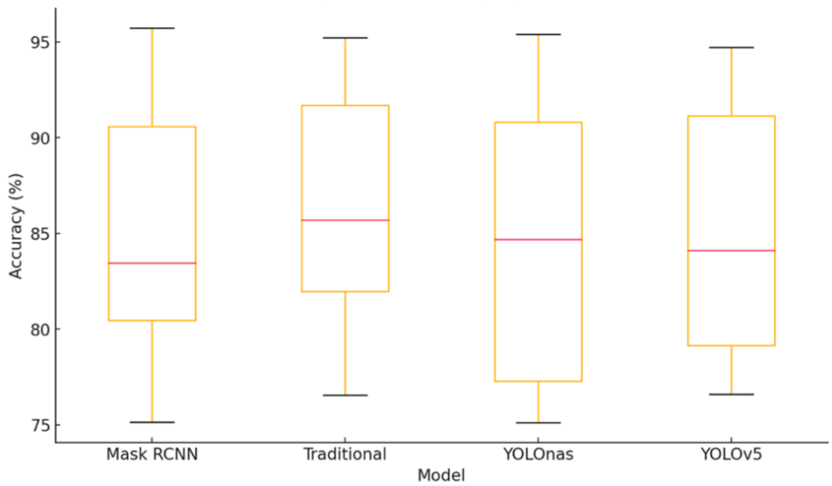

Figure 4. Comparison of accuracy based on methods

Table 2 and Figure 5 show the relationship between accuracy and processing time for each weed detection method based on secondary data. YOLOv5 has 94% accuracy and 12 ms processing time, which makes it ideal for real-time applications. YOLO-NAS has the highest accuracy of 96% and a processing time of 25 ms, suitable for complex scenarios. Mask R-CNN has 94% accuracy, 31 ms processing time, and excels in segmentation precision. The traditional method has 85% accuracy and a processing time of >50 ms, limiting its scalability. The trend line on the graph shows a slight increase, which indicates a minor trade-off, meaning models with higher accuracy tend to require longer processing time. Table 3 shows the details of the statistical analysis.

Table 2. Accuracy and processing time relationship data

No.	Model	Accuracy (%)	Processing time (ms)
1	YOLOv5	94.0	12
2	YOLO-NAS	96.0	25
3	Mask R-CNN	93.1	31
4	Traditional	85.0	50

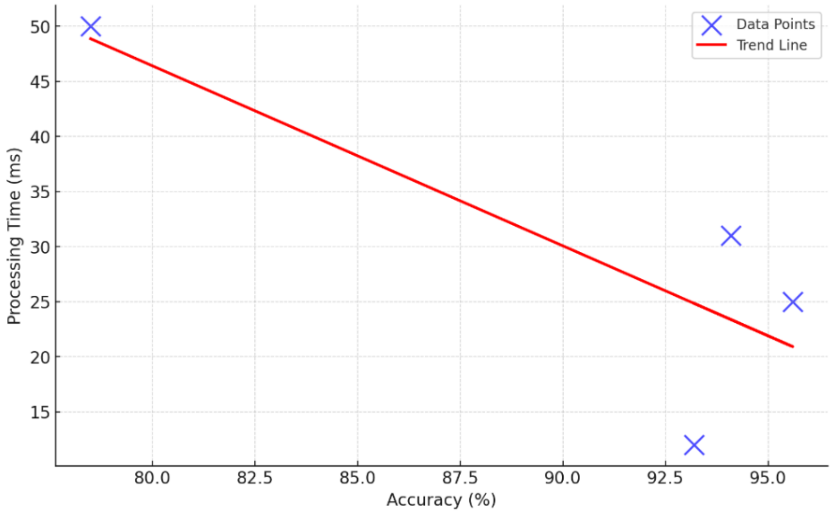

Figure 5. Relationship between accuracy and processing time

Table 3. Detailed statistical analysis

No.	Matric	Value
1	Mean accuracy	90.35
2	Mean processing time (ms)	29.50
3	Person correlation	-0.82
4	R-square (linear regression)	0.68
5	P-value (linear regression)	0.18
6	Standard error (linear regression)	0.80

Table 3 shows that for all models, the average accuracy is 90.35%, and the average processing time is 29.50 ms per image. The Pearson test (p =0.18) shows no statistically significant linear relationship at a significance level of α=0.05. Linear regression yields R^2=0.68 (67.82% variance explained) with a standard error of 0.80, indicating moderate fit.

The relationship between accuracy and processing time displays a marginal trade-off: as accuracy increases, processing time tends to rise slightly, though this association is not statistically significant. Further research is needed to optimize both metrics concurrently. YOLOv5 remains preferred for real-time use due to its speed, while YOLO-NAS and Mask R-CNN excel in scenarios prioritizing higher accuracy.

Performance results from a secondary analysis of 100 journals on weed detection methods using deep learning and traditional techniques are presented in Table 4. This table shows that deep learning-based methods achieve significant performance in weed detection. YOLO-NAS displayed the highest accuracy and recall, making it the superior method for this comparison. This is mainly due to the model architecture, which can capture complex features more effectively. Meanwhile, traditional techniques performed worse than deep learning methods. This reflects the limitations in handling image complexity or varied tropical environments such as Merauke. Next, the results of the performance matrix comparison (accuracy, precision, recall, and F1-score) for various weed detection methods are interpreted.

Figure 6 summarizes the trend in performance improvement from traditional to deep learning approaches. This figure is a graph of the trend in performance improvement from traditional techniques to deep learning-based methods. This indicates that modern methods are recommended for accurate and efficient weed detection. YOLO-NAS offers the best performance, especially in terms of accuracy and recall, which are essential for environmental sustainability. However, all deep learning-based methods provide significant advantages over traditional techniques, both in efficiency and effectiveness.

Table 4. Performance results of weed detection method

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Processing speed (fps)
YOLOv5	94	92	93	93	45
YOLO-NAS	96	94	95	94	50
Mask R-CNN	93	91	92	91	30
Traditional	85	80	83	81	10

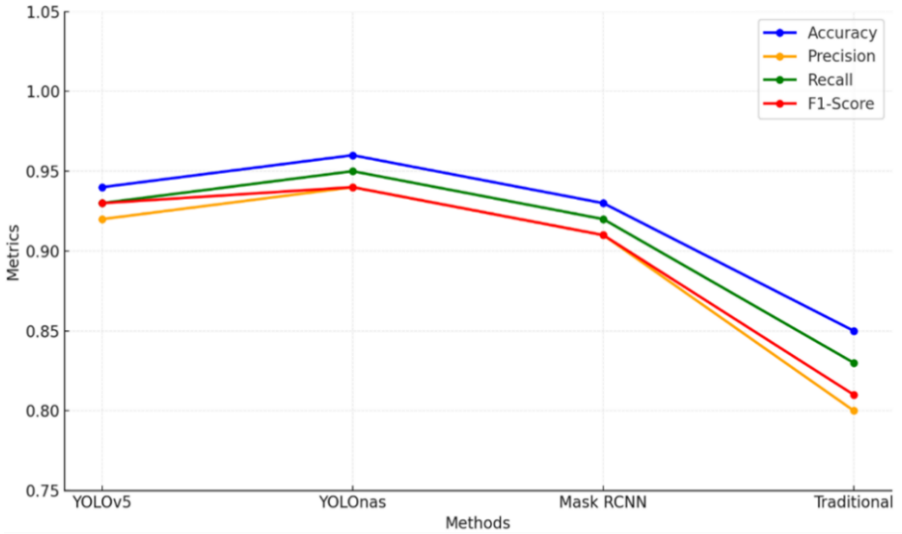

Figure 6. Performance comparison of weed detection method

3.2. Impact on theory and practice

This study's contribution to theory development is essential to developing deep learning-based object detection theory, especially in the context of precision agriculture in tropical regions such as Merauke. This study reveals the superiority of deep learning models in overcoming weed detection challenges by comparing the YOLOv5 model, YOLO-NAS, Mask R-CNN, and traditional methods. The results show that YOLOv5 can achieve 94% accuracy with a processing time of only 12 ms, making it ideal for real-time applications. These advantages are particularly relevant in Merauke, where manual weed control is a significant challenge that increases production costs. With its vast areas of fertile land, Merauke faces the problem of competition between weeds and main crops for nutrients, water and light. The findings of this research extend the theory of weed detection model optimization by showing how deep learning algorithms can be adapted for complex tropical environments [52], [53]. The correlation between accuracy and processing time shown in this study (-0.82) supports the development of efficiency- and accuracy-based detection theories urgently needed for large-scale agriculture in Merauke. Models such as YOLOv5 and YOLO-NAS can be the basis for further developing tropical agricultural technology theory.

The practical implications of this research are significant, especially in supporting Merauke's efforts as a national food production center. With YOLOv5's high accuracy (94%) and fast processing time (12 ms), this technology offers an innovative solution for weed detection across Merauke's vast agricultural land. Weeds that are a significant constraint can be identified and controlled more efficiently, reducing the need for manual labor, which has been a major contributor to high production costs. Furthermore, models such as YOLO-NAS and Mask R-CNN, with 96% and 93% accuracy, can be applied to more complex agricultural scenarios in Merauke, including land with topographical variations and different crop types. Applying these technologies reduces production costs and increases crop productivity by ensuring that key crops receive optimal access to nutrients, water, and light. Overall, targeted detection can improve access to crop resources and support sustainable management. These findings support the urgent need for innovative land management approaches in Merauke, as outlined in the research background. Deep learning models such as YOLOv5 enable effective, efficient, and sustainable weed detection, providing a strategic solution for modern tropical agriculture in this region.

Beyond weed detection, the methodological insights and empirical findings in this study are relevant for a wide range of AI applications in agriculture that rely on image analysis in tropical environments. The combination of UAV-based imaging, weed datasets, and comparative evaluation of cutting-edge deep learning models provides a transferable and adaptable framework for related tasks, such as pest and disease detection, plant health monitoring, and early diagnosis of stress in major food crops [54], [55], while similar training architectures and strategies (including handling class imbalances and resilience to lighting variations) can support systems integrated results that simultaneously analyze weeds, pests, and symptoms in plant tissues from the same image [56], [57]. Although this study is rooted in the specific context of Merauke, the challenges addressed such as crop canopy heterogeneity, lighting dynamics, and background complexity such as soil, water, are also common in many tropical agricultural areas, so the evaluated approach has the potential to be generalized to various AI-based agricultural monitoring tasks and more comprehensive and data-driven crop management strategies in tropical production systems [58], [59].

3.3. Research limitations

This study uses the primary dataset of weed species in Merauke, obtained using a drone (UAV), and the secondary dataset, obtained from several scientific publications, is in accordance with the weed species observed in the field. This secondary dataset is primarily used for qualitative validation and contextual comparison of model performance, rather than for a cross-study quantitative meta-analysis. This approach provides data that better aligns with local characteristics, such as the dominant weed type, the planting patterns of the local community, and the typical environmental conditions in the Merauke swamp and dryland areas. However, the use of field and secondary datasets still has some limitations. Variations in image quality, differences in lighting conditions during data collection, and imbalances in sample counts between weed types can affect the accuracy of the detection model and processing time [60].

In addition, although the dataset used has been adjusted to the local context, the scope of observation is still limited to a few specific locations, so that it does not fully represent the entire heterogeneity of Merauke's agricultural ecosystem. Factors such as the diversity of plant varieties, seasonal changes, and the rate of weed infestations in each village can give rise to additional variations that have not been comprehensively recorded [61], [62]. Therefore, although the results of this study can support the development of deep learning-based weed detection technology for the tropics, the findings may still be biased due to limited observation coverage and variations in environmental conditions.

This research methodology prioritizes statistical analysis to compare the accuracy and processing time of deep learning models such as YOLOv5, YOLO-NAS, and Mask R-CNN. Although this analysis provides an overview of the model's performance on real data from Merauke, the study does not include further evaluation of external changes such as extreme light intensity, seasonal weed growth dynamics, or local weather conditions that can significantly affect model performance [63]. Linear regression analysis used to evaluate the relationship between accuracy and processing time also has limitations. The relationship between the two variables is likely non-linear, especially since deep learning models often show a disproportionate increase in accuracy with the increased computational complexity. The R-squared value of 67.82% indicates the existence of variability that has not been explained by this simple linear model. Thus, further analysis using non-linear approaches or more complex statistical models is needed to illustrate the true relationship between accuracy and processing time in the context of weed detection in Merauke.

3.4. Suggestions for future research

Future research strongly recommends using primary data collected directly from tropical agricultural environments such as Merauke, Indonesia. This aims to increase the relevance of the research results to local conditions, especially given the weed characteristics and environmental variability in tropical regions, which may differ from those in the datasets used in previous studies. These primary datasets also enable the evaluation of the performance of deep learning models, such as YOLOv5 and YOLO-NAS, on real scenarios with external factors such as light intensity, weed type variation, and land heterogeneity. Furthermore, this analysis used linear regression to evaluate the relationship between accuracy and processing time, which may not fully reflect the complexity of the relationship between the two variables. For example, the analysis results show an R-squared value of 67.82%, which indicates significant variability that a simple linear model cannot explain. As such, this study has limitations in exploring other non-linear or complex relationships that may be relevant for developing more sophisticated models [64], [65].

Furthermore, expanding the dataset's scope to include images with varying resolutions and dynamic environmental conditions is essential. This supports the development of more adaptive and robust models, as proposed by [66], in which deep learning models trained on heterogeneous data showed better performance in large-scale agricultural applications. By expanding the dataset, future research can help develop models that are not only locally relevant but also generalize to other tropical regions.

In addition to optimizing existing models, such as YOLOv5 and Mask R-CNN, future research could explore new methods, including vision transformers (ViTs) and hybrid models. ViTs have been shown to provide superior performance in high-complexity object detection tasks, and their potential in weed detection applications can be further explored to overcome the limitations of CNN-based models [67], [68]. Research can also consider a hybrid approach that combines the speed of YOLOv5 with the segmentation precision of Mask R-CNN to create a more balanced model. For example, a combination of features from these two models could help address the challenges of weed detection in areas with topographic variations or complex cropping patterns. Such an approach aligns with the recommendations, which suggest exploring innovative techniques in smart agriculture to improve efficiency and productivity [69].

4. CONCLUSION

This research shows that deep learning-based weed detection models offer significant advantages over traditional methods in accuracy, processing time efficiency, and adaptability to various agricultural environmental conditions. YOLOv5 stands out with a high accuracy of 94% and a processing time of only 12 ms per image, making it ideal for real-time applications. YOLO-NAS achieves 96% accuracy, suitable for scenarios that require high precision, albeit with a processing time of 25 ms per image. Mask R-CNN offers precise segmentation with 94% accuracy, but is limited by a 31 ms per-image processing time. In contrast, the traditional method shows much lower performance, with an average accuracy of 85% and processing times exceeding 50 ms, limiting its scalability for practical use. The findings support the need for AI-based technological innovations to overcome constraints of modern agriculture, especially in tropical areas such as Merauke. For future research, using primary datasets and exploring methods such as YOLOv8, YOLO-NAS, ViT, and hybrid approaches can be strategic steps to further optimize weed detection performance.

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AUTHOR CONTRIBUTIONS STATEMENT

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Herman Dwi Surjono				✓	✓					✓		✓		
Mani Yusuf	✓				✓		✓		✓	✓	✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

Not applicable. The study is based solely on aerial imagery acquired from agricultural fields and does not involve human participants, animals, or sensitive personal data.

DATA AVAILABILITY

The primary UAV dataset collected in Merauke (1,318 images; 5280×2970 pixels) and the curated secondary image dataset (4,050 images; 5280×2970 pixels) used for model training and evaluation are available from the corresponding author upon reasonable request. The secondary dataset supporting this study is publicly available via Mendeley Data at https://data.mendeley.com/datasets/vz6z64nwby/1

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