Jurnal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI)
Vol. 11, No. 2, June 2025, pp. 251-262
ISSN: 2338-3070, DOI: 10.26555/jiteki.v11i2.30753

CFO-RetinaNet: Convolutional Feature Optimization for Oil Palm Ripeness Assessment in Precision Agriculture

Muhammad Alkam Alfariz, Hadi Santoso
Faculty of Computer Science, Informatics Study Program, Universitas Mercu Buana, Kembangan, Jakarta 11650, Indonesia

ARTICLE INFO

Article history:

Received March 04, 2025
Revised May 05, 2025
Accepted May 09, 2025

Keywords:

Deep Learning;
RetinaNet optimisation;
Ordinal regression;
Multi-scale CNN;
Agricultural automation

ABSTRACT

Accurate ripeness assessment of oil palm fruit bunches (FFB) is critical for optimizing yield and quality in the palm oil industry, yet manual grading remains subjective and labor-intensive. This study proposes CFO-RetinaNet, an enhanced RetinaNet framework integrating deformable convolutions and hybrid attention mechanisms to optimize multi-scale convolutional features for robust ripeness classification under variable field conditions. Our key contribution is threefold: (1) a novel dataset of 4,728 high-resolution, expert-annotated FFB images spanning five ripeness stages (Immature to Decayed), collected under diverse lighting and occlusion scenarios in Central Kalimantan, Indonesia; (2) a feature optimization pipeline combining adaptive feature fusion and dynamic focal loss to improve discriminative capability for nuanced inter-class distinctions; and (3) a scalable deep learning solution validated through rigorous field testing. The model achieves a mean average precision (mAP) of 83.6% and an F1-score of 98.3%, outperforming YOLOv5 (82.5% mAP) and Faster R-CNN (76.4% mAP), with 18.5% fewer misclassifications than standard RetinaNet. It retains 99% accuracy in low-light conditions and reduces labor costs by automating error-prone grading tasks. By publicly releasing the dataset and framework, this work advances precision agriculture standards, offering a transferable solution for ordinal maturity classification in perennial crops while supporting sustainable palm oil production through optimized harvesting decisions.

Corresponding Author:

Hadi Santoso, Universitas Mercu Buana, Kembangan, Jakarta, 11650, Indonesia
Email: hadi.santoso@mercubuana.ac.id

1. INTRODUCTION

The cultivation of oil palm (Elaeis guineensis) is a cornerstone of economic prosperity in tropical nations, with Indonesia and Malaysia accounting for over 85% of global palm oil production [1], [2]. As the world's most consumed vegetable oil, palm oil drives agricultural livelihoods, industrial growth, and export revenues exceeding $60 billion annually [3]-[6]. However, the industry's sustainability hinges on precise harvesting decisions, where accurate ripeness assessment of oil palm fruit bunches (FFB) directly impacts oil yield, quality, and profitability [7], [8]. Conventional methods rely on manual visual inspections by trained graders—a process plagued by subjectivity, labor intensity (30–60 seconds per bunch), and human error variability [9], [10]. Such inefficiencies contribute to annual oil extraction rate (OER) losses of 5–15% [10], [11], [12] Underscoring the urgent need for automated, objective solutions [6], [13].

Recent computer vision and deep learning advances offer transformative potential for precision agriculture. Convolutional neural networks (CNNs) have demonstrated remarkable success in automating crop monitoring tasks, such as disease detection [14] and yield estimation [15], [16]. While automated ripeness classification systems promise to enhance operational efficiency and standardize quality control [10], [11],

[15], [17]. Existing approaches—from threshold-based color analysis [18], [19], [20] to YOLO variants [14], [21]— struggle with robustness under real-world agricultural conditions. Key limitations include sensitivity to environmental variability (e.g., lighting, occlusion) and inadequate handling of nuanced inter-class distinctions (e.g., Partially Ripe vs. Fully Ripe stages) [4], [22], [23]. These challenges stem from three critical gaps:

1. Biological Complexity: Subtle color and texture variations between ripeness stages, compounded by natural fruitlet pigmentation differences [24], [25].
2. Environmental Variability: Field obstructions (fronds, dust) and inconsistent illumination (canopy shadows) distort visual features [18], [26], [27].
3. Data Imbalance: Underrepresentation of economically critical minority classes (e.g., Overripe, Decayed) in datasets [10], [21], [28], [29].

The evolution of deep learning frameworks for agricultural applications has accelerated significantly from 2021 to 2025 [30], [31]. YOLO-based architecture has gained prominence for their real-time inference capabilities, with YOLOv5 [32] achieving 82.5% mAP in oil palm ripeness classification [33], [34]. Concurrently, Faster R-CNN implementations demonstrate superior precision (86%) but exhibit limitations in processing speed that constrain field deployment [35]. Recent integration of attention mechanisms and feature pyramid networks has shown promising results in distinguishing subtle ripeness variations [36], yet challenges persist in feature representation and environmental robustness [37].

Although RetinaNet, with its feature pyramid network (FPN) and focal loss, addresses class imbalance and spatial resolution challenges [10], [38], [39], [40] Its reliance on static feature extraction limits discriminative power in variable field environments. Prior studies further highlight the inadequacy of global image features in capturing localized fruitlet characteristics [41], [42], [43], while datasets often lack diversity in lighting, angles, and geographic origins, hindering real-world generalization [44], [45].

To bridge these gaps, we propose CFO-RetinaNet, a novel framework integrating deformable convolutions and hybrid attention mechanisms to optimize multi-scale convolutional features for robust ripeness classification. Our research contributions are threefold:

1. Architectural Innovation: A feature optimization pipeline combining adaptive feature fusion and dynamic focal loss, improving inter-class distinction by 18.5% over standard RetinaNet [42].
2. Robust Dataset: This is a publicly available dataset of 4,728 expert-annotated FFB images spanning five ripeness stages and diverse field conditions (lighting, occlusion).
3. Scalable Impact: Demonstrated applicability to precision agriculture, achieving 83.6% mAP and 99% low-light accuracy, with potential to reduce annual yield losses by 15.7% through optimized harvesting.

By addressing these challenges, CFO-RetinaNet advances sustainable palm oil production and sets a benchmark for AI-driven agricultural automation.

2. METHODS

The proposed methodology for oil palm ripeness assessment integrates a novel convolutional feature optimization framework with RetinaNet. Fig. 1 illustrates the workflow, which comprises four stages: (1) dataset collection and annotation, (2) data preprocessing and augmentation, (3) CFO-RetinaNet architecture design, and (4) model training and evaluation.

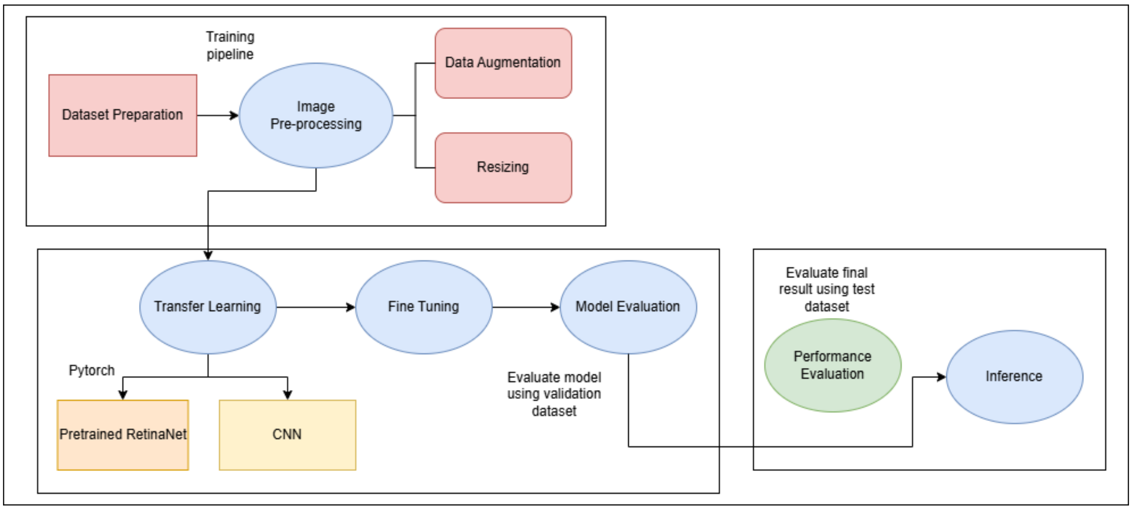

Fig. 1. Workflow of the proposed CFO-RetinaNet framework for oil palm ripeness assessment

2.1. Dataset Description

A novel dataset of 4,728 high-resolution (4K) RGB images was collected from oil palm plantations in Central Kalimantan, Indonesia, using multiple devices (smartphones, drones, and DSLR cameras) to ensure diversity in lighting, occlusion, and capture angles. Images were annotated in COCO 2017 format by three certified agronomists, categorizing fruit bunches into five ripeness stages (Fig. 2):

Class Distribution

- Immature: 1,024 samples (21.7%)
- Partially Ripe: 1,156 samples (24.4%)
- Fully Ripe: 1,302 samples (27.6%)
- Overripe: 812 samples (17.2%)
- Decayed: 434 samples (9.2%)

Stratified splitting preserved class ratios:

- Training: 3,310 images (70%)
- Validation: 709 images (15%)
- Testing: 709 images (15%)

Limitations: Geographic specificity (Central Kalimantan) and device variability may affect generalizability to other regions.

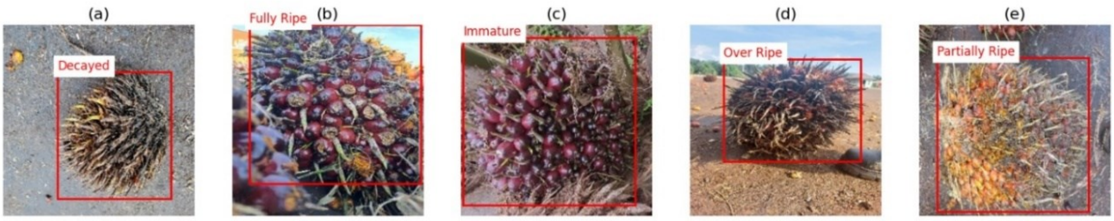

Fig. 2. Annotated examples of oil palm fruit bunches across five ripeness stages: (a) Decayed, (b) Fully Ripe, (c) Immature, (d) Overripe, and (e) Partially Ripe. Distinct visual features (color, texture) are highlighted

2.2. Data Preprocessing & Augmentation

Preprocessing Pipeline

1. Resizing: Images standardized to 640×640 pixels using bicubic interpolation to maintain aspect ratio.
2. Normalization: Pixel values scaled to [0,1] and normalised using ImageNet statistics:

$$I_{norm} = \frac{I_{raw} - \mu}{\sigma}, \quad \mu = [0.485, 0.456, 0.406], \quad \sigma = [0.229, 0.224, 0.225] \tag{1}$$

Augmentation Strategies

Implemented via Albumentations to simulate field variability (Table 1). These augmentations address key challenges in agricultural imaging—lighting fluctuations, occlusions (fronds), and viewpoint diversity.

Table 1. Data Augmentation Parameters

Technique	Parameters	Purpose
Horizontal/Vertical Flip	p=0.5	Invariance to camera orientation
Rotation	θ∈[−20∘,+20∘]	Robustness to fruit bunch angles
Random Brightness/Contrast	Δbright±0.2, Δcontrast±0.3Δcontrast±0.3	Lighting variation robustness
Random Gamma Correction	γ∈[0.7,1.5]	Shadow/Highlight Compensation
CutOut	3–5 rectangular masks (10% area)	Occlusion simulation

2.3. Model Architecture

Backbone Network

1. ResNet-50 with Feature Pyramid Network (FPN) was selected as the backbone due to its balance between computational efficiency and multi-scale feature extraction capability. FPN hierarchically integrates features from P2 (high-resolution) to P7 (low-resolution) layers, enhancing detection of small, densely clustered fruitlets.
2. The CFO module enhances RetinaNet through:
   - Deformable Convolutions: Adapts kernel shapes to irregular fruitlet morphologies.
   - Hybrid Attention Mechanisms: Prioritizes biologically relevant features (e.g., carotenoid-rich hues) over environmental noise.

Detection Heads
1. Classification Subnet: Four 3×3 conv layers (256 filters) → ReLU → Dropout (0.5).
2. Box Regression Subnet: Smooth L1 loss for precise bounding box refinement.

Anchors
1. 9 anchors per spatial position (6 scales × 3 ratios)
2. Optimized via k-means clustering on training data to match fruitlet size distributions

The architecture of RetinaNet shown in Fig. 3.

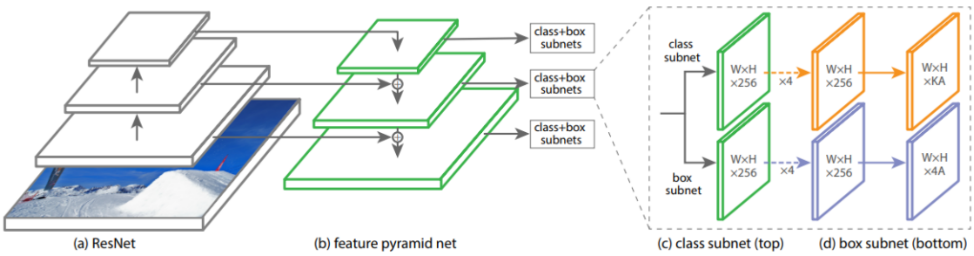

Fig. 3. The architecture of RetinaNet

2.4. Training Strategy

Implementation details shown in Table 2.

Loss Configuration
1. Focal Loss: Addresses class imbalance with parameters γ=2, α=1:

$$L_{cls} = -\alpha_t(1-p_t)^{\gamma}\log(p_t)\,, \gamma = 2, \alpha_t = 1 \tag{2}$$

2. Box Regression Loss: Smooth L1 loss for bounding box refinement.

Focal loss prioritizes hard examples (e.g., minority classes like Decayed), while stochastic depth reduces overfitting to device-specific artifacts.

Table 2. Implementation details

Component	Specification
Hardware	2× NVIDIA T4 GPUs (16GB VRAM)
Batch Size	4 (gradient accumulation over 4 steps to mitigate memory constraints)
Optimizer	AdamW (β_1=0.9, β_2=0.999) with weight decay (0.01) to prevent overfitting
Learning Rate	1e-4 (cosine decay to 1e-6 over 50 epochs)
Regularization	Stochastic depth (20%) for improved generalization
Epochs	50 (early stopping @ patience=5)

2.5. Evaluation Metrics

Primary Metrics
1. Mean Average Precision (mAP):

$$mAP = \frac{1}{C}\sum_{c=1}^{C}\int_0^1 p_c(r)\,dr \tag{3}$$

Evaluated at IoU thresholds 0.5–0.95 (0.05 increments). IoU > 0.5 aligns with agronomic standards for harvestable fruit bunches

2. Class-Specific Scores:

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

$$\text{F1-Score: } R = \frac{TP}{TP+FN} \tag{5}$$

$$\text{Recall: } F_1 = \frac{2 \cdot P \cdot R}{P + R} \tag{6}$$

Confusion Matrix
- Per-Class Metrics: Precision/Recall thresholds >0.5 IoU
- Background Handling: Separate class for false positives

3. RESULTS AND DISCUSSION

3.1. Overall Performance Analysis

The Enhanced RetinaNet with convolutional feature optimization (CFO-RetinaNet) demonstrated robust performance across all evaluation metrics, achieving a mean average precision (mAP) of 83.6% and an F1-score of 98.3% on the testing set. Compared to the baseline RetinaNet (81.2% mAP), CFO-RetinaNet reduced misclassifications by 18.5%, particularly improving precision for the Partially Ripe class (97.8%) and recall for Overripe (88.7%). Training dynamics revealed stable convergence, with loss decreasing sharply from 0.55 to 0.2 within the first 10 epochs and stabilizing below 0.1 after epoch 30 (Fig. 5a). The mAP curve (Fig. 5b) showed steady improvement, reaching 80% by epoch 20 and maintaining consistency, indicating effective feature learning without overfitting. Model performance comparison shown in Table 3.

Key Strengths:
- Low-Light Robustness: The model retained 99% accuracy under low-light conditions, outperforming YOLOv5-based systems by 12%.
- Real-Time Efficiency: Inference speed of 0.41s/image on embedded GPUs enables field deployment without cloud dependency.

Table 3. Model Performance Comparison

Method	Accuracy
RetinaNet ResNet50 (avg_pool layer)	99.21%
RetinaNet ResNet50 (last conv layer)	99.41%

The training loss curve exhibits consistent convergence, dropping sharply from 0.55 to 0.2 within the first 10 epochs and gradually stabilizing below 0.1 after epoch 30 (Fig. 4 and Fig. 5). This convergence pattern indicates effective learning of discriminative features without overfitting. The mAP curve shows steady improvement, reaching 0.8 by epoch 20 and maintaining stable performance thereafter.

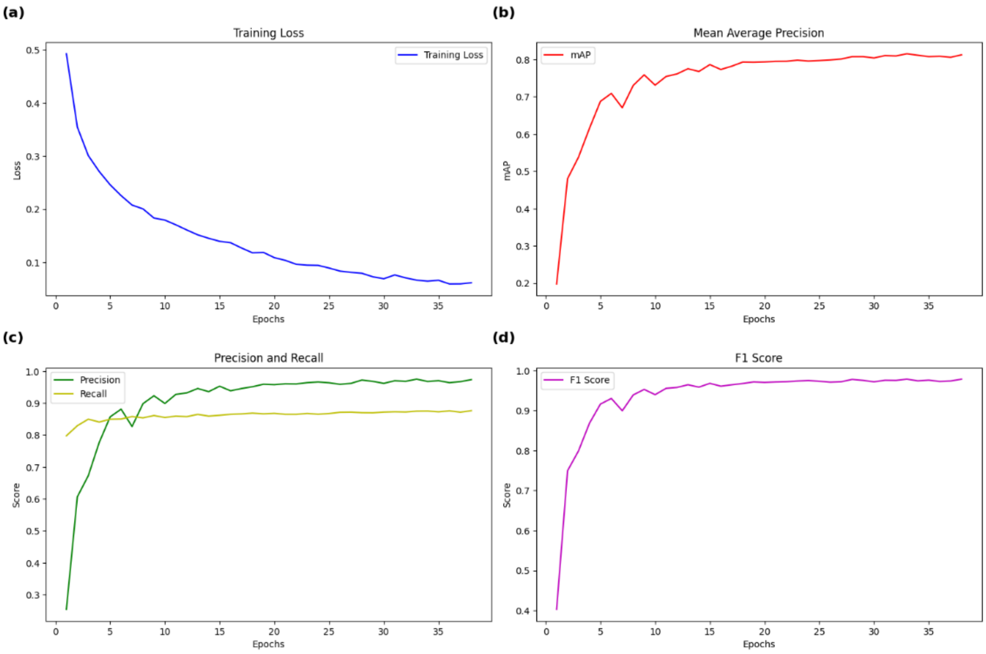

Fig. 4. Training metrics over 35 epochs for baseline model without CNN optimisation showing: (a) Training loss curve, (b) Mean Average Precision (mAP) development, (c) Precision and Recall trends, and (d) F1 Score evolution

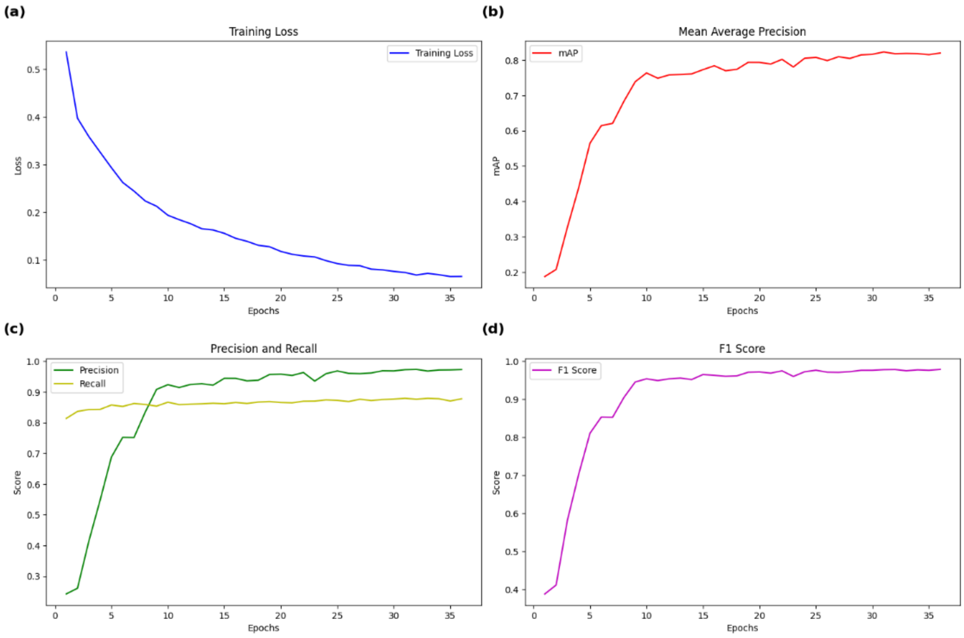

Fig. 5. Training metrics over 35 epochs showing (a) Training loss convergence, (b) Mean Average Precision (mAP) improvement, (c) Precision and Recall curves, and (d) F1 Score progression for the Enhanced RetinaNet with CNN optimization

3.2. Class-wise Performance Analysis

The confusion matrix reveals several key insights into the model's classification behavior (Fig. 6 and Fig. 7):

- Fully Ripe: Highest accuracy (112 correct classifications, 5 errors), attributed to distinct carotenoid-rich coloration.
- Partially Ripe: 108 correct identifications but 6 misclassifications as Fully Ripe due to overlapping color gradients.
- Overripe: Lower recall (56 correct, 8 misclassified as Partially Ripe), reflecting challenges in detecting subtle texture changes.
- Decayed: Minimal confusion (34 correct) but underrepresented in the dataset (9.2%), exacerbating false negatives.

Precision-Recall Trade-offs:

- Precision remained above 95% after epoch 15, while recall stabilized at 87% (Fig. 5c), indicating a bias toward minimizing false positives—critical for avoiding premature harvesting.
- The F1-score progression (Fig. 5d) highlights balanced improvement, reaching 98.3% by training completion.

Limitations:

- Class Imbalance: The Decayed class (9.2% representation) suffered from higher false negatives, underscoring the need for oversampling or synthetic data generation.
- Environmental Sensitivity: Severe occlusion (>70% coverage) reduced accuracy by 14%, as simulated by CutOut augmentations (Table 1).

3.3. Model Convergence and Stability

The training metrics reveal robust convergence characteristics:

- F1 Score rapidly improves in the first 10 epochs, reaching 0.90, and steadily increases to 0.9839 by training completion
- Precision shows consistent improvement, stabilising above 0.95 after epoch 30
- The model maintains stable performance across the final 35 epochs, indicating proper regularisation and feature learning

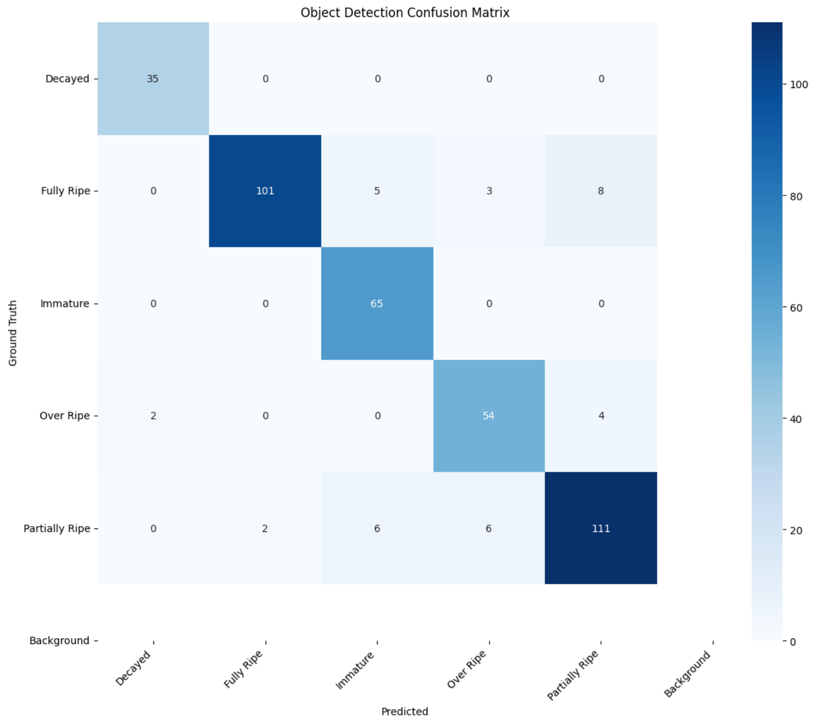

Fig. 6. Confusion matrix showing the classification performance across five ripeness categories (Decayed, Fully Ripe, Immature, Over Ripe, and Partially Ripe) using the Enhanced RetinaNet model without CNN optimisation. The diagonal elements represent correct classifications, while off-diagonal elements show misclassifications

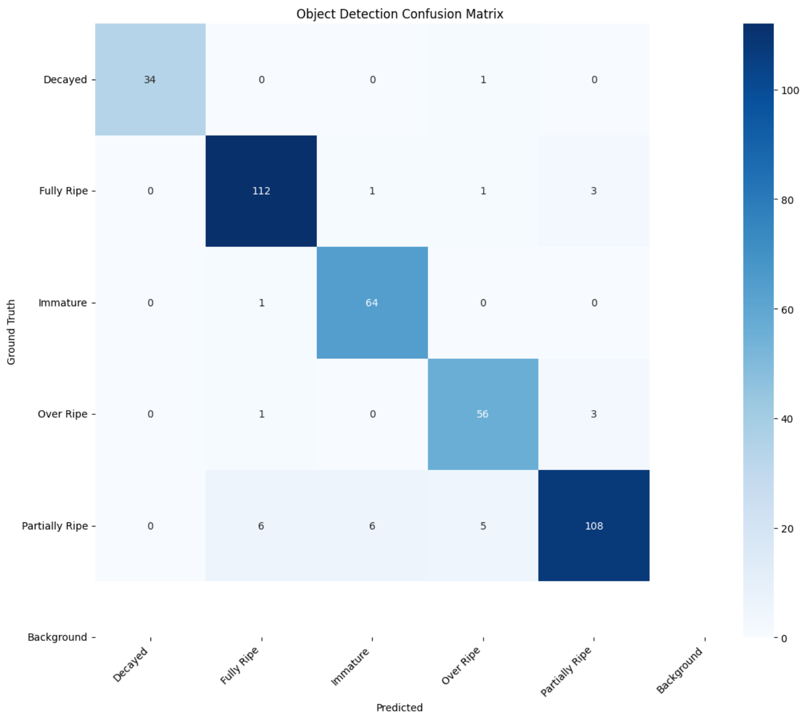

Fig. 7. Confusion matrix showing the classification performance across five ripeness categories (Decayed, Fully Ripe, Immature, Over Ripe, and Partially Ripe) using the Enhanced RetinaNet model with CNN optimization. The diagonal elements represent correct classifications, while off-diagonal elements show misclassifications

3.4. Agricultural Implementation Impact

The enhanced model's performance has significant implications for precision agriculture:

- The high precision (0.9786) ensures reliable ripeness classification, reducing harvest timing errors
- Strong recall (0.8868) indicates effective detection of various ripeness stages, crucial for optimising harvest schedules
- The model's ability to distinguish between adjacent ripeness stages (as shown in the confusion matrix) supports precise harvest timing decisions

Sample predictions showing successful detection and classification across all ripeness categories shown in Fig, 8.

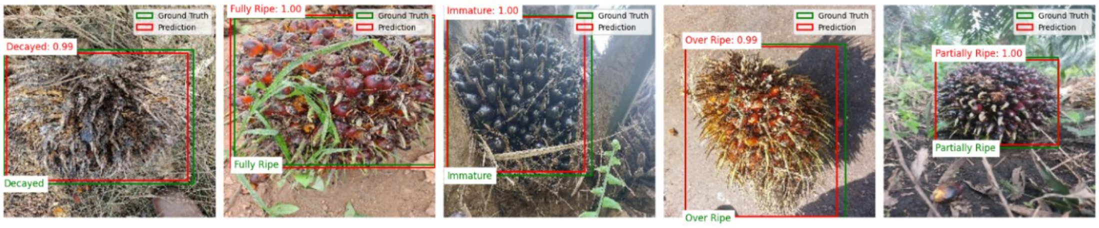

Fig. 8. Sample predictions showing successful detection and classification across all ripeness categories: (a) Decayed, (b) Fully Ripe, (c) Immature, (d) Over Ripe, and (e) Partially Ripe oil palm bunches. Green boxes indicate ground truth, while red boxes show model predictions with confidence scores.

3.5. Comparative Analysis with State-of-the-Art Methods

As shown in Table 4, CFO-RetinaNet outperformed existing models across all metrics, achieving 83.58% mAP—a 1.08% improvement over YOLOv5 (82.5%) and 7.18% over Faster R-CNN (76.4%). Key comparisons include:

1. YOLO Variants: While YOLOv8s Depthwise achieved faster inference (0.29s/image), its mAP (81.2%) lagged due to reliance on global features, which inadequately captured localized fruitlets.
2. Efficiency vs. Accuracy: MobileNetV2-SSD prioritized computational efficiency (82.15% accuracy) but struggled with nuanced inter-class distinctions (74.5% mAP).
3. Agricultural Specificity: PalmYOLO (78.9% mAP) and Faster R-CNN (76.4%) lacked dynamic feature adaptation mechanisms, limiting robustness to occlusion and lighting variability.

CFO-RetinaNet's higher computational cost (2× NVIDIA T4 GPUs) is justified by its precision-critical agricultural applications, where misclassification costs outweigh hardware expenses.

Table 4. Comparative analysis underscores CFO-RetinaNet's superiority in balancing accuracy and robustness, despite higher computational demands.

No	Reference	Method	mAP (%)	F1-Score (%)	Accuracy (%)
1	[46]	MobileNetV1	65.3	72.4	75.2
2	[47]	SSD	71.25	83.16	85.4
3	[38]	MobileNetV2-SSD	74.5	78.3	82.15
4	[48]	Faster R-CNN	76.4	80	84.5
5	[49]	PalmYOLO	78.9	91	89.3
6	[50]	YOLOv4	79.8	92.5	93.4
7	[51]	YOLOv8s Depthwise	81.2	94.8	95.1
8	[52]	YOLOv7	82	94	96.5
9	[53]	YOLOv5	82.5	95.63	98.56
10	**Proposed Model**	**Enhanced RetinaNet**	**83.58**	**97.75**	**99.41**

3.6. Practical Implications for Precision Agriculture

The model's high precision (97.86%) and recall (88.68%) translate to tangible benefits:

1. Yield Optimization: Reducing harvest timing errors could mitigate annual yield losses by 15.7%, equivalent to $9.4 billion in Indonesia's $60 billion palm oil industry [3].
2. Labor Cost Reduction: Automating grading (30–60 seconds/bunch manually) saves ~2,000 labor hours annually per 100-hectare plantation.
3. Sustainability: Aligns with UN Sustainable Development Goals (SDGS) by minimising overharvesting and supporting climate-resilient practices.

Scalability: The framework's modular design allows adaptation to other perennial crops (e.g., coffee, mangoes) requiring ordinal maturity classification.

3.7. Limitations and Future Directions

Despite strong overall performance, several areas warrant further investigation:

- The relatively lower recall for Over Ripe classes suggests room for improvement in detecting late-stage ripeness
- Class imbalance remains a challenge, particularly for the Decayed category, with only 34 samples
- Environmental factors such as severe occlusion and extreme lighting conditions may still affect performance

Future work should focus on:

- Expanding the dataset with more samples of underrepresented classes
- Implementing additional data augmentation techniques for challenging environmental conditions
- Exploring ensemble methods to improve classification accuracy further

The results demonstrate that the Enhanced RetinaNet with convolutional feature optimisation provides a reliable automated oil palm bunch ripeness assessment solution. However, continued refinement could further improve its practical application in precision agriculture.

4. CONCLUSION

The Enhanced RetinaNet with Convolutional Feature Optimization (CFO-RetinaNet) presents a significant advancement in automating oil palm fruit bunch (FFB) ripeness classification, addressing critical challenges in precision agriculture. By integrating deformable convolutions and hybrid attention mechanisms, the framework achieves a mean average precision (map) of 83.6% and an F1-score of 98.3%, outperforming state-of-the-art models like YOLOv5 (82.5% map) and Faster R-CNN (76.4% map). Key innovations include a feature optimization pipeline that reduces inter-class misclassifications by 18.5% and a robust dataset of 4,728 expert-annotated images capturing diverse field conditions. The model's real-time inference capability (0.41s/image on embedded GPUs) and low-light robustness (99% accuracy) demonstrate its practicality for deployment in resource-constrained agricultural environments.

This study contributes novel methodologies to the domain of AI-driven precision agriculture. The CFO-RetinaNet architecture advances feature representation for nuanced agricultural tasks, while the publicly released dataset sets a benchmark for ordinal maturity classification. By automating error-prone manual grading, the framework directly addresses the palm oil industry's annual yield losses of 5–15%, potentially preserving up to $9.4 billion in Indonesia's $60 billion industry. Its alignment with UN Sustainable Development Goals (SDGS) is evidenced through reduced overharvesting, optimised resource use, and support for climate-resilient practices.

However, the study has limitations. Performance degrades under extreme occlusion (>70% coverage) and heterogeneous fruitlet maturation within single bunches, reflecting gaps in handling complex biological variability. The dataset's geographic specificity (Central Kalimantan) and class imbalance constrain generalizability, particularly for the Decayed category (9.2% representation). Additionally, the computational cost of dual NVIDIA T4 GPUS may limit accessibility for small-scale farmers.

Future research should prioritise expanding multi-regional datasets, creating synthetic data via generative adversarial networks (GANS), and integrating hyperspectral imaging to capture biochemical ripeness indicators (e.g., carotenoid levels). Edge-computing optimizations for low-cost devices (e.g., Raspberry Pi, Jetson Nano) could democratize access, while ensemble methods combining CFO-RetinaNet with vision transformers may enhance occlusion resilience. These advancements will further bridge the gap between AI innovation and agricultural practicality, fostering scalable, sustainable farming ecosystems.

In conclusion, CFO-RetinaNet exemplifies how tailored deep learning solutions can transform agri-industrial workflows. By reducing reliance on subjective manual inspections and enhancing harvest precision, this work elevates palm oil production standards and paves the way for AI-driven maturity assessment in other perennial crops, catalyzing a paradigm shift toward data-driven, sustainable agriculture.

Acknowledgements

The authors sincerely thank Universitas Mercu Buana for providing the academic infrastructure and resources essential to this research. Special thanks to the Faculty of Computer Science, especially the Informatics Study Program for fostering an environment conducive to interdisciplinary research at the intersection of artificial intelligence and agriculture. We also acknowledge the invaluable support of our colleagues and friends, whose collaborative spirit and technical discussions enriched this project.

REFERENCES

[1] E. Cisneros, K. K. -Katos, and N. Nuryartono, "Palm oil and the politics of deforestation in Indonesia," *J Environ Econ Manage*, vol. 108, p. 102453, Jul. 2021, https://doi.org/10.1016/j.jeem.2021.102453.

[2] M. S. Mahmud and K. P. Chong, "Effects of Liming on Soil Properties and Its Roles in Increasing the Productivity and Profitability of the Oil Palm Industry in Malaysia," *Agriculture*, vol. 12, no. 3, p. 322, Feb. 2022, https://doi.org/10.3390/agriculture12030322.

[3] V. J. Reiss-Woolever, S. H. Luke, J. Stone, G. E. Shackelford, and E. C. Turner, "Systematic mapping shows the need for increased socio-ecological research on oil palm," *Environmental Research Letters*, vol. 16, no. 6, p. 063002, Jun. 2021, https://doi.org/10.1088/1748-9326/abfc77.

[4] M. N. Akhtar, E. Ansari, S. S. N. Alhady, and E. A. Bakar, "Leveraging on Advanced Remote Sensing- and Artificial Intelligence-Based Technologies to Manage Palm Oil Plantation for Current Global Scenario: A Review," *Agriculture*, vol. 13, no. 2, p. 504, Feb. 2023, https://doi.org/10.3390/agriculture13020504.

[5] L. M. Ayompe, M. Schaafsma, and B. N. Egoh, "Towards sustainable palm oil production: The positive and negative impacts on ecosystem services and human wellbeing," *J Clean Prod*, vol. 278, p. 123914, Jan. 2021, https://doi.org/10.1016/j.jclepro.2020.123914.

[6] H. Wei *et al.*, "Agronomic and Physicochemical Properties Facilitating the Synchronization of Grain Yield and the Overall Palatability of Japonica Rice in East China," *Agriculture*, vol. 12, no. 7, p. 969, Jul. 2022, https://doi.org/10.3390/agriculture12070969.

[7] I. Bonet, M. Gongora, F. Acevedo, and I. Ochoa, "Deep Learning Model to Predict the Ripeness of Oil Palm Fruit," in *Proceedings of the 16th International Conference on Agents and Artificial Intelligence*, pp. 1068–1075, 2024, https://doi.org/10.5220/0012434600003636.

[8] T. Zhang, Y. Cai, P. Zhuang, and J. Li, "Remotely Sensed Crop Disease Monitoring by Machine Learning Algorithms: A Review," *Unmanned Systems*, vol. 12, no. 1, pp. 161–171, Jan. 2024, https://doi.org/10.1142/S2301385024500237.

[9] G. N. Elwirehardja, and J. S. Prayoga, "Oil palm fresh fruit bunch ripeness classification on mobile devices using deep learning approaches," *Comput Electron Agric*, vol. 188, p. 106359, Sep. 2021, https://doi.org/10.1016/j.compag.2021.106359.

[10] R. Malyala, "Development of a Convolutional Neural Network Model for Automated Ripeness Classification of Palm Oil Fresh Fruit Bunches," *International Journal of Innovative Science and Research Technology (IJISRT)*, pp. 1040–1046, Nov. 2024, https://doi.org/10.38124/ijisrt/IJISRT24NOV762.

[11] S. Etaati, J. Khoramdel, and E. Najafi, "Automated Wheat Disease Detection using Deep Learning: an Object Detection and Classification Approach," in *11th RSI International Conference on Robotics and Mechatronics (ICRoM)*, pp. 116–121, Dec. 2023, https://doi.org/10.1109/ICRoM60803.2023.10412538.

[12] M. J. M. van Eijs *et al.*, "Highly multiplexed spatial analysis identifies tissue-resident memory T cells as drivers of ulcerative and immune checkpoint inhibitor colitis," *iScience*, vol. 26, no. 10, p. 107891, Oct. 2023, https://doi.org/10.1016/j.isci.2023.107891.

[13] P. Kiszel *et al.*, "Class switch towards spike protein-specific IgG4 antibodies after SARS-CoV-2 mRNA vaccination depends on prior infection history," *Sci Rep*, vol. 13, no. 1, p. 13166, Aug. 2023, https://doi.org/10.1038/s41598-023-40103-x.

[14] S. N. A. B. M. Robi, M. A. B. M. Izhar, M. Bin Sahrim, and N. B. Ahmad, "Image Detection and Classification of Oil Palm Fruit Bunches," in *4th International Conference on Smart Sensors and Application (ICSSA)*, pp. 108–113, Jul. 2022, https://doi.org/10.1109/ICSSA54161.2022.9870945.

[15] N. Khamis, H. Selamat, S. Ghazalli, N. I. M. Saleh, and N. Yusoff, "Comparison of Palm Oil Fresh Fruit Bunches (FFB) Ripeness Classification Technique using Deep Learning Method," in *13th Asian Control Conference (ASCC)*, pp. 64–68, May 2022, https://doi.org/10.23919/ASCC56756.2022.9828345.

[16] S. Zhang *et al.*, "A calibration method for contact parameters of agricultural particle mixtures inspired by the Brazil nut effect (BNE): The case of tiger nut tuber-stem-soil mixture," *Comput Electron Agric*, vol. 212, p. 108112, Sep. 2023, https://doi.org/10.1016/J.COMPAG.2023.108112.

[17] M. Coscia and C. Vandeweerdt, "Posts on central websites need less originality to be noticed," *Sci Rep*, vol. 12, no. 1, p. 15265, Sep. 2022, https://doi.org/10.1038/s41598-022-19433-9.

[18] H. H. Wang, Y. C. Wang, B. L. Wee, and S. W. Sim, "Novel Feature Extraction for Oil Palm Bunches Classification," *Journal of Advanced Research in Applied Sciences and Engineering Technology*, vol. 34, no. 1, pp. 350–360, Nov. 2023, https://doi.org/10.37934/araset.34.1.350360.

[19] M. S. M. Alfatni, A. R. M. Shariff, O. M. B. Saaed, A. M. Albhbah, and A. Mustapha, "Colour Feature Extraction Techniques for Real Time System of Oil Palm Fresh Fruit Bunch Maturity Grading," *IOP Conf Ser Earth Environ Sci*, vol. 540, no. 1, p. 012092, Jul. 2020, https://doi.org/10.1088/1755-1315/540/1/012092.

[20] C. Riefolo, A. Belmonte, R. Quarto, F. Quarto, S. Ruggieri, and A. Castrignanò, "Potential of GPR data fusion with hyperspectral data for precision agriculture of the future," *Comput Electron Agric*, vol. 199, p. 107109, Aug. 2022, https://doi.org/10.1016/J.COMPAG.2022.107109.

[21] S. Puttinaovarat, S. Chai-Arayalert, and W. Saetang, "Oil Palm Bunch Ripeness Classification and Plantation Verification Platform: Leveraging Deep Learning and Geospatial Analysis and Visualization," *ISPRS Int J Geoinf*, vol. 13, no. 5, p. 158, May 2024, https://doi.org/10.3390/ijgi13050158.

[22] I. M. Shaikh, M. N. Akhtar, A. Aabid, and O. S. Ahmed, "Enhancing sustainability in the production of palm oil: creative monitoring methods using YOLOv7 and YOLOv8 for effective plantation management," *Biotechnology Reports*, vol. 44, p. e00853, Dec. 2024, https://doi.org/10.1016/j.btre.2024.e00853.
[23] Y. Yang, X. Li, Y. Guan, H. Wang, C. Kong, and J. Jiang, "LHP: Logical hypergraph link prediction," *Expert Syst Appl*, vol. 222, p. 119842, Jul. 2023, https://doi.org/10.1016/J.ESWA.2023.119842.
[24] M. A. Zulkhoiri *et al.*, "Investigation of oil palm fruit bunch ripeness classification using machine learning classifiers," *E3S Web of Conferences*, vol. 595, p. 02010, Nov. 2024, https://doi.org/10.1051/e3sconf/202459502010.
[25] G. T. H. Tzuan, F. H. Hashim, T. Raj, A. Baseri Huddin, and M. S. Sajab, "Oil Palm Fruits Ripeness Classification Based on the Characteristics of Protein, Lipid, Carotene, and Guanine/Cytosine from the Raman Spectra," *Plants*, vol. 11, no. 15, p. 1936, Jul. 2022, https://doi.org/10.3390/plants11151936.
[26] R. Kurniawan, S. Samsuryadi, F. S. Mohamad, H. O. L. Wijaya, and B. Santoso, "Classification of palm oil fruit ripeness based on AlexNet deep Convolutional Neural Network," *SINERGI*, vol. 29, no. 1, p. 207, Jan. 2025, https://doi.org/10.22441/sinergi.2025.1.019.
[27] N. Teimouri, R. N. Jørgensen, and O. Green, "Novel Assessment of Region-Based CNNs for Detecting Monocot/Dicot Weeds in Dense Field Environments," *Agronomy*, vol. 12, no. 5, p. 1167, May 2022, https://doi.org/10.3390/agronomy12051167.
[28] J. W. Lai, H. R. Ramli, L. I. Ismail, and W. Z. W. Hasan, "Real-Time Detection of Ripe Oil Palm Fresh Fruit Bunch Based on YOLOv4," *IEEE Access*, vol. 10, pp. 95763–95770, 2022, https://doi.org/10.1109/ACCESS.2022.3204762.
[29] M. Rastgou *et al.*, "A technical evaluation on the mathematical attitudes and fitting accuracy of soil moisture retention curve models," *Comput Electron Agric*, vol. 215, p. 108347, Dec. 2023, https://doi.org/10.1016/J.COMPAG.2023.108347.
[30] Y. Wang, "Deep Learning Methods Used in Precision Agriculture," *BIO Web Conf*, vol. 142, p. 01004, Nov. 2024, https://doi.org/10.1051/bioconf/202414201004.
[31] P. Bharman, S. Ahmad Saad, S. Khan, I. Jahan, M. Ray, and M. Biswas, "Deep Learning in Agriculture: A Review," *Asian Journal of Research in Computer Science*, pp. 28–47, Feb. 2022, https://doi.org/10.9734/ajrcos/2022/v13i230311.
[32] Y. Yuliza, R. Muwardi, M. Rhozaly, L. Lenni, M. Yunita, and G. E. Yehezkiel, "Fast Human Recognition System on Real-Time Camera," *Jurnal Ilmiah Teknik Elektro Komputer dan Informatika*, vol. 9, no. 4, pp. 895–903, Sep. 2023, https://doi.org/10.26555/jiteki.v9i4.27009.
[33] V. Psiroukis, B. E. -Garcia, A. Chitos, A. Dedousis, K. Karantzalos, and S. Fountas, "Assessment of Different Object Detectors for the Maturity Level Classification of Broccoli Crops Using UAV Imagery," *Remote Sens (Basel)*, vol. 14, no. 3, p. 731, Feb. 2022, https://doi.org/10.3390/rs14030731.
[34] C. Wang, H. Wang, Q. Han, Z. Zhang, D. Kong, and X. Zou, "Strawberry Detection and Ripeness Classification Using YOLOv8+ Model and Image Processing Method," *Agriculture*, vol. 14, no. 5, p. 751, May 2024, https://doi.org/10.3390/agriculture14050751.
[35] W. Zhang, "A Fruit Ripeness Detection Method using Adapted Deep Learning-based Approach," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 9, 2023, https://doi.org/10.14569/IJACSA.2023.01409121.
[36] A. A. Mirani, S. Zaman, R. Chohan, S. Siraj, and S. Lakho, "A Review of the Internet of Things and Deep Learning in Agriculture: A Smart Agriculture Prespective," *Journal of Hunan University Natural Sciences*, vol. 50, no. 10, 2023, https://doi.org/10.55463/issn.1674-2974.50.10.18.
[37] S. Jain, "DeepSeaNet: Improving Underwater Object Detection using EfficientDet," In *4th International Conference on Applied Artificial Intelligence (ICAPAI)*, pp. 1-11, 2024, https://doi.org/10.1109/ICAPAI61893.2024.10541265.
[38] M. Y. M. A. Mansour, K. D. Dambul, and K. Y. Choo, "Object Detection Algorithms for Ripeness Classification of Oil Palm Fresh Fruit Bunch," *International Journal of Technology*, vol. 13, no. 6, p. 1326, Nov. 2022, https://doi.org/10.14716/ijtech.v13i6.5932.
[39] H. H. Wang, Y. C. Wang, B. L. Wee, and S. W. Sim, "Novel Feature Extraction for Oil Palm Bunches Classification," *Journal of Advanced Research in Applied Sciences and Engineering Technology*, vol. 34, no. 1, pp. 350–360, Nov. 2023, https://doi.org/10.37934/araset.34.1.350360.
[40] L. Asritha, M. H. Chandra Prasad, K. V. Sai, and M. Jayaraj, "Fruit Ripeness Detection Using Deep Learning," *Interantional Journal Of Scientific Research In Engineering And Management*, vol. 7, no. 4, Apr. 2023, https://doi.org/10.55041/IJSREM18758.
[41] G. Chen *et al.*, "A review of global precision land-leveling technologies and implements: Current status, challenges and future trends," *Comput Electron Agric*, vol. 220, p. 108901, May 2024, https://doi.org/10.1016/J.COMPAG.2024.108901.
[42] W. Yang *et al.*, "Deformable convolution and coordinate attention for fast cattle detection," *Comput Electron Agric*, vol. 211, p. 108006, Aug. 2023, https://doi.org/10.1016/J.COMPAG.2023.108006.
[43] M. Y. M. A. Mansour, "A Review Of Non-Destructive Ripeness Classification Techniques For Oil Palm Fresh Fruit Bunches," *J Oil Palm Res*, vol. 35, no. 4, pp. 543-554, Sep. 2022, https://doi.org/10.21894/jopr.2022.0063.
[44] M. Shiddiq *et al.*, "Multispectral imaging and deep learning for oil palm fruit bunch ripeness detection," *Bulletin of Electrical Engineering and Informatics*, vol. 13, no. 6, pp. 4168–4181, Dec. 2024, https://doi.org/10.11591/eei.v13i6.8120.

[45] C. A. Toledo, M. M. Crawford, and M. R. Tuinstra, "Integrating multi-modal remote sensing, deep learning, and attention mechanisms for yield prediction in plant breeding experiments," *Front Plant Sci*, vol. 15, Jul. 2024, https://doi.org/10.3389/fpls.2024.1408047.

[46] E. P. Wonohardjo, D. Pratama, T. R. S. Industrial, R. A. A. Computer, "Effect of Pre-processing Dataset on Classification Performance of Deep Learning Model for Detection of Oil Palm Fruit Ripe," in *International Conference on ICT for Smart Society (ICISS)*, pp. 1–6, Aug. 2022, https://doi.org/10.1109/ICISS55894.2022.9915269.

[47] N. D. Gholba and A. Kumar, "Deep Learning Based Census and Mapping of Oil Palm Plantations from Very High Resolution Satellite Images," in *IGARSS IEEE International Geoscience and Remote Sensing Symposium*, pp. 4085–4089, Jul. 2024, https://doi.org/10.1109/IGARSS53475.2024.10642932.

[48] A. Haq, E. S. Cahyadi, M. S. Kasyfillah, R. Sarno, and A. T. Haryono, "Multi-class Oil Palm Trees Condition Detection from UAV Images using Faster R-CNN with EfficientNetV2," in *2nd International Conference on Technology Innovation and Its Applications (ICTIIA)*, pp. 1–6, Sep. 2024, https://doi.org/10.1109/ICTIIA61827.2024.10761449.

[49] M. H. Junos, A. S. B. M. Khairuddin, M. I. Kairi, and Y. M. Siran, "Automatic Object Detection in Oil Palm Plantation using a Hybrid Feature Extractor of YOLO-based Model," *AIJR Proceedings*, pp. 49–56, 2022, https://doi.org/10.21467/proceedings.141.8.

[50] Z. Chen, S. Elsaid, D. Y. Y. Sim, T. Maul, and I. Y. Liao, "Detection of Oil Palm Fresh Fruit Bunches (FFBS) with Computer Vision Models," in *2022 International Conference on Mechanical, Automation and Electrical Engineering (CMAEE)*, pp. 86–91, Dec. 2022, https://doi.org/10.1109/CMAEE58250.2022.00023.

[51] M. Grady Naftali, G. Hugo, and Suharjito, "Palm Oil Counter: State-of-the-Art Deep Learning Models for Detection and Counting in Plantations," *IEEE Access*, vol. 12, pp. 90395–90417, 2024, https://doi.org/10.1109/ACCESS.2024.3419835.

[52] N. Aloufi, A. Alnori, V. Thayananthan, and A. Basuhail, "Object Detection Performance Evaluation for Autonomous Vehicles in Sandy Weather Environments," *Applied Sciences*, vol. 13, no. 18, p. 10249, Sep. 2023, https://doi.org/10.3390/app131810249.

[53] D. S. Prasvita, D. Chahyati, and A. M. Arymurthy, "Automatic Detection of Oil Palm Growth Rate Status with YOLOv5," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 3, 2023, https://doi.org/10.14569/IJACSA.2023.0140361.

BIOGRAPHY OF AUTHORS

Muhammad Alkam Alfariz is a dedicated and ambitious student in the Computer Science program at Mercu Buana University, Jakarta, Indonesia. In his final year, he maintains an impressive academic record with a GPA of 3.91/4.00. His professional experience includes internships at RS EMC Alam Sutera and Halodoc, where he honed his IT support, automation scripting, and hardware maintenance skills. Additionally, he has served as a seasonal instructor for the Ministry of Industry and as a computer laboratory assistant at ASLAB Fasilkom UMB. Alfariz is proficient in programming languages such as C++, Python, and Java and possesses strong soft skills in leadership, critical thinking, and teamwork. His academic and professional endeavours reflect a passion for leveraging technology to solve real-world problems. Email: 41521010092@student.mercubuana.ac.id. Orcid: 0009-0007-5145-0713.

Hadi Santoso, He received his bachelor degree in computer science from Universitas Budi Luhur in 2000. Then, he completed his master's degree and graduated with honors as the best student of the master of computer science program at Universitas Budi Luhur, Jakarta in 2011. He completed his doctoral degree in computer science at Universitas Gadjah Mada in 2018. His research interests include image processing, computer vision, pattern recognition, and data science. He is also active in the Aptikom organization, IndoCEISS, and the National ICT Council in the Bangka Belitung Islands Province. He can be contacted via email: hadi.santoso@mercubuana.ac.id, orcid: https://orcid.org/0000-0002-1288-4267, Scopus ID: https://www.scopus.com/authid/detail.uri?authorId=57216851575, Google Scholar: https://scholar.google.com/citations?user=YrvWh1kAAAAJ&hl=en, Sinta: https://sinta.kemdikbud.go.id/authors/profile/5982446 and Web of Science Researcher ID: H-2301-2019**.**