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A Systematic Literature Review of Palm Oil Maturity Detection via Deep Learning Approaches

Sorotan Kajian Sistematik Berkenaan Pengesanan Kematangan Kelapa Sawit Melalui Pendekatan Pembelajaran Mendalam

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ABSTRACT

An accurate classification of oil palm fresh fruit bunches (FFB) by maturity level is crucial for maximizing the oil yield and maintaining product quality. While manual inspection remain widely practice, it is limited by the subjectivity and inefficiency, especially in large-scale plantation environments. As a result, non-destructive approaches that incorporates computer vision and sensor technologies have emerged as promising alternatives. Hence, this review aims to (1) summarize existing studies that have applied deep learning to detect oil palm maturity, (2) examine the methodological and practical challenges that hinder the real-world deployment of these systems, and (3) discuss the future directions to advance the oil palm industry. The analysis demonstrates that despite deployment challenges, YOLO hold strong potential for automating palm oil maturity assessment. By consolidating existing knowledge and highlighting critical research gap, this review provides a clearer understanding of the field and oulines a pathway for transitioning these technologies from experimental validation to reliable field deployment.

Keywords**:** Palm Oil; Fresh Fruit Bunches (FFB); maturity detection; YOLO; deep learning

ABSTRAK

Ketepatan suatu pengelasan buah tandan segar kelapa sawit (FFB) mengikut tahap kematangan buah adalah sangat penting bagi memastikan hasil dan kualiti minyak sawit berada pada tahap yang terbaik. Walaupun pemeriksaan secara manual masih diamalkan secara meluas, namun kaedah tersebut amat terbatas oleh faktor kesubjektifan dan ketidakcekapan, terutamanya dalam persekitaran ladang yang berskala besar. Sehubungan dengan itu, pendekatan yang tidak memusnahkan yang menggabungkan penglihatan komputer dan teknologi sensor telah muncul sebagai alternatif yang berpotensi. Justeru, sorotan kajian ini bertujuan untuk (1) membuat ringkasan kajian-kajian lepas mengenai penggunaan pembelajaran mendalam dalam mengesan kematangan kelapa sawit, (2) meneliti cabaran metodologi dan praktikal yang menghalang penggunaan sistem ini dalam dunia sebenar, dan (3) membincangkan hala tuju masa hadapan bagi memajukan industry kelapa sawit. Analisis menunjukkan bahawa walaupun terdapat cabaran pelaksanaan, YOLO mempunyai potensi yang sangat besar untuk membuat penilaian kematangan kelapa sawit secara automatik dan tepat. Dengan menggabungkan pengetahuan yang ada serta menekankan jurang penyelidikan yang kritikal, sorotan kajian ini memberikan pemahaman yang lebih jelas tentang bidang ini serta menggariskan hala tuju untuk peralihan teknologi daripada pengesahan eksperimen kepada pelaksanaan lapangan yang boleh dipercayai.

Kata kunci**:** Kelapa Sawit; Buah Tandan Segar (FFB); pengesanan kematangan; YOLO; pembelajaran mendalam

INTRODUCTION

Palm oil has become one of the most significant products in the global vegetable oil industry. More than 80% of the world's supply is produced by Malaysia and Indonesia, making them the largest producers. The demand for palm oil keeps on rising year by year. This rising is mainly driven by the oil’s versatility, as it is widely used across a broad range of consumer goods including food products, cosmetics, soaps, biofuels, and pharmaceutical applications.

In the palm oil industry, processing efficiency can be directly reduced, and the quality of the extracted oil can be compromised when fresh fruit bunches (FFB) are harvested at either the unripe or overripe stage. This negatively affects the economic returns of the palm oil industry. Therefore, the ability to accurately determine the maturity of oil palm FFB is crucial, as it helps to maximise oil extraction rates while maintaining the overall quality of the palm oil.

Traditionally, this classification has been carried out manually by plantation workers where they solely rely on their visual inspection and experience. While this method remains widely practiced, it tends to be subjective and often inconsistent. This is due to a few factors such as different skill levels, environmental conditions, and worker fatigue (Bonet et al. 2024). On top of that, manual assessment can be labor-intensive and also time-consuming. This makes it less effective for large-scale operations that often require speed, precision, and scalability.

Researchers have favored non-destructive technologies that aim to automate the classification process. According to Wang et al. (2015), approaches such as machine vision systems, spectral imaging, and thermal sensors are used to detect physical and chemical characteristics of the fruit without damaging it. These methods offer faster and more objective assessments in classifying the maturity of the fruit. Hence, it contributes to improve the productivity and operational efficiency on plantations (Wang et al. 2015; Mahanti et al. 2022).

Recently, deep learning has emerged as a powerful tool for object detection and classification tasks. Algorithms such as Convolutional Neural Networks (CNN) and You Only Look Once (YOLO) have a strong capability in recognizing and classifying complex visual patterns, particularly in determining the maturity of oil palm FFB. These models offer near real-time results without compromising accuracy. Hence, deep learning has become a promising approach for smart farming applications and automated harvesting systems in the palm oil industry.

Therefore, this review aims to (1) summarize the existing research on deep learning applications for oil palm FFB maturity detection, (2) examine the methodology and practical challenges for real-world deployment of deep learning models, and (3) discuss the future directions to advance the oil palm industry.

The remainder of this study is outlined as follows, where Section 2 details the PRISMA-guided methodology applied for the systematic literature search. In Section 3, this review presents a summary of the reviewed studies, followed by a discussion of the main challenges, and the future research direction. Finally, a summary of the key findings and their significance for the palm oil industry is provided at the conclusion of the review.

METHODOLOGY

The review of palm oil maturity detection was conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Page *et al.* 2021). A thorough search was performed in the SCOPUS database on 14th March 2025 to identify research papers on palm oil maturity detection. The terms "Palm oil Detection" and "Maturity Detection" were executed during the inquiry process. The query used was *TITLE-ABS-KEY (palm AND oil AND detection) AND PUBYEAR > 2018 AND PUBYEAR < 2026 AND (LIMIT-TO (EXACTKEYWORD , "Palm Oil") OR LIMIT-TO (EXACTKEYWORD , "Oil Palm") OR LIMIT-TO (EXACTKEYWORD , "Detection Method") OR LIMIT-TO (EXACTKEYWORD , "Deep Learning") OR LIMIT-TO (EXACTKEYWORD , "Object Detection") OR LIMIT-TO (EXACTKEYWORD , "Malaysia") OR LIMIT-TO (EXACTKEYWORD, "Fruits") OR LIMIT-TO (EXACTKEYWORD , "Oil Palm Plantations")).*

In the initial search string, any specific algorithm names such as “YOLO” and “CNN” or domain-specific terms like “fresh fruit bunches”, were intentionally excluded. This is crucial to ensure a more comprehensive collection of relevant studies because limiting the search to any specific terms could have missed other relevant papers that used alternative deep learning models or referred to the fruit using different terminology, such as “palm fruit” or “loose fruit”. Therefore, a broad search was conducted first in order to capture a broader scope of literature that is related to oil palm maturity detection using deep learning. The identified studies were then filtered using the following specific selection criteria:

(1) Publication Years: Research published between 2019 and 2025 was considered to ensure the relevance of the latest advancements.
(2) Publication Status: Only final publications were included, reflecting high-quality, peer-reviewed studies.
(3) Language: Only English-language articles were considered.
(4) Relevance: Articles were selected based on their primary focus on applying deep learning models to the visual detection or classification of oil palm fruit bunch maturity.

Figure 1 presents the PRISMA 2020 flow diagram of a systematic selection process for review. The selection aimed to retrieve the most relevant literature related to oil palm maturity classification using deep learning based on the selection criteria mentioned above. The process started with an initial search of the SCOPUS database covering the period from 2019 to March 2025 and identified 518 records.

From 518 records identified, title-based screening and document type filters were applied. Then, only journal articles, conference papers, and book chapters were retained. Automated keyword rules at the title level excluded studies outside the scope of this review which includes topics related to chemical analysis, biodiesel production, spectroscopy-based laboratory methods, chromatography, and socioeconomic assessments. In the screening stage, resulted in 259 records were moving forward to eligibility stage.

Next, the process continued with the eligibility stage which includes two rounds of abstract screening and full-text retrieval steps. First, abstract screening is assessed on the topical and methodological focus of each study. Records were excluded if they did not explicitly address oil palm or FFB maturity tasks, or if they do not employ any deep learning or computer vision models for detection, classification or grading. This step has excluded 179 records, leaving 80 records eligible for further evaluation.

The 80 remaining records were proceeded to manual screening step where the abstracts of each record were carefully examined to verify the relevance of the study based on authors' judgements. This step led to the exclusion of 59 records, leaving 21 records that met all the criteria. Then, from these 21 records, only 15 publications were available as open-access full-texts and could be successfully retrieved. As of PRISMA 2020 recommendations, accessibility of the full-text publication is essential for a reliable assessment of relevance and methodological quality. These 15 publications were therefore included in the final qualitative synthesis.

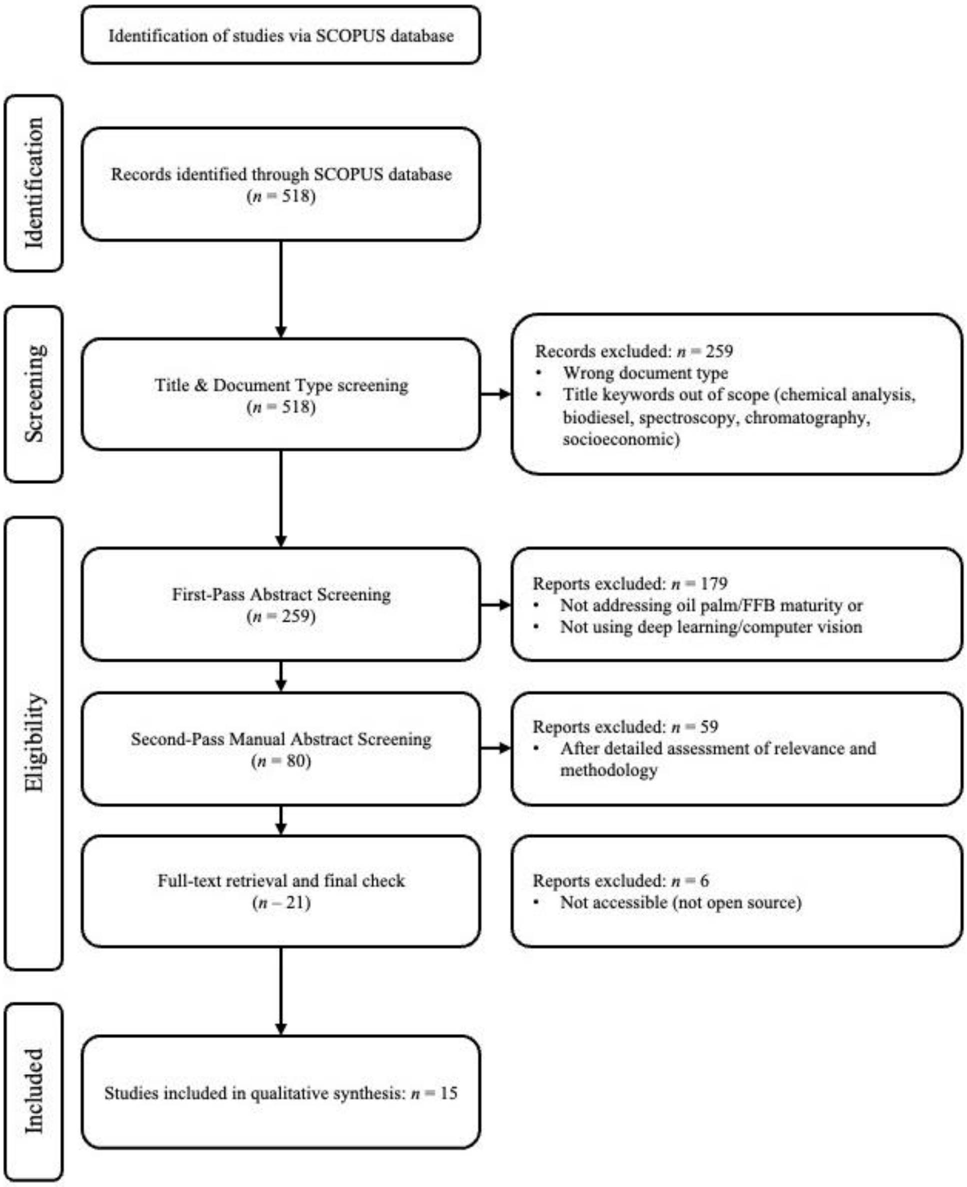

FIGURE 1. PRISMA 2020 flow diagram for systematic review.

Figure 2 shows the number of publications included in the final qualitative synthesis by their year of publication. As shown in Figure 2, research activity in this area has generally increased from 2020 to 2024. There are two relevant studies that were identified in 2020 indicating early interest among researchers and industry players in adapting deep learning in palm oil agriculture. However, a slight decline in 2021 is observed, with only one study published. This may be due to global research disruptions during the COVID-19 pandemic, which includes restricted fieldwork, limited experimental access, and shifting research priorities.

As shown in Figure 2, an increase in the number of publications is observed, with three and five studies published in 2022 and 2023, respectively. The increasing trend shows in 2022 to 2023 reflects an increasing academic recognition among researchers regarding the potential of employing deep learning within oil palm agriculture especially in maturity detection and classification. Although there is a slight reduction observed in 2024, but the publication volume remains higher compared to the number of publications in the earlier years. This is not a decrease in interest but rather due to incomplete database indexing because some recent publications may not yet be fully available at the time of data collection.

Table 1 shows the summary of the final 15 studies that are included for review. Based on the summary shown in Table 1, there is a clear evolution in maturity detection tasks in the oil palm industry. The summary contains the core aspects of each study, which includes the data description, methodological approach, and key results. Following this comparative table, the next section will discuss the challenges that hinder the deployment of the deep learning models and propose future research directions to advance the field.

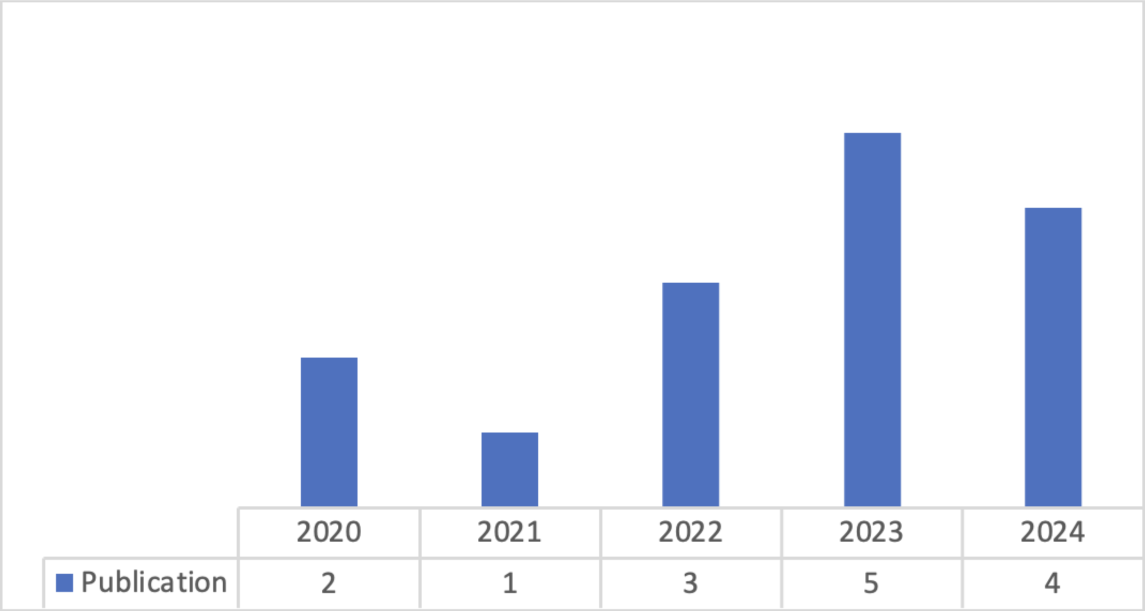

FIGURE 2. The distribution of the research paper reviewed.

TABLE 1. Summary of studies on oil palm maturity detection using deep learning

Author(s) & Year	Data Description	Methodology	Key Result
Prasetyo et al.(2020)	• 100 FFB images scrapped from the internet. • Images resulted in 536 annotations in COCO format. • Dataset divided into five partitions for cross-validation.	• Used the Faster R-CNN algorithm for detection. • Evaluated Inception V2 and ResNet architectures. • Applied 5-fold cross-validation to prevent overfitting.	• Success indicated by average F1 scores above 80%. • ResNet 50 achieved the highest F1 score of 86%. • Model successfully automated detection and calculation.
Syaifuddin et al.(2020)	• 99 total palm images collected for grading. • Data split into 78 training and 21 testing samples. • Fruits classified as raw, mature, or overcooked.	• GLCM method used for texture feature extraction. • Feature selection performed via backward regression. • Built a first-order Sugeno fuzzy inference system.	• Training data achieved an accuracy of 73.07%. • Testing data achieved an accuracy of 71.4%. • System effectively identified maturity from outer colour.

Mohd Basir Selvam et al. (2021)	• 1500 images per class for three maturity levels. • Images captured at 3024x4032 resolution. • Final training utilized a set of 1000 images.	• Employed the YOLOv3 algorithm for real-time detection. • Darknet framework used for training and testing. • Used pre-trained weights for transfer learning.	• Highest accuracy reached 95.18% mAP at 5000 iterations. • Learning saturation and overfitting occurred at 6000 iterations. • System successfully differentiated maturity levels.
Mohd Robi et al.(2022)	• 175 images collected from internet sources. • Data augmented to 350 images to prevent overfitting. • Split into 70% training, 20% verification, and 10% testing.	• Compared YOLOv3, YOLOv4, and their "tiny" variants. • Applied fine-tuning using pre-trained YOLO weights. • Configuration included 2000 to 4000 iterations.	• YOLOv4 achieved the highest accuracy of 98.70%. • One-class detection peaked at 98.97% mAP. • Demonstrated higher precision than YOLOv3 models.
Mansour et al.(2022)	• 328 ground-based images of oil palm FFB. • Data balanced to 304 images across four classes. • Categories included ripe, unripe, half-ripe, and over-ripe.	• Comparison of YOLOv5, MobileNetV2 SSD, and EfficientDet. • Models trained for 300 epochs on 640x640 resolution. • YOLOv5 used CSPNet-based backbone for feature extraction.	• YOLOv5m performed best with a mAP of 0.842. • YOLOv5 models outperformed EfficientDet in all metrics. • MobileNetV2 SSD was suitable for mobile but less accurate.
Lai et al.(2022)	• 490 ripe FFB images captured on-tree. • Images captured at 1920×1080 resolution. • Variation induced via different angles and lighting.	• Utilised the YOLOv4 model for real-time detection. • Integrated with Robot Operating System (ROS). • Compared YOLOv4, YOLOv4-CSP, and YOLOv4-tiny.	• Achieved 87.9% mAP and 82% recall during testing. • Real-time detection speed averaged 21 FPS. • Successfully detected ripe bunches in varied environments.
Daud et al.(2023)	• 2140 tree images and 490 loose fruitlet images used. • Data collected from smallholder plantation areas. • Images captured using handheld DJI Osmo Pocket.	• YOLOv5 for tree detection and YOLOv4 for fruitlets. • Tree tracking used to avoid redundant counting. • Readiness predicted by the count of loose ground fruitlets.	• Palm tree detection achieved a mAP of 97.79%. • Fruitlet detection achieved a mAP of 85.45%. • Classification accuracy reached 91.34% with 3-fruitlet threshold.
Junior & Suharjito(2023)	• 929 frames extracted from 49 training videos. • Augmented to 4645 images using photometric techniques. • Testing performed on single and multi-class video sets.	• Comparison of YOLOv4 variants, SSD, and EfficientDet. • Tested hyperparameter tuning and frozen layers. • Combined geometric and photometric data augmentation.	• YOLOv4-Tiny 3L was best for real-time (90.56% mAP). • Detection was 9x faster than EfficientDet-D0. • Geometric augmentation improved object localization significantly.
Salim & Suharjito(2023)	• 4160 images collected from South Kalimantan mills.	• YOLOv4-tiny optimized using a Genetic Algorithm (GA). • GA used to find the optimal learning rate.	• GA identified an optimal learning rate of 0.007465. • YOLOv4-tiny (GA) achieved a mAP of 99.70%.

	• Six maturity classes including empty and abnormal. • Data split into training, validation, and testing sets.	• Integrated Early Stopping (ES) to reduce training costs.	• Early Stopping reached high mAP with fewer iterations.
Suharjito et al.(2023)	• 7256 total images (14,757 objects) from smartphone videos. • Captured at palm oil mill grading areas. • Included six categories of FFB ripeness.	• Compared quantized YOLOv4 and YOLOv4-tiny models. • Models converted using TensorFlow Lite for mobile. • Applied both 8-bit and 16-bit quantization.	• YOLOv4-fp16 performed 12% better than YOLOv4-tiny in mAP. • Model achieved a mAP of 65.53% across categories. • Successfully detected complex class categories on mobile.
Wijaya et al. (2023)	• 4156 images collected from Riau Province. • Categorized into 6 classes including Raw and Empty. • Split into 70% training, 20% testing, and 10% validation.	• Comparison of YOLOv4, Tiny, Tiny_3l, and CSP models. • Integrated color and texture information for detection. • Hyperparameters tuned with Adam optimizer.	• YOLOv4 model outperformed others with 99.85% mAP • Achieved an average IoU of 89.95%. • Demonstrated high precision in identifying texture attributes.
Naftali et al. (2024)	• Video dataset of FFB attached to trees in Central Kalimantan. • Includes five classes, abnormal, ripe, underripe, unripe, flower. • Presents challenges like low contrast and occlusion.	• Introduced YOLOv8s Depthwise model for efficiency. • Compared against YOLOv6, YOLOv7, YOLOv8l, and Faster R-CNN. • Utilised ONNX Runtime and FP16 quantization.	• YOLOv8s Depthwise achieved 0.75 mAP50 and 0.164 MAE. • Compact model size of 10.6 MB after quantization. • Outperformed previous research in speed and accuracy.
Junos et al. (2024)	• 1281 images captured at Sime Darby oil palm estate. • Four bunch ripeness classes, ripe, underripe, overripe, unripe. • Standard DOM Dome network camera used for capture.	• Developed improved YOLOv3 tiny with hybrid feature extractor. • Hybrid network used MBConv and DenseNet modules. • Adopted SPP structure and CIoU localization loss.	• Achieved a mAP of 94.37% and F1-score of 0.89. • Real-time detection at 4.8 FPS on NVIDIA Jetson Nano. • Size reduction of over 72% compared to YOLOv3/v4.
Josdaan et al. (2024)	• 3024 images from Roboflow with six maturity classes. • Included Rotten, Underripe, Unripe, Ripe, and Empty classes. • Images resized to 224x224 pixels with normalization.	• Evaluated YOLOv8 models from "nano" to "extra-large". • Used CSPDarknet-AA backbone and GIoU loss. • Compared Adam and AdamW optimizers across 20 epochs.	• YOLOv8m identified as the most balanced option. • Achieved Top-1 accuracy of 0.9885. • Average processing speed reached 14.68 iterations/second.
Shiddiq et al. (2024)	• 2000 multispectral images (1000 ripe, 1000 unripe). • Captured on a moving conveyor system.	• Combined multispectral imaging with YOLOv4 tiny. • Reflectance intensities evaluated for different levels.	• Achieved an average ripeness detection accuracy of 99.66%. • Real-time speed ranged between 3.32 and 3.62 FPS.

	• LED array used eight visible and IR wavelengths.	• Custom YOLO model trained on Google Colab.	• Ripe FFB showed 7.75% higher reflectance than unripe.

CHALLENGES HINDERING DEPLOYMENT OF DEEP LEARNING MODELS

One of the significant challenges identified throughout this review is high environmental variability that are commonly found in oil palm plantations. This variability negatively impacts the ability to train and implement deep learning models in real-world environments. Lighting conditions such as strong sunlight or shadows will significantly alter the colour and texture appearance of FFB. Occlusions due to fronds, branches or neighbouring bunches are also common and often obscure the view of the target fruit. These occlusions prevent the model from learning a robust visual understanding of the target fruit and therefore reduce the accuracy.

In addition, another significant challenge is the slight visual distinction between ripeness stages. The transition from under-ripe to ripe and over-ripe is often marked by only minor changes in color. This factor is further worsened by natural variations in fruit appearance across different regions and by the varying heights at which bunches grow. Consequently, models relying on standard RGB imaging may lack the sensitivity to detect these very similar spectral gradients and are prone to misclassification errors.

In addition, dataset fragmentation and inherent limitations of existing research significantly restrict generalisation, as most studies analysed relatively small datasets or isolated images of harvested bunches taken in controlled conditions. These conditions did not reflect the complex, cluttered backgrounds or the different angles at which bunches remain on the tree. Additionally, the lack of a uniform and unambiguous definition of ripeness categories among the studies makes it difficult to compare model performance across works.

Finally, practical deployment is hindered by the complexity of various models. Although more advanced architectures like YOLOv4 and YOLOv8 produce accurate results, they can be too heavy for limited resource environments. Deploying these systems in remote field settings requires careful optimization of the models so that they can perform with high accuracy and speed while running efficiently on low-cost smartphones or embedded devices.

FUTURE RESEARCH DIRECTION

In order to overcome the discussed challenges and ensure practical adoption, future research should pursue four focused directions. The field needs to go beyond conventional RGB-based analysis by integrating multimodal sensor data. Focusing on spectroscopic imaging or any other sensing technologies that can be used to identify internal ripeness indicators will complement eye observations, which are often unreliable under environmental conditions. This approach is building upon the promising proof of concept by Shiddiq et al. (2024).

Subsequently, future research needs to prioritize the development of standardized open-access benchmark datasets. These datasets should reflect the full diversity of ideal real-world conditions which includes the occlusion and lighting variations, while still conforming to a single maturity classification scheme. This is because a standard definition of maturity and a more consistent dataset would be beneficial to enhance the robustness of model evaluation.

Model tuning is another key research area for making deep learning models faster and more suitable for field applications. Future research should focus on methods for lightweighting and quantization of deep learning architectures. This includes designing architectures that are both accurate and efficient enough to run on devices with limited computational power, directly addressing the trade-off observed by Mansour et al. (2022) and Naftali et al. (2024).

Finally, future research could concentrate on integrating and validating entire functioning systems with industry partners. Systems or deep learning models need to be tested in real plantations and mills. The goal is to move beyond refining computer models into research that translates directly into practical use. Factors such as usability, pricing, and acceptance of users must be considered because in practice, these systems are not only successful when it comes to accuracy but also due to system dependability, user acceptance and cost-efficacy.

CONCLUSION

In a nutshell, this systematic review highlights the strong potential of deep learning models, particularly YOLO variants and CNN-based architectures, in automating oil palm FFB maturity detection. The reviewed studies have shown consistent improvement in accuracy, with most of the models having achieved mAP scores more than 90% under controlled conditions. The models also provide a real-time classification of ripeness stages from unripe to overripe.

However, this study also focuses on the critical challenges that hinder the models from being employed in real-world settings, such as environmental variability, occlusion, dataset fragmentation, and computational demands. The discussion underscores the gap between laboratory success and field deployment. By addressing these challenges through optimized and lightweight models with multimodal sensing, the technology promises to maximize palm oil extraction, reduce subjectivity in traditional manual assessments, and improve the overall quality of the palm oil.

The integration of deep learning systems or models holds valuable implications for the palm oil industry, including fostering a higher oil extraction rate, mitigating labor shortages, and promoting sustainable practices under global demand pressures. As research evolves toward enhancing model robustness for complex field conditions, these innovations are expected to drive economic returns, supply chain transparency, and environmental sustainability. This marks a significant step in the digital transformation of the oil palm industry.

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