A Mini Review on Sensor and Artificial Intelligence Approaches for Ripeness Detection and Classification of Oil Palm Fresh Fruit Bunch

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ABSTRACT

An accurate assessment of oil palm Fresh Fruit Bunch (FFB) ripeness is vital to maximize oil yield and ensure product quality. For a decade traditional method such as visual inspection and loose fruit counting remains common,due to simplicity but face limitations including subjectivity, labor shortage and low scalability. This review evaluates advances in sensor-based and artificial intelligence (AI) approaches for ripeness detection. The focus is on computer vision and deep learning models, multispectral and hyperspectral imaging as well as sensor-based systems. The integration of Internet of Things (IoT) and edge computing is also examined for real-time deployment. Based on the study, AI-driven methods, including Convolutional Neural Networks (CNNs) and YOLO frameworks, achieve accuracies above 95% in ripeness classification. Hyperspectral imaging combined with machine learning predicts oil content with more than 90% accuracy, while low-cost sensors demonstrate up to 94% accuracy in field conditions. IoT-enabled frameworks enhance scalability through continuous monitoring and localized decision-making. However, adoption is reminded limited due to high costs, computational demands, environmental variability and limited standardized datasets. Beyond technical constrains, socioeconomic barriers such as lack of expertise, inadequate infrastructure and affordability constrain adoption in resources limited context. As an assumption, a future research should prioritize on cost-effective sensors, adaptive algorithms, hybrid solutions and open-access datasets. It should also complement with supportive policies and farmer training to enhance accessibility to the new technology approach. The integration of artificial intelligence with imaging and sensor-based technologies constitutes a transformative approach for sustainable, scalable, and precise detection of FFB ripeness, thereby facilitating the advancement of the palm oil industry toward precision agriculture.

Keywords: Oil Palm, Fresh Fruit Bunch (FFB), Ripeness Detection, Computer Vision, Machine Learning, IoT, Hyperspectral Imaging

INTRODUCTION

Over 35% of the world vegetable oil is contributing by oil palm (Elais guineensis) (FAQ, 2023). Accurate assessment of Fresh Fruit Bunch (FFB) ripeness is essential to optimize oil yield and product quality, as harvesting at the wrong stage leads to reduced oil content or compromised oil quality (Nasution et al., 2022). Figure 1 illustrates the color changes in FFB from young to unripe (MPOB, 2003). As the demand for sustainable and efficient palm oil production grows, there is a strong need for automated and scalable ways to detect fruit ripeness.

For a decade traditional detection method such as visual inspection and loose fruit counting has been the industries mainstay. Figure 2, shown how workers identify, detect and classify ripe oil palm fruits upon their arrival at the palm oil processing mill. These approaches rely on human observation of mesocarp color changes from green to orange and red as well as the number of detached fruits in a bunch (MPOB, 2003, Fadilah et.al, 2014). Although these methods are cost-effective, they have limitations in terms of subjectivity, labor dependency, and inconsistencies, particularly in large-scale operations (Lai et al., 2023). Furthermore, the increasing labor shortages in major producing regions such as Malaysia and Indonesia underscore the urgent need to adopt technological solutions for ripeness assessment (Razali et al., 2016; Shiddiq et al., 2024).

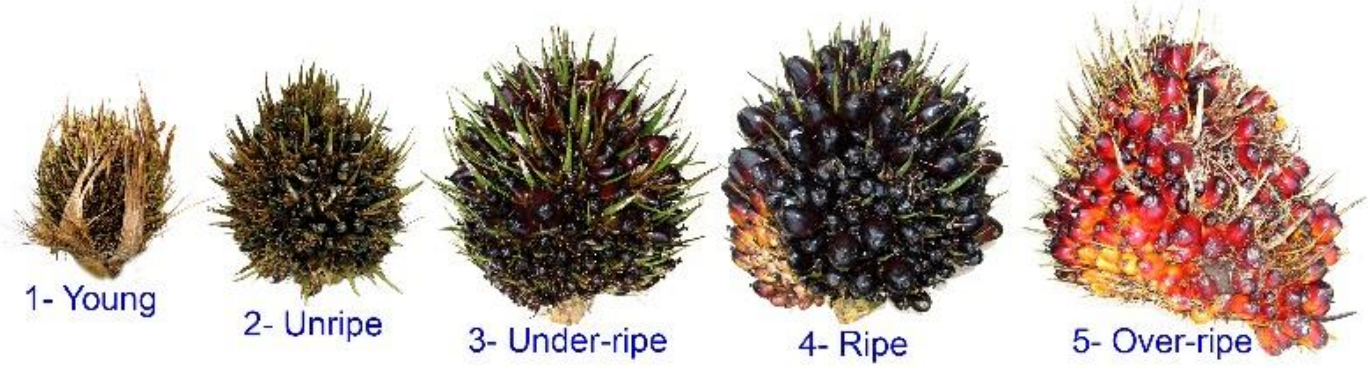

Fig. 1 The color changes of oil palm fresh fruit bunch from young until over ripe

Fig. 2 Identification and classification process of ripe oil palm fresh fruit bunches at the processing mill

Recent advances in sensor-based technologies, computer vision and machine learning have shown promising results in automating ripeness detection. Convolutional Neural Networks (CNNs) can extract intricate visual features such as color, texture and shape from digital images, achieving classification accuracies exceeding 99% (Ashari et al., 2022). Cutting-edge object detection models like YOLOv8 improve real-time performance, making them suitable for large-scale deployment (Priyadi et al., 2023). Additionally, multispectral and hyperspectral imaging provide non-destructive, high-resolution assessments of fruit maturity through spectral analysis (Shiddiq et al., 2024). These technologies, when integrated with IoT frameworks, can deliver real-time, remote monitoring and predictive analytics, transforming how oil palm plantations operate (Goh et al., 2024).

Despite various advancements, challenges still persist. High costs, the need for skilled operators and environmental variability (such as lighting conditions and fruit orientation) hinder the widespread adoption of these technologies (Harmiansyah et al., 2024). In addition, the lack of standardized datasets for model training and evaluation limits the generalizability of AI-based solutions (Omar et al., 2024). Therefore, the development of more cost-effective, scalable, and robust technologies capable of operating under diverse agricultural conditions is highly needed.

This review examines the latest innovations in sensor-based and AI-driven ripeness detection for oil palm FFBs, while also exploring IoT integration and addressing the socioeconomic and adoption challenges associated with these technological advancements.

TRADITIONAL APPROACH

Accurate detection of oil palm Fresh Fruit Bunch (FFB) ripeness is essential for optimizing oil extraction yields, minimizing waste, and maintaining consistent product quality. For decades, manual methods including visual inspection and loose fruit counting have been the industry’s primary means for ripeness assessment. However, as well as global demand for sustainable palm oil increases, the limitations of these traditional approaches have become increasingly, particularly in terms of accuracy, scalability, and operational efficiency (Ghazalli et al., 2023; Lai et al., 2023). This section reviews these conventional methods in detail, emphasizing their limitations and the necessity for technological advancements

Visual Inspection and Loose Fruit Counting

Visual inspection remains the most widely used method for assessing oil palm ripeness due to its simplicity and low-cost implementation (MPOB, 2012). This process relies on human workers visually analyzing the mesocarp color of FFBs progressing from green (immature) to yellow-orange (ripe) in purpose to determine optimal harvesting times (Nasution et al., 2022). Typically, a fully ripe bunch exhibits 10%–15% loose fruits around the tree base, providing a secondary indicator of ripeness (Sabri et al., 2018). Despite its ubiquity, this approach is highly subjective and prone to error, as it depends on the experience and judgment of individual workers (Shiddiq et al., 2023).

Recent studies highlight the limitations of these manual processes. A study by Mansour (2022) revealed that visual inspection misclassified FFB ripeness by 18%–22%, leading to substantial oil yield losses. Moreover, Suharjito et al. (2022) found that human-based assessments vary significantly under poor lighting conditions and adverse weather, reducing classification accuracy by up to 30% in real-world settings. This inconsistency is further amplified in large plantations where the volume of FFBs overwhelms human capacity, causing delays and errors in ripeness identification.

In addition to accuracy concerns, labor dependency is a significant drawback. The Malaysian Palm Oil Board (MPOB, 2023) estimates that labor shortages, exacerbated by COVID-19 disruptions, reduce annual oil palm yields by 15%–20%. This is especially problematic in Malaysia and Indonesia, which together account for over 85% of global palm oil production (Lai et al., 2023). As skilled workers become scarce and the industry faces growing pressure to transition toward automated and data-driven solutions (Razali et al., 2016).

Challenges of Traditional Method

While manual techniques remain cost-effective and accessible, their practical application in large-scale commercial plantations is becoming increasingly untenable. These challenges fall into four categories such as labor dependency and shortage, subjectivity and inconsistency, environmental sensitivity and scalability issues.

Labor Dependency and shortages

The reliance on skilled human labor makes the system vulnerable to labor shortages. According to Omar et al. (2024), the Malaysian palm oil industry faced a 32% decline in harvest efficiency between 2020 and 2023 due to migrant labor shortages. As plantations expand, the inefficiency of manual methods poses a barrier to meeting growing global demands (Ghazalli et al., 2023).

Subjectivity and inconsistency

The reliance on skilled human labor makes the system vulnerable to labor shortages. According to Omar et al. (2024), the Malaysian palm oil industry faced a 32% decline in harvest efficiency between 2020 and 2023 due to migrant labor shortages. As plantations expand, the inefficiency of manual methods poses a barrier to meeting growing global demands (Ghazalli et al., 2023).

Environmental Sensitivity

The traditional methods are susceptible to environmental conditions such as poor lighting, rainfall, and dense foliage. Suharjito et al. (2022) reported a 24% reduction in accuracy during rainy seasons due to altered mesocarp coloration. Furthermore, Gunawan et al. (2023) demonstrated that ripeness detection through visual inspection fails when fruit bunches are partially occluded, contributing to an increased error margin.

Scalability Issues

Manual methods are time-consuming and impractical for large-scale plantations. The reliance on skilled human labor makes the system vulnerable to labor shortages. Mansour (2022) found that a trained worker can assess only 20–25 FFB/hour, whereas automated technologies can process up to 200 FFB/hour, demonstrating the inefficiency of human-based methods for high-throughput production. According MPOB (2023), the Malaysian palm oil industry faced a harvest efficiency between 2020 and 2023 due to migrant labor shortages. As plantations expand, the inefficiency of manual methods poses a barrier to meeting growing global demands (Ghazalli et al., 2023). Summary for advantages and limitation for traditional approaches is shown in Table I.

TABLE I summary of traditional approaches

Method	Advantages	Limitation
Visual inspection	Cost effective, simple, wisely adopted and minimal technical expertise required	Subjective, labor intensive, labor prone, inconsistent under pure lighting, occlusion
Loose Fruit Counting	- Provides additional ripeness indication	- Time-consuming and imprecise for large-scale use
Hybrid Manual Method	- Combines human decision-making with tech	- Still requires substantial manual oversight

RECENT ADVANCES TECHNOLOGY

Emerging sensor-based and AI-driven techniques offer a non-destructive and real-time assessment of FFB ripeness to overcome the limitations of traditional methods. Nevertheless, the emerging technology also led to several innovations aimed at enhancing ripeness detection. Hybrid systems, which combine human oversight with automated monitoring, help reduce human error while maintaining the flexibility of manual approaches (Suharjito et al., 2023). Mobile applications equipped with computer vision provide workers with real-time ripeness assessments, thereby supporting decision-making in the field (Shiddiq et al., 2024). In addition, low-cost sensors capable of measuring moisture and capacitive properties are being tested as affordable, field-ready solutions to deliver real-time data for smallholder farms (Aziz et al., 2023). These approaches also contribute to improved efficiency and accuracy, full-scale automation, address labor shortages and advance ripeness detection. Three emergence technology driven will be explained are computer vision and machine learning, multispectral and hyperspectral imaging and sensor-based technology.

Computer Vision and Machine Learning

Computer vision is a technology that processes digital images to interpret and analyze visual information. In the context of FFB ripeness detection, deep learning techniques, especially CNNs are frequently employed to process those images. CNN have become a dominant approach in the detection of oil palm FFB ripeness due to capability of automatically extracting hierarchical visual features such as color, texture, and shape, which are closely associated with maturity levels. This automated feature extraction reduces the subjectivity inherent in manual assessments and improves classification consistency (Sunyoto et al., 2022).

Within this domain, lightweight architectures such as MobileNetV1 and V2 have been increasingly adopted due to their efficiency and suitability for edge-based applications. Notably, Suharjito et al. (2022) demonstrated that MobileNetV1 outperformed AlexNet, achieving an accuracy of 92% in FFB ripeness detection, thus underscoring its potential for real-time, resource-constrained environments. Conversely, deeper networks such as ResNet-50 have shown superior capability in feature representation and classification accuracy; however, their reliance on higher computational resources presents a limitation for deployment in large-scale plantation settings (Alfatni et al., 2022).

To overcome the challenges posed by environmental noise and variability in field conditions, hybrid approaches have also been explored. For instance, Shiddiq et al. (2023) reported that integrating CNNs with Artificial Neural Networks (ANNs) enhanced robustness under noisy conditions, achieving an accuracy rate of 93.5%. Collectively, these findings suggest that while lightweight models offer practical deployment advantages, deeper and hybrid architectures provide higher accuracy and resilience, indicating the importance of selecting models based on the trade-off between computational efficiency and robustness in real-world plantation environments.

In summary, a computer vision system combined with deep learning models offer automated, scalable and highly accurate solutions for ripeness detection. Advances in Convolutional Neural Networks (CNNs) and real-time object detection frameworks like YOLO (You Only Look Once) have significantly improved performance in large-scale plantations (Ashari et al., 2022; Priyadi et al., 2023).

Multispectral and Hyperspectral Imaging

Multispectral Imaging (MSI) and Hyperspectral Imaging (HSI) are advanced non-destructive approaches increasingly applied in oil palm Fresh Fruit Bunch (FFB) ripeness detection, as both extend beyond the visible spectrum to capture biochemical changes associated with maturity. MSI typically utilizes 3–10 spectral bands, with key wavelengths such as 680 nm (chlorophyll degradation) and 900 nm (moisture content) serving as reliable ripeness indicators (Minarni, 2024). Its non-invasive nature enables real-time monitoring under both laboratory and field conditions (Shiddiq et al., 2023).

In contrast, HSI acquires hundreds of contiguous spectral bands, providing higher spectral resolution and precision. Statistical methods such as Partial Least Squares (PLS) and Principal Component Analysis (PCA) regression have been employed to process HSI data, achieving up to 90% accuracy in oil content prediction (Shiddiq et al., 2022). Recent developments include lightweight HSI sensors integrated with drones for large-scale plantation monitoring (Chan et al., 2022) and hybrid models combining HSI with machine learning algorithms, such as Artificial Neural Networks (ANNs), to improve robustness under variable field conditions (Lee et al., 2023). Collectively, MSI offers cost-effective adaptability for field applications, while HSI delivers high-resolution predictive capability, particularly when integrated with machine learning techniques.

Both MSI and HSI provide a non-destructive tool for assessing oil palm FFB ripeness by capturing biochemical changes across visible and near-infrared wavelengths. MSI offers cost-effective adaptability for field applications, while HSI delivers high-resolution predictive capability, particularly when integrated with machine learning and drone-based monitoring. However, widespread adoption is constrained by equipment cost, computational demands such as storage required for data processing and scalability challenge (Shiddiq et al., 2024). Therefore, the future research should highlight on affordable sensors, efficient algorithms and IoT-based integration.

Sensor based technology

Sensor-based technologies have become increasingly important in enhancing the detection of oil palm Fresh Fruit Bunch (FFB) ripeness, offering non-visual, non-destructive alternatives to traditional manual methods. These technologies measure physical and chemical properties such as moisture content, capacitanceand volatile organic compounds (VOCs) which change dynamically during the ripening process (Misron et al., 2020). Inductive and capacitive sensors are among the most widely used in this industry. Inductive sensors have demonstrated up to 88% accuracy in detecting moisture-related changes in FFBs (Misron et al., 2020), while capacitive sensors achieved 91% accuracy in differentiating ripe from unripe fruits (Aziz et al., 2014). These approaches provide low-cost, real-time monitoring solutions that are particularly suitable for field deployment.

Another promising advancement is electronic nose (E-nose) systems, which analyze VOC emissions as biochemical indicators of ripening. Siddiq et al. (2021) developed an E-nose system using MOS gas sensors (MQ3, MQ5, MQ135), achieving 94.2% accuracy in classifying ripeness stages. While such systems perform well under controlled conditions, ongoing research is exploring their reliability under variable plantation environments.

Recent studies highlight that integrating multisensory systems with deep learning frameworks can further improve performance, achieving classification accuracies exceeding 90% in field conditions (Lee et al., 2022). Hybrid approaches that combine sensor data with imaging technologies supported by cloud-based AI platforms. This approach also shown potential to improve robustness against environmental variability while reducing operational costs (Gunawan et al., 2024; Goh et al., 2025). Collectively, these findings underscore the significant role of sensor-based technologies as a foundation for developing automated, scalable and sustainable ripeness detection systems.

IoT and Edge Computing Integration

The integration of Internet of Things (IoT) and edge computing technologies has emerged as a transformative enabler for real-time monitoring and data-driven decision-making in oil palm plantations. IoT frameworks allow seamless connectivity between sensors, mobile applicationsand cloud services. Its supporting large-scale deployment and remote accessibility. Edge AI systems, as demonstrated by Goh et al. (2024), process ripeness data locally at the device level which can reduce the dependencyon centralized computation. This localized processing significantly improves response times and supports scalability across plantations.

In parallel, Wireless Sensor Networks (WSNs) have enabled continuous and remote tracking of FFB ripeness, optimizing harvesting schedules and enhancing operational efficiency (Salim et al., 2023). Furthermore, low-cost wireless IoT solutions have proven effective in extending monitoring capabilities to remote plantation areas where connectivity is limited (Omar et al., 2023). By combining edge computing, WSNs, and AI-driven analytics, plantations can move toward a more resilient and efficient ecosystem for ripeness assessment.

In summary, these advances demonstrate that IoT and edge computing are not merely complementary technologies but essential components in scaling sensor-based solutions from experimental setups to real-world plantation applications. When fully integrated with multisensory data and AI-driven classification models, IoT-enabled systems have the potential to transform ripeness detection into a fully automated, scalable and sustainable process within the palm oil industry. Summary for recent advances technology approach apply for oil pam industries is illustrated in Table II.

TABLE II summary of RECENT ADVANCE Technology approaches

Technology	Model	Accuracy	Application	Benefit
YOLO Models	YOLOv4, YOLOv8	91-96.7%	Real-time object detection	Fast, scalable, accurate
Vision Transformers	ViT-B/16	97.3%	High-resolution feature analysis	Superior long-range visual dependencies
MSI and HSI	PCA, PLS Regression	90-95%	Spectral biochemical detection	Non-invasive, high-resolution monitoring
Sensor Systems	Inductive, Capacitive	88-94.2%	Physical property assessment	Real-time, robust in dynamic conditions
YOLO Models	YOLOv4, YOLOv8	91-96.7%	Real-time object detection	Fast, scalable, accurate

FINDING AND DISCUSSION

The shifting from traditional to automated technology for ripeness detection in FFBs has led a significant improvement in accuracy, efficiency and scalability. Advancements in machine learning (ML), multispectral and hyperspectral imaging, sensor-based systems and embarking of IoT and edge computing integration have significantly enhanced the accuracy and efficiency of oil palm FFB ripeness detection. These emerging technologies address many of the limitations inherent in traditional methods, such as labor dependency, subjectivity, and inconsistency.

Further section presented the comparative analysis of traditional and emerging approaches. Technology barrier and performance evaluation should be overcome to ensure broad adoption in the palm oil industry.

Comparative Analysis of Traditional vs Emerging Current Technology

The transition from manual to automated ripeness detection in oil palm reflects the broader evolution toward precision agriculture and data-driven decision-making. Traditional methods like visual inspection and loose fruit counting are still widely used because they are simple and inexpensive. However, they are subjective, labor-intensive, and not suitable for large-scale applications that require higher accuracy and efficiency (Shiddiq et al., 2023; Priyadi et al., 2023).

Among machine learning models, CNNs and YOLO have shown strong performance, with MobileNet and ResNet reaching 92–93% accuracy in controlled settings (Suharjito et al., 2022), while YOLOv8 improves real-time detection by achieving 96.7% accuracy with faster processing (Priyadi et al., 2023).

Multispectral and hyperspectral imaging provide non-invasive and precise methods for detecting biochemical ripening indicators. Combined with Partial Least Squares (PLS) regression, Hyperspectral Imaging (HSI) can achieve 93%–95% accuracy in predicting oil content and assessing early maturity (Shiddiq et al., 2022), while drone-mounted sensors make large-scale, real-time monitoring possible (Lee et al., 2023).

Sensor-based technologies such as inductive, capacitive, and electronic nose systems offer cost-effective and portable solutions for in-field applications. Capacitive sensors have achieved 91% accuracy (Aziz et al., 2023), while electronic noses have reached 94.2% accuracy by detecting volatile organic compounds (Siddiq et al., 2021).

Overall, the integration of AI, imaging, and sensor significantly improve the accuracy, efficiency, and scalability of ripeness detection compared to traditional methods. CNNs and YOLO frameworks achieve classification accuracies above 95%, while multispectral and hyperspectral imaging provide biochemical maturity indicators with more than 90% accuracy (Shiddiq et al., 2022). Low-cost capacitive and inductive sensors also show promising performance, with accuracies between 88–94%, making them more feasible for

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smallholder adoption. Table III summarizes the methods, accuracy, strengths, and limitations of traditional approaches versus emerging technologies currently being explored in the oil palm industry.

Challenge and Limitation on current technology

Although automated approaches to oil palm fruit ripeness detection demonstrate high accuracy, their widespread adoption is constrained by several key challenges. First, the deployment of advanced imaging systems and AI models remains costly, as they require specialized hardware and substantial computational resources (Mansour et al., 2022). Second, environmental variability including fluctuating lighting conditions, occlusions and background interference reduces the robustness and reliability of image-based models in real plantation settings (Harmiansyah et al., 2024). Third, hyperspectral imaging and deep learning techniques generate large, complex datasets that demand high storage capacity and processing power, thereby limiting their feasibility for mobile or edge-based applications (Shiddiq et al., 2024). These limitations indicate that future research should focus on developing cost-effective, resource-efficient and environmentally robust systems to enable scalable and practical implementation of automated ripeness detection in the oil palm industry.

TABLE III COMPARATIVE OVERVIEW BETWEEN of traditional approaches VS CURRENT TECHNOLOGY

Approach	Model / Method	Accuracy	Strengths	Limitations
Traditional Methods	Visual inspection, loose fruit counting	– NA	Simple, low cost, widely used	Subjective, labour-intensive, not scalable
Machine Learning	- MobileNet, ResNet (CNNs) - YOLOv8 - YOLO, Faster R-CNN, CNN	- 92%–93% (Suharjito et al., 2022) - 96.7%(Priyadi et al., 2023) -95% (Espinoza et. Al, 2023)	High accuracy, scalable, suitable for automation; YOLO offers real-time detection;	Computationally demanding; requires large datasets; environmental variations reduce robustness, sensitive to lightning and acclusion
Spectral Imaging	- Multispectral Imaging (MSI) - Hyper-spectral Imaging (HSI + PLS regression)	- 93%–95% (HSI, Shiddiq et al., 2022)	Non-invasive, detects biochemical changes; drone integration enables large-scale monitoring (Chan et al., 2022)	High equipment cost; large data storage and processing needs
Sensor-Based Systems	- Inductive sensors - Capacitive sensors - E-nose	- 91% (Aziz et al., 2014) - 94.2% (Siddiq et al., 2021)	Portable, cost-effective, real-time field use	Sensitive to environmental variability; limited scalability

Challenge and Limitation on current technology

Automated methods for detecting oil palm fruit ripeness have shown promising levels of accuracy, but their use in real plantations is still limited by several challenges. One major barrier is cost: hyperspectral sensors and the specialized hardware needed to run advanced AI models remain expensive and out of reach for many growers (Mansour et al., 2022). Environmental factors such as changes in lighting, rainfall, fruit occlusion and background noise often reduce the consistency and reliability of image-based models in actual field settings (Harmiansyah et al., 2024).

Techniques like hyperspectral imaging and deep learning also produce large and complex datasets that require significant storage space and processing power whereby it difficult to deploy on mobile or edge devices (Shiddiq et al., 2024). Apart of the technical issues, socioeconomic gap in rural areas highlights the need for expertise, infrastructure, and intensive training to enable farmers to use available tools more efficiently and effectively.

FUTURE RECOMMENDATION

Recent advances technology in FFB ripeness detection has shown a great potential. However, the technology application is still limited by high costs, environmental variability, dataset constraints, and accessibility issues. These barriers must be addressed to make future systems more affordable, efficient, and sustainable across different plantations.

A key priority is to develop affordable and scalable solutions. Current multispectral and hyperspectral systems, especially drone-based platforms, remain too expensive for wide adoption (Chan et al., 2022). Future research should focus on hybrid approaches that combine low-cost sensors with lightweight AI models. For example, capacitive sensors integrated with smartphone-based CNNs can balance affordability and accuracy. Edge AI and modular solutions can also support real-time, on-site assessment without heavy dependence on cloud infrastructure

Image and sensor-based methods often face difficulties in the field because of inconsistent in lighting, rainfall and fruit occlusion (Suharjito et al., 2022). Therefore, enhancing environmental robustness is crucial. Future research should focus on adaptive sensing, robust algorithms and advanced learning strategies. Techniques such as transfer learning and self-supervised learning can also make these systems more reliable in unpredictable plantation environments.

Expanding dataset availability and improving model generalization is another critical area. The lack of standardized, large-scale, annotated datasets across diverse regions limits current AI-based models (Espinoza et al., 2023). Future efforts should prioritize the creation of open-access datasets and explore synthetic data generation techniques, such as Generative Adversarial Networks (GANs), to improve model robustness and scalability.

The integration of IoT and edge computing also holds significant promise. Wireless sensor networks coupled with edge AI can support continuous monitoring and localized decision-making (Goh et al., 2024). Research should aim to optimize low-power IoT platforms and ensure interoperability with cloud systems, creating scalable and resource-efficient monitoring frameworks.

Finally, improving accessibility for smallholder farmers is crucial for industry-wide adoption. Low-cost mobile apps and IoT-enabled tools designed for field use can make advanced detection technologies more accessible. Policy support through government incentives, public–private partnerships, and digital agriculture programs will also play an important role. In addition, training modules are needed to improve digital literacy among farmers and workers.

By addressing all these priorities, future research can unlock the transformative potential of automated ripeness detection, positioning the palm oil industry as a leader in precision agriculture that is efficient, sustainable and resilient in the face of global challenges.

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REFERENCES

1. Abbas, Z. (1994). A microstrip sensor for determination of harvesting time for oil palm fruits (Doctoral dissertation, Universiti Pertanian Malaysia).
2. Abbas, Z., & Khalid, K. (2010). Application of microwave moisture sensor for determination of oil palm fruit ripeness. Measurement Science Review, 10(1), 7–14.
3. Abd Rahman, M. N. A. (2016). Enhancing oil extraction rates from palm fruit using advanced harvesting techniques. Journal of Agricultural Engineering, 45(3), 245–259.
4. Alamar, M. C., Aleixos, N., Amigo, J. M., Barbin, D., & Blasco, J. (2024). Hyperspectral imaging techniques for quality assessment in fresh horticultural produce and prospects for measurement of mechanical damage. In Mechanical damage in fresh horticultural produce: Measurement, analysis and control (pp. 69–90). Springer.
5. Alfatni, M. S. M., Khairunniza-Bejo, S., Marhaban, M. H. B., Saaed, O. M. B., Mustapha, A., & Shariff, A. R. M. (2022). Towards a real-time oil palm fruit maturity system using supervised classifiers based on feature analysis. Agriculture, 12(9), 1461.
6. Aliteh, N. A., Minakata, K., Tashiro, K., Wakiwaka, H., Kobayashi, K., Nagata, H., & Misron, N. (2020). Fruit battery method for oil palm fruit ripeness sensor and comparison with computer vision method. Sensors, 20(3), 637.
7. Ashari, S., Yanris, G. J., & Purnama, I. (2022). Oil palm fruit ripeness detection using deep learning. Sinkron: Jurnal dan Penelitian Teknik Informatika, 6(2), 649–656.
8. Astuti, I. F., Nuryanto, F. D., Widagdo, P. P., & Cahyadi, D. (2019, July). Oil palm fruit ripeness detection using K-nearest neighbour. In Journal of Physics: Conference Series (Vol. 1277, No. 1, p. 012028). IOP Publishing.
9. Aziz, A. A., Ismail, A. H., Ahmad, R. B., Isa, C. M. N. C., Farook, R. S. M., Husin, Z., & Shakaff, A. M. (2014, August). Design of a capacitive sensor for oil palm fresh fruit bunch maturity grading. In Proceedings of the 2nd International Conference on Electronic Design (ICED) (pp. 443–445). IEEE.
10. Chan, Y. K., Koo, V. C., Zahisham, M. Z. A., Lim, K. M., Connie, T., Lim, C. S., & Abidin, H. (2022). Design and development of a drone-based hyperspectral imaging system. In IGARSS 2022–2022 IEEE International Geoscience and Remote Sensing Symposium (pp. 4200–4203). IEEE.
11. Cueva, J. E., & Chamorro, J. I. (2023). Machine learning and deep learning for fruit identification: A systematic review. Journal of Theoretical and Applied Information Technology, 101(1).
12. Endan, J., Ibrahim, R., Ahmad, Z., & Yunus, R. (2011). Palm oil quality monitoring in the ripening process of fresh fruit bunches. Journal of Food Science and Engineering.
13. Espinoza, S., Aguilera, C., Rojas, L., & Campos, P. G. (2024). Analysis of fruit images with deep learning: A systematic literature review and future directions. IEEE Access, 12.
14. Fadilah, N. O., & Mohamad-Saleh, J. U. (2014). Color feature extraction of oil palm fresh fruit bunch image for ripeness classification. In Proceedings of the 13th International Conference on Applied Computer and Applied Computational Science (pp. 51–55).
15. Ghazalli, S. A., Baharum, A., Yaakob, Z., & Manurung, H. (2023). Short review on palm oil fresh fruit bunches ripeness and classification techniques. Journal of Advanced Research in Applied Mechanics.
16. Groß, T., Hashim, N., Khairunniza-Bejo, S., Aziz, S. A., & Zude-Sasse, M. (2016, August). Maturity stages of oil palm fresh fruit bunches using multispectral imaging method. In III International Conference on Agricultural and Food Engineering (Vol. 1152, pp. 71–76).
17. Harun, N. H., Awang, M., Mahmud, R., Rahim, A. A., & Ramli, N. (2013). Investigations on a novel inductive concept frequency technique for the grading of oil palm fresh fruit bunches. Sensors, 12(2), 285–293.
18. Husein, I. R., Ningsih, S. A., & Alfahrezi, G. (2023, August). Oil content and free fatty acid prediction of oil palm fresh fruit bunches using multispectral imaging and partial least square algorithm. In Proceedings of the 4th International Seminar on Science and Technology (ISST 2022) (Vol. 7, p. 143). Springer.
19. Lai, J. W., Ramli, H. R., Ismail, L. I., & Hasan, W. Z. W. (2023). Oil palm fresh fruit bunch ripeness detection methods: A systematic review. Agriculture, 13(1), 156.

20. Lee, C. C., Koo, V. C., Lim, T. S., Lee, Y. P., & Abidin, H. (2023). Early detection of BSR disease in oil palm trees through hyperspectral analysis with MLP-based algorithm. Advances and Challenges in Science and Technology, 127.
21. Lee, C. C., Ooi, P. C., Ong, H. C., Ismail, M. A., & Chee, S. S. (2022). A multi-layer perceptron-based approach for early detection of BSR disease in oil palm trees using hyperspectral images. Heliyon, 8(4), e09234.
22. Lim, K. S., Nazri, B. A., Rusik, W. R., Hamid, A. A. H. A., Ooi, C. W., Udos, W., & Ahmad, H. (2024). Laser remote sensor for oil palm fruit ripeness assessment. In Photonic technologies in plant and agricultural science (Vol. 12879, pp. 115–122). SPIE.
23. Malaysian Palm Oil Board. (2003). Oil palm fruit grading manual. Selangor: MPOB.
24. Malaysian Palm Oil Board. (2023). Labour shortage continues to affect oil palm industry. Retrieved from https://prestasisawit.mpob.gov.my/en/palmnews/news/36059
25. Mansour, M. Y. M. A., Dambul, K. D., & Choo, K. Y. (2022). Object detection algorithms for ripeness classification of oil palm fresh fruit bunch. International Journal of Technology, 13(6), 1326–1335.
26. Misron, N., Aliteh, N. A., Harun, N. H., Tashiro, K., Sato, T., & Wakiwaka, H. (2016). Relative estimation of water content for flat-type inductive-based oil palm fruit maturity sensor. Sensors, 17(1), 52.
27. Misron, N., Kamal Azhar, N. S., Hamidon, M. N., Aris, I., Tashiro, K., & Nagata, H. (2020). Effect of charging parameter on fruit battery-based oil palm maturity sensor. Micromachines, 11(9), 806.
28. Mustaffa, A., Arith, F., Peong, N. I. F., Jaffar, N. R., Linggie, E. L., Mustafa, A. N., & Ali, F. A. (2022). Segregation of oil palm fruit ripeness using color sensor. Indonesian Journal of Electrical Engineering and Computer Science, 25(1), 130–137.
29. Nasution, M. A., et al. (2022). Determination of RGB and grayscale value on palm oil (Elaeis guineensis Jacq.) fresh fruit bunch (FFB) images using MATLAB. Jurnal Penelitian Kelapa Sawit, 30(1).
30. Priyadi, M. R. A. (2023, September). Comparison of YOLOv8 and EfficientDet4 algorithms in detecting the ripeness of oil palm fruit bunch. In Proceedings of the 2023 10th International Conference on ICT for Smart Society (ICISS) (pp. 1–7). IEEE.
31. Razali, H. (2011). A novel technology application in agriculture research. International Research Journal of Applied and Basic Sciences, 2(11), 408.
32. Sabri, N., Ismail, I., Salleh, W. W., Nasir, M. H. M., & Hafeez, H. (2018). Palm oil fresh fruit bunch ripeness grading identification using color features. Journal of Fundamental and Applied Sciences, 9(4S), 563–579.
33. Shiddiq, M., Candra, F., Anand, B., & Rabin, M. F. (2024). Neural network with k-fold cross validation for oil palm fruit ripeness prediction. TELKOMNIKA (Telecommunication Computing Electronics and Control), 22(1), 164–174.
34. Shiddiq, M., Saktioto, S., Salambue, R., Wardana, F., Dasta, V. V., Harmailil, I. O., & Wahyudi, D. (2024). Multispectral imaging and deep learning for oil palm fruit bunch ripeness detection. Bulletin of Electrical Engineering and Informatics, 13(6), 4168–4181.
35. Shiddiq, M., Sitohang, L. B., Husein, I. R., Ningsih, S. A., Hermonica, S., & Fadlilah, A. (2021). Electronic nose based on MOS gas sensor to characterize ripeness of oil palm fresh fruits. Jurnal Teknik Pertanian Lampung, 10(2), 170–182.
36. Shiddiq, M., Sugito, Y., Nurhida, H., Faiz, F., Mawarni, D., & Karmini, N. (2022). Wavelength selection of multispectral imaging for oil palm fresh fruit ripeness classification. Applied Optics, 61(14), 3894–3902.
37. Shidiq, M. R., et al. (2022). Crude palm oil (CPO) quality analysis of Elaeis guineensis at Palm Oil Mill PT. Sinar Pandawa, Labuhanbatu Regency (based on free fatty acid levels, water content, and impurities). Jurnal Pembelajaran dan Biologi Nukleus.
38. Suharjito, E. P., & Pratama, D. (2022). Effect of pre-processing dataset on classification performance of deep learning model for detection of oil palm fruit ripeness. In Proceedings of the 2022 International Conference on ICT for Smart Society (ICISS) (pp. 1–6). IEEE.
39. Suharjito, A., Nugeraha, D. U., Franz, A. J., & Marimin. (2023). Real-time oil palm fruit grading system using smartphone and modified YOLOv4. IEEE Access.

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40. Suharjito, J., Koeswandy, Y. P., Debi, N., Nurhayati, P. W., Asrol, M., & Marimin. (2023). Annotated datasets of oil palm fruit bunch piles for ripeness grading using deep learning. Scientific Data, 10(1), 72.
41. Sulaiman, N. F., Pauline, O., Kiow, L. W., Huong, L. K., & Fong, G. S. (2020). Automatic grading system for oil palm fruit ripeness. Communications in Computational and Applied Mathematics, 2(1).
42. Sunyoto, A., & Muhammad, A. H. (2022). Detection of palm fruit maturity using convolutional neural network method. Journal of Artificial Intelligence and Applications, 2(2), 33–37.
43. Utom, S. L., Mohamad, E. J., Rahim, R. A., Yeop, N., Ameran, H. L. M., Kadir, H. A., & Pusppanathan, J. (2018). Non-destructive oil palm fresh fruit bunch (FFB) grading technique using optical sensor. International Journal of Integrated Engineering, 10(1).
44. Valentine, S. C., Alfred, R., Fui, F. S., Shamrie Sainin, M., & Iswandono, Z. (2022, August). Classification of oil palm fresh fruit bunches (FFB) based on its maturity colour using convolutional neural network (CNN) approach. In International Conference on Computational Science and Technology (pp. 583–594). Springer.
45. Yeow, Y., Abbas, Z., & Khalid, K. (2010). Application of microwave moisture sensor for determination of oil palm fruit ripeness. Measurement Science Review, 10(1), 7–14.
46. You, K. Y. (2006). Application of open-ended coaxial sensor to determine oil palm fruit ripeness (Doctoral dissertation, Universiti Putra Malaysia).