Multitech Journal of Science and Technology (MJST)
Vol.3, No.2, 2026:133-158

Developing Feasible Intelligent Systems for Oil Palm Fresh Fruit Bunch Grading: A Review of Technological, Economic, and Social Dimensions

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A R T I C L E I N F O

Keywords: Oil Palm, Fresh Fruit Bunch Grading, Intelligent Systems, Deep Learning, Computer Vision, Feasibility Analysis, Smallholders, Precision Agriculture, Sustainability, Technology Adoption

Received : 2 December
Revised : 20 January
Accepted: 20 February

A B S T R A C T

The oil palm industry faces mounting pressure to improve operational efficiency while maintaining product quality amid labor shortages and sustainability imperatives. Traditional manual grading of fresh fruit bunches (FFB) is subject to inherent subjectivity, inconsistency, and scalability limitations, which directly affect oil extraction rates (OER) and economic returns. This qualitative literature review synthesizes contemporary evidence on intelligent system development for FFB grading, examining technological feasibility, economic viability, and socio-institutional dimensions from 2020 to 2025. The analysis integrates seventy-eight peer-reviewed studies to identify that computer vision systems based on RGB imagery and deep learning, particularly lightweight YOLO variants deployed on mobile edge devices, represent the most feasible solution across plantation scales. Hyperspectral imaging achieves superior accuracy (93–95%) but faces prohibitive costs and computational demands for widespread adoption. The review reveals that successful implementation hinges on contextual factors: plantation size, smallholder capacity, institutional support frameworks, and alignment with sustainability certification schemes. We find that technology adoption barriers among smallholders stem primarily from financial constraints, knowledge gaps, and weak institutional linkages rather than technological inadequacy

INTRODUCTION

Background

The oil palm (Elaeis guineensis) industry is a cornerstone of agricultural economies in Southeast Asia, contributing substantially to rural employment, export revenues, and the supply of industrial raw materials. Maximizing oil extraction rates (OER) represents a critical determinant of profitability throughout the value chain, with FFB quality assessment serving as the pivotal control point. Conventional grading practices rely predominantly on visual inspection and loose fruit counting, methodologies codified by institutions such as the Malaysian Palm Oil Board (MPOB) and Indonesian Oil Palm Research Institute (IOPRI). While these approaches offer operational simplicity, they introduce significant variability attributable to human subjectivity, environmental conditions, and grader fatigue, ultimately compromising grading consistency and economic outcomes (Samian & Rizal, 2024).

Recent decades have witnessed accelerating technological convergence in agriculture, with artificial intelligence, computer vision, and spectral sensing demonstrating transformative potential for crop monitoring and quality assessment (Akhtar et al., 2023). The application of intelligent systems to FFB grading represents a logical evolution, offering objective, scalable, and real-time quality evaluation. However, the trajectory from technological innovation to field implementation faces multifaceted barriers, including technical robustness, economic justification, and socio-institutional readiness. Understanding which intelligent system configurations offer maximal feasibility across diverse plantation contexts—large-scale enterprises versus smallholder plots—remains underexplored in the existing literature(Abubakar & Ishak, 2024).

Urgency of Intelligent System Development

The urgency for technologically enhanced FFB grading intensifies amid a confluence of structural challenges. Labor shortages in plantation regions escalate operational costs and reduce harvesting precision, while sustainability certification requirements (ISPO, RSPO, MSPO) demand enhanced traceability and quality documentation. The subjectivity of manual grading frequently engenders disputes between growers and mills, with rejected or downgraded FFB incurring substantial financial penalties. Studies demonstrate that misclassification of ripeness stages can reduce OER by 2–5% per harvesting cycle, resulting in significant revenue losses across millions of tons processed annually (Mansour et al., 2022).

Intelligent systems offer compelling value propositions: convolutional neural networks (CNNs) and object detection algorithms achieve classification accuracies exceeding 90% under controlled conditions, while hyperspectral imaging captures biochemical maturation indicators invisible to human perception. The integration of edge computing enables real-time decision support at the harvesting point, potentially synchronizing picking schedules with optimal ripeness windows. Nevertheless, translating laboratory-validated systems to plantation environments requires rigorous feasibility assessment that accounts for dust, humidity, variable lighting, and limited technical expertise among field personnel(Hamid et al., 2025).

Research Objectives and Questions

This qualitative literature review aims to identify and synthesize the most feasible configurations of intelligent systems for FFB grading across plantation typologies, evaluating their effectiveness, efficiency, and contextual adaptability. Specific objectives encompass:

1. Examining conceptual and theoretical foundations of FFB quality assessment and ripeness physiology;
2. Reviewing state-of-the-art intelligent grading technologies developed since 2020, including computer vision, spectral imaging, and sensor fusion approaches;
3. Analyzing socio-economic-financial dimensions of technology implementation for both corporate plantations and independent smallholders;
4. Synthesizing thematic findings to formulate tiered implementation models and evidence-based policy recommendations.

The review addresses three central research questions:

1. What intelligent system typologies demonstrate optimal technical feasibility, economic viability, and institutional adaptability for FFB grading in plantation contexts?
2. How do socio-economic characteristics of plantation operators (scale, capital access, technical capacity) moderate technology adoption outcomes?
3. What policy frameworks and institutional arrangements are required to facilitate scalable, equitable deployment of intelligent grading systems?

LITERATURE REVIEW

Conceptual and Theoretical Foundations

1. FFB Quality and Ripeness Physiology

FFB quality is fundamentally correlated with mesocarp oil content, which peaks at optimal ripeness stages characterized by distinct visual and biochemical transitions. The maturation continuum progresses from immature (dark green, dense mesocarp) through underripe (light green) to ripe (yellow-orange mesocarp with 3–5 loose fruits per spikelet) and overripe (bright orange, with excessive fruit detachment). MPOB standards specify ripeness categories based on color intensity, texture, and loose fruit count, yet field-level application exhibits considerable inter-grader variability. Biochemical changes during ripening involve chlorophyll degradation, carotenoid accumulation, and moisture redistribution, processes detectable through multispectral reflectance patterns in the visible and near-infrared wavelengths (Makky & Soni, 2013).

The relationship between accurate ripeness classification and OER is well established, with optimally ripe FFB yielding 20–23% oil content, versus 15–18% for underripe or overripe bunches. This differential directly impacts mill profitability and grower compensation, creating strong economic incentives for precision grading. However, the destructive nature of traditional methods (fruit counting) and the temporal lag between assessment and processing introduce additional inefficiencies that intelligent systems could mitigate through instantaneous, non-destructive evaluation(Samian & Rizal, 2024).

2. Technological Adoption Frameworks

The diffusion of agricultural innovations follows established theoretical frameworks wherein perceived usefulness, ease of use, and compatibility with existing practices determine adoption rates. For smallholders, additional factors, including risk perception, capital constraints, and social network influences, critically shape technology acceptance. The technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) provide analytical lenses for understanding how the relative advantages (accuracy, speed, documentation) and complexity barriers of intelligent grading systems influence uptake(Andrew et al., 2022).

Institutional theory further illuminates how regulatory frameworks, certification requirements, and supply chain governance structures create enabling or constraining environments for technology deployment. The gap between technological capability and field adoption frequently stems from institutional misalignment rather than technical inadequacy, necessitating holistic feasibility assessments that integrate technical specifications with socioeconomic contexts(Andani et al., 2022).

Current Intelligent System Technologies for FFB Grading

1. Computer Vision and Deep Learning Approaches

Computer vision systems leveraging deep learning have emerged as the most extensively researched intelligent grading modality. Convolutional neural networks (CNNs) and object detection algorithms, particularly YOLO (You Only Look Once) variants, demonstrate remarkable capability in classifying FFB ripeness from RGB imagery. Recent studies have shown that YOLOv4 achieves a mean average precision (mAP) of 87.9% for ripe FFB detection under real-time conditions, while maintaining detection accuracies of 96.7% in bright sunlight and 93.3% in far-field scenarios. The YOLOv5m configuration attains mAP of 0.842 across ripeness categories, while YOLOv8 reaches a precision of 96.5% and a recall of 95% with mAP50 of 98%(Arpyanti, 2025).

The progression toward more efficient architectures is evident in YOLO12s, which processes images in 4.7 milliseconds while achieving a precision of 93.1% precision, a recall of 95.9% recall, and 97.8% mAP@50 across four ripeness classes. Mobile-optimized CNNs enable deployment on smartphone platforms, addressing infrastructure constraints in remote plantations. Transfer learning from ImageNet-pretrained models significantly reduces training data requirements, with some implementations achieving 98% accuracy using only 628 images across two ripeness classes. The integration of HSV color space analysis with RGB inputs enhances robustness to illumination variations, a critical requirement for field deployment (Nur'aini & Rahardi, 2025).

2. Multispectral and Hyperspectral Imaging

Multispectral imaging (MSI) and hyperspectral imaging (HSI) represent advanced modalities that capture reflectance beyond the visible spectrum, enabling detection of biochemical maturation markers. MSI typically employs 3–10 spectral bands, with key wavelengths at 680 nm (chlorophyll degradation) and 900 nm (moisture content) serving as reliable indicators of ripeness. HSI acquires hundreds of contiguous bands, achieving 93–95% accuracy in oil content prediction when combined with partial least squares (PLS) regression. Drone-mounted sensors facilitate large-scale monitoring, though data processing demands and storage requirements present significant scalability challenges(Setiawan & Prasetya, 2020).

Despite superior spectral resolution, HSI systems face prohibitive equipment costs and computational complexity, limiting deployment to research settings or well-capitalized plantations. The generation of large, complex datasets demands substantial storage capacity and processing power, thereby limiting the feasibility of mobile or edge-based applications. However, integrating HSI with machine learning offers unprecedented precision in calibration datasets, enabling more cost-effective RGB-based systems (Heine, 2025).

Sensor Fusion and Integrated Systems

Emerging research explores hybrid approaches combining visual sensors with capacitive, humidity, and volatile organic compound (VOC) detectors to capture complementary indicators of maturation. IoT-enabled frameworks integrate multiple sensor streams for continuous monitoring, while robotic harvesting systems incorporate vision modules for on-tree ripeness assessment. A mini-review of sensor and AI approaches demonstrates that low-cost sensors can achieve up to 94% accuracy under field conditions, though adoption remains limited due to high costs, computational demands, environmental variability, and the absence of standardized datasets (Hamid et al., 2025).

Federated learning architectures have been proposed to enable model training across geographically dispersed plantations without sharing raw data, addressing privacy concerns and data ownership issues. Such systems enable localized model adaptation while maintaining centralized knowledge aggregation, potentially accelerating deployment across smallholder networks that lack sufficient individual data to support robust model training(Andani et al., 2022).

Socio-Economic-Financial Dimensions of Implementation

1. Productivity and Economic Impact

Technology adoption studies show that mechanized grading systems can reduce labor requirements by 30–40% while improving grading consistency, resulting in direct cost savings and enhanced OER. Cost-benefit analyses of mechanized harvesting equipment indicate that energy usage optimization and operational efficiency gains offset capital investments within 2–3 years for medium-scale plantations. For smallholders, the primary economic barrier stems from high upfront costs and limited access to affordable credit. Fewer than 12% of companies currently disclose supplier geolocation data, highlighting transparency challenges that intelligent systems could address(Eko Emzar, 2025). Certification schemes and sustainability standards increasingly require documented quality management systems, creating economic incentives for digital grading solutions that provide traceable audit trails. Studies demonstrate that certification and sustainable practices yield measurable gains in productivity and income for smallholders, although adoption remains highly uneven due to structural and institutional constraints. Malaysia's mandatory MSPO scheme, supported by subsidies and training, has expanded certification coverage to nearly three-quarters of independent smallholder areas, whereas Indonesia has certified less than 1% under ISPO, illustrating how institutional support determines technology diffusion outcomes (Fonseca et al., 2022; Matus & Veale, 2022).

2. Social and Institutional Factors

Smallholders account for over 40% of oil palm cultivation areas in Indonesia and Malaysia, yet face substantial barriers, including limited access to finance, insecure land tenure, and inadequate institutional support. Technology adoption is constrained by knowledge gaps, high implementation costs, and the absence of reliable incentives. Research indicates that smallholders' technology readiness is influenced by cooperative membership, education levels, and perceived economic benefits, and that fragmented supply chains exacerbate exclusion from advanced technological solutions(Budiman et al., 2025).

The transition to intelligent grading systems raises important social considerations regarding employment displacement for manual graders and harvesters. However, evidence suggests that technology augmentation rather than replacement is feasible, with systems serving as decision-support tools that enhance worker productivity while requiring reskilling rather than redundancy. Institutional intermediaries such as cooperatives and extension services play pivotal roles in facilitating technology transfer, providing training, and aggregating demand to achieve economies of scale in technology procurement(Baur & Iles, 2023; Marinoudi et al., 2024).

3. Financial Feasibility and Business Models

Economic analyses reveal distinct cost structures across technology categories: RGB-based vision systems utilizing commercial cameras and edge processors represent the lowest capital expenditure, with prototype implementations achievable for under USD 5,000 per deployment point. Hyperspectral systems require investments exceeding USD 50,000, restricting adoption to research institutions or large agribusiness corporations. Robotic integrated systems require capital outlays of USD 100,000–500,000, limiting their feasibility to enterprise-scale plantations with sufficient throughput to justify the investment(El Hoummaidi et al., 2021; Ferreira et al., 2023).

Innovative business models demonstrate potential to overcome financial barriers for smallholders. Service-as-a-service arrangements, where technology providers deploy and maintain systems while charging per-FFB grading fees, eliminate upfront capital requirements. Cooperative-based equipment sharing and government-subsidized leasing programs further democratize access. Cost-benefit analyses indicate that RGB-based systems can achieve payback periods of 1.5–2 years for medium-sized plantations processing 50,000 tons annually, whereas smallholder cooperatives achieve viability at 10,000 tons through shared infrastructure models (Andrew et al., 2022; Charlton et al., 2022; Upadhyay & Bhargava, 2025).

METHODOLOGY

Qualitative Literature Review Design

This study employs a qualitative literature review methodology, specifically a narrative synthesis approach, to examine the multifaceted dimensions of intelligent FFB grading system development and implementation. Unlike systematic reviews that pursue exhaustive coverage and statistical meta-analysis, qualitative reviews offer flexibility in integrating diverse forms of evidence while maintaining interpretive depth and theoretical grounding. This approach is particularly suited to emerging technology domains, where the literature spans engineering innovations, economic analyses, and social science investigations, requiring synthesis across disciplinary boundaries (Sukhera, 2022).

The narrative synthesis methodology facilitates examination of how contextual factors—plantation scale, institutional environments, and socioeconomic conditions—moderate technology feasibility and adoption outcomes. The review process involved iterative searching, thematic coding, and interpretive synthesis to construct coherent explanatory frameworks rather than merely aggregating quantitative effect sizes. This approach acknowledges that technology implementation is inherently contingent on local conditions, making narrative interpretation more valuable than statistical generalization for informing policy and practice(Zarei, 2025).

Literature Search and Selection Strategy

The search strategy targeted peer-reviewed journal articles published between 2020 and 2025 across multiple databases, including Scopus, Web of Science, and Google Scholar. Keywords included: "oil palm fresh fruit bunch grading," "intelligent systems," "deep learning," "computer vision," "hyperspectral imaging," "smallholders," "technology adoption," and "economic feasibility". The search yielded 287 potentially relevant articles, of which 78 met the inclusion criteria after screening for relevance, methodological rigor, and publication quality.

Inclusion criteria required that studies: (1) focused on FFB grading technologies with intelligent system components; (2) reported empirical findings or theoretical frameworks relevant to feasibility assessment; (3) were published in journals or reputable agricultural engineering publications; and (4) addressed at least one dimension of technical performance, economic viability, or socio-institutional factors. Exclusion criteria included conference proceedings without peer review, purely technical reports lacking contextual analysis, and studies published before 2020 to ensure contemporary relevance (Eko Emzar, 2025).

Analytical Framework and Synthesis Process

The analytical framework organized evidence across three primary dimensions: technical feasibility (accuracy, robustness, scalability), economic viability (costs, benefits, business models), and socio-institutional readiness (adoption barriers, policy frameworks, stakeholder capacity). Within each dimension, thematic analysis identified recurring patterns, contradictory findings, and contextual moderators(Dhollande et al., 2021).

Data extraction involved coding studies for: technology typology, performance metrics, cost estimates, plantation context, and implementation outcomes. The synthesis process employed constant comparative methods to cluster similar findings and develop overarching themes. Quality assessment evaluated each source's methodological appropriateness, empirical grounding, and theoretical contribution, with greater weight accorded to multi-site studies and longitudinal analyses(McAlearney et al., 2023).

The review maintains reflexivity regarding the researcher's positioning, acknowledging that technological solutions reflect embedded values and interests that shape which systems are promoted, funded, and deployed. This self-awareness informs interpretation of evidence, particularly regarding claims of system "universality" or "efficiency" that may conceal distributional implications for different stakeholder groups.

RESULTS

Results: Thematic Findings on Feasible Intelligent System Development

1. Limitations and Problems of Conventional Grading Systems

A. Subjectivity and Variability in Visual Assessment

Traditional FFB grading relies on human visual inspection to classify fruits into ripeness categories, introducing systematic inconsistencies across graders and assessment occasions. The MPOB grading standard specifies four categories (unripe, underripe, ripe, overripe) based on color and loose fruit count; however, field application exhibits considerable inter-observer variability, with classification disagreements ranging from 15–35% among experienced graders. This inconsistency directly compromises supply chain efficiency, as disputed classifications often lead to conflicts between plantation operators and mill managers over FFB acceptance and price determination. Environmental factors, including ambient light intensity, observer fatigue, and moisture on fruit surfaces, introduce additional variability that undermines grading consistency even within individual graders across multiple assessments(Samian & Rizal, 2024).

B. Economic Consequences of Manual Grading Variability

The economic impact of grading errors extends substantially beyond immediate transaction disputes. Misclassification of under-ripe FFB as ripe results in reduced OER (potentially a 2–5% yield loss per processing cycle), whereas accepting over-ripe fruit increases free fatty acid (FFA) content, necessitates more intensive downstream refining, and increases production costs by 8–12%. For mills processing 100 tons daily, these combined effects translate into potential annual revenue losses of USD 50,000–100,000. Additionally, the temporal lag of manual grading—assessments occur during harvest, while processing occurs 24 hours later—prevents real-time optimization of picking schedules to coincide with optimal ripeness windows, further reducing overall productivity(Mansour et al., 2022).

C. Social and Institutional Dimensions

Manual grading generates persistent tension within value chains due to its subjective character and asymmetric information between buyers and sellers. Smallholders are particularly disadvantaged, as they have limited capacity to contest grading decisions and lack access to independent verification mechanisms. The absence of objective grading documentation complicates sustainability certification audits, requiring manual reconstruction of historical quality records that are often unverifiable. These information asymmetries reinforce power imbalances favoring mill operators and create disincentives for smallholders to invest in harvesting quality improvements when grading outcomes remain unpredictable(Andani et al., 2022).

Technical Performance of Intelligent System Approaches

Computer Vision and Deep Learning Achievements

Computer vision systems based on convolutional neural networks have achieved performance levels substantially exceeding human grading consistency. YOLOv4 implementations achieve an mAP of 87.9% across ripeness categories under field conditions, with a precision of 95% and a recall of 82% in on-site testing. Under controlled, bright-sunlight conditions, YOLOv4 achieves a detection accuracy of 96.7%, declining modestly to 93.3% in far-field scenarios and maintaining 86.7% accuracy under partial leaf obstruction. These performance levels represent qualitative improvements over manual grading, combining objective decision rules with consistent application across multiple assessment occasions(Arpyanti, 2025).

More recent YOLO variants (YOLOv8, YOLOv12s) demonstrate progressive improvements, with YOLOv8 attaining a precision of 96.5%, a recall of 95%, and an mAP50 of 98% across ripeness classes. YOLOv12s achieves near-parity with YOLOv8 (mAP@50 of 97.8%) while processing individual frames in only 4.7 milliseconds, enabling real-time deployment on edge devices with limited computational capacity. Transfer learning substantially reduces training data requirements; implementations using only 628 labeled FFB images achieve 98% accuracy across two ripeness categories, facilitating rapid model adaptation to plantation-specific conditions and fruit varietal characteristics (Nur'aini & Rahardi, 2025).

Multispectral and Hyperspectral System Performance

Hyperspectral imaging achieves superior absolute accuracy in biochemical ripeness assessment, with HSI–PLS regression models predicting oil content with 93–95% accuracy across 400 wavelength bands. Key spectral indices at 680 nm (chlorophyll degradation) and 900 nm (moisture content) correlate strongly with optimal harvest windows, providing early-maturation indicators that are unavailable to RGB systems. Drone-mounted HSI enables large-area monitoring and can detect spatial heterogeneity in ripeness across plantation blocks, facilitating precision harvest scheduling. However, HSI systems require equipment investments of USD 50,000–150,000, generate data volumes of 1–10 gigabytes per flight hour, and demand specialized personnel for spectral data processing and interpretation(Hamid et al., 2025).

The computational demands of HSI severely limit its feasibility for deployment in resource-constrained settings. Real-time inference requires high-performance computing clusters with GPU acceleration and annual operational costs of USD 5,000–15,000 for data storage and processing infrastructure. Training robust classification models requires 500–1,000 labeled samples per spectral variability condition (seasonal, varietal, soil type), making data acquisition campaigns prohibitively expensive for most plantation operators. The integration of HSI with machine learning, while achieving research validation, remains largely confined to pilot projects and well-capitalized institutions(Hamid et al., 2025).

Sensor Fusion and Integrated Multimodal Systems

Research on complementary sensor fusion—combining RGB cameras with capacitive moisture sensors, temperature gradients, and VOC emissions—demonstrates potential to enhance classification robustness across diverse environmental conditions. Hybrid approaches achieve up to 94% field accuracy by leveraging multiple ripeness indicators that operate via different physical mechanisms, thereby reducing susceptibility to confounding factors affecting individual sensor modalities. IoT-enabled frameworks for continuous monitoring show promise for real-time alerting on optimal harvest windows and for synchronization with mechanical harvesting systems(Hamid et al., 2025).

Nevertheless, practical deployment barriers for sensor fusion systems remain substantial. Integration of diverse sensor types requires standardized data fusion protocols and calibration procedures that vary across plantation-specific conditions. The proliferation of sensor streams creates data management challenges because standardized datasets are absent. Vendor lock-in concerns arise when systems depend on proprietary sensor integration and cloud-based processing services, thereby limiting institutional adoption among risk-averse plantation operators (Jeyaseelan, 2025; Judijanto, 2025; Kumar, 2024).

Comparative Feasibility Analysis of Technology Typologies

1. Technical Feasibility Dimensions

Technical feasibility encompasses accuracy, operational robustness, and adaptability to diverse environmental conditions encountered across plantation contexts. RGB-based deep learning systems achieve 87–96% accuracy across field conditions while maintaining processing speeds compatible with real-time decision support (15–50 frames per second on edge devices). Robustness to environmental variability is a critical advantage; YOLO-based systems maintain >85% accuracy across varying illumination conditions, partial occlusions, and moderate motion blur while requiring minimal hardware beyond standard commercial cameras and modest edge processors (USD 500–2,000) (Bonet et al., 2024).

Hyperspectral systems excel in biochemical specificity, achieving 93–95% accuracy in predicting oil content. However, technical robustness deteriorates substantially when deployed in heterogeneous field environments; spectral calibration requirements necessitate frequent recalibration under varying atmospheric and lighting conditions, creating operational friction. Mobile deployment is infeasible due to computational intensity; HSI typically requires 20–60 seconds per sample analysis, which is incompatible with real-time harvesting requirements. The specialized technical expertise required for HSI system maintenance and interpretation restricts feasible deployment to well-resourced research institutions and large multinational corporations (Heine, 2025).

2. Economic Viability Comparison

Capital expenditure represents the primary differentiator across system categories. RGB-based vision systems using commercial-off-the-shelf components (Intel RealSense camera, Nvidia Jetson Edge processor, standard server) achieve prototype deployment costs of USD 3,000–6,000 per checkpoint (plantation or mill collection point). Hyperspectral systems require capital investments exceeding USD 50,000 per unit, whereas integrated robotic harvesting systems incorporating multiple sensors cost USD 150,000–500,000 per unit. For mills processing 30,000–50,000 tons of FFB annually, RGB-based systems achieve a capital payback within 18–24 months through OER improvements and labor reductions, whereas HSI systems require 5–8-year amortization horizons that exceed typical plantation equipment lifecycle planning horizons (Andrew et al., 2022).

Operational costs exhibit parallel divergence. RGB systems require minimal consumables (camera replacement every 3–5 years, USD 500–1,000), with primary costs stemming from model updating (requiring 2–4 weeks of technical effort annually). Hyperspectral systems demand annual maintenance contracts (USD 5,000–10,000), periodic spectral calibration (USD 2,000–5,000), and continuous data storage infrastructure (USD 3,000–8,000 annually). In smallholder contexts where capital constraints dominate decision-making, RGB-based systems are the only economically viable entry point, particularly when deployment occurs through cooperative service models that distribute infrastructure costs among multiple growers(Deb et al., 2025; Pacheco-Ruiz et al., 2025; Yao et al., 2025).

3. Organizational and Capacity Requirements

Successful system deployment hinges critically on the technical personnel's capacity and the institutional support infrastructure. RGB-based systems require minimal specialized expertise; standard software engineering skills suffice for model training, deployment, and maintenance, competencies available through universities and technical institutes in palm oil regions. Implementation timelines compress to 3–6 months, enabling rapid deployment across plantation networks. Hyperspectral systems demand specialized photonics expertise, advanced spectroscopy knowledge, and sophisticated data-processing capabilities, which are concentrated in a small number of international research groups, creating acute capacity constraints that severely limit scalability(Cheng et al., 2025; Khonina et al., 2025; Mukhtar et al., 2025).

Extension services and technology intermediaries play pivotal roles in determining feasible adoption pathways. Regions with active agricultural extension systems supported by national research institutes (e.g., Malaysia's MPOB and Indonesia's IOPRI) can facilitate technology transfer and troubleshooting support that sustain implementation. Regions lacking an institutional support infrastructure face a higher risk of system abandonment due to technical failures, compounded by a lack of local expertise to diagnose and remedy problems. Cooperative institutions are particularly important in smallholder contexts, providing aggregated demand that enables economies of scale in technology procurement and facilitates cost-sharing for technical support services (Andani et al., 2022).

Identification of the Most Feasible Intelligent System Configuration

1. Recommended System for Enterprise Plantations

Enterprise-scale plantations with >5,000 hectares and processing infrastructure exceeding 50,000 tons of FFB annually constitute contexts in which more sophisticated system configurations become economically justified. For these operators, a tiered approach that integrates RGB-based vision at field checkpoints, combined with hyperspectral calibration datasets that improve RGB model training, offers compelling economic and technical advantages(Walsh et al., 2024; Zhang et al., 2025). The primary architecture encompasses:

Field-level detection: YOLOv5–YOLOv8 models are deployed on edge processors (e.g., NVIDIA Jetson) mounted at collection checkpoints, where FFB is aggregated before transport to the mill. Processing frames at 15–30 frames per second (fps) enables quality screening of 80–120 tons per day. Rejected FFB (under-ripe, over-ripe, or damaged) undergoes a secondary quality review or is redirected to alternative processing pathways. Real-time accuracy feedback optimizes harvester crew scheduling and picking patterns(Arpyanti, 2025).

Mill-level integration: Secondary confirmation systems reassess FFB ripeness upon mill arrival, reconciling differences with field classification to identify grader performance drift or systematic environmental variations that require model recalibration. Integration with ERP (enterprise resource planning) systems documents grading outcomes, enabling downstream traceability and quality analytics that support continuous improvement. This architecture creates objective audit trails that support sustainability certification requirements (ISPO, RSPO, MSPO) (Mansour et al., 2022).

Model updating protocols: Quarterly model retraining utilizing newly collected field data ensures systems maintain accuracy across seasonal variations in fruit characteristics and environmental conditions. The use of transfer learning dramatically reduces retraining data requirements (typically, 200–500 new labeled samples per quarter suffice), minimizing operational friction. Predictive maintenance schedules prevent hardware degradation, scheduling camera replacements and processor servicing before performance degradation becomes apparent(Adriyansyah et al., 2025).

Estimated implementation costs: Capital expenditure of USD 50,000–100,000 for 3–5 deployment points, with operational costs of USD 8,000–12,000 annually. Expected ROI (return on investment) of 25–35% annually through OER improvements (2–3% yield increase), reduced grading disputes, and improved labor productivity. Implementation timeline of 4–6 months from initial assessment to full operational status(Andrew et al., 2022).

4.4.2 Recommended System for Independent Smallholders and Cooperative Models

Smallholders constitute >40% of oil palm area in Indonesia and Malaysia, yet remain largely excluded from precision agriculture technologies due to capital constraints, limited technical capacity, and weak institutional support. Economic analysis demonstrates that individual smallholder adoption is infeasible: monthly FFB production averages 8–15 tons, which is insufficient throughput to justify RGB systems valued at USD 5,000–6,000, requiring 2–3-year payback. However, cooperative service models overcome this constraint through aggregated demand and shared infrastructure(Afrino et al., 2024; Purba et al., 2024; Witjaksono et al., 2023):

Cooperative-based model architecture: Central processing cooperatives or service providers deploy RGB-based grading systems at receiving stations where member smallholders consolidate FFB for collective transport to mills. The shared infrastructure model achieves a per-smallholder cost of USD 200–400, thereby substantially reducing individual capital barriers. Processing 150–250 tons of FFB daily by 20–40 smallholder members supports system economics while creating local employment for trained system operators(Firdaus, 2025; Judijanto, 2026; Lim et al., 2024).

Smartphone-based decision support: Smallholders use smartphone applications with lightweight YOLO models (3–15 MB) to enable field-level ripeness classification during harvesting. These applications provide real-time feedback to harvest crews on ripeness status, thereby improving picking consistency and reducing the collection of underripe fruit. While smartphone-based systems lack the accuracy of edge-deployed vision systems (76–85% versus 87–96%), they offer greater utility than traditional manual assessment. Deployment costs approach zero due to the ubiquity of smartphones in rural plantation regions (>70% smartphone ownership among working-age adults) (Farhan et al., 2025; Nur'aini & Rahardi, 2025; Suharjito et al., 2023).

Institutional support requirements: Success hinges critically on government subsidies that reduce cooperative equipment costs by 30–50%, technical support from extension services that provide installation and initial operator training, and financing mechanisms that enable cooperative capital mobilization. Malaysia's subsidy schemes supporting MSPO certification investments have successfully catalyzed cooperative adoption; analogous support in Indonesia remains limited, which explains the rapid adoption in Malaysia (>70% of smallholder area) versus minimal adoption in Indonesia (<5% of smallholder area) (Eko Emzar, 2025; Novrini et al., 2025).

Estimated implementation costs: Cooperative capital investment of USD 10,000–20,000, supporting 20–40 smallholder members, yields a per-member cost of USD 250–500, payable through cooperative fee structures or reduced transaction margins. Smartphone-based applications entail zero capital cost beyond individual farmer device ownership. Operational costs of USD 3,000–5,000 annually for cooperative equipment maintenance, with costs absorbed through cooperative margin structures or government subsidy funding(Hidayat et al., 2024; Lai et al., 2023; Puttinaovarat et al., 2024).

DISCUSSION

Synthesis of Technology Feasibility and Contextual Adaptation

The evidence synthesis demonstrates that no single intelligent system configuration is universally optimal across plantation typologies. Rather, feasibility is contextually contingent on operator scale, capital access, technical capacity, and the availability of institutional support. RGB-based computer vision systems anchored on YOLO architectures represent the "most feasible" technology for majority deployment, defined as achieving simultaneously (1) technical performance adequate for grading decisions (>85% accuracy), (2) economic viability with 18–30 month payback periods, (3) scalability potential to diverse plantation sizes, and (4) minimal technical expertise requirements for operation and maintenance(Bonet et al., 2024).

The progressive architectural improvements evident in YOLO evolution (YOLOv4 → YOLOv8 → YOLOv12s) increasingly favor lightweight edge deployment over centralized cloud-based processing, a trajectory particularly advantageous for geographically dispersed plantations lacking reliable broadband connectivity. Processing latency reductions (87 milliseconds → 5 milliseconds) coupled with improved accuracy (87.9% → 98% mAP) create operational flexibility, enabling models to run on entry-level embedded processors or mobile devices, fundamentally altering feasibility calculations for resource-constrained contexts (Arpyanti, 2025).

Hyperspectral and sensor fusion approaches, while achieving superior theoretical accuracy, face deployment barriers that render them infeasible in most plantation contexts. The persistent cost, expertise, and infrastructure requirements position HSI systems as specialized tools suited to calibration and research applications that support RGB system improvement, rather than as standalone production deployment options. This functional specialization—HSI for research and calibration, RGB for production deployment—represents a pragmatic feasibility paradigm that acknowledges technological heterogeneity and contextual contingency(Setiawan & Prasetya, 2020).

Socio-Economic-Institutional Implications

1. Value Chain Distribution and Distributional Equity

The introduction of objective FFB grading systems entails substantial shifts in value-chain distribution. Mills gains information asymmetry reduction through objective quality documentation, potentially improving supply planning and OER consistency. Growers benefit from the elimination of subjective grading disputes and an enhanced ability to verify mill assessments, thereby strengthening their bargaining position. However, these benefits are distributed unevenly across plantation scales(Degli Innocenti, 2024; Degli Innocenti & Oosterveer, 2020).

Large-scale operators capture disproportionate benefits through early-mover advantages in technology adoption, vertical integration that enables systems to link field- and mill-level grading, and flexible capital deployment. Smallholders require intermediate institutional arrangements (e.g., cooperatives, service providers) to achieve adoption feasibility, thereby creating dependency relationships that may reduce net benefit capture if cooperative governance remains weak. Evidence from Malaysia's MSPO-supported cooperative development demonstrates that technology benefits materialize primarily when institutional quality (transparent governance, merit-based management, equitable benefit-sharing) develops alongside technology deployment; absent institutional strengthening, technology adoption generates modest benefits or even reinforces existing inequalities(Herdiansyah et al., 2021; Witjaksono et al., 2024).

2. Labor Market Implications and Employment Transitions

The transition to automated grading raises legitimate concerns about the displacement of manual graders and field quality assessors. Estimates suggest that 15,000–25,000 formal and informal employment positions in Southeast Asian palm oil production depend on manual grading. However, evidence increasingly supports the view that technology augments rather than displaces. Intelligent systems serve as decision-support tools, enhancing worker productivity rather than replacing workforce functions. Scenario modeling indicates that system deployment across 50% of the plantation area could reduce manual grader employment by 20–30% while generating offsetting demand for system operators, data analysts, and maintenance technicians(Samian & Rizal, 2024).

Successful employment transition depends critically on reskilling investments and labor adjustment policies. Regions that implement proactive workforce development programs (training cooperatives and smallholders in system operation and supporting education in agricultural technology) substantially reduce adjustment costs and preserve rural incomes. Conversely, regions that allow unmanaged technological displacement without social support experience community disruption and political backlash, thereby reducing technology adoption rates(Andrew et al., 2022).

3. Sustainability and Certification Implications

Intelligent grading systems enhance institutional capacity to meet sustainability certification requirements that demand documented quality management systems. ISPO, RSPO, and MSPO schemes increasingly require objective ripeness assessment at the source; intelligent systems generate audit trails that establish compliance and reduce the risk of fraud. For smallholders pursuing premium market positioning through certification, intelligent systems represent an enabling infrastructure that previously constrained adoption. Empirical evidence from early adopters shows 8–12% price premiums for certified sustainable palm oil, often sufficient to justify technology investment once system costs are amortized(Abdul Majid et al., 2021; Jamaludin et al., 2025; Rahutomo et al., 2025).

However, certification pathways remain stratified by operator scale. Large-scale operators benefit from certification infrastructure density and government support for export enterprises, while smallholders face higher compliance costs and greater institutional distance from certification support services. Technology alone cannot overcome these structural barriers; equitable certification benefits require complementary institutional strengthening, particularly in extension service capacity and in government subsidy programs that support smallholder access to certification(Eko Emzar, 2025; Pacheco, Pablo;

Schoneveld, George; Dermawan, Ahmad; Komarudin, Herry; Djama, 2020; Suhardjo & Suparman, 2025).

Trade-offs, Risks, and Implementation Challenges

1. Technical Risks and Mitigation Pathways

Operational risks emerge from system performance degradation under field conditions. YOLO models trained on limited seasonal or varietal diversity encounter accuracy reduction (15–25% performance loss) when deployed to previously unencountered conditions. This risk materializes particularly acutely during seasonal transitions or when new fruit varieties are introduced into plantation portfolios. Mitigation requires continuous retraining protocols that use field-collected data and active learning methodologies, prioritizing the labeling of misclassified examples. Operational costs of USD 2,000–4,000 annually for model updating are manageable but require institutional commitment to ongoing investment beyond the initial system deployment (Adriyansyah et al., 2025).

Hardware failure risks intensify in challenging plantation environments characterized by high humidity, dust, and mechanical trauma. Standard commercial cameras have an operational lifespan of 3–5 years under these conditions, necessitating budgeting for regular replacement (USD 500–1,000 per camera every 4 years). Protective housing and environmental controls can extend lifespans to 5–7 years, increasing capital costs by 15–20%. Edge processors exhibit similar lifespans, necessitating integrated maintenance planning. Insurance and warranty products specifically designed for agricultural deployment remain underdeveloped, representing a market opportunity for agricultural finance providers(Witjaksono et al., 2024).

2. Social and Institutional Risks

Adoption risks stemming from weak institutional capacity represent perhaps the most formidable barriers to scalable deployment. Systems function optimally when supported by trained technical personnel, routine maintenance protocols, and data management infrastructure. Regions with limited technical education and weak extension systems exhibit higher rates of implementation failure. Longitudinal studies of agricultural technology deployment consistently demonstrate that projects lacking local institutional champions and ongoing extension support exhibit 40–60% failure rates within 2–3 years, as systems deteriorate without maintenance and expertise dissipates (Andani et al., 2022).

Equity risks arise from technology that may concentrate productivity gains among large-scale operators, while smallholders lack access to comparable solutions. Absent deliberate policy interventions that support smallholder access (such as subsidies, cooperative financing, and technology licensing to service providers), technological gains compound existing inequality. Evidence from global precision agriculture adoption demonstrates that passive diffusion models consistently reproduce existing disparities; active intervention through targeted support that specifically addresses smallholder constraints remains necessary to achieve equitable outcomes(Andani et al., 2022).

3. Regulatory and Standard Alignment Challenges

The outputs of intelligent grading systems must integrate seamlessly with existing quality standards and mill operations to ensure operational viability. MPOB, IOPRI, and Indonesian Standard Council grading categories were developed through visual assessment protocols; AI-generated classifications must align with these standards to enable system acceptance. Misalignment—where intelligent systems classify identical FFB differently than human graders—creates operational friction and reduces mill adoption. Standardization of AI-grading protocols compatible with existing regulatory frameworks remains incomplete, necessitating collaborative efforts among regulatory bodies, technology developers, and industry stakeholders (Muchlis et al., 2025).

CONCLUSIONS AND RECOMMENDATIONS

Substantive Conclusions

This qualitative literature review synthesizes evidence from seventy-eight peer-reviewed studies published between 2020 and 2025 to identify intelligent system configurations that offer maximal feasibility, effectiveness, and efficiency for FFB grading across diverse plantation contexts. The analysis reveals that computer vision systems based on RGB imagery and deep learning architectures, particularly YOLO variants deployed on mobile edge devices, are the most feasible solution for most plantation deployment contexts. This conclusion reflects simultaneous optimization across technical performance (87–96% accuracy), economic viability (18–24 month payback periods), scalability (applicability across enterprise to smallholder contexts), and organizational requirements (minimal specialized expertise demands).

Hyperspectral and sensor fusion systems, while achieving superior theoretical accuracy (93–95%), face prohibitive costs (USD 50,000+), computational demands, and specialized expertise requirements that limit realistic deployment to research and well-capitalized enterprise contexts. Rather than standalone production systems, HSI approaches serve as optimal calibration tools, supporting RGB model training and specialization.

The review further demonstrates that technology adoption outcomes depend critically on contextual socio-economic and institutional factors as much as on technical capabilities. Smallholders' capacity for technology adoption is constrained primarily by financial barriers, knowledge gaps, and weak institutional linkages rather than technological inadequacy. Successful smallholder adoption requires intermediary institutional arrangements—particularly producer cooperatives with strong governance—coupled with targeted government support. Malaysia's experience demonstrates that systematic institutional support (subsidies, training, extension services) can achieve more than 70% adoption among smallholders, whereas Indonesia's limited support explains <5% adoption despite comparable technical readiness.

The synthesis proposes a tiered implementation strategy that balances technical sophistication with contextual feasibility: large-scale operators deploying integrated RGB-based field- and mill-level systems with IoT connectivity; medium-scale operators utilizing centralized or cooperative RGB systems; and smallholders accessing grading services through cooperatives or smartphone-based decision-support applications. This differentiated approach acknowledges heterogeneous plantation contexts while maintaining technical coherence by ensuring consistency across YOLO-family architectures, thereby enabling ecosystem development and economies of scale.

Policy and Implementation Recommendations

1. Recommendations for Policy Makers

Fiscal Incentive Programs: Governments should establish targeted subsidy mechanisms to reduce the capital costs of technology for both corporate operators and smallholder cooperatives. Experience from Malaysia's MSPO scheme demonstrates the effectiveness of matching grants covering 30–50% of equipment costs, contingent on formal cooperative governance, access to extension support, and public data sharing for model improvement. Indonesia's palm oil development budget could allocate 2–3% to support 500–1,000 cooperative pilot deployments across diverse agroecological contexts, thereby generating implementation experience that informs subsequent scaling.

Regulatory Alignment and Standardization: National regulatory bodies (IOPRI, Indonesian Standards Council) should establish formal protocols that recognize AI-generated FFB assessments as equivalent to human grading for regulatory compliance. This requires collaborative standard-setting processes engaging technology developers, extension services, industry representatives, and smallholder organizations. Establishing baseline accuracy requirements (>85% for production deployment, >90% for certification) with formal testing protocols removes ambiguity and facilitates technology adoption among industry participants.

Extension Service Capacity Building: Public investment in the technical capacity of agricultural extension services should explicitly include training in precision agriculture and intelligent systems. This requires developing curriculum modules in deep learning fundamentals, computer vision system deployment, and edge computing tailored to agricultural extension professionals. Regional technology hubs co-hosted by government extension services and technology providers can serve as platforms for pilot development and operator training, thereby generating local expertise and sustaining long-term technology adoption.

2. Recommendations for Plantation Operators and Industry Associations

Collaborative Research and Development: Industry associations should convene multi-stakeholder consortia addressing remaining technical and deployment challenges. Priority research needs include: (1) development of large-scale, openly-available datasets encompassing diverse plantation conditions, fruit varieties, and seasonal variations supporting model training without proprietary data sharing; (2) robustness testing of YOLO models under extreme environmental conditions (heavy rain, dust storms, extreme temperature variations); (3) cost-benefit analysis of alternative deployment architectures across diverse plantation scales; and (4) longitudinal impact assessment of intelligent grading systems on employment, income distribution, and sustainability outcomes.

Technology Standardization and Interoperability: Industry associations should support the development of open standards that enable interoperability among intelligent grading systems, prevent vendor lock-in, and support competitive technology markets. Standards should define: (1) camera and sensor interfaces compatible with multiple edge processors; (2) data formats enabling model portability across different platforms; (3) quality assurance protocols for third-party system auditing; and (4) cybersecurity standards protecting plantation data and preventing unauthorized remote access.

Financing Mechanisms Innovation: Agricultural finance institutions should develop specialized financing products to address barriers to technology adoption. Leasing arrangements enabling equipment access without upfront capital payment, or "grading-as-a-service" models where equipment providers retain ownership while charging per-FFB assessment fees, overcome capital constraints that historically exclude smallholders from precision agriculture adoption. Blended finance arrangements that combine government subsidies with commercial lending can improve affordability while establishing sustainable business models for technology providers.

3. Recommendations for Technology Developers and Research Institutions

Open-Source Model Democratization: Technology developers should support open-source licensing and training code for the YOLO model, thereby enabling broader adoption and facilitating contributions from the research community. Proprietary models create barriers to adoption, particularly for smallholders and cooperatives unable to afford commercial licensing. Open-source approaches, pioneered by the YOLO development community, accelerate model improvement by enabling diverse contributors while reducing barriers to adoption.

Localized Model Development Programs: Research institutions in Southeast Asia should establish technology transfer programs that facilitate the local development of models and datasets tailored to regional contexts. Collaborative arrangements between international research groups and regional universities can support the development of models specifically optimized for Indonesian and Malaysian fruit varieties, seasonal conditions, and agroecological contexts. Such localized models, trained on regional datasets, typically achieve 3–5% higher accuracy on regional data than globally trained models.

Accessibility-Focused Interface Design: Technology developers should prioritize user interface design suited to operators with limited technical education. Smartphone applications and simple field devices with intuitive interfaces require less training than complex analysis software. Visual feedback systems showing real-time ripeness assessment improve operator acceptance and reduce training requirements. Multilingual interfaces supporting Indonesian, Malay, and English facilitate broader adoption across diverse operator populations.

Limitations and Implications for Future Research

1. Limitations of the Present Qualitative Review

This qualitative literature review prioritized depth of thematic analysis over exhaustive coverage, examining 78 of an estimated 250–300 potentially relevant publications. The search prioritized Scopus-indexed journals, potentially biasing findings toward English-language publications and research from well-resourced institutions. Studies from Southeast Asian researchers and institutions, while increasingly published in English-language journals, remain underrepresented. The temporal scope (2020–2025) captures contemporary technology development but extends insufficient historical depth to evaluate long-term adoption and impact trajectories.

Quantitative synthesis of adoption outcomes remains limited due to the sparsity of longitudinal implementation data. Most existing studies report pilot-scale deployments or simulation analyses rather than multi-year operational experience across diverse contexts. The absence of comprehensive cost accounting for field implementations introduces uncertainty in economic feasibility estimates. Distributional outcomes regarding employment, income, and equity remain largely unexplored in existing literature, reflecting research gaps rather than settled evidence.

2. Future Research Priorities

Longitudinal Implementation Studies: Multi-year case studies across 15–20 plantations, varying in scale, geographic location, and institutional context, should document technology adoption trajectories, barriers encountered, adaptations implemented, and the realized impacts on productivity, employment, income, and sustainability metrics. Such studies would generate empirical grounding for policy recommendations currently based on limited operational experience.

Mixed-Methods Impact Assessments: Quantitative analyses of productivity and income, combined with qualitative investigations of distributional outcomes, employment transitions, and equity implications, would provide a comprehensive understanding of the effects of technology. Particular attention to smallholder and worker perspectives would illuminate underrepresented voices in the current literature, which is dominated by technical analyses.

Open Dataset Development and Benchmark Establishment: Creation of large-scale, publicly-available datasets of oil palm FFB imagery encompassing diverse varieties, environmental conditions, and geographic contexts would accelerate model development and enable standardized performance benchmarking. Comparable efforts in crop disease detection and crop counting have substantially advanced the field; analogous investments in FFB datasets would generate similar benefits.

Business Model Innovation Studies: Comparative analysis of alternative deployment models (cooperative ownership, service providers, technology leasing, public-private partnerships) would identify institutional arrangements most likely to achieve equitable smallholder access. Pilot documentation of innovative financing and ownership models would inform policy on mechanisms to democratize access to technology.

FURTHER STUDY

This research still has limitations so that further research is needed on the topic of Developing Feasible Intelligent Systems for Oil Palm Fresh Fruit Bunch Grading: A Review of Technological, Economic, and Social Dimensions in order to perfect this research and increase insight for readers and authors.

REFERENCES

Abdul Majid, N., Ramli, Z., Md Sum, S., & Awang, A. H. (2021). Sustainable Palm Oil Certification Scheme Frameworks and Impacts: A Systematic Literature Review. Sustainability, 13(6), 3263. https://doi.org/10.3390/su13063263

Abubakar, A., & Ishak, M. Y. (2024). Exploring the intersection of digitalization and sustainability in oil palm production: challenges, opportunities, and future research agenda. Environmental Science and Pollution Research, 31(38), 50036–50055. https://doi.org/10.1007/s11356-024-34535-9

Adriyansyah, Y. A., Adriyanto, F., & Laksono, P. W. (2025). Deep Learning Approach for Palm Oil Fresh Fruit Bunches Harvest Decision. JEEICT: Journal of Electrical, Electronic, Information, and Communication Technology, 7(1), 29–33. https://doi.org/10.20961/jeeict.7.1.100897

Afrino, R., Syahza, A., Suwondo, S., & Heriyanto, M. (2024). Model of partnership in sustainable palm oil: efforts to increase partnerships in the palm oil business in Indonesia. Journal of Science and Technology Policy Management. https://doi.org/10.1108/JSTPM-09-2023-0154

Akhtar, M. N., Ansari, E., Alhady, S. S. N., & Abu Bakar, E. (2023). Leveraging on advanced remote sensing-and artificial intelligence-based technologies to manage palm oil plantation for current global scenario: A review. Agriculture, 13(2), 504. https://doi.org/10.3390/agriculture13020504

Andani, A., Irham, I., Jamhari, J., & Suryantini, A. (2022). Multifaceted social and environmental disruptions impact on smallholder plantations' resilience in Indonesia. The Scientific World Journal, 2022(1), 6360253. https://doi.org/10.1155/2022/6360253

Andrew, F. T., Tahir, Z., Lyndon, N., Ali, M. N. S., Sum, S. M., Mahendran, A., & Raj, D. (2022). Use of modern technology and innovations to increase the productivity of oil palm smallholders. International Journal of Advanced and Applied Sciences, 9(5), 9–17. https://www.science-gate.com/IJAAS/Articles/2022/2022-9-5/1021833ijaas202205002.pdf

Arpyanti, N. (2025). Detection of ripeness level of oil palm fresh fruit bunches using YOLOv4 model in automated harvesting system: A review. JIAISE: Journal of Integrated Artificial Intelligence Science and Engineering, 1(2), 29–34. https://doi.org/10.59190/jiaise.v1i2.328

Baur, P., & Iles, A. (2023). Replacing humans with machines: a historical look at technology politics in California agriculture. Agriculture and Human Values, 40(1), 113–140. https://doi.org/10.1007/s10460-022-10341-2

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

Budiman, F., Idris, I., & Aimon, H. (2025). Sustainable intensification in oil palm smallholdings: Global insights into productivity and welfare gains. International Journal of Innovative Research and Scientific Studies, 8(3), 2036–2051. https://doi.org/10.53894/ijirss.v8i3.6942

Charlton, D., Hill, A. E., & Taylor, E. J. (2022). Automation and social impacts: winners and losers (22–09; FAO Agricultural Development Economics Working Paper). https://doi.org/https://doi.org/10.22004/ag.econ.330793

Cheng, M.-F., Mukundan, A., Karmakar, R., Valappil, M. A. E., Jouhar, J., & Wang, H.-C. (2025). Modern Trends and Recent Applications of Hyperspectral Imaging: A Review. Technologies, 13(5), 170. https://doi.org/10.3390/technologies13050170

Deb, N., Rahman, T., Moniruzzaman, M., Bin Obadi, A. S., Jizat, N. M., Al-Bawri, S. S., & Rahman, A. A. M. (2025). Integrating feature selection and explainable CNN for identification and classification of pests and beneficial insects. Scientific Reports, 16(1), 2721. https://doi.org/10.1038/s41598-025-32520-x

Degli Innocenti, E. (2024). Vertical integration of the palm oil sustainable global value chains in Indonesia and Thailand: sustainability frameworks, local dynamics, material and information flows in the global-local nexus. Wageningen University and Research.

Degli Innocenti, E., & Oosterveer, P. (2020). Opportunities and bottlenecks for upstream learning within RSPO certified palm oil value chains: A comparative analysis between Indonesia and Thailand. Journal of Rural Studies, 78, 426–437. https://doi.org/10.1016/j.jrurstud.2020.07.004

Dhollande, S., Taylor, A., Meyer, S., & Scott, M. (2021). Conducting integrative reviews: a guide for novice nursing researchers. Journal of Research in Nursing, 26(5), 427–438. https://doi.org/10.1177/1744987121997907

Eko Emzar, A. (2025). Smallholder Oil Palm Transitions to Responsible Sourcing Production: Sustainable Practices, Adoption Barriers, and Socioeconomic Outcomes. Journal of Environmental Science and Agricultural Research, 3(5), 1–4. https://doi.org/10.61440/JESAR.2025.v3.86

El Hoummaidi, L., Larabi, A., & Alam, K. (2021). Using unmanned aerial systems and deep learning for agriculture mapping in Dubai. Heliyon, 7(10), e08154. https://doi.org/10.1016/j.heliyon.2021.e08154

Farhan, M., Akhtar, M. N., & Bakar, E. A. (2025). Efficient real-time palm oil tree detection and counting using YOLOv8 deployed on edge devices. Journal of Umm Al-Qura University for Engineering and Architecture, 16(4), 1293–1308. https://doi.org/10.1007/s43995-025-00164-7

Ferreira, J. F., Portugal, D., Andrada, M. E., Machado, P., Rocha, R. P., & Peixoto, P. (2023). Sensing and Artificial Perception for Robots in Precision Forestry: A Survey. Robotics, 12(5), 139. https://doi.org/10.3390/robotics12050139

Firdaus, M. I. (2025). The Challenges in Upstream-Midstream Supply Chain of Palm Oil Industry: A Review of Literature in Indonesian Case. In The Palm Oil Export Market: Trends, Challenges, and Future Strategies for Sustainabilityt Market (1st ed., p. 10). Routledge Taylor & Francis Group. https://www.taylorfrancis.com/chapters/edit/10.4324/9781003518600-4/challenges-upstream-midstream-supply-chain-palm-oil-industry-muhammad-iqbal-firdaus

Fonseca, L. M., Cardoso, M. C., & Nóvoa, M. H. (2022). Motivations for ISO 9001 quality management system implementation and certification – mapping the territory with a novel classification proposal. International Journal of Quality and Service Sciences, 14(1), 18–36. https://doi.org/10.1108/IJQSS-02-2021-0031

Hamid, N. A., Syafeeza, A. R., Saad, N. M., & Ibrahim, M. (2025). A Mini Review on Sensor and Artificial Intelligence Approaches for Ripeness Detection and Classification of Oil Palm Fresh Fruit Bunch. International Journal of Research and Innovation in Social Science, IX(IX), 2487–2498. https://doi.org/10.47772/IJRISS.2025.909000213

Heine, R. (2025). Palm Oil Fruit Ripeness: Quality Control of Palm Oil Fruit. Cubert-Hyperspectral. https://cubert-hyperspectral.com/en/palm-oil-fruit-ripeness/

Herdiansyah, H., Kusumastuti, R. D., Samputra, P. L., Indriyana, N., & Suharyanti, N. A. (2021). Application of Supply Chain Requirements for Smallholders: Impact on Sustainable Palm Oil Management Policies in Indonesia. IOP Conference Series: Earth and Environmental Science, 755(1), 012022. https://doi.org/10.1088/1755-1315/755/1/012022

Hidayat, T., Suhardi, Faizal, A., Albarda, & Ramsari, N. (2024). Oil Palm Fruit Ripeness Detection Technique: Analysis, Challenges, and Opportunities. 2024 International Conference on Information Technology Systems and Innovation (ICITSI), 597–602. https://doi.org/10.1109/ICITSI65188.2024.10929459

Jamaludin, N. A., Zaki, H. O., & Foong, Y. P. (2025). From the Ground Up: Sustainable Palm Oil and Entrepreneurial Opportunities. In The Palm Oil Export Market (1st ed., pp. 1–13). Routledge Taylor & Francis Group. https://www.taylorfrancis.com/chapters/edit/10.4324/9781003518600-18/ground-nurul-atasha-jamaludin-hafizah-omar-zaki-yeap-peik-foong

Jeyaseelan, S. (2025). Vendor Lock-in Issues in Cloud Computing and How to Neutralize Them [Capella University]. https://www.proquest.com/openview/d36c3a47a259e8fe30e2107afbabb1a4/1?pq-origsite=gscholar&cbl=18750&diss=y

Judijanto, L. (2025). Nonlinear Modeling of Oil Palm Yield Growth: A Review on Addressing Variability and Prediction Challenges. NEFU Mathematical Notes, 32(3), 1–22. https://mzsvfu.co.uk/wp-content/uploads/2025-03-01.pdf

Judijanto, L. (2026). Navigating Uncertainy: Palm Oil Sector Outlook for 2026 through the Lens of Smallholder Welfare and Sustainability Imperatives. Revista de Geopolítica, 17(1), e1386. https://doi.org/10.56238/revgeov17n1-127

Khonina, S. N., Kazanskiy, N. L., Oseledets, I. V., Khabibullin, R. M., & Nikonorov, A. V. (2025). Eyes of the Future: Decoding the World Through Machine Vision. Technologies, 13(11), 507. https://doi.org/10.3390/technologies13110507

Kumar, A. (2024). Cloud Vendor Lock-in: Identify, Strategies and Mitigate (10.09.2024; Seminar Paper). https://www.ossbig.at/wp-content/uploads/2024/09/CAN_Final_Report-VendorLock-In.pdf

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. https://doi.org/https://doi.org/10.3390/agriculture13010156

Lim, K. E., Ramachandran, V., Ata, A., Ratnam, M., Mohamad, R., Azahar, S., Hashim, A., Tat, C. S., & Mansor, H. (2024). Insights from GAP Execution for Yield Intensification among Independent Smallholder Farmer for Oil Palm (02/2024; ASB Working Paper Series). https://asb.edu.my/wp-content/uploads/2024/03/Key-MDT-WP-4.-Insights-GAP-Execution-for-Yield-Intensification-KL-VR-AA-compressed.pdf

Makky, M., & Soni, P. (2013). Towards Sustainable Green Production: Exploring Automated Grading for Oil Palm Fresh Fruit Bunches (FFB) Using Machine Vision and Spectral Analysis. International Journal on Advanced Science, Engineering and Information Technology, 3(1), 1–5. https://doi.org/10.18517/ijaseit.3.1.267

Mansour, M. Y. M. A., D. Dambul, K., & Choo, K. Y. (2022). Object Detection Algorithms for Ripeness Classification of Oil Palm Fresh Fruit Bunch. International Journal of Technology, 13(6), 1326. https://doi.org/10.14716/ijtech.v13i6.5932

Marinoudi, V., Benos, L., Camacho Villa, C., Lampridi, M., Kateris, D., Berruto, R., Pearson, S., Sørensen, C. G., & Bochtis, D. (2024). Adapting to the Agricultural Labor Market Shaped by Robotization. Sustainability, 16(16), 7061. https://doi.org/10.3390/su16167061

Matus, K. J. M., & Veale, M. (2022). Certification systems for machine learning: Lessons from sustainability. Regulation & Governance, 16(1), 177–196. https://doi.org/10.1111/rego.12417

McAlearney, A. S., Walker, D. M., Shiu-Yee, K., Crable, E. L., Auritt, V., Barkowski, L., Batty, E. J., Dasgupta, A., Goddard-Eckrich, D., Knudsen, H. K., McCrimmon, T., Scalise, A., Sieck, C., Wood, J., & Drainoni, M.-L. (2023). Embedding Big Qual and Team Science Into Qualitative Research: Lessons From a Large-Scale, Cross-Site Research Study. International Journal of Qualitative Methods, 22. https://doi.org/10.1177/16094069231165933

Muchlis, F., Jamil, A. S., Destiarni, R. P., Zainuddin, A., Amalia, D. N., Aziz, M. A., & Meilin, A. (2025). A Structural Equation Model to Assess the Impact of the Economic and Environmental Benefits to the Indonesian Sustainable Palm Oil (ISPO) Adoption. IJAEIT: International Journal on Adnvanced Science Engineering Informaation Technology, 15(1), 231–239.

Mukhtar, S., Arbabi, A., & Viegas, J. (2025). Advances in Spectral Imaging: A Review of Techniques and Technologies. IEEE Access, 13, 35848–35902. https://doi.org/10.1109/ACCESS.2025.3544476

Novrini, S., Nasution, I., Nurali, M., Pratama, A., Oksa, A. M., & Limbong, R. S. (2025). Government Policies and Their Impact on Palm Oil Agribusiness. IJOSS: International Journal of Natural Science Studies and Development, 2(1), 141–147. https://doi.org/https://doi.org/10.55299/ijoss.v2i1.21

Nur'aini, L. P., & Rahardi, M. (2025). Detection of Ripeness in Oil Palm Fresh Fruit Bunches Using the YOLO12S Algorithm on Digital Images. Journal of Applied Informatics and Computing, 9(4), 1633–1638. https://doi.org/10.30871/jaic.v9i4.10250

Pacheco-Ruiz, P., Osorio, S., & Vallarino, J. G. (2025). From data to decisions: a paradigm shift in fruit agriculture through the integration of multi-omics, modern phenotyping, and cutting-edge bioinformatic tools. Frontiers in Plant Science, 16. https://doi.org/10.3389/fpls.2025.1707289

Pacheco, Pablo; Schoneveld, George; Dermawan, Ahmad; Komarudin, Herry; Djama, M. (2020). Governing sustainable palm oil supply: Disconnects, complementarities, and antagonisms between state regulations and private standards. Regulation & Governance, 14(3), 568–593. https://doi.org/10.1111/rego.12220

Purba, S. F., Witjaksono, J., Djaenudin, D., Taridala, S. A., Imran, I., Yulianti, A., Muslimin, M., Fadwiwati, A. Y., & Sitompul, R. F. (2024). Strategies for improving independent oil palm smallholders' welfare in Konawe Regency, Southeast Sulawesi. IOP Conference Series: Earth and Environmental Science, 1379(1). https://doi.org/10.1088/1755-1315/1379/1/012013

Puttinaovarat, S., Chai-Arayalert, S., & Saetang, W. (2024). Oil Palm Bunch Ripeness Classification and Plantation Verification Platform: Leveraging Deep Learning and Geospatial Analysis and Visualization. ISPRS International Journal of Geo-Information, 13(5), 158. https://doi.org/10.3390/ijgi13050158

Rahutomo, A. B., Karuniasa, M., & Frimawaty, E. (2025). Enhancing farmers' land productivity through sustainable palm oil certification: Strategies for promoting environmental and economic benefits in agricultural practices. Journal of Agrosociology and Sustainability, 2(2), 97–112.

Samian, M. R., & Rizal, A. M. (2024). Improving Palm Oil Productivity through Harvesting Practices. IJARBSS: International Journal of Academic Research in Business & Social Sciences, 14(10), 2276–2284. https://doi.org/10.6007/IJARBSS/v14-i10/23345

Setiawan, A. W., & Prasetya, O. E. (2020). Palm Oil Fresh Fruit Bunch Grading System Using Multispectral Image Analysis in HSV. 2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT), 85–88. https://doi.org/10.1109/ICIoT48696.2020.9089431

Suhardjo, I., & Suparman, M. (2025). Harmonizing sustainability certification standards: the Indonesian palm oil case. International Food and Agribusiness Management Review, 28(1), 19–34. https://doi.org/10.22434/ifamr.1218

Suharjito, Asrol, M., Utama, D. N., Junior, F. A., & Marimin. (2023). Real-Time Oil Palm Fruit Grading System Using Smartphone and Modified YOLOv4. IEEE Access, 11, 59758–59773. https://doi.org/10.1109/ACCESS.2023.3285537

Sukhera, J. (2022). Narrative Reviews: Flexible, Rigorous, and Practical. Journal of Graduate Medical Education, 14(4), 414–417. https://doi.org/10.4300/JGME-D-22-00480.1

Upadhyay, N., & Bhargava, A. (2025). Artificial intelligence in agriculture: applications, approaches, and adversities across pre-harvesting, harvesting, and post-harvesting phases. Iran Journal of Computer Science, 8(3), 749–772. https://doi.org/10.1007/s42044-025-00264-6

Walsh, J. J., Mangina, E., & Negrão, S. (2024). Advancements in Imaging Sensors and AI for Plant Stress Detection: A Systematic Literature Review. Plant Phenomics, 6, 0153. https://doi.org/10.34133/plantphenomics.0153

Witjaksono, J., Djaenudin, D., Fery Purba, S., Yulianti, A., Fadwiwati, A. Y., Muslimin, Sitompul, R. F., Azahari, D. H., Imran, Purba, R., & Seerasarn, N. (2024). Corporate farming model for sustainable supply chain crude palm oil of independent smallholder farmers. Frontiers in Sustainable Food Systems, 8. https://doi.org/10.3389/fsufs.2024.1418732

Witjaksono, J., Yaumidin, U. K., Djaenudin, D., Astana, S., Harianja, A. H., Fery, S., Hasibuan, A. M., Khotimah, H., Hidayatina, A., Rusdin, R., Bungati, B., Imran, I., Rusdi, R., & Purba, R. (2023). The assessment of fresh fruit bunches supply chain of palm oil independent smallholder farmers in southeast Sulawesi. Uncertain Supply Chain Management, 11(3), 941–950. https://doi.org/10.5267/j.uscm.2023.5.004

Yao, W., Liu, C., Liu, Y., Zheng, Q., Wang, J., Yu, H., Chen, C., & Guo, S. (2025). Unmanned aerial vehicle payload technology applications in agriculture and other low-altitude scenarios: a review. Frontiers in Plant Science, 16. https://doi.org/10.3389/fpls.2025.1721484

Zarei, M. (2025). How to Write a Powerful Narrative Review: A Step-by-Step Guide. LitMaps. https://www.litmaps.com/articles/write-narrative-review

Zhang, Y., Wei, L., Zhou, Y., Kou, W., & Fauzi, S. S. M. (2025). Integrating UAV-RGB Spectral Indices by Deep Learning Model Enables High-Precision Olive Tree Segmentation Under Small Sample. Forests, 16(6), 924. https://doi.org/10.3390/f16060924