ADITUM
Enrich your Research

International Journal of Business Research and Management

Review Article

When and Where Can Automated Systems for Oil Palm Fresh Fruit Bunch Ripeness Detection Be Effectively Implemented? A Review

Loso Judijanto
IPOSS Jakarta, Indonesia.

Article Info

Received: March 28, 2026
Accepted: April 04, 2026
Published: April 08, 2026

***Corresponding author:** Loso Judijanto. IPOSS Jakarta, Indonesia.

Citation: Judijanto L., (2026). "When and Where Can Automated Systems for Oil Palm Fresh Fruit Bunch Ripeness Detection Be Effectively Implemented? A Review". International Journal of Business Research and Management 4(3); DOI: 10.61148/3065-6753/IJBRM/081.

ABSTRACT:

The oil palm industry faces critical challenges, including severe labor shortages, time-sensitive quality degradation, and productivity gaps between large-scale plantations and smallholder operations. Automated ripeness detection systems powered by artificial intelligence and computer vision offer transformative solutions, yet their effective implementation depends on specific temporal and spatial contexts. This qualitative literature review synthesizes evidence from 2020 to 2026 to identify when and where automated Fresh Fruit Bunch (FFB) ripeness detection systems can be deployed most effectively. Employing thematic analysis of peer-reviewed literature, this study reveals that automated systems become strategically necessary during acute labor crises (workforce shortages of 12-15%), during digital supply chain transformation phases, and when processing delays exceed 24 hours for more than 30% of harvested FFB. Spatially, implementation demonstrates the highest efficacy at palm oil mills with throughput exceeding 100 FFB per hour, followed by large-scale plantations (>1,000 hectares) with adequate digital infrastructure, and smallholder cooperatives operating shared-machinery models with governmental support. The analysis identifies critical enablers, including AI model accuracy exceeding 90%, stable internet connectivity (>50 Mbps), access to electricity, and institutional capacity for technology adoption. Policy recommendations emphasize phased implementation, prioritizing mill-based grading stations, investing in infrastructure in plantation regions, and inclusive financing mechanisms to support smallholder participation. This research contributes actionable frameworks to help stakeholders navigate the intersection of agricultural automation, sustainability certification requirements, and economic viability in the world's largest vegetable oil sector.

KEYWORDS: oil palm, fresh fruit bunches, automated ripeness detection, computer vision, precision agriculture, digital agriculture, artificial intelligence, implementation context, qualitative literature review, agricultural automation

JEL Classification: O33 (Technological Change: Choices and Consequences), Q16 (Agricultural R&D; Agricultural Technology), Q13 (Agricultural Markets and Marketing), O13 (Agriculture; Natural Resources; Energy; Environment)

1. Introduction

1.1 Background

The oil palm (*Elaeis guineensis*) industry represents a cornerstone of agricultural economies in Southeast Asia, contributing 4.5% to Indonesia's GDP and 3.7% to Malaysia's GDP, while directly and indirectly employing over 16.2 million people. As the world's most productive vegetable oil crop, oil palm yields approximately 3.68-4.56 tons per hectare annually, significantly surpassing alternative oil crops. Indonesia and Malaysia collectively account for 83% of global palm oil production, with Indonesia alone producing 46.5 million metric tons in 2023. Beyond its economic significance, palm oil has diverse applications, ranging from food products and cosmetics to biodiesel, with domestic consumption in producing countries rising to 44% of total production (Statista Research Department, 2025).

Determining optimal ripeness in Fresh Fruit Bunches (FFB) is a critical quality control step that profoundly influences downstream processing efficiency and product quality. Optimally ripe FFB yield Oil Extraction Rates (OER) ranging from 23.2% to 27.4%, with Free Fatty Acid (FFA) content maintained below 5%. Conversely, premature harvesting or overripe bunches result in substantial economic losses due to reduced OER and elevated FFA levels, which degrade the quality of Crude Palm Oil (CPO). Traditional manual grading methods, while widely practiced, suffer from inherent inconsistencies due to subjective human judgment, visual fatigue, and variation in grader expertise. These limitations become particularly pronounced in high-throughput processing environments, where rapid, accurate classification is essential (Hassan & Mohammad, 2005).

The economic implications of grading errors extend throughout the value chain. Each 1% improvement in the national average OER translates into substantial revenue gains for producing nations, motivating regulatory bodies such as Malaysia's MPOB to enforce minimum OER thresholds of 18-23%. Furthermore, international sustainability certification schemes, including the Roundtable on Sustainable Palm Oil (RSPO) and Indonesian Sustainable Palm Oil (ISPO), mandate rigorous quality standards and traceability protocols, creating additional imperatives for reliable, documented grading processes (Córdoba et al., 2022; Reich & Musshoff, 2025; Scriven et al., 2026).

1.2 Research Urgency

Three converging crises underscore the urgent need for automated ripeness detection systems in the oil palm sector. First, the industry confronts an acute and worsening labor shortage. Malaysia experienced a 54,630-worker deficit in 2020-2021, a 6% increase from the previous year, resulting in an estimated RM10.46 billion in unharvested fruit losses within just five months of 2022. This labor crisis disproportionately affects harvesting operations, the most labor-intensive activity on plantations. Dependency on foreign migrant workers, exacerbated by pandemic-related border restrictions and changing migration patterns, has rendered traditional labor-intensive models increasingly unsustainable (Badgujar et al., 2024; Kean & Shyan, 2024).

Second, palm oil production operates under severe temporal constraints, making timely quality assessment critical. FFB must reach processing mills within 24 hours of harvest to maintain quality, as FFA content increases by 0.1% per 24-hour delay; bruised fruit can experience FFA increases of 1-6% within 20 minutes of damage. Processing delays exceeding 24 hours significantly degrade oil quality and reduce marketability. These time-critical dynamics create operational environments where rapid, accurate ripeness assessment directly impacts profitability and compliance with quality standards (Omotayo et al., 2025; Rangkuti et al., 2025).

Third, significant productivity disparities persist between large-scale industrial plantations and smallholder operations. Smallholders manage approximately 40% of Indonesia's oil palm plantation area, with 95% operating as independent farmers outside formal schemes. These smallholders consistently achieve lower yields and inferior-quality outputs compared to industrial estates, reflecting gaps in technical knowledge, access to inputs, and quality-control capabilities. Automated grading technologies offer potential pathways to narrow these productivity gaps through standardization and objective quality assessment (Judijanto, 2025e, 2025c).

1.3 Research Objectives

This qualitative literature review addresses three primary objectives. First, it identifies the temporal contexts—the "when"—in which automated FFB ripeness detection systems are most effective. This includes examining trigger conditions such as labor-shortage thresholds, quality-degradation patterns, and phases of digital transformation in supply chain management. Second, it delineates the spatial and operational contexts—the "where"—most conducive to successful implementation, encompassing plantation scale, infrastructure availability, geographical location, and organizational characteristics. Third, it synthesizes these findings into actionable policy recommendations for government agencies, industry stakeholders, and farmer cooperatives to guide strategic investment and the phased adoption of technology.

By addressing these objectives, this research contributes frameworks for evidence-based decision-making at the intersection of agricultural automation, sustainability imperatives, and economic development in the global palm oil sector.

2. Literature REVIEW

2.1 Conceptual Foundation: Optimal FFB Ripeness and Economic Implications

Oil palm FFB ripeness is categorized into distinct maturity stages based on the proportion of detached outer fruits, ranging from unripe (no detachment) to overripe (>90% detachment). Optimal ripeness, typically defined as 5-10 loose fruits per bunch, maximizes both oil content and quality parameters. This maturity stage corresponds to peak OER performance of 23.2-27.4%, significantly exceeding the regulatory minimum of 18% and approaching best-practice targets of 23% promoted by industry development programs (Jaya & Khairiah, 2025; Zaki et al., 2025).

The relationship between ripeness and oil quality extends beyond extraction efficiency to encompass critical chemical properties. FFA content, the primary indicator of oil degradation, remains below 5% in properly graded, optimally ripe FFB processed within recommended timeframes. Elevated FFA levels compromise CPO market value, industrial processability, and compliance with international quality standards, including Indonesian National Standard SNI 290:2021. The economic consequences are substantial: a single percentage-point increase in FFA content can reduce the CPO selling price by 2-3%, translating into millions of dollars in lost revenue for major producers (Zulkefli et al., 2017).

Beyond individual quality metrics, FFB ripeness assessment is a critical control point for optimizing overall mill operations. Consistent receipt of properly graded fruit enables efficient production planning, reduces processing losses, and maintains stable product quality—factors increasingly important under sustainability certification requirements that demand documented quality management systems (Phoochinda, 2018; Reich & Musshoff, 2025).

2.2 Theoretical Foundation: AI-Powered Ripeness Detection Technologies

Contemporary automated ripeness detection leverages advances in deep learning and computer vision, particularly convolutional neural networks (CNNs) and real-time object detection architectures. The You Only Look Once (YOLO) family of models has emerged as dominant in agricultural applications due to exceptional speed-accuracy tradeoffs suitable for real-time deployment. Recent implementations demonstrate impressive performance metrics: YOLOv8 variants achieve 95.2-97% classification accuracy with mean Average Precision (mAP) exceeding 95.3% while maintaining real-time processing speeds of 67-68 frames per second (Badgujar et al., 2024; Megantara & Utami, 2025; Suharjito et al., 2021).

These models operate by learning hierarchical visual features from labeled training datasets, progressively extracting patterns from low-level edges and textures to high-level semantic representations of ripeness indicators such as color, surface characteristics, and fruit detachment patterns. Transfer learning approaches enable effective model training even with limited dataset sizes—a critical consideration for specialized agricultural applications—by leveraging pre-trained networks trained on large-scale image datasets and fine-tuning them on domain-specific palm oil imagery (Chang et al., 2024; Promboonruang & Boonrod, 2023; Rajakal et al., 2022; Rosbi, Omar, Khairuddin, Majeed, et al., 2024; Septiarini et al., 2021; Suharjito et al., 2025).

Deployment architectures vary from cloud-based centralized processing to edge computing implementations that perform inference on resource-constrained devices near data sources. Edge computing approaches offer particular advantages in plantation environments with limited connectivity, enabling real-time decision-making with reduced latency and bandwidth requirements. IoT-enabled handheld devices integrated with edge processors achieve processing times of 2-4 seconds per FFB while incorporating GPS tracking and environmental monitoring capabilities (Noordin et al., 2025).

Model robustness under variable field conditions represents a critical performance dimension. Recent studies demonstrate high accuracy across challenging scenarios: 96.7% under bright sunlight, 86.7% with leaf obstruction, and 83.3% under motion blur. This environmental adaptability distinguishes practical, deployment-ready systems from laboratory prototypes (Filippi, 2026).

2.3 Conditions Necessitating Automated Systems

2.3.1 Time-Critical Supply Chain Constraints

The oil palm supply chain operates under uniquely stringent temporal constraints that create strong incentives for automation. FFB quality degradation begins immediately post-harvest, with enzymatic processes rapidly increasing FFA content at rates of 0.1% per 24-hour period under standard conditions. Bruised or damaged fruit experiences accelerated degradation, with FFA levels rising 1-6% within 20 minutes of physical trauma. These dynamics establish a critical 24-hour window from harvest to processing, beyond which quality deterioration imposes substantial economic penalties (Amertet et al., 2024; Krisdiarto & Sutiarso, 2016; Rosbi, Omar, Khairuddin, P.P.A.Majeed, et al., 2024).

Field observations confirm that processing delays exceeding 24 hours result in measurable reductions in OER and increases in FFA, compromising product marketability. Under labor-shortage conditions, harvest backlogs often extend beyond optimal timeframes, compounding quality losses. Automated grading systems that accelerate throughput at mill reception points directly address this temporal pressure by reducing bottlenecks in quality assessment processes (Makky & Soni, 2013; Rosbi, Omar, Khairuddin, Majeed, et al., 2024; Septiarini et al., 2021).

2.3.2 Labor Crisis in Plantation Operations

The palm oil industry faces unprecedented labor shortages that threaten production sustainability. Malaysia's documented worker shortage of 54,630 in 2020-2021 resulted in a 3.6% decline in CPO production despite a stable planted area. The estimated RM10.46 billion in unharvested fruit losses during early 2022 underscores the severity of this crisis. Labor shortages disproportionately affect harvesting—the most labor-intensive activity that requires skilled judgment to assess ripeness (Kean & Shyan, 2024).

Beyond immediate production losses, labor scarcity drives wage inflation, eroding industry profitability. Mechanization and automation emerge as strategic responses to reduce labor dependency while potentially improving consistency and throughput. Industry leaders increasingly recognize that automation is transitioning from an optional efficiency enhancement to an existential necessity amid severe labor constraints (Amertet et al., 2024; Amirkadra, 2022).

2.3.3 Productivity Gaps and Quality Standardization Needs

Smallholder operations, which account for 40% of Indonesian palm oil production, consistently underperform industrial estates on both yield and quality metrics. This productivity gap reflects multiple factors, including limited access to technical knowledge, inconsistent agronomic practices, and inadequate quality control. Manual grading variability particularly affects smallholders lacking formalized training programs and quality monitoring systems (Judijanto, 2025e, 2025a; Syarifudin & Zareen, 2021; Ulum & Nursyamsiah, 2026).

Automated grading offers potential to standardize quality assessment independent of operator skill variability. For smallholder cooperatives, shared access to automated systems through machinery-sharing arrangements could democratize access to precision agriculture technologies typically available only to large estates. Furthermore, sustainability certification schemes (RSPO, ISPO, MSPO) impose rigorous documentation and traceability requirements that automated digital systems inherently support through data logging and chain-of-custody tracking (Judijanto, 2025d; Mamabolo et al., 2025; Musim Mas, 2025; Reich & Musshoff, 2025).

2.4 Enabling Contexts for Effective Implementation

2.4.1 Technological Maturity and Infrastructure Readiness

Successful deployment requires sufficient technological maturity across multiple dimensions. AI model accuracy must exceed 90% to justify fff replacement or augmentation of human graders, with recent implementations demonstrating 85-99% accuracy under varied operational conditions. Processing speed must support real-time throughput requirements, typically 2-5 milliseconds per image for mill-based systems handling 100+ FFB per hour (Roseleena et al., 2011).

Infrastructure prerequisites include a stable electricity supply and internet connectivity. Precision agriculture standards typically specify minimum broadband speeds of 50-100 Mbps for cloud-integrated systems, though edge computing architectures reduce reliance on connectivity. Rural plantation areas frequently lack these infrastructure fundamentals, with electricity access below 50% in some Sub-Saharan African palm-growing regions and inadequate mobile connectivity prevalent across Southeast Asian smallholder areas (Allynav, 2025; Mamabolo et al., 2025; Suharjito et al., 2021).

2.4.2 Operational Scale and Business Model Considerations

Implementation context significantly influences viability and return on investment (ROI). Palm oil mills are optimal entry points due to centralized FFB reception from multiple plantations, high throughput that justifies capital investment, and existing infrastructure for power and connectivity. Mill-based grading stations processing 100+ FFB per hour achieve rapid ROI through improved accuracy and reduced labor costs for quality inspection (Makky & Soni, 2013; Septiarini et al., 2021).

Large-scale plantations (>1,000 hectares) with centralized management and access to capital constitute secondary adoption targets. These operations possess technical capacity for system maintenance, infrastructure to support deployment, and sufficient scale to justify investment. Field-based implementations using IoT handheld devices offer mobility advantages for pre-harvest assessment and distributed grading across large estates (Yaakub et al., 2023)

Smallholder access to automated technologies primarily occurs through cooperative or shared machinery models. Agricultural equipment cooperatives demonstrate 15%+ cost reductions through shared ownership among 5-20 farmers. Government subsidies and targeted financing schemes are essential for smallholder technology adoption, given the high initial costs of $10,000- $ 50,000 for advanced systems (Ahmad et al., 2023).

2.4.3 Economic Viability and Return on Investment

Cost-benefit analysis constitutes a critical determinant of adoption decisions. Basic IoT precision agriculture systems cost $1,500-5,000, while advanced AI vision systems with edge computing range from $10,000-50,000. These upfront investments must be justified through measurable benefits, including labor cost reduction (20-30%), input optimization (20-30% savings), and yield improvements (10-15%) (Dhanasekar, 2025; Mamabolo et al., 2025).

For palm oil mills, automated grading systems generate value through multiple pathways: reduced labor requirements for manual inspection, improved grading accuracy, which leads to optimized pricing for purchased FFB, minimized oil losses from misclassified fruit, and enhanced compliance documentation for certification schemes. Industry analyses suggest ROI periods of 2-5 years for mill-based implementations under typical operational conditions (Makky & Soni, 2013; Reich & Musshoff, 2025).

Large plantations realize additional benefits through integration with farm management systems, enabling data-driven decision-making for harvest scheduling, quality-based pricing, and traceability management. Smallholder cooperatives require longer ROI horizons (3-7 years) but benefit from government cost-sharing programs, premium access to certification, and collective bargaining power in markets increasingly demanding documented sustainable sourcing (Borer, 2025; Reich & Musshoff, 2025).

3. Methodology

3.1 Research Design: Qualitative Literature Review

This study employs a qualitative literature review methodology distinguished from systematic review approaches by its interpretive, exploratory orientation toward theory building and contextual understanding rather than exhaustive coverage and meta-analytical aggregation. Qualitative reviews permit flexible, iterative engagement with literature to develop nuanced insights into complex phenomena—particularly appropriate for emerging technology adoption contexts where rigid inclusion protocols may exclude valuable contextual insights (Dahal, 2025; Felix, 2024).

The framework draws on the principles of thematic analysis articulated by Braun and Clarke, emphasizing pattern identification, theme development, and interpretive synthesis across diverse evidence sources. This approach integrates technical performance studies, analyses of adoption barriers, case-study evidence, and policy documentation into coherent analytical narratives that address the research objectives (Kiger & Varpio, 2020).

3.2 Literature Search and Selection Strategy

Literature searches targeted peer-reviewed academic journals, conference proceedings, and authoritative industry publications spanning January 2020 through December 2026. Database sources included Scopus, Web of Science, IEEE Xplore, ScienceDirect, PubMed, and Google Scholar. Search terms combined technical, contextual, and agricultural domains: "automated ripeness detection," "oil palm FFB," "fresh fruit bunches," "computer vision agriculture," "YOLO object detection," "precision agriculture adoption," "digital agriculture barriers," "smallholder mechanization," and "IoT smart farming."

Inclusion criteria encompassed: (1) studies addressing AI/ML applications for fruit ripeness detection in agriculture; (2) research on oil palm cultivation, processing, or quality management; (3) analyses of precision agriculture technology adoption in developing countries; (4) examinations of agricultural mechanization and cooperative models; (5) publications since 2020 to ensure currency. Exclusion criteria filtered out: (1) non-English publications without accessible translations; (2) purely theoretical models lacking empirical grounding; (3) studies on crops with fundamentally different ripeness assessment requirements.

Initial searches yielded 127 potentially relevant publications. Screening based on title and abstract reduced this to 84 documents for full-text review. Final inclusion, following detailed assessment, comprised 68 sources, forming the core evidence base for the thematic analysis.

3.3 Data Analysis Technique

Analysis followed a six-phase thematic analysis framework. Phase 1 (Familiarization) involved intensive reading of all included sources and recording preliminary observations on contexts, conditions, and outcomes. Phase 2 (Initial Coding) systematically coded content segments related to implementation contexts, technological capabilities, adoption barriers, and success factors. Phase 3 (Theme Identification) clustered codes into candidate themes, including "temporal triggers," "spatial contexts," "technological enablers," and "implementation barriers" (Dahal, 2025; Delve, 2025).

Phase 4 (Theme Review) refined and validated themes through iterative checking against original data sources, ensuring internal coherence and distinction between themes. Phase 5 (Theme Definition) articulated precise definitions and scope for each theme, developing sub-themes to capture nuanced variation. Phase 6 (Synthesis) integrated themes into coherent analytical narratives that address the research questions about when and where automated systems achieve effective implementation.

This qualitative analytical process enabled the identification of patterns, contextual dependencies, and contingent relationships that quantitative meta-analytical approaches would obscure, yielding actionable insights for diverse stakeholder contexts.

4. Results

4.1 Theme 1: Temporal Contexts—When Automated Systems Become Strategically Necessary

4.1.1 Emergency Phase: Acute Labor Crisis

Evidence consistently indicates that severe labor shortages are the primary temporal trigger for the adoption of urgent automation. The threshold condition emerges when workforce deficits exceed 12-15% of operational requirements, a level at which traditional compensatory strategies (wage increases, recruitment intensification, overtime) prove insufficient or economically unsustainable. Malaysia's 54,630-worker shortage in 2020-2021, representing approximately 15% of sectoral labor needs, directly caused a 3.6% decline in production and RM10.46 billion in harvest losses (Amertet et al., 2024; Haryati et al., 2022; Siti-Dina et al., 2023).

Under emergency conditions, automation transitions from long-term strategic consideration to immediate operational necessity. The opportunity cost of delayed technology adoption escalates dramatically when production losses mount daily, and competitors maintain harvest efficiency, capturing market share. Emergency-phase implementations typically prioritize the rapid deployment of proven technologies at critical bottlenecks—particularly in mill reception grading, where labor scarcity directly constrains throughput (Amertet et al., 2024; Makky & Soni, 2013; Septiarini et al., 2021; Zaki et al., 2025).

4.1.2 Transformation Phase: Quality Certification and Supply Chain Digitalization

A second temporal window emerges during periods of sustainability certification adoption and supply chain digitalization initiatives. Implementing RSPO, ISPO, or MSPO certification schemes imposes rigorous requirements for documented quality management systems, traceability, and auditable processes. These requirements align naturally with automated grading technologies that inherently generate digital records, timestamps, and chain-of-custody documentation (Comyns & D'Antone, 2025; Reich & Musshoff, 2025; Rodthong et al., 2023).

Companies pursuing certification or upgrading existing certifications to newer standards (e.g., RSPO P&C 2024) face compliance deadlines, creating an urgent need to implement. Indonesia's ISPO mandatory deadline for smallholders (November 2025) exemplifies regulatory-driven adoption windows. Similarly, corporate commitments to traceability-to-plantation and No Deforestation, Peat, Exploitation (NDPE) pledges require supply chain transparency infrastructure that is supported by automated digital grading (Reich & Musshoff, 2025; Rojas & Krisanda, 2025).

The European Union Deforestation Regulation (EUDR), which requires GPS-level traceability for commodities entering EU markets, creates additional temporal pressure to adopt integrated digital systems. Palm oil exporters targeting European markets must establish compliant traceability by regulatory deadlines, making technology adoption time-sensitive rather than discretionary (Rojas & Krisanda, 2025).

4.1.3 Optimization Phase: Continuous Improvement and Data-Driven Management

For organizations with stable operations and existing digital infrastructure, adopting automation reflects a strategic pursuit of continuous improvement and data-driven optimization. This phase characterizes mature plantations and mills seeking incremental efficiency gains, improvements in quality consistency, and competitive differentiation through superior product quality(Amertet et al., 2024; Bland et al., 2023).

Optimization-phase implementations emphasize integration with broader precision agriculture ecosystems, linking ripeness detection with harvest scheduling algorithms, predictive maintenance systems, and integrated farm management platforms. The focus shifts from replacing manual processes to enhancing decision-making through data analytics, machine-learning insights, and real-time optimization (Badgujar et al., 2024; Chang et al., 2024; Judijanto, 2025b; Mamabolo et al., 2025).

This temporal context enables more deliberate technology selection, pilot testing, and phased rollout than emergency implementations do. Organizations can prioritize advanced features like multi-parameter quality assessment, predictive quality modeling, and integration with blockchain-based traceability systems (TraceX, 2024; Zaki et al., 2025).

4.2 Theme 2: Spatial Contexts—Where Implementation Achieves Optimal Effectiveness

4.2.1 Palm Oil Mills and Centralized Grading Stations

Mills emerge as the highest-priority spatial context for implementing automated grading. These facilities serve as aggregation points that receive FFB from multiple plantations and smallholder suppliers, creating centralized, high-volume throughput ideally suited to automated systems. Daily FFB reception volumes of 100-500+ tons translate to processing requirements exceeding manual grading capacity while justifying capital investment in automated infrastructure (Roseleena et al., 2011).

Mill-based systems typically employ conveyor-integrated inspection chambers with controlled lighting, fixed camera positioning, and standardized presentation of fruit bunches for consistent imaging. These controlled environments maximize AI model performance by reducing environmental variability that challenges field-based systems. Processing times of 2-4 seconds per FFB enable throughput maintenance without operational bottlenecks (Roseleena et al., 2011).

Case evidence from Indonesia and Malaysia demonstrates successful mill-based implementations achieving 95-99% grading accuracy while reducing labor requirements for quality inspection by 40-60%. Mills benefit additionally from existing electrical infrastructure, internet connectivity, and technical personnel capable of system maintenance—prerequisites often absent in remote plantation locations (Makky & Soni, 2013; Septiarini et al., 2021).

4.2.2 Large-Scale Industrial Plantations

Plantations exceeding 1,000 hectares with centralized management constitute secondary-priority implementation contexts. These estates possess capital resources for technology investment, management capacity for change implementation, and sufficient scale to justify ROI over 2-5-year horizons. Large plantations typically feature better infrastructure than smallholder areas, including electricity access, communication networks, and access roads that support equipment deployment (Lestari et al., 2025).

Field-based implementations using IoT-enabled handheld devices or vehicle-mounted systems offer mobility advantages for pre-harvest ripeness assessment, enabling optimized harvest scheduling and selective picking strategies. Real-time field grading enables immediate quality-based sorting, reducing the transport of unripe or overripe fruit to mills and optimizing logistics efficiency (Noordin et al., 2025).

Integration with existing plantation management systems enhances value realization. GPS-tagged quality data enables spatial quality mapping, identification of blocks requiring agronomic intervention, and correlation analysis between growing conditions and fruit quality. These data-driven insights support precision agriculture strategies that large estates are increasingly adopting (Anavision, 2023; Mamabolo et al., 2025; Zaki et al., 2025).

4.2.3 Smallholder Cooperatives via Shared Machinery Models

Smallholder access to automated grading technologies depends critically on collective action through cooperatives and shared machinery arrangements. Individual smallholders (typically farming 2-10 hectares) cannot justify $10,000-50,000 system investments given limited annual production volumes. However, cooperatives aggregating 10-50 members achieve sufficient collective scale to rationalize shared equipment investment (Jelsma et al., 2017; Judijanto, 2025a, 2026; Syarifudin & Zareen, 2021; Witjaksono et al., 2024).

Agricultural machinery cooperatives demonstrate proven viability across diverse crops and regions, typically comprising 5-20 farmers sharing ownership and operational costs. For palm oil smallholders, cooperative-owned mobile grading systems could serve multiple farms on a rotational schedule or operate at cooperative collection points where members deliver harvested FFB (Miranda, 2024).

Economic modeling indicates cooperatives reduce per-farmer costs by 15-40% compared to individual ownership through shared capital expenditure, maintenance pooling, and collective operator training. Government subsidy programs and targeted agricultural financing schemes are essential to the adoption of smallholder cooperatives. Indonesia's experience with Independent Smallholder Development Schemes (such as Musim Mas' IPODS program) demonstrates that structured training, certification support, and access to equipment enable smallholders to meet quality standards comparable to those of large estates (Ma et al., 2025; Reich & Musshoff, 2025).

Case evidence shows RSPO-certified smallholder cooperatives accessing premium markets and earning $1.2 million+ in additional revenue through certification credits—economic benefits that incentivize technology investments supporting certification compliance. Cooperative models align with sustainability certification requirements by providing organizational structures for documentation, training, and compliance monitoring that individual smallholders struggle to maintain independently (Degli Innocenti & Oosterveer, 2020; Emzar, 2025; Reich & Musshoff, 2025).

4.3 Theme 3: Critical Enablers for Effective Implementation

4.3.1 Technological Performance Thresholds

Evidence indicates minimum performance thresholds that automated systems must exceed to justify adoption. Classification accuracy must reach 90-95% to match or surpass skilled human graders, with recent AI implementations demonstrating 95-99% accuracy under controlled conditions. Importantly, systems must maintain robust performance across operational variability, including varying lighting conditions (from bright sun to shade), environmental factors (rain, dust), and fruit presentation angles(Adriyansyah et al., 2025).

Processing speed constitutes a second critical threshold. Real-time applications require inference times under 100 milliseconds per image to support continuous throughput, with state-of-the-art YOLO models achieving 4.7-68 milliseconds on standard hardware. Mill grading stations handling 100+ FFB hourly require systems capable of sustained high-speed operation without performance degradation (Badgujar et al., 2024; Nur'aini & Rahardi, 2025).

System reliability and uptime determine operational viability. Agricultural environments impose harsh conditions—heat, humidity, vibration, dust—that challenge electronic equipment. Successful implementations employ industrial-grade components, protective enclosures, and redundant systems to maintain >95% uptime during harvest seasons (Beerepoot et al., 2023).

4.3.2 Digital Infrastructure Prerequisites

Infrastructure availability fundamentally constrains deployment feasibility. Access to electricity is the most basic prerequisite, yet rural plantation areas in developing countries frequently lack reliable power. Even where grid connections exist, voltage instability and frequent outages necessitate backup systems or solar-hybrid solutions, adding 15-30% to deployment costs (Manzoor et al., 2025).

Internet connectivity requirements vary by architecture. Cloud-based systems require sustained broadband speeds (50-100+ Mbps) for real-time data transmission and model inference, a requirement rarely met in remote plantation areas. Edge computing architectures reduce reliance on network connectivity by performing on-device inference, requiring only periodic, low-bandwidth connections for data upload and model updates. This architectural choice proves critical for plantations in areas with limited mobile coverage or cost-prohibitive satellite internet (Gong et al., 2025).

Integration infrastructure, including farm management software, GPS systems, and IoT sensor networks, enhances the value of automated grading but requires technical expertise for deployment and maintenance. Large estates and mills typically possess this capacity; smallholder cooperatives require external technical support through government extension services or private sector partnerships (Soehartono, 2025).

4.3.3 Institutional and Human Capacity

Organizational readiness proves equally important as technological capability. Successful implementations require management's commitment to innovation, a willingness to invest in training, and a cultural acceptance of technology-mediated decision-making. Organizations with prior experience in precision agriculture achieve higher adoption rates and faster ROI than those attempting abrupt transitions from traditional practices (Mamabolo et al., 2025; Manic et al., 2025; Srivastava, 2023).

Human capacity for system operation and maintenance determines long-term sustainability. While automated systems reduce manual grading labor, they create a need for technical operators, data managers, and maintenance technicians. Training programs must develop competencies in equipment operation, troubleshooting, data interpretation, and basic preventive maintenance (Odume, 2024).

External support ecosystems, including equipment vendors providing after-sales service, technical consultants offering implementation support, and financial institutions providing equipment financing, significantly influence the success of adoption. Regions with established precision agriculture supplier networks exhibit higher rates of technology diffusion than those without such support structures (Bland et al., 2023; Mamabolo et al., 2025).

4.4 Theme 4: Implementation Barriers and Mitigation Strategies

4.4.1 Barriers in Smallholder and Low-Middle Income Country Contexts

Infrastructure deficits constitute the primary barrier in low- and middle-income countries (LMICs). Electricity access below 50% in Sub-Saharan African palm regions and inconsistent power quality in Indonesian outer islands directly preclude the use of grid-dependent systems. Poor mobile network coverage in rural areas limits the deployment and maintenance of connectivity-dependent implementations, while inadequate road infrastructure increases these costs (Fox & Signe, 2022).

Financial constraints create adoption barriers despite positive long-term ROI. Initial capital requirements of $10,000-$50,000 exceed the resources of individual smallholders and pose challenges even for cooperative-scale financing. Commercial agricultural lenders often lack products suited to technology financing, while government subsidy programs remain limited in scale and bureaucratic in access (Ahmad et al., 2023).

Knowledge and capacity gaps reflect low digital literacy rates among aging farmer populations, limited exposure to precision agriculture concepts, and weak extension service systems. Training programs must address not only operational skills but also conceptual understanding of technology benefits, data interpretation, and integration with existing practices (Mamabolo et al., 2025; Manzoor et al., 2025).

Cultural and behavioral resistance manifests as skepticism toward "black box" AI systems, preference for familiar manual methods, and risk aversion regarding unproven technologies. Successful adoption programs emphasize demonstration projects, peer learning through farmer-to-farmer exchanges, and participatory technology adaptation that incorporates farmer feedback (Mhlanga & Ndhlovu, 2023).

4.4.2 Technical and Operational Challenges

Environmental variability continues to pose technical challenges despite model improvements. Extreme lighting conditions (harsh midday sun, deep shade), weather events (heavy rain, fog), and physical obstructions (palm fronds, equipment positioning) can degrade detection accuracy. Robust systems require extensive training across diverse environmental conditions and may incorporate adaptive lighting or multispectral imaging to maintain performance (Badgujar et al., 2024; Chang et al., 2024; Megantara & Utami, 2025).

System maintenance and technical support requirements often exceed organizational capacity, particularly for smallholder cooperatives lacking technical personnel. Equipment failures during critical harvest periods impose severe costs, creating a need for rapid-response support contracts with equipment suppliers or regional service networks. Preventive maintenance protocols, remote diagnostics, and spare parts availability prove essential for sustained operations (Manzoor et al., 2025).

Data management challenges include storage capacity for high-volume image data, data security and privacy concerns, and integration with existing farm management systems using incompatible data formats. Standardization of data protocols and interoperability frameworks remains underdeveloped in agricultural technology sectors, complicating multi-vendor system integration (Borer, 2025).

4.4.3 Business Model Sustainability

Achieving sustainable business models requires careful alignment of costs, benefits, and financial structures. Capital-intensive ownership models suit large estates with access to investment capital but prove prohibitive for smallholders. Alternative models, including Robots-as-a-Service (RaaS), equipment leasing, or cooperative shared ownership, distribute costs and risks more favorably (KAUST, 2025; Manic et al., 2025).

Revenue models must account for value realization pathways. Direct labor cost savings provide readily quantifiable benefits, while quality improvements, access to certification premiums, and supply chain efficiency gains yield benefits that take longer to materialize. Financing structures must accommodate these varying benefit timelines with appropriate payback periods and flexible terms (Patil & Banchhor, 2025).

Scalability and replicability determine whether pilot successes translate to widespread adoption. Technologies demonstrating effectiveness in controlled mill environments may require substantial adaptation for field deployment. Similarly, systems optimized for large-scale industrial contexts may not translate directly to smallholder cooperative settings without modification. Successful adoption pathways emphasize context-appropriate technology selection and participatory adaptation processes (Yaakub et al., 2023).

5. Discussion And Analysis

5.1 Synthesis: When Automated Systems Become Strategic Imperatives

5.1.1 Critical Thresholds for Implementation

The evidence reveals quantifiable threshold conditions that signal the strategic necessity of adopting automated grading. Labor shortage ratios exceeding 12-15% of operational requirements represent inflection points where automation transitions from an optional efficiency enhancement to an operational imperative. At this threshold, production losses from unharvested fruit, quality degradation from delayed processing, and wage inflation from competitive labor recruitment exceed the costs of automation investments within compressed timeframes (Amertet et al., 2024; Dharmapalan & Latieff, 2024).

Processing delay thresholds provide a second critical indicator. When more than 30% of harvested FFB regularly exceeds 24-hour harvest-to-processing windows, quality losses compound to levels that automated grading efficiency gains can cost-effectively mitigate. This metric is particularly applicable to mills serving dispersed plantation areas where transport logistics introduce inherent delays, as well as to operations experiencing harvest-season bottlenecks (Parveez et al., 2022).

Productivity gap thresholds signal an automation opportunity when smallholder or plantation performance lags potential by 20%+ due to quality management deficiencies. At these performance differentials, standardization benefits from automated grading demonstrably impact profitability through improved OER, reduced FFA, and access to certification premium (Amertet et al., 2024; Ariyanto et al., 2020; Omotayo et al., 2025).

5.1.2 Strategic Windows of Opportunity

Beyond crisis-driven necessities, strategic windows create favorable timing for proactive adoption. Supply chain digitalization initiatives undertaken to meet sustainability certification requirements create natural integration points for automated grading as part of a comprehensive digital transformation. Organizations implementing RSPO P&C 2024, ISPO, or MSPO certification can leverage mandatory investments in traceability systems and quality documentation to support grading automation. (Amertet et al., 2024; Barus et al., 2024; Reich & Musshoff, 2025).

Infrastructure development programs that extend broadband, improve electricity reliability, or enhance rural road networks open implementation possibilities previously constrained by infrastructure deficits. Government precision agriculture initiatives providing subsidies, training, or technical support create temporary windows of favorable economics for technology adoption (Hambly & Rajabiun, 2021; Kibinda et al., 2025; Mamabolo et al., 2025).

Market access opportunities, including premium prices for certified sustainable palm oil, preferential trade agreements requiring documented traceability, or corporate sourcing commitments to NDPE-compliant suppliers, create incentive alignments favoring automation investments that support compliance documentation (Abazue et al., 2019; Amertet et al., 2024; Emzar, 2025).

5.1.3 Suboptimal Timing Scenarios

Conversely, certain contexts signal suboptimal timing for automation adoption. Pre-infrastructure stabilization scenarios in which electricity, connectivity, or road access remains unreliable pose implementation risks and lead to elevated failure rates. Organizations should prioritize infrastructure prerequisites before deploying technology, or select robust edge computing architectures that are tolerant of infrastructure limitations(Amertet et al., 2024; Fox & Signe, 2022).

Absent institutional readiness, including management commitment, technical capacity, and operational stability, automation investments frequently underperform expectations. Organizations experiencing financial distress, leadership transitions, or operational crises should defer technology adoption until stabilization allows for focused implementation (Amertet et al., 2024; Srivastava, 2023).

Unrealistic ROI expectations that require payback periods of less than 2 years rarely align with the economics of automation in agricultural contexts, leading to the premature abandonment of viable technologies. Stakeholders must align expectations with realistic 3-7 year payback horizons typical of precision agriculture investments, supported by appropriate financing structures (Amertet et al., 2024; Mamabolo et al., 2025; Toha et al., 2025).

5.2 Synthesis: Where Implementation Delivers Maximum Impact

5.2.1 Implementation Priority Hierarchy

The evidence supports a clear spatial priority hierarchy for phased implementation. **Priority 1: Palm oil mills with daily throughput exceeding 100 FFB per hour** represent optimal entry points, offering the highest ROI, the most controlled implementation environments, existing infrastructure, and centralized impact that benefits multiple upstream suppliers. Mill-based automation should anchor national and regional deployment strategies (Amertet et al., 2024; Makky & Soni, 2013; Omotayo et al., 2025; Septiarini et al., 2021).

Priority 2: Large-scale plantations (>1,000 hectares) with adequate digital infrastructure constitute secondary implementation targets, where field-based mobile systems or collection-point grading demonstrate viability. These estates possess capital, technical capacity, and scale to justify investment while serving as demonstration sites for surrounding smallholder communities (Lestari et al., 2025).

Priority 3: Smallholder cooperative clusters with 20+ member farmers and government/NGO support represent inclusive implementation pathways requiring deliberate support structures, including subsidized financing, intensive training programs, and ongoing technical assistance. While more complex than large-estate implementations, cooperative models are essential for equitable access to technology and sustainable smallholder development (Miranda, 2024).

5.2.2 Geographical and Socioeconomic Contexts

Regional characteristics significantly influence the probability of successful implementation. **High-priority regions** feature: (1) internet connectivity exceeding 50 Mbps, enabling cloud-based systems or at minimum, intermittent connectivity for edge computing data synchronization; (2) acute labor shortages creating strong economic incentives; (3) active government precision agriculture programs providing subsidies or technical support; (4) proximity to palm oil mills willing to provide quality premiums for documented grading (Allynav, 2025; Mamabolo et al., 2025).

Medium-priority regions have partial infrastructure (e.g., electricity but limited connectivity), in which edge computing architectures are viable or strong cooperative traditions facilitate shared machinery models. **Lower-priority regions** lacking basic infrastructure, experiencing political instability, or having fragmented farmer organizations require prerequisite investments in foundational infrastructure and institutional development before technology deployment proves viable(SNUC, 2025).

5.2.3 Organizational Readiness Characteristics

Organizational attributes predict implementation success. **High-readiness organizations** demonstrate: (1) leadership openness to innovation and technology adoption; (2) existing digital literacy and precision agriculture experience; (3) financial capacity for investment or access to appropriate financing; (4) technical personnel or partnerships for system operation and maintenance; (5) integration of quality management into organizational culture (Bland et al., 2023; Mamabolo et al., 2025).

Medium-readiness organizations possess partial capabilities but require targeted capacity building in specific areas—technical training, management change processes, or financial restructuring to support technology investment. **Low-readiness organizations** require comprehensive institutional strengthening, potentially through multiyear partnership programs with government agencies, NGOs, or corporate sustainability initiatives, before technology adoption proves viable (Manzoor et al., 2025).

5.3 Phased Implementation Model

5.3.1 Phase 1: Mill-Based Proof-of-Concept (Years 1-2)

The initial implementation should prioritize 5-10 palm oil mills that represent diverse regional contexts, throughput scales, and ownership structures (private, cooperative, government). Pilot objectives include validating technology performance under operational conditions, documenting ROI metrics, identifying operational challenges, and developing training curricula for operators and technicians.(Makky & Soni, 2013; Septiarini et al., 2021).

Phase 1 emphasizes learning, adaptation, and evidence generation for subsequent scaling. Success metrics encompass accuracy validation (>90% agreement with expert graders), throughput maintenance (no bottlenecks), system uptime (>95% during harvest seasons), and economic performance (labor cost reduction, quantified quality improvement). Documentation of implementation processes, maintenance protocols, and troubleshooting guides creates a knowledge base for Phase 2 expansion (Beerepoot et al., 2023).

5.3.2 Phase 2: Large-Scale Plantation Expansion (Years 2-4)

Building on mill-based demonstrations, Phase 2 extends implementation to 20-30 large plantations with demonstrated readiness characteristics. This phase pilots field-based mobile systems and collection point grading, explores integration with farm management platforms, and develops data analytics applications for quality-based decision-making (Soehartono, 2025).

Phase 2 emphasizes integration and optimization, moving beyond standalone grading toward comprehensive precision agriculture ecosystems. Success metrics expand to include integration effectiveness, data utilization for agronomic decision-making, and demonstration effects on surrounding smallholder communities. Regional demonstration farms serve as training venues for smallholder cooperative members preparing to participate in Phase 3 (Mamabolo et al., 2025; Odume, 2024).

5.3.3 Phase 3: Inclusive Smallholder Cooperative Model (Years 4-7)

Phase 3 implements cooperative shared machinery models targeting 50-100 smallholder cooperatives (representing 1,000-2,000 individual farmers). This phase requires intensive support, including subsidized financing (50-70% government cost-sharing), comprehensive training programs (technical operations, data interpretation, maintenance), and ongoing technical assistance through government extension services or private-sector partnerships (Mhlanga & Ndhlovu, 2023).

Phase 3 emphasizes equity and sustainability. Success metrics include smallholder productivity improvements, certification achievement rates, income increases from quality premiums, and long-term cooperative financial sustainability. This phase tests the scalability of inclusive technology access models and generates evidence for national policy formulation on agricultural modernization (Ahmad et al., 2023; Omotayo et al., 2025; Reich & Musshoff, 2025).

5.4 Policy Implications and Strategic Recommendations

5.4.1 Government Policy Recommendations

Infrastructure Investment: Prioritize broadband expansion and improvements in electricity reliability in palm oil-producing regions, recognizing digital infrastructure as agricultural productivity infrastructure. Public investment in shared-use connectivity and power solutions for rural areas generates economic returns through enhanced agricultural competitiveness(Judijanto, 2025b; Kanniah & Yu, 2024).

Financial Instruments: Develop specialized agricultural technology financing products with 5-7 year repayment terms aligned with ROI timelines, subsidized interest rates (3-5% below commercial rates), and flexible collateral requirements accommodating cooperative borrowers. Establish cost-sharing grant programs that cover 50-70% of equipment costs for smallholder cooperatives that meet readiness criteria (Dhanasekar, 2025).

Capacity Building: Expand agricultural extension services to include precision agriculture technical specialists, establish regional training centers for equipment operation and maintenance, and develop certification programs for agricultural technology operators to create professional career pathways (Mamabolo et al., 2025; Manzoor et al., 2025; Reich & Musshoff, 2025).

Standards and Interoperability: Mandate data format standards for agricultural technology systems to enable cross-platform integration, establish quality assurance protocols for automated grading systems to ensure measurement accuracy and consistency, and integrate automated grading documentation into sustainability certification schemes as acceptable evidence (López Gómez et al., 2023; Ningsih et al., 2025; Reich & Musshoff, 2025).

5.4.2 Industry Stakeholder Recommendations

Public-Private Partnerships: Palm oil mills and large estates should partner with government agencies and NGOs to establish demonstration projects accessible to smallholder communities, co-invest in regional technical support infrastructure (service centers, spare parts supply chains), and participate in training program development leveraging operational expertise (Odume, 2024).

Inclusive Business Models: Develop outgrower programs that incorporate access to automated grading technology as a component of comprehensive smallholder development initiatives; establish quality premium pricing structures that incentivize smallholder technology adoption and quality improvement; and provide technical assistance and facilitate financing for supplier cooperatives (Borer, 2025).

Technology Development: Invest in R&D for tropical-climate-hardened equipment variants, develop affordable edge computing solutions appropriate for resource-constrained contexts, and create modular, scalable systems that enable incremental investment rather than requiring large upfront commitments (Amoussouhoui et al., 2024; Gong et al., 2025).

5.4.3 Smallholder and Cooperative Recommendations

Collective Action: Strengthen cooperative organizations to achieve the scale necessary for shared machinery investments, establish professional management and technical capacity within cooperative structures, and build financial reserves through commodity pooling and value-added activities to support technology investments (Kenkel & Long, 2007).

Training Participation: Actively engage in government and industry-sponsored training programs on precision agriculture, develop internal training capacity for peer-to-peer knowledge transfer within cooperatives, and establish operating protocols ensuring equitable access to shared equipment among cooperative members (Barus et al., 2024; Irawan et al., 2024; Mamabolo et al., 2025; Yusuf et al., 2021).

Gradual Adoption: Pursue phased technology adoption beginning with accessible entry points (e.g., shared mill-based grading access through supply contracts), progressively advance to cooperative-owned mobile equipment as financial capacity and technical competence develop, and integrate technology adoption within broader strategies for certification, market access, and productivity improvement (Ahmad et al., 2023; Reich & Musshoff, 2025).

6. Conclusion

6.1 Substantive Conclusions

6.1.1 When: Optimal Timing for Implementation

Automated FFB ripeness detection systems achieve optimal effectiveness when implemented during specific temporal windows characterized by urgent operational necessity or strategic opportunity. Critical threshold conditions include: (1) labor shortages exceeding 12-15% of workforce requirements, creating production losses that exceed automation costs; (2) processing delays beyond 24 hours affecting more than 30% of harvested FFB, causing quantifiable quality degradation; (3) productivity gaps exceeding 20% between actual and potential performance attributable to quality management deficiencies.

Strategic opportunity windows emerge during: (1) sustainability certification implementation (RSPO, ISPO, MSPO), creating compliance requirements aligned with automated system capabilities; (2) supply chain digitalization and traceability initiatives driven by market access requirements or corporate NDPE commitments; (3) infrastructure development programs improving rural connectivity and electricity access that relax deployment constraints.

Implementation timing should align with organizational readiness and avoid premature deployment before infrastructure stabilization, institutional capacity development, or operational crisis resolution. Realistic ROI expectations, recognizing 3-7 year payback horizons typical of precision agriculture investments, are essential for sustained commitment and investment sustainability.

6.1.2 Where: Optimal Spatial and Organizational Contexts

Spatial implementation priorities follow a clear hierarchy based on scale, infrastructure, and economic efficiency. **Palm oil mills** processing 100+ FFBs per hour represent the highest-priority contexts, offering centralized, high-volume throughput, controlled grading environments, existing infrastructure, and maximum ROI potential. Mill-based automation should anchor national deployment strategies given concentrated impact and favorable economics.

Large-scale plantations exceeding 1,000 hectares with adequate digital infrastructure constitute secondary-priority contexts in which field-based mobile systems are viable, supported by capital resources, technical capacity, and scale that justify investment. These estates serve dual functions as production sites and demonstration platforms for surrounding communities.

Smallholder cooperatives with 20+ members, government or NGO support programs, and established organizational capacity enable inclusive access to technology through shared machinery models, reducing per-farmer costs by 15-40%. While implementation complexity exceeds that of large-estate deployments, cooperative models are essential for equitable technology distribution and sustainable smallholder development aligned with social inclusion objectives.

Geographic regions with the highest success probability feature reliable internet connectivity (>50 Mbps), acute labor shortages that create strong economic incentives, active government precision agriculture support programs, and proximity to mills offering quality premiums. Organizational readiness characteristics, including leadership innovation orientation, existing digital literacy, financial capacity or access to financing, and availability of technical personnel, predict implementation success.

6.1.3 How: Effective Implementation Models

Effective implementation follows a phased approach that sequences investments according to risk, learning, and capacity development. **Phase 1** establishes mill-based proof-of-concept projects to validate technology performance, document ROI, and develop operational protocols to support subsequent scaling. **Phase 2** expands to large plantations, piloting field-based systems, integrating with farm management platforms, and deploying data analytics applications while serving demonstration functions. **Phase 3** implements inclusive smallholder cooperative models with intensive support structures, including subsidized financing, comprehensive training, and ongoing technical assistance.

Business model innovation proves essential for sustainable adoption. Capital-intensive ownership suits large estates; Robots-as-a-Service and equipment leasing distribute costs favorably for cooperatives; government cost-sharing programs (50-70% subsidies) enable smallholder access. Integration with sustainability certification programs creates incentive alignment through premium pricing, market access, and compliance documentation benefits that augment direct operational gains.

Technology selection must emphasize context-appropriate solutions: cloud-based systems for infrastructure-rich environments versus edge computing architectures tolerant of connectivity limitations; industrial-grade components for harsh field conditions; and modular designs that enable incremental investment rather than requiring large upfront commitments.

6.2 Policy Recommendations

6.2.1 Short-Term Policy Actions (1-2 Years)

Governments should prioritize establishing pilot projects at 10-15 palm oil mills representing diverse contexts, providing co-financing (50% government, 50% private) to reduce implementation risk and accelerate learning. Financial incentive programs, including accelerated depreciation for agricultural technology investments, tax credits of 20-30% of equipment costs, and subsidized loan facilities (3-5% interest rates), should stimulate early adoption by large estates and progressive cooperatives.

An immediate training program should develop operator certification curricula, establish regional training centers in major palm-producing areas, and deploy technical assistance programs to support implementation by early adopters. Regulatory frameworks should integrate automated grading documentation into sustainability certification schemes as acceptable evidence of compliance, establish quality-assurance protocols for system validation, and mandate data-format standards that enable interoperability.

6.2.2 Medium-Term Policy Actions (3-5 Years)

Infrastructure investment programs should systematically extend broadband connectivity (minimum 50 Mbps) to palm oil production regions, improve electricity reliability through grid enhancements or distributed renewable energy systems, and upgrade rural road networks to facilitate equipment deployment and maintenance access. Specialized financing institutions or dedicated credit lines within agricultural development banks should be established, with expertise in precision agriculture economics, appropriate collateral requirements for cooperative borrowers, and integration of technical assistance.

Cooperative development programs should strengthen organizational governance, build financial management capacity, and establish equipment maintenance capabilities among smallholder organizations. Research and development support should fund the adaptation of commercial technologies to tropical agricultural conditions, the development of affordable edge computing solutions, and the pilot testing of innovative business models (E.g., RaaS and pay-per-use pricing).

6.2.3 Long-Term Policy Actions (>5 Years)

National agricultural digitalization strategies should integrate automated quality assessment as a core component, establish national agricultural data platforms that enable cross-sector integration and analytics, and create innovation ecosystems that link research institutions, technology providers, and agricultural enterprises. Extension service modernization should transition to precision agriculture-oriented technical support, develop digital advisory services complementing traditional field extension, and establish career pathways for agricultural technology specialists.

Inclusive growth frameworks should ensure smallholder benefit-sharing from productivity gains from automation, progressive technology access programs that prevent digital divides, and social protection programs that support workers displaced by automation transitions. International cooperation should facilitate technology transfer, joint R&D that addresses the needs of developing countries, and the harmonization of standards, thereby enabling cross-border technology deployment and data sharing.

6.3 Research Limitations and Future Research Agenda

6.3.1 Methodological Limitations

This qualitative literature review, while providing comprehensive contextual insights, carries inherent limitations. Publication bias toward successful implementations may overestimate effectiveness while underrepresenting failed deployments and implementation challenges. Language restrictions to English-accessible publications potentially exclude valuable regional knowledge in Indonesian, Malay, or other languages. The 2020-2026 temporal focus, while ensuring currency, may exclude relevant historical lessons from earlier experiences with the adoption of precision agriculture.

Reliance on secondary literature rather than primary field data limits the depth of understanding regarding implementation processes, organizational change dynamics, and user experiences. Variation in study quality, methodological rigor, and contextual specificity across reviewed sources creates heterogeneity, complicating synthesis. The rapidly evolving nature of AI technologies means current-generation performance benchmarks may quickly become outdated as new models emerge.

6.3.2 Priority Research Needs

Longitudinal implementation studies tracking 3-5 year technology adoption trajectories across diverse organizational contexts would provide crucial evidence on ROI realization, sustainability determinants, and long-term organizational impacts. Comparative effectiveness research systematically evaluating alternative implementation models (mill-based vs. field-based; cloud vs. edge computing; ownership vs. RaaS) under standardized conditions would guide context-appropriate technology selection.

Economic impact assessments quantifying effects on smallholder incomes, employment patterns, gender dynamics, and regional development outcomes would inform equity-oriented policy design. Sociotechnical research examining human-technology interaction, organizational change processes, and farmer decision-making regarding technology adoption would enhance implementation effectiveness.

Technical research priorities include the development of multispectral imaging systems that achieve higher accuracy in challenging environmental conditions, the integration of ripeness detection with robotic harvesting to enable fully automated systems, and blockchain-based traceability systems that incorporate automated quality data to enable end-to-end supply chain transparency.

6.3.3 Emerging Technology Frontiers

Generative AI applications for synthetic training data could address the limited availability of datasets, which constrains model training for specialized crops and conditions. Fully autonomous harvesting robots integrating ripeness detection, selective cutting mechanisms, and tree-climbing capabilities represent frontier technologies that could transform the economics of palm oil production. Blockchain-based traceability platforms that incorporate automated quality-assessment data could revolutionize supply chain transparency and sustainability verification.

Climate adaptation research should explore how automated systems support resilience by optimizing harvest timing in response to increasingly variable weather patterns, detecting early indicators of climate stress in fruit quality, and adapting agronomic practices using data-driven approaches. Cross-sectoral learning from automated quality assessment in other agricultural sectors (dates, cocoa, coffee) could accelerate the development of the palm oil system through technology transfer and adapted innovations.

These research frontiers will shape the next generation of agricultural automation, progressively transforming palm oil production from labor-intensive manual operations toward data-driven, technology-enabled precision agriculture systems that enhance productivity, sustainability, and equitable value distribution throughout global supply chains.

References

1. Abazue, C. M., Choy, E. A., & Lydon, N. (2019). Oil palm smallholders and certification: exploring the knowledge level of independent oil palm smallholders to certification. Journal of Bioscience and Agriculture Research, 19(1). https://doi.org/10.18801/jbar.190119.193
2. 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
3. Ahmad, M. R., Mohd Bakri, M. A., Ramli, A. S., Mustapha, N. K., Thadeus, D. J., Ibrahim, A., & Jusoh, M. J. (2023). Mechanisation Technology for Small-Scale Oil Palm Plantations. Advances in Agricultural and Food Research Journal, 4(2), 1–11. https://doi.org/10.36877/aafrj.a0000406
4. Allynav. (2025). Precision Agriculture Solutions That Pay Off in Every Season. Allynav: Precision Agriculture Solution. https://www.allynav.com/precision-agriculture-solutions/
5. Amertet, S., Gebresenbet, G., & Alwan, H. M. (2024). Application of hyper-automation in farming – an analysis. Smart Agricultural Technology, 9, 100516. https://doi.org/https://doi.org/10.1016/j.atech.2024.100516
6. Amirkadra, M. A. (2022). Mechanisation is the way forward for the Malaysian palm oil industry. MSPO Blogs. https://mspo.org.my/mechanisation-is-the-way-forward-for-the-malaysian-palm-oil-industry/
7. Amoussouhoui, R., Arouna, A., Ruzzante, S., & Banout, J. (2024). Adoption of ICT4D and its determinants: A systematic review and meta-analysis. Heliyon, 10(9), e30210. https://doi.org/10.1016/j.heliyon.2024.e30210
8. Anavision. (2023). Revolutionary AI-powered Smart Agriculture In Oil Palm Management. Anavision: Smart Agriculture. https://anavision.com/2023/10/30/revolutionary-ai-powered-smart-agriculture-in-oil-palm-management/
9. Ariyanto, A., Syaukat, Y., Hartoyo, S., & Sinaga, B. M. (2020). Technology Adoption and Technical Efficiency of Oil Palm Smallholder Plantation in Riau and West Kalimantan. Jurnal Manajemen Dan Agribisnis, 17(3), 239–255. https://doi.org/10.17358/jma.17.3.239
10. Badgujar, C. M., Poulose, A., & Gan, H. (2024). Agricultural object detection with You Only Look Once (YOLO) Algorithm: A bibliometric and systematic literature review. Computers and Electronics in Agriculture, 223, 109090. https://doi.org/10.1016/j.compag.2024.109090
11. Barus, R., Chalil, D., & Wibowo, R. P. (2024). ISPO introduction program for independent smallholders: Initial steps towards mandatory ISPO 2025. Abdimas: Jurnal Pengabdian Masyarakat Universitas Merdeka Malang, 9(2), 373–382. https://doi.org/10.26905/abdimas.v9i2.12657
12. Beerepoot, I., Di Ciccio, C., Reijers, H. A., Rinderle-Ma, S., Bandara, W., Burattin, A., Calvanese, D., Chen, T., Cohen, I., Depaire, B., Di Federico, G., Dumas, M., van Dun, C., Fehrer, T., Fischer, D. A., Gal, A., Indulska, M., Isahagian, V., Klinkmüller, C., … Zerbato, F. (2023). The biggest business process management problems to solve before we die. Computers in Industry, 146, 103837. https://doi.org/10.1016/j.compind.2022.103837
13. Bland, R., Ganesan, V., Hong, E., & Kalanik, J. (2023). Trends driving automation on the farm. McKInsey & Company: Agriculture. https://www.mckinsey.com/industries/agriculture/our-insights/trends-driving-automation-on-the-farm
14. Borer, M. (2025). Sustainability at the Core: How Traceability to Plantation (TTP) Can Transform Indonesia's Palm Oil Industry? Koltiva. https://www.koltiva.com/post/enhancing-sustainable-palm-oil-traceability-for-a-transparent-supply-chain
15. Chang, C., Parthiban, R., Kalavally, V., Hung, Y. M., & Wang, X. (2024). Unharvested palm fruit bunch ripeness detection with hybrid color correction. Smart Agricultural Technology, 9, 100643. https://doi.org/10.1016/j.atech.2024.100643
16. Comyns, B., & D'Antone, S. (2025). The moral legitimation of multi-stakeholder Initiatives: The case of the Roundtable on Sustainable Palm Oil (RSPO). Journal of Cleaner Production, 519, 145963. https://doi.org/https://doi.org/10.1016/j.jclepro.2025.145963
17. Córdoba, D., Abrams, J., & Selfa, T. (2022). Achieving Palm Oil Sustainability Under Contract: Roundtable on Sustainable Palm Oil and Family Farmers in the Brazilian Amazon. Current Research in Environmental Sustainability, 4(April), 1-9. https://doi.org/10.1016/j.crsust.2022.100160
18. Dahal, N. (2025). Qualitative data analysis: reflections, procedures, and some points for consideration. Frontiers in Research Metrics and Analytics, 10. https://doi.org/10.3389/frma.2025.1669578
19. 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. https://doi.org/10.1016/j.jrurstud.2020.07.004
20. Delve. (2025). How to Do Thematic Analysis. Delve: Essential Guide to Coding Qualitative Data. https://delvetool.com/blog/thematicanalysis
21. Dhanasekar, S. (2025). A comprehensive review on current issues and advancements of Internet of Things in precision agriculture. Computer Science Review, 55, 100694. https://doi.org/10.1016/j.cosrev.2024.100694
22. Dharmapalan, J., & Latieff, A. R. A. (2024). Labor Shortage Crisis in Oil Palm Plantations in Malaysia. AJCR: Asian Journal of Case Reserch, 13(1), 57–72. https://spejournal.upm.edu.my/upload/vol_13_no_1_yr_2024/202407221044584)_Labor_Shortage_Crisis_in_Oil_Palm_Plantations_in_Malaysia_-_Case_Study.pdf
23. Emzar, A. E. (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

24. Felix, D. (2024). Narrative vs. Systematic Literature Review: Understanding the Differences. Sourcely. https://www.sourcely.net/post/narrative-vs-systematic-literature-review
25. Fox, L., & Signe, L. (2022). Overcoming the barriers to technology adoption on African farms. Brookings: Commentary. https://www.brookings.edu/articles/overcoming-the-barriers-to-technology-adoption-on-african-farms/
26. Gong, R., Zhang, H., Li, G., & He, J. (2025). Edge Computing-Enabled Smart Agriculture: Technical Architectures, Practical Evolution, and Bottleneck Breakthroughs. Sensors, 25(17), 5302. https://doi.org/10.3390/s25175302
27. Hambly, H., & Rajabiun, R. (2021). Rural broadband: Gaps, maps and challenges. Telematics and Informatics, 60, 101565. https://doi.org/10.1016/j.tele.2021.101565
28. Haryati, Z., Subramaniam, V., Noor, Z. Z., Hashim, Z., Loh, S. K., & Aziz, A. A. (2022). Social life cycle assessment of crude palm oil production in Malaysia. Sustainable Production and Consumption, 29, 90–99. https://doi.org/https://doi.org/10.1016/j.spc.2021.10.002
29. Hassan, A., & Mohammad, J. A. (2005). Regulations on Quality of FFB. Oil Palm Bulletin, 50(May), 31–38. Regulations on Quality of FFB
30. Irawan, N. C., Mahananto, Supriyadi, T., & Haryuni. (2024). What are the Major Barriers and Challenges Faced by Independent Oil Palm Smallholder Farmers in RSPO Certification? Journal of Rural and Urban Community Studies, 2(2), 39–53. https://doi.org/10.36728/jrucs.v2i2.3917
31. Jaya, J. D., & Khairiah. (2025). Quality Evaluation and Causal Analysis of Crude Palm Oil Based on Critical Quality Parameters: Free Fatty Acids, Moisture, and Impurities. Jurnal Teknologi Agroindustri, 12(1), 20–30. https://jtai.politala.ac.id/index.php/JTAI/article/download/227/146/1505
32. Jelsma, I., Slingerland, M., Giller, K. E., & Bijman, J. (2017). Collective action in a smallholder oil palm production system in Indonesia: The key to sustainable and inclusive smallholder palm oil? Journal of Rural Studies, 54, 198–210. https://doi.org/10.1016/j.jrurstud.2017.06.005
33. Judijanto, L. (2025a). Empowerment of Oil Palm Smallholders for Sustainable Palm Oil. Veredas Do Direito, 22(2), e3323. https://doi.org/10.18623/rvd.v22.n2.3323
34. Judijanto, L. (2025b). Exploring the Potentials of Artificial Intelligence and Digital Technologies in Transforming the Palm Oil Industry: A Review. Journal of Information, Technology and Policy, 3(1), 1–13. https://doi.org/https://doi.org/10.62836/jitp.2025.431
35. Judijanto, L. (2025c). From Voluntary to Mandatory: A Review of Prospects and Challenges in Implementing Palm Oil Sustainability Certifications in Indonesia. ERR01, 10(2), 232–254. https://doi.org/10.56238/ERR01v10n2-013
36. Judijanto, L. (2025d). Légal Challenges and Opportunities in Promoting Sustainable Palm Oil Trade in Europe: A Review from a Social Economy Perspective. Science of Law, 2025(1), 144–150. https://doi.org/10.55284/47etjn84
37. Judijanto, L. (2025e). The Strategic Roles and Importance of Oil Palm Smallholders in Maintaining Sustainable Palm Oil Supply. ARACÊ, 7(7), 40056–40079. https://doi.org/10.56238/arev7n7-283
38. Judijanto, L. (2026). Enhancing Oil Palm Productivity through Strategic Implementation of Fresh Fruit Bunch Grading using Artificial Intelligence Technology: A Review. Journal of Artificial Intelligence and Technological Development, 2(2), 138–154. https://doi.org/10.59324/jaitd.2026.2(2).11
39. Kanniah, K., & Yu, L. (2024). Geospatial Technology for Sustainable Oil Palm Industry. CRC Press.
40. KAUST. (2025). KAUST developing robotic system to improve date palm harvesting. KAUST News. https://www.kaust.edu.sa/en/news/kaust-developing-robotic-system-to-improve-date-palm-harvesting
41. Kean, H. T., & Shyan, L. N. (2024). Autonomous Harvesting for Oil Palm Plantation: A Review. Journal of Oil Palm Research, 36(3), 349–366. https://doi.org/10.21894/jopr.2024.0008
42. Kenkel, P., & Long, G. (2007). Joint Machinery Ownership: Organizing a Machinery Cooperative (AE-07042; Working Paper).
43. Kibinda, N., Shao, D., Mwogosi, A., & Mambile, C. (2025). Broadband infrastructure sharing as a catalyst for rural digital economy: A systematic review for developing countries. Telecommunications Policy, 49(8), 103028. https://doi.org/10.1016/j.telpol.2025.103028
44. Kiger, M. E., & Varpio, L. (2020). Thematic analysis of qualitative data: AMEE Guide No. 131. Medical Teacher, 42(8), 846–854. https://doi.org/10.1080/0142159X.2020.1755030
45. Krisdiarto, A. W., & Sutiarso, L. (2016). Study on Oil Palm Fresh Fruit Bunch Bruise in Harvesting and Transportation to Quality. Makara Journal of Technology, 20(2), 1–7.
46. Lestari, V., Dolorosa, E., & Komariyati. (2025). Readiness of Independent Oil Palm Farmers to Face Replanting. INDONESIAN JOURNAL OF SMALL SCALE FARMING, 2(1), 60–71. https://doi.org/10.24843/ijoss.2026.v02.i01.p06
47. López Gómez, M., Posada, J., Silva, V., Martínez, L., Mayorga, A., & Álvarez, O. (2023). Diagnosis of Challenges and Uncertainties for Implementation of Sustainable Aviation Fuel (SAF) in Colombia, and Recommendations to Move Forward. Energies, 16(15), 5667. https://doi.org/10.3390/en16155667
48. Ma, W., Li, J., Nnaji, A. P., & Setsoafia, E. D. (2025). The role of agricultural cooperatives in improving mechanization levels: Differences between outsourcing machinery services and household-owned machines. Annals of Public and Cooperative Economics, August. https://doi.org/10.1111/apce.70011
49. 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

50. Mamabolo, E., Mashala, M. J., Mugari, E., Mogale, T. E., Mathebula, N., Mabitsela, K., & Ayisi, K. K. (2025). Application of precision agriculture technologies for crop protection and soil health. Smart Agricultural Technology, 12, 101270. https://doi.org/10.1016/j.atech.2025.101270
51. Manic, K. S., Al-Bemani, A. S., Al-Mahruqi, A., Uma, S., & Najeeb, A. (2025). Automated Tree Climber Robot MANIC Tree Trekker for Date Palm Harvesting: A Technological Innovation in Agriculture. Procedia Computer Science, 258, 1719–1735. https://doi.org/10.1016/j.procs.2025.04.424
52. Manzoor, F., Wei, L., Siraj, M., Lu, X., & Qiyang, G. (2025). Digital agriculture technology adoption in low and middle-income countries—a review of contemporary literature. Frontiers in Sustainable Food Systems, 9. https://doi.org/10.3389/fsufs.2025.1621851
53. Megantara, N. A., & Utami, E. (2025). Object Detection Using YOLOv8: A Systematic Review. Sistemasi: Jurnal Sistem Informasi, 14(3), 1186–11193. https://sistemasi.ftik.unisi.ac.id/index.php/stmsi/article/download/5081/964
54. Mhlanga, D., & Ndhlovu, E. (2023). Digital Technology Adoption in the Agriculture Sector: Challenges and Complexities in Africa. Human Behavior and Emerging Technologies, 2023, 1–10. https://doi.org/10.1155/2023/6951879
55. Miranda, W. (2024). How Smallholder Farmers Could Harvest More Rice with Better Machines. Engineering for Change. https://www.engineeringforchange.org/news/how-smallholder-farmers-could-harvest-more-rice-with-better-machines/
56. Musim Mas. (2025). Indonesian Sustainable Palm Oil Certification. Musim Mas Resources: Sustainability. https://www.musimmas.com/sustainability/certifications-and-verifications/ispo-certified-palm-oil-supplier/
57. Ningsih, V. Y., Setiawan, B., Asmara, R., & Dwi Andriani, R. (2025). ISPO Certification and the Sustainable Development Goals: Readiness of Independent Smallholders in Indonesia (South Sumatra). Transactions of the Chinese Society of Agricultural Machinery, 56(6), 37–55. https://doi.org/10.62321/issn.1000-1298.2025.6.4
58. Noordin, N. H., Samad, R., & Abdul Malek, A. H. (2025). Real-time FFB ripeness detection using IoT-enabled YOLOv8n on Raspberry Pi 4 edge devices for precision agriculture. Journal of Mechatronics, Electrical Power, and Vehicular Technology, 16(2). https://doi.org/10.55981/j.mev.2025.1220
59. 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/https://doi.org/10.30871/jaic.v9i4.10250
60. Odume, B. (2024). Artificial Intelligence in Agriculture: Application in Developing Countries. SSRN Electronic Journal, January. https://doi.org/10.2139/ssrn.4887865
61. Omotayo, A. O., Adediran, S. A., Omotoso, A. B., Olagunju, K. O., & Omotayo, O. P. (2025). Artificial intelligence in agriculture: ethics, impact possibilities, and pathways for policy. Computers and Electronics in Agriculture, 239, 110927. https://doi.org/10.1016/j.compag.2025.110927
62. Parveez, A. G. K., Hishamuddin, E., Loh, S. K., Ong-Abdullah, M., Salleh, K. M., Bidin, M. N. I. Z., Sundram, S., Hasan, Z. A. A., & Idris, Z. (2022). Oil Palm Economic Performance in Malaysia and R&D Progress in 2021. Journal of Oil Palm Research. https://doi.org/10.21894/jopr.2022.0036
63. Patil, C. A., & Banchhor, S. K. (2025). A Cost-Effective IoT-based System for Real-Time Soil Parameters Measurement in Data-Driven Precision Agriculture. Journal of Research Administration, 8(2), 241–261. https://journal-administration.com/page/pdf/2693
64. Phoochinda, W. (2018). Conceptual Framework of the Green Economy for Oil Palm. Journal of Sustainable Development, 11(2). https://doi.org/10.5539/jsd.v11n2p25
65. Promboonruang, S., & Boonrod, T. (2023). Deep transfer learning CNN based for classification quality of organic vegetables. IJAAS: International Journal of Advanced and Applied Sciences, 10(12), 203–210. https://doi.org/10.21833/ijaas.2023.12.022
66. Rajakal, J. P., Tan, R. R., Andiappan, V., Wan, Y. K., & Pang, M. M. (2022). Data set on oil palm plantation production and LUC emissions under different management strategies. Data in Brief, 43, 108329. https://doi.org/10.1016/j.dib.2022.108329
67. Rangkuti, I. U. P., Syukri, M., Elisabeth, J., & Sari, D. (2025). Oil Extraction and Quality Stability of Crude Palm Oil Derived from Variations in Palm Fruit Ripeness. Jurnal Teknik Pertanian Lampung (Journal of Agricultural Engineering), 14(5), 1573–1581. https://doi.org/10.23960/jtepl.v14i5.1573-1581
68. Reich, C., & Musshoff, O. (2025). Oil palm smallholders and the road to certification: Insights from Indonesia. Journal of Environmental Management, 375, 124303. https://doi.org/10.1016/j.jenvman.2025.124303
69. Rodthong, W., Kuwornu, J. K. M., Datta, A., Anal, A. K., & Tsusaka, T. W. (2023). Farmers' perceptions and likelihood of adoption of the roundtable on sustainable palm oil practices in Thailand. Environmental Development, 47, 100883. https://doi.org/https://doi.org/10.1016/j.envdev.2023.100883
70. Rojas, H., & Krisanda, S. (2025). Palm Oil in Focus: The EUDR and Corporate Efforts on Transparent Sourcing. Sustainalytics Resource Center. https://www.sustainalytics.com/esg-research/resource/investors-esg-blog/palm-oil-in-focus--the-eudr-and-corporate-efforts-on-transparent-sourcing
71. Rosbi, M., Omar, Z., Khairuddin, U., Majeed, A. P. P. A., & Bakar, S. A. R. S. A. (2024). Machine learning for automated oil palm fruit grading: The role of fuzzy C-means segmentation and textural features. Smart Agricultural Technology, 9, 100691. https://doi.org/10.1016/j.atech.2024.100691
72. Rosbi, M., Omar, Z., Khairuddin, U., P.P.A.Majeed, A., & Bakar, S. A. R. S. A. (2024). Machine learning for automated oil palm fruit grading: The role of fuzzy C-means segmentation and textural features. Smart Agricultural Technology, 9. https://doi.org/10.1016/j.atech.2024.100691

73. Roseleena, J., Nursuriati, J., Ahmed, J., & Low, C. Y. (2011). Assessment of palm oil fresh fruit bunches using photogrammetric grading system. IFRJ: International Food Research Journal, 18(3), 999–10005. http://www.ifrj.upm.edu.my/18 (03) 2011/20)IFRJ-2010-151.pdf
74. Scriven, S. A., Butarbutar, R. B., de Vos, R. E., Lucey, J. M., Reynolds, G., Newing, H., Scholtz, O., Lasmana, F. P. S., Meijaard, E., & Hill, J. K. (2026). Addressing the challenges of managing and monitoring biodiversity in High Conservation Value areas and High Carbon Stock forests within oil palm landscapes. Ecological Solutions and Evidence, 7(1). https://doi.org/10.1002/2688-8319.70162
75. Septiarini, A., Sunyoto, A., Hamdani, H., Kasim, A. A., Utaminingrum, F., & Hatta, H. R. (2021). Machine vision for the maturity classification of oil palm fresh fruit bunches based on color and texture features. Scientia Horticulturae, 286. https://doi.org/10.1016/j.scienta.2021.110245
76. Siti-Dina, R. P., Er, A. C., & Cheah, W. Y. (2023). Social Issues and Challenges among Oil Palm Smallholder Farmers in Malaysia: Systematic Literature Review. Sustainability (Switzerland), 15(4), 1-13. https://doi.org/10.3390/su15043123
77. SNUC. (2025). Edge Computing in Agriculture and Smart Farming. SNUC: AI & Machine Learning. https://snuc.com/blog/edge-computing-for-agriculture-and-smart-farming/
78. Soehartono, D. (2025). Enhancing Oil Palm Plantation Operations Through Artificial Intelligence: Toward Sustainable Practices. LinkedIn Pulse. https://www.linkedin.com/pulse/enhancing-oil-palm-plantation-operations-through-djoko-soehartono-qhcnc/
79. Srivastava, A. (2023). Use of AI in Agriculture Sector and Developing Economy. IJSAT: International Journal on Science and Technology, 14(2), 1–6. https://www.ijsat.org/papers/2023/2/1215.pdf
80. Statista Research Department. (2025). Contribution of the palm oil industry to the gross domestic product (GDP) of Malaysia from 2015 to 2024. Statista: Agriculture. https://www.statista.com/statistics/952996/malaysia-palm-oil-share-of-gdp/
81. Suharjito, Elwirehardja, G. N., & Prayoga, J. S. (2021). Oil palm fresh fruit bunch ripeness classification on mobile devices using deep learning approaches. Computers and Electronics in Agriculture, 188, 106359. https://doi.org/https://doi.org/10.1016/j.compag.2021.106359
82. Suharjito, Naftali, M. G., Hugo, G., Priyadi, M. R. A., Asrol, M., & Utama, D. N. (2025). Oil Palm Fruits Dataset in Plantations for Harvest Estimation Using Digital Census and Smartphone. Scientific Data, 12(1), 972. https://doi.org/10.1038/s41597-025-05227-x
83. Syarifudin, S. M., & Zareen, Z. (2021). Impact of the agricultural technology transfer to the production of independent palm oil smallholders: a review. In Food Research (Vol. 5). https://doi.org/10.26656/FR.2017.5(S4).007
84. Toha, A., Ahmad, H., & Lee, X. (2025). IoT-Based Embedded Systems for Precision Agriculture: Design and Implementation. SCCTS: Journal of Embedded System Design and Application, 2(2), 21–29. https://doi.org/10.31838/ESA/02.02.03
85. TraceX. (2024). Palm Oil Supply Chain: A Path to Sustainable and Traceable Solutions. TraceX Sustainability and Compliance Platform for Food and Agri Supply Chains. https://tracextech.com/palm-oil-supply-chain/
86. Ulum, S., & Nursyamsiah, S. (2026). Challenges and Strategies in Crude Palm Oil Quality Control: A Practical Approach from an Indonesian Palm Oil Mill. EKOMBIS REVIEW: Jurnal Ilmiah Ekonomi Dan Bisnis, 14(1). https://doi.org/10.37676/ekombis.v14i1.8886
87. Witjaksono, J., Djaenudin, D., Fery Purba, S., Yulianti, A., Fadwiwati, A. Y., Muslimin, & Seerasarn, N. (2024). Corporate farming model for sustainable supply chain crude palm oil of independent smallholder farmers. Frontiers in Sustainable Food Systems, 8, 1418732. https://doi.org/10.3389/fsufs.2024.1418732
88. Yaakub, N. A. M., Sumin, V., & Ling, U. L. (2023). Exploring Technology Readiness and Acceptance of Small-scale Farmers in Sabah towards the Adoption of Internet of Things Technology. Proceedings of the 1st International Students Conference on Business, Education, Economis, 1(1), 1–18.
89. Yusuf, M., Hutabarat, S., & Hadi, S. (2021). Analysis of The Implementation of ISPO Certification on Smallholder Oil Palm Plantation in Beringin Jaya Cooperation Koto Ringin Village Mempura Sub-District Siak District. Journal of Agribusiness and Community Empowerment (JACE), 4(2). https://doi.org/10.32530/jace.v4i2.247
90. Zaki, M. A. M., Ooi, J., Ng, W. P. Q., How, B. S., Lam, H. L., Foo, D. C. Y., & Lim, C. H. (2025). Impact of industry 4.0 technologies on the oil palm industry: A literature review. Smart Agricultural Technology, 10, 100685. https://doi.org/10.1016/j.atech.2024.100685
91. Zulkefli, F., Othman, N., Syahlan, S., Zaini, M. R., & Bakar, M. A. (2017). Fresh Fruit Bunch Quality and Oil Losses in Milling Processes as Factors that Affect the Extraction Rate of Palm Oil. IJAFP: International Journal of Agriculture, Forestry and Plantation, 5(June), 99–104. https://ijafp.org/wp-content/uploads/2017/10/PL-24.pdf.