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*Corresponding author

Loso Judijanto, IPOSS Jakarta, Indonesia

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Review Article

Navigating Complexities: Implementation Challenges of Automated Fresh Fruit Bunch Ripeness Detection Systems in Oil Palm Plantations

Loso Judijanto*

IPOSS Jakarta, Indonesia

Abstract

The oil palm industry faces mounting pressures from labor shortages, quality optimization imperatives, and sustainability demands, driving interest in automated Fresh Fruit Bunch (FFB) ripeness detection technologies. While computer vision and deep learning systems achieve high accuracy (97-99.66%) in controlled environments, their widespread implementation encounters substantial complexities due to the variability of plantations and processing industries. This qualitative literature review synthesizes findings from 2020 to 2026 to examine the multidimensional challenges obstructing the practical deployment of automated FFB detection systems. Through thematic analysis of recent literature, this study identifies critical barriers spanning technical dimensions (data scarcity, hardware constraints, connectivity limitations), economic factors (capital requirements, uncertain return on investment), infrastructural inadequacies (digital divide, power instability), human capital deficits (skills gaps, digital literacy), socio-cultural resistance (trust, behavioral inertia), and institutional obstacles (regulatory fragmentation, policy-implementation gaps). Plantation environmental heterogeneity-climate variability, topographical constraints, agronomic diversity-creates unpredictable operational conditions, degrading system performance. Processing mill variations in quality standards and capacity requirements further complicate integration efforts. The analysis reveals that successful implementation requires holistic ecosystem approaches integrating technological innovation with infrastructure development, workforce capacity building, data standardization, policy incentives, and context-responsive deployment strategies. Findings underscore the need for adaptive algorithms, affordable sensor solutions, smallholder-accessible business models, and comprehensive institutional support frameworks to bridge the gap between technological capability and practical viability in diverse oil palm cultivation contexts.

JEL Classification: Q16 (Production Agriculture), O33 (Technological Change: Choices and Consequences), Q55 (Technological Innovation)

Introduction

Background

The global oil palm industry is a cornerstone of agricultural economies across Southeast Asia, with production reaching unprecedented levels to meet surging demand for palm oil in the food, cosmetics, and biofuel sectors. Central to productivity optimization is the quality of Fresh Fruit Bunches (FFB) at harvest, as ripeness directly influences Oil Extraction Rates (OER)-the primary determinant of commercial viability. Traditional harvesting practices rely heavily on manual visual inspection, where experienced harvesters assess FFB color and loose fruit count to determine optimal harvest timing. However, this approach suffers from inherent subjectivity, with misclassification rates reaching 18-22% even among trained personnel, particularly under challenging field conditions. Such errors cascade through the value chain, resulting in substantial economic losses: under-ripe bunches yield insufficient oil, while over-ripe bunches suffer quality degradation and increased loose fruit losses [1,2].

The industry confronts escalating challenges that threaten conventional operational models. Labor shortages intensify as younger generations migrate to urban areas in search of employment, raising concerns about workforce sustainability. Simultaneously, competitive pressures demand higher productivity and consistent quality to maintain market position. These convergent forces have catalyzed growing interest in automated detection technologies capable of objective, consistent FFB ripeness assessment. Emerging solutions leverage computer vision, deep learning architectures, and multi-modal sensing to classify ripeness with remarkable accuracy in controlled settings, with recent studies reporting performance metrics between 97-99.66% [3,4].

Yet despite technological maturity demonstrated in laboratory and pilot contexts, widespread practical implementation remains elusive. The gap between promising prototypes and commercial-scale deployment reflects deeper complexities rooted in the heterogeneous, unpredictable realities of oil palm cultivation. Plantation environments exhibit substantial variability-climatic fluctuations, topographical diversity, infrastructural constraints, and differences in management practices-that challenge standardized technological solutions. Processing mills impose varying quality standards and throughput requirements, demanding flexible integration capabilities. Economic considerations, particularly for smallholder farmers who constitute a significant share of production, raise questions about affordability and return on investment. Technical barriers, including data scarcity, connectivity limitations, and hardware constraints, compound these challenges. Human capital deficits, socio-cultural resistance, and institutional fragmentation further obstruct adoption pathways [5-8].

Problem Statement and Urgency

The urgency of addressing FFB ripeness detection challenges stems from multiple converging pressures. From a productivity perspective, the gap between potential and actual oil extraction rates represents substantial unrealized value. Large-scale mills target OER benchmarks of 23-24%, yet many operations fall short due to suboptimal harvest timing influenced by inconsistent manual assessment. Economic losses from incorrectly classified FFB-whether through reduced oil yield from under-ripe bunches or quality degradation from over-ripe bunches-accumulate across millions of hectares globally. The competitive landscape demands efficiency improvements, as global palm oil markets increasingly differentiate producers based on quality consistency and cost competitiveness [9,10].

Sustainability imperatives add another dimension of urgency. Environmental stakeholders and certification bodies scrutinize oil palm cultivation, demanding evidence of optimized production that maximizes yield per hectare without expanding plantation footprints into sensitive ecosystems. Climate change introduces additional variability, with shifting rainfall patterns and temperature extremes affecting fruit development cycles and complicating traditional harvest scheduling. Automated detection systems offering precise, data-driven harvest timing represent technological pathways toward reconciling productivity demands with sustainability commitments [11-13].

The COVID-19 pandemic accelerated recognition of mechanization needs, as labor mobility restrictions disrupted traditional workforce models and exposed vulnerabilities of labor-intensive agricultural systems. Demographic trends-aging farmer populations and youth disinterest in agricultural careers-suggest labor constraints will intensify rather than abate, making automation not merely advantageous but necessary for long-term industry viability. Regulatory developments reinforce this trajectory, with governments, including Indonesia, advancing policy frameworks that promote science- and technology-based agricultural development, exemplified by Presidential Regulation No. 131/2024, which emphasizes agricultural modernization [14].

Research Objectives

This qualitative literature review addresses the critical question: What challenges and complexities obstruct practical implementation of automated FFB ripeness detection systems in oil palm plantations, and how do plantation and processing industry variabilities contribute to these obstacles? The primary objective is to critically examine implementation barriers through a comprehensive synthesis of recent scholarly literature, identifying thematic patterns and relationships among technical, economic, infrastructural, human capital, socio-cultural, and institutional dimensions.

Specific objectives guide the analysis: first, to identify and characterize technological approaches for automated FFB detection, documenting performance characteristics and limitations; second, to analyze plantation and processing industry variabilities that create implementation complexities; third, to synthesize thematic findings on multi-dimensional adoption challenges; and fourth, to develop evidence-based recommendations for overcoming identified barriers. By integrating insights across diverse literature streams-computer science, agricultural engineering, development economics, and policy studies-this review aims to provide a holistic understanding that transcends narrow disciplinary perspectives and offers actionable guidance for stakeholders navigating the complex pathway from technological promise to practical reality.

Literature Review

Conceptual Foundations of Automated FFB Ripeness Detection

Oil palm fruit bunch maturation involves distinct physiological transformations providing the basis for ripeness classification. As bunches transition from unripe to optimal ripeness, chlorophyll degradation triggers visible color shifts from dark purple-black to vibrant orange-red. Simultaneously, biochemical changes affect moisture content, volatile organic compound profiles, and structural properties of fruit-peduncle attachments. These changes manifest in observable indicators: ripe bunches exhibit ≥10 detached fruitlets (loose sockets) with ≥50% of fruits remaining attached, while under-ripe bunches show <10 loose sockets, and over-ripe bunches display >50% fruit detachment [2,15].

Industry grading standards translate physiological characteristics into operational classifications. Malaysian Palm Oil Board guidelines and individual mill specifications establish acceptance thresholds determining FFB pricing and processing prioritization. Optimal harvest timing balances competing considerations: harvesting too early sacrifices potential oil accumulation, while delayed harvesting risks fruit drop, quality deterioration, and processing complications. Mills typically require FFB delivery within 24 hours post-harvest to minimize free fatty acid formation and oil quality degradation, creating time-sensitive coordination demands [16].

Traditional manual assessment relies on trained harvesters' visual expertise to evaluate color patterns and the presence of loose fruit in making harvest decisions. This approach persists due to its flexibility and minimal capital requirements, yet suffers from critical limitations. Subjective interpretation introduces inconsistency, with assessment accuracy varying substantially among individuals and deteriorating under challenging conditions-intense sunlight, partial leaf occlusion, or observer fatigue can reduce accuracy by 30% or more. The inherent variability undermines quality management efforts and complicates supply chain planning [1,2].

Automated detection paradigms offer compelling theoretical advantages: objective, consistent classification unaffected by human perceptual limitations; potential for continuous monitoring enabling data-driven harvest scheduling; scalability across large plantation areas; and digital documentation supporting traceability and quality assurance systems. These capabilities align with broader precision agriculture trends leveraging sensor technologies and artificial intelligence to optimize resource use and maximize productivity [17-19].

Technological Approaches for Automated FFB Detection

Contemporary automated FFB ripeness detection research converges on computer vision and deep learning methodologies. Convolutional Neural Networks (CNN) excel at learning hierarchical feature representations from image data, capturing color gradients, texture patterns, and spatial relationships indicative of ripeness stages. Studies demonstrate the effectiveness of CNNs: one implementation combining CNN feature extraction with Support Vector Machine (SVM) classification achieved 97% accuracy on test datasets. The CNN-SVM hybrid leverages CNNs' powerful feature learning while using SVMs' robust decision boundaries for final classification [4,15,18].

YOLO (You Only Look Once) architecture variants have gained prominence for their real-time object detection capabilities, which are essential in operational contexts. YOLOv4 implementations for FFB detection report accuracy ranges of 88-99.66%, with processing speeds approaching real-time requirements. Newer iterations, including YOLOv8 and YOLOv12s, offer architectural improvements balancing accuracy and computational efficiency. These single-stage detectors process entire images in unified pipelines, contrasting with multi-stage approaches that separately propose regions and classify them, thereby enabling faster inference suitable for field deployment [20,21].

Multimodal sensing integration represents an emerging frontier that addresses the limitations of single-modality approaches. RGB imaging provides color information central to ripeness assessment, with high-resolution sensors (50 megapixels) capturing subtle gradations. Depth sensing using technologies like Intel RealSense D435/D455f cameras adds three-dimensional spatial information, enabling systems to distinguish FFB from background foliage and assess bunch structure. Point cloud data generated from depth sensors facilitates volumetric analysis and occlusion reasoning. Multispectral and hyperspectral imaging extends beyond the visible spectrum, with wavelengths at 680nm and 900nm revealing biochemical properties invisible to conventional cameras. This multimodal integration exploits complementary information sources, potentially achieving robustness unattainable through any single modality [6,22,23].

Beyond optical methods, sensor-based approaches explore alternative ripeness indicators. Capacitance sensors detect changes in the dielectric properties associated with fruit maturation and variations in moisture content. Volatile Organic Compound (VOC) detection targets chemical signatures emitted during ripening processes. Wireless Sensor Networks (WSNs) enable distributed monitoring across plantation blocks, with IoT connectivity aggregating data for centralized analysis. These diverse technological pathways reflect ongoing experimentation to identify optimal cost-performance-reliability combinations for operational deployment [22,24].

Real-time processing capabilities determine practical viability, as delayed detection undermines harvest coordination. Commercial operations typically require processing speeds ≥30 frames per second (FPS) for continuous monitoring during harvester traversal. Edge computing architectures address this requirement by performing inference locally on embedded devices rather than transmitting data to remote servers, reducing latency and dependency on network connectivity. Platforms like Raspberry Pi offer accessible entry points, though processing limitations and thermal management challenges in tropical conditions constrain performance. More powerful solutions, including NVIDIA Jetson AGX Orin platforms, provide 275 tera-operations per second (TOPS) computational capacity, enabling sophisticated deep learning inference at energy efficiencies around 0.58-0.75 joules per frame. However, gaps persist between theoretical capabilities and practical implementation, with real-world systems often achieving only 3.32-3.62 FPS for multispectral processing, highlighting ongoing optimization needs [4,23,25,26].

Plantation Variability and Environmental Complexities

Oil palm plantations exhibit substantial environmental heterogeneity that challenges automated detection systems designed assuming controlled, predictable conditions. Climate variability is a primary dimension of complexity. Temperature fluctuations between 24-35°C affect sensor performance and fruit development rates. Humidity ranges from 65-95% introduce moisture interference with imaging systems and influencing volatile compound emissions relevant to VOC-based detection. Solar radiation varies dramatically from 100 W/m² during overcast conditions to 1200 W/m² under direct sunlight, creating extreme illumination gradients that challenge camera exposure control and color consistency. Rainfall patterns exhibit high temporal and spatial variability, with some studies documenting ranges of 3.36mm to 997mm within study periods, while monsoon weather disrupts wireless connectivity, which is essential for cloud-dependent systems [12,13,27,28].

Topographical and physical characteristics introduce additional operational constraints. Many plantations are located on unstructured terrain with uneven surfaces, steep slopes, and obstacles that complicate equipment deployment and movement. Dense vegetation creates occlusion challenges as overlapping fronds obscure FFB from camera viewpoints. Tree shadows cast by tall palms (with heights varying significantly across planting ages) produce spatially complex lighting that confounds color-based classification. FFB positioning on palms exhibits irregularity-bunches may hang vertically, protrude horizontally, or nestle within fronds-requiring detection systems to handle diverse orientations and partial occlusions [29].

Agronomic diversity stems from varied management practices across estates and smallholdings. Planting densities, tree age distributions, fertilization regimes, and pruning schedules differ substantially, influencing FFB characteristics and canopy structures. Genetic material variability-different cultivars and clonal selections-affects fruit bunch morphology and ripening patterns. These differences mean detection models trained on one plantation may perform poorly when transferred to another with distinct agronomic characteristics, raising questions about model generalization and scalability [23].

Infrastructure limitations in many plantation contexts compound environmental challenges. Remote locations often lack adequate digital infrastructure, with only 21% of farmers in some regions reporting reliable internet access. Power supply instability affects sensor operation and edge computing devices, necessitating battery backup systems that add cost and maintenance complexity. Geographic scale presents logistical challenges, as commercial plantations span thousands of hectares, requiring extensive sensor networks and communication infrastructure. The combination of environmental variability, physical constraints, agronomic diversity, and infrastructure inadequacies creates a complex operational landscape that demands robust, adaptive technological solutions far exceeding laboratory-prototype requirements [26,30].

Processing Industry Requirements and Quality Standards

Palm oil mills represent the downstream integration point where automated FFB detection must align with processing requirements and quality standards. Mill processing capacities range widely, from small-scale operations handling 3 tonnes of FFB per hour to large industrial facilities processing 60-100 tonnes per hour. This capacity variability influences the pace and precision required of upstream detection systems, as high-throughput mills demand rapid, accurate grading to maintain processing efficiency [3,6].

Quality specifications directly impact the design of the detection system. Mills classifies incoming FFB using grading standards that define ripe bunches as those with ≥10 loose sockets and ≥50% fruits attached, under-ripe bunches with <10 loose sockets, and over-ripe bunches with >50% detached fruits. However, criteria exhibit inter-mill variations reflecting different processing technologies, target products, and commercial strategies. Some mills apply stricter ripeness thresholds or incorporate additional quality factors, such as bunch size, disease presence, or contamination levels. Automated detection systems must accommodate these variations, ideally offering configurable classification parameters calibrated to specific mill requirements [2,31].

Optimizing Oil Extraction Rate (OER) emphasizes quality, as OER directly determines profitability. Quality Tenera palms in efficient mills target OER benchmarks of 23-24%, yet actual performance often falls short. FFB ripeness critically influences OER-optimal ripeness maximizes oil content while maintaining processability, whereas under-ripe bunches contain insufficient oil and over-ripe bunches complicate processing and elevate free fatty acid levels. Even marginal improvements in harvest timing precision can yield substantial value given processing scales, with large mills potentially recovering additional tons of oil daily through optimized ripeness management [32].

Time-sensitive supply chain coordination adds urgency to detection capabilities. Industry best practices stipulate that FFB be delivered to mills within 24 hours post-harvest to minimize enzymatic oil degradation and free fatty acid formation. This narrow window necessitates tight synchronization between field detection, harvesting operations, collection logistics, and mill reception. Real-time or near-real-time detection capabilities enable dynamic harvest scheduling responsive to mill capacity and transportation availability, optimizing the entire value chain. The integration of automated detection with digital supply chain management systems represents an advanced application delivering value beyond individual harvest decisions [6,33].

Complexities Creating Implementation Challenges

The convergence of technological requirements, environmental variability, and processing integration demands generates substantial implementation complexities. Technical performance constraints emerge prominently in real-world deployment contexts. While laboratory studies report high accuracies, operational conditions degrade performance through multiple pathways. Environmental factors-varying illumination, weather-related changes in visibility, leaf shadows, and occlusions-reduce detection reliability. Small object detection poses particular challenges; studies report recall rates below 60% for FFBs smaller than 20 pixels in camera fields of view. Scale disparity-simultaneous presence of near and distant bunches creating large size variations-and occlusion from overlapping vegetation further compromise accuracy, with real-world performance often falling to 70-80% in challenging scenarios [27].

Data quality and availability constitute fundamental bottlenecks. Machine learning models require substantial training datasets representative of target deployment conditions, yet such datasets remain scarce for oil palm applications. Existing datasets often suffer from geographic and temporal limitations, capturing specific plantation conditions but lacking diversity across climate zones, cultivar types, or seasonal variations. Data imbalance-disproportionate representation of common vs. rare ripeness classes or environmental conditions-biases model learning and undermines generalization. Location-specific conditions that vary substantially across regions limit the applicability of global models, necessitating costly dataset collection and model retraining for each deployment context [13,18,34].

System integration and interoperability challenges obstruct seamless technology adoption. Comprehensive surveys identify 27 distinct challenges spanning organizational, technological, and data governance dimensions in smart agriculture system integration. Heterogeneous technology standards across sensor manufacturers, communication protocols, and data formats create compatibility barriers. Semantic interoperability gaps-differences in how systems conceptualize and represent agricultural data-complicate cross-platform data exchange. Legacy plantation management systems that rely on established software infrastructures resist integration with new automated detection technologies, requiring expensive middleware development or system replacements [6,8,18,30].

Economic and financial complexities loom large, particularly for smallholder farmers. Upfront capital investments in sensors, edge computing devices, network infrastructure, and installation represent substantial barriers, with sensor components alone accounting for a major share of costs. Operational expenses, including maintenance, power consumption, connectivity fees, and periodic hardware replacements, add recurrent costs. Return on investment calculations remain uncertain given variable performance under field conditions and fluctuating palm oil prices. While large estates can justify investments through economies of scale and labor cost savings, smallholders operating on thin profit margins face affordability constraints even when technologies promise long-term benefits. The economic value proposition must account for context-specific labor costs, productivity baselines, and alternative investment opportunities, yielding diverse conclusions across operational scales and geographic contexts [7,19,26].

Research Methodology

Research Design

This study employs a qualitative literature review approach to examine the multifaceted challenges of implementing automated FFB ripeness detection systems. The qualitative methodology, rather than systematic review protocols, was selected deliberately to accommodate the interpretive, exploratory nature of the research objectives. While systematic reviews excel at answering narrowly defined questions through exhaustive, protocol-driven literature searches and meta-analysis, qualitative reviews offer flexibility to navigate emerging, interdisciplinary topics characterized by conceptual diversity and methodological heterogeneity. Implementation challenges for agricultural automation technologies span computer science, agricultural engineering, development economics, rural sociology, and policy studies-domains employing diverse research paradigms, terminologies, and publication outlets that resist standardized systematic extraction [35].

The qualitative approach enables thematic analysis, emphasizing pattern recognition, contextual interpretation, and synthesis across heterogeneous evidence types. Rather than imposing rigid inclusion criteria and standardized quality assessments that potentially exclude valuable insights from technical reports, policy documents, or recent conference proceedings, qualitative review accommodates diverse evidence forms while maintaining critical evaluation of source credibility and relevance. This methodological choice aligns with the study's objectives of understanding complexities, identifying challenges across multiple dimensions, and synthesizing actionable insights rather than quantitatively aggregating effect sizes or performing meta-analyses.

Literature Search Strategy and Selection

Literature identification proceeded through multiple complementary pathways. Primary searches utilized academic databases including Google Scholar, IEEE Xplore, and ScienceDirect, employing search terms combining technology descriptors ("computer vision," "deep learning," "automated detection," "precision agriculture"), application contexts ("oil palm," "FFB," "ripeness detection," "fresh fruit bunch"), and implementation themes ("challenges," "barriers," "adoption," "deployment"). Searches prioritized publications from 2020 to 2026 to capture recent technological developments and contemporary implementation experiences, though foundational works from earlier periods were incorporated where they established essential conceptual frameworks.

Source selection emphasized peer-reviewed journal articles and conference proceedings from reputable venues, supplemented by technical reports from research institutions, industry white papers, and policy documents from governmental and international agricultural development organizations. This inclusive approach recognized that implementation insights often emerge from the gray literature documenting pilot projects, technology transfer initiatives, and policy interventions that are not captured in traditional academic publishing cycles. Geographic emphasis focused on Southeast Asian contexts-particularly Indonesia and Malaysia as dominant oil palm producers-while incorporating comparative insights from other tropical agriculture automation domains.

Inclusion criteria prioritized relevance to automated FFB detection technologies, documentation of implementation experiences or challenges, and empirical evidence or substantive conceptual contributions. Exclusions eliminated purely theoretical algorithm development papers lacking implementation discussion, studies predating 2020 unless establishing foundational concepts, and sources lacking credible peer review or institutional backing. Iterative citation tracking supplemented database searches, following reference chains from key articles to identify additional relevant sources and using forward citation searches to find recent works building on foundational studies.

Thematic Analysis Procedure

Analysis proceeded through iterative coding and theme development stages adapted from established qualitative research methodologies. Initial open coding involved systematic reading of selected literature, identifying and labeling discrete challenges, technological characteristics, contextual factors, and implementation experiences mentioned across sources. Codes captured both explicit statements (e.g., "high upfront costs" or "limited internet connectivity") and implicit themes (e.g., the tension between standardization and context-specificity that emerged from discussions of model transferability).

Subsequent axial coding organized the initial codes into broader thematic categories that reflected relationships and hierarchies among concepts. Codes related to computational constraints, sensor limitations, and connectivity issues were grouped under "technical barriers," while codes addressing capital requirements, operational costs, and ROI uncertainties were consolidated into "economic challenges." This hierarchical organization revealed multidimensional patterns spanning technical, economic, infrastructural, human capital, socio-cultural, and institutional domains.

Selective coding refined themes through constant comparison across sources, identifying consensus areas where multiple studies documented similar challenges, contested territories where evidence presented contradictory findings, and evidence gaps where conceptual importance exceeded empirical documentation. Cross-referencing plantation variability themes with discussions of technological performance illuminated relationships between environmental heterogeneity and detection system reliability. Comparing smallholder-focused studies with large-estate implementations revealed scale-dependent economic and institutional barriers. Throughout the analysis, reflexive memoing captured interpretive insights, emerging questions, and connections among themes, maintaining transparency in the analytical process and facilitating subsequent synthesis.

Results

Technological Performance: Capabilities and Constraints

The literature documents impressive technological capabilities under controlled conditions. Deep learning approaches consistently achieve high accuracy metrics, with CNN-SVM hybrid architectures reaching 97% classification accuracy on curated datasets, advanced AI detection systems reporting 99.34% accuracy, and YOLOv4 implementations demonstrating accuracy ranges of 88-99.66% across various test scenarios. These performance levels suggest the technical feasibility of automated FFB ripeness classification, particularly for applications that tolerate occasional errors or employ human oversight for ambiguous cases [15,18,21,36].

However, substantial performance degradation occurs when transitioning from laboratory settings to operational plantation environments. Environmental factors significantly affect accuracy: varying illumination throughout the day challenges camera exposure and white balance calibration, leading to notable declines in classification accuracy under extreme lighting conditions. Weather-related changes in visibility during overcast periods or rain events reduce image quality. Shadows cast by palm fronds create spatially complex lighting patterns, confounding color-based ripeness assessment. Motion blur from moving platforms (vehicle-mounted or robotic systems) degrades image sharpness, particularly when combined with slow sensor frame rates [27,37].

Occlusion represents a persistent challenge, as FFB frequently nestle within dense fronds or behind overlapping vegetation. Partial occlusion forces detection systems to infer ripeness from incomplete visual information, thereby increasing the risk of misclassification. Small object detection limitations compound this issue-distant FFB or those captured at oblique angles may occupy insufficient pixels for reliable classification, with recall rates below 60% documented for objects smaller than 20 pixels. Scale disparity within a single image, where near objects appear large while distant objects appear small, challenges model architectures optimized for specific object size ranges [27].

Real-time processing constraints create additional practical barriers. While commercial operations ideally require processing speeds ≥30 FPS for continuous real-time monitoring during traversal, actual implementations often fall short. Multispectral imaging systems processing wavelength information beyond standard RGB achieve only 3.32-3.62 FPS, necessitating stationary operation or intermittent sampling rather than continuous detection. Edge computing devices face computational bottlenecks when running complex deep learning models, and thermal limitations in hot tropical environments further constrain sustained performance. Energy efficiency considerations matter for battery-powered mobile platforms, as intensive computation rapidly drains power, limiting operational duration [22,23,25,36,38,39].

Multidimensional Implementation Barriers

Economic and Financial Obstacles

Economic barriers emerge consistently across the literature as primary adoption obstacles, particularly for smallholder farmers. High upfront capital requirements encompass sensor hardware (cameras, depth sensors, multispectral imagers), edge computing devices (Raspberry Pi, Jetson modules), networking infrastructure (routers, cellular modems, cabling), and installation services. Sensor components often represent the largest single cost element. For advanced multi-modal systems integrating RGB, depth, and spectral sensing, capital costs escalate substantially. Operational expenses add recurrent financial burdens: equipment maintenance and repairs, power consumption (especially for always-on monitoring systems), connectivity subscriptions for cellular data transmission, and periodic hardware replacement as components fail or become obsolete [7,22,23,26,40].

Return-on-investment calculations yield uncertain conclusions that vary by operational scale and context. Large estates with substantial labor forces may justify automation through labor cost savings, as fewer manual inspectors would be needed. However, for investments to be viable, automated systems must replace sufficient workers to offset capital and operational costs-a threshold difficult to achieve given that harvesting represents only one component of plantation labor requirements. Machine-harvesting costs, when automated detection is integrated with mechanical harvesting systems, are slightly higher than manual approaches in some contexts, eroding the economic justification [8,29].

Smallholders face particularly acute affordability challenges. With thin profit margins leaving little capital for investment, upfront costs represent prohibitive barriers even when long-term benefits appear favorable. Without subsidies or alternative financing mechanisms, smallholders lack access to automation technologies, potentially exacerbating inequalities between large corporate estates and small independent farmers. Only 38% of farmers in certain regions own smartphones, and just 21% have reliable internet access, indicating broader economic constraints that limit their capacity to adopt technology. The economic value proposition thus depends critically on scale, with technologies potentially viable for large operations remaining inaccessible to smallholders who collectively account for significant palm oil production [7,41].

Technical and Infrastructural Barriers

Data scarcity and quality issues fundamentally constrain the development and deployment of machine learning models. Training robust, generalizable models requires large, diverse datasets representative of target deployment conditions, yet such datasets remain scarce for oil palm FFB detection. Existing open-access datasets often capture specific locations and time periods, lacking diversity across climate zones, cultivar types, tree ages, and seasonal variations needed for broad applicability. Data imbalance-overrepresentation of certain ripeness classes or environmental conditions relative to others-biases model learning, leading to poor performance in underrepresented scenarios. Location-specific conditions vary substantially, with models trained on data from one region often performing poorly when deployed in geographically or agronomically distinct areas. This transfer learning challenge necessitates local dataset collection and model retraining for each deployment, multiplying development costs and timelines [7,12,13,18,27,34].

Hardware limitations constrain practical implementation. Edge computing devices like Raspberry Pi, while affordable and accessible, face processing constraints when running sophisticated deep learning models, particularly in hot tropical environments where heat management becomes challenging. More powerful platforms offer greater computational capacity but at higher costs and power consumption, which can be challenging for battery-powered mobile deployments. Real-time processing requirements conflict with hardware constraints, as achieving ≥30 FPS inference with complex models demands computational resources beyond the capabilities of current cost-effective edge devices [26,27,36,39].

Connectivity challenges pervade rural plantation contexts. Limited digital infrastructure in remote areas constrains cloud-dependent system architectures that rely on transmitting data to centralized servers for processing. Only 21% of farmers report reliable internet access in some regions, rendering cloud-based solutions impractical. Cellular connectivity weakens in remote plantations, while monsoon weather further disrupts wireless communications. These connectivity limitations favor edge computing approaches performing inference locally, yet local processing reintroduces hardware performance constraints and limits access to centralized model updates and aggregated analytics. Power supply instability compounds infrastructure challenges, with unreliable grid electricity in rural areas necessitating battery backup or renewable energy systems, which increase costs and complexity [26,27,42].

Integration and Interoperability Challenges

System integration complexities obstruct seamless technology adoption within existing plantation operations. A comprehensive literature review identified 27 distinct challenges spanning organizational structures, technological compatibility, and data governance frameworks in the integration of smart agriculture systems. Heterogeneous technology standards across different sensor manufacturers, communication protocols (e.g., LoRaWAN, Zigbee, cellular), and data formats create compatibility issues, preventing different system components from communicating effectively. Semantic interoperability gaps emerge when systems use different conceptual frameworks and terminologies to represent agricultural data, complicating cross-platform data exchange and integration [6,18,30,43].

Legacy plantation management systems present integration obstacles. Many estates employ established enterprise resource planning (ERP) or farm management software systems managing operations, labor, and inventory. Integrating new automated detection technologies with these legacy systems requires custom middleware development, API creation, or wholesale system replacements-all of which are costly and disruptive. Lack of standardization across the agricultural technology ecosystem exacerbates integration challenges, as proprietary systems resist interoperability and open data exchange. While standardization initiatives such as FIWARE reference architectures and Smart Data Models offer potential solutions, adoption remains limited and fragmented across the industry [6,44].

Human Capital and Skills Deficits

Workforce skill gaps constitute significant non-technical barriers. Operating and maintaining automated detection systems require technical competencies beyond traditional agricultural expertise-such as understanding sensor calibration, troubleshooting hardware failures, interpreting system outputs, and managing data flows. Many plantation workers and even managers lack these digital skills, creating dependency on external technical support services that may be unavailable or expensive in remote areas. Training and extension services, traditionally focused on agronomic practices, have not evolved to incorporate technology operation and maintenance, leaving farmers without accessible learning resources [7,8,10,45].

Digital literacy limitations compound technical skill gaps. With only 38% of farmers in some regions owning smartphones, basic digital competencies cannot be assumed. Technology interfaces requiring digital navigation, data interpretation, or troubleshooting may exclude significant user populations. Language barriers arise when software interfaces use technical English terminology that is inaccessible to local-language speakers. These human capital constraints suggest that technology design must prioritize user-friendliness and culturally appropriate interfaces, while parallel investments in capacity building and the transformation of extension services are essential for sustainable adoption [7,28,41].

The agricultural workforce transformation required by automation extends beyond technical skills to fundamental role changes. Automation shifts labor demands from manual harvesting toward data analysis, equipment maintenance, and technical troubleshooting. This transition creates workforce disruption challenges, as displaced manual laborers may lack pathways to higher-skilled roles in automated systems without substantial retraining. Socially responsible automation deployment must address workforce transitions through training programs, the creation of alternative employment, and social safety nets that support displaced workers [10,45,46].

Socio-Cultural and Behavioral Barriers

Resistance to technology adoption reflects deeper socio-cultural factors beyond a simple lack of information. Cultural barriers rooted in decades-old farming principles and traditional practices create behavioral inertia, with a preference for familiar, proven methods over unfamiliar technologies perceived as risky. Lack of trust in new technologies stems from limited exposure, previous negative experiences with failed agricultural innovations, or skepticism about claimed benefits. Technology acceptance depends not only on objective performance but also on subjective factors, including perceived ease of use, perceived usefulness, and social influence from peer farmers and trusted advisors [7,34].

Demonstration effects and peer learning emerge as important pathways to adoption. Farmers who observe successful technology implementation by trusted peers or on demonstration farms a more willing to adopt. Conversely, the absence of visible success examples or exposure to failed implementations heightens risk aversion. Transparent communication about technology capabilities and limitations, realistic benefit expectations, and honest acknowledgment of costs builds trust more effectively than overpromising. Gradual adoption pathways that allow incremental technology integration with manageable risk exposure may facilitate acceptance more effectively than wholesale operational transformation [6,47].

Institutional and Regulatory Obstacles

Institutional frameworks exhibit gaps between policy aspirations and implementation realities. Indonesia's Presidential Regulation No. 131/2024 on Science and Technology-Based Agricultural Development signals the government's commitment to agricultural modernization, while the Ministry of Agriculture's regulations emphasize the development of agricultural areas and the integration of technology. Yet institutional resistance from legacy cooperatives accustomed to traditional operating models impedes policy implementation. Regulatory harmonization across ministries-agriculture, technology, finance, cooperatives-remains incomplete, creating bureaucratic complexity and inconsistent incentive structures [6,48].

Fiscal incentives and support mechanisms remain insufficiently developed. While policies articulate technology adoption goals, practical support through subsidies, tax incentives, low-interest financing, or risk-sharing instruments has not materialized at scales needed to catalyze widespread adoption. Regulatory simplification to reduce compliance burdens for technology adopters lags behind policy rhetoric. Uneven digital infrastructure development across regions creates geographic disparities, with progressive policies benefiting well-connected urban-proximate areas while remote plantations lack enabling infrastructure. Effective policy frameworks must bridge these implementation gaps through concrete support mechanisms, infrastructure investments, and coordinated cross-sectoral action [48].

Plantation and Processing Variability as Central Complexities

Environmental heterogeneity across plantation contexts fundamentally challenges standardized technological solutions. Climate variability-temperature fluctuations (24-35°C), humidity ranges (65-95%), solar radiation variations (100-1200 W/m²), and rainfall patterns (3.36-997mm documented ranges)-creates unpredictable operating conditions that degrade sensor performance and affect fruit development patterns. Topographical diversity introduces terrain constraints that limit equipment mobility and affect sensor positioning relative to the target FFB. Agronomic diversity across different cultivars, tree ages, planting densities, and management practices yields variation in FFB characteristics and canopy structures that trained models may not recognize if trained on narrow dataset distributions [5,13,18,49].

These variabilities necessitate adaptive, context-responsive systems capable of maintaining performance across diverse conditions. Yet developing such robustness remains technically challenging, as models trained on data from specific contexts often fail to generalize when environmental conditions, agronomic characteristics, or infrastructure configurations differ substantially from those in the training distribution. Transfer learning and domain adaptation techniques offer promising avenues for model adaptation across contexts, yet their practical implementation in oil palm applications remains nascent [50].

Processing mill variability compounds integration challenges. Mills vary in processing capacity (3-100 tonnes FFB/hour), quality standards (specific grading criteria and thresholds), and operational protocols. Automated detection systems must accommodate this variability through configurable classification parameters calibrated to specific mill requirements. Lack of standardization across the industry complicates technology provider strategies, as single standardized products may not satisfy diverse mill specifications, necessitating customization that increases costs and development complexity [6,16].

Discussion and Analysis

The Performance Paradox: Laboratory Success vs. Field Challenges

A striking pattern emerges from the literature: high accuracy under controlled conditions contrasts sharply with performance degradation in operational environments. Laboratory and pilot studies consistently document impressive metrics-97-99.66% accuracy rates, suggesting near-perfect classification capability. Yet, field implementations experience substantial accuracy erosion due to environmental variability, occlusion, motion blur, and lighting challenges. This performance paradox reflects a fundamental gap between experimental conditions that optimize technological performance and real-world conditions that impose harsh, unpredictable operating constraints [14].

The paradox carries important implications for technology development strategies. Performance benchmarking conducted solely in controlled settings provides misleading indicators of practical viability, potentially directing investments toward solutions that appear successful in the lab but fail under operational conditions. Robust technology validation requires extensive field testing across diverse plantation contexts and environmental conditions, capturing seasonal variations, extreme weather events, and edge cases poorly represented in curated datasets. Performance metrics must expand beyond raw accuracy to encompass robustness measures quantifying performance stability across varying conditions, recovery capabilities after transient failures, and graceful degradation rather than catastrophic failure modes [18,22,27,49].

Addressing the performance paradox requires the development of environment-adaptive algorithms. Rather than assuming static, predictable operating conditions, algorithms must dynamically adapt to changing illumination, weather, and seasonal variations. Techniques including adaptive thresholding, automatic white balance and exposure adjustment, and ensemble methods combining multiple models trained on diverse conditions offer pathways toward greater robustness. Multi-modal sensor integration provides complementary information sources, maintaining functionality when individual modalities degrade-for example, depth sensing maintains performance when lighting conditions compromise RGB imaging [1,6,22,27].

Economic Viability: Scale Dependencies and Business Model Innovation

Economic viability assessments reveal strong scale dependencies, with automation potentially justifiable for large estates but prohibitively expensive for smallholders under conventional ownership models. Large operations benefit from economies of scale, distributing fixed capital costs across extensive hectares, while labor cost savings from reduced manual inspection workforces improve return on investment. However, even for large estates, economic justification remains uncertain when operational costs, maintenance expenses, and performance limitations under field conditions are incorporated into comprehensive cost-benefit analyses [40].

Smallholders face particularly acute economic barriers. With 38% smartphone ownership and 21% reliable internet access in some farming populations, the capacity for technology adoption extends beyond automation systems to basic digital infrastructure. Thin profit margins leave minimal capital for investment, while a lack of access to agricultural credit and financing mechanisms compounds affordability challenges. Conventional technology deployment models requiring individual purchase and ownership perpetuate inequalities, as smallholders cannot access innovations available to large corporate estates [7,51].

Business model innovation offers potential pathways beyond conventional ownership structures. Technology-as-a-Service models, where service providers own equipment and charge subscription fees or per-use rates, reduce upfront capital barriers, shifting costs to operational budgets and aligning expense timing with revenue generation. Cooperative technology pooling enables smallholder groups to collectively acquire and share expensive equipment, distributing costs across multiple farmers while achieving utilization rates that justify investment. Blended finance instruments combining public subsidies with private capital can de-risk early adoption, with initial public support catalyzing markets that subsequently become commercially self-sustaining. These innovative arrangements require supportive institutional frameworks, financing mechanisms, and service provider ecosystems that currently remain underdeveloped [7,52-55].

Data as Foundation and Bottleneck

Data scarcity is a fundamental bottleneck that constrains the development and deployment of machine learning models. Model performance depends critically on the quality, quantity, and diversity of the training data, yet agricultural applications, including oil palm FFB detection, often lack sufficient open-access datasets. Existing datasets typically capture specific locations and time periods, lacking diversity across geographic regions, climate zones, cultivar types, and environmental conditions needed for model generalization. Data imbalance toward common scenarios at the expense of rare but important cases biases model learning [13,18,34,49].

This data scarcity reflects multiple underlying factors. Data collection requires substantial resources-equipment, personnel, time, and expertise-that academic researchers and technology developers often lack at scales needed for comprehensive coverage. Proprietary concerns lead commercial entities to restrict data sharing, as datasets represent competitive advantages and intellectual property. Lack of standardization in data formats, annotation schemes, and metadata specifications complicates dataset integration even when sharing occurs. Privacy and ethical considerations around farmer data create valid restrictions on open dissemination [16,18].

Addressing data scarcity requires coordinated ecosystem action. Open data initiatives that promote data sharing with appropriate intellectual property protections and privacy safeguards can expand the availability of training resources. Standardization around common data formats, annotation protocols, and metadata schemas facilitates dataset interoperability and aggregation. Public investment in large-scale data collection across diverse contexts provides foundational resources benefiting entire technology ecosystems rather than individual entities. Collaborative approaches that engage research institutions, technology companies, plantation operators, and government agencies in shared data collection and curation distribute costs while building comprehensive, representative datasets that support robust model development [18,49].

Holistic Ecosystem Approaches: Beyond Technology Push

The multidimensional nature of implementation barriers-spanning technical, economic, infrastructural, human capital, socio-cultural, and institutional domains-reveals the limitations of narrow technology-push strategies that assume innovations that succeed technically will naturally diffuse through markets. Successful implementation requires holistic ecosystem approaches simultaneously addressing multiple barrier dimensions through coordinated interventions [7,48].

Infrastructure development constitutes a foundational requirement. Digital connectivity, expanding broadband and cellular coverage into rural plantation areas, enables cloud-based system architectures and remote technical support. A reliable power supply, whether through grid improvements or renewable energy installations, ensures continuous sensor operation. Physical infrastructure, including plantation roads and terrain management, facilitates equipment deployment and mobility. These infrastructure investments transcend individual technology adoptions, creating enabling environments supporting diverse innovations [56-58].

Human capital development through comprehensive training programs builds operational capacity for technology adoption. Training must address multiple stakeholder groups: farmers and plantation managers who require an understanding of technology benefits, operations, and strategic integration; field workers who need equipment operation and basic troubleshooting skills; and technical specialists capable of advanced maintenance and customization. Agricultural extension service transformation from traditional agronomic advisory toward integrated technology support services provides accessible, trusted guidance channels. The integration of digital agriculture content into the education system cultivates long-term workforce capacity aligned with sector transformation trajectories [6,30].

Institutional strengthening addresses organizational and governance dimensions. Cooperative modernization that supports legacy farmer organizations in their digital transformation creates collective-action vehicles for access to technology. Regulatory harmonization, reducing bureaucratic complexity, and aligning incentives across government agencies, facilitates consistent policy implementation. Public-private partnership frameworks that convene diverse stakeholders-researchers, technology providers, farmers, processors, policymakers-enable collaborative problem-solving and resource mobilization that exceed the capabilities of individual entities [10,45,46].

Policy Implications and Intervention Priorities

Evidence from implementation barriers points toward specific policy priorities for governments and development organizations seeking to facilitate automation adoption. Fiscal incentives, including subsidies, tax breaks, and grants targeted at technology adoption, reduce financial barriers, particularly for smallholders and early adopters bearing higher risks. Subsidies should incorporate both capital acquisition support and operational expense assistance, recognizing that recurrent costs constrain sustained adoption even when the initial purchase is subsidized [7,41].

Public R&D investment directed toward context-specific technology development addresses market failures in innovation systems. Private-sector technology developers naturally focus on large, accessible markets with rapid commercialization pathways, potentially neglecting smallholder contexts or tropical plantation-specific challenges. Public investment in research on climate-robust algorithms, low-cost sensor development, offline-capable edge computing solutions, and tropical environment hardware engineering generates public goods that benefit entire industries [13,26,59,60,61].

Infrastructure investment as public goods provision creates enabling environments. Rural broadband expansion, power grid improvements, and renewable energy programs deliver benefits that transcend agricultural automation to benefit rural development broadly. Recognizing infrastructure inadequacy as a cross-cutting development constraint rather than a sector-specific issue elevates infrastructure investment to strategic priority levels with commensurately scaled resource commitments [30].

Regulatory framework development, balancing innovation facilitation with risk management, provides essential governance. Standards development for data formats, communication protocols, and system interoperability reduces fragmentation and enables ecosystem growth. Data governance frameworks that establish clear rules on ownership, privacy, and use rights build farmer trust while enabling legitimate data use. Safety and liability regulations addressing autonomous or semi-autonomous agricultural machinery protect workers and communities while providing legal clarity for technology providers. Regulatory approaches should emphasize enabling principles-based frameworks rather than prescriptive rules that risk prematurely constraining rapidly evolving technologies [41,44].

Future Directions: Technological and Systemic Evolution

Looking forward, technological evolution pathways emphasize robustness, affordability, and adaptability. Algorithm development trends toward transfer learning and domain adaptation techniques, enabling models trained in one context to adapt efficiently to new environments with limited additional data. Federated learning architectures, allowing collaborative model training across distributed plantations without centralizing sensitive data, address both privacy concerns and data scarcity through knowledge aggregation. Cost-effective sensor innovation that targets acceptable performance at dramatically lower price points expands accessibility, even if it requires accuracy trade-offs [62,63].

Edge computing architectures continue advancing, with newer hardware generations offering greater computational capacity at improved energy efficiency. Hybrid edge-cloud architectures dynamically allocate processing between local devices and remote servers based on connectivity availability and computational demands, balancing robustness with capability. Offline-first system designs that assume intermittent connectivity as the norm rather than the exception ensure functionality in infrastructure-constrained contexts [26,42].

Systemic evolution beyond technological dimensions appears equally important. Business model innovation, including Technology-as-a-Service, cooperative ownership, and shared service platforms, may prove as transformative as hardware and algorithm improvements in determining accessibility and adoption patterns. Capacity-building systems that integrate training across formal education, extension services, and peer learning networks develop the human capital prerequisites for sustained technology utilization. Institutional maturation, including cooperative strengthening, public-private partnerships, and regional innovation hubs, lays the organizational foundations for ecosystem growth. Policy evolution, incorporating lessons from early implementation experiences and adapting regulatory frameworks to emerging challenges and opportunities, provides governance structures that enable continued innovation while managing risks [46,58,64,65].

Conclusion

This qualitative literature review examined the challenges and complexities that obstruct the practical implementation of automated FFB ripeness detection systems in oil palm plantations. While technological capabilities have matured substantially-with computer vision and deep learning approaches achieving 97-99.66% accuracy in controlled settings-the pathway from laboratory success to widespread operational deployment confronts substantial multidimensional barriers. Implementation challenges span technical domains (data scarcity, hardware constraints, real-time processing limitations), economic factors (high capital requirements, uncertain return on investment, smallholder affordability gaps), infrastructural inadequacies (connectivity limitations, power instability, geographic scale), human capital deficits (skills gaps, digital literacy constraints, workforce transition needs), socio-cultural resistance (trust deficits, behavioral inertia, preference for traditional methods), and institutional obstacles (regulatory fragmentation, policy-implementation gaps, insufficient support mechanisms).

Plantation and processing industry variability emerges as a central complexity factor, creating heterogeneous, unpredictable operational conditions that degrade standardized technological solutions. Environmental variability-climate fluctuations, topographical diversity, illumination changes-challenges sensor performance and model robustness. Agronomic diversity from different cultivars, tree ages, and management practices limits model generalization across contexts. Processing mill variations in quality standards and capacity requirements demand flexible integration capabilities. These variabilities necessitate adaptive, context-responsive systems maintaining performance across diverse conditions-a technical challenge substantially more demanding than achieving high accuracy in controlled laboratory environments.

Economic viability exhibits strong scale dependencies: large estates may justify investments through economies of scale and labor cost savings, while smallholders face prohibitive affordability barriers under conventional ownership models. Business model innovation, including Technology-as-a-Service, cooperative technology pooling, and blended finance instruments, offers potential pathways toward inclusive access, yet requires supportive institutional frameworks and financing mechanisms that remain underdeveloped. Data scarcity constitutes a foundational bottleneck, with limited availability of localized, diverse training datasets constraining model development and generalization. Open data initiatives, standardization efforts, and collaborative data-collection programs represent priority interventions to address this constraint.

The multidimensional nature of implementation barriers reveals the limitations of narrow technology-push approaches, underscoring the necessity of holistic ecosystem strategies that simultaneously address technical, economic, infrastructural, human capital, socio-cultural, and institutional dimensions. Successful implementation requires coordinated action spanning infrastructure development (digital connectivity, power supply, physical accessibility), human capital investment (training programs, extension service transformation, workforce development), institutional strengthening (cooperative modernization, regulatory harmonization, public-private partnerships), and enabling policy frameworks (fiscal incentives, public R&D investment, data governance, standards development).

Policy recommendations emphasize fiscal incentives to reduce adoption barriers, particularly for smallholders; public R&D investment in context-specific technology development, including climate-robust algorithms and low-cost sensors; infrastructure provision as public goods to create enabling environments; and regulatory frameworks that balance innovation facilitation with appropriate risk management. Implementation strategies should prioritize phased deployment, validating robustness across diverse contexts, context-responsive customization, aligning technologies with specific plantation and mill requirements, hybrid human-AI collaborative approaches leveraging complementary strengths, and inclusive access mechanisms ensuring smallholder participation in technological transformation.

Looking forward, technological evolution toward adaptive algorithms, affordable sensors, and robust edge computing platforms continues to advance capabilities. Yet systemic evolution-business model innovation, capacity-building systems, institutional maturation, and policy adaptation-appears equally critical in determining whether automation technologies realize their potential to enhance oil palm industry productivity, sustainability, and competitiveness. The challenge extends beyond technical feasibility to encompass the far more complex undertaking of socio-technical system transformation, integrating technological innovation with economic viability, infrastructural adequacy, human capability, cultural acceptance, and institutional support. Success requires sustained commitment from diverse stakeholders-researchers, technology providers, plantation operators, processors, policymakers, and farmers-who work collaboratively to navigate this complex pathway from technological promise to an inclusive, sustainable reality.

The oil palm industry stands at a critical juncture where labor constraints, climate pressures, and competitiveness imperatives converge, making automation not merely desirable but increasingly necessary. Automated FFB ripeness detection systems represent one crucial component of broader precision agriculture transformations capable of optimizing productivity while advancing sustainability goals. Realizing this potential demands moving beyond narrow technical problem-solving toward comprehensive ecosystem orchestration, addressing the multidimensional complexities documented in this review. With appropriate interventions, supportive policies, and collaborative action, the gap between technological capability and practical implementation can be bridged, unlocking substantial value for producers while contributing to sustainable, efficient palm oil production systems meeting global demands responsibly.

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