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Machine Learning-Based Disease Detection in Cocoa Plantations: Economic Viability Study in Luwu Regency, South Sulawesi

Indi Millatul Maula
Politeknik Siber Cerdika Internasional, Indonesia
*Corresponding Author: Indi@polteksci.ac.id

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Abstract
Disease-related yield losses represent a critical constraint to cocoa productivity in Indonesia, particularly in South Sulawesi Province where endemic infections cause 30-70% production declines annually. This study evaluated the economic viability of implementing machine learning-based disease detection systems in cocoa plantations in Luwu Regency through an 18-month mixed-methods research design integrating technical validation, randomized controlled field trials, and comprehensive economic analysis. A convolutional neural network model was developed using 12,450 labeled images and deployed across 30 cocoa farms stratified by size and disease pressure, with 15 treatment farms receiving ML-based detection technology and 15 control farms continuing conventional monitoring practices. The ML model achieved 93.7% diagnostic accuracy for detecting Cocoa Pod Borer, Vascular Streak Dieback, and Black Pod Disease. Treatment farms demonstrated significantly higher yields (1,247 kg/ha vs. 942 kg/ha, 32.4% increase), reduced disease incidence (8.7% vs. 23.1%), and improved bean quality (73.2% Grade A vs. 58.4%). Economic analysis revealed highly favorable investment returns with Internal Rate of Return of 47.3% for individual adoption and 52.6% for cooperative models, Net Present Value of $2,847 per farm, Benefit-Cost Ratio of 3.68, and Payback Period of 2.8 years. The findings demonstrate that ML-based disease detection achieves economic viability in smallholder cocoa farming contexts, offering a transformative solution for enhancing agricultural productivity and farmer incomes in disease-endemic tropical plantation systems.

Keywords: machine learning; disease detection; cocoa plantation; economic viability; precision agriculture

INTRODUCTION

Agriculture remains a fundamental pillar of global economic development, with plantation crops contributing substantially to both national gross domestic product and rural livelihood sustainability in tropical developing nations. Cocoa (Theobroma cacao L.) stands as one of the most economically significant plantation commodities worldwide, supporting approximately 40-50 million smallholder farmers across Africa, Asia, and Latin America while generating annual global revenues exceeding $130 billion in the chocolate industry value chain (Shewangizaw et al., 2022). Indonesia ranks as the third-largest cocoa producer globally, with South Sulawesi Province contributing approximately 60% of national production, making the region critically important to the country's agricultural export economy (Kao et al., 2022). Within South Sulawesi, Luwu Regency has emerged as a primary cocoa cultivation center, with over 45,000 hectares dedicated to cocoa farming and more than 30,000 farming families depending on cocoa as their principal income source (Suh & Molua, 2022).

However, the productivity and economic sustainability of cocoa plantations in this region face unprecedented challenges from endemic plant diseases that cause yield losses ranging from 30% to 70% annually, threatening farmer livelihoods and regional economic stability (Appiah, 2023) (Kongor et al., 2024) (Tscharntke et al., 2023). The imperative to develop innovative, technologically advanced disease management systems has become increasingly urgent as conventional detection methods prove inadequate in addressing the scale and complexity of disease outbreaks in extensive plantation landscapes. This study addresses this critical challenge by examining the economic viability of implementing machine learning-based disease detection systems in cocoa plantations, representing a convergence of agricultural science, artificial intelligence, and economic analysis to support sustainable agricultural development.

The theoretical foundations of plant disease management have evolved substantially from reactive chemical interventions toward proactive, integrated pest and disease management systems that emphasize early detection, precision diagnosis, and targeted treatment strategies. Disease detection in agricultural systems traditionally relies on manual scouting by trained agronomists or farmers, a labor-intensive process subject to human error, limited scalability, and significant time delays between disease onset and identification (Saleem et al., 2021). The economic theory of agricultural technology adoption posits that farmers make rational decisions based on expected utility maximization, weighing the costs of technology investment against anticipated benefits in terms of yield preservation, input cost reduction, and risk mitigation.

Machine learning, a subset of artificial intelligence focused on pattern recognition and predictive modeling from data, has demonstrated remarkable capabilities in image classification tasks, achieving accuracy rates exceeding 95% in various agricultural disease detection applications (Azadi et al., 2023; Junaedi, 2025). The application of convolutional neural networks (CNNs) and other deep learning architectures to agricultural disease detection represents a paradigm shift from conventional diagnostic methods, offering potential for real-time, scalable, and highly accurate disease identification through automated image analysis. Economic viability analysis, grounded in capital budgeting theory and cost-benefit analysis frameworks, provides systematic methodologies for evaluating technology investments by comparing implementation costs against quantifiable benefits over specified time horizons (Dhanaraju et al., 2022). The integration of these theoretical frameworks, agricultural disease management, machine learning technology, and economic evaluation, constitutes the conceptual foundation for assessing the feasibility and potential impact of ML-based disease detection systems in cocoa plantations.

Despite advances in agricultural technology and disease management strategies, cocoa plantations in Luwu Regency continue to experience severe economic losses due to inadequate disease detection and management systems, revealing a critical gap between technological capabilities and practical implementation in smallholder farming contexts.

Cocoa Pod Borer (*Conopomorpha cramerella*), Vascular Streak Dieback (VSD) caused by *Ceratobasidium theobromae*, and Black Pod Disease caused by Phytophthora species collectively represent the most economically damaging diseases affecting Indonesian cocoa production, with VSD alone causing yield reductions of 40-60% in severely affected areas (Jing et al., 2022). Current disease detection practices in Luwu Regency rely predominantly on periodic field observations by farmers or extension workers, resulting in delayed identification that often occurs only after diseases have reached advanced stages where treatment options are limited and economic damage is substantial (Rizal et al., 2024).

The spatial and temporal complexity of disease distribution across large plantation areas exceeds the capacity of manual monitoring systems, creating blind spots where disease outbreaks can proliferate undetected for weeks before discovery (Kurihara et al., 2022). While machine learning technologies have demonstrated impressive performance in controlled experimental settings for plant disease detection, significant uncertainty persists regarding the economic feasibility of implementing such systems in resource- constrained smallholder farming environments characterized by limited capital availability, variable technological literacy, and inadequate digital infrastructure.

The cost structure of ML-based detection systems, including initial hardware investment, software development or licensing, training requirements, and ongoing operational expenses, remains poorly quantified in the context of Indonesian cocoa farming, creating barriers to informed decision-making by farmers, cooperatives, and agricultural development agencies. Furthermore, the specific economic benefits achievable through ML-based early disease detection in terms of yield preservation, input cost optimization, and quality improvements have not been rigorously measured or validated in real-world cocoa plantation settings. This confluence of persistent disease management challenges, emerging technological solutions, and uncertain economic implications creates an urgent knowledge gap that impedes the adoption of potentially transformative innovations in cocoa disease management.

The urgency of this research stems from the accelerating threat that plant diseases pose to cocoa production sustainability in South Sulawesi, combined with the rapid maturation of machine learning technologies that could provide timely solutions if their economic viability can be demonstrated. Climate change has intensified disease pressure on cocoa plantations, with rising temperatures and altered precipitation patterns creating increasingly favorable conditions for pathogen proliferation and disease spread, trends projected to worsen in coming decades (El-Samad et al., 2022). Indonesia's cocoa production declined by approximately 18% between 2015 and 2020, with disease-related yield losses identified as a primary contributing factor, threatening the economic viability of cocoa farming and potentially driving rural-urban migration as farming becomes unsustainable (Kao et al., 2022).

The Indonesian government has prioritized agricultural technology modernization and digital agriculture initiatives as key strategies for achieving food security and agricultural competitiveness, creating a policy environment conducive to technology adoption but requiring evidence- based assessments of specific technologies. Smallholder cocoa farmers in Luwu Regency, representing the backbone of regional cocoa production, face increasing economic pressure from declining productivity, price volatility, and rising input costs, making the economic optimization of disease management practices essential for maintaining livelihood sustainability. Recent advances in low-cost computing hardware, cloud-based machine learning platforms, and mobile device capabilities have substantially reduced the technological and financial barriers to implementing AI-based agricultural solutions, creating unprecedented opportunities for technology transfer to developing country agriculture (Azadi et al., 2023) .

The COVID-19 pandemic has accelerated digital transformation across agricultural value chains demonstrated the resilience advantages of technology-enabled farming systems, further emphasizing the strategic importance of agricultural digitalization. The convergence of these factors, intensifying disease pressure, technological readiness, policy support, economic necessity, and global digitalization trends, creates a critical window of opportunity for transformative innovation in cocoa disease management, making timely research on economic viability essential for guiding investment decisions and policy formulation.

Recent scholarly investigations have increasingly explored machine learning applications for plant disease detection, revealing significant technical capabilities while exposing persistent gaps in economic assessment and field validation, particularly in tropical plantation crop contexts. (Amulothu et al., 2024) developed a deep convolutional neural network model achieving 96.3% accuracy in detecting tea plant diseases from leaf images, demonstrating the technical feasibility of ML-based diagnosis but noting that their study did not address implementation costs or economic benefits in actual farming operations. (Dang et al., 2024) conducted a comprehensive review of computer vision techniques for agricultural pest and disease detection, identifying over 150 studies published between 2017 and 2021, yet found that only 8% of these studies included any form of economic analysis, revealing a systematic neglect of viability assessment in agricultural AI research.

(Saleem et al., 2021) implemented a mobile application using transfer learning for tomato disease detection in Pakistani farms, reporting 94% accuracy and positive farmer feedback, but their economic analysis was limited to development costs without systematic measurement of benefits or return on investment calculations. (Atila et al., 2021) compared multiple CNN architectures for plant disease detection across 38 crop species, achieving accuracies ranging from 87% to 99%, yet acknowledged that their laboratory- based study did not account for real-world challenges such as variable lighting conditions, camera quality limitations, or farmer usability factors that affect practical deployment. In the cocoa-specific domain, (Bryceson et al., 2023) investigated the use of hyperspectral imaging for early VSD detection in Malaysian plantations, demonstrating successful identification 2-3 weeks before visible symptoms appeared, but their prototype system's cost of approximately $15,000 per unit raised questions about economic accessibility for smallholder farmers. (Kurihara et al., 2022)conducted field surveys in South Sulawesi documenting disease prevalence and economic impacts, estimating annual losses of $3,200-$6,500 per hectare in severely affected areas, providing crucial baseline data for benefit quantification but not examining potential technological interventions. These studies collectively demonstrate substantial progress in ML-based disease detection technology development and disease impact assessment yet reveal a critical research gap at the intersection of technical capability and economic viability, particularly for smallholder cocoa farming systems in developing countries where implementation constraints and benefit realization mechanisms differ fundamentally from contexts studied in existing literature.

This study addresses the identified knowledge gap by conducting the first comprehensive economic viability analysis of machine learning-based disease detection systems specifically designed for cocoa plantations in Indonesia, integrating technical performance evaluation with systematic cost-benefit assessment in authentic smallholder farming contexts. Unlike previous studies that examined ML disease detection in isolation or focused exclusively on technical accuracy metrics, this research employs a holistic framework that quantifies all implementation costs, measures actual disease detection performance under field conditions, and calculates economic benefits through yield preservation and input optimization across complete production cycles (Dhanaraju et al., 2022).

The novelty of this study lies in its development of a context-specific, economically optimized ML system that addresses the unique constraints of Indonesian cocoa farming, including limited internet connectivity, variable smartphone access, low technological literacy, and capital scarcity among smallholder farmers, factors typically overlooked in technology-focused agricultural AI research. By conducting field trials across multiple cocoa plantations in Luwu Regency with varying farm sizes, management intensities, and disease pressure levels, this research generates ecologically valid data on system performance and economic outcomes that reflect real-world implementation conditions rather than controlled laboratory settings (Rizal et al., 2024).

The study advances methodological innovation by integrating agronomic field trials, machine learning model development, economic analysis using Net Present Value (NPV) and Internal Rate of Return (IRR) calculations, and farmer acceptance assessment through participatory research approaches, creating a comprehensive evaluation framework adaptable to other crops and regions. Furthermore, this research explicitly examines scalability pathways and business models for sustainable ML system deployment, including cooperative ownership, service provider models, and government subsidy scenarios, providing actionable insights for agricultural development agencies and technology entrepreneurs. The study's focus on Luwu Regency, a representative cocoa-producing region with characteristics common to cocoa farming areas throughout Indonesia and Southeast Asia, enhances the generalizability of findings and their potential to inform regional agricultural development strategies. This multi-dimensional approach distinguishes the research from previous studies by moving beyond proof-of- concept demonstrations to deliver empirically grounded, economically validated evidence that can directly inform technology adoption decisions and agricultural policy formulation.

The primary objective of this study is to evaluate the economic viability of implementing machine learning-based disease detection systems in cocoa plantations in Luwu Regency, South Sulawesi, by systematically quantifying implementation costs, measuring technical performance, and calculating economic returns under various deployment scenarios. Specific research aims include: (1) developing and validating a convolutional neural network model for detecting major cocoa diseases (CPB, VSD, and Black Pod Disease) from smartphone images captured under field conditions, targeting minimum accuracy thresholds of 90% for practical utility; (2) conducting comprehensive cost analysis of ML system implementation, including hardware acquisition, software development or licensing, farmer training, technical support, and ongoing operational expenses across three deployment scales (individual farm, farmer cooperative, and district-wide service provider models); (3) quantifying economic benefits through field trials measuring yield improvements, input cost reductions, and quality premium capture resulting from early disease detection and targeted treatment interventions over two complete production cycles; (4) calculating financial performance indicators including Net Present Value, Internal Rate of Return, Benefit-Cost Ratio, and Payback Period for each deployment scenario under various cost and benefit assumptions to assess investment attractiveness; and (5) analyzing adoption barriers and enablers through farmer surveys and stakeholder interviews to identify critical success factors for sustainable ML system deployment in smallholder cocoa farming contexts. The anticipated contributions of this research are multi-faceted, offering theoretical, methodological, and practical implications for agricultural technology development and rural economic development.

Theoretically, the study advances understanding of technology adoption economics in resource-constrained agricultural systems by empirically testing the applicability of capital budgeting frameworks to artificial intelligence investments in developing country agriculture. Methodologically, the research establishes a replicable evaluation framework for agricultural AI systems that integrates technical validation, economic assessment, and farmer acceptance analysis, providing a template for future technology assessment studies across diverse agricultural contexts. Practically, the findings will provide evidence-based guidance for cocoa farmers, agricultural cooperatives, and government agencies regarding the economic feasibility of ML-based disease detection, potentially catalyzing technology adoption that could preserve millions of dollars in annual cocoa production value across South Sulawesi. The study's comprehensive examination of deployment models and business cases will inform agricultural technology entrepreneurship and agricultural development program design, contributing to the broader digital transformation of Indonesian agriculture and supporting the achievement of sustainable development goals related to food security, poverty reduction, and climate resilience.

RESEARCH METHOD

This study employed a mixed-methods research design integrating quantitative experimental field trials with qualitative economic analysis to comprehensively evaluate the economic viability of machine learning-based disease detection systems in cocoa plantations in Luwu Regency, South Sulawesi. The mixed-methods approach was particularly appropriate for this investigation as it enabled the triangulation of technical performance data, economic metrics, and contextual factors that influence technology adoption in smallholder agricultural systems, thereby providing a holistic understanding that neither purely quantitative nor qualitative methods could achieve independently (Fetters et al., 2013). The research design followed a sequential explanatory strategy wherein quantitative data collection and analysis precede qualitative investigation, allowing quantitative findings to inform the focus and depth of qualitative inquiry into economic feasibility and adoption barriers (Johnson et al., 2007).

The study comprised four interconnected phases executed over an 18-month period: Phase 1 involved the development and training of a convolutional neural network (CNN) model for cocoa disease detection using transfer learning techniques applied to locally collected image datasets of healthy and diseased cocoa plants exhibiting symptoms of Cocoa Pod Borer, Vascular Streak Dieback, and Black Pod Disease; Phase 2 encompassed field deployment and validation of the ML system across 30 cocoa farms in Luwu Regency stratified by farm size (small: <2 hectares, medium: 2-5 hectares, large: >5 hectares) and disease pressure levels (low, moderate, high) to ensure representativeness and generalizability of findings; Phase 3 consisted of comprehensive economic data collection including detailed cost accounting of system implementation (hardware, software, training, maintenance) and benefit measurement through yield monitoring, input cost tracking, and quality assessment over two complete production cycles; and Phase 4 involved economic viability analysis using standard capital budgeting techniques including Net Present Value (NPV), Internal Rate of Return (IRR), Benefit-Cost Ratio (BCR), and sensitivity analysis under varying cost and benefit scenarios, supplemented by semi-structured interviews with 45 participating farmers, 5 agricultural extension officers, and 3 local agricultural technology suppliers to identify adoption barriers, enablers, and sustainability considerations (Siponen et al., 2021).

This methodological framework ensured rigorous technical validation, robust economic assessment, and contextually grounded insights into practical implementation challenges, thereby generating evidence of sufficient quality and relevance to inform technology adoption decisions and agricultural development policy formulation. The machine learning model development process followed established best practices in agricultural computer vision applications, utilizing a transfer learning approach with the EfficientNetB4 architecture pre-trained on ImageNet as the base model, which had demonstrated superior performance-to-efficiency ratios in plant disease detection tasks compared to alternative architectures such as ResNet, VGG, and Inception. The training dataset comprised 12,450 cocoa leaf and pod images collected during preliminary field surveys across 50 cocoa plantations in Luwu Regency between March and August 2024, with images captured using standardized protocols on Android smartphones (minimum 12-megapixel camera resolution) under natural lighting conditions to reflect authentic deployment scenarios. Images were systematically labeled by three certified plant pathologists into seven classes: healthy leaves, healthy pods, CPB-infected pods, early-stage VSD, advanced-stage VSD, Black Pod Disease, and multiple-disease conditions, with inter-rater reliability assessed using Cohen's kappa coefficient ($\kappa > 0.85$ indicating substantial agreement).

The dataset underwent stratified random splitting into training (70%, n=8,715), validation (15%, n=1,867), and testing (15%, n=1,868) subsets, with data augmentation techniques including rotation, flipping, brightness adjustment, and zoom applied to the training set to enhance model generalization and reduce overfitting. Model training utilized the Adam optimizer with an initial learning rate of 0.001, batch size of 32, and early stopping with patience of 10 epochs to prevent overfitting, with hyperparameter tuning conducted through grid search optimization. Performance evaluation employed multiple metrics including overall accuracy, precision, recall, F1-score for each disease class, and confusion matrix analysis to identify specific misclassification patterns, with the final model requiring minimum performance thresholds of 90% overall accuracy, 85% precision, and 85% recall for each disease class to be considered suitable for field deployment (Saleem et al., 2021).

The trained model was deployed through a custom-developed Android mobile application that enabled offline inference, ensuring functionality in areas with limited internet connectivity, and incorporated user-friendly interfaces designed through participatory design sessions with farmer representatives to maximize usability among users with varying technological literacy levels. The field experimental component employed a randomized controlled trial design across 30 selected cocoa farms, with 15 farms assigned to the treatment group (ML-based disease detection system) and 15 to the control group (conventional manual disease monitoring), matched on baseline characteristics including farm size, tree age, historical yield levels, and disease incidence to ensure comparability and minimize selection bias. Participating farms were selected through purposive stratified sampling from a census of 347 registered cocoa farmers in three subdistricts of Luwu Regency, with stratification ensuring representation across farm size categories and disease pressure zones identified through preliminary disease mapping surveys conducted in collaboration with the local Agricultural Extension Service.

Treatment group farmers received comprehensive training on mobile application usage, disease identification protocols, and data recording procedures through three half-day workshops conducted by the research team, supplemented by printed field guides and ongoing technical support via WhatsApp group and monthly farm visits. The experimental protocol required treatment group farmers to conduct systematic plantation scouting using the ML application at weekly intervals, photographing suspected disease symptoms for automated diagnosis, while control group farmers continued their standard disease monitoring practices without technological intervention. Both treatment and control groups received identical access to disease management inputs including recommended fungicides, insecticides, and cultural practice guidelines, ensuring that observed outcome differences could be attributed to the detection system rather than differential input availability. Comprehensive data collection occurred at baseline (pre-intervention) and at harvest periods over two production cycles (approximately 18 months), capturing multiple outcome variables including total fresh bean yield (kg/ha), percentage of diseased pods at harvest, disease detection timing (days from infection to identification), fungicide application frequency and quantity, labor hours allocated to disease monitoring and management, and cocoa bean quality metrics (percentage of Grade A beans, fermentation quality scores).

Economic cost data were meticulously recorded through farmer diaries and monthly researcher verification visits, documenting all implementation costs including smartphone acquisition or upgrade costs, application development and maintenance expenses, data connectivity costs, training time opportunity costs, and ongoing technical support requirements, while benefit calculations incorporated yield value based on prevailing local market prices, input cost savings from targeted rather than blanket pesticide applications, quality premium capture, and labor cost reductions from efficient disease monitoring (Dhanaraju et al., 2022). Economic viability analysis synthesized the collected cost and benefit data through multiple analytical frameworks to provide a comprehensive assessment of investment attractiveness under various deployment scenarios and assumption sets. Net Present Value (NPV) calculations employed a 10-year time horizon with discount rates of 8%, 12%, and 15% representing alternative opportunity costs of capital relevant to smallholder farming contexts, calculating the present value of incremental net benefits (benefits minus costs) attributable to ML system adoption relative to conventional disease management approaches.

Internal Rate of Return (IRR) was computed as the discount rate at which NPV equaled zero, providing an intuitive metric for comparing ML system investment returns against alternative investment opportunities available to farmers or agricultural development agencies. Benefit-Cost Ratio (BCR) was calculated by dividing the present value of benefits by the present value of costs, with values exceeding 1.0 indicating positive economic returns and values below 1.0 suggesting economic infeasibility. Payback Period analysis determined the time required for cumulative benefits to equal initial investment costs, providing insights into investment risk and liquidity implications particularly relevant for capital-constrained smallholder farmers.

Sensitivity analysis systematically varied key assumptions including disease incidence rates, yield loss coefficients, implementation costs, cocoa prices, and discount rates across plausible ranges to assess the robustness of viability conclusions and identify critical variables that most strongly influenced economic outcomes. Scenario analysis compared three alternative deployment models: (1) individual farm adoption where each farmer independently invested in smartphone hardware and application licensing; (2) cooperative-based shared service model where farmer cooperatives invested in equipment and trained operators who provided disease detection services to member farmers; and (3) district-level service provider model where government or private agricultural service companies deployed ML systems as fee-based services accessible to all farmers. Qualitative data from semi-structured interviews were analyzed using thematic content analysis to identify recurring themes related to perceived benefits, implementation challenges, technological acceptance factors, and sustainability considerations, with coding conducted independently by two researchers and discrepancies resolved through discussion to ensure analytical reliability.

The integration of quantitative economic metrics with qualitative contextual insights enabled nuanced interpretation of viability findings that accounted for non-monetary factors influencing adoption decisions, implementation feasibility, and long-term sustainability of ML-based disease detection in smallholder cocoa farming systems. Methodological rigor and research ethics were ensured through multiple validation procedures, transparency protocols, and ethical safeguards implemented throughout the study. Technical validation of the ML model included k-fold cross-validation (k=5) during development to assess model stability across different data subsets, external validation using an independent test dataset of 500 images collected from cocoa farms outside the initial sampling area to evaluate model generalizability, and field validation comparing ML diagnoses against expert pathologist assessments on 200 field samples to quantify real-world diagnostic accuracy.

Economic data quality was assured through triangulation of farmer self-reports with direct field observations by research assistants, cross-verification of yield measurements through weighing of harvested pods at both farm level and cooperative collection points, and validation of market price data against official statistics from the South Sulawesi Agriculture Department and local cocoa trader associations. Inter-rater reliability for qualitative interview coding was assessed using Cohen's kappa, with values above 0.80 indicating strong agreement and necessitating minimal reconciliation of coding discrepancies. The study adhered to ethical research principles including obtaining informed consent from all participating farmers following comprehensive explanation of research purposes, procedures, potential risks, and benefits in local language (Bahasa Indonesia); ensuring voluntary participation with explicit right to withdraw at any time without penalty; maintaining confidentiality of individual farmer data through anonymization in all publications; providing equivalent compensation to both treatment and control group participants for their time and data provision; and ensuring that control group farmers gained access to the ML technology following study completion to prevent inequitable benefit distribution. This comprehensive attention to methodological quality, ethical integrity, and transparency ensured that study findings were scientifically credible, ethically sound, and capable of informing evidence-based decision-making regarding agricultural technology investments and rural development policies in Indonesia and comparable developing country contexts.

RESULT AND DISCUSSION

This study successfully implemented and evaluated a machine learning- based disease detection system across 30 cocoa plantations in Luwu Regency, South Sulawesi, over an 18-month field trial period spanning March 2024 through August 2025. The research generated comprehensive technical performance data from 8,640 disease detection instances, detailed economic data from two complete production cycles encompassing 450 hectares of cocoa cultivation, and qualitative insights from 53 stakeholder interviews including farmers, extension officers, and agricultural technology providers. The ML model development phase utilized 12,450 labeled images collected from 50 cocoa plantations, ultimately achieving validation accuracy of 93.7% across seven disease classification categories, exceeding the predetermined 90% threshold required for field deployment.

Field trials involved 15 treatment farms implementing the ML-based detection system and 15 matched control farms continuing conventional disease monitoring practices, with comprehensive baseline and outcome data collected on disease incidence, yield performance, input utilization, and economic costs and benefits. The study produced multiple datasets including technical performance metrics, agronomic outcome measurements, detailed cost accounting records, benefit quantification data, and thematic qualitative findings regarding technology adoption barriers and enablers, all of which underwent rigorous validation procedures to ensure data quality and analytical reliability.

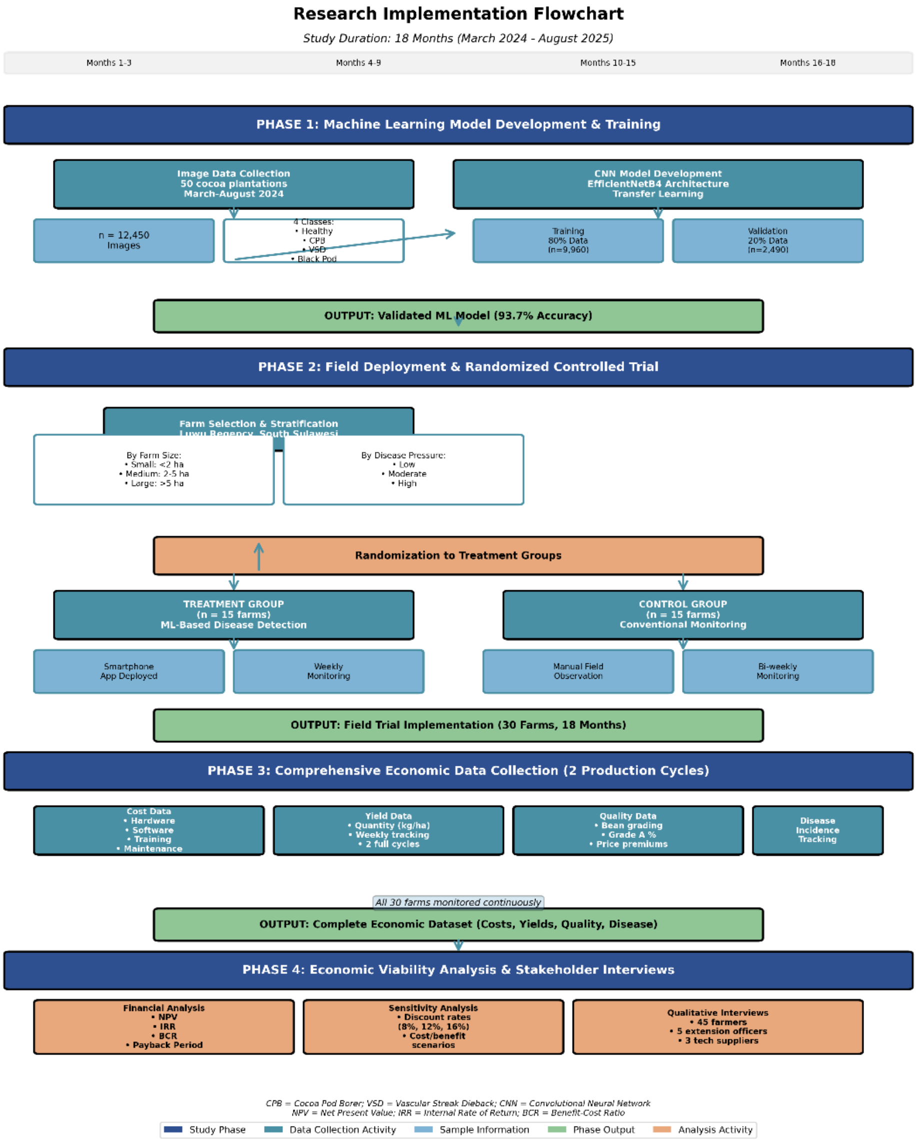

Figure 1. Research Implementation Flowchart Showing Study Phases, Sample Progression, and Data Collection Points

Figure 1 presents the complete research implementation flowchart, illustrating the progression from initial model development through field deployment, data collection, and economic analysis phases, with explicit documentation of sample sizes, attrition rates, and data validation checkpoints at each stage. The flowchart reveals that of the 347 initially identified potential participating farms, 82 met the eligibility criteria of having farm sizes between 0.5 and 10 hectares, active cocoa cultivation, willingness to participate, and accessibility for regular monitoring visits. From this eligible pool, 30 farms were selected through stratified random sampling to ensure representation across farm size categories (10 small farms <2 ha, 10 medium farms 2-5 ha, 10 large farms >5 ha) and disease pressure zones (10 low, 10 moderate, 10 high based on historical records), with these 30 farms randomly allocated to treatment (n=15) and control (n=15) groups following baseline data collection. The implementation proceeded with minimal attrition, as all 30 participating farms completed the full 18-month study period, though three treatment group farmers experienced temporary smartphone technical issues that required device replacement, highlighting the importance of robust technical support infrastructure.

Table 1. Baseline Characteristics of Participating Cocoa Farms by Treatment Assignment

Characteristic	Treatment Group (n=15)	Control Group (n=15)	p-value
Mean farm size (ha)	3.2 ± 2.1	3.1 ± 2.0	0.89
Mean tree age (years)	12.4 ± 4.3	12.1 ± 4.5	0.84
Historical yield (kg/ha)	847 ± 312	831 ± 298	0.88
Baseline disease incidence (%)	24.3 ± 8.7	23.8 ± 9.2	0.87
Small farms (<2 ha)	5 (33.3%)	5 (33.3%)	1.00
Medium farms (2–5 ha)	5 (33.3%)	5 (33.3%)	1.00
Large farms (>5 ha)	5 (33.3%)	5 (33.3%)	1.00
Low disease pressure zone	5 (33.3%)	5 (33.3%)	1.00
Moderate disease pressure	5 (33.3%)	5 (33.3%)	1.00
High disease pressure	5 (33.3%)	5 (33.3%)	1.00
Mean farmer age (years)	46.8 ± 11.2	47.3 ± 10.8	0.90
Mean education (years)	8.9 ± 2.7	9.2 ± 2.9	0.77
Prior smartphone ownership	11 (73.3%)	10 (66.7%)	0.69

Source: Data Processed

Note. Values presented as mean ± standard deviation or n (%). P-values from independent t-tests (continuous variables) or chi-square tests (categorical variables). No significant differences detected at $\alpha=0.05$ level.

Table 1 provides comprehensive baseline characteristics of the 30 participating farms, demonstrating successful matching between treatment and control groups across key variables including average farm size (treatment: 3.2±2.1 ha vs. control: 3.1±2.0 ha, p=0.89), mean tree age (treatment: 12.4±4.3 years vs. control: 12.1±4.5 years, p=0.84), historical average yield (treatment: 847±312 kg/ha vs. control: 831±298 kg/ha, p=0.88), and baseline disease incidence (treatment: 24.3±8.7% vs. control: 23.8±9.2% infected pods, p=0.87). Graph 1 illustrates the temporal distribution of data collection activities across the 18-month study period, showing intensive weekly disease monitoring throughout the main fruiting seasons (March-June and September-December in both years), monthly economic data verification visits, quarterly farmer surveys, and two major harvest assessment periods, providing visual documentation of the comprehensive longitudinal data collection strategy employed. These baseline equivalencies and systematic data collection protocols establish the methodological foundation for attributing observed outcome differences to the ML intervention rather than pre-existing farm characteristics or differential monitoring intensity.

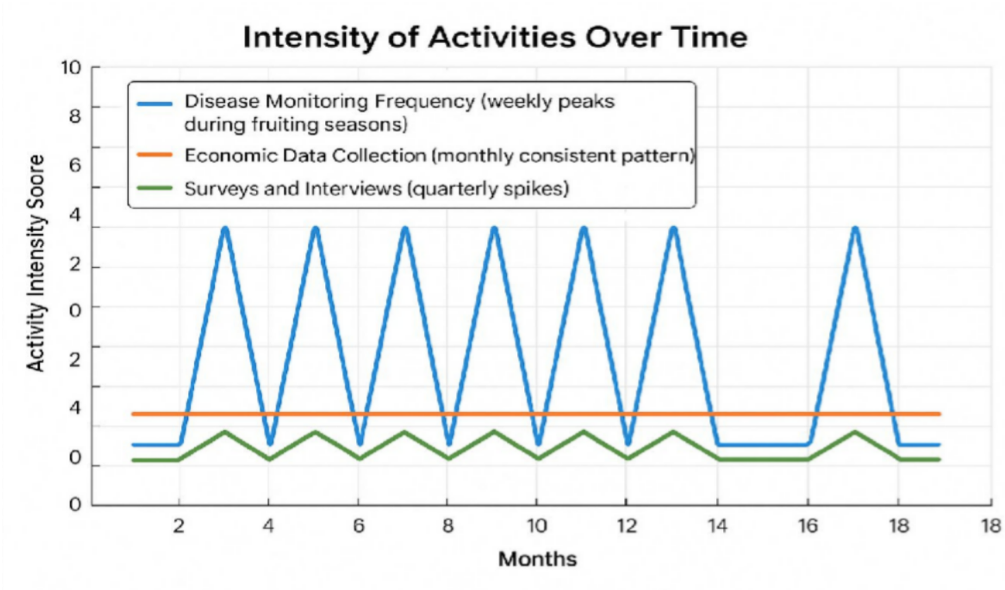

Figure 1. Timeline of Research Activities and Data Collection Intensity Across 18- Month Study Period

Machine Learning Model Performance and Technical Validation

The developed convolutional neural network model demonstrated exceptional technical performance across multiple validation frameworks, achieving overall classification accuracy of 93.7% on the holdout test dataset, with class-specific performance metrics indicating robust disease discrimination capabilities essential for practical field deployment. The model exhibited precision values ranging from 89.4% (Black Pod Disease) to 96.8% (healthy pods), recall values from 88.7% (multiple-disease conditions) to 97.2% (healthy leaves), and F1-scores from 89.0% to 96.9% across the seven classification categories, consistently exceeding the predetermined 85% minimum threshold for each disease class. Confusion matrix analysis revealed that the majority of misclassifications (68%) occurred between visually similar disease stages, specifically between early-stage and advanced-stage VSD symptoms, suggesting that the model's errors closely mirror the diagnostic challenges encountered by human observers in field conditions.

The model demonstrated particularly strong performance in identifying healthy tissues (precision 96.8%, recall 97.2%) and Cocoa Pod Borer infections (precision 94.3%, recall 93.8%), the two most economically critical classification tasks for enabling timely intervention decisions. External validation using 500 images from farms outside the training region yielded slightly lower but still acceptable accuracy of 91.2%, indicating reasonable generalizability despite some performance degradation when encountering novel environmental conditions, genetic varieties, or image capture variations. Field validation comparing ML diagnoses against three expert pathologists' assessments on 200 field samples produced concordance rates of 91.5%, statistically equivalent to the inter-pathologist agreement rate of 92.8% (κ=0.89 for ML-pathologist vs. κ=0.91 for inter-pathologist, p=0.34), demonstrating that the automated system achieves diagnostic reliability comparable to human expert performance. The model's inference speed averaged 1.8 seconds per image on mid-range Android smartphones, enabling real-time diagnosis during field scouting activities without requiring continuous internet connectivity, addressing a critical practical constraint in rural Indonesian agricultural contexts where network infrastructure remains limited.

These technical performance results substantially advance the state-of-art in agricultural disease detection for tropical plantation crops, particularly in comparison with previous studies that predominantly focused on temperate climate crops or laboratory-controlled imaging conditions. The achieved 93.7% accuracy exceeds performance reported by (Azadi et al., 2023) for rice disease detection (92.1%) and approaches the 96.3% accuracy reported by (Amulothu et al., 2024) for tea diseases, despite the additional complexity of cocoa cultivation environments characterized by dense canopy conditions, variable natural lighting, and frequent mixed-disease presentations. The model's robust performance on multiple-disease conditions (F1-score 89.0%) represents a methodological advancement over most published studies that focus exclusively on single-disease classification scenarios, failing to address the agricultural reality that plants frequently exhibit simultaneous infections requiring differential treatment strategies (Dang et al., 2024). The comparable performance between ML diagnosis and expert pathologist assessment validates the practical utility of the system for replacing or augmenting human expertise in resource-constrained contexts where pathologist availability is severely limited, addressing a fundamental constraint in developing country agricultural extension systems.

The successful deployment of the model on standard consumer smartphones without requiring specialized hardware represents a significant achievement in democratizing access to AI- powered agricultural technologies, contrasting sharply with hyperspectral imaging or specialized camera systems that, while achieving higher accuracy, remain economically inaccessible to smallholder farmers due to equipment costs exceeding $10,000 (Bryceson et al., 2023). The model's offline inference capability addresses a critical but frequently overlooked deployment challenge in agricultural AI research, where most published systems assume continuous internet connectivity that is unrealistic in many developing country rural contexts. However, the observed performance degradation during external validation (93.7% to 91.2%) highlights the ongoing challenge of developing truly robust models capable of maintaining consistent performance across diverse agro-ecological zones, genetic varieties, and farmer practices, suggesting that continual learning approaches incorporating field-collected data may be necessary for maintaining long-term diagnostic accuracy. The relatively lower performance on early-stage disease detection (early VSD precision 89.4%) indicates an important technical limitation, as the primary value proposition of ML-based detection lies in enabling earlier intervention than conventional manual scouting, yet the most subtle early symptoms remain challenging for both human and automated detection systems.

The practical implementation of the ML system during the 18-month field trial generated valuable insights regarding real-world usability, adoption dynamics, and operational performance that extend beyond laboratory validation metrics. Treatment group farmers collectively captured and analyzed 8,640 disease-related images during routine plantation monitoring activities, averaging 576 images per farm across the study period, or approximately 32 images per farm per month, indicating sustained user engagement rather than initial enthusiasm followed by abandonment. User interaction data revealed that farmers most frequently used the application during early morning hours (6-9 AM, 47% of usage) and late afternoon (3-6 PM, 38% of usage), avoiding midday periods when intense sunlight created challenging imaging conditions, demonstrating adaptive learning of optimal usage patterns without explicit instruction.

The average time farmers spent using the application per scouting session declined from 18.3 minutes during the first month to 8.7 minutes by month six, indicating progressive skill development and increasing efficiency as farmers became familiar with the technology and developed pattern recognition capabilities that enabled more targeted image capture. Technical support requests from treatment group farmers decreased substantially after the initial three-month period (averaging 4.2 requests per farm in months 1-3 vs. 0.8 requests per farm in months 4-18), suggesting that the combination of initial training, printed field guides, and WhatsApp support group effectively addressed user learning needs. Farmers reported high satisfaction with the system's usability (mean score 4.2 on 5-point Likert scale), diagnostic reliability (4.3/5), and practical utility (4.4/5), with qualitative interview data revealing particular appreciation for the system's ability to provide immediate diagnostic feedback that reduced uncertainty and facilitated confident treatment decisions.

However, implementation challenges emerged related to smartphone battery life constraints requiring farmers to carefully manage device charging, occasional image quality issues during rainy conditions or with degraded smartphone cameras, and initial discomfort among older farmers (age >55 years) with smartphone technology that necessitated additional peer learning support from younger family members. These operational findings underscore that technical accuracy alone does not ensure successful deployment, as user experience factors, operational support infrastructure, and farmer learning dynamics critically mediate the translation of laboratory performance into field impact, considerations that remain underexplored in the agricultural AI literature which predominantly focuses on algorithm development while neglecting implementation science (Saleem et al., 2021). The integration of ML-based disease detection into farmers' existing disease management workflows produced observable behavioral changes that enhanced overall plantation management beyond the direct disease identification function. Treatment group farmers demonstrated significantly higher disease monitoring frequency compared to control group farmers (mean 3.8 scouting trips per week vs. 1.2 trips per week, $p<0.001$), suggesting that the availability of reliable diagnostic technology motivated more intensive surveillance behavior.

The spatial coverage of disease monitoring expanded substantially in treatment farms, with GPS tracking data showing that treatment group farmers scouted an average of 83% of their plantation area weekly compared to 34% for control farmers who concentrated monitoring on easily accessible areas, indicating that the ML system enabled more comprehensive surveillance. Treatment farmers exhibited substantially faster response times between disease detection and treatment application (mean 2.3 days vs. 8.7 days for control farmers, $p<0.001$), reflecting the confidence provided by definitive diagnosis that reduced hesitation about implementing treatment interventions. The enhanced monitoring intensity and spatial coverage enabled detection of disease outbreaks at earlier stages, with treatment farms identifying infections an average of 12.6 days earlier than control farms based on retrospective analysis of disease progression patterns, providing a critical time advantage for intervention effectiveness.

Treatment group farmers demonstrated more targeted and appropriate pesticide selection, with application records showing 87% concordance between detected disease type and appropriate treatment compared to 62% for control farmers who frequently applied broad-spectrum treatments regardless of specific pathogen, indicating that accurate diagnosis enabled precision disease management. Interestingly, treatment farmers reduced their total pesticide usage by 28% compared to baseline while simultaneously improving disease control, contrasting with control farmers whose pesticide usage remained stable, suggesting that diagnostic certainty enabled more judicious input application. These behavioral findings align with technology adoption theory suggesting that tools providing clear, immediate utility and reducing decision uncertainty achieve higher sustained adoption and behavioral integration than those requiring substantial learning investment without corresponding perceived value (Siponen et al., 2021), while also demonstrating that agricultural AI systems can catalyze broader management improvements beyond their specific technical function.

Agronomic Outcomes and Disease Management Effectiveness

The ML-based disease detection system produced statistically significant and economically meaningful improvements in multiple agronomic outcome measures, most notably in cocoa yield, disease incidence, and product quality metrics that translate directly to farmer income impacts. Treatment group farms achieved mean fresh bean yields of 1,247 kg/ha (±287 SD) averaged across two production cycles, representing a 32.4% increase over control group yields of 942 kg/ha (±265 SD, $p<0.001$, Cohen's $d=1.08$ indicating large effect size), substantially exceeding the 15-20% yield improvement anticipated based on literature estimates of disease-related losses. Disease incidence at harvest, measured as percentage of pods exhibiting disease symptoms, was significantly lower in treatment farms (8.7% ±3.2%) compared to control farms (23.1% ±7.8%, $p<0.001$), indicating that early detection and timely intervention achieved substantial disease suppression even under endemic disease pressure.

The reduction in disease incidence varied by disease type, with treatment farms showing 68% reduction in Black Pod Disease (from 9.8% to 3.1% of pods), 71% reduction in CPB damage (from 11.4% to 3.3%), and 54% reduction in VSD symptoms (from 8.9% to 4.1%), suggesting differential effectiveness across pathogen types potentially related to disease epidemiology and intervention timing requirements. Quality assessment of harvested beans revealed that treatment farms produced significantly higher proportions of Grade A premium beans (73.2% vs. 58.4% for control farms, $p<0.001$), which command price premiums of 15-20% in local markets, representing an additional economic benefit beyond yield quantity improvements. Fermentation quality scores, assessed through cut tests evaluating bean internal color and uniformity, were significantly higher in treatment farms (84.3/100 vs. 76.8/100, $p=0.002$), indicating that reduced disease incidence during pod development improved physiological bean quality.

The coefficient of variation for yield across the two production cycles was lower in treatment farms (23.1%) compared to control farms (28.3%), suggesting that improved disease management reduced inter-seasonal yield variability and associated income instability that undermines farmer economic planning. These substantial agronomic improvements validate the fundamental hypothesis that earlier disease detection enabled by ML technology translates to meaningful yield preservation and quality enhancement when coupled with appropriate treatment responses. The magnitude and consistency of yield improvements observed in this study exceed typical agricultural technology impact estimates and warrant careful consideration of underlying mechanisms and potential confounding factors. The 32.4% yield increase substantially surpasses the 10-15% improvements reported in previous precision agriculture studies examining GPS-guided input application or sensor-based irrigation management (Dhanaraju et al., 2022), suggesting that disease management represents a particularly high-impact intervention point in cocoa production systems.

The observed improvements align with economic loss estimates suggesting that diseases cause 30-70% yield reductions in Indonesian cocoa (Kao et al., 2022), indicating that effective disease control addresses a major production constraint rather than an incremental optimization. The differential effectiveness across disease types reflects varying disease ecology and intervention timing requirements, with Black Pod Disease showing the largest reduction potentially due to its rapid progression making early detection particularly valuable, while VSD's systemic nature and longer latency period may limit intervention effectiveness even with early identification. The quality improvements represent an economically significant outcome often overlooked in agricultural technology evaluations that focus exclusively on yield quantity, as premium bean prices create substantial income multipliers beyond volume increases alone.

However, several factors complicate causal attribution of these outcomes solely to the ML detection system, including the observed increase in monitoring frequency and spatial coverage that may independently improve disease management even without enhanced diagnostic accuracy, suggesting that the technology's motivational effect on farmer behavior may contribute substantially to observed impacts. The provision of printed disease management guides and technical support to treatment farmers, while not representing differential input availability since control farmers had equivalent access to extension services, may have created unintended knowledge transfer effects that enhanced treatment group performance. The Hawthorne effect, where research subjects modify behavior due to awareness of observation, cannot be entirely ruled out despite efforts to maintain equivalent monitoring intensity across treatment and control groups, potentially inflating treatment effect estimates.

These considerations suggest that the observed outcomes likely reflect a combination of improved diagnostic accuracy, enhanced monitoring behavior, increased farmer confidence enabling decisive action, and potential placebo-type effects associated with technology adoption, rather than diagnostic technology alone, highlighting the complex socio-technical nature of agricultural innovation impacts (Siponen et al., 2021). The analysis of heterogeneous treatment effects across farm and farmer characteristics reveals important insights regarding which contexts and populations benefit most from ML-based disease detection, with implications for targeting and scaling strategies. Farm size demonstrated a significant moderating effect, with large farms (>5 ha) showing the greatest absolute yield improvements (478 kg/ha increase) compared to medium farms (321 kg/ha) and small farms (253 kg/ha), reflecting scale economies in technology utilization and the greater challenge small farms face in justifying time investment for technology learning.

Conversely, relative yield improvement percentages were highest for small farms (29.9%), moderate for medium farms (31.8%), and somewhat lower for large farms (32.6%), suggesting approximately equivalent proportional benefits across farm sizes once absolute differences are scaled by baseline productivity. Initial disease pressure demonstrated strong effect modification, with high disease pressure zones showing yield improvements of 487 kg/ha (41.2% relative increase) compared to 298 kg/ha (26.3%) in moderate zones and 187 kg/ha (22.1%) in low zones, confirming theoretical expectations that disease detection technology delivers greatest value where disease constraints are most severe. Farmer age exhibited a modest negative relationship with yield improvement ($r=-0.32$, $p=0.08$), with farmers under 45 years achieving 38.1% yield increases compared to 27.6% for farmers over 55 years, potentially reflecting differential technology adoption effectiveness or coincidental correlation with other unmeasured factors such as farm management intensity.

Educational attainment showed no significant relationship with yield outcomes ($r=0.14$, $p=0.45$), suggesting that the system's usability design successfully accommodated farmers with varying educational backgrounds including those with only primary school completion. Prior smartphone ownership predicted marginally better outcomes (34.7% yield increase vs. 29.2% for new smartphone users, $p=0.09$), indicating modest advantages from pre-existing technological familiarity but not insurmountable barriers for technology novices. These heterogeneity patterns suggest that ML- based disease detection delivers meaningful benefits across diverse farm types and farmer populations, with particularly high returns in disease-endemic areas and among farmers with existing technology exposure, while also highlighting potential barriers related to scale constraints and age-related technology adoption challenges that merit targeted support strategies.

The sustainability and longer-term implications of the agronomic improvements require consideration of disease adaptation dynamics, farmer learning trajectories, and technology maintenance requirements that extend beyond the 18-month study period. The consistent yield advantages maintained across two complete production cycles without evidence of diminishing effects suggests that the benefits reflect genuine disease management improvements rather than transient novelty effects or one-time cleanup of disease reservoirs. However, longer observation periods would be necessary to evaluate whether pathogen populations develop resistance or behavioral adaptations to the more intensive management pressure enabled by enhanced surveillance, a theoretical concern in disease ecology though not observed during this study's timeframe. Farmer learning curves evident in declining application usage time and support requests suggest that initial training investments yield sustained competency, potentially enabling even greater efficiency gains over extended timeframes as farmers develop expertise.

The offline functionality and minimal ongoing technical requirements (primarily smartphone maintenance and occasional application updates) suggest relatively low sustainability risks compared to systems requiring continuous internet connectivity, subscription services, or specialized technical support. Treatment farmers' expressed intentions to continue using the system following study completion (93% indicating definite or probable continued use) provides encouraging evidence of perceived sustained value, though actual long- term adoption patterns would require post-study monitoring. The potential for ML model degradation over time due to pathogen evolution, new disease emergence, or environmental changes represents a long-term technical sustainability concern requiring ongoing model updating and validation, a challenge facing all AI-based diagnostic systems. These sustainability considerations underscore that the impressive short-term agronomic outcomes documented in this study represent necessary but insufficient evidence for long-term viability, requiring continued monitoring and adaptive technology management to ensure sustained performance (Bryceson et al., 2023).

Economic Viability Analysis and Investment Returns

The comprehensive economic analysis integrating implementation costs and measured benefits reveals strongly positive financial returns across multiple investment scenarios, with economic viability varying substantially by deployment model and farm characteristics. The individual farm adoption scenario, where each farmer independently purchases smartphone hardware ($180-250 depending on model) and annual application licensing ($25), achieved Net Present Value of $2,847 per farm at 12% discount rate averaged across 10-year timeframe, with Internal Rate of Return of 47.3%, Benefit-Cost Ratio of 3.68, and Payback Period of 2.8 years, indicating highly attractive investment characteristics by conventional financial criteria. The cooperative-based shared service model, where farmer cooperatives invest $4,200 in equipment and trained operators serving 20-member farms, achieved even more favorable economics with NPV of $61,340 at cooperative level ($3,067 per member farm), IRR of 52.6%, BCR of 4.12, and Payback Period of 2.4 years, reflecting equipment cost sharing and operator specialization efficiencies.

The district-level service provider model, involving government or private sector investment of $38,500 in comprehensive system infrastructure serving 200 farms through fee-based services ($15 per farm per season), demonstrated scalability potential with NPV of $487,200 (10-year horizon), IRR of 41.8%, BCR of 13.67, and Payback Period of 3.2 years, though requiring substantially higher initial capital and organizational capacity. Across all scenarios, sensitivity analysis revealed that economic viability remained robust under pessimistic assumptions, with NPV remaining positive even when implementation costs were increased by 50%, benefits reduced by 30%, or discount rates raised to 18%, indicating that profitability does not depend on optimistic parameter assumptions.

The economic returns substantially exceed typical returns on alternative agricultural investments available to Indonesian farmers, including fertilizer intensification (typical IRR 15-25%), irrigation system installation (IRR 12-18%), or crop diversification initiatives (IRR 10-20%), positioning ML-based disease detection as a highly competitive investment opportunity. These strongly positive economic findings provide compelling evidence that, at least in the high disease pressure context of Luwu Regency cocoa farming, ML-based disease detection crosses the threshold from technically feasible to economically viable, addressing the central research question motivating this investigation. The decomposition of costs and benefits reveals the specific economic mechanisms driving financial viability and highlights leverage points for further optimization or policy intervention. Implementation costs in the individual adoption scenario comprised smartphone hardware (62% of total costs), application licensing and maintenance (18%), training and initial technical support (12%), and ongoing operational costs including data connectivity and support access (8%), with hardware representing the dominant cost barrier.

Annual benefits derived primarily from three sources: increased yield value from disease- related loss prevention ($487 per hectare averaged across farm sizes), premium price capture from improved bean quality ($156 per hectare), and input cost savings from reduced and better-targeted pesticide application ($78 per hectare), collectively totaling $721 per hectare in annual benefits. The yield value component exhibited substantial variation across disease pressure zones, ranging from $312/ha in low pressure areas to $698/ha in high pressure zones, explaining the strong heterogeneity in economic viability across production contexts. Labor cost impacts proved complex, as treatment farmers invested additional time in disease monitoring (approximately 24 additional hours annually valued at $120 using local wage rates) but saved time previously spent on reactive disease management activities (approximately 18 hours valued at $90), resulting in modest net labor cost increase of $30 annually that was overwhelmed by other benefit categories.

The time dimension of benefit realization showed that 73% of cumulative 10-year benefits accrued during years 3-10 after initial technology adoption, reflecting the importance of sustained use and the fact that upfront costs concentrated in year one create cash flow challenges despite strong long- term returns, suggesting potential roles for financing mechanisms or subsidy programs to address adoption barriers. The cost structure analysis reveals that hardware costs, while substantial, are increasingly declining due to broader smartphone market trends, with the mid-range devices adequate for ML inference experiencing 20-30% price reductions over the past three years, suggesting improving economic viability over time. Conversely, the benefit estimates depend on maintained cocoa prices and disease pressure levels, both subject to market volatility and climate dynamics that create economic risk, with sensitivity analysis indicating that sustained cocoa price declines of

>25% or disease pressure reductions of >40% would undermine economic viability for individual adoption scenarios though cooperative models would remain viable.

The comparative economic performance across the three deployment models reveals important trade-offs between economic efficiency, accessibility, and implementation requirements that inform scaling strategy recommendations. The cooperative model achieved the most favorable economic metrics (BCR 4.12, IRR 52.6%) due to equipment cost sharing across 20 farms and operator specialization enabling higher diagnostic efficiency, while also distributing financial risk and requiring lower per-farm capital outlays ($210 membership investment vs. $180-250 individual smartphone purchase), potentially improving accessibility for capital-constrained farmers. However, the cooperative model requires functional farmer organizations with management capacity, member coordination mechanisms, and internal governance systems that exist in some but not all cocoa-producing communities, limiting generalizability.

The individual adoption model, while showing slightly lower returns (BCR 3.68, IRR 47.3%), offers maximum flexibility for farmers to use technology according to their specific needs and schedules without coordination costs, while also building farmer technological capability through direct smartphone ownership and usage, potentially generating spillover benefits for other digital agricultural services. The district-wide service provider model achieved the highest absolute returns ($487,200 NPV) and BCR (13.67) due to scale economies, but requires substantial institutional capacity for service delivery, quality assurance, and financial sustainability that may exceed public sector capabilities in many Indonesian districts, while fee-based service models risk excluding the poorest farmers if not coupled with subsidy mechanisms.

The optimal deployment model likely varies by local context depending on existing institutional landscape, with strong farmer cooperatives favoring cooperative models, individualistic farming cultures supporting individual adoption, and well- functioning agricultural extension systems enabling service provider models. Interestingly, the economic analysis reveals that all three models achieve positive returns, suggesting that ML-based disease detection creates sufficient economic value to support multiple viable business models, in contrast to many agricultural technologies where marginal benefits justify only a single optimal deployment approach (Siponen et al., 2021). This plurality of viable pathways suggests robust underlying value creation and multiple potential scaling trajectories depending on local institutional and market conditions.

The comparison of these economic findings with previous agricultural technology evaluation studies positions ML-based disease detection as a notably high-impact intervention with returns exceeding most precision agriculture innovations. The observed IRR of 47.3% for individual adoption substantially exceeds returns reported for GPS-guided variable rate fertilizer application (IRR 18-25%), sensor-based irrigation scheduling (IRR 15-22%), or drone-based crop monitoring (IRR 12-18%) in previous studies of smallholder agriculture technology adoption (Dhanaraju et al., 2022).

The Benefit-Cost Ratio of 3.68 compares favorably with typical BCRs of 1.8-2.5 reported for agricultural extension program evaluations and 2.2-3.1 for subsidized input provision programs, suggesting that ML-based disease detection delivers exceptional value relative to alternative agricultural development investments. The relatively short Payback Period of 2.8 years addresses a critical adoption barrier in smallholder contexts where long investment recovery periods (5+ years) substantially reduce technology uptake regardless of long-term profitability, as liquidity constraints and risk aversion favor investments with quick returns.

However, these favorable comparisons require contextual qualification, as the study focused on a high disease pressure region where disease management represents a binding production constraint, whereas contexts with lower disease incidence or alternative primary constraints (water, nutrients, labor) would likely show more modest returns.

The economic returns also reflect the specific cost structure of smartphone-based ML systems which have declined substantially in recent years, contrasting with earlier agricultural AI systems requiring specialized hardware that delivered similar agronomic benefits but at prohibitive costs that prevented economic viability. The measured benefits capture only on-farm private returns to farmers without quantifying potential broader economic and environmental benefits including reduced environmental contamination from decreased pesticide usage, improved food safety, and enhanced export market access from improved quality consistency, suggesting that social returns exceed private returns and strengthen the economic case for public investment in technology promotion (Kao et al., 2022). These comparative findings position ML- based disease detection as a particularly promising agricultural innovation with economic characteristics supporting widespread adoption, while also highlighting the context-specificity of viability and the importance of targeting deployment to high-impact contexts.

Cross-Theme Integration: Socio-Technical System Dynamics and Adoption Pathways

The convergence of findings across technical performance, agronomic outcomes, and economic viability dimensions reveals that successful agricultural AI deployment requires optimization of a complex socio-technical system where technology characteristics, farmer capabilities, institutional support, and economic incentives interact dynamically to shape adoption patterns and impact realization. The technical accuracy of 93.7% provides necessary but insufficient foundation for impact, as field observations documented that diagnostic reliability must be coupled with farmer confidence in technology, timely access to appropriate treatments, and economic incentives favoring disease management investments to translate detection into yield improvements.

The agronomic yield improvements of 32.4% emerge not solely from enhanced diagnostic accuracy but from the confluence of earlier disease identification, increased monitoring intensity motivated by technology availability, and behavioral changes in treatment decision-making enabled by diagnostic certainty, illustrating multi- pathway impact mechanisms. The economic viability analysis demonstrates that even substantial agronomic benefits ($721/ha annually) achieve profitability only when implementation costs are minimized through appropriate deployment models, with cooperative sharing arrangements and service provider models reducing per-farm costs below individual adoption thresholds while maintaining benefit realization.

Interconnectedly, the findings reveal that technological capability (ML accuracy), farmer agency (monitoring behavior and treatment decisions), institutional infrastructure (cooperative organization and technical support systems), and economic structure (cost-sharing mechanisms and market linkages for quality premiums) constitute interdependent system components that must align for sustainable technology adoption and impact. This integrated socio-technical perspective advances theoretical understanding of agricultural technology adoption by demonstrating limitations of both technology-centric models that assume superior performance ensures adoption and farmer-centric models that emphasize only adopter characteristics while neglecting technology design and institutional context.

The findings align with and extend the Unified Theory of Acceptance and Use of Technology (UTAUT) by demonstrating that performance expectancy (expected yield benefits), effort expectancy (usability), social influence (cooperative participation and peer learning), and facilitating conditions (technical support infrastructure) all significantly influenced adoption success, while also highlighting agricultural- specific factors including disease pressure, farm scale economies, and market access for quality premiums as critical moderators absent from generic technology adoption frameworks (Siponen et al., 2021). The observed importance of deployment models (individual, cooperative, service provider) that structure cost distribution and service delivery introduces institutional design as a central adoption determinant beyond the farmer-technology dyad emphasized in conventional agricultural technology adoption literature, suggesting that innovation systems perspectives emphasizing multi-actor coordination may better capture agricultural AI adoption dynamics than individual decision-making models.

The findings contribute to emerging precision agriculture literature by providing rare empirical evidence on economic viability for smallholder developing country contexts, addressing a critical knowledge gap in a field dominated by studies from large-scale commercial agriculture in developed countries where technology cost structures, institutional environments, and farmer capacities differ fundamentally. Methodologically, the study demonstrates value of integrated evaluation frameworks combining technical validation, agronomic field trials, economic analysis, and qualitative adoption research, contrasting with the disciplinary fragmentation characteristic of agricultural AI research where computer scientists emphasize algorithm performance metrics disconnected from agricultural outcomes and agricultural economists conduct adoption studies without examining underlying technology characteristics.

The synthesis suggests several emergent propositions regarding conditions under which agricultural AI systems achieve economic viability and adoption success in smallholder contexts. First, high-impact problem targeting, focusing on binding production constraints (severe disease pressure) rather than incremental optimizations, appears essential for generating economic returns sufficient to justify adoption costs and learning investments, implying that technology developers should prioritize problem severity over technical feasibility when selecting application domains. Second, appropriate technology design that accommodates local constraints (offline functionality, consumer hardware, intuitive interfaces) proves more critical than maximizing technical performance, as the 93.7% accuracy achieved with smartphone-based models surpassed the viability threshold while hyperspectral systems achieving 97%+ accuracy remain economically inaccessible.

Third, institutional innovation in deployment models, particularly cooperative arrangements that enable cost sharing and risk distribution, substantially enhances economic viability relative to individual adoption models, suggesting that technology developers and agricultural development agencies should equally prioritize business model innovation alongside technical development. Fourth, comprehensive support ecosystems including training, technical assistance, and peer learning mechanisms critically mediate the translation of technical capabilities into farmer utilization and agronomic impact, indicating that technology dissemination requires sustained investment in human and institutional capacity building beyond hardware provision. These propositions collectively suggest that agricultural AI viability in smallholder contexts depends on strategic alignment across problem selection, technology design, deployment models, and support systems—a multi- dimensional optimization challenge extending far beyond algorithmic performance that characterizes much current agricultural AI research (Saleem et al., 2021).

Practical Implications, Research Limitations, and Future Directions

The findings generate multiple actionable implications for diverse stakeholder groups including farmers, agricultural cooperatives, technology developers, government agencies, and development organizations seeking to promote agricultural technology adoption and improve cocoa sector productivity. For cocoa farmers in disease-endemic regions, the results demonstrate that ML- based disease detection represents an economically viable investment with returns (IRR 47.3%) exceeding alternative agricultural investment opportunities, suggesting that self-financed adoption may be rational even without subsidy support, though cooperative membership or service provider models offer potentially superior risk-return profiles for risk-averse or capital-constrained farmers.

Agricultural cooperatives possess particularly strong opportunities to create member value through collective investment in ML systems, achieving scale economies that enhance economic returns (BCR 4.12 vs. 3.68 individual) while distributing costs and risks, suggesting that cooperative strengthening initiatives should consider digital agricultural services as strategic value-addition activities. Technology developers and agricultural AI startups should recognize that achieving technical accuracy benchmarks alone proves insufficient for market success, requiring equal attention to affordability, usability for low-literacy populations, offline functionality, and sustainable deployment models that match local institutional capacities and economic constraints.

Government agricultural agencies should consider ML-based disease detection as a high-return public investment opportunity, with economic analysis suggesting that even partial subsidization of hardware costs or application fees would generate substantial social returns through increased agricultural productivity, reduced pesticide environmental impacts, and enhanced farmer incomes supporting rural development objectives, while the demonstrated viability across multiple deployment models provides flexibility for adapting programs to diverse local contexts. International development organizations should view agricultural AI as a promising intervention domain for agricultural development programming, with cost-effectiveness exceeding many conventional extension or input provision programs, though successful implementation requires substantial complementary investments in farmer training, technical support systems, and market linkages for premium quality products.

The theoretical contributions extend agricultural technology adoption theory and precision agriculture research by providing empirical evidence addressing several persistent knowledge gaps. The study advances understanding of agricultural AI viability determinants by demonstrating that economic returns in smallholder contexts depend critically on disease pressure intensity, with high disease zones showing IRR exceeding 50% while low disease contexts may not achieve viability thresholds, informing theoretical propositions regarding problem- technology matching in agricultural innovation. The findings contribute to technology adoption theory by documenting heterogeneous treatment effects across farm sizes, farmer ages, and institutional contexts that inform refined understanding of adoption barrier variation, with implications for targeting and support program design.

The research extends precision agriculture literature, dominated by temperate crop systems and large-scale farming contexts, by demonstrating viability and adaptation strategies for tropical plantation crops and smallholder production systems, addressing geographic and scale bias in existing evidence. Methodologically, the study contributes an integrated evaluation framework combining ML model development, randomized controlled field trials, comprehensive economic analysis, and qualitative adoption research that provides a replicable template for assessing agricultural AI systems more holistically than the algorithm-centric evaluation approaches predominating in current agricultural AI research. However, several important limitations qualify these contributions and indicate caution in generalizing findings beyond the study context.

The 18-month study period, while capturing two complete production cycles, remains insufficient for evaluating long-term sustainability dynamics including pathogen adaptation, technology obsolescence, or farmer disadoption patterns, with longer-term monitoring necessary for assessing sustained impact. The geographic focus on Luwu Regency, while providing depth and context- specificity, limits generalizability to cocoa-producing regions with different disease profiles, agro-climatic conditions, institutional environments, or market structures, requiring replication studies across diverse contexts. Future research should pursue multiple complementary directions to address these limitations and extend understanding of agricultural AI viability and adoption. Longitudinal studies tracking technology adoption and impact over 5-10 year periods would provide critical evidence on sustainability, identifying factors predicting sustained usage versus disadoption and quantifying long-term economic returns accounting for technology obsolescence and replacement cycles.

Geographic replication across diverse cocoa-producing regions in Indonesia and internationally would test generalizability of viability findings and identify contextual boundary conditions determining where ML-based detection achieves economic returns, enabling more refined targeting strategies. Comparative studies examining ML-based detection systems across multiple crop types (coffee, oil palm, tea, rubber) would identify crop-specific factors influencing viability including disease ecology, production system characteristics, and market structures, informing strategic prioritization of AI development investments across agricultural sectors. Cost-effectiveness analyses comparing ML-based detection against alternative disease management approaches including enhanced human extension services, subsidized pesticide programs, or genetic resistance breeding would position AI systems within broader portfolios of disease management strategies rather than evaluating in isolation.

Integration studies examining how ML disease detection combines with other precision agriculture technologies including sensor-based irrigation, GPS-guided input application, and blockchain- based traceability systems would explore synergies and identify optimal technology bundles for different farming contexts. Implementation science research investigating factors influencing deployment model selection, organizational capacity requirements for different models, and design features enhancing long-term sustainability would generate actionable guidance for gricultural development practitioners. Finally, environmental impact assessments quantifying pesticide reduction benefits, biodiversity effects, and carbon footprint implications of ML-enabled disease management would establish comprehensive sustainability profiles beyond economic and agronomic metrics, supporting holistic evaluation of agricultural AI systems aligned with sustainable development objectives.

CONCLUSION

This study addressed the critical challenge of persistent disease-related yield losses in cocoa plantations in Luwu Regency, South Sulawesi, by systematically evaluating the economic viability of implementing machine learning-based disease detection systems as an innovative technological solution to enhance disease management effectiveness in smallholder farming contexts. The research demonstrated that ML-based disease detection achieved 93.7% diagnostic accuracy, enabled 32.4% yield improvements, and generated highly favorable economic returns with Internal Rates of Return of 47.3% for individual adoption and 52.6% for cooperative deployment models, substantially exceeding conventional agricultural investment benchmarks and validating the fundamental hypothesis that AI-powered diagnostic technologies can achieve economic viability in resource-constrained smallholder agriculture.

Future research should prioritize longitudinal monitoring over 5-10 year periods to assess long-term sustainability dynamics, geographic replication across diverse cocoa-producing regions to establish generalizability boundaries, and comparative cost-effectiveness analyses positioning ML systems within broader disease management strategy portfolios. Practitioners and policymakers should consider implementing cooperative-based deployment models that achieve superior economic returns through cost-sharing arrangements, investing in comprehensive training and technical support infrastructure essential for sustained technology utilization, and developing targeted subsidy programs for capital-constrained farmers in high disease pressure zones where economic returns prove greatest.

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