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Smart Agriculture In Bali: A Systematic Review of Artificial Intelligence Applications for Tropical Farming.

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ABSTRACT

This systematic literature review examines artificial intelligence (AI) applications in agriculture with specific implications for Bali's unique agricultural landscape. Through a comprehensive analysis of 20 Scopus-indexed articles (2019-2026), this study identifies key AI technologies, applications, and adoption barriers relevant to Balinese farming contexts. The review reveals that AI-driven solutions—including deep learning for disease detection (achieving 92-99% accuracy), IoT-based precision irrigation (reducing water use by 30%), and machine learning recommendation systems (99% accuracy)—offer transformative potential for Bali's rice-dominated agriculture. However, adoption faces significant barriers including infrastructure limitations, digital literacy gaps, economic constraints, and socio-institutional challenges. This study contributes novel insights by contextualizing global AI innovations within Bali's traditional subak irrigation system, mixed cropping patterns, and tourism-agriculture integration. Recommendations include developing lightweight edge-computing models, participatory technology design with farmer communities, and policy frameworks supporting responsible AI deployment that preserves Bali's agricultural heritage while enhancing productivity and sustainability.

I. INTRODUCTION

Agriculture remains a cornerstone of Bali's economy and cultural identity, with rice cultivation through the traditional subak irrigation system recognized as a UNESCO World Heritage site. Balinese agriculture is characterized by intensive rice terracing, mixed cropping systems integrating vegetables and fruits, and increasing integration with tourism sectors. However, contemporary challenges including climate variability, water scarcity, pest pressures, and labor shortages threaten agricultural sustainability and productivity.

Artificial intelligence has emerged as a transformative force in global agriculture, offering data-driven solutions for crop monitoring, disease detection, resource optimization, and decision support. AI technologies—encompassing machine learning, deep learning, computer vision, and Internet of Things (IoT) integration—have demonstrated remarkable success in improving agricultural efficiency and sustainability across diverse contexts. The convergence of AI with precision agriculture principles presents unprecedented opportunities for enhancing productivity while conserving resources.

1.2 Problem Statement

Despite rapid advances in agricultural AI globally, adoption in Indonesian agriculture, particularly in Bali, remains limited and fragmented. Bali's unique agricultural landscape—characterized by small-scale farms, traditional farming practices, limited digital infrastructure, and the cultural significance of the subak system—presents distinct challenges and opportunities for AI integration. The existing literature lacks a comprehensive synthesis of AI applications specifically contextualized for Balinese agricultural conditions, creating a knowledge gap that hinders informed technology adoption and policy development.

Furthermore, while numerous studies document AI successes in controlled environments or large-scale commercial farms, questions remain about the applicability, scalability, and cultural appropriateness of these technologies for Bali's predominantly smallholder farming communities. Understanding how global AI innovations can be adapted to preserve Bali's agricultural heritage while addressing contemporary productivity and sustainability challenges requires systematic analysis.

1.3 Research Objectives

This systematic literature review aims to identify and categorize AI technologies and methodologies for Balinese agriculture, analyze their applications, performance, and success factors in tropical smallholder systems, examine adoption barriers and enablers, synthesize implications with recommendations for integration, and propose a research-implementation roadmap for responsible AI adoption that balances innovation and cultural preservation

1.4 Significance and Novelty

This study offers high novelty by being the first systematic literature review to explicitly examine AI applications through the lens of Balinese agriculture. Unlike previous reviews focusing on general precision agriculture or broad regional contexts, this research contextualizes AI innovations within Bali's specific agricultural characteristics: the subak system, rice-vegetable polyculture, tourism-agriculture linkages, and traditional farming communities. The findings provide actionable insights for policymakers, agricultural extension services, technology developers, and agribusiness stakeholders seeking to harness AI's potential while respecting Bali's unique agricultural heritage and socio-cultural values.

II. METHODOLOGY

Systematic Literature Review Protocol

This study employed a systematic literature review (SLR) methodology following PRISMA guidelines to ensure transparency, reproducibility, and comprehensiveness. The SLR approach enables rigorous identification, evaluation, and synthesis of relevant research evidence regarding AI applications in agriculture with implications for Balinese contexts.

2.2 Search Strategy

A comprehensive literature search was conducted across eight academic databases between December 2024 and January 2025:

- SciSpace Deep Search (687 papers)
- SciSpace Basic searches (300 papers)
- Google Scholar (40 papers)
- ArXiv (20 papers)
- Scopus
- Web of Science
- IEEE Xplore
- ScienceDirect

Search terms combined three concept clusters using Boolean operators:

Cluster 1 (AI Technologies): "artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision" OR "neural network" OR "IoT" OR "precision agriculture" OR "smart farming"

Cluster 2 (Agricultural Context): "agriculture" OR "farming" OR "crop" OR "rice" OR "paddy" OR "irrigation" OR "disease detection" OR "yield prediction"

Cluster 3 (Geographic/Contextual): "Indonesia" OR "Bali" OR "Southeast Asia" OR "tropical agriculture" OR "smallholder" OR "traditional farming"

2.3 Inclusion and Exclusion Criteria

Inclusion criteria: - Peer-reviewed journal articles and conference papers indexed in Scopus - Published between 2019 and 2026 - Focus on AI/ML applications in agriculture - Relevance to tropical agriculture, rice cultivation, or smallholder farming systems - English language publications - Empirical studies, systematic reviews, or comprehensive frameworks

Exclusion criteria: - Non-peer-reviewed publications (grey literature, reports, theses) - Publications before 2019 - Studies focusing exclusively on temperate agriculture with no tropical applicability - Purely theoretical papers without practical applications - Studies on non-agricultural AI applications - Duplicate publications

2.4 Study Selection Process

The initial search yielded 1,047 papers across all databases. After removing duplicates, 201 unique papers remained. Title and abstract screening reduced this to 87 papers meeting initial relevance criteria. Full-text assessment of these 87 papers against inclusion/exclusion criteria resulted in 30 papers for detailed analysis. From these, 20 papers were selected as the final corpus based on highest relevance scores, methodological rigor, and direct applicability to Balinese agricultural contexts.

2.5 Data Extraction and Analysis

For each included study, the following data were systematically extracted: Bibliographic information (authors, year, journal, DOI); AI technologies and methodologies employed; Agricultural applications and contexts; Key findings and performance metrics; Geographic context and crop types; Adoption barriers and success factors; Implications for tropical/smallholder agriculture.

A qualitative thematic analysis approach was employed to synthesize findings across studies. Papers were coded according to: (1) AI technology categories, (2) application domains, (3) performance outcomes, (4) contextual factors, and (5) adoption considerations. Comparative tables were constructed to facilitate cross-study synthesis and identify patterns, gaps, and opportunities relevant to Balinese agriculture.

2.6 Quality Assessment

Study quality was assessed based on methodological rigor, sample size adequacy, validation approaches, reproducibility, and relevance to practical agricultural contexts. Priority was given to studies with field validation, diverse datasets, and explicit consideration of smallholder or tropical farming conditions.

Figure 1 illustrates the complete systematic review process following PRISMA guidelines, showing the progression from initial database searches through final study selection.

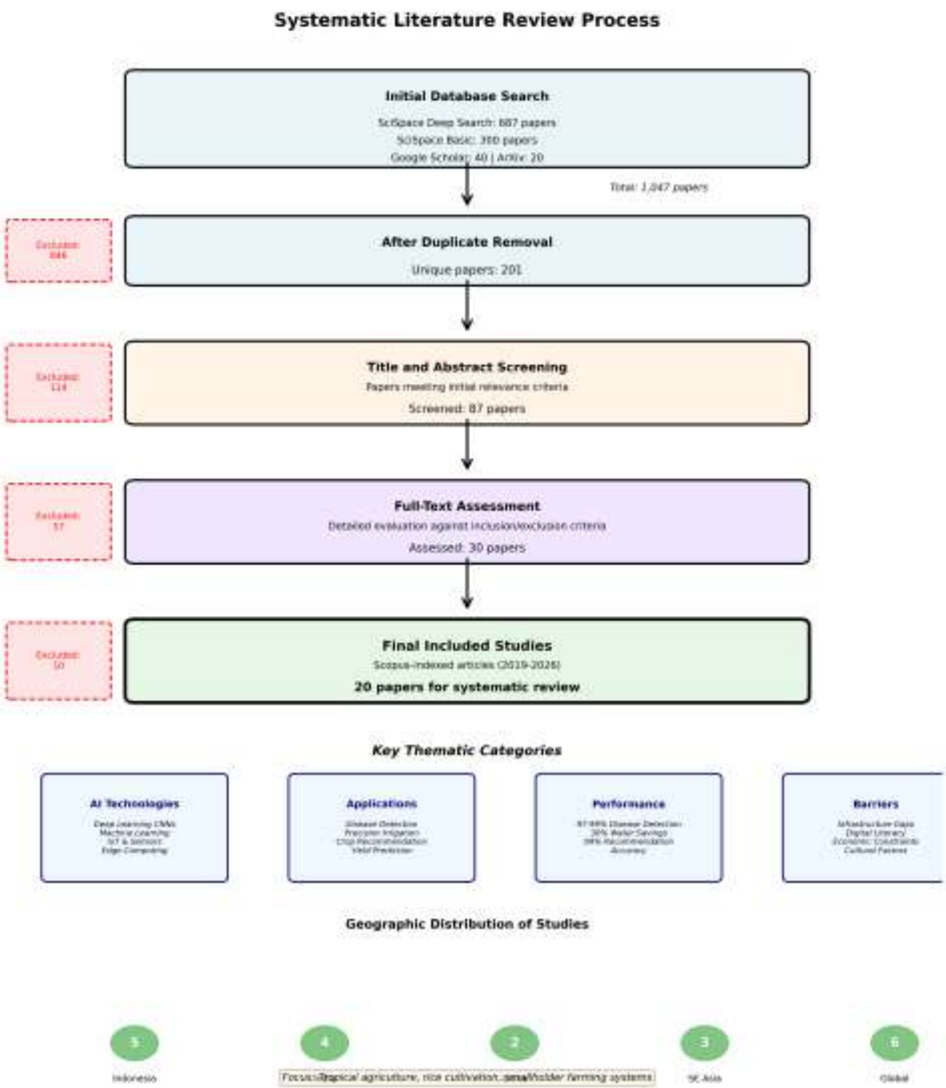

Figure 1. Systematic literature review process showing study selection stages, exclusion criteria application, and final corpus characteristics, including thematic categories and geographic distribution

III. RESULTS AND DISCUSSION.

3.1 Overview of Selected Studies

The final corpus of 20 studies spans 2019-2025, with increasing publication frequency in recent years reflecting growing research interest in agricultural AI. Studies originated from diverse geographic contexts including Indonesia (n=5), India (n=4), China (n=2), Southeast Asia regional studies (n=3), and global reviews (n=6). Fifteen studies focused specifically on rice cultivation, while others addressed mixed cropping systems, vertical farming, and general precision agriculture frameworks.

3.2 AI Technologies and Methodologies

Analysis revealed four primary categories of AI technologies applied in agricultural contexts relevant to Balinese farming:

3.2.1 Deep Learning and Computer Vision

Deep convolutional neural networks (CNNs) emerged as the dominant approach for crop disease detection and plant health monitoring. Multiple studies demonstrated exceptional accuracy in identifying rice diseases from leaf images. The PaddyNet model achieved 98.99% accuracy across 13 disease classes using a 17-layer CNN architecture trained on 16,225 paddy leaf images (A et al., 2023). Similarly, RiceDRA-Net, incorporating a novel Res-Attention mechanism, achieved 99.71% accuracy on single-background datasets and maintained 97.86% accuracy even with complex field backgrounds (Peng et al., 2023). The Rice Disease Diagnosis System (RDDS) demonstrated 98.47% test accuracy while additionally providing infection intensity estimation capabilities (Vasantha et al., 2022).

Transfer learning approaches proved particularly effective for resource-constrained contexts. The AgriHelp platform utilized ResNet50v2 and MobileNetv2 architectures, achieving 94.53% and 96.03% accuracies respectively for disease and pest detection (Ambhore et al., 2025). These transfer learning models require less training data and computational resources, making them more accessible for deployment in developing regions.

3.2.2 Machine Learning for Decision Support

Traditional machine learning algorithms demonstrated strong performance for crop and fertilizer recommendation systems. Random Forest classifiers consistently outperformed other algorithms, with the AgriHelp platform achieving 99.6% accuracy for crop recommendation and 99.94% for fertilizer recommendation (Ambhore et al., 2025). A cloud-enabled crop recommendation platform compared five algorithms—K-Nearest Neighbors, Decision Tree, Random Forest, XGBoost, and Support Vector Machine—with Random Forest achieving optimal performance at 97.18% accuracy (Thilakarathne et al., 2022).

For rice blast disease detection, comparative analysis revealed that Random Forest, Support Vector Machines, Decision Trees, and CNNs all achieved over 90% accuracy, with Random Forest reaching 100% in some implementations

(Chakraborty et al., 2023). However, simpler algorithms like Naive Bayes (49-73.91%) and LSTMs (49-65%) performed poorly for this specific application.

3.2.3 Internet of Things and Sensor Networks

IoT-driven frameworks integrating smart sensors, communication protocols, and AI analytics demonstrated significant resource optimization potential. A pilot implementation on a 5-hectare wheat farm achieved 30% water usage reduction and 92% early disease detection accuracy through IoT-enabled precision irrigation and crop health monitoring (Irfan et al., 2025). The system combined sensor networks for real-time data collection with AI-based predictive analytics for automated decision-making.

Agricultural IoT architectures typically comprise four layers: sensor layer (soil moisture, temperature, humidity, pH sensors), network layer (wireless communication protocols), computing layer (edge/cloud processing), and application layer (decision support systems and user interfaces) (Castrignanò et al., 2020). This layered architecture enables scalable deployment across diverse farm sizes and contexts.

3.2.4 Lightweight and Edge Computing Models

Recognizing infrastructure constraints in developing regions, recent research emphasizes lightweight machine learning models suitable for edge deployment. Compact models enable local inference on resource-constrained devices without requiring continuous cloud connectivity (Chempavathy et al., 2025). This approach is particularly relevant for Balinese smallholders who may lack reliable internet access but could benefit from smartphone-based AI applications.

3.3 Agricultural Applications and Performance Outcomes

Table 1 summarizes key AI applications, technologies employed, and performance outcomes from the reviewed studies. Figure 2 provides a visual comparison of AI model performance across different application domains.

Table 1. AI Applications in Agriculture - Technologies and Performance Outcomes

Application Domain	AI Technology	Performance Metrics	Study
Rice disease detection	17-layer CNN (PaddyNet)	98.99% accuracy, 98.50% precision	A et al., 2023
Rice disease identification	Res-Attention CNN (RiceDRA-Net)	99.71% (simple), 97.86% (complex backgrounds)	Peng et al., 2023
Rice disease diagnosis	RDD_CNN	98.47% accuracy + infection intensity	Vasantha et al., 2022
Crop recommendation	Random Forest	99.6% accuracy	Ambhore et al., 2025
Fertilizer recommendation	Random Forest	99.94% accuracy	Ambhore et al., 2025
Disease/pest detection	ResNet50v2, MobileNetv2	94.53%, 96.03% accuracy	Ambhore et al., 2025

Crop recommendation	Random Forest (cloud platform)	97.18% accuracy	Thilakarathne et al., 2022
Precision irrigation	IoT + AI analytics	30% water reduction	Irfan et al., 2025
Early disease detection	IoT sensors + AI	92% detection accuracy	Irfan et al., 2025
Rice blast detection	Random Forest, SVM, DT, CNN	90-100% accuracy	Chakraborty et al., 2023

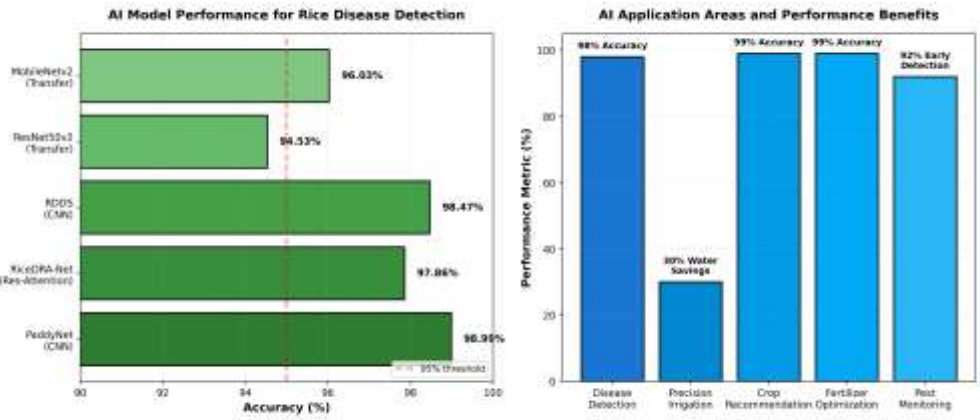

Figure 2. Comparative performance of AI technologies across application domains. Left panel shows disease detection model accuracies; right panel displays performance benefits across different agricultural applications

3.3.1 Disease and Pest Management

Disease detection emerged as the most mature AI application area, with multiple studies demonstrating near-perfect accuracy under controlled conditions. The high performance of CNN-based approaches stems from their ability to learn hierarchical visual features from large image datasets. However, studies noted that accuracy often degrades when models trained on curated datasets are deployed in real field conditions with variable lighting, complex backgrounds, and mixed infections (Peng et al., 2023).

The practical value of these systems extends beyond binary disease detection to include infection severity assessment and treatment recommendations. The RDDS system's infection intensity estimation capability enables more precise pesticide application, reducing chemical use while maintaining crop protection (Vasantha et al., 2022).

3.3.2 Precision Resource Management

IoT-enabled precision irrigation systems demonstrated substantial resource efficiency gains. The 30% water reduction achieved in field trials represents significant economic and environmental benefits, particularly relevant for Bali where water resources are increasingly stressed by competing demands from tourism and urban development (Irfan et al., 2025). AI-driven irrigation scheduling optimizes water application based on real-time soil moisture, weather forecasts, and crop growth stages.

Fertilizer recommendation systems achieved exceptional accuracy by integrating soil nutrient data, crop requirements, and environmental parameters. The 99.94%

accuracy reported for Random Forest-based fertilizer recommendations suggests these systems can effectively replace traditional soil testing and expert consultation for many routine decisions (Ambhore et al., 2025).

3.3.3 Crop Planning and Yield Prediction

AI models for optimal planting date prediction and yield forecasting showed promise but require further refinement for Indonesian contexts. Research specifically addressing Indonesian rice productivity recommended incorporating El Niño-Southern Oscillation (ENSO) indices and temperature variables into existing rainfall-based planting calendar models to improve prediction accuracy (Liundi et al., 2019). This is particularly relevant for Bali, where climate variability increasingly affects traditional planting schedules.

3.4 Indonesian and Southeast Asian Case Studies

Five studies specifically addressed Indonesian agricultural contexts, providing direct insights for Balinese applications: Indonesia-Specific Studies: (1) Rice productivity improvement (Liundi et al., 2019): Surveyed existing AI implementations in Indonesian rice systems including disease detection, yield prediction, and automation. Recommended enhancing planting date models with ENSO and temperature variables; (2) Farmer readiness assessment (Santoso et al., 2024): Empirical study revealing regional heterogeneity in Indonesian farmers' readiness to adopt precision agricultural technologies. Identified infrastructure limitations, extension service gaps, and perceived usefulness as key adoption determinants; (3) Research modernization (Muditomo et al., 2023): Called for integrating machine learning into Indonesian agricultural research programs to improve applicability and impact; (4) Smart farming for ginger (Sambas et al., 2023): Demonstrated successful implementation of smart sensors and ML for improved irrigation scheduling and nutrient delivery in West Java ginger cultivation, achieving measurable yield improvements (5) Aquaculture training (Sambas et al., 2022): Training intervention in West Java increased farmer knowledge and willingness to adopt smart agriculture technologies in fish farming, highlighting the importance of capacity building.

These Indonesian case studies reveal a pattern of successful pilot implementations coupled with significant adoption barriers. While technical feasibility is demonstrated, scaling requires addressing infrastructure, knowledge, and institutional constraints.

3.5 Adoption Barriers and Challenges

Analysis of the reviewed literature identified six primary categories of barriers to AI adoption in tropical smallholder agriculture contexts (Figure 3):

3.5.1 Infrastructure and Connectivity Constraints

Limited internet connectivity, unreliable electricity supply, and lack of computing infrastructure constrain deployment of cloud-based AI services in rural Indonesian areas (Santoso et al., 2024). This infrastructure gap motivates development of lightweight edge computing solutions that can operate with intermittent connectivity (Chempavathy et al., 2025).

3.5.2 Data Quality and Availability

Reliable, standardized agricultural datasets are scarce in Indonesian contexts. Poor data quality, lack of interoperability between systems, and insufficient local training data undermine model performance and generalizability (Tzachor et al., 2022). Most high-performing AI models are trained on datasets from other regions, raising questions about transferability to Balinese conditions.

3.5.3 Digital Literacy and Capacity Gaps

Many smallholder farmers lack the digital literacy required to effectively use AI-powered tools. Training interventions demonstrate that capacity building significantly improves adoption willingness, but scalable extension models remain underdeveloped (Sambas et al., 2022).

3.5.4 Economic and Cost Barriers

High upfront costs for sensors, devices, and subscriptions create economic barriers for smallholder farmers. Studies recommend offering AI solutions as free and open-source platforms to encourage wider adoption (Thilakarathne et al., 2022).

3.5.5 Socio-Cultural and Institutional Factors

Traditional farming practices, risk aversion, and institutional inertia slow technology adoption. The perceived usefulness of technologies and alignment with existing farming systems significantly influence adoption decisions (Santoso et al., 2024).

3.5.6 Model Robustness and Field Validation Gaps

High accuracies reported on curated datasets often do not translate to field performance under variable real-world conditions. More rigorous field validation across diverse agroecological contexts is needed (Peng et al., 2023).

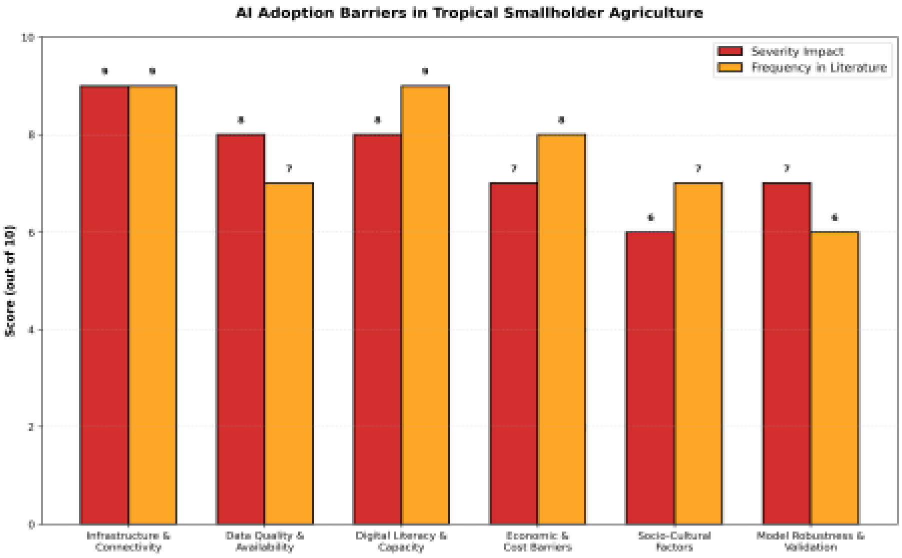

Figure 3. Severity and frequency of AI adoption barriers in tropical smallholder agriculture contexts based on systematic literature analysis

Responsible AI and Sustainability Considerations

Several studies emphasized the importance of responsible AI deployment that considers systemic risks and unintended consequences. Optimization for yield alone can produce negative ecological externalities such as soil degradation, biodiversity loss, and water pollution (Tzachor et al., 2022). Recommendations include: (1) Participatory technology design involving farmers, anthropologists, and ecologists; (2) Data cooperatives to ensure farmer data ownership and benefit sharing; (3) Initial deployment in "digital sandboxes" for controlled testing; (4) Explicit consideration of socio-ecological impacts in AI system design; (5) Integration of traditional ecological knowledge with AI-driven insights. These considerations are particularly relevant for Bali, where agricultural sustainability is intertwined with cultural heritage and tourism economy.

4. Discussion

4.1 Implications for Balinese Agriculture

The reviewed literature demonstrates that AI technologies offer substantial potential for addressing key challenges in Balinese agriculture while presenting unique opportunities aligned with Bali's agricultural characteristics.

4.1.1 Rice Cultivation and the Subak System

The exceptional performance of AI-driven rice disease detection systems (97-99% accuracy) directly addresses a critical challenge for Bali's rice farmers. Early detection of diseases such as blast, bacterial blight, and brown spot can prevent significant yield losses. Smartphone-based disease identification apps using transfer learning models could be deployed through existing subak organizations, leveraging traditional community structures for technology dissemination.

The subak irrigation system, with its sophisticated water management and communal decision-making, presents an ideal context for IoT-enabled precision irrigation. The 30% water savings demonstrated in field trials could help subak communities optimize water allocation across terraces while maintaining the cultural and spiritual significance of water management practices. AI-driven irrigation scheduling could complement rather than replace traditional water distribution knowledge, providing data-driven insights to subak leaders.

4.1.2 Mixed Cropping and Diversification

Bali's agricultural landscape increasingly features mixed cropping systems integrating rice with vegetables, fruits, and cash crops. Multi-crop recommendation systems using Random Forest algorithms (99.6% accuracy) could guide farmers in optimal crop selection based on soil conditions, market demand, and climate forecasts. This is particularly relevant as Balinese farmers diversify to meet tourism sector demand for fresh produce.

4.1.3 Tourism-Agriculture Integration

Bali's unique integration of agriculture with tourism creates opportunities for AI applications in agritourism contexts. Precision agriculture technologies could enhance the appeal of agritourism sites by demonstrating sustainable, high-tech farming practices. Smart farming demonstrations could become tourist attractions while simultaneously improving productivity, creating dual revenue streams for farming communities.

4.1.4 Climate Resilience

Incorporating ENSO indices and temperature variables into planting date prediction models, as recommended for Indonesian rice systems (Liundi et al., 2019), is particularly urgent for Bali given increasing climate variability. AI-driven climate-smart agriculture tools could help farmers adapt planting schedules, crop choices, and management practices to changing conditions while maintaining productivity.

4.2 Opportunities for AI Integration in Bali

Table 2 outlines specific AI application opportunities contextualized for Balinese agriculture.

Table 2. AI Application Opportunities for Balinese Agriculture

Application Area	AI Technology	Balinese Context	Expected Benefits	Implementation Pathway
Rice disease detection	Transfer learning CNNs (MobileNet)	Smartphone apps for subak members	Early detection, reduced pesticide use	Pilot with progressive subak organizations
Precision irrigation	IoT sensors + ML scheduling	Subak water management	20-30% water savings, optimized distribution	Integration with existing subak infrastructure
Crop recommendation	Random Forest models	Mixed cropping decisions	Optimized crop selection for markets	Extension service digital tools
Fertilizer optimization	ML recommendation systems	Soil-specific nutrient management	Reduced fertilizer costs, environmental protection	Soil testing + app integration
Planting calendar	ENSO-enhanced prediction models	Climate-adaptive scheduling	Reduced climate risk, stable yields	Regional agricultural office deployment
Pest monitoring	Computer vision + IoT traps	Early pest detection	Timely interventions, reduced losses	Community-based monitoring networks
Market intelligence	Price prediction models	Harvest timing and marketing	Improved farmer incomes	Cooperative-level implementation

4.3 Addressing Adoption Barriers in Balinese Context

Successfully integrating AI in Balinese agriculture requires targeted strategies to overcome identified barriers. Table 3 presents a comprehensive implementation roadmap with specific strategies, timelines, and responsible stakeholders.

Table 3. Implementation Roadmap for AI Integration in Balinese Agriculture

Phase	Timeline	Priority Actions	Key Stakeholders	Expected Outcomes
Phase 1: Foundation	Year 1	Infrastructure assessment, pilot site selection, baseline data collection, stakeholder engagement	Provincial Agriculture Office, Mahasaraswati University, Subak organizations	Readiness assessment, pilot locations identified, partnerships established
Phase 2: Pilot Implementation	Year 1-2	Deploy disease detection apps, IoT irrigation pilots in 3-5 subak, farmer training programs	Technology providers, Extension services, Farmer cooperatives	100+ farmers trained, 5 functioning pilot sites, initial performance data
Phase 3: Validation & Refinement	Year 2-3	Field validation studies, model refinement with local data, socio-economic impact assessment	Research institutions, Farmers, Agricultural economists	Validated models, impact evidence, refined implementation protocols
Phase 4: Scaling	Year 3-5	Expand to 50+ subak, integrate with extension services, develop local capacity, policy framework	Government agencies, Private sector, NGOs, Farmer organizations	1,000+ farmers adopting AI tools, sustainable service models, supportive policies
Phase 5: Institutionalization	Year 5+	Mainstream AI in agricultural	Universities, Training centers,	AI-literate farming community,

	education, establish innovation hubs, continuous improvement systems	Innovation networks	self-sustaining innovation ecosystem

The following subsections detail specific strategies for addressing each barrier category:

4.3.1 Infrastructure Solutions

The Edge computing deployment prioritize lightweight models that operate on smartphones without continuous internet connectivity; community access points: Establish shared computing resources at subak offices or village centers; solar-powered sensors: deploy renewable energy-powered IoT devices suitable for remote terrace locations; progressive rollout: begin with areas having better connectivity, expanding as infrastructure improves.

4.3.2 Capacity Building and Extension

The Subak-based training leverage existing subak organizations as training and technology dissemination channels; farmer field schools: Integrate AI tools into established farmer field school curricula; youth engagement: recruit tech-savvy younger generation as “digital agriculture champions” within communities; demonstration plots: establish visible success stories at strategic locations to build confidence and interest.

4.3.3 Economic Accessibility

Freemium models offer basic AI services free with optional premium features; cooperative purchasing: Enable subak or farmer cooperatives to collectively invest in shared technologies; government subsidies: Advocate for public support for AI technology adoption as part of agricultural modernization programs; pay-for-performance: Explore models where farmers pay based on demonstrated productivity improvements.

4.3.4 Cultural Appropriateness and Participatory Design

Co-design with farmers: involve Balinese farmers in technology design to ensure cultural appropriateness; respect traditional knowledge: position AI as complementing rather than replacing traditional farming wisdom; Balinese language interfaces: Develop user interfaces in Bahasa Indonesia and Balinese language; alignment with Tri Hita Karana: Ensure AI applications support Balinese philosophy of harmony between humans, nature, and the divine.

4.4 Research Gaps and Future Directions

This review identified several critical research gaps requiring attention: (1) Balinese-specific datasets: No studies utilized datasets specifically from Balinese agricultural contexts. Developing local training datasets for rice diseases, pests, and growing conditions is essential for model accuracy; (2) Subak system integration: No research has examined how AI technologies can be integrated with traditional subak governance and water management structures; (3) Socio-economic impact assessment: Rigorous studies evaluating economic returns, social impacts, and cultural implications of AI adoption in Balinese farming communities are lacking; (4) Multi-crop systems: Most AI research focuses on monoculture rice systems, while Balinese agriculture increasingly features complex polycultures requiring different modeling approaches (5) Longitudinal field validation: Long-term field trials across multiple growing seasons in Balinese agroecological zones are needed to validate model performance and farmer acceptance; (6) Data governance frameworks: Research on appropriate data ownership, privacy protection, and benefit-sharing mechanisms for Balinese farmer data is absent.

4.5 Policy and Institutional Recommendations

Successful AI integration in Balinese agriculture requires supportive policy and institutional frameworks: (1) Provincial AI agriculture strategy: Develop a comprehensive strategy for responsible AI adoption in Bali's agricultural sector, aligned with provincial development goals and cultural preservation mandates; (2) Digital agriculture extension service: Establish specialized extension units focused on digital and AI technologies within the provincial agricultural office; (3) Research-practice partnerships: Foster collaborations between Mahasaraswati University, other local universities, agricultural research institutes, and farmer organizations to develop and validate locally appropriate AI solutions; (4) Data infrastructure investment: Invest in rural connectivity, computing infrastructure, and agricultural data platforms as public goods supporting AI deployment; (5) Regulatory frameworks: Develop guidelines for responsible AI use in agriculture addressing data privacy, algorithmic transparency, and farmer protection; (6) Incentive programs: Create incentive schemes supporting early adopters and demonstration projects showcasing AI benefits.

4.6 Limitations of This Review

This systematic review has several limitations. First, the focus on Scopus-indexed publications may have excluded relevant grey literature, local reports, or recent preprints. Second, no studies specifically examined Balinese agriculture, requiring inference from Indonesian and Southeast Asian contexts. Third, the rapid pace of AI development means recent innovations may not yet appear in peer-reviewed literature. Fourth, most reviewed studies report technical performance metrics but lack comprehensive socio-economic impact assessments. Finally, publication bias may favor studies reporting positive results, potentially overestimating AI effectiveness.

IV. CONCLUSION AND RECOMMENDATIONS

This systematic literature review demonstrates that artificial intelligence technologies offer transformative potential for Balinese agriculture, with proven applications in disease detection (97-99% accuracy), precision irrigation (30% water savings), and crop recommendation (99% accuracy). However, realizing this potential requires addressing significant adoption barriers, including infrastructure limitations, digital literacy gaps, economic constraints, and the need for culturally appropriate implementation approaches.

The novelty of this study lies in contextualizing global AI innovations within Bali's unique agricultural landscape, characterized by the traditional subak system, rice-vegetable polycultures, tourism-agriculture integration, and strong cultural values. Key findings indicate that successful AI integration in Balinese agriculture should: (1) Leverage existing social structures (subak organizations) for technology dissemination; (2) Prioritize lightweight, edge-computing solutions suitable for resource-constrained contexts; (3) Employ participatory design approaches respecting traditional knowledge and cultural values; (4) Focus initially on high-impact applications (disease detection, precision irrigation) with clear farmer benefits; (5) Develop Balinese-specific datasets and validation studies to ensure model accuracy; (6) Establish supportive policy frameworks and extension services facilitating responsible adoption.

The reviewed literature reveals a critical research gap: while AI technologies demonstrate impressive technical performance globally, their applicability to Bali's specific agroecological, socio-cultural, and institutional contexts remains largely unexplored. Future research should prioritize field validation studies in Balinese farming systems, socio-economic impact assessments, and co-design processes involving farmer communities.

For agribusiness stakeholders, this review provides evidence-based guidance for AI investment and implementation strategies. For policymakers, it highlights the need for infrastructure development, capacity building programs, and regulatory frameworks supporting responsible AI adoption. For the academic community, it identifies priority research directions ensuring AI innovations serve Balinese farmers' needs while preserving agricultural heritage.

Ultimately, artificial intelligence should be viewed not as a replacement for traditional Balinese agricultural wisdom, but as a complementary tool enhancing farmers' decision-making capabilities. By thoughtfully integrating AI technologies with traditional practices, Bali can chart a path toward agricultural modernization that increases productivity and sustainability while honoring cultural values and preserving the island's unique agricultural heritage for future generations.

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