

Implementation of Artificial Intelligence in Intelligent Agricultural Systems for Agrotechnological Transformation for Daily Life.

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ABSTRACT

The development of artificial intelligence (AI) technology has brought a significant transformation in the agrotechnology sector, transforming conventional agricultural practices into efficient and sustainable smart farming systems. This study aims to systematically analyze the implementation of artificial intelligence in agrotechnology to support farmers' daily agricultural practices. A systematic literature review (SLR) was conducted by analyzing 170 Scopus-indexed scientific publications published between 2022 and 2025. The results of the study show that AI has been implemented in various aspects of agrotechnology including: (1) computer vision-based plant disease detection system with reported accuracy levels reaching up to 98% in controlled experimental settings., (2) an integrated IoT platform for real-time monitoring of land and plant conditions, (3) a machine learning-based recommendation system for irrigation and fertilization management, (4) UAV technology with deep learning for land mapping and scouting, and (5) digital twin for simulation and optimization of production systems. The implementation of federated learning enables collaboration between farmers in the development of models without compromising data privacy. In conclusion, The findings indicate that AI-based solutions significantly enhance agricultural productivity, resource efficiency, and sustainability, resource efficiency, and sustainability of agriculture in daily life. The implications of this study guide farmers, practitioners, and academics in adopting AI technology for the transformation of agrotechnology towards smart and sustainable agriculture.

I. INTRODUCTION

The emergence of Industry 4.0 and Society 5.0 has fundamentally transformed various sectors in various sectors of life, including the agricultural sector, which is the backbone of global food security (Sharma et al., 2023). Artificial Intelligence (AI) is a core enabling technology in digital transformation, offering advanced data-driven decision-making capabilities, and has opened up new opportunities in optimizing agrotechnology practices for farmers' daily

lives. The integration of AI in agricultural systems not only increases productivity but also presents practical solutions to the various challenges that farmers face in their daily activities (Addas et al., 2023).

Indonesian agriculture, particularly in Bali, faces complex challenges such as land constraints, climate variability, and pest infestations, such as land limitations, climate change, pest and disease attacks, and the efficient use of water resources and fertilizers. Conventional farming methods that are still predominantly used are often less efficient in decision-making and require a lot of time and effort. In this context, the implementation of AI offers innovative solutions that can be applied in farmers' daily activities to improve the effectiveness and efficiency of agricultural production (Orchi et al., 2023).

The development of AI technology has resulted in various practical applications in agrotechnology that can be used in daily life, ranging from smartphone-based plant disease detection systems, real-time monitoring of land conditions using IoT sensors, to automated recommendation systems for irrigation and fertilization (Padmavathi et al., 2024). Computer vision and deep learning technology allow farmers to identify plant diseases simply by photographing leaves using smartphones, providing instant treatment recommendations (Harakannanavar et al., 2022).

The novelty of this research lies in a comprehensive study of the implementation of AI in agrotechnology, which focuses on practical applications for the daily lives of farmers, especially in the context of tropical agriculture, such as in Indonesia. Unlike previous studies that tended to be theoretical or focused on high technology that is difficult for small farmers to access, this study integrates the perspectives of affordable edge computing technologies, federated learning, and IoT for real implementation in the field. The purpose of this study is to comprehensively examine the implementation of AI in smart agricultural systems for agrotechnological transformation in daily life, identify the most applicable and affordable AI technologies for farmers, and formulate strategic recommendations for the adoption of AI technology in the context of Indonesian agriculture (H. Li et al., 2022).

II. METHODOLOGY

This study adopts a systematic literature review (SLR) methodology following a structured and replicable protocol to examine the implementation of AI in agrotechnology. The SLR approach was chosen because it is able to provide a comprehensive and structured analysis of the latest developments in AI technology in agriculture based on high-quality scientific publications.

Data Collection. Data were collected through systematic searches across multiple academic databases, including on various international academic databases, including SciSpace, Google Scholar, ArXiv, and PubMed. The search keywords used were: "artificial intelligence agriculture", "machine learning precision farming", "deep learning crop disease detection", "IoT smart farming", and "computer vision plant monitoring". The search is focused on the publication of the 2022-2025 period to ensure the relevance and novelty of the information (Balram & Kumar, 2022).

The inclusion criteria applied include: (1) Scopus-indexed articles or high-reputable publications, (2) focus on the application of AI for agrotechnology, (3) discussing practical implementation for daily life, (4) publications in English, and (5) available full-text. From an initial pool of 460 articles, a screening process based on predefined inclusion and exclusion criteria was conducted through the initial search. A screening process was carried out based on titles and abstracts. Duplicate articles are eliminated using reference management software(X. Li et al., 2023). The screening resulted in 170 unique articles relevant to the research topic.

Data Analysis. Each article is assessed for quality based on the following criteria: (1) journal/conference reputation, (2) methodological clarity, (3) relevance to the topic, (4) novelty of contributions, and (5) quality of data and analysis. The data extracted from each article includes: the type of AI technology used, specific applications in agrotechnology, implementation methodologies, system outcomes and accuracy, and practical implications for farmers' daily lives. The synthesis was performed by categorizing the selected articles based on AI technology and application domains, and based on technology and application themes.

Table 1. Article Distribution Based on AI Technology Category

Technology Categories	Number of Articles	Percentage (%)
Computer Vision & Deep Learning	58	34.1
IoT & Edge Computing	42	24.7
Machine Learning & Predictive Analytics	35	20.6
UAV & Remote Sensing	20	11.8
Federated Learning & Cloud Computing	15	8.8

This study uses the ADDIE (Analysis, Design, Development, Implementation, Evaluation) framework, which is adapted to analyze the stages of AI system implementation in agrotechnology. The validity of the study results is ensured through triangulation of sources, which involves comparing findings from various databases and types of publications.

III. RESULTS AND DISCUSSION.

Computer Vision and Deep Learning for Plant Disease Detection

The application of computer vision and deep learning has significantly improved plant disease detection accuracy in plant disease detection for farmers' daily lives. The smartphone-based detection system allows farmers to identify diseases by simply photographing the leaves of the plant, providing an instant diagnosis with up to 98% accuracy (Harakannanavar et al., 2022). This technology utilizes Convolutional Neural Networks (CNNs) that have been trained using thousands of images of plant diseases from various conditions.

Orchi et al. (2023) developed a plant disease detection automation system that integrates conventional machine learning with deep transfer learning. The

system uses pre-trained models such as ResNet, VGG, and Inception that are fine-tuned with the PlantVillage dataset. The results showed that the transfer learning approach provides superior accuracy (96-98%) compared to training from scratch (85-90%), with a much shorter training time.

The practical implementation of a disease detection system for farmers' daily lives has been developed (Talavera et al., 2023) through a field-based recommender system that can operate offline. This system is specifically designed for smallholder farmers in areas with limited internet connectivity. The developed mobile app stores AI models locally on smartphones, enabling real-time diagnosis of plant diseases without the need for an internet connection.

Table 2. Comparison of the Accuracy of Various Deep Learning Architectures for Plant Disease Detection

Model Architecture	Accuracy (%)	Inference Time (ms)	Model Size (MB)	Mobile Compatibility
VGG-16	96.5	180	528	Low
ResNet-50	97.2	120	98	Medium
MobileNetV2	95.8	45	14	Height
EfficientNet-B0	97.8	55	29	Height

Source: Adapted from Orchi et al. (2023) and Harakannanavar et al. (2022)

IoT and Edge Computing for Real-Time Monitoring

The integration of the Internet of Things (IoT) with edge computing has brought an affordable, real-time monitoring solution to farmers' daily lives. (Hossain et al., 2023) developed an intelligent IoT-based system that combines plant type prediction and disease detection using Raspberry Pi as an edge device. This system demonstrates the feasibility of low-cost AI deployment in small-scale farming environments with limited budgets, as it uses low-cost hardware but is still able to perform machine learning in real-time (Kumar et al., 2023).

The IoT system architecture for smart farming includes three main layers: (1) Sensing Layer, consisting of various sensors (soil moisture, temperature, humidity, pH, NPK), (2) Edge Computing Layer, which performs data preprocessing and inference of AI models locally, and (3) Cloud Layer for storage, advanced analytics, and dashboard monitoring. Balram & Kumar (2022) demonstrated the implementation of this system for crop field monitoring and disease detection at a very affordable implementation cost (< \$200 per hectare).

Padmavathi et al. (2024) developed an IoT-based prediction and classification framework for smart farming using adaptive multi-scale deep networks (MA-CNN-LSTM). This system integrates data from multiple sensors to make multi-aspect predictions, including yield prediction, disease classification, optimal irrigation scheduling, and fertilizer recommendation. The system achieved an accuracy of 96.8% for disease classification and a MAE (Mean Absolute Error) of 5.2% for yield prediction.

The implementation of edge computing provides several significant advantages for farmers' daily lives: (1) Reduced Latency – decisions can be made in real-time, (2) Bandwidth Efficiency – saves data costs, (3) Privacy Preservation – sensitive data can be processed locally, (4) Reliability – systems can still operate

even if the internet connection is lost, and (5) Cost Efficiency - reduces cloud computing costs for model inference.

Machine Learning for Irrigation and Fertilization Management

Machine learning applications for irrigation and fertilization management have had a significant impact on improving the efficiency of water and nutrient resource use. Smart weather data management systems developed using machine learning are able to predict evapotranspiration (ET₀) with an accuracy equivalent to the FAO standard Penman-Monteith method, but only require minimal input data from local sensors (Sharma et al., 2023).

The ML-based irrigation recommendation system integrates data from soil moisture sensors, weather forecasts, crop type, and growth stages to produce optimal irrigation scheduling. The implementation of this system has shown water savings of up to 30-40% compared to conventional irrigation methods, without reducing crop productivity (Alsallakh et al., 2023).

Table 3. Comparison of the Efficiency of Various Irrigation Management Methods

Irrigation Methods	Water Consumption (L/m ²)	Yield (tons/ha)	Water Use Efficiency
Conventional (Manual)	1200	8.5	0.71
ML-based Smart System	720	9.3	1.29

Source: Adapted from Alsallakh et al. (2023)

UAV and Remote Sensing for Mapping and Scouting

Unmanned Aerial Vehicle (UAV) technology, or drones integrated with AI, has provided an efficient solution for land mapping and scouting in farmers' daily lives. Raptis et al. (2023) developed an end-to-end precision agriculture UAV-based (CoFly) platform tailored to field characteristics. The system automates mission planning, data acquisition, orthomosaic processing, and on-demand close-up flights for anomaly detection(Raptis et al., 2023).

The novelty of the CoFly platform lies in the ability to adapt mission planning that adjusts flight parameters based on specific terrain characteristics and monitoring objectives. The system uses deep learning to analyze the initial imagery and identify areas that require more detailed inspection. This approach reduces flight time by up to 40% and battery consumption by up to 35% compared to full systematic coverage.

The implementation of deep learning for UAV imagery analysis covers a wide range of applications: (1) Weed Detection - identifying and mapping weed distribution, (2) Disease Detection - early detection of plant diseases from spectral changes, (3) Crop Health Assessment - monitoring plant vigor using vegetation indices (NDVI, NDRE), (4) Yield Estimation - prediction of crop yields based on canopy characteristics, and (5) Irrigation Management - identification of water stress zones for precision irrigation.

Digital Twin and Federated Learning for Collaboration

The concept of digital twins in precision agriculture represents a new paradigm in farm management. (Shamia et al., 2023) explore the use of digital

twins for precision agricultural monitoring using AI. Digital twins are virtual replicas of physical systems (farms) that are continuously updated with real-time data from sensors, providing a platform for simulation, optimization, and predictive maintenance(Chen et al., 2024).

Federated Learning represents a breakthrough in collaborative AI model development while preserving data privacy. (Muhammad & Kusharki, 2023)Implement federated learning for collaborative crop disease monitoring in wheat production. In federated learning, multiple farms can contribute to the training of a global model without sharing their raw data. Each farm conducts local training using its own data, and then only model updates (gradients) are shared with the central server for aggregation.

Table 4. Comparison of Centralized vs Federated Learning for Agricultural AI

Aspects	Centralized Learning	Federated Learning
Data Privacy	Low	Height
Communication Cost	Height	Low
Model Accuracy	Height	Height (comparable)
Scalability	Limited	Good

Federated learning is particularly relevant in contexts where data privacy and ownership are critical concerns, such as the Indonesian context, where many farmers are concerned about the privacy and ownership of their data. This system enables collaboration in the development of robust and generalized AI models, while respecting the data sovereignty of individual farmers.

Practical Implementation and Sustainability

Bridging the gap between research prototypes and real-world implementation remains a critical challenge in AI-driven agriculture for the adoption of AI technology by farmers. Several strategies have proven effective: (1) Low-Cost Hardware Solutions using Raspberry Pi and smartphones with a total hardware cost of < \$150 (Hossain et al., 2023), (2) Offline-Capable Applications that can operate without the internet (Talavera et al., 2023), (3) User-Friendly Interfaces with local languages, (4) Cooperative and Service Models for shared ownership of expensive equipment, and (5) Training and Extension Services for knowledge transfer.

The implementation of AI in agrotechnology makes a significant contribution to sustainability: (1) Resource Efficiency by reducing water consumption (30-40%) and fertilizer use (25-35%), (2) Reduced Chemical Use through early disease detection and targeted pesticide application (reduction up to 50%), (3) Carbon Footprint Reduction through optimized farm operations, (4) Biodiversity Protection by reducing chemical runoff, and (5) Climate Resilience through predictive analytics helping farmers adapt to climate variability (Wang & Su, 2024) (Zhang et al., 2024).

The development of cloud-native architectures and multi-cloud systems has facilitated the deployment of scalable AI systems for agrotechnology (Kumar et al., 2023; Chen et al., 2024). This system automatically routes computation tasks to the most cost-effective cloud provider, reducing latency and operational costs.

Integration with weather data management using ML/XGBoost for ET₀ estimation provides optimal irrigation schedules (Li et al., 2023). The application of UAVs with drone-based crop disease detection using CNN pipelines has been implemented with satisfactory results (Rahman & Chowdhury, 2023). A comprehensive review of in-farm AI applications shows great potential for agrotechnological transformation (Azizi, 2024)

IV. CONCLUSION AND RECOMMENDATIONS

Based on the results of a comprehensive study of 170 scientific publications for the 2022-2025 period, it can be concluded that artificial intelligence has presented a fundamental transformation in agrotechnology for farmers' daily lives. The implementation of AI in smart agriculture includes five main pillars: (1) Computer vision and deep learning for plant disease detection with up to 98% accuracy, (2) IoT and edge computing for real-time monitoring of land conditions at affordable costs, (3) Machine learning for irrigation and fertilization management optimization with 30-40% resource savings, (4) UAVs with AI for efficient mapping and scouting, and (5) Digital twin and federated learning for simulation and collaboration without compromising on privacy (Rahman & Chowdhury, 2023).

The novelty of the implementation of AI in agrotechnology lies in the integration of edge computing technology that allows real-time inference with low-cost hardware, federated learning that facilitates collaboration between farmers while preserving data privacy, and offline-capable applications that are accessible to areas with limited connectivity. The impact of AI implementation on sustainability is very significant, including water use efficiency (30-40%), reduction of fertilizer inputs (25-35%), reduction of pesticide use (up to 50%), and increase of plant productivity (10-20%).

Based on the findings of the research, strategic recommendations for stakeholders include: For Farmers, start adopting AI technology from low-cost and user-friendly solutions such as smartphone-based disease detection, join cooperatives for expensive shared ownership equipment, and actively participate in training programs. For the Government: Develop a comprehensive policy framework to support AI adoption, provide subsidies and incentives for technology acquisition, establish demonstration farms and extension services, invest in infrastructure in rural areas, and facilitate public-private partnerships. For Academics: Focus research on locally-relevant problems, develop lightweight models for edge devices, conduct field trials with farmer participation, and create open-source datasets. For Industry: Design user-friendly and affordable solutions, provide comprehensive technical support, develop flexible business models, collaborate with farmers for co-creation, and ensure data privacy in system design. For UNMAS Denpasar: Integrate AI and precision agriculture in the Agrotechnology curriculum, establish smart farm facilities, develop training programs for farmers, foster industry collaboration, and conduct applied research for local agricultural challenges.

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