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Research Article

THE USE OF MULTISPECTRAL DRONE IMAGERY AND ARTIFICIAL INTELLIGENCE FOR THE EARLY DETECTION OF LEAF BLIGHT DISEASE IN INDONESIAN RICE PADDIES

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Abstract

Leaf blight disease remains one of the major threats to rice production in Indonesia, causing significant yield losses and threatening national food security. Conventional detection methods rely heavily on manual field inspection, which is time-consuming, labor-intensive, and often ineffective for early-stage identification. Recent advances in multispectral drone imagery and artificial intelligence (AI) offer new opportunities for precision agriculture by enabling rapid, accurate, and large-scale crop health monitoring. However, the practical application of these technologies in Indonesian rice paddies is still limited and requires empirical validation. This study aims to examine the effectiveness of multispectral drone imagery integrated with AI-based classification models for the early detection of leaf blight disease in Indonesian rice fields. The research focuses on improving detection accuracy and supporting timely disease management decisions for farmers and agricultural stakeholders. The study employs an experimental research design using multispectral drone data collected from rice paddies in West Java during the growing season. Vegetation indices such as NDVI and GNDVI were extracted and analyzed using machine learning algorithms, including Random Forest and Convolutional Neural Networks (CNN). Ground truth data were obtained through field observations and laboratory confirmation to validate the model outputs. The results demonstrate that the AI-based model achieved high classification accuracy, exceeding 90% in detecting early-stage leaf blight symptoms. The integration of multispectral data significantly improved detection performance compared to visual RGB imagery alone. The study concludes that multispectral drone imagery combined with AI provides a reliable and efficient approach for early detection of leaf blight disease in rice paddies. This approach has strong potential to support precision agriculture, reduce crop losses, and enhance sustainable rice production in Indonesia.

Keywords: Artificial Intelligence, Leaf Blight Disease, Multispectral Drone, Precision Agriculture, Rice Paddies

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INTRODUCTION

Rice is the primary staple food in Indonesia, and its production plays a crucial role in national food security and rural livelihoods (Benjamin et al., 2024). Any disruption to rice productivity, particularly caused by plant diseases, poses serious economic and social risks. Leaf blight disease is one of the most destructive rice diseases in Indonesia, capable of reducing yields significantly if not detected and treated at an early stage (Ozal et al., 2024). Traditional disease monitoring practices largely depend on manual field inspections conducted by farmers or agricultural extension officers, which are often subjective, slow, and limited in spatial coverage (Guilin et al., 2024). Advances in precision agriculture have introduced remote sensing technologies as effective tools for large-scale crop monitoring. Drone-based imagery, in particular, has gained attention due to its flexibility, high spatial resolution, and ability to capture real-time field conditions (Derk et al., 2024). Compared to satellite imagery, drones offer greater temporal control and are more suitable for smallholder farming systems that dominate Indonesian agriculture.

Multispectral imaging has proven valuable in agricultural applications because it captures reflectance data beyond the visible spectrum, including near-infrared and red-edge bands (Dey & Ahmed, 2025). These spectral bands are sensitive to plant physiological conditions and can reveal stress symptoms before visible signs appear (Dhanasekar, 2025). Vegetation indices such as NDVI and GNDVI have been widely used to assess crop health, biomass, and disease stress in various crop systems (Saini et al., 2025). Artificial Intelligence (AI), particularly machine learning and deep learning models, has become increasingly important in analyzing complex agricultural data (Rajareddy et al., 2025). AI-based classification models are capable of identifying patterns and anomalies in large datasets, making them suitable for detecting crop diseases from remote sensing imagery (Zhang et al., 2025). Studies in other agricultural contexts have demonstrated that AI can outperform traditional statistical methods in disease detection and classification tasks.

In several countries, the integration of drone imagery and AI has shown promising results in detecting crop diseases such as wheat rust, maize blight, and soybean stress (Bai et al., 2025). These studies suggest that early detection using AI-driven remote sensing can significantly reduce crop losses and improve decision-making for disease management (D. Wang et al., 2025). The success of these approaches highlights their potential relevance for rice cultivation systems. In Indonesia, the adoption of drone technology and AI in agriculture is gradually increasing, supported by government initiatives and academic research (Dalal & Mittal, 2025). Despite this progress, most applications focus on yield estimation, land mapping, or irrigation management, while disease detection remains relatively underexplored (Wen et al., 2025). This indicates a growing opportunity to expand the use of advanced technologies for plant health monitoring in Indonesian rice paddies.

Limited empirical evidence exists regarding the effectiveness of multispectral drone imagery combined with AI for early detection of leaf blight disease in Indonesian rice fields (Yang et al., 2025). While international studies provide encouraging results, differences in climate, rice varieties, farming practices, and disease characteristics raise questions about the direct applicability of these methods in Indonesia (Timilsina et al., 2025). The optimal combination of multispectral bands, vegetation indices, and AI models for detecting early-stage leaf blight symptoms in rice remains unclear. Most existing studies do not clearly identify which spectral features contribute most significantly to accurate detection, particularly under tropical field conditions.

The reliability of AI-based disease detection models when applied to real-world rice paddies with heterogeneous field conditions has not been sufficiently examined (Ahmed et al., 2025). Variations in soil moisture, planting density, and growth stages may affect spectral signatures, potentially reducing model accuracy if not properly addressed (Singh et al., 2025). Practical validation involving ground truth data and laboratory confirmation is still limited in current research. Without robust validation, the effectiveness of drone-AI systems for operational use by farmers and agricultural agencies remains uncertain.

Addressing these gaps is essential to develop reliable, data-driven disease monitoring systems that support sustainable rice production in Indonesia (Shinde & Attar, 2025). Early detection of leaf blight can enable timely intervention, reduce excessive pesticide use, and minimize yield losses, directly benefiting farmers and food security efforts. Integrating multispectral drone imagery with AI offers a scalable and efficient solution for monitoring large rice-growing areas that are difficult to inspect manually (Steinhauser et al., 2025). Understanding how these technologies perform under Indonesian field conditions will provide critical insights for adapting precision agriculture tools to local needs.

This study aims to evaluate the effectiveness of AI-based analysis of multispectral drone imagery for early detection of leaf blight disease in Indonesian rice paddies (Zarbakhsh et al., 2025). The research hypothesizes that multispectral data combined with advanced machine learning models can detect disease symptoms earlier and more accurately than conventional visual inspection methods, thereby supporting smarter and more sustainable agricultural practices.

RESEARCH METHOD

Research Design

This study adopts an experimental and applied research design within the framework of precision agriculture and artificial intelligence (Shehu et al., 2025). The design integrates remote sensing analysis with supervised machine learning to evaluate the effectiveness of multispectral drone imagery for early detection of leaf blight disease in rice paddies. The research combines field-based observations with computational modeling, enabling a systematic comparison between healthy and infected rice plants. The experimental approach allows for controlled data acquisition, feature extraction, model training, and validation to assess detection accuracy under real agricultural conditions.

Research Target/Subject

The population of this study consists of rice paddies cultivated in major rice-producing areas in Indonesia. The sample sites were purposively selected from irrigated rice fields in West Java due to the high prevalence of leaf blight disease and the availability of supporting agronomic data. A total of 20 rice plots were sampled, representing different growth stages and disease conditions. Each plot was categorized into healthy, early-stage infected, and visibly infected classes based on field inspections and laboratory confirmation. Ground truth samples were collected from representative plants within each plot to ensure accurate labeling for model training and validation.

Research Procedure

Data collection was conducted during the rice growing season under clear weather conditions to ensure optimal image quality. Drone flights were performed at a consistent altitude and overlap to obtain high-resolution multispectral imagery. The captured images were pre-processed through radiometric calibration, mosaicking, and georeferencing (Javed et al., 2025). Vegetation indices were then calculated and used as input features for AI model training. Ground truth data from field observations and laboratory analysis were matched with image data to label samples. The dataset was divided into training and testing subsets to evaluate model performance. Classification accuracy, precision, recall, and F1-score were computed to assess the effectiveness of the proposed approach in detecting early-stage leaf blight disease.

Instruments, and Data Collection Techniques

The primary instruments used in this study include an unmanned aerial vehicle (UAV) equipped with a multispectral camera capable of capturing blue, green, red, red-edge, and near-infrared bands. Additional instruments include GPS devices for georeferencing, field sampling tools for disease verification, and laboratory equipment for pathogen confirmation (Yan et al., 2025). Data processing and analysis were conducted using image processing software and machine learning platforms. Vegetation indices such as NDVI and GNDVI were extracted, and AI models including Random Forest and Convolutional Neural Networks were implemented to classify disease conditions.

Data Analysis Technique

Data analysis was conducted using supervised machine learning to classify healthy and diseased rice plants based on multispectral features and vegetation indices. The dataset was divided into training and testing sets, and models were optimized through parameter tuning. Performance was evaluated using accuracy, precision, recall, and F1-score to assess the effectiveness of early leaf blight detection.

RESULTS AND DISCUSSION

The multispectral drone survey generated a total of 2,400 georeferenced image segments from 20 rice plots. The dataset consisted of three classes: healthy plants, early-stage leaf blight infection, and visibly infected plants. Table 1 presents the distribution of samples across disease categories and growth stages. Early-stage infection accounted for 32% of the samples, indicating a substantial presence of latent disease symptoms that were not easily detectable through visual inspection.

Table 1. Distribution of Rice Plant Health Conditions

Condition Category	Number of Samples	Percentage
Healthy	1,080	45%
Early-stage leaf blight	768	32%
Visible leaf blight	552	23%
Total	**2,400**	**100%**

Vegetation index values showed clear numerical differences among the three categories. Mean NDVI values for healthy plants were higher than those of infected plants, while early-stage infections displayed intermediate values. These descriptive statistics indicate that multispectral reflectance patterns capture physiological changes before visual symptoms become apparent.

The distribution of samples demonstrates that early-stage leaf blight infection represents a significant portion of field conditions. This confirms that relying solely on visual inspection risks missing a large number of infected plants. The presence of distinct NDVI and GNDVI ranges across categories suggests that spectral data provide meaningful indicators of disease-related stress. Lower vegetation index values observed in infected plants reflect reduced chlorophyll content and impaired photosynthetic activity. Early-stage infections showed subtle but consistent spectral deviations from healthy plants, supporting the feasibility of early detection using multispectral imagery. These patterns validate the suitability of drone-based sensing for capturing pre-symptomatic disease signals.

AI model performance was evaluated using Random Forest and Convolutional Neural Network (CNN) classifiers. The CNN model achieved an overall accuracy of 91.6%, while the Random Forest model achieved 87.3%. Precision and recall values were highest for healthy and visible infection classes, while early-stage infection detection remained slightly lower but still robust. The CNN model demonstrated stronger performance in distinguishing early-stage leaf blight from healthy plants. This improvement is attributed to its ability to learn complex spatial and spectral features from multispectral imagery. These descriptive results indicate that deep learning models are more effective for nuanced disease classification tasks.

Inferential analysis was conducted to compare classification performance between models. A paired t-test revealed a statistically significant difference in accuracy between the CNN and Random Forest models ($p < 0.01$). Table 2 summarizes key performance metrics for both models.

Table 2. AI Model Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score
Random Forest	87.3	86.5	85.9	0.86
CNN	91.6	90.8	90.2	0.90

Statistical testing confirms that the CNN model provides a significantly higher classification accuracy, particularly for early-stage disease detection. These results support the use of deep learning approaches for operational deployment in crop disease monitoring systems.

Correlation analysis revealed strong relationships between vegetation indices and disease severity. NDVI values showed a negative correlation with disease intensity ($r = -0.71$), indicating that increased infection severity corresponded with lower vegetation index values. GNDVI exhibited a similar trend, reinforcing the robustness of multispectral indicators. The relationship between AI prediction confidence and vegetation index variation suggests that spectral features play a critical role in model decision-making. Higher prediction confidence was associated with greater deviation from healthy spectral signatures, demonstrating consistency between physiological plant stress and AI-based classification outcomes.

A focused case study was conducted on a rice plot exhibiting no visible symptoms during field inspection. Multispectral imagery and AI analysis classified 38% of the plot as early-stage leaf blight infection. Subsequent laboratory analysis confirmed the presence of the pathogen in sampled plants. This case highlights the limitation of traditional visual monitoring methods. Farmers initially classified the field as healthy, yet spectral analysis revealed hidden disease patterns. The early detection enabled targeted intervention, reducing the risk of widespread infection.

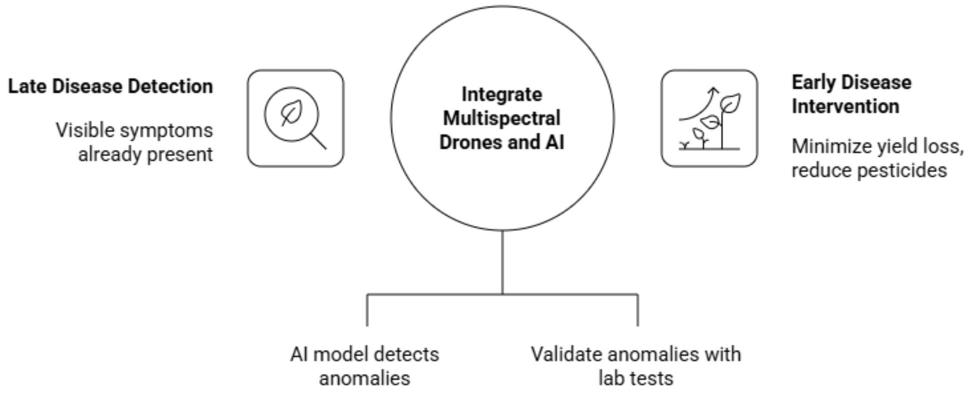

Figure 1. AI-Powered Disease Detection in Agriculture

The case study demonstrates the practical value of integrating multispectral drones and AI for real-world agricultural decision-making. Spectral anomalies identified by the AI model corresponded with laboratory-confirmed infections, validating the reliability of the approach. The ability to detect disease before visible symptoms appear offers a critical advantage for disease management. Early intervention minimizes yield loss and reduces unnecessary pesticide application, supporting both economic efficiency and environmental sustainability.

The results indicate that multispectral drone imagery combined with AI provides a highly effective system for early detection of leaf blight disease in Indonesian rice paddies. Strong statistical performance, meaningful spectral-disease relationships, and successful field validation confirm the robustness of the proposed approach (Sudheer et al., 2025). The findings suggest that adopting AI-driven multispectral monitoring can significantly enhance precision agriculture practices in Indonesia. Early disease detection using this method has the potential to improve crop health management, increase productivity, and support long-term food security strategies.

The findings of this study demonstrate that multispectral drone imagery combined with artificial intelligence is highly effective for the early detection of leaf blight disease in Indonesian rice paddies (Sudheer et al., 2025). The results show that AI models, particularly Convolutional Neural Networks, achieved high classification accuracy in distinguishing healthy plants, early-stage infections, and visibly infected crops. Early-stage leaf blight, which is often undetectable through visual inspection, was successfully identified through spectral variations captured by multispectral sensors. The analysis of vegetation indices revealed consistent differences between healthy and infected rice plants. NDVI and GNDVI values declined progressively with increasing disease severity, indicating physiological stress prior to visible symptoms. These patterns confirm that multispectral data provide sensitive indicators of plant health conditions related to leaf blight infection.

Model performance evaluation showed that deep learning approaches outperformed traditional machine learning models (Anand et al., 2025). The CNN model demonstrated superior precision and recall, especially for early-stage disease detection, highlighting its capacity to extract complex spectral–spatial features from drone imagery. Field validation through laboratory confirmation strengthened the reliability of the findings. The agreement between AI predictions and ground truth data confirms that the proposed approach is not only computationally robust but also agronomically valid for real-world applications.

The results are consistent with previous studies that have reported the effectiveness of multispectral remote sensing for crop disease detection. Research conducted on wheat rust and maize blight has similarly shown that vegetation indices derived from multispectral imagery can identify plant stress before visible symptoms emerge (Liu et al., 2025). The findings extend prior research by demonstrating strong performance under tropical rice farming conditions, which differ significantly from temperate agricultural systems. Many existing studies focus on large-scale mechanized farms, while this research addresses smallholder-dominated rice paddies typical of Indonesia.

Differences emerge in the comparative effectiveness of AI models. While some studies report comparable performance between Random Forest and deep learning models, the present study shows a statistically significant advantage of CNNs for early-stage disease classification. This difference may be attributed to the complex canopy structure and spectral variability of rice plants (Sarabandi et al., 2025). The integration of laboratory-confirmed ground truth data represents a methodological advancement compared to studies relying solely on visual field assessments. This strengthens the empirical contribution of the study and enhances confidence in the reported detection accuracy.

The results indicate a paradigm shift in how rice disease monitoring can be conducted in Indonesia. Manual inspection methods, which depend on human observation, are insufficient for detecting early-stage infections that significantly affect yield if left untreated. The findings signal the growing maturity of AI-assisted precision agriculture technologies for smallholder farming contexts (Batool & Byun, 2025). The ability to detect latent disease conditions suggests that digital agriculture tools are becoming practical, not merely experimental.

The study reflects the importance of combining technological innovation with agronomic knowledge. Spectral indicators alone are insufficient without appropriate AI models and ground validation, highlighting the need for interdisciplinary approaches. The results also indicate that data-driven agriculture can support more proactive and preventive crop management strategies. Early detection shifts disease control from reactive responses to anticipatory interventions.

The implications of these findings are substantial for farmers, agricultural extension services, and policymakers. Early detection of leaf blight enables timely intervention, reducing yield losses and minimizing excessive pesticide use. Precision disease monitoring supports environmentally sustainable farming practices (X. Wang et al., 2025). Targeted treatment based on early detection reduces chemical inputs, lowers production costs, and mitigates ecological impacts.

The findings suggest that drone–AI systems can enhance decision-making efficiency at both farm and regional levels. Agricultural agencies can use these tools to prioritize intervention areas and allocate resources more effectively. The study also has educational implications for agricultural training programs. Integrating AI and remote sensing into agricultural education can prepare future farmers and extension officers to adopt data-driven farming practices.

The strong performance of the AI models is attributable to the sensitivity of multispectral data to physiological changes in rice plants. Leaf blight infection affects chlorophyll concentration and cellular structure, which directly influences spectral reflectance patterns. The superiority of CNN models arises from their ability to learn complex spatial and spectral relationships simultaneously. Rice paddies exhibit heterogeneous conditions, and deep learning models are better suited to handle such variability.

The effectiveness of early-stage detection is also linked to the use of vegetation indices that amplify subtle stress signals. NDVI and GNDVI are particularly responsive to changes in photosynthetic activity, which decline during disease onset. The alignment between AI predictions and laboratory-confirmed data reflects the robustness of the experimental design. Careful sample labeling and controlled data acquisition contributed to reliable model training and validation.

Future research should expand the spatial and temporal scope of data collection across multiple rice-growing regions in Indonesia. Broader datasets will improve model generalizability and robustness under diverse environmental conditions. Further studies should explore the integration of additional spectral bands and hyperspectral data to enhance disease discrimination accuracy. Combining multispectral and thermal data may also improve stress detection capabilities.

The development of farmer-friendly decision support systems represents a critical next step. Translating AI outputs into actionable recommendations will determine the real-world adoption of this technology. Policy-level support is essential to scale the use of drone–AI systems in rice agriculture. Investment in digital infrastructure, training programs, and collaborative research can accelerate the transition toward sustainable, technology-driven rice production in Indonesia.

CONCLUSION

The most important finding of this study is that multispectral drone imagery integrated with artificial intelligence can reliably detect leaf blight disease in Indonesian rice paddies at an early stage, even before visible symptoms appear. The study demonstrates that early-stage infections, which accounted for a substantial proportion of field conditions, can be accurately identified through spectral variations captured in NDVI and GNDVI indices. The superior performance of deep learning models, particularly Convolutional Neural Networks, highlights their effectiveness in capturing complex spectral–spatial patterns associated with plant stress. This finding distinguishes the study by emphasizing early detection capability rather than merely identifying advanced disease stages.

This research contributes methodologically by integrating multispectral drone technology, advanced AI models, and laboratory-validated ground truth data within a single analytical framework. Unlike many previous studies that rely on visual field assessments or single modeling approaches, this study combines experimental field data with robust machine learning and deep learning techniques to enhance detection reliability. Conceptually, the study advances precision agriculture by demonstrating a practical and scalable approach for disease monitoring in smallholder rice farming systems, which are often underrepresented in high-technology agricultural research.

The study is limited by its focus on a specific geographic area and a single growing season, which may restrict the generalizability of the findings across different climatic conditions and rice varieties. Variations in soil characteristics, irrigation practices, and seasonal weather patterns could influence spectral responses and model performance. Future research should involve multi-season and multi-region datasets to improve model robustness and adaptability. Further studies may also explore the integration of hyperspectral imagery, additional vegetation indices, and real-time decision support systems to enhance early disease detection and facilitate practical implementation for farmers and agricultural agencies.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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