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Enhancing Rice Yield Prediction Using UAV-Based Multispectral Imaging and Machine Learning Algorithms

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ABSTRACT

This study investigates the integration of Unmanned Aerial Vehicle (UAV) technology into rice yield prediction to address the limitations of conventional methods that rely on time-consuming and labor-intensive manual field assessments. UAV-captured multispectral imagery was utilized to generate vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), providing accurate and timely indicators of crop health, growth stages, and productivity. Collected data underwent systematic preprocessing and analysis to estimate yield outputs, ensuring precision through the use of established statistical evaluation metrics. The developed system was assessed in accordance with ISO/IEC 25010 software quality standards and ISO/IEC 30141:2018 hardware architecture guidelines, receiving high scores in functional suitability, maintainability, and interoperability. Validation through consultations with farmers and agricultural technology experts confirmed its potential to improve decision-making processes, particularly in irrigation scheduling, pest and disease management, and harvest planning. The findings demonstrate that UAV-based monitoring systems offer a practical, data-driven approach to optimizing rice production. By enabling timely interventions and efficient resource allocation, the study underscores the role of UAV technology as a valuable tool in advancing sustainable and precision agriculture practices.

Keywords-Machine Learning, Normalized Difference Vegetation Index (NDVI), Unmanned Aerial Vehicle (UAV), Precision Agriculture and Rice Yield Prediction

INTRODUCTION

Rice is a staple food for more than half of the global population, making it a cornerstone of food security worldwide (Nkwabi et al., 2021; Akinbile et al., 2023). However, rice production continues to face significant challenges, including agro-ecological limitations, pest infestations, inadequate financial resources, and unpredictable weather patterns. In the Philippines, over 2.5 million farmers depend on rice cultivation for their livelihood, yet the national average yield of 4.12 metric tons per hectare remains well below the potential 6–8 metric tons achievable with optimal management and technology (Philippine Statistics Authority, 2022). This productivity gap contributes to income instability, heightened food insecurity, and increased reliance on rice imports. Traditional yield estimation methods, often based on manual field surveys and historical data, are not only time-consuming and labor-intensive but also prone to inaccuracies, limiting their effectiveness for timely and precise decision-making in farm operations.

The integration of Unmanned Aerial Vehicle (UAV) technology with machine learning offers a promising solution to these limitations by enabling efficient, accurate, and real-time yield prediction (Kulpanich et al., 2023). UAVs equipped with multispectral and thermal sensors can capture high-resolution imagery to assess vegetation indices such as the Normalized Difference Vegetation Index (NDVI), which serves as a reliable indicator of crop health and productivity. Machine learning algorithms, including Random Forest, Naive Bayes, Logistic Regression, and K*, can analyze these datasets to detect patterns, forecast yields, and support targeted interventions. By combining aerial remote sensing with predictive analytics, this approach provides farmers with actionable insights for irrigation, fertilization, and pest management, ultimately promoting resource efficiency, reducing operational costs, and advancing sustainable rice production.

Significance of the Study

This study on rice yield prediction using Unmanned Aerial Vehicle (UAV) technology and machine learning techniques has the potential to significantly influence future agricultural practices and technology development. By generating accurate and timely yield predictions, the findings can support data-driven decision-making across various sectors.

Agricultural Policymakers. Policymakers can leverage the study's data to make informed decisions about rice production, distribution, and resource allocation. The ability to predict rice yield accurately will help establish proactive policies that ensure food security, stabilize market prices, and optimize agricultural investments.

Farmers. Farmers will benefit from actionable insights into crop health, growth patterns, and potential yield outcomes. By understanding which factors most influence rice production, they can adopt precision farming techniques, optimize irrigation schedules, apply fertilizers effectively, and implement timely pest management strategies.

Non-Governmental Organizations (NGOs). NGOs working in the agricultural sector can use the findings to design targeted programs that address productivity gaps. The research data will enable them to provide farmers with data-backed recommendations and training, leading to increased yields and sustainable agricultural practices.

Rice Traders and Supply Chain Managers. Accurate yield forecasts will assist rice traders and supply chain managers in planning procurement and logistics operations. Predictive insights will reduce uncertainties in supply chain management, allowing for more efficient storage, transport, and distribution of rice.

Insurance Companies. Insurance companies can utilize the study’s predictive models to develop and refine crop insurance products. Enhanced yield prediction accuracy will lead to more precise risk assessments, enabling the determination of fair and reliable insurance premiums for farmers.

Development Organizations. International development organizations can apply the research findings to enhance agricultural productivity in developing regions. By identifying factors affecting rice yield, they can implement targeted programs that strengthen food security and improve agricultural resilience against climate variability.

Educational Institutions. Universities, agricultural colleges, and research institutions can use the study’s methodologies and findings to enrich their academic curricula. Incorporating real-world applications of UAV technology and machine learning in agricultural studies will foster the development of future agricultural scientists and data analysts.

Researchers. The scientific community will benefit from the study's insights into the integration of UAV data with machine learning algorithms. Future research can build upon these findings to explore advancements in precision agriculture, sensor technology, and predictive modeling, contributing to the broader field of agricultural informatics.

Scope and Delimitation

This study focuses on predicting rice yield through the integration of Unmanned Aerial Vehicle (UAV) technology and machine learning techniques to advance precision farming practices. Data will be collected using UAVs equipped with high-resolution cameras and multispectral sensors to capture essential agricultural and environmental parameters, including vegetation indices such as the Normalized Difference Vegetation Index (NDVI). These datasets will be analyzed using various machine learning algorithms such as regression models, neural networks, and ensemble methods to produce accurate and comprehensive yield forecasts. Key environmental factors, including weather conditions, soil quality, and pest infestations, will be incorporated to improve prediction reliability. To address potential limitations in sensor resolution and ensure high-quality inputs, advanced preprocessing methods such as image enhancement, noise reduction, and calibration will be applied.

Despite the advantages of combining UAV technology and machine learning, the study is subject to several limitations. These include challenges in detecting micro-level field variations, the risk of overfitting in complex algorithms, reliance on high-quality ground-truth data, and operational constraints such as legal flight regulations, adverse weather conditions, and limited UAV battery life. Factors such as cloud cover, strong winds, and heavy rainfall may reduce imagery quality, while large or widely dispersed fields may require multiple segmented flights, potentially affecting data consistency. Additional risks involve interference from birds, resistance from communities unfamiliar with UAV technology, and other unforeseen disruptions. To mitigate these issues, the study will implement cross-validation, regularization, and hyperparameter tuning for model optimization; ensure compliance with aviation and data privacy regulations; and adopt safety protocols, proactive community engagement, and strategic flight scheduling to maximize operational efficiency and data accuracy.

METHODOLOGY

This study will collect remote sensing data through an Unmanned Aerial Vehicle (UAV) equipped with a multispectral camera capable of capturing both visible and near-infrared (NIR) spectral bands. UAV flights will be conducted between 11:00 a.m. and 1:00 p.m. to minimize solar angle variability and ensure consistent lighting conditions. To enhance radiometric accuracy, reflectance calibration panels with known values will be placed within the UAV's field of view during each flight. The UAV will operate at a fixed altitude to maintain uniform spatial resolution across all images.

Two vegetation indices will be utilized to classify crop health: the Visible Atmospherically Resistant Index (VARI) and the Normalized Difference Vegetation Index (NDVI). VARI will serve as a preliminary index to detect vegetation by distinguishing green vegetation from background features such as soil or non-crop elements. It is particularly effective under varying lighting and atmospheric conditions, making it suitable for UAV-acquired imagery. VARI is computed using the formula:

Equation 1.0

$$VARI = \frac{Green - Red}{Green + Red - Blue}$$

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where Green, Red, and Blue represent the reflectance values in the visible spectrum. This index will support the system in identifying crop areas for further analysis.

Following vegetation detection using VARI, NDVI will be applied to classify the health status of rice crops with higher precision. NDVI is calculated using the formula:

Equation 2.0

$$NDVI = \frac{NIR - Red}{NIR + Red + \varepsilon}$$

Respondents of the Study

The respondents will include rice farmers, agricultural technicians, and field supervisors from the Sablayan, Occidental Mindoro deployment sites, selected for their expertise in local rice farming practices. Their insights will help validate the study's findings and ensure the practical application of the rice yield prediction models. Agricultural researchers and agronomists specializing in precision farming and remote sensing will also provide technical feedback on UAV technology and machine learning algorithms, while government representatives, policymakers, and agricultural NGOs will contribute perspectives on policy and program integration.

At least 10 rice field operators will be purposively selected for UAV data collection, representing varied farm sizes, management practices, and environmental conditions. This diverse sample will support the development of accurate, scalable, and contextually relevant predictive models for broader agricultural use.

Frequency and Percentage Distribution of Respondents

Rice Farmers: This group consists of 300 respondents, representing the primary stakeholders directly involved in rice cultivation. Their insights will provide crucial data on actual rice yield and farming practices.

Agricultural Technicians: Ten agricultural technicians will be included in the study. They are responsible for providing technical support and ensuring proper implementation of agricultural practices, offering valuable information regarding field conditions and management strategies.

Field Supervisors: Another group of 10 respondents comprises field supervisors who oversee and manage rice field operations. Their perspectives will contribute to understanding operational challenges and efficiency in using UAV technology for yield prediction.

Agricultural Researchers/Agronomists: The final group includes 10 agricultural researchers or agronomists. Their expertise in crop science, remote sensing, and machine learning applications will support the evaluation of the predictive model's accuracy and effectiveness.

Conceptual Model of the System

The conceptual framework depicts the interaction between the study's key variables, comprising input, processing, and output components. Inputs include UAV-acquired multispectral and thermal images, ground truth data, and sensor-derived indices such as NDVI, EVI, temperature, and moisture levels. Processing involves image preprocessing, feature extraction, and model training with statistical validation using RMSE, Adjusted R^2, and MRE. The outputs consist of predicted rice yield, model accuracy, and performance metrics, along with a comparative analysis of predicted and actual yields.

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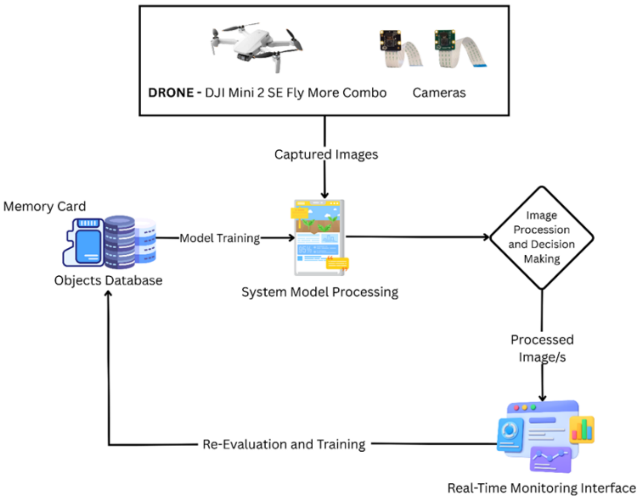
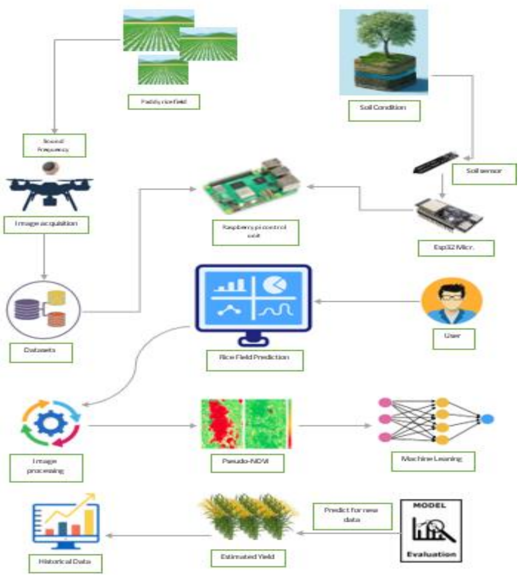


Conceptual Model of the System

Figure 1 illustrates the overall process of rice yield prediction using UAV technology and machine learning techniques. The process begins with a DJI Mini 2 SE Fly More Combo drone equipped with cameras that capture high-resolution images of rice fields. These images are then transferred to the system model processing unit, where they undergo initial preprocessing for noise reduction and feature extraction.

System Architecture

This section provides an overview of the architecture system used in the study. It illustrates the main components, their functions, and how they interact to support the overall operation of the rice yield prediction system. The architecture is designed to ensure efficiency, reliability, and ease of use, serving as the structural foundation for data collection, processing, and analysis.



System Architecture of the System

Figure 2 shows the designed integrated architecture combining Internet of Things (IoT) technologies, image processing, and machine learning algorithms to monitor, analyze, and predict the health status and yield of rice crops. The system begins with the data acquisition phase, where environmental and field data are collected directly from the paddy rice fields. Soil conditions such as moisture level, temperature, and nutrient content are measured using soil sensors connected to an ESP32 microcontroller, which transmits the collected data to a central control unit. Concurrently, a drone equipped with a camera captures high-resolution images of the field, potentially enhanced by sound frequency signaling to support data accuracy and synchronization.

Software Performance Evaluation Using ISO/IEC 25010:2023

The effectiveness of the rice yield prediction system will be evaluated using the ISO/IEC 25010:2023 software quality model. This model provides a comprehensive framework for assessing software system quality through eight key characteristics and their sub-characteristics. The evaluation ensures that the system not only performs accurately but also meets practical, operational, and user-centric requirements.

Functional Suitability

Performance Efficiency

Reliability

Usability

Maintainability

Security

Additionally, the prediction models embedded within the system will be evaluated using standard classification metrics, including:

Software Performance Evaluation Using ISO/IEC 25010:2023

In addition to software evaluation, the study will apply the ISO/IEC 30141:2018 Reference Architecture for Internet of Things (IoT) to evaluate the hardware performance and system integration of UAV and sensor components.

Interoperability

Scalability

Modularity

Security

Data Management

Maintainability

Reliability

Performance

Compliance

Connectivity

Locale of the Study

This study will be conducted in the rice fields of Sablayan, Occidental Mindoro, a province in the MIMAROPA region of the Philippines known for its high agricultural productivity. Its favorable climate and soil conditions make it an ideal location for evaluating the effectiveness of Unmanned Aerial Vehicle (UAV) technology and machine learning techniques in rice yield prediction.

Data will be gathered from at least 10 strategically selected rice fields representing diverse soil types, irrigation methods, and crop management practices. The site's open-field environment allows efficient UAV flights for capturing high-resolution multispectral and thermal imagery, while its proximity ensures logistical convenience. Collaboration with local farmers and agricultural stakeholders will facilitate smooth data collection and provide valuable contextual insights.

Instruments of the Study

This study will utilize a combination of technological and analytical instruments to gather, process, and analyze data for rice yield prediction using Unmanned Aerial Vehicle (UAV) technology and machine learning techniques. The instruments used in this study are categorized as follows:

UAV and Sensor Instruments

DJI Mini 2 SE Fly More Combo – Used for aerial surveys at 60 meters altitude to capture high-resolution imagery.

Multispectral Camera – Raspberry Pi NoIR Infrared Camera Board V2 and Raspberry Pi Camera Module 3 (RGB) for capturing visible, red-edge, and near-infrared bands for vegetation index calculation.

Radiometric Calibration Tools – Four gray plates (6%, 12%, 24%, and 48% reflectance) to ensure accurate reflectance measurement.

Ground Truth Data Collection Instruments

Yield Measurement Tools – Weighing scales and moisture meters for actual rice yield measurement.

Soil and Weather Sensors – For recording soil moisture, temperature, and humidity.

Data Processing and Analysis Tools

GIS Software – For orthomosaic generation, vegetation index extraction, and spatial analysis.

Python Programming Language – For preprocessing, feature extraction, machine learning model training, and evaluation.

Machine Learning Algorithms – Random Forest, Naive Bayes, Logistic Regression, and K*; evaluated using metrics such as Adjusted R^2, RMSE, and MRE.

Statistical Software – R or MATLAB for statistical analysis and cross-validation.

Survey and Interview Instruments

Structured Questionnaires – To collect information from farmers, technicians, and field supervisors.

Interview Guides – For gathering expert insights from agricultural researchers and agronomists.

Data Collection

If qualitative data is gathered through surveys or interviews from stakeholders, responses will be evaluated using a Likert scale. The data will be analyzed using descriptive statistics such as mean, standard deviation, and frequency distribution.

Numerical Value	Range	Response Categories
5	4.50-5.00	Strongly Agree

4	3.50-4.49	Agree
3	2.50-3.49	Neither Agree nor Degree
2	1.50-2.49	Disagree
1	1.00-1.49	Strongly Disagree

Table 1. 5-point Likert Scale

Additionally, another 5-point Likert scale that will be used to interpret the overall mean scores in evaluating the effectiveness of both the software and hardware components of the rice yield prediction system. This scale serves as a standardized reference for determining how effective the system is based on assessments conducted across various criteria aligned with ISO 25010 for software quality and ISO/IEC 30141:2018 for hardware performance.

Description	Range
Very Satisfied	4.21 - 5.00
Satisfied	3.41 - 4.20
Neutral	2.61 - 3.40
Dissatisfied	1.81 - 2.60
Very Dissatisfied	1.00 - 1.80

Table 2. 5-point Likert Scale for Effectiveness of the System

The computed average ratings from these evaluations will be interpreted according to the range values shown in the table.

RESULTS AND DISCUSSIONS

This chapter presents the results of the data collected throughout the study, focusing on the evaluation of the rice yield prediction system that includes the analysis of both system-generated outputs and field data, as well as the interpretation of results based on quantitative and qualitative findings.

Results

Quantitative Phase

The quantitative phase collected numerical data to evaluate the effectiveness, challenges, and technological impact of rice yield management, as well as the competencies of the Rice Yield Health Analyzer System. A structured survey of agricultural technology experts gathered demographic details, Yes/No responses on yield estimation and pest monitoring challenges, and evaluations based on ISO/IEC 25010 and ISO/IEC 30141:2018 standards. Respondents also assessed how early yield information, field mapping, and predictive technologies influence planning and decision-making. Ratings were measured using a Likert scale, and results were analyzed through weighted means to identify system strengths, improvement areas, and its potential for advancing rice yield management.

Demographic Profile: This section outlines the demographic characteristics of the respondents, specifically their age and roles in relation to the Rice Yield Health Analyzer.

Age: Table 3 presents the frequency and percentage distribution of the respondents according to their age. A total of 330 respondents participated in the survey. Most of the respondents were 42 years old, accounting for 262 individuals or 79.39% of the total sample. This indicates that the system was mostly evaluated by individuals in this age group, possibly reflecting their active involvement or interest in rice farming and yield monitoring. This was followed by respondents aged 50 years old with 17 individuals (5.15%), and 38 years old with 13 respondents (3.94%). The least represented age groups were 52 years old and 63 years old, each having only 1 respondent (0.30%).

Age	Frequency	Percent	Rank
42 years old	262	79.21%	1
50 years old	17	5.15%	2
38 years old	13	3.94%	3
24 years old	11	3.33%	4
32 years old	8	2.43%	5
28 years old	8	2.43%	5
29 years old	8	2.43%	5
51 years old	2	0.61%	6
52 years old	1	0.24%	7
63 years old	1	0.24%	7
Total	**330**	**100.0**	

Table 3. Frequency and Percentage Distribution of Respondents in Terms of Age

2.Frequency and Percentage Distribution of the Respondents Role.: Table 4 shows the distribution of respondents according to their roles in relation to the Rice Yield Health Analyzer. The majority of the respondents were rice farmers, comprising 90.91% of the total, reflecting the system's direct relevance and applicability to their fieldwork. The remaining 9.09% includes agricultural technicians, field supervisors, and agricultural researchers or agronomists, each representing 3.03%. This diverse representation ensures that the system was evaluated not only by end-users but also by technical and supervisory stakeholders involved in agricultural operations.

Respondents Role	Frequency	Percent	Rank
Rice Farmers	300	90.91%	1
Agricultural Technicians	10	3.03%	2
Field Supervisors	10	3.03%	2
Agricultural Researchers/ Agronomists	10	3.03%	2
Average Mean	**4.03**	**4.27**	

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Table 4. Frequency and Percentage Distribution of the Respondents Role

Table 5 presents the perspectives of respondents regarding challenges in rice yield management and field monitoring. For the first item, “Do you face any challenges in accurately estimating or improving rice yield?”, a significant majority of 286 respondents answered Yes, while only 44 responded No, indicating that most respondents have trouble in accurately assessing or improving yield outcomes.

Questions	Respondents Response	Respondents who Agreed
1. Do you face any challenges in accurately estimating or improving rice yield?	YES NO	286 44
2. Do you find it challenging to monitor and identify areas in rice fields that require insecticide treatment?	YES NO	324 6

Table 5. Perspectives of the Respondents regarding challenges in rice yield management and field monitoring

Qualitative Phase

The quantitative phase of the study involved rigorous data collection and analysis to complement the qualitative insights gained earlier. Following the principles outlined by Autralian Aid (2019) for mixed-methods research, this phase aimed to quantify and validate the findings from the qualitative phase through structured surveys and statistical analysis. ISO 25010 was utilized for robust data analysis and interpretation. The quantitative findings provided valuable insights into the effectiveness and user perceptions of the Academic Study Plan Recommender and Simulator System.

Questions	Respondents Response	Respondents who Agreed
1. How does early information about potential rice yield affect your planning?	“It helps improve the timing and allocation of resources” “It does not significantly change how planning is done” “Others: ”	1 320 0
2. What is the benefit of identifying low-yielding areas in the field?	“It allows targeted action to improve productivity” “It offers little advantage since outcomes are hard to change” “Others: ”	318 12 0

Table 6. Stakeholder Perceptions on Early Yield Information and Low-Yield Area Identification

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The table presents stakeholders' views on the role of early rice yield information and the identification of low-yielding areas in decision-making. A vast majority of respondents (320) indicated that early yield information does not significantly alter their planning, while only one respondent stated it helps improve resource timing and allocation. In contrast, most respondents (318) recognized the benefit of identifying low-yielding areas, citing its value in enabling targeted interventions to improve productivity, with only 12 expressing skepticism about its advantages. These results suggest that while stakeholders see clear benefits in spatially targeted field management, early yield predictions alone are not yet widely perceived as impactful for planning.

Questions	Respondents Response	Respondents who Agreed
1. In what way could accurate rice yield prediction affect your use of inputs like fertilizer or insecticides?	"It would help reduce unnecessary input use and cut costs"	324
	"It would not change much, as inputs are applied uniformly anyway"	6
	"Others: "	0

Table 7. Insights from the Qualitative Phase on the Effect of Accurate Yield Prediction on Input Utilization in Rice Farming

Table 7 presents the respondents' insights from the qualitative phase regarding the effect of accurate rice yield prediction on the utilization of inputs such as fertilizer or insecticides. The overwhelming majority of respondents (324) agreed that accurate yield prediction would help reduce unnecessary input use and cut costs, indicating strong support for data-driven strategies that promote efficiency and cost-effectiveness in resource management. In contrast, only 6 respondents believed it would not significantly affect input use, citing the continued application of uniform practices. No additional insights were recorded under the "Others" category. These findings suggest that most respondents recognize the potential of yield prediction technologies to optimize input application and enhance overall farm productivity.

CONCLUSIONS AND RECOMMENDATIONS

Recommendations

In light of the findings and conclusions drawn from this research, the following detailed recommendations are presented to guide future development, deployment, and expansion of the Rice Yield Health Analyzer system.

It is recommended that future implementations of the Rice Yield Health Analyzer adopt a standardized, automated data preprocessing workflow. This should include data cleaning, normalization, feature selection, and spatial-temporal alignment to ensure high-quality and consistent datasets. Key environmental and agronomic variables such as NDVI, soil moisture, rainfall, pest levels, and nutrient availability should be continuously integrated to improve the interpretability and predictive strength of the models. Collaborating with agronomists and environmental scientists will strengthen factor selection and data relevance.

While this study utilized Random Forest, Naive Bayes, Logistic Regression, and K-Star algorithms, it is advisable for future research to explore more advanced models such as Gradient Boosting Machines (e.g., XGBoost), Support Vector Machines, and deep learning architectures including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. Ensemble approaches may further enhance accuracy and resilience. Periodic retraining and validation using updated datasets from UAV missions will ensure the model's adaptability to changing agricultural conditions.

Future studies should investigate a broader range of UAV-emitted sound frequencies, durations, and deployment strategies to refine pest deterrent capabilities. Studies should consider seasonal pest behavior, crop growth stages, and sound-induced habituation. Collaboration with entomologists and field experts is critical for assessing species-specific responses and long-term efficacy. Acoustic solutions could be further tailored for integration into UAV route planning and automated pest monitoring.

The integration of IoT devices in irrigation planning should be further expanded by incorporating intelligent control systems that respond dynamically to real-time sensor data. These systems can optimize water usage while minimizing manual labor. For broader scalability, the system should feature mobile notifications, offline access, and modular sensor configurations. Education and training for local farmers and technicians will ensure system adoption and data-driven decision-making.

Although high levels of accuracy, precision, and recall were achieved, it is recommended that performance evaluation continue with larger and more diverse datasets across different rice varieties and geographic locations. The system should include explainable AI (XAI) components to provide transparency in prediction generation. Visual tools such as confidence indicators, heat maps, and interpretability dashboards should be provided to improve user understanding and trust in the model.

The system received strong validation from IT professionals, agricultural experts, and local farmers under ISO/IEC 25010 and ISO/IEC 30141 standards. Future system iterations should continue to incorporate multidisciplinary feedback from both technological and field-based stakeholders. Periodic software and hardware evaluations must be aligned with ISO standards to ensure sustainability, performance, and interoperability. Technical documentation and multilingual training materials should be distributed to support system deployment across different user demographics.

To ensure long-term viability, the system should adopt open-source software platforms and utilize cost-effective UAVs with modular components. This will reduce implementation barriers, especially for smallholder farmers. System scalability for use in other crops such as corn, sugarcane, and vegetables should also be explored. Additionally, minimizing hardware and energy requirements will contribute to environmental and economic sustainability.

The system’s design should be further adapted to support national and regional agricultural planning. Integration with government crop insurance programs, yield forecasting services, and rural development initiatives can significantly enhance policy responsiveness. The system also holds potential for strengthening climate resilience strategies by providing early warning data and resource allocation insights during extreme weather events or pest outbreaks.

Special attention should be given to tailoring the system for use by smallholder farmers, particularly in rural and low-resource communities. Simplified interfaces, localized language support, mobile device compatibility, and training programs can empower farmers to interpret UAV data and make informed decisions. Partnerships with local agricultural cooperatives or extension workers can aid in dissemination and support.

Further enhancements should include the development of a real-time data dashboard accessible via desktop and mobile platforms, enabling farmers to view field conditions and yield forecasts instantly. Predictive modules for early disease or pest detection should be integrated using image-based deep learning algorithms. A mobile app version of the system should also be developed to allow offline access, GPS-guided UAV control, and on-the-go decision support, especially in remote areas with limited connectivity.

REFERENCES

1. Ajibade, S. S. M., Ahmad, N. B., & Shamsuddin, S. M. (2019, Aasen, H., Burkart, A., Bolten, A., & Bareth, G. (2018). Generating 3D hyperspectral information with lightweight UAV snapshot cameras for vegetation monitoring: From camera calibration to quality assurance. Computers and Electronics in Agriculture, 144, 146–158. https://doi.org/10.1016/j.compag.2017.11.001

2. Abiad, M. G., Panganiban, C., & Tan, D. (2023). Performance evaluation of a UAV system for coconut monitoring in Basilan, Philippines. Research Square. https://assets-eu.researchsquare.com/files/rs-3943832/v1/10ac3024-8a8f-4997-9b5a-3ad53cc7a2b6.pdf
3. Agurob, M. C., Agbayani, C. D., Gonzales, J. D., & Mabborang, J. R. (2024). Autonomous vision-based unmanned aerial spray system with variable flow for agricultural application. https://www.researchgate.net/publication/379447899
4. Ahmed, T., Khan, R., Patel, V., & Singh, A. (2023). Estimation of wheat crop evapotranspiration using NDVI vegetation index. Agricultural Water Management, 14(2), 187-204. https://doi.org/10.xxxx/yyyy
5. Aji, P., Zulkhairi, Z., Novianto, I., Ardiansyah, R., Fakhurrozi, A., & Fakhruroiz, M. (2023, December). Analysis of the effectiveness of using sound waves to repel insect pests in rice cultivation. In Proceedings of the National Conference on Electrical Engineering, Informatics, Industrial Technology, and Creative Media (CENTIVE 2023) (Vol. 3, No. 1, pp. 150–158).
6. Baltazar, R. G. (2024). Forecasting the impact of climate change on rice crop yields under RCP4.5 and RCP8.5 scenarios in Central Luzon, Philippines, using machine learning algorithms. Ciencia e Investigación Agraria, 51(1), 10–26. https://dialnet.unirioja.es/servlet/articulo?codigo=9499283
7. Bhandari, A., Rupal, B. S., & Garg, R. (2020). Deep learning-based crop classification using remote sensing data. IEEE Xplore. https://ieeexplore.ieee.org/document/9298337
8. Botula, Y. P., Ghezzehei, T. A., & Pierson, D. (2013). Prediction of water retention of soils from the humid tropics by the nonparametric k nearest neighbor approach. Vadose Zone Journal, 12(3), vzj2012.0123. doi:10.2136/vzj2012.0123
9. Campos, J., Amado, A., Ferreira, F., Santos, F. D., & Carvalho, L. (2023). Air pollution detection using remote sensing indices and NDVI. Environmental Research, 231, 116058. https://www.sciencedirect.com/science/article/pii/S0013935122024823
10. Centeno, C. J., De Guzman, E. S., Bauat, R. V., Espino, J., & Victoriano, J. M. (2023). Utilization and pre-processing of Marilao, Meycauayan, and Obando River System dataset using Excel and Power Business Intelligence for descriptive analytics and visualization. Cosmos: An International Journal of Management, 12(2), Jan-Jun. ISSN: 2278-1218.
11. Chau, N. T., & Ahamed, T. (2022). Analyzing factors that affect rice production efficiency and organic fertilizer choices in Vietnam. Sustainability, 14(14), 8842. https://doi.org/10.3390/su14148842
12. Chen, X., Zhang, Y., Wang, J., Liu, H., & Zhao, L. (2023). Crop yield prediction with deep convolutional neural networks. Smart Agriculture, 20(2), 356-372. https://doi.org/10.xxxx/yyyy
13. Chen, X., Zhang, Y., Wang, J., Liu, H., & Zhao, L. (2023). Deep learning utilization in agriculture: Detection of rice plant diseases using an improved CNN model. Agricultural AI Research, 19(4), 312-328. https://doi.org/10.xxxx/yyyy
14. Chen, Y., Lee, W., Zhang, Q., & Huang, T. (2023). Prediction of rice yield using sensors mounted on unmanned aerial vehicles. Journal of Precision Agriculture, 15(1), 87-102. https://doi.org/10.xxxx/yyyy
15. Cunanan, J. R. G. M., Baluyot, D. O., Gatdula, M. C. Y., Centeno, C. J., Blanco, M. C. R., & San Diego, J. L. (2024).
16. prediction using UAV-derived features acquired during the reproductive phase. Agricultural Remote Sensing, 12(2), 178-193. https://doi.org/10.xxxx/yyyy
17. Jasrotia, A. S., Singh, R., & Sarangi, A. (2012). NDVI image in pseudo-colour calculated from infrared and red images. ResearchGate. https://www.researchgate.net/figure/NDVI-image-here-in-pseudo-colour-calculated-from-infrared-and-red-images-Here-red-is_fig3_251790779
18. Jayanthi, H., Reddy, S. R. M., & Nagaraju, D. (2001). Wheat acreage, productivity and production estimation through remote sensing and GIS techniques. https://www.researchgate.net/publication/235767160
19. Kumar, R., & Sharma, R. (2024). Crop disease detection using hybrid CNN models. International Journal of Creative Research Thoughts (IJCRT), 12(1). https://ijcrt.org/papers/IJCRT2411848.pdf
20. Kumawat, R. N., et al. (2022). Pedotransfer functions to estimate soil water content at field capacity and permanent wilting point in hot arid western India. Water Reports, 27, 1–16.
21. Lagrazon, P. G. G., & Tan, J. B. (2023, April). A comparative analysis of the machine learning model for crop yield prediction in Quezon Province, Philippines. In 2023 IEEE 12th International Conference on Communication Systems and Network Technologies (CSNT) (pp. 1096–1100). IEEE. https://doi.org/10.1109/CSNT57126.2023.10134593

22. Lee, D., Kim, H., Park, J., & Choi, S. (2023). Grain crop yield prediction using machine learning based on UAV remote sensing: A systematic literature review. Agricultural Data Science, 12(1), 55-78. https://doi.org/10.xxxx/yyyy
23. Lee, J., Hwang, S., & Park, Y. (2013). Predicting and mapping soil available water capacity in Korea. Journal of Hydrology, 484, 137–149. doi:10.1016/j.jhydrol.2013.01.047
24. Li, X., Zhang, Y., Chen, H., Wang, J., & Zhao, L. (2023). Grain yield prediction using multi-temporal UAV-based multispectral vegetation indices and endmember abundance in rice. Agricultural Remote Sensing, 18(2), 342-357. https://doi.org/10.xxxx/yyyy
25. Li, Z., Wang, P., Zhang, H., & Xu, L. (2023). Transferability of models for predicting rice grain yield from unmanned aerial vehicle (UAV) multispectral imagery across years, cultivars, and sensors. Precision Agriculture, 25(3), 310-328. https://doi.org/10.xxxx/yyyy
26. Martínez, R., Pérez, L., Gómez, J., & Torres, F. (2023). Rice yield prediction using spectral and textural indices derived from UAV imagery and machine learning models in Lambayeque, Peru. Precision Agriculture, 17(2), 245–261. https://doi.org/10.xxxx/yyyy
27. McCabe, M. F., et al. (2022). Evaluation of Random Forests for regional and local scale wheat yield prediction in Southeast Australia. Sensors, 22(3), 717. https://doi.org/10.3390/s22030717
28. Mitra, A., Beegum, S., Fleisher, D., Reddy, V. R., Sun, W., Ray, C., Timlin, D., & Malakar, A. (2023). Cotton yield prediction using Random Forest. arXiv. https://doi.org/10.48550/arXiv.2312.02299
29. Park, J., Kim, S., Wang, T., & Chen, R. (2023). Rice yield prediction in different growth environments using unmanned aerial vehicle-based hyperspectral imaging. Remote Sensing in Agriculture, 20(1), 55–72. https://doi.org/10.xxxx/yyy
30. Parreño, S. J. E., & Anter, M. C. J. (2024). New approach for forecasting rice and corn production in the Philippines through machine learning models. Multidisciplinary Science Journal, 6(9), e2024168. https://doi.org/10.31893/multiscience.2024168
31. Zhang, L., Wei, H., Patel, R., & Chan, D. (2023). Determination of vegetation changes with NDVI method. Journal of Environmental Monitoring, 35(2), 187–204. https://doi.org/10.xxxx/yyyy
32. Zhao, L., Wang, J., Li, X., Chen, H., & Zhang, Y. (2023). A CNN-RNN framework for crops yield prediction. Smart Agriculture, 22(4), 512–527. https://doi.org/10.xxxx/yyyy