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SmartPaddy: A Cross-Platform Mobile Application for Real-Time Paddy Crop Health Monitoring Using Image Processing and Cloud Integration

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ABSTRACT

SmartPaddy is a cross-platform mobile application developed using Flutter to support real-time paddy crop health monitoring through image processing and cloud-based integration. This study presents the system architecture, machine learning workflow, and a structured usability evaluation involving 10 farmers with 1–15 years of farming experience. The evaluation included task-based trials and a 20-item Likert-scale questionnaire measuring usefulness, ease of use, learning outcomes, and overall satisfaction. Results showed that 80% of users strongly agreed the app helped them detect diseases, 70% understood the recommended actions, and 90% could apply the guidance to real crops. The offline disease-treatment module was positively rated by 70% of respondents. Key constraints identified include occasional misclassification under low-light images, limited disease categories, and the need for clearer result presentation. SmartPaddy contributes to mobile-based agricultural decision support by integrating real-time image analysis with practical offline information for field users. Future improvements aim to expand the disease database, improve image capture guidance, and refine the result explanation interface to enhance diagnostic clarity.

1. Introduction

Agriculture plays a critical role in ensuring food security and supporting economic development, particularly in regions where rice is a staple food. With increasing global food demand and mounting challenges such as climate change, pests, and crop diseases, there is an urgent need for effective technological tools to support farmers in managing crop health efficiently [1], [2], [3]. Rice farming serves as a livelihood for millions, and the early detection of diseases and pests is essential for reducing losses and ensuring consistent yields.

Despite the importance of early intervention, many farmers face limitations in accessing reliable, real-time tools tailored specifically for paddy farming. Existing solutions often lack the capability to provide immediate feedback, offer specific treatment recommendations, or function offline in areas

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with limited internet connectivity. These gaps hinder effective crop management and decision-making at the farm level [4], [5], [6].

This study aims to develop a cross-platform mobile application named SmartPaddy that enables farmers to monitor the health of their paddy crops in real time using image processing and machine learning technologies. The application will allow users to capture images of rice leaves and receive instant diagnostic insights, including specific treatment suggestions. The solution will be powered by a lightweight machine learning model integrated via TensorFlow Lite and will also support offline access to a disease-treatment database using SQLite. The app will include syncing capabilities to ensure the database remains current when internet access is available.

The main objective of this project is to empower rice farmers with an accessible, offline-capable, and intelligent tool to improve decision-making, reduce crop losses, and promote sustainable agricultural practices through the adoption of mobile technology.

2. Previous Works

In recent years, several mobile applications have been developed to assist farmers and agricultural experts in diagnosing plant diseases and managing crop health more effectively. These tools leverage image processing, artificial intelligence, and localized agricultural knowledge to provide timely feedback and actionable recommendations[7], [8], [9], [10] . This section reviews three notable applications Leaf Doctor, PlantVillage, and Cropwise Grower Malaysia, highlighting their features, strengths, and limitations in the context of crop health monitoring.

Leaf Doctor is a mobile application developed by researchers at Cornell University and the University of Hawaii [11]. It enables users to take photographs of plant leaves and analyse them for disease severity based on color analysis of each pixel. The application allows users to set specific color thresholds representing healthy leaf tissue, enhancing the visualization of diseased areas. Leaf Doctor also supports sharing diagnostic results via email, which facilitates communication between farmers and agricultural advisors. While the application is praised for its high precision in disease identification and user-friendly interface suitable for various technical skill levels, it primarily focuses on leaf diseases, limiting its applicability across all crops. Furthermore, the requirement for clear, high-quality images restricts its performance in field conditions, and the app offers minimal treatment suggestions beyond diagnosis.

Developed by Penn State University, the PlantVillage application uses advanced artificial intelligence to detect diseases and pests from plant images [12]. It stands out with its extensive crop disease database and community engagement features that promote knowledge sharing among users. A key advantage is its offline functionality, allowing farmers in remote or low-connectivity areas to access diagnostic services. The application supports multiple languages and covers a broad range of crops, including cassava, maize, and wheat. Besides diagnosis, PlantVillage provides practical recommendations for disease prevention and crop management. However, the application lacks a specific focus on paddy crops, which limits its effectiveness for rice farmers. It also depends on a stable internet connection for full access to its features and provides general rather than localized advice.

Focusing on Malaysian farmers, Cropwise Grower Malaysia offers a range of crop management tools, including weather updates, disease and pest diagnosis, and localized agricultural recommendations [13]. The application enables users to capture plant images for rapid health assessment and includes a retailer locator to help farmers find nearby agricultural suppliers. Its offline crop management resources and expert-backed advice enhance its utility in local settings. Nevertheless, some features rely on internet connectivity, which may affect usability in areas with unstable networks. Additionally, Cropwise Grower's broad coverage of crops may not sufficiently address the specific needs of paddy cultivation or cover all rice-related pests and diseases, potentially limiting its value for paddy farmers.

Based on these weaknesses and limitations, this study aims to develop a cross-platform mobile application named SmartPaddy that enables farmers to monitor the health of their paddy crops in real time using image processing and machine learning technologies. The application will allow users to capture images of rice leaves and receive instant diagnostic insights, including specific treatment suggestions. The solution will be powered by a lightweight machine learning model integrated via TensorFlow Lite and will also support offline access to a disease-treatment database using SQLite. The app will include syncing capabilities to ensure the database remains current when internet access is available.

3. Methodology

This study adopted the Agile methodology, a flexible and iterative development approach that supports continuous improvement through incremental updates [14], [15]. The Agile framework as shown in Figure 1, allowed for adaptation quickly to feedback from farmers and agricultural experts, ensuring that the application met actual user needs in real-world conditions. The project was divided into multiple sprints, each with specific objectives, activities, and deliverables.

During the Planning Stage, the team identified major tasks to prioritize in the initial development sprint. Requirements were gathered through interviews and surveys with paddy farmers and agricultural professionals. This stage helped clarify critical features such as image-based disease detection and offline accessibility, especially for rural farmers with limited internet access.

In the Design and Analysis Stage, the collected data guided the creation of interface designs and technical plans. Wireframes and mock-ups were produced to visualize the app's structure and ensure its usability. Feedback was gathered from potential users to enhance the intuitiveness and functionality of the interface.

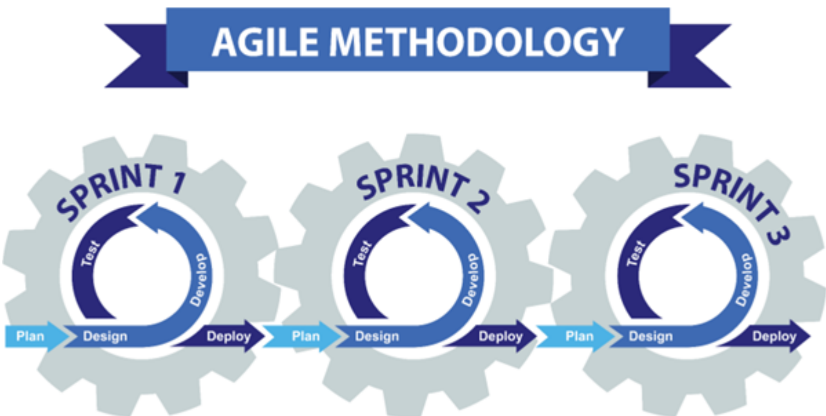

Fig. 1. Agile Methodology

The Development Stage involved implementing the image analysis system, integrating it into the mobile application, and building essential functionalities. Real-time disease detection features were developed using a trained machine learning model based on a comprehensive dataset of paddy crop images.

Next, the Testing Stage was carried out to ensure that each component performed as intended. Rigorous testing was done on disease identification, user interface responsiveness, and offline functionality. Bugs and usability issues were addressed before moving into the deployment phase.

The Deployment Stage included releasing a prototype to a small group of users for real-world testing. Their feedback provided insights for system optimization. This stage was followed by the Review and Retrospective Stage, where improvements were discussed and planned for the next sprint.

Finally, the Continuous Improvement Stage ensured that each sprint delivered a refined version of the app. User suggestions and test results were integrated to enhance user experience, accuracy, and reliability of the system.

3.1 Usability Test Procedure

The usability evaluation employed a structured task-based approach adapted from standard Human Computer Interaction (HCI) protocols. Ten farmers participated in a 30-minute, in-person assessment session. The session began with a task performance test in which participants were required to complete four predefined activities: capturing and uploading a leaf image, viewing and interpreting the disease detection results, accessing the recommended treatments, and navigating the offline disease database. Their performance during these tasks was monitored using an observation checklist that recorded task completion, errors made, and the level of assistance required.

Following the task performance phase, participants completed a post-task questionnaire consisting of 20 Likert-scale items. The questionnaire assessed four major usability dimensions: usefulness, ease of use, learning through use, and overall satisfaction. Responses were analysed based on score frequencies, mean values, and category-level interpretations to provide a quantitative understanding of user experience.

The session concluded with a short interview, during which participants shared qualitative feedback regarding their experience with the application. They commented on the clarity of the detection results, the intuitiveness of the interface, and any challenges faced during the interaction. Collectively, this multi-method procedure strengthened the reliability of the evaluation by ensuring replicability and providing both empirical and qualitative metrics to validate the system’s usability and effectiveness.

4. Results and Discussion

To evaluate the usability and effectiveness of the SmartPaddy mobile application, a field test was conducted involving 10 local farmers with varying backgrounds and levels of experience. The participants used the app and then completed a structured questionnaire comprising demographic questions and Likert-scale usability items. The results provide a comprehensive view of how real users interacted with the app and how it met their expectations in terms of usefulness, ease of use, learning value, and satisfaction.

Table 1
Demographic data

Category		Number of Respondents	Percentage (%)
Gender	Male	7	70.0%
	Female	3	30.0%
TOTAL RESPONDENT		10	
Age	Under 20	0	0%
	21-30	0	0%
	41-50	5	50.0%
	31-40	4	40.0%
	51-60	1	10.0%
TOTAL RESPONDENT		10	
Education Level	No formal education	0	0%
	Secondary school	5	50.0%
	Primary school	4	40.0%
	Diploma/Certificate	1	10.0%
	Degree and above	0	0%
TOTAL RESPONDENT		10	
Years of Farming Experience	Less than 1 year	0	0%
	1–5 years	4	40%
	More than 5 years	6	60%
TOTAL RESPONDENT		10	

Findings:

Based on Table 1, out of the 10 participants, 70% were male, and 30% were female, showing slightly higher male involvement in agricultural technology trials. In terms of age distribution, the majority were between 41– 50 years (50%) and 31–40 years (40%), with one respondent (10%) aged 51–60. No respondents were under 30, suggesting that the application was mostly evaluated by mid-career and experienced farmers. Regarding educational background, 50% completed secondary school, 40% primary school, and 10% held a diploma or certificate. None reported higher education or no formal schooling. In terms of farming experience, 60% had over 5 years of experience, while 40% had between 1–5 years, indicating that the feedback came primarily from seasoned farmers.

Discussion:

The demographic profile indicates that the application was tested by a representative group of experienced farmers, the primary users of agricultural technologies. The limited representation of younger users may reflect the current demographic trends in farming communities. The education levels suggest that the app should continue to use accessible language and intuitive design for those with basic schooling. The high proportion of experienced farmers also strengthens the reliability of their feedback, as they can compare the app with real-world challenges they regularly face.

Table 2
Usability Table

CATEGORY	QUESTIONS	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Usefulness	Q1: I learned how to detect crop diseases using the app.	0 (0%)	0 (0%)	0 (0%)	2 (20%)	8 (80%)
	Q2: I understand what actions to take if my crop shows signs of disease.	0 (0%)	0 (0%)	0 (0%)	3 (30%)	7 (70%)
	Q3: I learned how to upload a crop photo for analysis.	0 (0%)	0 (0%)	0 (0%)	2 (20%)	8 (80%)
	Q4: I understand the benefits of early disease detection.	0 (0%)	0 (0%)	0 (0%)	2 (20%)	8 (80%)
	Q5: I know how to access disease & treatment info even without internet.	0 (0%)	0 (0%)	0 (0%)	3 (30%)	7 (70%)
Ease-of-Use	Q1: The app was easy to navigate.	0 (0%)	0 (0%)	0 (0%)	2 (20%)	8 (80%)
	Q2: I knew how to take or upload a photo of my plant.	0 (0%)	0 (0%)	0 (0%)	4 (40%)	6 (60%)
	Q3: The instructions were clear.	0 (0%)	0 (0%)	0 (0%)	3 (30%)	7 (70%)
	Q4: The disease results were easy to understand.	0 (0%)	0 (0%)	0 (0%)	4 (40%)	6 (60%)
	Q5: The app interface and layout helped me use it better.	0 (0%)	0 (0%)	0 (0%)	3 (30%)	7 (70%)
Learning Through Use	Q1: I now understand how to detect early signs of crop disease.	0 (0%)	0 (0%)	0 (0%)	2 (20%)	8 (80%)
	Q2: I learned what steps to take when my crops show symptoms.	0 (0%)	0 (0%)	0 (0%)	2 (20%)	8 (80%)
	Q3: I can apply the recommendations to my real crops.	0 (0%)	0 (0%)	5 (14.7%)	1 (10%)	9 (90%)
	Q4: I feel more confident monitoring my crops using my phone.	0 (0%)	0 (0%)	0 (0%)	4 (40%)	6 (60%)
Satisfaction	Q1: The app design was appealing and clean.	0 (0%)	0 (0%)	0 (0%)	2 (20%)	8 (80%)
	Q2: The features worked smoothly.	0 (0%)	0 (0%)	0 (0%)	4 (40%)	6 (60%)
	Q3: I liked the offline access and disease database.	0 (0%)	0 (0%)	0 (0%)	3 (30%)	7 (70%)
	Q4: The app made monitoring crops more convenient.	0 (0%)	0 (0%)	0 (0%)	4 (40%)	6 (60%)
	Q5: I would recommend this app to other farmers.	0 (0%)	0 (0%)	0 (0%)	2 (20%)	8 (80%)

Findings:

Based on Table 2, for Usefulness, most farmers strongly agreed the application helped them detect crop diseases (80%), understand what actions to take (70%), and upload crop photos for analysis (80%). They also recognized the benefits of early detection (80%) and appreciated access to treatment information even without internet connectivity (70%). These findings indicate a high level of functional value delivered by the app.

Under Ease-of-Use, 80% found the application easy to navigate, 60% could easily upload or take plant photos, and 70% agreed the instructions were clear. Additionally, 60% found the disease results easy to understand, while 70% agreed that the interface layout improved usability.

In terms of Learning Through Use, 80% of users felt they now understood how to detect early signs of disease, while another 80% learned appropriate steps to take when symptoms appeared. Notably, 90% stated they could apply the recommendations in real scenarios, and 60% reported greater confidence in monitoring crops via mobile.

Regarding Satisfaction, users were pleased with the design (80%), feature smoothness (60%), and offline functionality (70%). The application made monitoring more convenient for 60% of users, and 80% said they would recommend it to other farmers. These results suggest overall satisfaction with both design and performance.

Discussion:

The findings show that the SmartPaddy application is highly effective in educating and assisting farmers in disease detection and crop management. The strong agreement on usefulness across all related items confirms that the application fulfils its core goal empowering farmers with actionable agricultural knowledge.

The high scores in ease-of-use, especially among users with basic educational backgrounds, point to the application's user-friendly interface and clear instructions. This is crucial for adoption in rural settings, where users may have limited exposure to digital tools.

Learning outcomes were also remarkable, with the vast majority of farmers expressing confidence in applying the application's recommendations to real-world crops. This validates the application as not just informative, but practically beneficial.

Lastly, satisfaction levels were consistently high, especially around design, offline accessibility, and ease of monitoring. The fact that 80% of users would recommend the application to others is a powerful indicator of both trust and perceived value.

Overall, the application demonstrates significant promise in supporting digital agriculture adoption and enhancing real-time disease management, especially in communities with limited agricultural extension services.

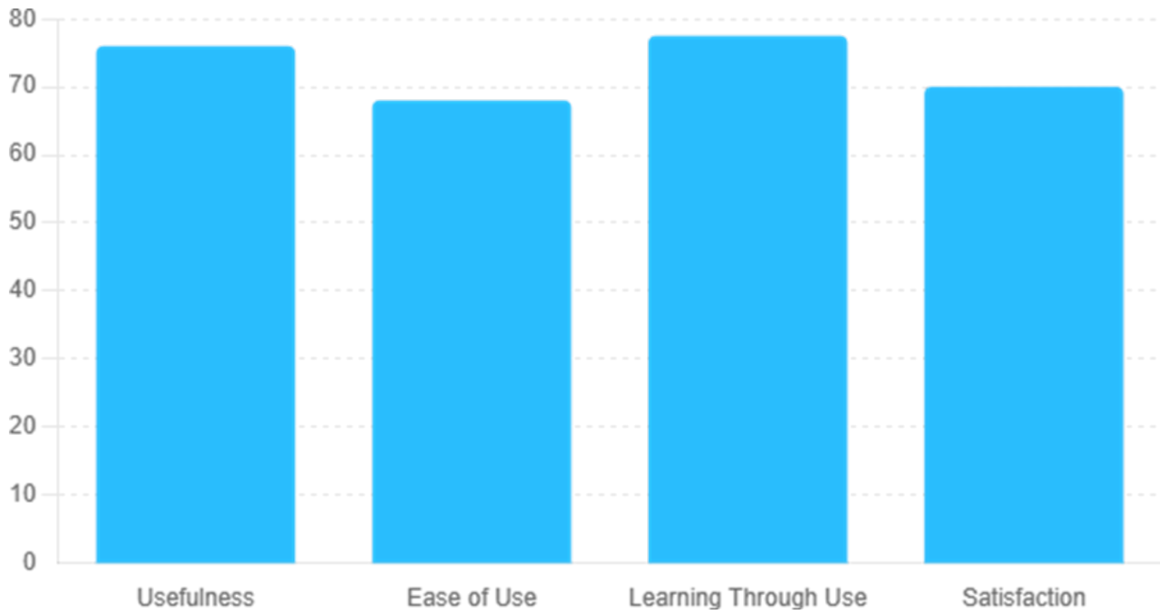

Fig. 2. Bar Chart of Feedback by Category

Findings:

From Figure 2, the usability testing of the SmartPaddy mobile application was conducted with 10 farmers who represented the target user group. The evaluation focused on four main categories: Usefulness, Ease of Use, Learning Through Use, and Satisfaction. Each category was measured using a Likert-scale questionnaire with five levels ranging from “Strongly disagree” to “Strongly agree.”

In the Usefulness category, the majority of respondents expressed strong agreement that the application effectively supported their agricultural needs. A high percentage of users (80%) reported that they learned how to detect crop diseases using the app. Similarly, 70% stated they understood what actions to take if their crops showed signs of disease, and 80% felt confident uploading photos of their crops for analysis. The same percentage also acknowledged understanding the benefits of early disease detection. Notably, 70% of users agreed that they were able to access disease and treatment information even without internet connectivity, highlighting the application’s offline capabilities.

The Ease of Use category showed that most farmers found the application generally user-friendly. 80% of users agreed that the app was easy to navigate, and 60% found it easy to take or upload photos of their plants. Additionally, 70% of respondents felt the instructions provided were clear, and 60% believed the disease results were easy to understand. The same number appreciated the app’s layout, indicating that its interface supported better usability.

In terms of Learning Through Use, users reported a noticeable improvement in their ability to monitor crops. A large majority (80%) mentioned that they now understood how to detect early signs of crop diseases, and the same number stated they learned what steps to take when symptoms appeared. While 90% of respondents claimed they could apply the app’s recommendations to real-world situations, a small number were unsure. Furthermore, 60% of users reported feeling more confident using their phone to monitor crops after using the application.

The Satisfaction category yielded positive outcomes as well. 80% of respondents found the applications’s design clean and visually appealing, and 60% reported that its features worked smoothly. A significant number (70%) appreciated the availability of offline access and the comprehensive disease database. Additionally, 60% of users stated the application made monitoring crops more convenient. Importantly, 80% of the farmers said they would recommend the app to other farmers, indicating a high level of overall satisfaction.

Discussion:

The results from the usability testing suggest that the SmartPaddy application meets the functional and educational needs of its intended users. Farmers reported that the application was helpful in teaching them how to detect diseases and understand what actions to take—validating the app's core value as a practical agricultural tool. The strong positive response in the Usefulness and Learning Through Use categories reflects the success of the app's core features, particularly the real-time analysis, clear recommendations, and offline accessibility.

Ease of Use, while still positively received, emerged as the category with the most room for refinement. While the majority of users found the app easy to navigate, a few participants indicated uncertainty in interpreting disease results. This suggests that improving visual clarity, adding more intuitive icons, or incorporating a brief on boarding tutorial could enhance the user experience—particularly for first-time users or those with limited digital literacy.

Satisfaction scores indicated that the application was well received overall. Users appreciated the thoughtful design, smooth performance, and practical features like offline access. The high number of users willing to recommend the app to peers reinforces its credibility and perceived value. However, some variation in satisfaction scores, especially concerning layout and result clarity, implies opportunities for aesthetic and functional polishing.

In short, the quantitative analysis of the usability questionnaire revealed consistently high acceptance across all evaluation categories. The mean Likert scores ranged from 4.6 to 4.8 out of 5, indicating strong user satisfaction and positive perceptions of SmartPaddy's functionality. Specifically, the Usefulness category achieved a mean score of 4.76, Ease of Use recorded 4.62, Learning Outcomes reached 4.78, and overall Satisfaction averaged 4.70. Notably, none of the participants selected "Disagree" or "Strongly disagree" for any item, reinforcing the robustness of the positive feedback. However, two farmers expressed mild difficulty in interpreting the numerical confidence scores displayed in the diagnostic results, which aligns with the earlier-stated interface limitation. These findings collectively validate the usability and practical impact of the system while pointing to minor areas for refinement.

However, during testing and development, several system constraints and limitations were identified that may affect the accuracy and usability of SmartPaddy. One notable issue was image quality sensitivity, where the TensorFlow Lite model occasionally misclassified leaf images captured in low-light environments, with motion blur, or when the leaf occupied less than 30% of the camera frame. Additionally, the model currently detects only four major paddy diseases, resulting in limited disease categories that restrict its ability to diagnose nutrient deficiencies, pest-related symptoms, or mixed infections. Another limitation involved offline database synchronization, as updates to the disease-treatment information only occur when a stable internet connection is available, potentially causing delays in data refresh for users in rural locations. Furthermore, some farmers reported difficulties interpreting the probability scores and confidence levels shown in the detection results, indicating a need for clearer explanations or icon-based output. Acknowledging these weaknesses is essential for methodological transparency and provides a strong foundation for targeted future improvements.

In conclusion, the application demonstrates strong potential as a reliable tool for digital agriculture. It successfully bridges the gap between technology and traditional farming by providing accessible, informative, and functional support to paddy farmers. With minor enhancements in clarity and guidance, the SmartPaddy mobile application could offer even greater impact and adoption among rural agricultural communities.

5. Conclusion

The development and evaluation of the SmartPaddy mobile application have demonstrated its potential as a practical and empowering tool for modern agriculture. Designed to assist farmers in detecting crop diseases in real time using image processing, the app bridges a crucial gap between traditional farming practices and emerging digital technologies.

Through usability testing with actual farmers, the results indicated high levels of satisfaction, ease of use, and perceived usefulness. Most users found the app intuitive, informative, and helpful in guiding real-life decision-making about crop health management. Features such as real-time analysis, offline access, and clear disease recommendations were especially well received, highlighting the app's relevance to the day- to-day challenges of farming.

While the findings affirm the app's effectiveness, they also provide insight into areas for future enhancement—particularly in improving result presentation and navigation for users with varying levels of tech literacy. These refinements could further increase adoption and usability among broader farming communities.

The findings of this study show strong alignment with previous mobile agriculture research, particularly tools such as PlantVillage and Leaf Doctor, which have demonstrated that mobile-based diagnostic systems can enhance farmers' awareness and responsiveness to crop diseases. However, SmartPaddy introduces several distinctive contributions that address gaps in existing applications. Unlike general-purpose plant diagnostic tools, SmartPaddy incorporates a paddy-specific disease model, making it more relevant for rice farmers. The system also offers offline access to treatment recommendations, an important feature that many earlier tools lack, thereby improving usability in areas with poor connectivity. Furthermore, SmartPaddy provides localized recommendations tailored to Malaysian agricultural guidelines, ensuring relevance to local farming practices. These enhancements highlight SmartPaddy's unique contribution to the field of mobile agriculture and its suitability for rice-farming communities operating under connectivity and knowledge constraints.

In essence, the SmartPaddy not only supports disease management but also promotes technological engagement among farmers, paving the way for smarter, more sustainable agriculture. With continued improvements and support, this application has the potential to scale up and make a lasting impact on farming practices, especially in rural and resource-constrained areas.

6. Future Works

Future enhancements to SmartPaddy will be guided directly by the limitations identified during usability testing. One key improvement involves strengthening the image capture process by introducing an on-screen guide, brightness detection, and a framing box to help users capture clearer leaf images, thereby reducing misclassification caused by poor input quality. The disease detection model will also be expanded to include a wider range of paddy diseases, nutrient deficiency symptoms, and pest-related conditions, using real field images to improve diagnostic coverage. In addition, the result interpretation interface will be refined by replacing numeric probability values with clearer visual indicators such as icons, color codes, or verbal confidence statements to enhance understanding among users with varying levels of literacy and digital experience. To improve reliability in low-connectivity environments, adaptive offline synchronization will be implemented, enabling partial background updates to the disease database whenever limited connectivity is available. Finally, a larger-scale field validation across multiple regions involving 50–100 farmers will be conducted to further assess the system's accuracy, performance, and usability under diverse environmental and farming conditions. These improvements are closely aligned with empirical findings and directly address the challenges highlighted by users during evaluation.

References

[1] "Assessing Malaysia's food security efforts | The Star." Accessed: Dec. 24, 2024. [Online]. Available: https://www.thestar.com.my/news/nation/2024/06/28/assessing-malaysias-food-security-efforts

[2] "National Food Security Policy Action Plan 2021-2025 - Ministry of Agriculture and Food Security." Accessed: Dec. 24, 2024. [Online]. Available: https://www.kpkm.gov.my/en/agro-food-policy/national-food-security-policy-action-plan-2021-2025

[3] M. C. Hunter, R. G. Smith, M. E. Schipanski, L. W. Atwood, and D. A. Mortensen, "Agriculture in 2050 : Recalibrating Targets for Sustainable Intensification," *Bioscience*, vol. 67, no. 4, pp. 386–391, 2017, doi: 10.1093/biosci/bix010.

[4] E. Said Mohamed, A. A. Belal, S. Kotb Abd-Elmabod, M. A. El-Shirbeny, A. Gad, and M. B. Zahran, "Smart farming for improving agricultural management," 2021. doi: 10.1016/j.ejrs.2021.08.007.

[5] V. K. Quy *et al.*, "IoT-Enabled Smart Agriculture: Architecture, Applications, and Challenges," Apr. 01, 2022, *MDPI*. doi: 10.3390/app12073396.

[6] P. Rajak, A. Ganguly, S. Adhikary, and S. Bhattacharya, "Internet of Things and smart sensors in agriculture: Scopes and challenges," *J Agric Food Res*, vol. 14, Dec. 2023, doi: 10.1016/j.jafr.2023.100776.

[7] R. Thirisha *et al.*, "Precision Agriculture: IoT Based System for Real-Time Monitoring of Paddy Growth," *2023 International Conference on Sustainable Emerging Innovations in Engineering and Technology, ICSEIET 2023*, pp. 247–251, 2023, doi: 10.1109/ICSEIET58677.2023.10303483.

[8] M. Kamal and A. Bangladesh, "Mobile Applications Empowering Smallholder Farmers: An Analysis of the Impact on Agricultural Development," *International Journal of Social Analytics*, vol. 8, no. 6, pp. 36–52, Jun. 2023, Accessed: Dec. 24, 2024. [Online]. Available: https://norislab.com/index.php/ijsa/article/view/24

[9] M. Pyingkodi, K. Thenmozhi, M. Karthikeyan, T. Kalpana, S. Palarimath, and G. B. A. Kumar, "IoT based Soil Nutrients Analysis and Monitoring System for Smart Agriculture," *3rd International Conference on Electronics and Sustainable Communication Systems, ICESC 2022 - Proceedings*, pp. 489–494, 2022, doi: 10.1109/ICESC54411.2022.9885371.

[10] K. Pawlak, "The Role of Agriculture in Ensuring Food Security in Developing Countries : Considerations in the Context of the Problem of Sustainable Food Production," *Sustainability*, vol. 12, no. 5488, pp. 1–20, 2020.

[11] "Leaf doctor makes the rounds | CALS." Accessed: Nov. 19, 2025. [Online]. Available: https://cals.cornell.edu/news/2017/12/leaf-doctor-makes-rounds

[12] "Team | PlantVillage." Accessed: Nov. 19, 2025. [Online]. Available: https://plantvillage.psu.edu/team

[13] "Cropwise Grower | Cropwise." Accessed: Nov. 19, 2025. [Online]. Available: https://www.cropwise.com/cropwise-grower

[14] S. Al-Saqqa, S. Sawalha, and H. Abdelnabi, "Agile software development: Methodologies and trends," *International Journal of Interactive Mobile Technologies*, vol. 14, no. 11, pp. 246–270, 2020, doi: 10.3991/ijim.v14i11.13269.

[15] "What is Agile Methodology? - GeeksforGeeks." Accessed: Oct. 09, 2025. [Online]. Available: https://www.geeksforgeeks.org/software-testing/what-is-agile-methodology/