Offline Augmented Reality and Artificial Intelligence for Pest and Disease Detection in Small-Scale Rice Farming

Lauren Genith Isaza Dominguez[1]; Oscar Agudelo Varela[2]; Fernando Riveros Sanabria[3]
[1,2,3]Facultad de Ciencias Básicas y Ingeniera, Universidad de los Llanos, Colombia, *lisaza@unillanos.edu.co*, *oscar.agudelo@unillanos.edu.co*, *friveros@unillanos.edu.co*

Abstract*– Small-scale rice farmers in resource-constrained rural regions experience persistent productivity losses due to limited access to advanced agricultural technologies for pest and disease management. This paper presents a work-in-progress study on the development of an offline software system integrating Augmented Reality (AR) and Artificial Intelligence (AI) to support real-time detection of pests and diseases directly in the field. The proposed system combines computer-vision-based detection, an AI-driven chatbot, and AR visualization through low-cost AR glasses, enabling farmers to receive actionable recommendations without continuous internet connectivity. The project follows a phased methodology encompassing data collection, prototype development, field testing, and system refinement. At the current stage, a balanced dataset of 2,000 rice images captured using Vuzix Blade 2 AR glasses has been annotated and used to train and test a YOLO11n-based object detection model in a desktop environment, producing preliminary qualitative detection and localization outputs. This work aims to improve crop management efficiency, reduce chemical inputs, and enhance agricultural sustainability, while establishing a foundation for future quantitative evaluation and large-scale deployment.

Keywords—Augmented reality, artificial intelligence, precision agriculture, pest and disease detection, rice cultivation

I. Introduction

Technological asymmetry in agriculture refers to unequal access to modern tools that enhance productivity, disproportionately affecting small-scale farmers. In Colombia, small agricultural holdings represent 48.3% of Agricultural Production Units and typically operate on less than three hectares [1]. These producers face structural barriers, including high technology adoption costs, limited access to credit, and insufficient agricultural extension services [2]. In rice cultivation, this asymmetry contributes to substantial yield gaps, with efficiency levels ranging from 40% to 95% across producers [3], reinforcing cycles of low productivity and rural poverty [4].

Limited access to monitoring technologies further exacerbates ineffective pest and disease management. In the absence of timely detection tools, farmers often rely on reactive practices, leading to excessive pesticide use, resistance development, and ecological imbalance [5]. Smart agriculture technologies that could mitigate these challenges remain largely inaccessible to small-scale producers due to cost, infrastructure requirements, and policy limitations [6]–[8]. Within this context, this work addresses the following research question: How can affordable, offline augmented reality (AR) and artificial intelligence (AI) technologies support pest and disease management in small-scale rice farming under rural connectivity constraints?

To address this research question, the present work pursues a set of applied objectives focused on the development, evaluation, and deployment of an offline AR- and AI-based system tailored to small-scale rice farming. First, the project seeks to develop an AI-powered chatbot capable of providing farmers with personalized, real-time guidance on pest and disease management, including pesticide use, with the aim of improving agricultural efficiency, promoting responsible resource use, and supporting adaptation to climate variability. Second, an AR-based application is designed to enable real-time visual detection of pests and disease symptoms directly on rice crops. Third, field tests are planned on small-scale rice farms in Meta, Colombia to evaluate system effectiveness in pest detection and its potential impact on yield improvement and loss reduction. Finally, the project includes the development of a comprehensive training module to accompany the AR system, providing farmers with educational resources on precision agriculture, pest management, and the integration of modern technologies into traditional agricultural practices.

II. Related Work

Agriculture 4.0 integrates technologies such as the Internet of Things (IoT), AR, AI, drones, and big data to optimize agricultural production [9]. Despite demonstrated benefits in precision monitoring and decision support, adoption among small-scale farmers remains limited. Technologies such as GPS-guided machinery, satellite systems, and IoT sensor networks are widely used in large-scale operations but remain financially and infrastructurally inaccessible to small producers [10]–[12].

Machine-learning-based crop disease detection systems frequently rely on cloud computing, creating barriers for rural regions with limited internet access [13]. Although emerging communication technologies such as 5G promise to enhance real-time agricultural monitoring, high infrastructure costs and limited rural coverage restrict applicability in many rural regions with limited connectivity, including rice-producing areas such as Meta, Colombia [14]. Rice production is further threatened by pests such as *Spodoptera frugiperda* and diseases including bacterial panicle blight (*Burkholderia glumae*) and rice blast (*Magnaporthe oryzae*), whose impacts are intensified by climate variability [15]–[17].

Recent efforts have explored AI-powered agricultural chatbots to support farmers, particularly in India, where systems such as FarmChat and Ama KrushAI provide agronomic guidance in low-literacy contexts [18], [19]. However, these systems typically depend on reliable connectivity, limiting their transferability to rural Colombian contexts. The present work addresses this gap by proposing an offline-capable AR and AI system tailored to small-scale rice farming.

III. Proposed System and Methodology

The proposed system integrates offline computer vision, AR visualization, and an AI-powered chatbot to support pest and disease management in small-scale rice cultivation. The system is designed to operate under rural conditions with limited or no internet connectivity, prioritizing low-cost hardware, local processing, and ease of use. Farmers interact with the system through a mobile device connected via Bluetooth to low-cost AR glasses, enabling hands-free operation in the field. Detected disease symptoms are visualized directly on rice plants using AR overlays, while an integrated chatbot provides contextual guidance related to pest control, pesticide use, irrigation, fertilization, and general crop management.

The methodology follows a phased approach that supports incremental validation of system components while aligning with real-world agricultural constraints. At the current stage, development focuses on data acquisition and feasibility testing, with subsequent phases addressing prototype integration, refinement, and field deployment.

A. Phase I: Research and Data Collection

The first phase focuses on hardware evaluation and dataset construction. Vuzix Blade 2 AR glasses are being assessed under simulated and real field conditions to determine their suitability for rural agricultural deployment. Evaluation criteria include physical durability (resistance to rainfall, temperature variation, and humidity), interface simplicity for users with limited technological experience, compatibility with Unity-based AR development, support for offline operation, and battery life sufficient for extended fieldwork.

Image data are currently being collected directly in rice fields in Meta, Colombia, following a structured protocol designed to capture variability in lighting, weather conditions, plant growth stages, and visible disease manifestations. Images are being captured using the Vuzix Blade 2 AR glasses to evaluate whether their onboard camera provides sufficient visual detail for lesion detection. Collected images are being annotated by agricultural experts to ensure reliable labeling of healthy and diseased regions. Ongoing quality checks are being performed to verify that image resolution, framing, and clarity are adequate for object-detection tasks.

An offline chatbot is being developed during this phase using validated agricultural knowledge sources, including local agronomic guidance and research databases. The chatbot is being optimized for voice-based interaction to reduce reliance on text input and to facilitate use by farmers with limited digital literacy.

B. Phase II: Prototype Development

The second phase addresses the integration of system components into a functional prototype. AR environments will be developed using Unity to enable visualization of detected disease regions directly within the user's field of view. Visual overlays are designed to remain minimal and interpretable under outdoor field conditions.

A lightweight object-detection pipeline based on the YOLO11n architecture is currently being trained and tested using the images captured with the AR glasses. At this stage, model training is exploratory and focused on feasibility validation rather than performance optimization. The objective is to verify that disease-related visual patterns captured by the AR glasses can be detected and localized using a standard object-detection framework. Model outputs are being evaluated qualitatively through bounding-box localization and confidence scoring.

The offline chatbot will be integrated with the AR system to enable contextual, voice-based recommendations triggered by detected disease regions. This integration is intended to allow users to transition seamlessly from visual detection to actionable guidance without requiring internet connectivity.

C. Phase III: System Refinement

The third phase will focus on improving system robustness and model performance. The image dataset will be expanded with additional samples collected under varied environmental conditions to support improved generalization. Detection model parameters will be refined to enhance localization accuracy and reduce false detections.

Software components will be further optimized for execution on low-cost mobile devices, with attention to power consumption, processing load, and stability during extended field use. Hardware and software components will be evaluated comparatively to justify final equipment selection based on cost, performance, and durability.

D. Phase IV: Deployment and Evaluation

The final phase will involve structured deployment across multiple small-scale rice farms in Meta, Colombia. Field testing will be conducted to evaluate system usability, operational stability, and practical value for pest and disease management under real agricultural conditions.

Training workshops will be delivered to support effective adoption, ensuring that farmers can independently operate the

AR system and integrated offline chatbot as part of routine crop management practices.

IV. RESULTS

This section presents interim results organized as a staged engineering validation workflow. Controlled feasibility tests using synthetic AR-style imagery were first conducted to assess camera suitability and lesion detectability. These were followed by real-field image acquisition and qualitative detection under agricultural conditions, and by practical evaluations of hardware operability and system integration for hands-free field use.

A. *Synthetic Feasibility Testing*

In real agricultural settings, acquiring large, well-controlled datasets of diseased rice plants presents significant challenges. Disease outbreaks are seasonal and sporadic, and individual plants often exhibit multiple overlapping stress factors, making it difficult to isolate samples affected by a single disease. In many cases, diseased plants may not be present at all during planned data-collection periods. These constraints complicate early-stage validation of AR-based detection pipelines, particularly when the objective is to assess hardware suitability and visual discriminability rather than to perform final disease classification.

To address this limitation, a complementary feasibility study was conducted using synthetic AR-based imagery. In this experiment, healthy rice images captured with the Vuzix Blade 2 smart glasses were modified using DALL·E 3 to introduce realistic disease lesions under controlled conditions. This approach enabled systematic evaluation of whether the AR-glass camera provides sufficient spatial resolution, contrast, and optical clarity to capture narrow rice blades and localized lesion patterns critical for computer-vision-based detection.

The resulting synthetic images were used to train a lightweight YOLOv11n (nano) object detection model, which was subsequently evaluated on real diseased AR images not used during training. The objective of this experiment was not to optimize classification performance or distinguish between disease types, but rather to verify end-to-end feasibility—specifically, whether lesions introduced on slim rice blades in AR-style imagery could be reliably detected and localized using a standard object-detection framework.

Results from this controlled experiment demonstrated that models trained on synthetic lesions generalized effectively to real AR images, achieving consistent detection and localization of symptomatic regions under realistic field perspectives, with detection performance reaching mAP@0.50 ≈ 0.79 under the tested conditions. These findings indicate that the first-person imagery captured by the AR glasses contains sufficient visual information for lesion detection, despite the thin geometry of rice leaves and the complex background structure of dense canopies. Moreover, the experiment supports the use of synthetic data as a practical tool for early-stage system validation when real diseased samples are limited or unavailable.

Within the context of the present work-in-progress system, these results provide supporting evidence for the suitability of the AR hardware and imaging modality. They also inform subsequent dataset-expansion and model-refinement phases by confirming that image quality, blade visibility, and lesion contrast captured by the AR glasses are adequate for downstream computer-vision tasks prior to large-scale field deployment.

B. *Field Validation Results*

Following the controlled feasibility evaluation described in the previous section, the project proceeded to real-field data acquisition under operational agricultural conditions. Image data were collected from rice plots at the FEDEARROZ experimental test field *(Federación Nacional de Arroceros de Colombia, National Federation of Rice Growers of Colombia)* in Meta, Colombia, under natural field conditions, capturing variability in lighting, weather, and crop appearance.

The resulting dataset consists of 2,000 labeled images, including 1,000 healthy plants and 1,000 plants exhibiting visible disease symptoms, forming a balanced dataset for feasibility testing. Diseased samples were annotated using bounding boxes labeled "ENF" (Spanish for *enfermo*, meaning diseased) to indicate affected regions.

Preliminary qualitative detection outputs were generated using a lightweight object-detection pipeline based on the YOLOv11n architecture. Initial results demonstrate bounding-box localization and confidence scoring on full field-of-view images captured under real cultivation conditions with the Vuzix Blade 2 AR glasses. At this stage, the dataset and model configuration are intended solely to validate end-to-end feasibility under real agricultural conditions, including the suitability of the AR glasses for image acquisition and the ability of the detection model to identify diseased regions from real field imagery. As such, the current setup does not yet support disease-type differentiation or optimized class generalization.

Figure 1 illustrates an example detection output with ENF-labeled bounding boxes over diseased regions. Ongoing work focuses on offline model optimization, AR integration, and preparation for structured field testing.

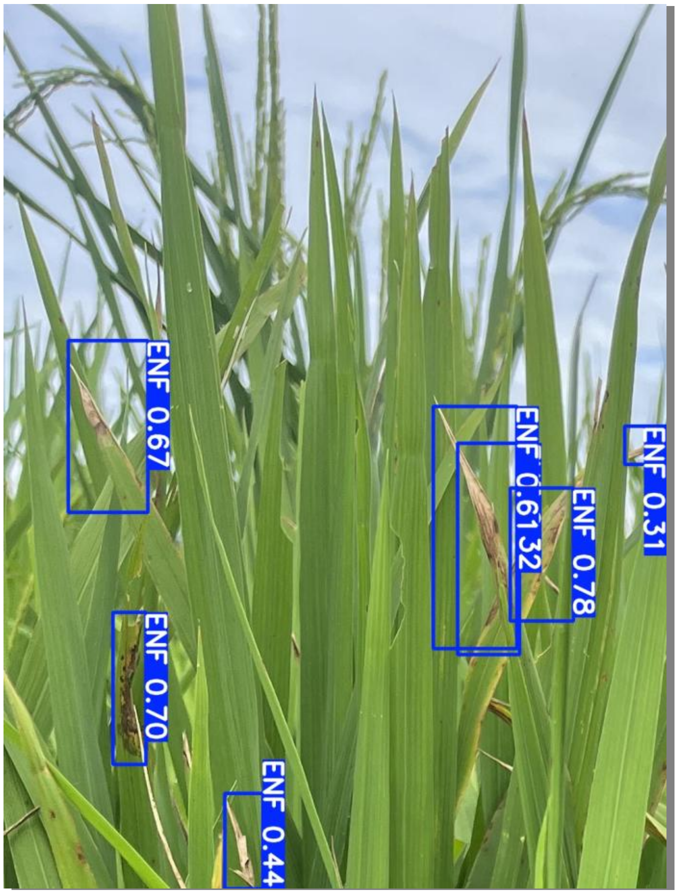

Fig. 1 Example qualitative detection output generated using the YOLO11n-based object detection pipeline, showing *ENF* (enfermo, diseased) bounding boxes over diseased regions in rice leaves captured under natural field conditions at the FEDEARROZ test field.

C. System Operability and Development

Alongside image acquisition and preliminary detection testing, the project has conducted practical evaluations of the AR glasses under real agricultural working conditions to assess their suitability as a primary interaction interface. Field use tests considered operational constraints typical of rice farming, including prolonged outdoor exposure, high ambient humidity, water and mud contact, glove use, and intense solar illumination. These evaluations also confirmed that the selected AR glasses provide sufficient battery autonomy for extended field sessions, maintain functional usability under direct sunlight with manageable glare effects, and allow stable hands-free operation without interfering with routine farming activities.

Based on these observations, the AR glasses were validated as an appropriate hardware choice for continued study and field deployment. Their physical form factor, onboard camera, audio output, and button-based input mechanisms enabled practical use in environments where handling smartphones or tablets would be impractical or unsafe. This hardware validation complements the visual feasibility results reported in Sections IV-A and IV-B by confirming that the imaging and interaction modality can be maintained reliably throughout typical fieldwork durations.

The system is currently under active development and focuses on engineering a hands-free AR decision-support workflow tailored to rice farmers operating in environments characterized by water, mud, gloves, and intermittent connectivity. In the proposed architecture, the AR glasses function as the primary user interface, enabling voice-based questioning and button-triggered image capture without requiring the farmer to directly interact with a mobile device during field operations. A mobile device carried by the farmer serves solely as a background compute and connectivity unit, receiving images and voice input from the glasses and logging all interactions locally for later analysis.

When network connectivity is available, the mobile device forwards captured images and associated voice queries to an AI-based analysis service and delivers spoken guidance back to the farmer through the glasses using text-to-speech. In the absence of connectivity, the system provides audio confirmation of successful capture and securely stores images and interaction logs for deferred processing. The current development phase prioritizes system feasibility, hands-free operability, power management, and robustness under real agricultural conditions rather than model accuracy or interface optimization, establishing a stable technical foundation for subsequent structured field evaluation with rice farmers in Colombia.

V. Conclusion and Future Work

This work-in-progress study has presented the initial development stages of an offline AR- and AI-based system for pest and disease detection in small-scale rice farming. The current contribution lies in the completion of real-field image acquisition using low-cost AR glasses, the construction of a balanced annotated dataset, and the generation of preliminary qualitative detection outputs using a YOLO11n-based model. Together, these results establish the feasibility of the proposed data pipeline and confirm the suitability of AR-based image capture for downstream computer-vision tasks under real cultivation conditions.

Subsequent project phases will focus on optimizing the detection model for offline execution on mobile hardware, expanding the dataset to improve generalization and disease-type differentiation, and integrating real-time AR visualization with chatbot-driven decision support. Structured field evaluations with small-scale farmers in Meta, Colombia, will be conducted to assess system usability, detection performance, and operational relevance.

Through these evaluations, the study seeks to examine the feasibility of using offline AR and AI-based tools to support pest and disease identification in smallholder farming contexts. Planned evaluation activities will focus on assessing system usability, response time, and the types of information provided to farmers during field interaction. Beyond the local case, the project is intended to generate transferable methodological and technical insights related to the deployment of offline AR and AI systems in rural environments with limited connectivity. The system architecture is designed to support scalability and iterative updating as additional agronomic data and knowledge become available, enabling future validation studies and broader replication in comparable agricultural contexts.

ACKNOWLEDGMENT

The authors acknowledge the support of Universidad de los Llanos for funding the research project (C01-02-2025-007), approved under Act No. 34 on December 12, 2024, which provided the academic context within which this review was developed.

REFERENCES

[1] Departamento Administrativo Nacional de Estadística (DANE), *Censo Nacional Agropecuario*, Bogotá, Colombia, Tech. Rep., 2019.

[2] B. L. Zuluaga, H. G. Arévalo, M. F. Díaz, and M. A. Sánchez, "Closing yield gaps in Colombian direct seeding rice systems: A stochastic frontier analysis," *Field Crops Research*, vol. 252, p. 107795, 2020.

[3] S. Ruzzante, R. Labarta, and A. Bilton, "Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature," *World Development*, vol. 146, p. 105599, 2021.

[4] W. D. Biru, M. Zeller, and T. K. Loos, "The impact of agricultural technologies on poverty and vulnerability of smallholders in Ethiopia," *Social Indicators Research*, vol. 147, pp. 517–544, 2020.

[5] Z. Fan, P. Wan, C. Zhou, and W. Lu, "Integrating water and insect pest management in agriculture," *Journal of Pest Science*, vol. 96, no. 2, pp. 275–290, 2023.

[6] J. P. Restrepo, J. C. Posada, and J. K. Balocchi, "Field evidence for positive certification outcomes on oil palm smallholder management practices in Colombia," *Agricultural Systems*, vol. 187, p. 103002, 2020.

[7] I. Bhakta, S. Phadikar, and K. Majumder, "State-of-the-art technologies in precision agriculture: A systematic review," *Journal of the Science of Food and Agriculture*, vol. 99, no. 11, pp. 4878–4888, 2019.

[8] A. P. Barnes, I. Soto, V. Eory, B. Beck, A. T. Balafoutis, B. Sánchez, and J. Vangeyte, "Exploring the adoption of precision agricultural technologies: A cross-regional study of EU farmers," *Land Use Policy*, vol. 80, pp. 163–174, 2019.

[9] Impacto TIC, "Agricultura 4.0 en Colombia: oportunidades y desafíos," 2023. [Online]. Available: https://impactotic.co/tecnologia/agricultura-4-0-en-colombia-oportunidades-y-desafios/. [Accessed: Jan. 2026].

[10] T. Mizik, "How can precision farming work on a small scale? A systematic literature review," *Precision Agriculture*, vol. 24, no. 1, pp. 384–406, 2023.

[11] M. Preti, F. Verheggen, and S. Angeli, "Insect pest monitoring with camera-equipped traps: Strengths and limitations," *Journal of Pest Science*, vol. 94, no. 1, pp. 203–217, 2021.

[12] D. Gao, Q. Sun, B. Hu, and S. Zhang, "A framework for agricultural pest and disease monitoring based on Internet of Things and unmanned aerial vehicles," *Sensors*, vol. 20, no. 5, p. 1487, 2020.

[13] T. Domingues, T. Brandão, and J. C. Ferreira, "Machine learning for detection and prediction of crop diseases and pests: A comprehensive survey," *Agriculture*, vol. 12, no. 9, p. 1350, 2022.

[14] W. Arrubla-Hoyos, M. Bohada, J. Orozco, C. Velásquez, J. C. Martínez-Rios, E. Osorio, F. Ramírez, and F. Rodríguez Gómez, "Precision agriculture and sensor systems applications in Colombia through 5G networks," *Sensors*, vol. 22, no. 19, p. 7295, 2022.

[15] A. Autio, T. Johansson, L. Motaroki, P. Minoia, and P. Pellikka, "Constraints for adopting climate-smart agricultural practices among smallholder farmers," *Agricultural Systems*, vol. 194, p. 103284, 2021.

[16] J. Echeverri-Rico et al., "Understanding the complexity of disease–climate interactions for rice bacterial panicle blight under tropical conditions," *PLOS ONE*, vol. 16, no. 5, p. e0252061, 2021.

[17] D. M. Vinchira-Villarraga et al., "Presence of phytopathogenic fungi and oomycetes on rice crops in Colombia," *African Journal of Microbiology Research*, vol. 14, no. 6, pp. 259–272, 2020.

[18] M. Jain, P. Kumar, I. Bhansali, Q. V. Liao, K. Truong, and S. Patel, "FarmChat: A conversational agent to answer farmer queries," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 2, no. 4, 2018.

[19] S. Negi, *Development and Assessment of an AI-Enabled Chatbot-Based Learning System as a Knowledge Aid for Swine Management*, Ph.D. dissertation, Indian Veterinary Research Institute, Izatnagar, India, 2024.