AgriVision: A Rice Pest and Disease Detection System Using YOLOv8m with Geospatial Alarm Logging

A Capstone Project Proposal of the

Information Technology in Mobile App and Web Development

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CHAPTER 1

INTRODUCTION

This chapter covers the Project Context, Purpose, Objectives, Scope, Limitations, and Project Framework. AgriVision is a digital system that utilizes computer vision and a multi-stakeholder surveillance network to support national food security, in alignment with the 2030 Agenda for Sustainable Development. Furthermore, it serves as a concrete implementation of Rice 4.0, which refers to the integration of artificial intelligence, automation, and data-driven technologies into rice farming and monitoring systems at both the field and governance levels.

Project Context

Rice production is the foundation of Philippine agricultural stability. It serves as the country's primary source of dietary energy, contributing roughly 58.0% of the population's daily caloric intake, while accounting for 35.7% of the average household's total daily food consumption by weight (Department of Science and Technology - Food and Nutrition Research Institute [DOST-FNRI], 2023). As the nation's primary staple crop, it supports the livelihoods of an estimated 2.4 million smallholder farmers (Department of Agriculture [DA], 2023) and remains central to achieving SDG 2 (Zero Hunger) by ensuring that the population has reliable access to safe, nutritious, and sufficient food throughout the year.

However, the Philippine rice sector is facing serious, overlapping threats. In 2024 alone, the El Niño phenomenon inflicted ₱15.3 billion in total agricultural losses, with the rice sector bearing ₱5.93 billion of that damage (Department of Agriculture [DA], 2024), a crisis heavily compounded by a succession of severe late-year typhoons. On top of climate-related shocks, chronic pest infestations heavily compromise food security; the Bureau of Plant Industry (BPI) notes that unmanaged pest pressures cause farmers to lose an average of 37% of their annual crop yields, with lowland varieties remaining highly vulnerable to outbreaks of rodents, stem borers, and planthoppers. Together, these pressures reveal a deep vulnerability in the sector's ability to protect its output.

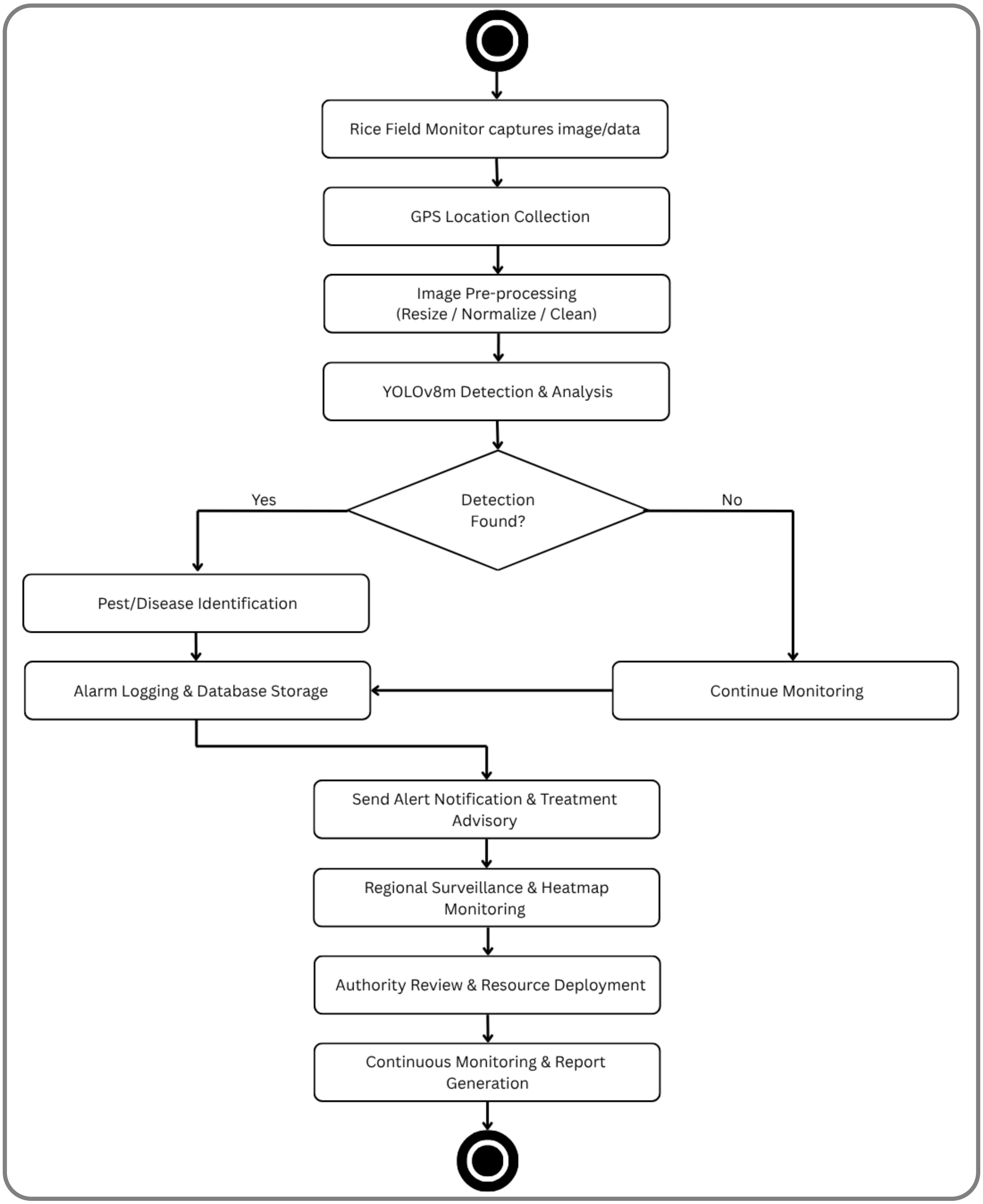
A major reason for this vulnerability is the inadequacy of current crop monitoring practices. Field-level pest surveillance still relies heavily on manual inspections, where farmers and Municipal Agricultural Extension Workers (AEWs) must physically walk through paddies to record observations, a process prone to delayed reporting and resource constraints. While macro-level systems like the Philippine Rice Information System (PRiSM) provide invaluable regional satellite mapping of rice area, planting dates, and disaster-induced yield losses, their mid-resolution imagery (such as 20-meter Sentinel-1 SAR data) is not designed for real-time, farm-level pest and disease detection. Consequently, a critical operational gap persists between the initial onset of an infestation and the deployment of a targeted response.

The consequences of this operational gap are both measurable and widespread. Pest infestations can lead to yield losses of 15% or more when left unmanaged, with damage spreading to adjacent fields in the absence of early detection systems (PhilRice, 2023; IRRI, 2023). Many smallholder farmers lack adequate diagnostic tools to distinguish between visually similar pests and diseases, while limited digital record systems restrict real-time tracking of pest movement across regions. These inefficiencies extend into the post-harvest stage, where rice losses range from about 10% to 20% depending on handling, storage, and transport conditions (PHilMech, 2023). Concurrently, fluctuations in palay farmgate prices, including periods around ₱25 per kilogram, reflect production and market pressures that affect consumer rice prices (Department of Agriculture, 2024). Ultimately, these compounding bottlenecks undermine SDG 12 (Responsible Consumption and Production) and contribute to persistent rural poverty, with farmer poverty incidence remaining around 30% (Philippine Statistics Authority, 2023).

Given these conditions, there is a clear and urgent need for an integrated diagnostic and surveillance system that addresses key gaps in Philippine agriculture, including limited real-time pest identification at the farm level, fragmented digital record systems for decision-making, and incomplete implementation of national digital agriculture initiatives such as the Agriculture and Fisheries Modernization Act (RA 8435) and related e-agriculture programs (DA, 2023; PhilRice, 2023). AgriVision addresses these gaps by deploying an optimized YOLOv8m detection engine within a multi-stakeholder web platform, converting field-level observations into centralized digital records that support faster and more informed agricultural decision-making (Ultralytics, 2023).

Figure 1

Project Context of Diagram of AgriVision



Purpose and Description of the Project

AgriVision is an integrated computer-vision ecosystem designed for the automated detection and longitudinal monitoring of rice pests and diseases, serving as a technology-driven bridge between individual field diagnostics and regional agricultural governance. The project provides a comprehensive diagnostic platform that empowers multiple stakeholders, particularly smallholder farmers, who receive instant on-field treatment advisories via mobile device cameras to mitigate immediate yield losses, thereby supporting SDG 2 (Zero Hunger). Simultaneously, it serves the research community by providing access to structured, geo-tagged datasets, enabling scientists to track biotype evolution and population trends across different Philippine climatic zones in support of terrestrial ecosystem resilience and SDG 15 (Life on Land).

For authority figures and agricultural heads, the system provides a centralized dashboard to monitor regional outbreak heatmaps and coordinate logistics, such as the deployment of mobile milling units under the Mobile Milling Facilities Act of 2025. The system is designed to achieve a mean Average Precision (mAP@0.5) of at least 94% across 16 rice health conditions through the application of architectural optimizations to the YOLOv8m baseline model. The system analyzes field images of standing crops submitted by farmers and field officers; detection classes cover both pre-harvest growth stages and applicable post-harvest conditions observable in standing crops, such as False Smut, Brown Spot, and Sheath Blight. Every detection event is automatically recorded in a secure database, facilitating regional surveillance that supports national food security monitoring and resource prioritization. Full automation of grain-sample analysis through dedicated post-harvest image datasets is identified as a direction for future model expansion.

Objectives

The primary objective of the study is to develop AgriVision, a web-based computer-vision ecosystem that optimizes the YOLOv8m architecture for high-precision rice pest and disease detection, and integrates an automated, location-linked alarm logging mechanism to support real-time regional surveillance and community-wide agricultural decision-making

Specifically, the project aims to:

1. Optimize a YOLOv8m model to identify and classify 16 rice health conditions, including a healthy class, across pest and disease categories, achieving at least 94 percent mAP@0.5, at least 90 percent precision, and at least 90 percent recall.

2. Implement an automated location-linked alarm logging mechanism that captures device-reported GPS coordinates where available, enabling zone-level geospatial aggregation for regional surveillance.

3. Provide an intuitive, responsive web interface that empowers farmers and the local community to receive instant treatment alerts and access structured pest management advisories, directly supporting SDG 2 (Zero Hunger) through yield preservation and SDG 9 (Industry, Innovation, and Infrastructure).

Scope and Limitations

AgriVision is a web-based computer-vision ecosystem designed for the automated diagnosis and regional surveillance of Philippine rice health across desktop and mobile browsers. Engineered for farmers, researchers, and municipal authorities, the system features secure authentication, real-time multiclass classification via an optimized YOLOv8m engine, and an automated GPS-linked alarm logging mechanism that aggregates data at the zone level to monitor regional outbreaks. To bridge the digital divide, farmers without smartphones are fully integrated into the scope through community-shared digital touchpoints or via proxy reporting by Municipal Agricultural Extension Workers (AEWs) who submit field data on their behalf. The computer vision module is configured to detect exactly 16 classes: Bacterial Blight, Bacterial Leaf Streak, Rice Blast, Brown Planthopper Infestation, Brown Spot, Dead Heart Damage, Downy Mildew, False Smut, Green Leafhopper Infestation, Leaf Folder Damage, Normal (Healthy Baseline), Rice Bug Infestation, Sheath Blight, Stem Borer Damage, Tungro Virus Disease, and Whorl Maggot Damage.

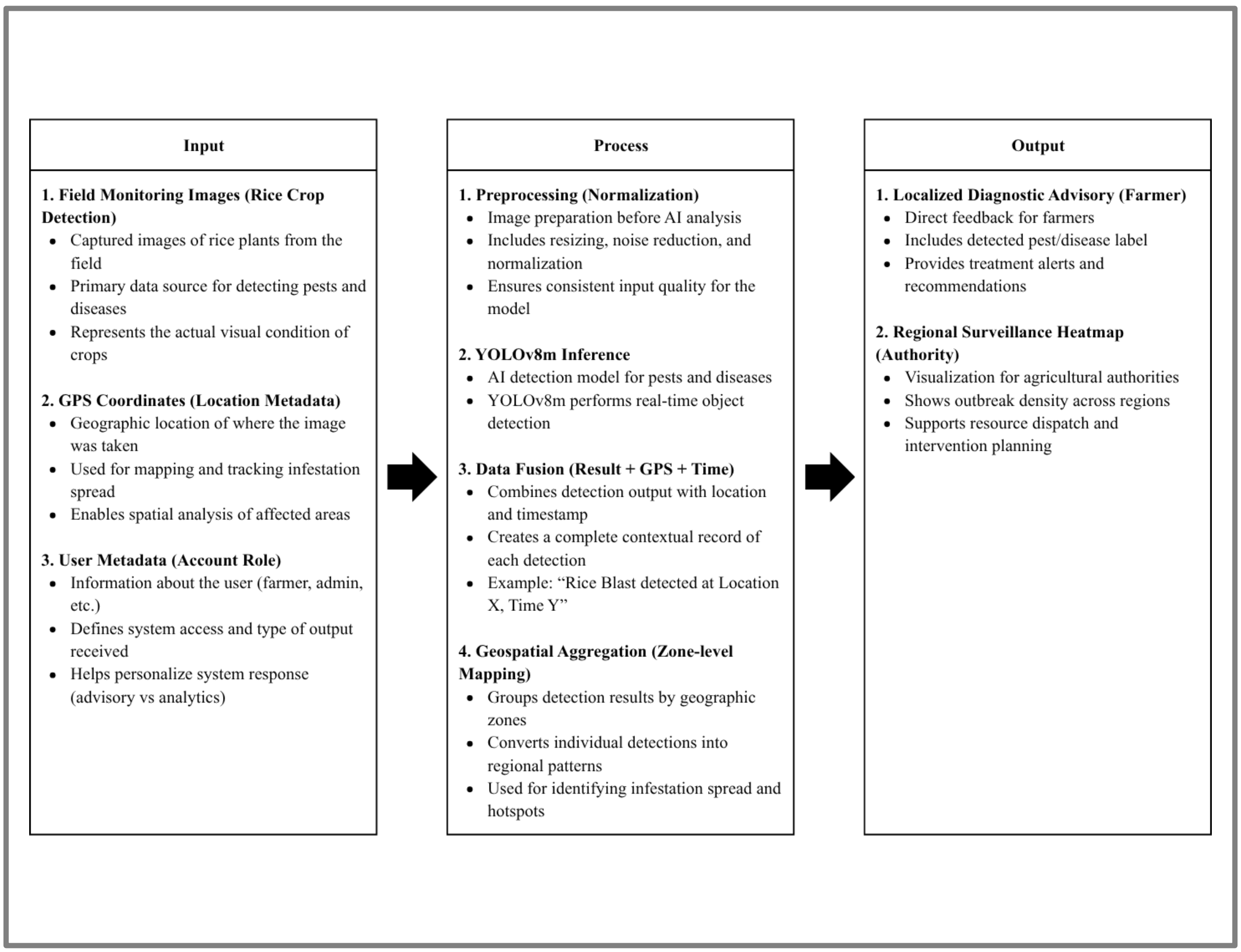
The system operates within distinct environmental, diagnostic, and technical boundaries. Detection accuracy is highly sensitive to external variables such as motion blur, low camera resolution, or poor field lighting, while GPS precision depends entirely on hardware capabilities and rural network availability. System diagnostics are strictly restricted to the 16 predefined training classes; emerging biological mutations or unmodeled pests will remain undetected until the dataset is updated and the model is retrained. Regarding post-harvest capabilities, the system only identifies post-harvest-relevant conditions visible on standing field crops, meaning that direct grain-sample inspection, milling quality grading, and storage monitoring are outside the current scope. Finally, because YOLOv8m inference and database operations run server-side, an active internet connection is mandatory; while photos can be captured offline, real-time diagnostic outputs and surveillance synchronization are unavailable without network connectivity.

Project Framework

The proponents employed the Input-Process-Output (IPO) model to describe the operational framework of AgriVision, illustrating how mobile-captured field image data is transformed into actionable regional food security intelligence.

Figure 2

Operational Framework of AgriVision



CHAPTER II

REVIEW OF RELATED LITERATURE AND STUDIES

This chapter reviews recent literature and studies published between 2020 and 2026, establishing the technical, operational, and policy foundations for the AgriVision ecosystem. The reviewed material is systematically organized into related literature and related studies across both local and foreign contexts, concluding with a synthesis that identifies the distinct research gap addressed by this project.

Related Literature

UN Sustainable Development Goals Report 2025. The report identifies digital connectivity within food systems as one of six critical transitions required to achieve the 2030 Agenda. It underscores that artificial intelligence (AI)-enabled precision agriculture tools are vital for closing productivity gaps in developing agricultural economies (United Nations, 2025). This directly contextualizes AgriVision within global frameworks for sustainable food security.

YOLO26 and YOLOv11 Benchmarks (2026). Recent iterations and comparative benchmarks in the *You Only Look Once* (YOLO) lineage demonstrate continued advancements in inference efficiency, spatial attention, and reduced post-processing overhead via optimized detection pipelines (Ultralytics, 2026). These structural developments justify selecting the YOLOv8m baseline model to achieve an optimal balance between mean Average Precision (mAP) and deployment stability in resource-constrained edge-and-web environments.

OECD Agricultural Policy Monitoring 2025. This report emphasizes that targeted, long-term investments in digital agricultural services create an enabling environment for sustained productivity growth. This is particularly critical in middle-income economies where smallholder farmers constitute the majority of the agricultural workforce (Organisation for Economic Co-operation and Development [OECD], 2025).

PhilRice Strategic Plan 2023–2028. This institutional roadmap advocates for an aggressive digital transformation agenda and a people-centric approach to boost national rice yields by 4% to 6% annually while minimizing production overhead (Philippine Rice Research Institute [PhilRice], 2023). The plan explicitly prioritizes precision agriculture technologies and community-level digital tools, providing direct institutional alignment for AgriVision.

Mobile Milling Facilities Act of 2025 (HB 1300). Enacted to address the estimated 14.8% to 20.3% post-harvest loss rates attributable to inaccessible municipal milling centers, this legislative mandate outlines a state-backed fleet of mobile milling facilities (Congress of the Philippines, 2025). This operational mandate creates a clear administrative need for the location-linked, aggregated alarm logging data produced by AgriVision to optimize fleet deployment decisions.

Agriculture Information System Act (HB 3362). This legislation establishes the National Agriculture Information System (NAIS) across all agricultural municipalities, creating an integrated digital infrastructure that connects local production data with centralized national databases (Congress of the Philippines, 2024). AgriVision's structured detection logs and geo-tagged records are architected to be highly compatible with the data structures envisioned by this act, supporting future institutional data integration.

Related Studies and/or Systems

RicePest-YOLO (2025). An enhanced YOLOv8m architecture achieved a mAP@0.5 of 94.3% while simultaneously reducing model parameters relative to the baseline, demonstrating that architectural refinements can improve detection accuracy without proportionally increasing computational cost (Chen et al., 2025). This study validates the architectural optimization approach planned for AgriVision and confirms that detection accuracy at the 94% threshold is achievable within a comparable class scope.

HDA-YOLO (2025). This study proposed a lightweight YOLOv8 model based on a hierarchical and densely-fused attention mechanism, improving mAP@0.5 by 2.4 percentage points and recall by 4.8 percentage points over the baseline model (Liu et al., 2025). The performance gains demonstrated in this study informed AgriVision's approach to attention-based model optimization.

YOLO-DP (2024). A specialized model based on YOLOv8m was designed to detect 15 common rice diseases and pests under complex real-world field conditions, introducing Triplet Attention mechanisms to improve sensitivity to small-scale lesion features (Zhang et al., 2024). The 15-class scope of YOLO-DP is closely comparable to AgriVision's 16-class dataset, providing a relevant performance baseline for cross-study evaluation.

Hybrid Deep Learning Model for Real-Time Rice Pest Detection. Laureta et al. (2025) presented a hybrid deep learning model that integrates Convolutional Neural Networks (CNNs) and YOLOv5 for real-time detection of eight Philippine rice pest species, achieving a mean Average Precision (mAP@0.5) of 96.8% under controlled field conditions. The study demonstrates the viability of YOLO-based architectures within Philippine crop contexts and serves as a direct benchmark for AgriVision's expanded 16-class detection target.

SARAi-ICMF Hubs (2025). Regional hubs operated through the Science for Agriculture, Aquaculture, and Resources Institute utilize satellite sensing and crop modeling for early warning of broad-scale agricultural stressors. While effective at the macro level, these systems do not provide farm-specific image diagnostics. AgriVision is designed to fill this micro-level gap by delivering field-specific pest identification that complements existing satellite-based surveillance infrastructure.

Convolutional Neural Networks for Rice Disease Diagnosis in the Philippine Context. Alonzo and Gonzales (2023) evaluated the effectiveness of Convolutional Neural Networks in diagnosing 14 rice diseases within the Philippine context, reporting a classification accuracy of 99% using a controlled laboratory image dataset. However, the study did not address real-timefield deployment or integration with authority-level reporting systems, both of which AgriVision directly implements.

Synthesis

AgriVision builds on the proven accuracy of YOLO-based detection models by addressing a critical gap in existing systems — the lack of integration between field-level pest and disease detection and centralized, authority-accessible surveillance networks. While prior studies confirm detection accuracy exceeding 94%, none implement geo-tagged alarm logging, multi-role dashboards, or alignment with national agricultural policy frameworks. AgriVision closes this gap by pairing an optimized YOLOv8m detection engine with a geospatial alarm logging system designed for multi-stakeholder use, fulfilling the mandates of the PhilRice 2023–2028 Strategic Plan, the Mobile Milling Facilities Act of 2025, and the Agriculture Information System Act, while directly advancing SDG 2 and SDG 9 by transforming individual field data into actionable intelligence for regional and national agricultural governance.

CHAPTER III

TECHNICAL BACKGROUND

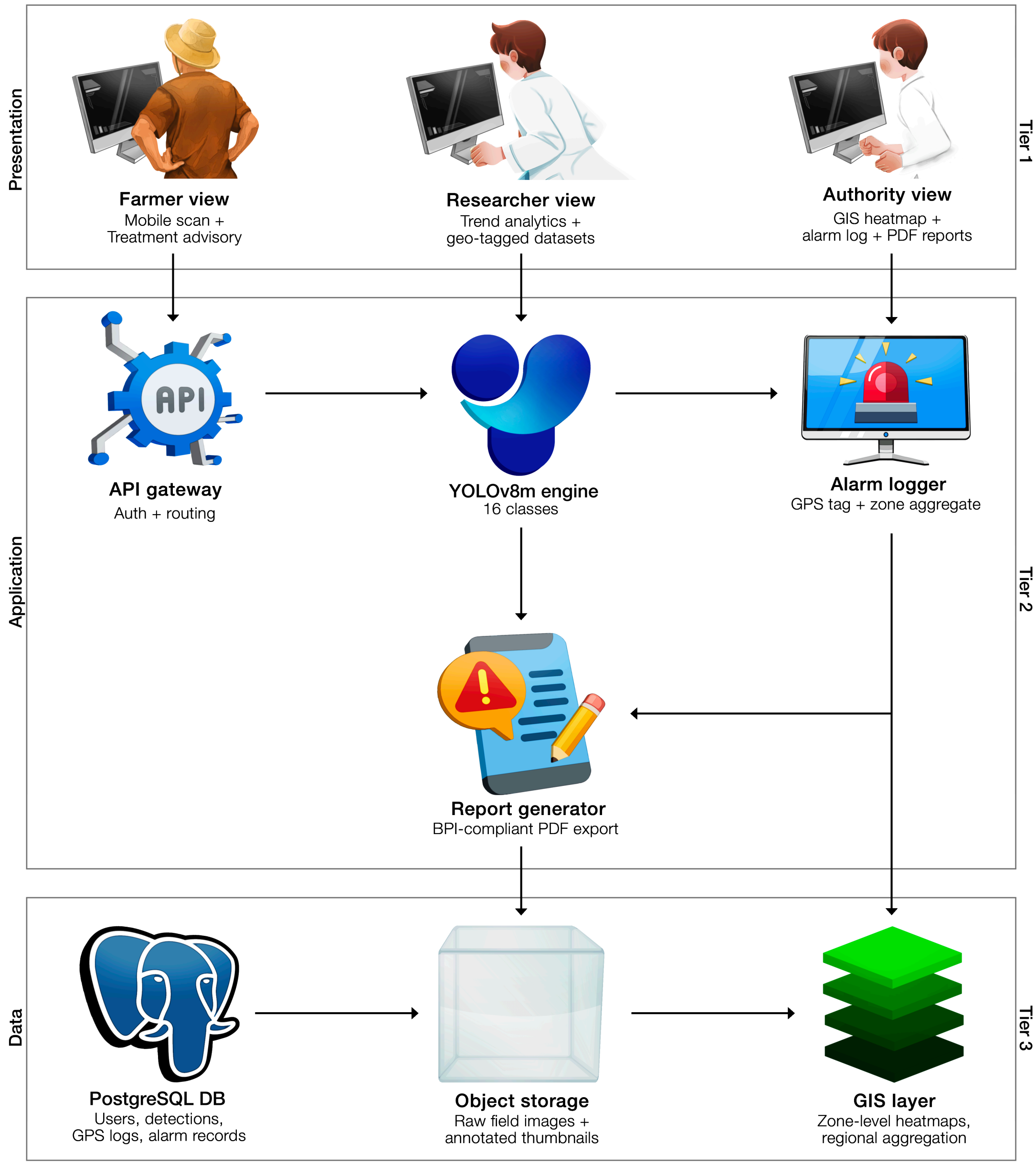
This chapter presents the technologies used in system development and provides an explanation of the technical decisions behind the proponents' selection. It outlines how each tool and framework contributes to the design and functionality of the system, supporting the achievement of the project objectives.

Overview of Current Technologies to Be Used in the System

The AgriVision system operates through three interconnected tiers that collectively support field-level detection up to authority-level governance. The Presentation tier accommodates three user roles: farmers access mobile scanning and treatment advisories, researchers retrieve trend analytics and geo-tagged datasets, and authorities monitor GIS heatmaps, alarm logs, and generated PDF reports. User requests are routed through an API gateway for authentication before submitted field images are processed by the YOLOv8m detection engine to identify conditions across 16 detection classes. Confirmed detections are recorded by the alarm logger with GPS coordinates and aggregated by geographic zone, then passed to the report generator for BPI-compliant PDF export. Supporting these processes, the Data tier maintains a PostgreSQL database for user profiles, detection logs, GPS records, and alarm data, an object storage component for raw field images and annotated thumbnails, and a GIS layer that organizes geospatial monitoring records.

Figure 3

System Architecture



Calendar of Activities

The Calendar of Activities follows a structured approach to ensure an efficient project workflow. It begins with Inquisition, where information is gathered, followed by Planning, which includes Brainstorming and Design. Next is Problem Solving, focusing on Issue Identification and Solution Implementation. The Development phase covers Prototyping, Coding, Testing, Deployment, and Releasing. Finally, Maintenance ensures the system's continuous improvement and long-term effectiveness.

Table 1

Calendar of Activities for First Semester

School Year 2025-2026

Month / Activity	August				September				October				November				December			
Inquisition																				
Planning																				
Brainstorming																				
Design																				
Problem Solving																				
Issue Identification																				
Solution Implementation																				
Deployment																				
Prototyping																				
Coding																				
Testing																				
Deployment																				
Releasing																				
Maintenance																				

Legend: Blue – Completed; Yellow – Incomplete

Table 1 outlines the First Semester schedule from August to December. Inquisition took place over 6 weeks starting in August. This was followed by Brainstorming (3 weeks) and Design (2 weeks) through October. Issue Identification spanned 3 weeks into mid-November, followed by Solution Implementation for 2 weeks. In December, Prototyping was scheduled for

4 weeks; as indicated by the yellow status, this phase remains in progress. Future tasks such as Coding, Testing, and Maintenance are slated for the following period.

Table 2

Calendar of Activities for Second Semester

School Year 2025-2026

Month Activity	January				February				March				April				May			
Inquisition																				
Planning																				
Brainstorming																				
Design																				
Problem Solving																				
Issue Identification																				
Solution Implementation																				
Deployment																				
Prototyping																				
Coding																				
Testing																				
Deployment																				
Releasing																				
Maintenance																				

Legend: Blue – Completed; Yellow – Incomplete

Table 2 outlines the activities for the Second Semester of School Year 2025–2026, covering January to May. The development phase commences in late January, followed by Coding, which spans several weeks into mid-February. Testing is allocated for one week in May, followed by Deployment and Releasing within the same month. Maintenance is projected to begin in the final week of May, completing the planned timeline for the semester.

Resources

The development of the system requires three key resources: hardware, software, and human expertise. These resources ensure the system's functionality, efficiency, and successful implementation.

Hardware Recommendation, In the development of the project, hardware development tools are needed for developing the system. The hardware requirements are presented in Table 3.

Table 3

Hardware Requirements

Minimum Hardware Requirements	Purpose
Processor • Apple M2 chip • 8 core CPU, 4 performance cores and 4 efficiency cores • 8 core GPU or optional 10 core GPU • 16 core Neural Engine • 100 GB/s memory bandwidth **Network** • Wi Fi 6 (802.11ax) • Bluetooth 5.3 • Supports one external display up to 6K at 60Hz **Storage** • 256GB SSD base model • Configurable to 512GB, 1TB, or 2TB SSD • Unified memory options: 8GB, 16GB, or 24GB **Operating System** • macOS (supports macOS Sequoia)	The hardware requirements for AgriVision ensure efficient AI-based image processing, real-time pest and disease detection, and geospatial data management. The Apple M2 chip provides sufficient processing power for YOLOv8 inference and backend operations, while unified memory and SSD storage support fast multitasking and data access. Wi-Fi 6 enables stable real-time connectivity, Bluetooth 5.3 supports device integration, and macOS provides a stable environment for system development and deployment.

Processor • Intel Core i7 13th Gen (or higher) • 14 cores (6 performance cores and 8 efficiency cores) • Intel Iris Xe Graphics or NVIDIA RTX 4050 (optional) • Intel AI Boost / NPU support (on newer chips) • Up to 12 MB cache Network • Wi Fi 6E (802.11ax) • Bluetooth 5.3 • Supports up to 2 external displays (4K or higher depending on model) Storage • 512GB SSD base model • Configurable to 1TB or 2TB SSD • Memory options: 16GB, 32GB DDR5 Operating System • Windows 11 Pro	The hardware requirements for AgriVision ensure efficient AI-based image processing, real-time pest and disease detection, and geospatial data management. The Intel Core i7 13th Gen processor supports YOLOv8 inference and backend processing, while higher RAM options improve multitasking across system components. SSD storage enables fast dataset access and model loading. Wi Fi 6E ensures stable real-time connectivity, Bluetooth 5.3 supports peripheral integration, and Windows 11 Pro provides a stable development and deployment environment.

Software Recommendation, In the development of the project, various software's are needed for developing the system. The software requirements are presented in Table 4.

Table 4

Software Requirements

Minimum Software Requirements	Purpose
React + Vue Laravel Postgresql Python VScode	The AgriVision software stack delivers a complete web-based pest and disease detection system. React provides a responsive frontend for capturing images, viewing results, and accessing alarm logs. Laravel manages backend logic, APIs, user authentication, and communication with the AI module. PostgreSQL stores user data, images, detection results, and historical records, while Python runs the YOLOv8-m model for accurate pest and disease detection. Visual Studio Code supports efficient development and collaboration. Together, these technologies enable automated, real-time detection and alarm logging to support timely, data-driven decisions for farmers.

Human Resources. In the development of the project, human expertise is needed for developing the system. The human resources are presented in Table 5.

Table 5

Human Resources

Recommended Users	Function
Rice Field Monitors (Users/Farmers)	They serve as the primary end-users who capture or upload images of rice crops using mobile devices or cameras, monitor detection results and alarm notifications, access field history and infestation records, and make informed decisions based on the pest and disease alerts generated by the system.
Admin (System Administrator)	The system administrator is responsible for the overall management of the platform. Their functions include managing user accounts, ensuring system security, updating datasets and detection models, monitoring system performance, and maintaining the continuous and reliable operation of the system.

Agricultural Researcher	The Agricultural Researcher focuses on scientific research related to rice production, pests, and diseases. Their function is to analyze detection data generated by the system, validate results against established agricultural research, and contribute to improving pest and disease management strategies, detection accuracy, and sustainable rice farming practices.
Software Developers	Software developers are responsible for creating, enhancing, and maintaining the AgriVision system. Their functions include designing and implementing system features, integrating the YOLOv8-m model, debugging, optimizing performance, and updating the web application in response to user feedback and technological advancements.
UI/UX Designer	The UI/UX Designer is responsible for designing and enhancing the user interface and overall user experience of the AgriVision system. Their function includes creating intuitive layouts, ensuring ease of navigation, improving accessibility, and optimizing interaction flows so that users—particularly farmers—can efficiently understand detection results, alerts, and system features.

Budgetary Estimate

Table 6

Budgetary Estimate

Estimated Man-Day		TOTAL BUDGET
	Software Subscription	
	2 COLAB Pro	₱ 1,215.02
	Tax	₱ 260
TOTAL ACTUAL COST		₱ 1,475.02
The estimated cost of the project is		₱ 1,475.02

CHAPTER IV

METHODOLOGY, RESULTS, AND DISCUSSION

This chapter presents the methods and procedures used in the development and evaluation of the AgriVision system. It explains the planned transition from raw agricultural image data to a deployed web-based rice pest and disease detection platform with alarm logging and geospatial monitoring capabilities.

Methodology

On Research Method. The study employed an applied research design with a quantitative approach to engineer and evaluate an optimized YOLOv8m object detection model across 16 rice health classes. Model evaluation was conducted under controlled experimental conditions utilizing a distinct, held-out test dataset. The performance benchmarks were established at a minimum threshold of 94% mean Average Precision mAP@0.5, 90% precision, and 90% recall. The experimental validation was extended through class-wise performance analytics and a confusion matrix evaluation to locate and isolate imbalanced class vulnerabilities.

On Systems Development Method. The system followed an Agile development methodology. This approach supports iterative improvement of the web application, cloud database, and authority dashboard. Development cycles include requirement gathering, planning, design, implementation, testing, and refinement based on stakeholder feedback from farmers and agricultural technicians.

On Inquisition. Requirement gathering involved consultations with rice farmers and municipal agricultural officers conducted during the second semester of Academic Year 2025–2026. The process identified the need for real-time crop health detection, simple result interpretation, timestamped logging, and a centralized monitoring system for authorities. These inputs defined the functional requirements of the AgriVision ecosystem, particularly the dual-output structure for farmer advisories and government surveillance data.

On Planning. Planning focused on system architecture and tool selection. The YOLOv8m model was selected for detection tasks due to its enhanced accuracy and favorable balance of inference speed among the YOLOv8 model family variants. The model was deployed using the Ultralytics framework. The backend uses Laravel for API handling, while a PostgreSQL database stores detection logs. A GPS-linked alarm logging structure was designed to support geospatial aggregation of pest and disease incidents across farming areas.

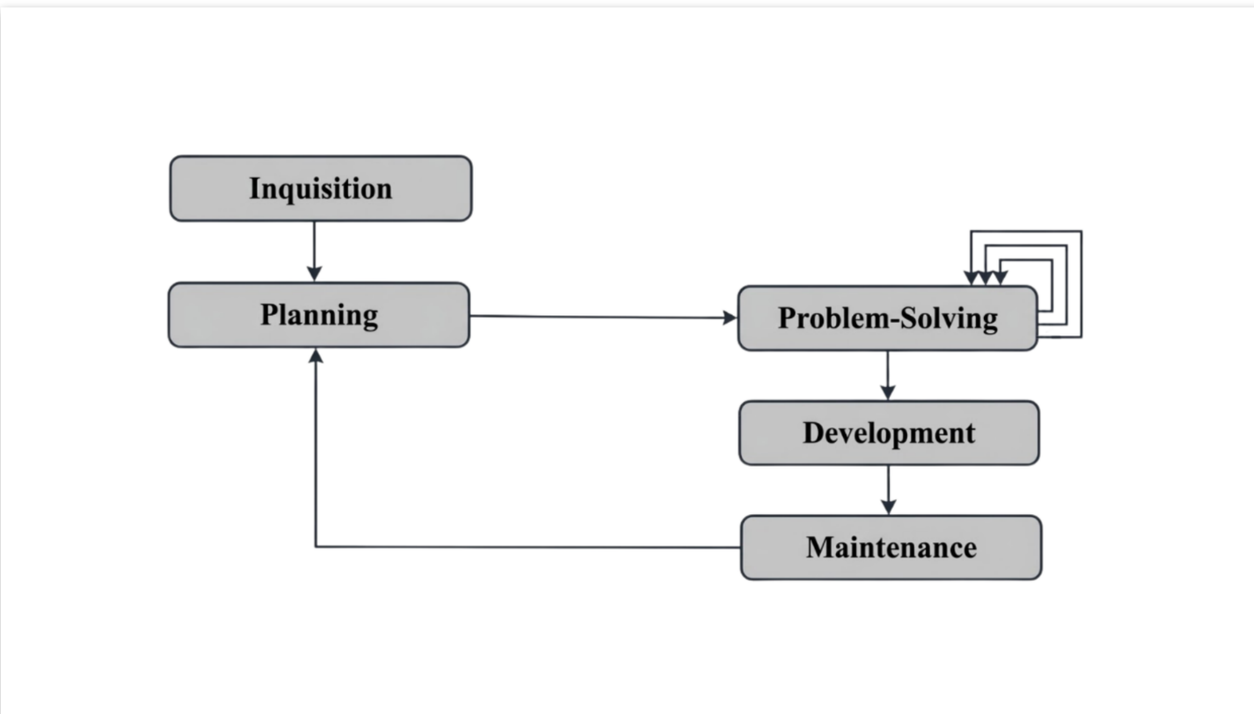
On Problem-Solving. Technical challenges anticipated during development include detecting small objects such as planthopper nymphs, overlapping leaf structures, and complex field backgrounds with variable lighting and occlusion. These challenges were addressed through model-level architectural enhancements applied to the baseline YOLOv8m detection pipeline, aimed at improving feature extraction and multi-scale object detection performance. These modifications improved detection performance for classes with subtle or small visual features, including Brown Planthopper Infestation and Bacterial Leaf Streak. Each architectural modification was evaluated through ablation testing to determine its individual contribution to model performance.

On Development. The development phase covers dataset preparation, model training, system integration, and deployment. A labeled dataset of 16 rice health classes sourced from public repositories and Philippine field collections contains 43,697 images and is split at an 80:10:10 ratio, with augmentation applied to underrepresented classes to improve robustness across varying field conditions. Training uses GPU-accelerated cloud infrastructure with transfer learning from COCO-pretrained YOLOv8m weights, and the final model is exported in ONNX format for optimized inference deployment. Each detection event is logged with class, confidence score, timestamp, user role, and GPS coordinates, then aggregated by geographic zone and displayed on the authority dashboard for monitoring and resource allocation. Ethical considerations were applied during development. All image and location data were collected with user consent and used only for pest and disease detection. No personal identifiers were stored, and location data was aggregated for regional analysis. Access to data was restricted to authorized users.

On Maintenance. The system maintenance phase will support continuous improvement of detection accuracy and dataset expansion. Model updates should include new pest variants and disease patterns as they are documented in Philippine agricultural surveillance records. The geospatial alarm logging system is monitored to ensure consistency in data collection and alignment with agricultural surveillance needs and national food security goals.

Figure 4

Agile Development Method



Requirement Analysis

The system requirements define two core functions. First, real-time rice pest and disease detection for farmers using image input. Second, structured alarm logging for agricultural authorities using geo-tagged detection records. These requirements ensure both immediate field-level diagnosis and long-term surveillance capability.

Requirement Discussion

Consultations with agricultural stakeholders confirmed the 16-class classification system and the need for a dual-user structure. Farmers require fast and simple diagnostic output, while authorities require aggregated geospatial data for outbreak monitoring and resource allocation planning. This validated the system design direction of AgriVision as both a diagnostic and surveillance tool.

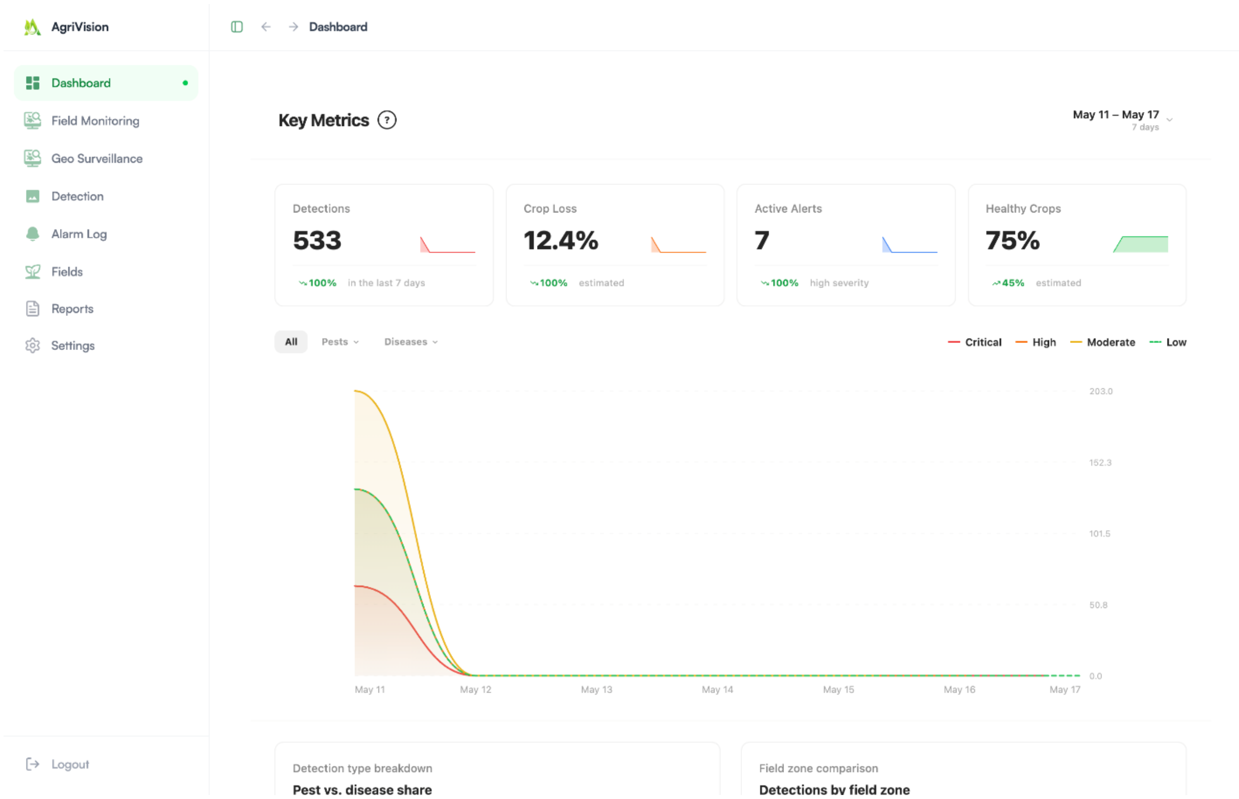
Design of Software, System, Product, and/or Processes

This section presents the initial design of the AgriVision system by describing its major components: the farmer-facing detection interface, the authority-facing surveillance dashboard, and the backend alarm logging architecture.

Dashboard. This page enables users to monitor and manage the agricultural surveillance system through an AI-powered interface that provides real-time pest and disease detection across monitored fields. It consolidates essential information such as field analytics, severity monitoring, geospatial field tracking, and automated PDF report generation to support efficient crop management and decision-making. Additionally, the dashboard includes interactive visualization tools powered by React and Chart.js, along with YOLOv8 integration for accurate detection and monitoring, as shown in Figure 5.

Figure 5

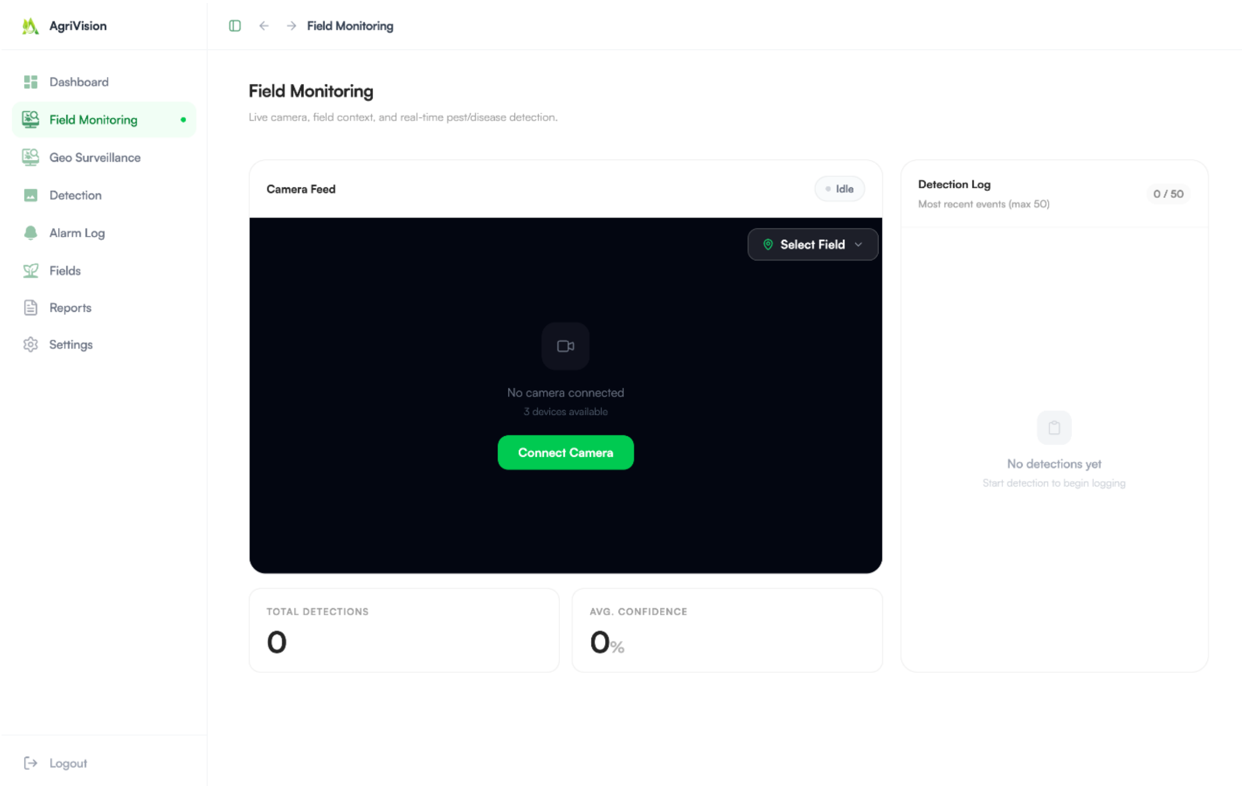
Dashboard



Field Monitoring. This page allows users to observe agricultural fields through live camera and drone feeds integrated with real-time YOLO-based pest and disease detection. It supports device and field selection, fullscreen monitoring, and overlays bounding boxes on video and image streams for accurate visualization of detected objects. Additionally, the system records detection logs, tracks confidence levels and detection counts, and supports both WebRTC and MJPEG streaming with a canvas-based renderer for efficient real-time monitoring, as shown in Figure 6.

Figure 6

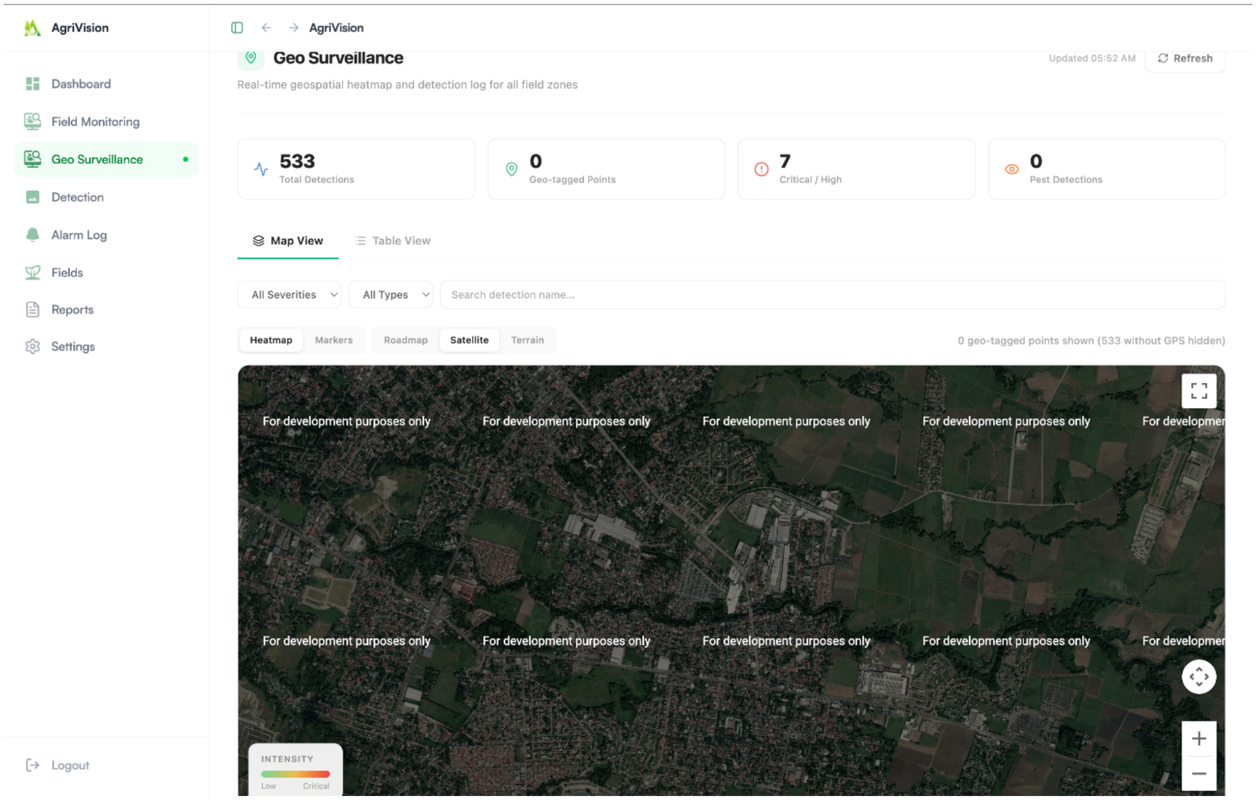
Field Monitoring



Geo Surveillance. This page enables users to visualize and analyze real-time agricultural pest and disease detections through an interactive geospatial monitoring system. It integrates Google Maps heatmap and marker views to display geotagged detection records, allowing users to monitor affected field locations efficiently. The system also supports severity-based filtering, search functionality, and type classification for organized pest and disease analysis. Additionally, it features live API integration with automatic data refresh, statistical overview cards, sortable detection tables, CSV export, pagination, and detailed map tooltips to support comprehensive field-level surveillance and decision-making, as shown in Figure 7.

Figure 7

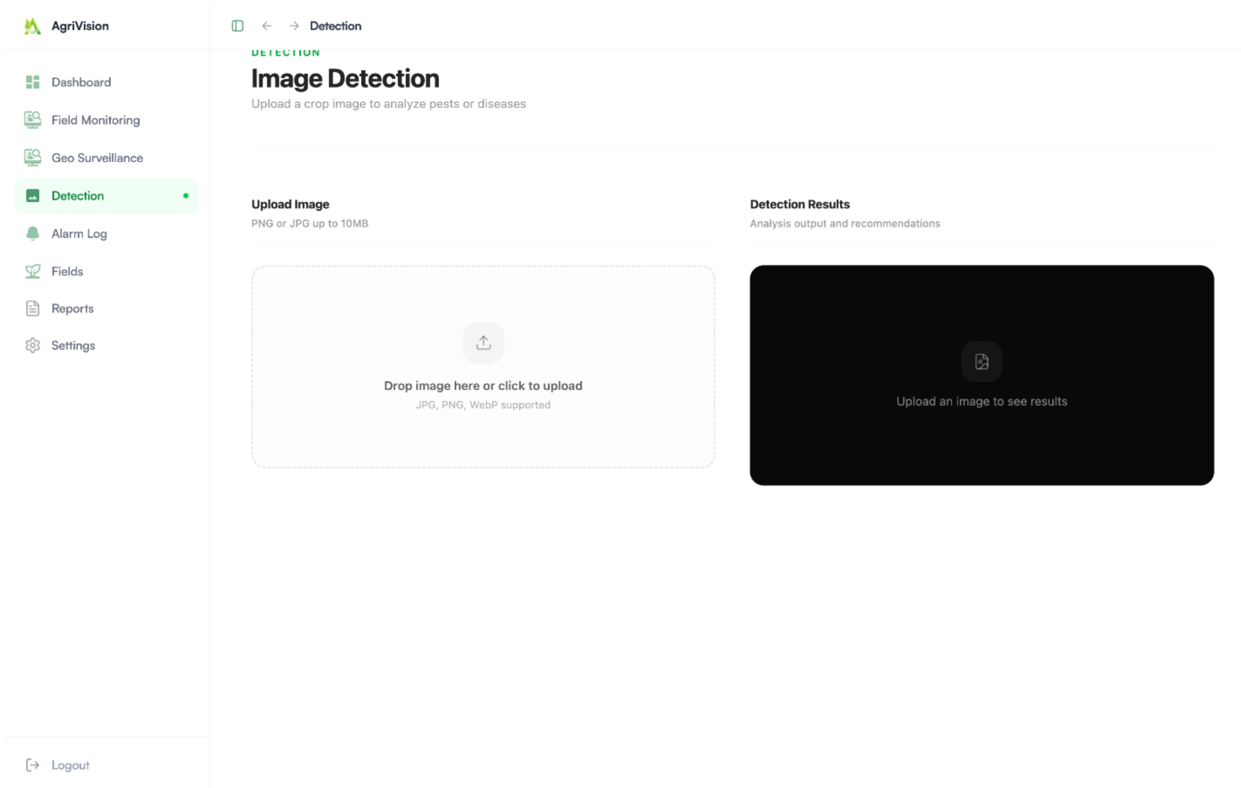
Geo Surveillance



Detection. This page allows users to upload crop images only for disease analysis through an interactive image detection interface. It supports drag-and-drop image uploading with image preview functionality and performs a simulated detection process to analyze possible crop threats. The system then displays detailed detection results, including disease type, confidence level, severity status, and recommended treatment actions. Additionally, users are provided with options to download detection results and clear uploaded images for new analysis sessions, as shown in Figure 8.

Figure 8

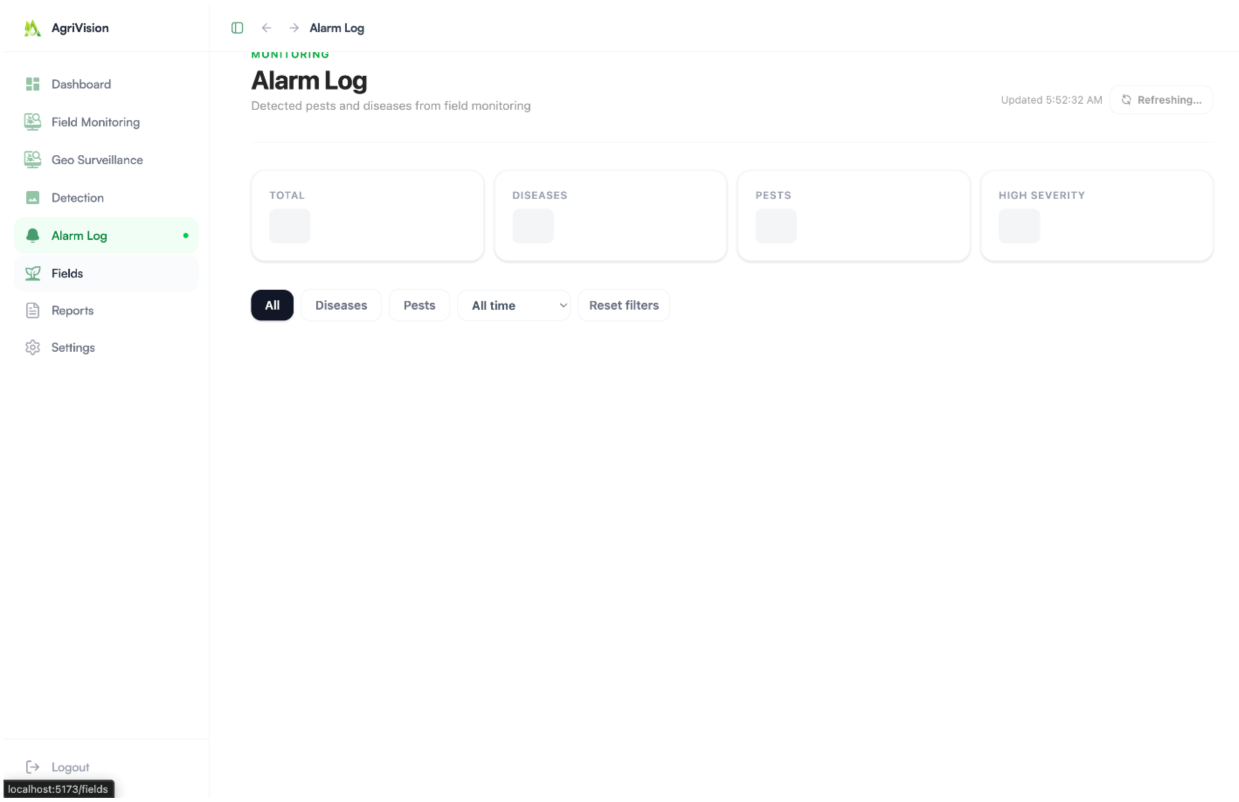
Detection



Alarm Log. This page enables users to monitor and manage detected rice pests and diseases through a centralized alarm logging system. It records real-time detection events and provides detailed information such as severity levels, confidence scores, affected field locations, and detection timestamps for efficient agricultural monitoring. The system also includes filtering and search tools to organize detection records, along with detailed field analysis and treatment recommendations to support rapid response and decision-making in pest and disease management, as shown in Figure 9.

Figure 9

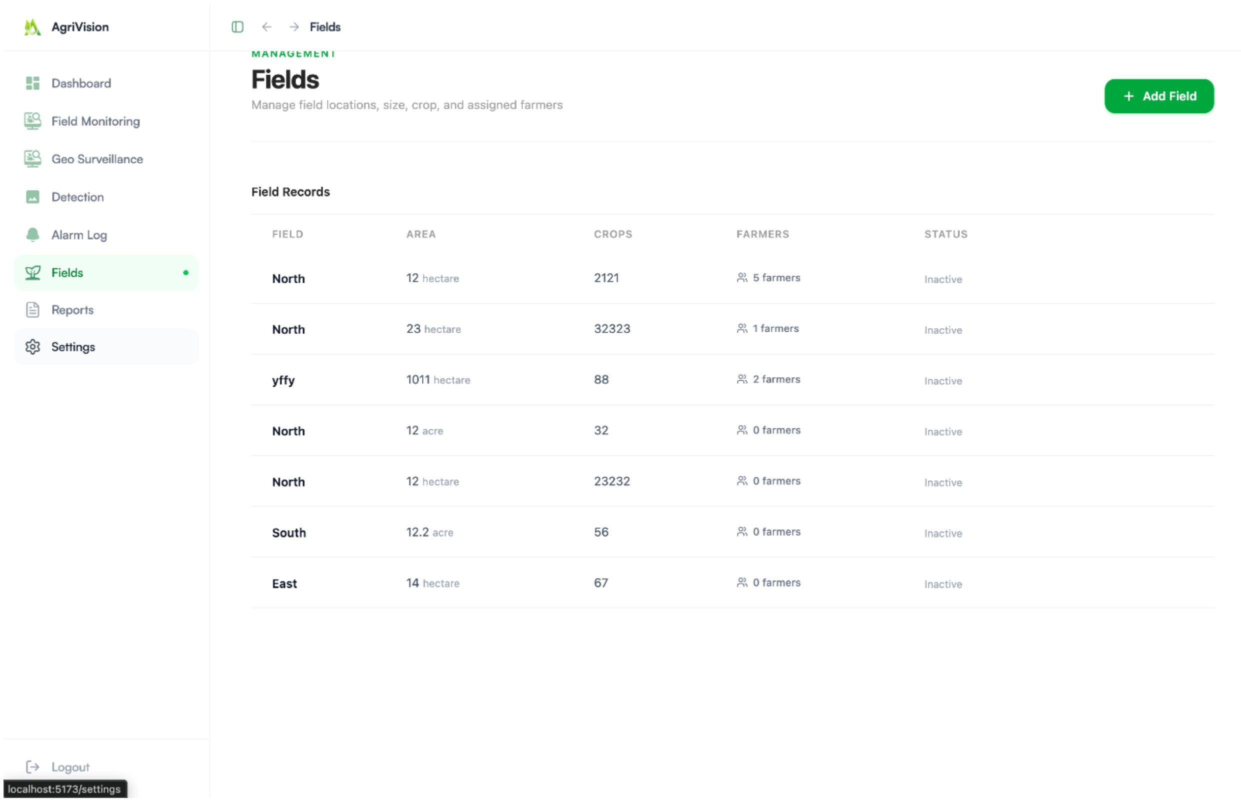
Alarm Log



Fields. This page allows users to manage agricultural field information through a React-based field management dashboard with full CRUD (Create, Read, Update, Delete) functionality. It supports field creation, editing, and deletion with integrated API connectivity for efficient data management and real-time updates. The system also enables farmer assignment for each field through modal-based management tools, allowing organized monitoring of field ownership and responsibilities. Additionally, the page includes responsive table and card layouts, monitoring status tracking, and a clean user interface for managing crop field records, area information, and associated farmers, as shown in Figure 10.

Figure 10

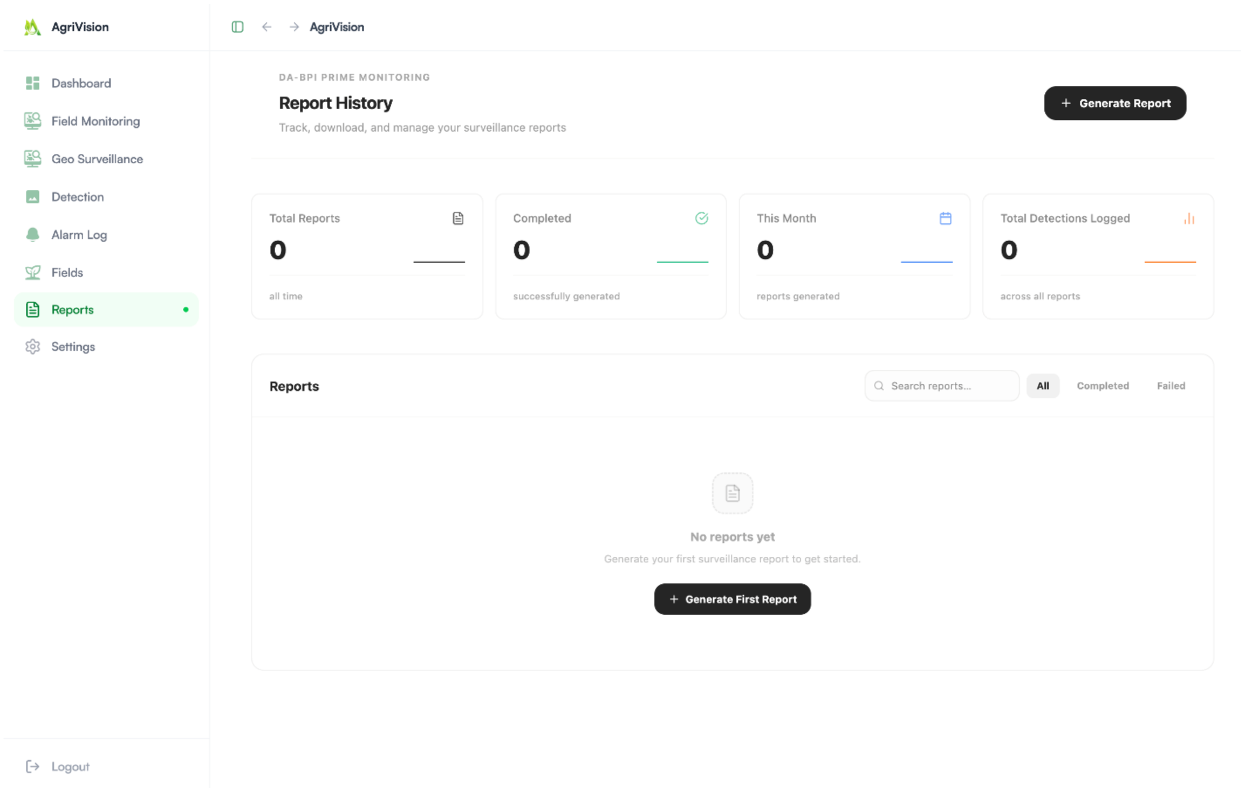
Fields



Reports. This page enables users to manage and generate agricultural surveillance reports through a React-based reports management dashboard with full report lifecycle functionality. It supports real-time report generation using live detection data and allows users to export reports in PDF format through jsPDF integration. The system also maintains report history using local storage management and provides tools for filtering, searching, and tracking report status for organized documentation. Additionally, the page includes report preview, delete, and re-download functions with modal-based interactions, along with statistical overview cards, report table interfaces, and severity-based analytics for monitoring pest and disease surveillance outputs, as shown in Figure 11.

Figure 11

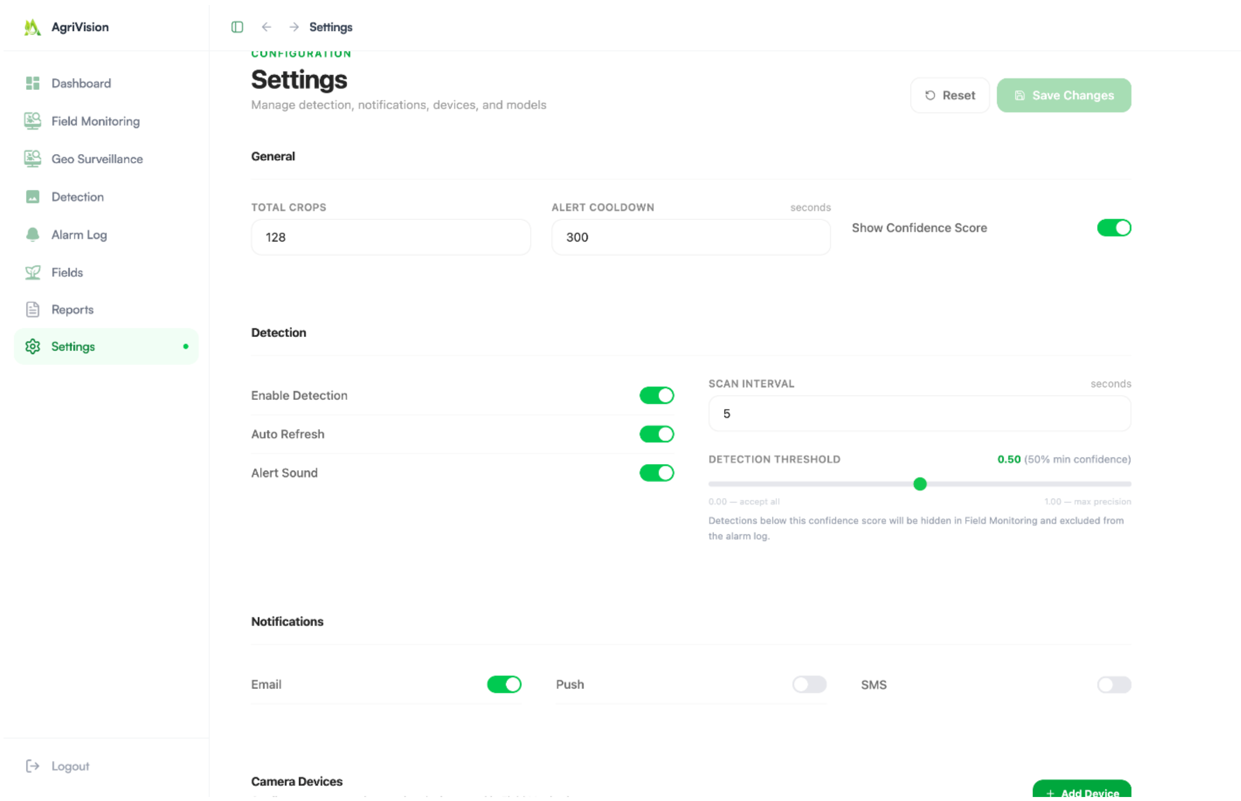
Reports



Settings. This page provides administrators with a centralized configuration panel for managing the agricultural monitoring system and its AI-powered surveillance features. It allows users to customize AI detection settings such as detection thresholds, notification preferences, and surveillance parameters for accurate monitoring performance. The system also supports the configuration of IP cameras and drone video streams for real-time field observation and detection. Additionally, administrators can manage pest and disease classifications, upload and update YOLO detection models, and configure system-wide settings necessary for efficient real-time agricultural surveillance and monitoring, as shown in Figure 12.

Figure 12

Settings



Implementation Plan

The AgriVision system has been fully developed and is prepared for final implementation and deployment. The implementation phase includes system integration, deployment of the YOLOv8m-based detection model, user validation, and final documentation of the web-based agricultural surveillance platform. This phase also covers the evaluation of the system's real-time pest and disease detection capability, geo-tagged alarm logging, and authority-level monitoring functions. Table 8 presents the Implementation Plan Schedule, outlining the timeline for model optimization, system integration, deployment, user acceptance testing, and final project completion.

Table 8

Implementation Plan Schedule

Activity	Start Date	End Date	Duration (Weeks)	Status
Requirement Gathering (Stakeholder Consultation: Farmers and, Researchers)	Jan 20, 2026	March 18, 2026	8 weeks	Completed
Dataset Curation, Annotation & Validation (16-Class Rice Health Dataset)	Feb 1, 2026	Feb 14, 2026	2 weeks	Completed
Model Development & Optimization YOLOv8m	Feb 1, 2026	Mar 7, 2026	5 weeks	Completed
Backend Development (Laravel API, Authentication, Alarm Logging, PostgreSQL Setup)	Feb 1, 2026	Mar 14, 2026	6 weeks	Completed
Frontend Development (React Web Application: Detection, Dashboard, Reports, Geo-Surveillance)	Feb 15, 2026	Mar 28, 2026	6 weeks	Completed
System Integration (AI Model + Backend + Frontend + GPS Alarm Logging Module)	Mar 15, 2026	Apr 4, 2026	3 weeks	Completed
System Testing & Evaluation (Accuracy, Precision, Recall, mAP@0.5.	Apr 5, 2026	May 2, 2026	4 weeks	Completed
Deployment (Server Hosting, Model Export ONNX, Live Web Deployment)	May 3, 2026	May 10, 2026	1 week	Completed
Final Documentation, Revision & Submission	May 13, 2026	May 17, 2026	4 days	Completed

CHAPTER V

CONCLUSION AND RECOMMENDATIONS

This chapter presents the conclusions and recommendations of the AgriVision project based on its development outcomes, evaluation results, and the related studies reviewed in Chapter 2.

The AgriVision YOLOv8m model was tested on a separate set of images not used during training and achieved a mAP@0.5 of 95.7%, which exceeds the 94% target benchmark established at the start of the study. This result confirms that the model can correctly identify rice pests and diseases in field images with a consistently high level of accuracy, demonstrating that automated image-based detection is a viable alternative to manual crop inspection in the Philippine agricultural context. Most of the 16 rice health conditions were detected reliably, with several classes such as dead-heart, downy-mildew, normal, and stem-borer reaching near-perfect AP scores of 0.99, indicating that the model has learned to distinguish these conditions with a high degree of confidence. The F1-Confidence curve recorded an overall score of 0.92 at a confidence threshold of 0.416, reflecting a strong and consistent balance between correctly identifying conditions and minimizing false detections across all classes. The Precision-Confidence curve reached 1.00 at a threshold of 0.974, and the Recall-Confidence curve recorded 0.99 at the lowest confidence threshold, further confirming the model's reliability across a wide range of operating conditions. The only class that performed below expectation was sheath-blight, which recorded a recall of 0.80 due to its visual similarity with other foliar disease conditions and a relatively higher rate of background misclassification. This limitation is consistent with findings in related literature where visually overlapping disease classes present a persistent challenge for detection models trained on field image datasets. Despite this, the overall performance of the model across 15 out of 16 classes meets or exceeds the targets set for the study. These results collectively confirm that AgriVision is technically feasible within its defined operating conditions and represents a functional prototype ready for a controlled pilot deployment in Philippine rice-growing communities, where it can serve both farmers needing immediate field diagnostics and authorities requiring structured surveillance data for regional decision-making.

The proponents recommended that:

1. More training images for sheath-blight should be collected and added in future versions of the model, since it is currently the hardest condition for the system to detect correctly due to how similar it looks to other leaf diseases.
2. Continued field testing across a wider range of farm locations, lighting conditions, weather variations, and camera devices is recommended to further validate and strengthen the model's performance beyond the current test areas.
3. Formal coordination with the Bureau of Plant Industry should be pursued to integrate the system's alarm logs and generated reports into existing government crop monitoring and damage assessment workflows at the municipal and provincial levels.

4. Future development phases should expand the detection scope beyond the current 16 classes to include emerging pest threats and newly documented disease variants that have been recently observed in Philippine rice-growing regions.
5. A structured and documented pilot deployment involving farmers and municipal agricultural workers across multiple provinces is recommended to formally measure system usability, field adoption rates, and the practical impact of the alarm logging feature on response time and crop loss prevention.
6. Integration with agricultural drones should be explored in future development phases, wherein unmanned aerial vehicles equipped with high-resolution cameras can be deployed over rice fields to capture close-up aerial images of crop conditions at scale. The model should be retrained and fine-tuned using a dedicated dataset of drone-captured imagery collected at varying altitudes and angles to account for the differences in perspective, resolution, and lighting compared to ground-level photographs. This enhancement would allow AgriVision to support large-area field surveillance more efficiently, enabling faster detection of pest and disease outbreaks across wider farm coverage that would otherwise be impractical through manual ground inspection or handheld device photography alone.

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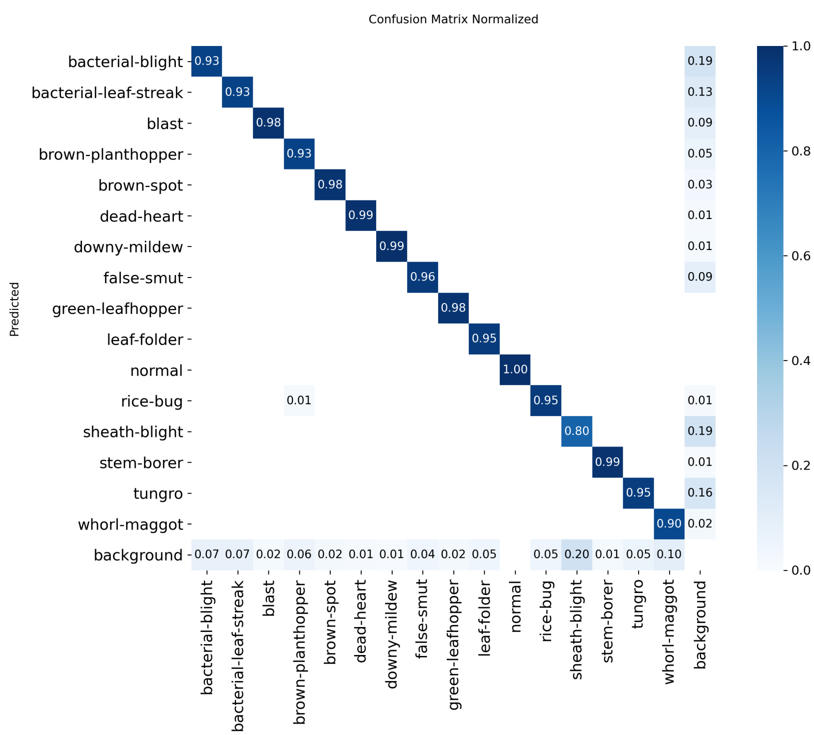
APPENDICES

APPENDIX A

Confusion Matrix of AgriVision YOLOv8m Model (16-Class Rice Health Detection)

Figure A.1 shows the confusion matrix generated from the evaluation of the trained YOLOv8m model using the held-out test dataset. The matrix presents the relationship between actual classes and predicted classes across the 16 rice health conditions. It highlights correct classifications along the diagonal and misclassifications outside the diagonal.

Figure A.1 Confusion Matrix Normalized of AgriVision



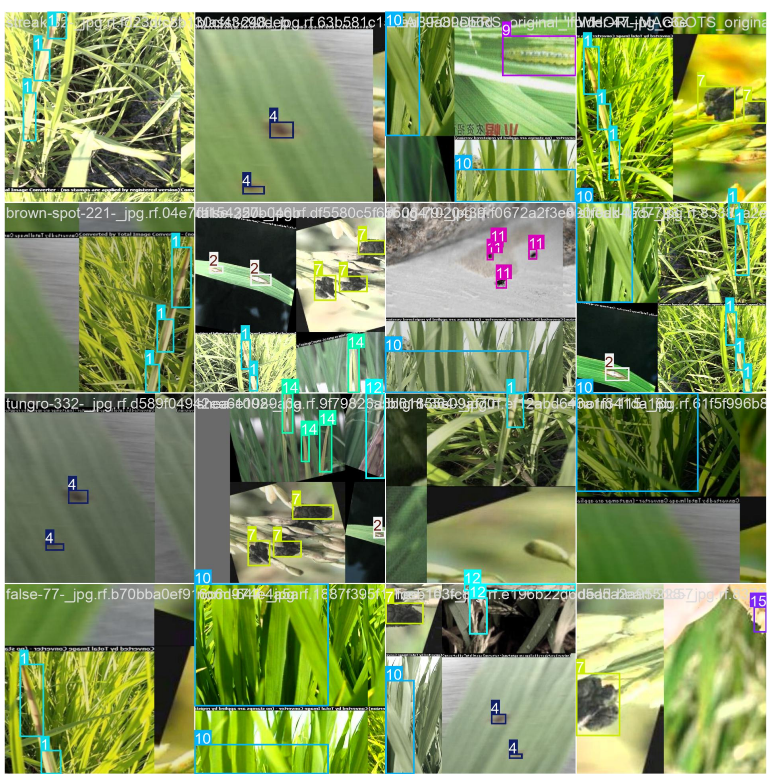
The confusion matrix provides detailed insight into the performance of the model across all classes. It shows how well the model correctly identifies each rice health condition and where classification errors occur. This allows evaluation of which classes are consistently recognized accurately and which classes are frequently confused due to similar visual features.

APPENDIX B

Sample Labeled Dataset Images per Class

Figure B.1 shows sample labeled images used for YOLOv8m training for rice pest and disease detection. The dataset includes 16 rice health conditions with annotated images per class collected from public datasets and field sources. Each image contains bounding box annotations marking pest presence or disease symptoms on rice crops. The dataset supports model training, validation, and testing under varied field conditions.

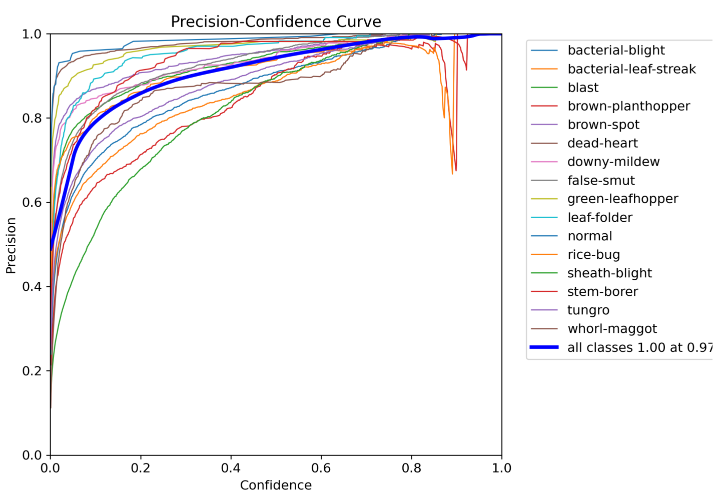
Figure B.1

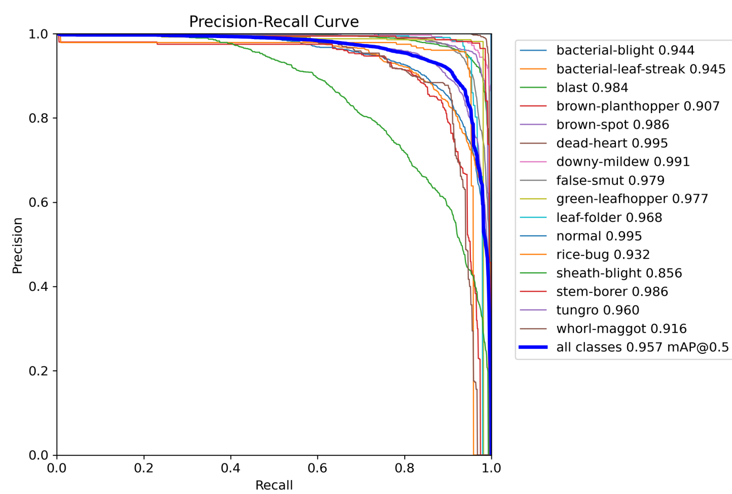


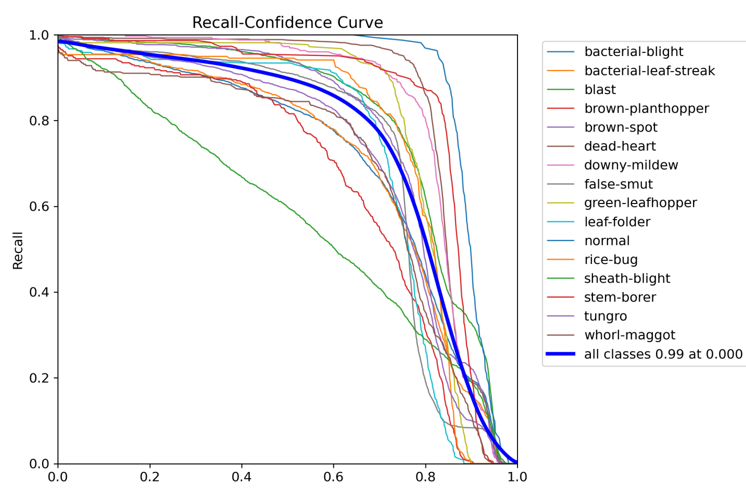
The samples provide evidence of balanced representation across classes and show the visual characteristics used by the model during training. Each image includes bounding box annotations indicating the location of pests or disease symptoms on rice crops. This appendix supports the dataset preparation process described in Chapter 4 and validates the quality of the training data used for model development.

APPENDIX C

Performance Metrics Summary of AgriVision YOLOv8m Model







This appendix presents the evaluation results of the AgriVision YOLOv8m model using Box Precision (BoxP), Box Recall (BoxR), and Box Precision-Recall (BoxPr) curves. BoxP shows how many predicted detections are correct, BoxR shows how many actual objects are correctly detected, and BoxPr shows the relationship between precision and recall across confidence thresholds. These graphs illustrate the model's detection performance for 16 rice health classes under test conditions and support the evaluation results presented in Chapter IV.