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AGROBOOST: AN AUTONOMOUS AGRICULTURAL INTELLIGENCE SYSTEM INTEGRATING SATELLITE IMAGERY, UNMANNED AERIAL VEHICLES, AND MACHINE LEARNING FOR EARLY CROP STRESS DETECTION

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Abstract: Undetected crop stress remains one of the principal causes of preventable agricultural loss worldwide, with the Food and Agriculture Organization (FAO) estimating that up to twenty percent of global crop yield is lost to conditions — water stress, plant disease, pest infestation, and nutrient deficiency — that could have been mitigated through earlier intervention. Existing monitoring approaches rely either on satellite remote sensing, which offers wide-area coverage but suffers from low revisit frequency (three to five days) and coarse spatial resolution (ten to thirty meters), or on manual field inspection, which is accurate but slow, costly, and difficult to scale.

This paper presents AgroBoost, an autonomous agricultural intelligence system that fuses satellite imagery, autonomous drone-based aerial inspection, and machine-learning-driven computer vision into a single continuous monitoring pipeline. The system identifies candidate problem zones from large-scale satellite scans, dispatches an autonomous drone for high-resolution close-range imaging of flagged areas, applies a trained detection model to classify disease, pest, and water-stress signatures, and delivers localized, actionable recommendations to farmers through a real-time dashboard. We describe the system architecture, the hardware and software stack, and a working prototype, and we discuss the system's potential agronomic, economic, and environmental impact relative to existing single-source monitoring approaches.

Keywords: precision agriculture; unmanned aerial vehicles; satellite remote sensing; computer vision; machine learning; crop stress detection; NDVI; smart farming

1. Introduction

Modern agriculture faces a persistent detection gap: the interval between the onset of a crop-health problem and the moment a farmer becomes aware of it. During this interval, water stress, disease, and pest infestations spread largely unchecked, converting a localized and treatable issue into field-scale damage. Because irrigation inefficiency, disease spread, and pest propagation are all time-sensitive processes, the cost of late detection compounds daily. Industry estimates place preventable global crop losses in the billions of dollars annually, a figure driven less by the absence of monitoring technology than by the coarseness and latency of the monitoring technology currently in use.

Two dominant paradigms currently address crop monitoring. The first, satellite-based remote sensing, provides valuable large-area vegetation indices such as the Normalized Difference Vegetation Index (NDVI) but is constrained by fixed orbital revisit schedules and moderate ground resolution, which together delay detection and obscure plant-level symptoms. The second, manual field inspection, can identify plant-level symptoms with high fidelity but does not scale economically across large or geographically dispersed farms and introduces human inconsistency into diagnosis. Neither paradigm, used in isolation, closes the detection gap quickly enough to prevent loss.

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This paper introduces AgroBoost, a system designed to close that gap by combining three complementary data sources — orbital satellite imagery, autonomous unmanned aerial vehicle (UAV) inspection, and an artificial-intelligence detection engine — into a single automated monitoring loop. The remainder of this paper is organized as follows. Section 2 reviews related approaches to remote and aerial crop monitoring. Section 3 formalizes the problem being addressed. Section 4 presents the proposed AgroBoost architecture. Section 5 describes the hardware and software implementation. Section 6 outlines the operational workflow. Section 7 discusses the prototype and preliminary results. Section 8 considers social and environmental impact, and Section 9 concludes with limitations and directions for future work.

2. Related Work

Satellite-based vegetation monitoring, most commonly built on multispectral missions such as Sentinel-2, has become a standard tool for regional-scale agricultural assessment. NDVI and related spectral indices derived from these platforms are effective at flagging broad vegetation-health trends but are inherently limited by orbital revisit intervals of several days and pixel resolutions on the order of ten to thirty meters — a granularity too coarse to isolate early, localized stress at the level of individual plants or plant rows.

A separate body of work has applied UAV-mounted sensors and cameras to close-range crop inspection. Drone-based platforms achieve centimeter-scale resolution and can be deployed on demand, but most reported systems function as manually piloted or manually triggered inspection tools rather than as an autonomous, continuously operating component of a larger monitoring pipeline; as a result they still depend on a human operator to decide where and when to fly.

Parallel advances in computer vision, particularly convolutional object-detection architectures such as the YOLO (You Only Look Once) family, have made real-time identification of plant disease lesions, pest presence, and canopy stress patterns computationally feasible on modest hardware. However, the literature on precision agriculture has tended to treat satellite sensing, aerial inspection, and machine-learning detection as separate research threads rather than as stages of one coordinated system. AgroBoost is positioned at the intersection of these three threads, proposing their integration into a closed-loop pipeline in which satellite data determines where to look, drone imagery determines what is happening, and a machine-learning model determines what to do about it.

3. Problem Statement

The core problem addressed by this work can be stated as follows: existing agricultural monitoring tools cannot deliver real-time, field-level, and actionable intelligence at a cost and scale accessible to individual farms. This shortfall manifests along four dimensions, summarized in Table 1.

Limitation	Description	Consequence
Low revisit frequency	Satellite passes occur every three to five days.	Disease and pests spread undetected between passes.
Coarse spatial	Typical resolution of ten to thirty	Early, plant-level stress

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Limitation	Description	Consequence
resolution	meters per pixel.	signatures are not visible.
Manual inspection dependency	Ground-truthing requires human field visits.	Slow, expensive, and inconsistent across large areas.
Generic reporting	Alerts lack field-specific, actionable guidance.	Farmers cannot translate data into timely decisions.

Table 1. Limitations of current single-source crop monitoring approaches.

A viable solution must therefore (i) narrow the temporal gap between problem onset and detection, (ii) achieve plant-level spatial resolution where satellite data is insufficient, (iii) remove dependence on continuous human labor for inspection, and (iv) translate raw detections into localized, actionable recommendations.

4. Proposed System: AgroBoost

AgroBoost addresses these requirements through a three-layer sensing architecture coupled to an intelligence and reporting layer. The design principle is complementary coverage: each technology compensates for the limitations of the others rather than duplicating their function.

Satellite Imaging Layer — provides large-scale, wide-area field monitoring and trend analysis, used to identify candidate zones of concern across the full extent of a farm.

Autonomous Drone Layer — performs high-resolution, close-range inspection of the zones flagged by the satellite layer, capturing plant-level imagery beyond satellite resolution limits.

Artificial Intelligence Layer — analyzes drone and satellite imagery to detect disease, pest presence, and water stress, converting raw imagery into classified, quantified observations.

Smart Dashboard and Alert Layer — presents findings to the farmer through instant alerts and specific, field-localized recommendations for action.

Because the drone is dispatched only to satellite-flagged regions rather than surveying an entire farm at high resolution, the system keeps flight time and computational load proportional to actual risk, allowing continuous operation without requiring exhaustive full-field aerial coverage on every cycle.

5. System Architecture and Implementation

5.1 End-to-End Data Flow

The system operates as a continuous monitoring loop rather than a one-time assessment. Satellite data triggers a large-scale field scan; regions exceeding a stress threshold are queued for drone inspection; the drone performs a high-resolution pass over the queued coordinates; the AI engine processes the resulting imagery for four target conditions — disease presence, water stress, pest

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activity, and general growth trend; and results are pushed to the farmer portal together with an alert where thresholds are exceeded.

This loop is designed to run continuously and automatically, without requiring a human operator to initiate each cycle.

5.2 Hardware Stack

The aerial platform consists of a quad-rotor drone equipped with a GPS module for autonomous navigation, a flight controller running PX4 Autopilot with MAVLink telemetry, four motors, a high-definition camera for image capture, a communication module for real-time data transfer, and a battery pack supporting a flight endurance of approximately twenty-five minutes per sortie.

5.3 Software Stack

The software layer is organized into four coordinated services. The AI detection engine is built on YOLOv8 and OpenCV in Python, providing real-time object detection for disease, pest, and stress signatures. Satellite data is processed using Sentinel-2 imagery with NDVI-based vegetation-index analysis. Time-series and geospatial observations are persisted in a PostgreSQL database extended with TimescaleDB for efficient handling of continuous sensor data. Finally, a React-based web dashboard renders real-time field status, alerts, and recommendations for the end user.

6. Operational Workflow

The system's operational cycle can be described in five sequential steps, illustrated in Table 2.

Step	Stage	Function
1	Scan	Satellite imagery identifies candidate problem hotspots across the field.
2	Collect	The autonomous drone captures high-resolution imagery of flagged coordinates.
3	Analyze	The AI engine detects disease, pest activity, and water stress in the captured imagery.
4	Recommend	The system generates localized, actionable guidance based on detected conditions.
5	Act	The farmer applies the recommended intervention, reducing crop loss and supporting higher yield.

Table 2. The five-stage AgroBoost operational workflow, from field scan to farmer action.

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7. Prototype Demonstration and Preliminary Results

A working prototype was developed to validate the proposed pipeline under field-test conditions. The prototype flight test exercised the full sensing loop — autonomous navigation, image capture, AI-based detection, and dashboard reporting — on a test plot. In this demonstration, the dashboard reported an aggregate crop-health index of eighty-seven percent, classified as favorable, while simultaneously flagging a localized water-stress condition in a specific field subsection for follow-up irrigation. This result illustrates the system's core value proposition: an overall field-health summary combined with sub-field-level, spatially precise flags that a purely satellite-based or purely manual approach would either miss or detect too late to act upon efficiently.

Table 3 summarizes how AgroBoost's fused approach compares with existing single-source solutions across the dimensions most relevant to early detection.

Existing Solutions	AgroBoost
Satellite only — no ground truth	Satellite and drone data fusion
Manual inspection required	Fully autonomous aerial inspection
Delayed decisions, on the order of days	AI-driven, near-real-time analysis
Generic, non-localized recommendations	Field-localized, personalized recommendations
No AI integration or explainability	Explainable, detection-based AI decisions

Table 3. Comparative summary of AgroBoost against representative existing monitoring approaches.

8. Social and Environmental Impact

Beyond its technical contribution, AgroBoost is intended to produce measurable agronomic and environmental benefits. Targeted intervention enabled by early detection is expected to increase productivity per unit area. Smart, data-driven irrigation guidance is designed to reduce water waste, with an estimated potential reduction in irrigation water use of approximately thirty percent relative to non-optimized scheduling. Early pest detection allows infestations to be addressed before they spread across a field, and precision application of chemical treatments — applied only where AI detection indicates a need — is expected to reduce overall chemical input relative to blanket-application practices. Collectively, by reducing preventable losses, the system is designed to improve net farmer income per season while supporting more sustainable, ecosystem-conscious farming practices. Consistent with FAO estimates that up to twenty percent of crop losses are preventable through earlier intervention, closing even a fraction of this detection gap represents a substantial aggregate economic and environmental benefit at scale.

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9. Limitations and Future Work

The current prototype has been validated on a limited test plot and has not yet been evaluated across diverse crop types, climates, or farm scales; broader field trials with quantitative accuracy metrics for disease, pest, and stress classification are a necessary next step. Planned extensions to the sensing layer include multispectral and thermal imaging cameras to expand the range of detectable stress signatures beyond what visible-spectrum imagery supports, integration of weather-forecast data to anticipate rather than only detect emerging conditions, and predictive AI models capable of forecasting stress onset ahead of visible symptoms.

On the platform side, planned work includes progressing toward fully autonomous multi-field missions and richer precision-agriculture analytics. In terms of scalability, the architecture is intended to generalize beyond the initial test crop to cotton, wheat, fruit orchards, vineyards, and greenhouse operations, and to scale from individual smallholder farms up to coordinated national agricultural programs.

10. Conclusion

This paper presented AgroBoost, an autonomous agricultural intelligence system that integrates satellite remote sensing, autonomous drone-based aerial inspection, and machine-learning-driven computer vision into a single continuous monitoring pipeline. By using satellite data to direct drone inspection toward the areas most likely to need it, and by applying a trained detection model to convert close-range imagery into localized, actionable guidance, AgroBoost is designed to close the temporal and spatial detection gap that limits existing single-source monitoring approaches. A working prototype demonstrated the feasibility of the full sensing-to-recommendation loop. Future work will focus on expanded field validation, additional sensing modalities, and predictive modeling, with the broader goal of making real-time, field-level agricultural intelligence accessible across farms of every scale.

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