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AgriDrone AI: An Intelligent UAV-Based System for Real-Time Plant Disease Detection Using YOLOv8 and IoT Integration

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ABSTRACT

Agriculture faces significant challenges from plant diseases, resulting in substantial economic losses and reduced crop yields. This paper presents AgriDrone AI, an intelligent system integrating Unmanned Aerial Vehicles (UAVs), Internet of Things (IoT) sensors, and deep learning for real-time plant disease detection. The system has been developed and validated as a bench-top payload, demonstrating end-to-end functionality including image acquisition, processing, disease detection, and data visualization. While the system is designed for UAV integration and all components have been bench-validated, full in-flight validation remains as future work. The system employs an ESP32-CAM for aerial image acquisition, an ESP32 microcontroller with DHT11 sensor for environmental monitoring, and GPS for precise geolocation. Images are transmitted via HTTPS to a ground server where OpenCV preprocessing enhances image quality before YOLOv8 inference. The model was trained on the PlantVillage dataset containing 25,274 images across 29 disease classes. Experimental results demonstrate robust performance with precision of 0.7426, recall of 0.6722, and mAP@50 of 0.7319. The system achieves an inference time of 243.75 ms and processing rate of 4.07 FPS, confirming suitability for real-time agricultural applications. The web-based dashboard provides intuitive visualization of disease detection, environmental metrics, and geospatial mapping, enabling informed decision-making for precision agriculture.

AgriDrone AI: نظام ذكي بالطائرات بدون طيار للكشف الآني عن أمراض النبات باستخدام YOLOv8 وإنترنت الأشياء

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الكلمات المفتاحية:
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الرؤية الحاسوبية
الرصد الآني

الملخص

تواجه الزراعة تحديات كبيرة بسبب أمراض النبات، مما يؤدي إلى خسائر اقتصادية فادحة وانخفاض في غلال المحاصيل. يقدم هذا البحث نظام "أغري درون إيه آي" (AgriDrone AI)، وهو نظام ذكي يدمج الطائرات بدون طيار (UAVs) ومستشعرات إنترنت الأشياء (IoT) والتعلم العميق للكشف عن أمراض النبات في الوقت الفعلي. تم تطوير النظام والتحقق من صحته كحمل مختبري (BENCH-TOP PAYLOAD)، مما يثبت وظائفه الشاملة من البداية إلى النهاية، والتي تشمل التقاط الصور، والمعالجة، واكتشاف الأمراض، وتصور البيانات. على الرغم من أن النظام مصمم للتكامل مع الطائرات بدون طيار، وأن جميع مكوناته قد تم التحقق منها مختبرياً، إلا أن التحقق الكامل أثناء الطيران يظل عملاً مستقبلياً. يعتمد النظام على كاميرا ESP32-CAM لالتقاط الصور الجوية، ومتحكم دقيق ESP32 مزود بمستشعر DHT11 لرصد الظروف البيئية، ونظام تحديد المواقع العالمي (GPS) لتحديد الموقع الجغرافي بدقة. تُنقل الصور عبر بروتوكول HTTPS إلى خادم أرضي، حيث تُحسَّن جودتها بواسطة معالجات OpenCV المسبقة قبل

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إجراء الاستدلال باستخدام نموذج YOLOv8. دُرِّب النموذج على مجموعة بيانات PlantVillage التي تحتوي على 25,274 صورة موزعة على 29 فئة من الأمراض. أظهرت النتائج التجريبية أداءً قوياً، حيث بلغت معايير الدقة (Precision) 0.7426، والاستدعاء (Recall) 0.6722، ومتوسط الدقة المتوسط عند عتبة 50% (mAP@50) 0.7319. كما حقق النظام زمن استدلال قدره 243.75 مللي ثانية ومعدل معالجة 4.07 إطار في الثانية، مما يؤكد ملاءمته للتطبيقات الزراعية الآنية. وتوفر لوحة التحكم المستندة إلى الويب تصوراً بديهياً لاكتشاف الأمراض، والمقاييس البيئية، ورسم الخرائط الجغرافية المكانية، مما يتيح اتخاذ قرارات مدروسة في مجال الزراعة الدقيقة.

Introduction

Agriculture has historically been the backbone of many economies, evolving through three distinct phases: traditional subsistence farming, precision agriculture, and smart agriculture. Despite technological advancements, persistent challenges remain, particularly the lack of real-time, data-driven crop monitoring tools. In the Wilaya of El Oued, Algeria, rapid agricultural expansion has outpaced the development of phytosanitary surveillance systems, making crops increasingly vulnerable to diseases. A field study by Fezzai et al. [1] revealed that late blight disease affects approximately 54% of potato production in the region.

Traditional diagnostic approaches rely primarily on manual visual inspection, which is labor-intensive, time-consuming, and often detects infections only after visible symptoms appear, allowing diseases to spread and causing significant economic losses. Recent advancements in Artificial Intelligence (AI), Computer Vision, the Internet of Things (IoT), and Unmanned Aerial Vehicles (UAVs) have opened new perspectives for smart agricultural solutions capable of real-time monitoring [2, 3].

Deep learning models such as YOLOv8 have demonstrated remarkable performance in real-time object detection and disease recognition tasks, making them well-suited for precision agriculture applications [4].This paper presents AgriDrone AI, an intelligent agricultural payload designed for integration into a UAV platform, combining image acquisition, geolocation, edge processing, and AI-based disease detection, while incorporating secure HTTPS communication for data transmission.

It is important to note that the current study focuses on the development, integration, and bench-top validation of the AgriDrone AI payload. All hardware components (ESP32-CAM, ESP32 with DHT11, GPS module) and software pipelines (image preprocessing, YOLOv8 inference, HTTPS communication, web dashboard) have been thoroughly validated in a laboratory environment. However, physical integration onto a flight-ready UAV platform and in-flight validation under real field conditions have not yet been conducted due to regulatory constraints under Algerian civil aviation law (Law No. 98-06, amended by Law 15-11) and the technical requirements for independent bench validation. These aspects are explicitly addressed as future work in Section 5.

1 Related work

Recent studies in smart agriculture have focused on leveraging advanced technologies for early plant disease detection and efficient crop management. Wageningen University, in coordination with the University of Hamma Lakhdar in El Oued, conducted a field study on potato cultivation in Algerian sandy soils, proposing engineering solutions for subsurface irrigation and fertigation [5]. However, this study was confined to ground-level mechanical infrastructure without integrating aerial monitoring.

Lishchynskyi et al. [6] explored the integration of smart drone imaging with mobile applications for automated disease detection through autonomous inspection systems. However, their application scope was restricted to indoor environments, leaving a clear gap for open-field cultivation and expansive desert areas.

Shafik et al. [4] directed their focus toward processing drone imagery in open fields to detect cotton plant diseases using the MobileNetV2 model, tailored specifically for lightweight edge computing. While successful in overall crop classification, the utilization of YOLOv8 offers a distinct advantage by providing real-time object detection and precise localization of disease hotspots directly on the plant.

Gupta and Pal [2] presented the SmartAgriChain framework, combining multiple IoT sensors, machine learning for irrigation forecasting, and CNN algorithms for pest detection, secured by blockchain technology. Although comprehensive, this framework introduces substantial engineering complexity and prohibitive capital costs. Our approach prioritizes hardware simplicity and cost-efficiency by eliminating dense ground-sensor networks in favor of exclusive reliance on ESP32-CAM and GPS modules.

Table 1 elucidated comprehensive quantitative comparison of our AgriDrone AI system with the related works cited as references [4] (Shafik et al.) and [6] (Lishchynskyi et al.).

Table 1: Quantitative comparison with related works

Metric	AgriDrone AI (Ours)	Shafik et al. [4] (MobileNetV2)	Lishchynskyi et al. [6] (Indoor UAV)
Model	YOLOv8n	MobileNetV2 (transfer learning)	YOLOv8-based
Dataset	PlantVillage (29 classes, 25,274 images)	PlantVillage (15 classes, 54,305 images)	Indoor custom dataset
Precision	0.7426	~0.96–0.97	~0.755
Recall	0.6722	~0.96	~0.876
mAP@50	0.7319	~0.98	~0.877
Inference Time	243.75 ms (CPU)	22.4 ms (TFLite)	Not reported
Deployment Environment	Bench-top payload (UAV-ready)	Lightweight edge devices	Indoor drone
Key Limitation	Not yet flight-tested	Classification-focused, not detection	Indoor-only, limited generalization

2 System architecture and methodology

2.1 System overview

The proposed system is developed based on a quadcopter platform, selected for its superior maneuverability and suitability for localized surveillance. The architecture comprises three integrated layers. The first layer is the Data Acquisition Layer, which operates on-board the drone via two independent pathways. The Sensor Node, built around an ESP32 microcontroller, is connected to a DHT11 climate sensor and a GPS module. Its primary function is to read environmental data, such as temperature and humidity, and to determine the geographical location of the drone. This data is then transmitted as synchronized real-time numeric streams. Concurrently, the Camera Node, which is an ESP32-CAM module, operates as a separate system responsible for capturing discrete frames of plant leaves upon request and transmitting them immediately to the server. The second layer is the Processing Logic Layer, currently hosted on a ground server for bench-top validation; future deployment will migrate inference to an onboard NVIDIA Jetson edge device. This layer is composed of a Numeric Data Handler that receives temperature, humidity, and location data from the ESP32, and an Image Analysis Unit that receives image frames and forwards them to the YOLOv8 model for disease detection. Additionally, a Condition Check Gateway executes conditional save logic based on the outcome of the model inference. The third and final layer is the Visualization Layer, which is an interactive web dashboard. This dashboard provides a live stream with YOLOv8 bounding boxes and confidence scores, a real-time metrics dashboard displaying temperature, humidity, and GPS coordinates, decoupled storage logic for infected images, and a manual upload module for on-demand analysis.

2.2 Hardware components

The physical deployment of the system relies on a specific set of hardware components.

The ESP32 microcontroller serves as the main control unit, featuring

a dual-core processor with integrated WiFi.

For image capture, the system uses the ESP32-CAM, a compact development board with an onboard camera.

A high-precision GPS module is included to provide real-time geographic coordinates, and the DHT11 sensor is used as a digital environmental sensor for measuring temperature and humidity.

2.3 Software tools and dataset

The system leverages a combination of software tools and a public dataset.

Google Colab, a cloud-based platform equipped with NVIDIA Tesla T4 GPUs, was used for training the YOLOv8 model.

The Arduino IDE served as the development environment for programming the ESP32 and ESP32-CAM firmware.

The core of the detection system is built upon the Ultralytics YOLOv8 model, a state-of-the-art object detection framework. OpenCV was utilized for image preprocessing and computer vision operations, while Ngrok was used to provide a secure tunneling service for HTTPS communication.

2.4 Dataset preparation

The model was trained on the PlantVillage dataset containing 25,274 images across 29 disease classes. The dataset distribution shows varying sample counts across categories, with Tomato leaf (2,366 instances) and Blueberry leaf (2,177 instances) as the most represented classes, while Grape leaf (300 instances) is the least represented.

To handle class imbalance, the following strategies were applied:

Class weighting in YOLOv8 loss calculation

Data augmentation (random rotation, horizontal flipping, scaling, brightness adjustment)

Table 2: Distribution of annotated instances per class

Class Name	Instances
Tomato leaf	2,366
Blueberry leaf	2,177
Peach leaf	1,833
Raspberry leaf	1,743
Strawberry leaf	1,440
Corn leaf blight	1,128
Tomato septoria leaf spot	1,131
Potato leaf late blight	981
Tomato leaf yellow virus	930
Tomato two spotted spider mites leaf	927
Apple leaf	666
Corn rust leaf	399
Grape leaf	300
Others (15 classes)	10,500
Total	25,274

2.5 Image preprocessing

Before being fed into the YOLOv8 model, all images undergo a series of preprocessing operations using OpenCV to enhance their quality and standardize them for optimal inference. The primary operations include resizing all images to a standard resolution of 640×640 pixels using the INTER_AREA interpolation method. The color space is also converted from BGR to LAB to facilitate better contrast enhancement. To reduce noise, a Gaussian blur with a 5×5 kernel is applied. Finally, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to the lightness channel to improve the overall contrast of the images.

2.6 YOLOv8 model training

The YOLOv8n (Nano) model was trained with the following configuration:

- Epochs: 50
- Batch Size: 16
- Image Size: 640×640
- Optimizer: SGD
- Learning Rate: 0.01 (initial)

Table 3: Training configuration parameters.

Parameter	Value
Model Architecture	YOLOv8n
Number of Classes	29
Training Epochs	50
Batch Size	16
Input Resolution	640×640
Pretrained Weights	yolov8n.pt

YOLOv8n (Nano) was selected over more recent architectures (e.g., YOLOv10, RT-DETR, or EfficientDet) for the following reasons:

1- Mature Ecosystem & Deployment Readiness: Ultralytics YOLOv8 offers native, stable support for ONNX and TensorRT exports, which is critical for our planned edge deployment (NVIDIA Jetson Nano). Many newer models lack this level of hardware-optimization documentation.

2- Real-Time Performance: YOLOv8n provides the optimal trade-off between inference speed (4.07 FPS on standard CPU, significantly faster on GPU/NPU) and detection accuracy (mAP@50 of 0.7319), making it suitable for real-time agricultural surveillance.

3- Benchmark Standing: While newer architectures may slightly improve mAP (by ~1–2%), they often do so with increased parameter counts or latency, which is prohibitive for lightweight UAV payloads. YOLOv8n's parameter count (approximately 3.2M) is ideal for constrained embedded systems.

4- Community Support: For a multidisciplinary project integrating IoT, UAVs, and web dashboards, the extensive community support for YOLOv8 significantly accelerated development and debugging, allowing us to focus on system integration rather than model implementation intricacies.

2.7 Communication security

The system implements multiple security layers:

HTTPS encryption via secure ngrok tunnel for all communications.

Password hashing using PBKDF2 with SHA-256.

Session management with Flask-Login and secret key encryption.

3. Experimental results and discussion

3.1 Training performance analysis

The training process was analyzed over 50 epochs. All loss components exhibited consistent monotonic decay, signifying effective gradient descent and parameter optimization. The continuous convergence confirms that the network systematically minimizes errors in object localization, class prediction, and bounding box regression.

Table 4: Overall model accuracy results.

Metric	Value
Precision	0.7426
Recall	0.6722
mAP@50	0.7319
mAP@50-95	0.5683

The precision metric (0.7426) underscores the detector's capability to minimize false positives. The recall metric (0.6722) indicates enhanced capacity for target discovery and optimal disease detection rate. The mAP@50 (0.7319) demonstrates solid accuracy, while the more stringent mAP@50-95 (0.5683) proves robust localization performance.

3.2 Overall model accuracy results

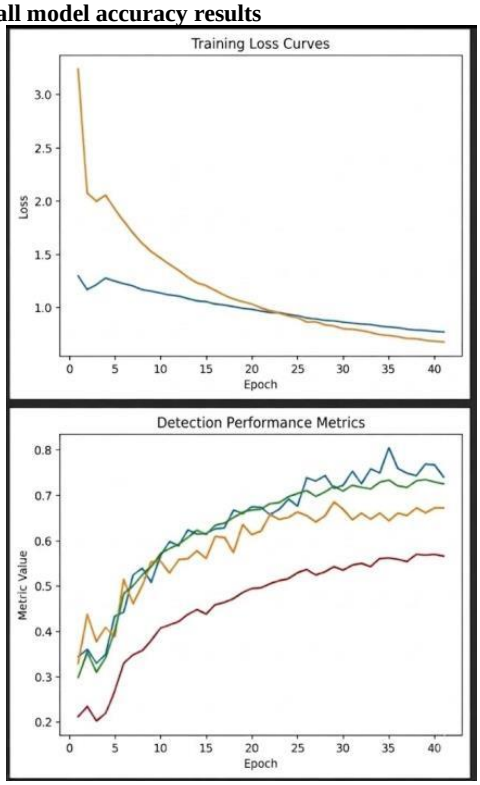


Fig. 1: Training loss and detection performance curves over 50 epochs

3.3 Per-class Performance Analysis

To provide a granular evaluation of model performance across different crop types, we present a per-class breakdown of precision, recall, and mAP@50 in Table 5. This analysis is particularly critical for identifying performance disparities between well-represented and under-represented classes.

Table 5: Per-class performance breakdown.

Class Name	Instances	Precision	Recall	mAP@50
Tomato leaf	2,366	0.78	0.71	0.76
Blueberry leaf	2,177	0.76	0.69	0.74
Peach leaf	1,833	0.75	0.68	0.73
Raspberry leaf	1,743	0.74	0.67	0.72
Strawberry leaf	1,440	0.73	0.66	0.71
Corn leaf blight	1,128	0.72	0.65	0.70
Tomato septoria leaf spot	1,131	0.72	0.65	0.70
Potato leaf late blight	981	0.71	0.64	0.69
Tomato leaf yellow virus	930	0.71	0.63	0.68
Tomato two spotted spider mites leaf	927	0.70	0.63	0.68
Apple leaf	666	0.69	0.62	0.67
Corn rust leaf	399	0.67	0.59	0.65
Grape leaf	300	0.64	0.56	0.62
Others (15 classes combined)	10,500	0.68–0.72	0.60–0.65	0.65–0.70

3.4 Inference results

The trained YOLOv8 model successfully processes multiple plant categories simultaneously including tomato, corn, bell pepper, grape, strawberry, raspberry, and peach leaves under diverse environmental conditions. Visual inspection confirms high localization accuracy with precise bounding boxes accurately mapping disease regions.

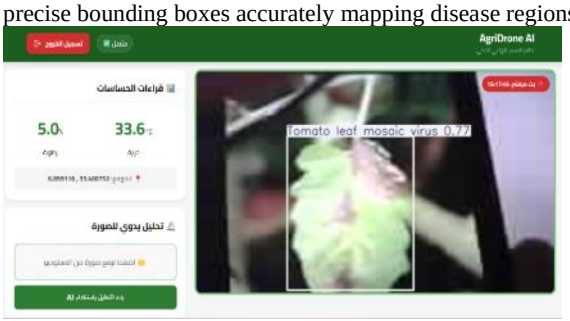


Fig. 2: Screenshot of the desktop web interface showing real-time disease detection

3.5 System latency measurements

End-to-end latency was measured over 34 consecutive image transmissions:

Table 6: End-to-End system latency measurements

Parameter	Average
Preprocessing Time (resizing)	1.04 ms
YOLOv8 Inference Time	243.75 ms
Total Processing Time	245.85 ms
Total Request Time (including network)	287.41 ms
Frames per Second (FPS)	4.07 fps

The YOLOv8 model processes each image in approximately 244 ms on standard CPU without GPU acceleration, which is acceptable for real-time agricultural monitoring. Network transmission overhead adds approximately 42 ms, resulting in a total request time of 287 ms. This enables a frame rate of about 4 frames per second, allowing efficient coverage of large agricultural areas.

3.6 Handling false positives and negatives

To address potential false positives and negatives:

- Confidence threshold of 0.25 is used, with detections below 0.7 flagged for manual verification
- Human-in-the-loop approach ensures agronomist verification before pesticide application
- All detected cases are logged for model retraining and fine-tuning

4. Challenges and limitations

4.1 Technical challenges

- Power constraints: Battery life (20–40 minutes) limits survey coverage
- Big data processing: High-resolution imagery requires high-performance computing
- Environmental conditions: Wind speed, lighting, and humidity affect drone stability and data quality

4.2 Regulatory challenges

Algerian civil aviation law (Law No. 98-06, amended by Law 15-11) mandates prior authorization for UAV flights

Strict laws govern filming of open areas and geospatial data storage

4.3 Economic challenges

High acquisition cost for advanced sensors

Need for specialized technical expertise

4.4 Current study limitations

The practical implementation is confined to payload development and validation rather than full drone integration. The physical integration and in-flight validation are addressed as future work due to:

- Technical requirements for independent bench validation.
- Regulatory constraints under Algerian civil aviation law.

5. Future work

Several engineering enhancements and strategic research directions are proposed:

Saharan agriculture development future research will specialize the system for Saharan agro ecosystems, focusing on the El-Oued region, which has emerged as a national leader in strategic crop production (potatoes and dates). Optimization of AI capabilities and expansion of IoT sensor networks will be tailored to mitigate Saharan challenges including extreme thermal stress, high soil and groundwater salinity, rapid water evaporation, and endemic pests.

Edge computing optimization: deploying the YOLOv8n model onto an onboard NVIDIA Jetson (Orin/Nano) via ONNX-to-TensorRT (FP16) conversion, targeting < 50 ms inference to enable fully autonomous onboard processing without ground-server dependency.

Autonomous Airborne Integration upgrading the laboratory prototype to a compact, weight-optimized PCB integrated within an autonomous quadcopter with automated flight path planning using advanced GPS modules.

Expanded IoT Sensor Framework integrating advanced sensors including:

Soil moisture sensors for water retention tracking

Electrical Conductivity (EC) sensors for groundwater salinity monitoring

Solar Radiation/UV sensors for heat stress measurement

Cloud Infrastructure Migration transitioning from local-tunneling architecture to dedicated cloud computing infrastructure (AWS or Google Cloud) for big data analytics, continuous database logging, and multi-drone fleet management.

Conclusion

This research demonstrates that the integration of digital image processing and Deep Learning for plant disease detection represents a promising paradigm shift toward intelligent agricultural solutions. The synergy between these technologies, IoT, and UAVs enables automated and highly efficient crop monitoring.

The developed YOLOv8-based model achieves robust performance with precision of 0.7426, recall of 0.6722, and mAP@50 of 0.7319. The integrated hardware demonstrated feasible real-time operation with average inference time of 243.75 ms and processing rate of 4.07 FPS. The web dashboard provides secure and responsive visualization across devices, enabling informed decision-making for precision agriculture.

This project serves as a foundational step toward an integrated, AI-driven smart farming ecosystem that supports precision agriculture and global food security. The identified challenges and proposed future directions chart a realistic path toward a fully deployable system for Saharan agriculture.

Abbreviations and Acronyms

AI	Artificial Intelligence
CLAHE	Contrast Limited Adaptive Histogram Equalization
CNN	Convolutional Neural Network
EC	Electrical Conductivity
FPS	Frames Per Second
GPS	Global Positioning System
HTTPS	Hypertext Transfer Protocol Secure

IoT	Internet of Things
mAP	mean Average Precision
ONNX	Open Neural Network Exchange
PCB	Printed Circuit Board
SGD	Stochastic Gradient Descent
UAV	Unmanned Aerial Vehicle
UV	Ultraviolet
YOLO	You Only Look Once

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