Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

A Robot-Ready AI Decision Support System for Real-Time Detection and Weather-Based Management of Potato Late Blight

Abderrahmane Larbi Aissa
University of Blida 1
Hani Brahim
University of Blida 1
Sara Bouraine
Centre de Développement des Technologies Avancées
Mohammed Islam Seghier
mohammedislamseghier@gmail.com
University M'Hamed Bougara
Hiba Bouabdellah
University of Blida 1
Dalila Hammadou
Centre de Développement des Technologies Avancées

Article

Keywords: Decision support system, Deep learning, Late blight, Potato crops, Smart agriculture

Posted Date: November 11th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11374948/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

A Robot-Ready AI Decision Support System for Real-Time Detection and Weather-Based Management of Potato Late Blight

Abderrahmane Larbi Aissa[1,2], Hani Brahim[1,2], Sara Bouraine[2], Mohammed Islam Seghier[3,2,*], Hiba Bouabdellah[1,2], Dalila Hammadou[2]

[1]Department of Electrical Engineering, University of Blida 1, 9022 Blida, Algeria
[2]Robotics and Industrial Automation Division, Center for Development of Advanced Technologies, 16081 Algiers, Algeria
[3]Institute of Electrical and Electronic Engineering, University M'Hamed Bougara, 35000 Boumerdes, Algeria

[*]Corresponding author: Mohammed Islam Seghier, mohammedislamseghier@gmail.com

E-mail addresses: abderrahmanelarbiaissa@yahoo.com (A. Larbi Aissa), hanibrahim29@yahoo.com (H. Brahim), s_bouraine@yahoo.fr (S. Bouraine), mohammedislamseghier@gmail.com (M. I. Seghier), bouabdellahhiba382@gmail.com (H. Bouabdellah), dhammadou@cdta.dz (D. Hammadou)

Acknowledgments. The authors would like to thank the "Institut National de la Protection des Végétaux (INPV)" for providing datasets of infected plants and the "Institut Technique des Cultures Maraîchères et Industrielles (ITCMI)" for supporting the field validation experiments.

Abstract. *Late blight is one of the most destructive plant diseases and a particular problem for Algerian potato farmers. Currently, most Algerian farmers still use traditional methods, such as weekly fungicide spraying, to prevent the disease from appearing and spreading. Others prefer to take the risk and avoid spraying due to the high cost and harm of these fungicides. The developed system addresses this issue with an intelligent Decision Support System (DSS) based on real-time blight detection by a YOLOv8 (You Only Look Once) model trained on a customized dataset and on online weather data. It provides the best-timed decisions and schedules for spraying. The system is built on the Robot Operating System 2 (ROS 2) framework for easy integration into a real robotic platform. The critical information is presented in a web interface, which allows the farmer to monitor and control the system's actions (like accepting or refusing spray missions or turning the camera on or off). The experiments demonstrate that the YOLOv8n model scored an overall mean average precision (mAP@0.5) of 0.920, with an overall precision of 0.885 and recall of 0.832. Furthermore, the DSS successfully integrates disease detection alerts and weather-based risk prediction to suggest accurately when to trigger spray missions. This combination of weather forecasting (as a proactive defense layer) and real-time artificial intelligence detection (as a reactive defense layer) aims to guarantee crop safety and minimize fungicide utilization, which could lead to lower costs and improved crop quality.*

Keywords. *Decision support system, Deep learning, Late blight, Potato crops, Smart agriculture.*

INTRODUCTION

Agriculture has served as the primary source of food for humans for a very long time. Indeed, it has become an important part of the global food security and a big sector in national economies. This role has become increasingly significant in the context of the rise in global population. In Algeria, agriculture contributed 12.9% to the national Gross Domestic Product (GDP) in 2023 (Banque d'Algérie 2024). Algerian farmers currently face many challenges to keep their crops healthy and maintain stability especially against plant diseases. Without continuous inspection and fast intervention, the results can lead to severe yield losses. Despite its economic importance, the agricultural sector in Algeria still relies heavily on the traditional practices such as spraying fungicides unconditionally every week. This leads to a higher cost and wasted effort, causing harm to the crop and its environment, as well as health risks for the farmers in contact with those chemicals. To address these challenges, farmers can benefit from an intelligent system capable of optimizing disease management and mitigating these risks.

Recent systems have adopted the artificial intelligence (AI)-based solutions, which have contributed to the modernization of methods of interaction with plant diseases and the field management (Kaplun et al. 2024). Concerning continuous inspection, there is a huge shift toward real-time object detection, where the most effective models used in this field are based on the deep learning and open-source datasets (Kaplun et al. 2024). The automation of inspection is still not a complete solution, because knowing that there is a problem is only the first step, this is where Decision Support Systems come in. The latest approaches are taking into consideration some factors such as meteorological information, soil conditions, marketing demands, land uses, and economic data (Zhai et al. 2020). In terms of taking action, some agricultural robots integrate a Decision Support System (DSS) to automate a range of tasks, including precision irrigation, targeted spraying of fungicides and variable-rate fertilization (Zhai et al. 2020), other works incorporate advanced vision systems for applications such as autonomous navigation and row-following, obstacle avoidance, plant counting (Zhai et al. 2020), and the visual detection of specific disease symptoms (Alhwaiti et al. 2025), weed infestations (Zhai et al. 2020). This diversity, from independent systems to complete systems, has led the agricultural sector to experience significant technological development.

In Algeria, one of the main crops used to achieve food security methods is the potato plant. However, a number of diseases, including late blight, harm the potato crop. *Phytophthora infestans* is the culprit behind late blight, a devastating disease in potato crop. Failure of the potato crop may result from this in extreme situations (Arora et al. 2014; Forbes and Landeo 2006).

Traditional weekly fungicide spraying is costly, environmentally harmful, and often inefficient in controlling late blight. To address this issue, this paper presents the development of an intelligent Decision Support System (DSS) designed to help farmers manage late blight in potato crops more effectively. The proposed system integrates: a real-time disease detector, a YOLOv8n (You Only Look Once, version 8, nano) network optimized on a custom hybrid dataset combining PlantVillage, Plant-Doc, and field images collected with the National Institute for Plant Protection (INPV) under real Algerian conditions, using hard negative mining to eliminate soil misclassification for real-time detection of *Phytophthora infestans*; a weather-based prediction module, and a decision support system based on the Robot Operating System 2 (ROS 2) with a farmer-friendly web interface. Together, these components provide both proactive and reactive crop protection while aiming to reduce unnecessary fungicide use.

Related Works

As the global demand for food increases, developing the agricultural sector has become extremely important. In this regard, many disease detection systems have been developed. Mathew and Mahesh (2022) have presented a study focused on detecting bacterial spot disease in bell pepper plants. They used the small version of YOLOv5 (YOLOv5s) and trained it on the PlantVillage dataset, which contains images of leaves with uniform backgrounds and good lighting, taken in a laboratory environment. They manually labeled 4,000 images, and the results achieved a mean average precision (mAP@0.5) value of 90.7%. In graphical representations, precision and recall reached nearly 99%. However, the model was only tested with images from the same dataset and was not deployed in a real-time application or tested with data from a real-world environment. Furthermore, it was used to detect very late symptoms of the disease. Similarly, Alhwaiti et al. (2025) worked with the PlantVillage dataset, using 4,222 images. They employed the YOLOv3 and YOLOv4 models for detecting diseases in peach leaves affected by bacterial spots and strawberry leaves with scorch disease. The results showed that the YOLOv4 model had high performance, with a recall of 99% and accuracy and precision of 98%. The

YOLOv3 model achieved 97% for accuracy, precision, and recall. They used it in real-time and proposed developing a user-friendly Android/iOS mobile application and planning for hardware integration. However, the system was still not tested in a real environment with real-life situations. In a different approach, Tao et al. (2025) developed an enhanced deep learning model based on YOLO11n, which is named CEFW-YOLO. It detects four common types of apple leaf diseases: Powdery mildew, Black rot, Apple scab, and Rust. The model was trained on a specialized apple leaf disease detection (ALD) dataset collected from real-world scenarios in an apple orchard in Laizhou, Yantai, Shandong Province, China. This dataset included 2,452 images captured under various natural conditions. The new model achieved a precision of 85.5%, a recall of 81.2%, and an mAP@0.5 value of 87.3%. The CEFW-YOLO model was developed to run in real-time and was tested with real images from a real environment but it has not yet been used in real scenarios or integrated into a practical application.

Moreover, it is always beneficial to be aware of the causes of a disease, and even more advantageous to be able to predict it. In this area, Radwan et al. (2025) made a comparison between a range of machine learning (ML) methodologies for plant disease prediction to study the correlation between diseases and weather in potato crops, covering two diseases: early blight and late blight. The system utilizes a comprehensive dataset of over 4,000 records of weather conditions available on the Kaggle platform. The experimental test achieved an accuracy of 0.9489 (approximately 94.9%). However, the system still needs more testing in a real-life environment and requires a very stable source of data. Furthermore, to predict cucumber downy mildew disease, the system developed by Wang et al. (2024) utilizes a CNN-LSTM (Convolutional Neural Network-Long Short-Term Memory) algorithm to establish the prediction model. The system gathers data from a weather station inside the greenhouse and another weather station in front of the greenhouse. This resulted in an average error of 6.6478% between the predicted and true values for all test sets, providing a really useful system, but one that still requires a lot of equipment to gather weather data.

To effectively use new technologies in the agricultural field, it is essential to establish a strong connection with the farmer, rather than a standalone system, a collaborative approach is required that aligns with the farmer's needs to facilitate the enhancement of their crops. In this context, Helps et al. (2024) evaluated four decision support systems (DSS) designed to help farmers optimize fungicide applications across different crops. For wheat crops, the te Beest DSS is used

to combat *Zymoseptoria tritici* (septoria tritici blotch) by processing weather data to determine if a reduced fungicide dose is safe, while the Crop Protection Online (CPO) uses rainfall thresholds to calculate precise spray timing and risk levels. For other crops, the Hutton Criteria DSS monitors temperature and humidity to signal the start of a weekly spraying program against potato late blight. Finally, the Agriculture and Horticulture Development Board (AHDB) *Sclerotinia* Stem Rot DSS provides real-time risk alerts for oilseed rape, allowing farmers to timing-dependently deploy protectant fungicides before infection occurs. All of these systems are prime examples of DSS, adept at processing large amounts of data and producing accurate recommendations. However, using multiple systems makes monitoring very difficult, especially when they are used without actuators, requiring the farmer to perform the actions manually. Many individual components that could help in the agricultural field are not used because they require a hardware environment and a platform to work properly. In one of the few examples of an integrated system, Kaplun et al. (2024) present a solution integrating a vision system, a weather prediction system, and a DSS for agricultural applications. The vision system utilizes two custom Convolutional Neural Networks (CNNs) and pre-trained models to recognize fruit health conditions, while the weather prediction component employs machine learning algorithms to forecast rainfall from weather data. The DSS combines information from both components to support actions such as irrigation control. The system also provides sensor monitoring, rainfall forecasts, and fruit condition prediction through dedicated interfaces.

This review demonstrates that while significant research has been focused on individual components of smart agricultural systems, a comprehensive, fully integrated solution remains elusive. A concise comparative summary of the aforementioned works is presented in Table 1. These works have presented powerful visual detectors or proactive weather models, but they generally operate in isolation. Even systems that combine multiple components, such as DSSs or integrated platforms, still exhibit critical gaps, including the lack of real-time visual feedback, absence of standardized robotic frameworks like ROS, and fragmented user interfaces. Therefore, Table 1 summarizes these limitations and provides a comparative overview of the reviewed studies.

Table 1 Comparative Analysis of Related Works

Study/Author	Visual Detection Model	Weather Prediction	DSS	Robotic Integration	ROS Framework	User Interface
Mathew and Mahesh (2022)	YOLOv5s	No	No	No	No	No
Alhwaiti et al. (2025)	YOLOv3/YOLOv4	No	No	No	No	No
Tao et al. (2025)	Custom YOLO	No	No	No	No	No
Radwan et al. (2025)	No	Yes (ML Models)	No	No	No	No
Wang et al. (2024)	No	Yes (CNN-LSTM)	No	No	No	No
Helps et al. (2024)	No	Yes (Rule-based)	Yes	No	No	No
Kaplun et al. (2024)	Yes (Custom CNNs)	Yes (ML Models)	Yes	Yes (Irrigation)	No	Yes (Multiple)
The proposed system	**YOLOv8n**	**Yes (API-based Algorithm)**	**Yes**	**Planned (Future Work)**	**Yes (ROS 2)**	**Yes (Unified)**

THE PROPOSED INTELLIGENT DECISION SUPPORT SYSTEM

This section presents the methodology of the proposed intelligent Decision Support System (DSS) for late blight management. The disease detection, weather prediction, decision logic, and web interface components were fully implemented and tested on the ROS 2 framework, while the physical robotic platform and the automated spraying mechanism were not built and remain future work.

SYSTEM ARCHITECTURE

The proposed system is built around a central Decision Support System (DSS). The architectural workflow of the integrated solution is shown in Fig. 1. Real-time image data from an RGB (red, green, blue) camera and environmental data obtained from meteorological application programming interfaces (APIs) are the two concurrent inputs that the system gets, which are developed in the ROS 2 framework, the image data is processed by the AI Detection Module, using

disease recognition and pattern analysis to detect visual symptoms of *Phytophthora infestans* on potato leaves. Its main function is to detect the late blight infections in real time. When a disease infection is positively identified, the module sends both a confirmation command and the corresponding image with detection data to the decision-making logic for further processing. At the same time to minimize crop losses, the weather-based prediction system monitors environmental conditions to forecast and mitigate threats before the disease emerges, and to identify the optimal spray time it performs risk assessment and timing analysis. The DSS, which acts as the main "brain", combines these two streams of weather conditions and real-time disease detection, and decides when to schedule a spray mission. To keep farmers in control the decision-making is connected to a user-friendly web interface that enables them to monitor the system live, receive web alerts, and make key decisions, including the selection of automatic or manual mode, approving spray schedules, or controlling the camera.

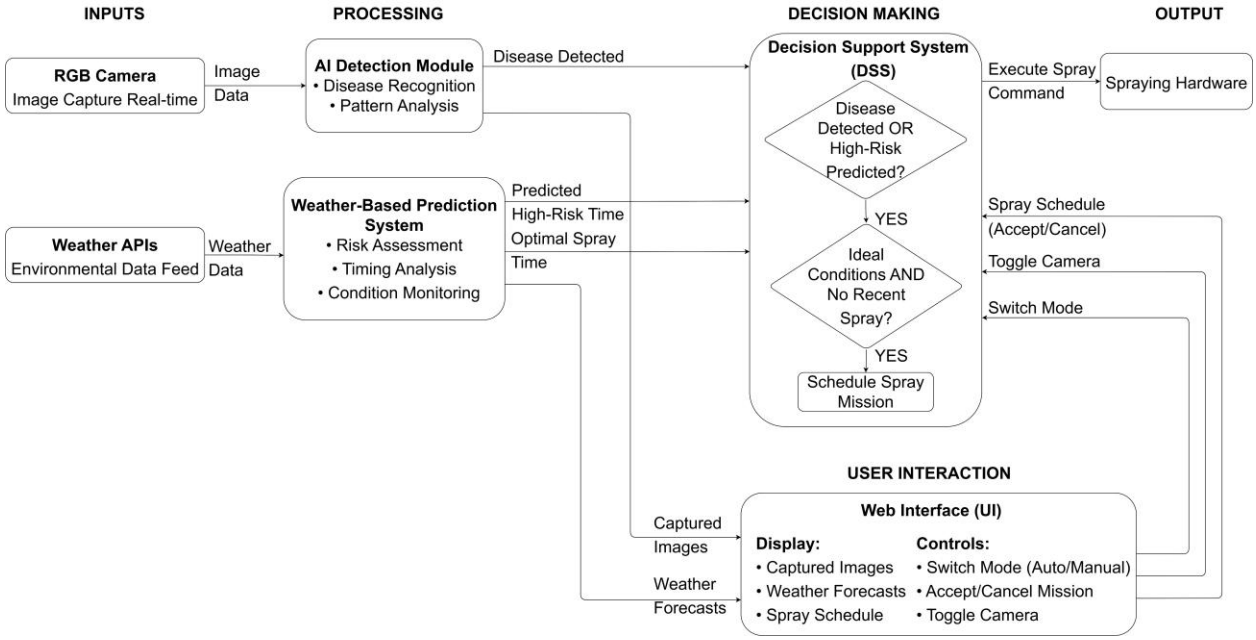


Fig. 1 Architectural workflow of the integrated decision support system, showing the data flow from initial inputs to the final robotic action and user interaction loop

VISUAL SYMPTOM DETECTION MODULE

Theoretical Background of YOLOv8

YOLO (You Only Look Once) is a real-time object detection algorithm that performs detection in a single forward pass of the network. Unlike traditional methods that use multi-stage pipelines or sliding windows, YOLO directly predicts bounding boxes and class probabilities in one step. This approach simplifies the detection process and enables fast and efficient real-time object detection.

YOLOv8, released in 2023 by Ultralytics, is a widely used version of the YOLO family of object detection models. It offers different scaled versions, including nano, small, medium, large, and extra-large, to adapt to various computational requirements. YOLOv8 is a multi-task model that supports object detection as well as other vision tasks such as segmentation and classification. Its architecture is composed of a backbone for feature extraction, a neck for feature fusion, and a decoupled detection head. Compared to previous versions, YOLOv8 introduces improvements such as the C2f module and an anchor-free design, which enhance detection accuracy and efficiency while maintaining real-time performance (Terven et al. 2023).

Model Selection

YOLOv8 was chosen for this system because it is a mature and stable iteration of the YOLO family that builds upon the established successes of its predecessors, such as YOLOv5 and YOLOv7, and offers several key enhancements that make it particularly suitable for this project. Firstly, it provides enhanced accuracy resulting from improvements in its backbone and neck architectures, which lead to better feature extraction capabilities. Secondly, YOLOv8 is engineered for faster inference speeds and is specifically optimized for edge devices. Furthermore, its adaptability is improved through advanced data augmentation techniques, enabling it to perform more robustly in dynamic agricultural environments characterized by variable lighting conditions and potential occlusions. Finally, YOLOv8 demonstrates strong scalability and compatibility with hybrid systems, for instance, facilitating integration with Deep Reinforcement Learning (DRL) for tasks like advanced robotic navigation and control, thereby supporting comprehensive precision agriculture solutions.

Between the two smaller variants of this architecture, YOLOv8n and YOLOv8s, a comparative evaluation on the project dataset showed that YOLOv8n was the more suitable choice for this task. Its lower capacity made it less prone to overfitting on a focused two class problem, and it produced qualitatively better detections of small blight spots without misclassifying soil, while YOLOv8s reached a comparable mean average precision but missed several of the smaller lesions. The training experiments also showed that a shorter training schedule was more effective for this dataset, and the number of epochs was accordingly set to 25, which gave the best balance between detection performance and training efficiency without the diminishing returns observed at longer training durations.

Dataset Preparation

The performance of a computer vision system critically hinges on the quality, diversity and relevance of the dataset used for its training and validation. To select an optimal dataset for plant disease detection, several key criteria were prioritized, including diversity in plant species, disease types, and imaging conditions such as lighting and viewing angles, as well as dataset size to ensure sufficient data for robust learning and to reduce overfitting. Additionally, data quality was considered in terms of high-resolution images with accurate annotations, along with compatibility with real-world robotic vision applications involving complex backgrounds and field conditions.

The dataset used for the training and validating the detection model was compiled from multiple sources to ensure variability and robustness (Fig. 2). The images used in this study to classify leaves of potatoes, were obtained from the publicly available 'PlantVillage' dataset (Hughes and Salathé 2015), which contributed 1,000 images of potato leaves with visible late blight symptoms and 200 images of healthy leaves (Fig. 2a), 'Plant-Doc' dataset (Singh et al. 2020) to account for various natural conditions environments, it provided 410 real-world field images (Fig. 2b). Additionally, the National Institute for Plant Protection (INPV), Algeria provided 80 images of infected potato plants from local field data, complemented by 10 self-captured photographs of potato plants captured at home. To complete the data collection, a hard negative dataset containing 500 images of non-leaf and non-blight objects (e.g., soil, background clutter) to reduce false positives (Fig. 2c).

All images were manually labeled on the Roboflow platform with two classes: "blight" (for the specific infected area) and "leaf" (for the entire leaf tissue). Although the source images were collected unevenly across the different datasets, the final labeled instance distribution between the two classes was kept close to balanced, with 8,307 "blight" and 8,064 "leaf" annotations, so that the model would learn to distinguish both features effectively. The resulting dataset contained 2,200 images.



(a) (b) (c)

Fig. 2 Example images from the custom dataset sources: (a) PlantVillage (Hughes and Salathé 2015; adapted, CC BY-SA 3.0), (b) Plant-Doc (Singh et al. 2020; photo: A. J. Gevens, University of Wisconsin–Madison, reproduced with permission), and (c) hard negative images

Training Strategy and Data Augmentation

The model was trained in the Google Colaboratory environment, leveraging NVIDIA Tesla T4 graphics processing units (GPUs). The training was configured for 25 epochs with an input image size of 800×800 pixels to enhance the detection of small, early-stage lesions, while all other hyperparameters were kept at their default values.

To improve the model's robustness and its ability to generalize to a range of field conditions, a comprehensive set of data augmentations were applied to the training set, including random flips, rotations, blurs, and exposure adjustments. This process effectively tripled the dataset size to 6,378 images.

Evaluation Metrics

The model's performance was evaluated using standard object detection metrics. The final trained YOLOv8n model demonstrated excellent performance on the validation set, achieving an overall mAP@0.5 of 0.920 and an mAP@0.5:0.95 of 0.691. The mAP@0.5 counts a detection as correct when its Intersection over Union (IoU) with the labeled box is at least 0.5, whereas the mAP@0.5:0.95 averages the results over IoU thresholds from 0.5 to 0.95 and is therefore a stricter measure, which explains its lower value.

The class-specific results were also strong, the "blight" class achieved a precision of 0.865 and a recall of 0.746. The "leaf" class achieved a precision of 0.905 and a recall of 0.918. These metrics confirm the model's reliability in accurately identifying blight symptoms while correctly distinguishing healthy leaves.

IMPLEMENTATION ENVIRONMENT

The detection model of the proposed system was trained using the Google Colaboratory

environment (Colab) to leverage its free temporary access to powerful NVIDIA Tesla T4 GPUs. For real-time detection and system testing, a Dell laptop equipped with an Intel Core i5 (8th generation) processor and 16 GB of RAM was used, together with a 1280 × 720 webcam operating at 30 frames per second. To evaluate the system under real agricultural conditions, field experiments were conducted at the Institut Technique des Cultures Maraîchères et Industrielles (ITCMI) in Algeria. As potatoes were out of season during the experimentation period, the system was challenged in the field with tomato, a crop of the same botanical family (Solanaceae) that is affected by late blight caused by the same pathogen, *Phytophthora infestans* (Nowicki et al. 2012). The software architecture was built upon a combination of modern frameworks and communication tools. The object detection is based on the YOLOv8 model, where both the nano and small variants were evaluated to balance accuracy and computational efficiency. To handle the communication between the different system nodes, the software was integrated into the Robot Operating System 2 (ROS 2). To integrate environmental data, external APIs were used including OpenWeatherMap API (OpenWeatherMap 2025) for temperature and general weather forecasts, Open-Meteo API for humidity, wind, and precipitation data.

In addition, a web interface serves as the primary point of interaction between the farmer and the underlying technologies. Developed using HTML, CSS, and JavaScript, the web-based interface is designed to be lightweight, accessible, and user-friendly across various devices. A Flask web server was implemented to manage system initialization and control processes. To ensure real-time communication between the web interface and the ROS 2 environment, rosbridge was used, establishing a WebSocket connection that allows seamless data exchange and remote system monitoring.

WEATHER-BASED PREDICTION SYSTEM

To enable proactive disease management, the system integrates a weather-based prediction module designed to forecast and mitigate threats before they emerge.

Data Source

For the weather data, two different sources have been used to get the best picture: OpenWeatherMap and Open-Meteo. OpenWeatherMap has been mainly used for temperature monitoring. However, given the fact that late blight is known to thrive in conditions of high humidity, it became apparent that a more precise source of this data was required. In this regard, Open-Meteo is a valuable resource, as it utilizes some of the leading global weather models to

provide highly accurate humidity forecasts. Preliminary comparison tests showed that its humidity forecasts were about 3% more accurate than those from OpenWeatherMap (Evcin and Erten 2024). By cross-referencing both data sources, the system can verify these environmental variables to more accurately determine if weather conditions are favorable for the disease to spread.

Prediction Algorithm

The prediction process is driven by a rule-based algorithm designed to identify critical environmental thresholds. This logic is integrated into a ROS 2 module titled “weather_reporter”, which queries data at ten-minute intervals. Initially, a detailed 48-hour weather outlook for the exact coordinates of the field is retrieved. Subsequently, a scan of the following 24-hour period is performed to monitor two primary criteria:

- *Danger Zones for Blight:* It flags any period where the temperature is between 10°C and 25°C and the humidity shoots above 90%. These are the optimal conditions for late blight development (Gevens and Wilbur 2015).
- *The Perfect Spraying Window:* It helps identify the best time for the deployment of the robot in the field. This is when the following criteria are met: there is no rain, the winds are calm (less than 10 m/s), and the temperature is between 0°C and 45°C.

The system's primary function is to identify the subsequent "danger zone" and then align it with the earliest possible "spraying window" thereafter. Once this has been established, the information is packaged and sent to the main decision-making part of the system, so that it knows exactly when to act.

DECISION LOGIC AND SCHEDULING

The design of the DSS integrates perceptual data and generates responsive actions. In order to achieve the necessary levels of modularity and robust inter-process communication, the entire software suite is constructed upon the ROS 2 framework.

The decision-making logic is composed of two main ROS 2 nodes (Fig. 3), “spray_scheduler” and “spray_decider”, which work in coordination to manage spraying operations. These nodes communicate asynchronously through a series of specialized ROS 2 topics, creating a decoupled and resilient system.

The system behavior is governed by the selected operating mode: in automatic mode, the mission is executed autonomously, while in manual mode, a user confirmation is required via the web interface before execution.

The “spray_scheduler” subscribes to data from the vision (/blight_detection) and weather (/weather_status) nodes, while the “spray_decider” acts on commands from the scheduler and provides feedback via a (/spray_log) topic.

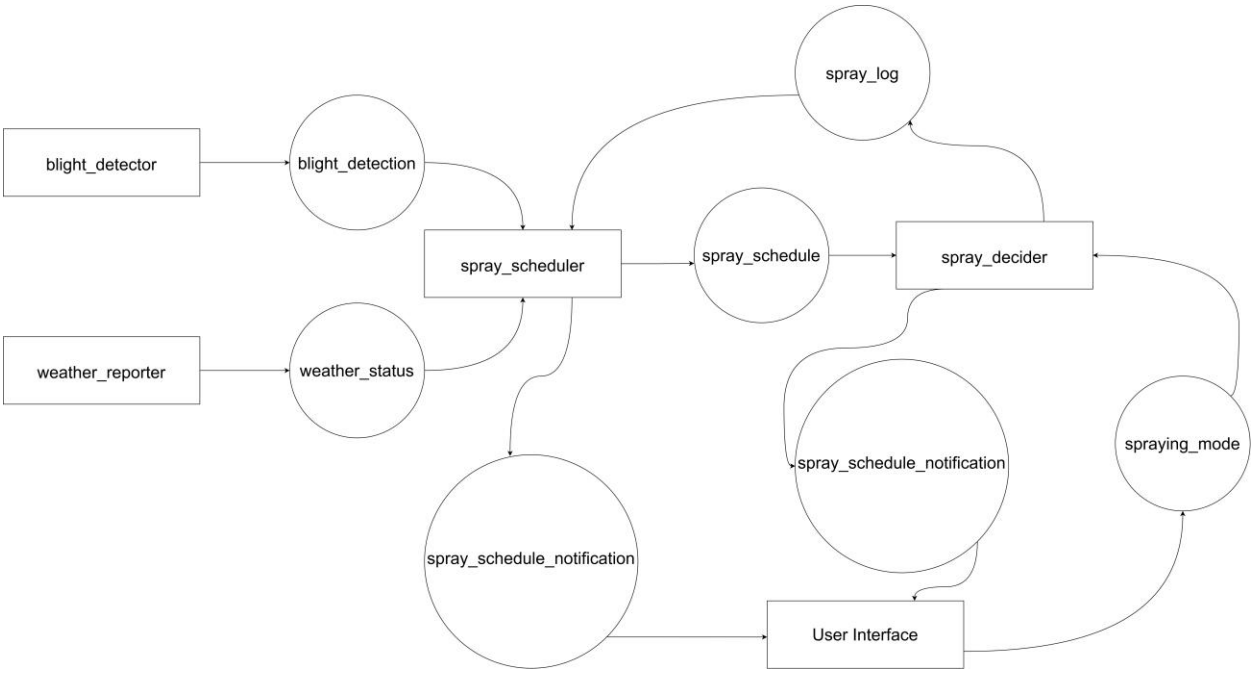


Fig. 3 Topic communication diagram of the decision logic. Rectangles are the nodes (including the web user interface), circles are the ROS 2 topics, and arrows show the direction of the messages

This process integrates both system communication and operational decision-making within a unified framework, the flow of information begins with the weather nodes where the “weather_reporter” node publishes comprehensive environmental data and Blight Favorability prediction and Spraying Suitability time to the “/weather_status” topic, and the “blight_detector” node sends out alerts on the “/blight_detection” topic upon identifying an infection, or manually through additional topics that facilitate user interaction such as the “/spraying_mode” topic which allows switching between manual and automatic operation, the “/spray_cancel” topic which allows a scheduled mission to be aborted, and the “/spray_command” topic which can be used to trigger an immediate spray.

The intervention logic and scheduling process is initiated by one of two triggers, the Proactive Trigger occurs when the “spray_scheduler” node monitors the (/weather_status) topic for a predicted "Blight-Suitable Time," allowing for preventative action before an outbreak occurs, while the Reactive Trigger is activated when a message on the (/blight_detection) topic from the

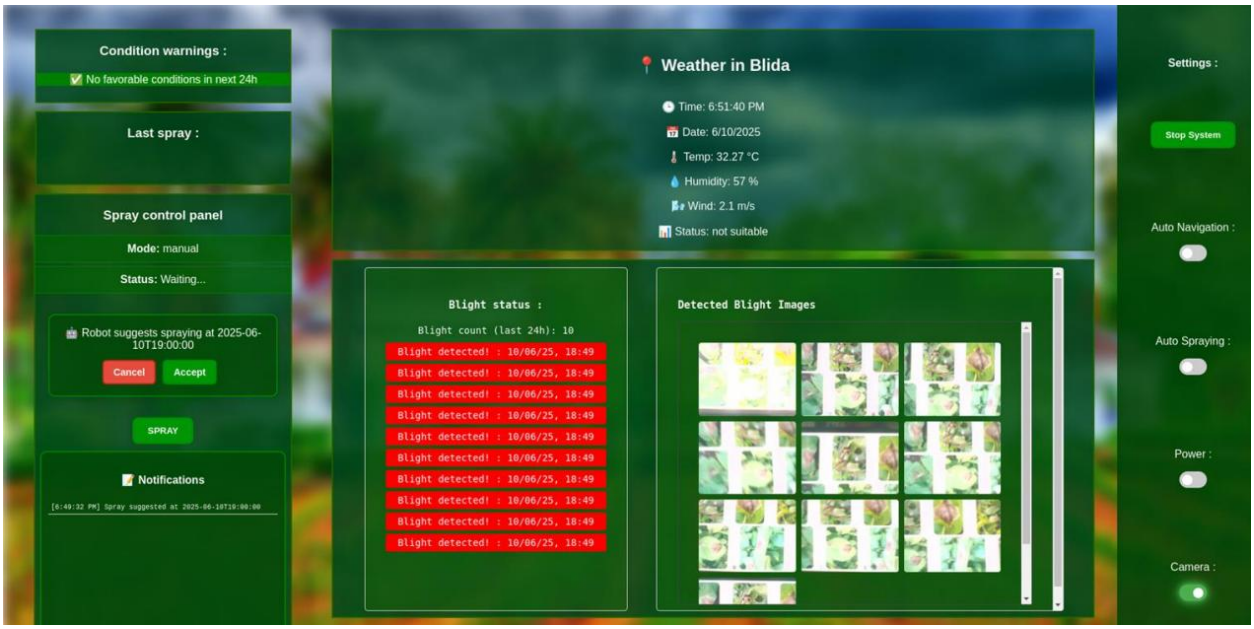
YOLOv8n node indicates a confirmed, active infection, which is treated as a high-priority event. Upon identifying a trigger, the “spray_scheduler” validates a set of constraints before proposing a spraying mission. It checks the weather data for the next "Spray-Suitable Time" to ensure safe and effective execution and consults an internal log to verify that no spray has been performed within the last 7 days, preventing unnecessary chemical application. This 7-day value is a design parameter of the scheduler rather than a biological constant, and it may need to be adapted to the recommended application interval of the fungicide in use. If all constraints are satisfied, the scheduler publishes a proposed mission time to the (/spray_schedule) topic, which is then consumed by the “spray_decider” node responsible for execution.

User Interface for System Monitoring and Control

To complement the decision logic and scheduling layer, a web-based user interface is employed as the principal point of interaction, enabling seamless remote monitoring and control of the system. Real-time interaction between the user and the robotic system is enabled through a lightweight web interface developed with standard HTML, CSS, and JavaScript. To establish a reliable connection between the web browser and the ROS 2 ecosystem, the rosbridge server is integrated, creating a persistent WebSocket communication channel that allows the ROS 2 network to function as a backend for data streaming and command execution. A minimal Flask server is also used to orchestrate system startup, enabling the launch of all required ROS 2 nodes directly from the interface with a single click.

The interface (Fig. 4) provides the farmer with a centralized dashboard to monitor system status and manage operational actions, ensuring continuous visibility over environmental conditions, detection results, and scheduled interventions. It also enables user interaction with the system through control commands and mode switching, ensuring that manual intervention can be performed when required, while maintaining synchronization with the underlying ROS 2 nodes and topics defined in the decision-making layer.

A dedicated status logging panel displays a log of recent spraying activities, providing the farmer with a clear history of performed interventions for monitoring and reference purposes.



377 **Fig. 4** The web-based user interface for the monitoring and control system

378 ## RESULTS

379 ### YOLOV8N DETECTION PERFORMANCE

380 Fig. 5 presents the quantitative evaluation of the YOLOv8n model, the F1-confidence curve (Fig.
381 5a) illustrates the balance between precision and recall, with an optimal F1-score of 0.86 achieved
382 at a confidence threshold of 0.454. The "leaf" class consistently maintains a higher F1-score than
383 the "blight" class, indicating more robust detection performance for healthy foliage. The recall-
384 confidence curve (Fig. 5b) shows that a high recall of 0.98 is maintained at a confidence threshold
385 of 0.000. As the confidence threshold increases, the recall gradually declines, with the "leaf" class
386 exhibiting superior recall stability compared to the "blight" class across the entire range. The
387 precision-confidence curve (Fig. 5c) demonstrates that the model attains a precision of 1.00 for all
388 classes at a confidence threshold of 0.856. Precision increases rapidly as the confidence threshold
389 rises, confirming the model's ability to minimize false positives at higher confidence levels, and
390 the precision-recall curve (Fig. 5d) confirms the model's effectiveness, with a mean Average
391 Precision (mAP) of 0.920 at an IoU threshold of 0.5. The "leaf" class achieves a higher average
392 precision of 0.959, compared to 0.882 for the "blight" class, illustrating strong overall
393 classification performance.

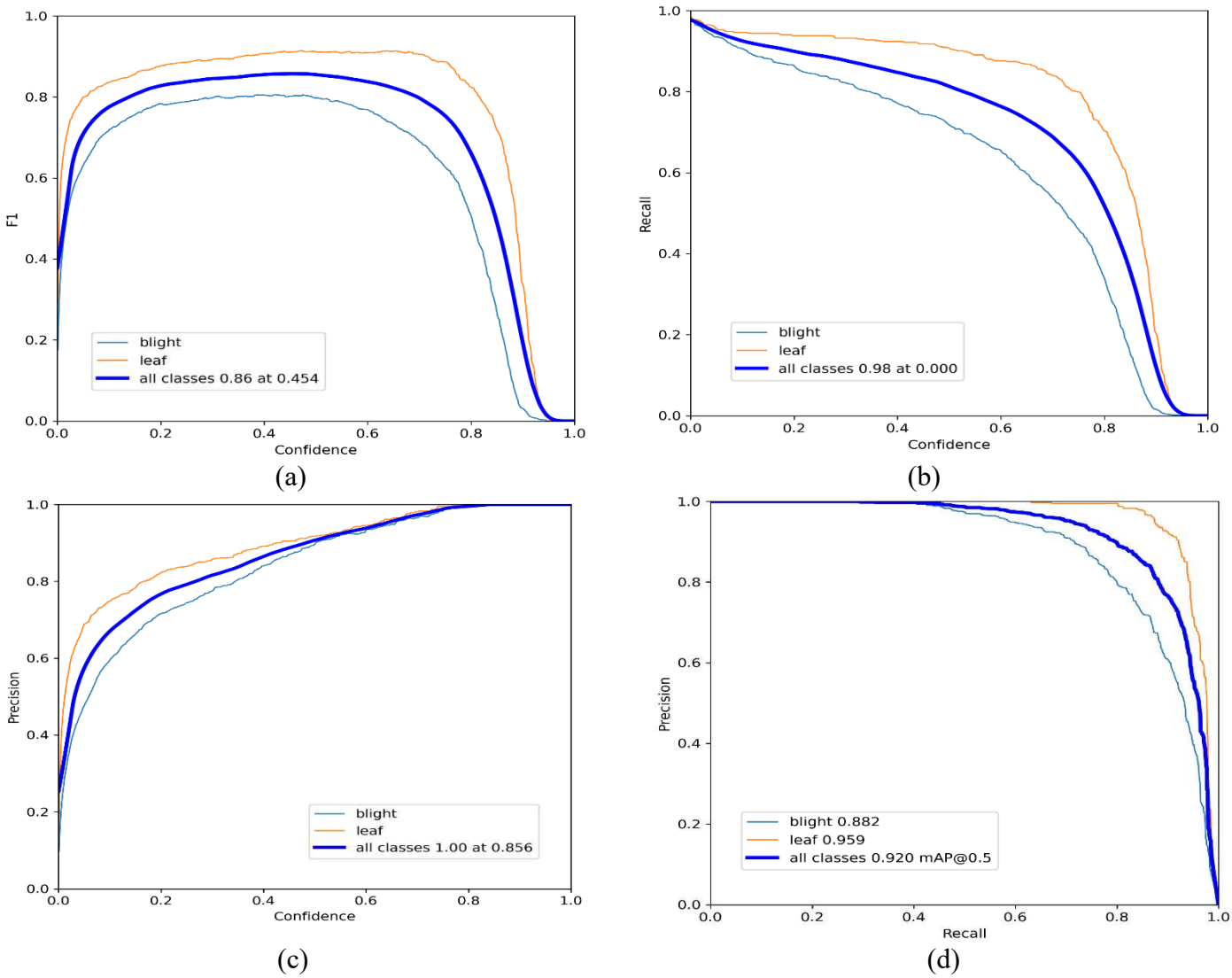


Fig. 5 YOLOv8n Performance Curves. (a) F1-Confidence Curve, (b) Recall-Confidence Curve, (c) Precision-Confidence Curve, and (d) Precision-Recall Curve

Table 2 Key Performance Metrics of the YOLOv8n Model on the Validation Set

Metric	Class: blight	Class: leaf	Overall
Precision	0.865	0.905	0.885
Recall	0.746	0.918	0.832
mAP@0.5	0.882	0.959	0.920
mAP@0.5:0.95	-	-	0.691

Table 2 summarizes the quantitative performance of the model for each class. The "leaf" class achieves the best results with a precision of 0.905, a recall of 0.918, and an mAP@0.5 of 0.959, indicating highly reliable detection of healthy leaves. In contrast, the "blight" class shows lower

performance, with a precision of 0.865, a recall of 0.746, and an mAP@0.5 of 0.882, reflecting more difficulty in detecting diseased regions. Overall, the model achieves a global mAP@0.5 of 0.920 and an mAP@0.5:0.95 of 0.691, with an overall precision of 0.885 and recall of 0.832, confirming good generalization performance. Furthermore, the final trained YOLOv8n model demonstrated high detection performance and reliability, achieving a mean Average Precision (mAP) of 0.920 at an IoU threshold of 0.5 (Fig. 5). These results confirm the effectiveness of the proposed detection model.

Further insight into the model's classification performance is provided by the confusion matrix, as outlined in Fig. 6. The matrix shows a high number of true positives for the 'blight' class (810) and 'leaf' class (456), confirming the model's effectiveness. It also highlights some misclassifications, such as 'background' being incorrectly predicted as 'blight' in 148 instances, which provides insight into the model's limitations.

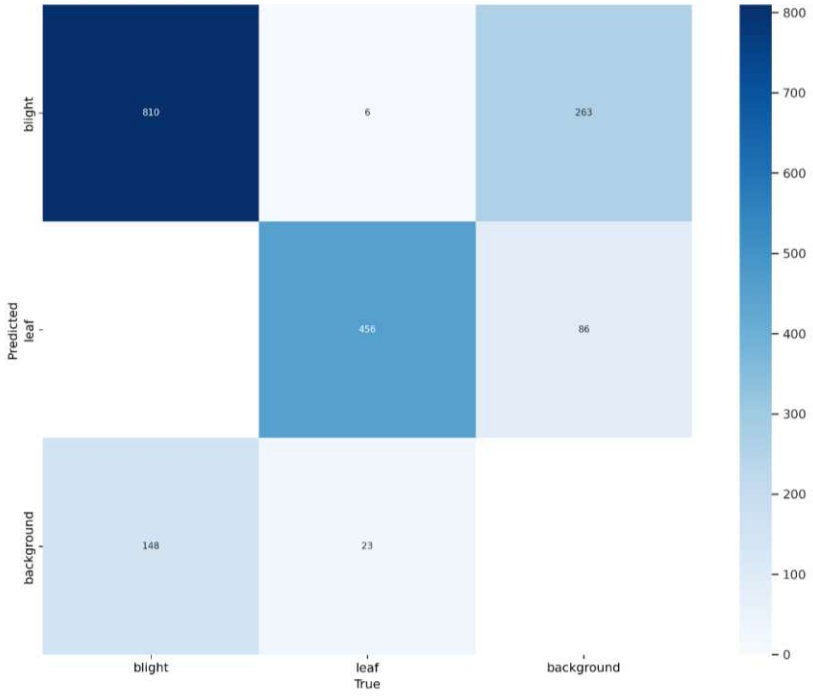
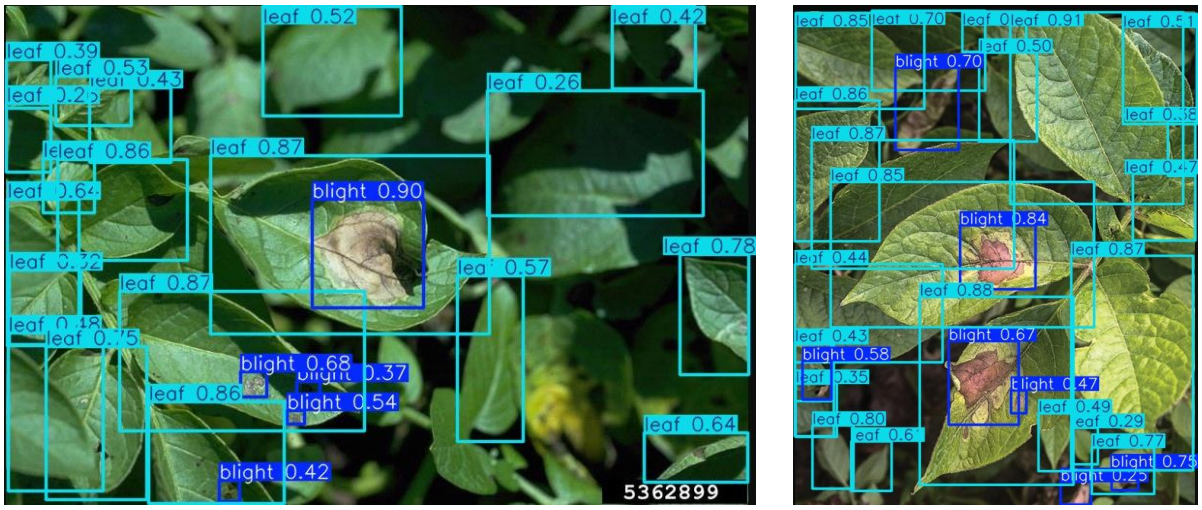


Fig. 6 Confusion Matrix for YOLOv8n Model

Qualitative Detection Examples

The qualitative behavior of the model is illustrated in Fig. 7 on two field photographs of potato leaves with late blight. In Fig. 7a, besides the larger lesion, the model also detected several small, early-stage lesions, which are the most difficult cases and the reason for the 800 × 800 pixel input size used in training. In Fig. 7b, lesions of different sizes were detected on overlapping leaves in a

dense canopy, together with the surrounding leaves. The hard negative mining dataset was introduced to reduce false positives on soil and other background elements; the remaining confusions between background and blight are quantified in the confusion matrix (Fig. 6).



(a) (b)

Fig. 7 Qualitative Detection Examples on field photographs of potato leaves with late blight, shown with the detections of the proposed model: (a) a larger lesion and several small, early-stage lesions (photo: Howard F. Schwartz, Colorado State University, Bugwood.org, CC BY 3.0 US) and (b) lesions of different sizes in a dense canopy (photo: Neil Gudmestad, North Dakota State University, reproduced with permission)

Field Deployment and On-Site Evaluation

For further real-world validation, the system was tested in an agricultural environment at ITCMI (Institut Technique des Cultures Maraîchères et Industrielles). The main objective was to evaluate the performance of the complete system under real field conditions, outside the laboratory.

The test was carried out on tomato plants in an outdoor environment under natural lighting conditions. The setup included real agricultural scenes with variations in illumination, complex backgrounds, and natural plant structures. This setting also challenged the detector, since tomato is a different host from the potato plants that make up most of the training images. Image acquisition and detection were performed in real time using a mobile phone camera connected through the ROS framework.

During the field experiment, the system showed good performance in real conditions. Late blight was present on some of the tomato plants at the site, and the model detected both the healthy leaves and a late blight lesion on an infected leaf in real time (Fig. 8). This result indicates that the detector, developed for potato, also recognizes the disease on tomato, the other major host of the

same pathogen, and that the system can work in real agricultural environments.

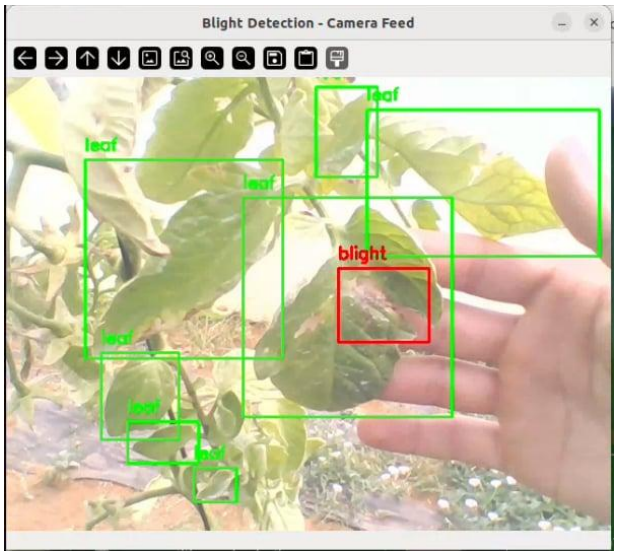


Fig. 8 Real-time Field Detection on Tomato. The model detects the healthy leaves (labeled "leaf") and a late blight lesion (labeled "blight") via the live camera feed

Weather Prediction Algorithm Performance

Given its rule-based nature, the weather prediction algorithm was assessed for operational reliability and adherence to its logical parameters, rather than statistical predictive accuracy. The validation process consisted of verifying the correctness of the rule-based decision logic defined in the Blight Favorability Model and the Spraying Suitability Model. This was achieved by testing the algorithm against real-time weather data and 48-hour forecast sequences, ensuring that all detected “Blight-Suitable” and “Spray-Suitable” periods strictly satisfied the predefined environmental thresholds. The generated outputs were then checked to confirm that the earliest predicted high-risk and optimal spraying windows were correctly identified and consistently published through the ROS 2 system. This confirmed the module's robustness. Throughout the testing phase, it reliably polled the external weather APIs every 10 minutes without failure. More critically, the system's analysis of the 24-hour forecast correctly identified every "Blight-Suitable" and "Spray-Suitable" period based on the programmed environmental thresholds.

Decision Support System Validation

The effectiveness of the decision support system was validated by observing its logical outputs in response to simulated and real-world triggers. In all test cases, the “spray_scheduler” correctly generated a spray suggestion in response to both proactive (weather-based) and reactive (visual detection) triggers. The constraint validation mechanism ensured that all scheduling rules were

respected before any mission proposal. Once a trigger is identified, the system checks its internal state and consults the "/spray_log" data to verify that no spraying operation has been performed within the last seven days. This 7-day spraying interval constraint prevents the scheduling of redundant treatments and was correctly enforced by the system throughout the tests.

Assessment of System Latency and Interface Responsiveness

The integrated system demonstrated effective real-time performance, a crucial component for successful field deployment. Quantitative measurements revealed that the YOLOv8n model processed images with an average inference speed of 9.8 ms per image, measured on the NVIDIA Tesla T4 GPU of the Google Colaboratory environment, a rate that comfortably supports live video analysis. During the system tests, the web user interface also remained highly responsive. The rosbridge WebSocket connection successfully facilitated instantaneous data streaming, delivering real-time updates for weather alerts, visual detections, and system status changes to the dashboard without perceptible delay.

Discussion

This section analyzes the experimental results, discusses the strengths and limitations of the proposed system, and compares it with existing approaches.

Analysis of Results

The validation tests demonstrate that the software architecture works precisely as designed. The visual detection module demonstrated particularly strong performance. The YOLOv8n model demonstrated its efficacy in detecting and localizing late blight, achieving an overall mAP@0.5 score of 0.920. A key advantage of this model is its precision. For the blight class, it reached 0.865, which is crucial as it means relatively few false alarms. This low false positive rate would help prevent unnecessary spraying once the system is paired with an automated sprayer. The recall value of 0.746 demonstrates the system's efficacy in identifying most authentic infections. However, the real-world tests conducted on tomato plants at the ITCMI site were the true tests. The model exhibited a high degree of robustness under actual field conditions, accurately differentiating between blight and soil as well as other background elements. This outcome directly corroborates the efficacy of the adopted strategy, which entailed the utilization of a custom hybrid dataset built with hard negative mining. Furthermore, the remaining components demonstrated consistent

functionality. The weather prediction and DSS modules ran their rule-based logic, exhibiting no errors in the execution of their functions. These modules consistently send out alerts regarding high-risk conditions and optimal spraying times. The model's fast inference speed (9.8 ms per image on a Tesla T4 GPU) and responsive web interface make it suitable for real-time use in the field.

Strengths of the Approach

The primary strength of this work lies in its holistic integration of a proactive weather-based prediction system and a reactive visual detection system. This dual-layer approach allows the system to anticipate threats while also confirming active infections, leading to a more efficient and reliable disease management strategy than standalone systems.

Further strengths include:

- Deployment readiness: The entire software architecture is built on the ROS 2 framework, thereby ensuring modularity, scalability, and a clear path for integration with physical robotic hardware.
- Real-world robustness: The use of a custom dataset with field imagery and hard negative mining has yielded a visual detection model that exhibits enhanced robustness in real-world conditions compared to models trained exclusively on lab-based datasets, such as PlantVillage. In the field, it also recognized late blight on tomato, the other major host of the same pathogen, which indicates good generalization beyond its training conditions.
- User-centric design: The unified web interface simplifies the complex underlying system, making it accessible to farmers and allowing for intuitive monitoring and control without requiring expertise in robotics or AI.

Limitations

The promising results of this work must be considered alongside its present limitations. For the detection module, challenges persist in highly unstructured environments, such as inconsistent lighting (e.g., direct sunlight, shadows), diverse leaf orientations and the presence of dust or debris that might mimic or obscure disease symptoms, which can still impede performance. In addition, the field evaluation was qualitative and was carried out on tomato, as potatoes were out of season; a quantitative evaluation in potato fields remains to be done. A separate consideration is the weather subsystem, which functions correctly but inherits the spatial resolution limits of its

external data feeds. This may result in the potential loss of critical microclimatic variations within a single field. Ultimately, these findings pave the way for a crucial subsequent phase, which entails the extension of the proposed solution to a complete robotic system. It is only through such in-situ evaluation that the technology's long-term operational viability can be fully gauged.

CONCLUSION AND FUTURE WORK

This paper presented a novel intelligent decision support system designed to address the significant challenge of managing late blight in potato crops, particularly for farmers in Algeria. The integration of a real-time YOLOv8n visual detector, a proactive weather-based prediction algorithm, and an intelligent DSS within the ROS 2 framework has yielded a holistic and robust solution for proactive threat mitigation. The findings of this study demonstrate that a hybrid dataset strategy, combined with lightweight deep learning models, is crucial for achieving effective performance in real-world agricultural settings. The experimental results confirm the effectiveness of the proposed system in providing accurate disease detection and improving the timing of intervention through real-time weather-aware decision support.

This work translates into a tangible tool for farmers: a unified web interface that brings crop health data and decision support together in one place, **e**nabling interventions that are not only timely but also precisely targeted, thereby supporting more sustainable agricultural management. From a technical standpoint, the main contribution lies in the development of an end-to-end software architecture that effectively bridges the gap between perceptual algorithms and actionable intelligence. It is anticipated that the real-world impact will be significant, with the potential to curtail unnecessary fungicide applications, reduce operational costs, and promote sustainable practices, starting in Algeria but with clear applicability to other regions.

Looking forward, the development roadmap will be guided by the limitations that have been identified. A short-term objective is to broaden the visual model’s diagnostic capabilities to include other common potato pathogens. There is also considerable value in augmenting the weather prediction system with on-site sensors to capture hyperlocal microclimates. The most critical next step, however, involves transitioning from software validation to integrated system testing. A long-term deployment on an autonomous robotic platform is essential to gather robust, quantitative data on the system's economic and environmental impact at scale.

Statements and Declarations

Funding: This research received no external funding.

Competing interests: The authors declare no conflict of interest.

Ethics approval and consent to participate: Not applicable.

Consent for publication: Not applicable.

Data availability: The public datasets used in this study (PlantVillage and Plant-Doc) are open source and are cited in the paper (Hughes and Salathé 2015; Singh et al. 2020). The work was carried out as part of a research project at a research laboratory, which places limitations on the provision of the remaining data. These data are available from the corresponding author on reasonable request, with the permission of the laboratory.

Author contributions: Abderrahmane Larbi Aissa: Writing – review & editing, Writing – original draft, Investigation, Validation, Software, Methodology, Conceptualization. Hani Brahim: Writing – review & editing, Investigation, Validation, Software, Methodology, Conceptualization. Sara Bouraine: Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization. Mohammed Islam Seghier: Writing – review & editing, Visualization. Hiba Bouabdellah: Writing – review & editing. Dalila Hammadou: Co-supervision.

References

Alhwaiti Y, Khan M, Asim M, Siddiqi MH, Ishaq M, Alruwaili M (2025) Leveraging YOLO deep learning models to enhance plant disease identification. Sci Rep 15:7969. https://doi.org/10.1038/s41598-025-92143-0

Arora RK, Sharma S, Singh BP (2014) Late blight disease of potato and its management. Potato J 41:16–40

Banque d'Algérie (2024) Rapport annuel 2023: évolution économique et monétaire. Banque d'Algérie. https://www.bank-of-algeria.dz/stoodroa/2024/08/Rapport-annuel-2023-Fr.pdf. Accessed 27 September 2026

Evcin E, Erten YM (2024) Comparison of different weather data acquisition methods. In: 2024 9th International Conference on Computer Science and Engineering (UBMK). IEEE, Antalya, pp 1–6. https://doi.org/10.1109/UBMK63289.2024.10773508

Forbes GA, Landeo JA (2006) Late blight. In: Gopal J, Khurana SMP (eds) Handbook of potato production, improvement, and postharvest management. CRC Press, Boca Raton, pp 279–314. https://doi.org/10.1201/9780429246623-8

Gevens A, Wilbur J (2015) Potato late blight: identification and management. University of

585 Wisconsin-Extension, Publication A4052-02.
586 https://learningstore.extension.wisc.edu/products/potato-late-blight-p1760
587 Helps JC, van den Bosch F, Paveley N, Jørgensen LN, Holst N, Milne AE (2024) A framework
588 for evaluating the value of agricultural pest management decision support systems. Eur J Plant
589 Pathol 169:887–902. https://doi.org/10.1007/s10658-024-02878-1
590 Hughes DP, Salathé M (2015) An open access repository of images on plant health to enable the
591 development of mobile disease diagnostics. arXiv:1511.08060.
592 https://doi.org/10.48550/arXiv.1511.08060
593 Kaplun D, Deka S, Bora A, Choudhury N, Basistha J, Purkayastha B, Mazumder IZ, Gulvanskii
594 V, Sarma KK, Misra DD (2024) An intelligent agriculture management system for rainfall
595 prediction and fruit health monitoring. Sci Rep 14:512. https://doi.org/10.1038/s41598-023-
596 49186-y
597 Mathew MP, Mahesh TY (2022) Leaf-based disease detection in bell pepper plant using YOLO
598 v5. Signal Image Video Process 16:841–847. https://doi.org/10.1007/s11760-021-02024-y
599 Nowicki M, Foolad MR, Nowakowska M, Kozik EU (2012) Potato and tomato late blight caused
600 by *Phytophthora infestans*: an overview of pathology and resistance breeding. Plant Dis 96:4–17.
601 https://doi.org/10.1094/PDIS-05-11-0458
602 OpenWeatherMap (2025) OpenWeatherMap API documentation.
603 https://openweathermap.org/api. Accessed 10 June 2025
604 Radwan M, Alhussan AA, Ibrahim A, Tawfeek SM (2025) Potato leaf disease classification using
605 optimized machine learning models and feature selection techniques. Potato Res 68:897–921.
606 https://doi.org/10.1007/s11540-024-09763-8
607 Singh D, Jain N, Jain P, Kayal P, Kumawat S, Batra N (2020) PlantDoc: a dataset for visual plant
608 disease detection. In: Proceedings of the 7th ACM IKDD CoDS and 25th COMAD. ACM, New
609 York, pp 249–253. https://doi.org/10.1145/3371158.3371196
610 Tao J, Li X, He Y, Islam MA (2025) CEFW-YOLO: a high-precision model for plant leaf disease
611 detection in natural environments. Agriculture 15:833.
612 https://doi.org/10.3390/agriculture15080833
613 Terven J, Córdova-Esparza DM, Romero-González JA (2023) A comprehensive review of YOLO
614 architectures in computer vision: from YOLOv1 to YOLOv8 and YOLO-NAS. Mach Learn
615 Knowl Extr 5:1680–1716. https://doi.org/10.3390/make5040083
616 Wang Y, Li T, Chen T, Zhang X, Taha MF, Yang N, Mao H, Shi Q (2024) Cucumber downy
617 mildew disease prediction using a CNN-LSTM approach. Agriculture 14:1155.
618 https://doi.org/10.3390/agriculture14071155
619 Zhai Z, Martínez JF, Beltran V, Martínez NL (2020) Decision support systems for agriculture
620 4.0: survey and challenges. Comput Electron Agric 170:105256.
621 https://doi.org/10.1016/j.compag.2020.105256