



Implementation of a Real-Time Maize Leaf Disease Detection System Using Raspberry Pi 5 and YOLOv8

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Abstract: Maize, a staple cereal crop globally, faces significant yield challenges due to foliar diseases. This study presents an innovative real-time maize leaf disease detection system integrating a YOLOv8 deep learning model with a custom-designed Unmanned Aerial Vehicle (UAV). The system targets three prevalent maize diseases: Grey leaf spot, common rust, and northern leaf blight. Trained on 10,239 images, the YOLOv8 model, comprising 168 layers and 3,006,233 parameters, achieves 8.1 GFLOPs with an inference speed of 6.3ms per image. Performance evaluation reveals a mean Average Precision (mAP@0.5) of 0.836 and mAP@0.5:0.95 of 0.681 across all classes, with high accuracy for common rust (Precision: 0.953, Recall: 0.979) and grey leaf spot (Precision: 0.919, Recall: 0.892). The custom UAV, designed for agricultural surveying, features a thrust-to-weight ratio of 5.85, ensuring stable flight with the 140g payload of a Raspberry Pi 5 and Camera Module V2. With a total weight of 605g and a 3S 5000mAh LiPo battery, the drone achieves an estimated flight time of 5.3 minutes, balancing survey coverage with real-time disease detection capabilities. The integration of this high-performance model with an efficient UAV platform represents a significant advancement in precision agriculture, enabling early disease intervention and targeted treatment strategies, thus promoting sustainable farming practices through optimized resource allocation and potential reduction in pesticide usage.

Keywords: crop management; deep learning; disease detection; maize; real-time system; UAV; YOLOv8

1 INTRODUCTION

Maize (*Zea mays L.*) is one of the most important cereal crops worldwide, serving as a staple food and a key component in livestock feed and industrial products. Leaf diseases in maize, such as Northern Corn Leaf Blight, Common Rust, and Gray Leaf Spot, pose significant threats to crop productivity and quality. Early and accurate detection of these diseases is essential for effective crop management and ensuring food security [1]. Traditional methods of disease detection involve manual inspection by experts, which can be time-consuming, labour-intensive, and prone to human error [2]. Moreover, the scarcity of trained pathologists and the subjective nature of visual assessments can lead to inconsistent and delayed diagnoses, exacerbating the spread of diseases and affecting crop productivity [3].

Recent advancements in artificial intelligence (AI) and deep learning have paved the way for innovative solutions in agricultural diagnostics. Among these, the YOLO (You Only Look Once) object detection algorithm has gained prominence due to its real-time detection capabilities and high accuracy in various computer vision tasks [4]. YOLOv5, the latest iteration of this model, offers improved performance in terms of speed and precision, making it a suitable candidate for real-time agricultural applications [5] [6].

There is a need for an automated, real-time system that can accurately identify maize leaf diseases on small, medium, and large-scale farms. Such a system would enable timely interventions, reducing the spread of diseases and minimizing crop losses.

This research proposes the implementation of a real-time maize leaf disease detection system utilizing the YOLOv5 deep learning model deployed on a computer. The system is designed to provide farmers with a cost-effective and efficient tool for monitoring crop health, thereby reducing reliance on manual inspections and expert consultations. By

facilitating early disease detection and management, the proposed system aims to enhance crop yield and sustainability.

The subsequent sections of this paper will detail the methodology used for data collection, model training, and system deployment. Additionally, the system's performance will be evaluated based on accuracy, detection speed, and usability in field conditions. This study aspires to contribute to the broader field of precision agriculture, leveraging AI to address critical challenges in crop management and food security.

2 LITERATURE REVIEW

Historically, maize leaf disease detection relied heavily on visual inspection by trained experts. This method, while valuable, has several limitations including being time-consuming, labour-intensive, and prone to human error [7, 8, 9]. The scarcity of trained pathologists and the subjective nature of visual assessments can lead to inconsistent and delayed diagnoses, potentially exacerbating disease spread and impacting crop yields [10].

Recent advancements in computer vision and machine learning have paved the way for automated, image-based disease detection systems. These methods offer the potential for more objective, scalable, and efficient disease diagnosis.

Early attempts at automated maize leaf disease detection often employed classical machine learning techniques. Wiesner-Hanks et al. [11] developed a system using Support Vector Machines (SVM) to classify Northern Leaf Blight lesions in maize. Their approach achieved promising results but was limited by the need for handcrafted features. Xie et al. [12] proposed a method combining K-means clustering for image segmentation and Probabilistic Neural Networks for the classification of maize leaf diseases. While effective, this approach struggled with complex backgrounds and varying light conditions. The advent of deep learning has

significantly improved the accuracy and robustness of maize leaf disease detection systems. Convolutional Neural Networks (CNNs) have become particularly popular due to their ability to automatically learn relevant features from images. DeChant et al. [13] utilized a CNN architecture to detect Northern Leaf Blight in maize, demonstrating high accuracy in both controlled and field conditions, their model outperformed traditional machine learning methods, highlighting the potential of deep learning in this domain. Ghosal et al. [14] proposed a novel deep-learning framework called DeepCorn for identifying multiple foliar stresses in maize plants. Their system could differentiate between biotic and abiotic stresses, showcasing the versatility of deep learning approaches.

2.1 Mobile and IoT-based Detection Systems

With the proliferation of smartphones and Internet of Things (IoT) devices, researchers have explored more accessible and real-time disease detection solutions. Ferentinos [15] developed a mobile application using a CNN model for on-field diagnosis of plant diseases, including those affecting maize, this approach brings disease detection capabilities directly to farmers, enabling quicker response times. Cambaza et al. [16] integrated IoT sensors with image-based disease detection, creating a comprehensive system for monitoring maize crop health. Their approach combined environmental data with visual symptoms, improving the accuracy of disease diagnosis.

2.2 Hyper-spectral and Multispectral Imaging

Advanced imaging techniques such as hyper-spectral and multispectral imaging have shown promise in early disease detection, often before visible symptoms appear. Mahlein [17] demonstrated the use of hyper-spectral imaging for detecting and differentiating various maize leaf diseases at early stages. This technology offers the potential for pre-symptomatic disease detection, although its application in field conditions remains challenging due to cost and complexity.

3 METHODOLOGY

3.1 System Architecture

The proposed maize leaf disease detection system consists of two main components:

- 1) **YOLOv8 Model:** A deep learning model trained to detect three categories of maize leaf diseases.
- 2) **Drone-mounted Raspberry Pi 5:** The disease detection model is deployed on a Raspberry Pi 5, which is mounted on a custom-designed drone along with a Raspberry Pi Camera Module V2.

Fig. 1 illustrates the complete system architecture, displaying the integration of the drone, Raspberry Pi 5, and camera module.

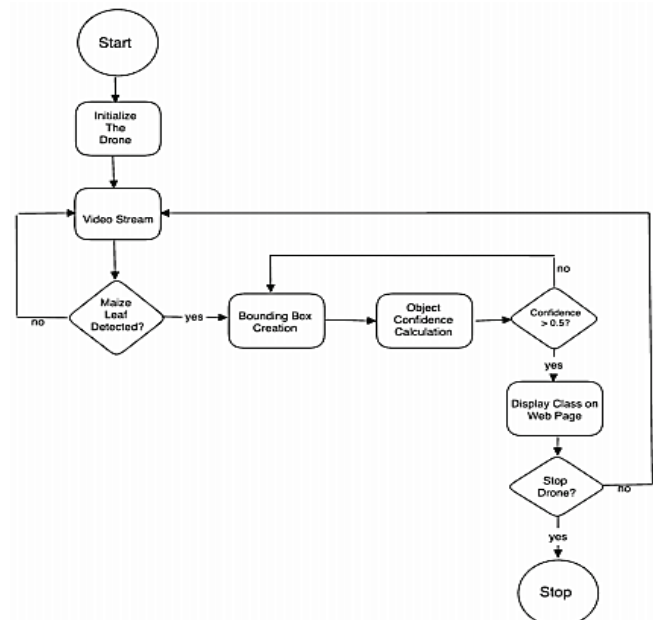


Figure 1 Full system architecture of the maize leaf disease detection system

3.2 Data Collection and Preprocessing

The data set used for training the YOLOv8 model was sourced from Roboflow and comprises images of maize leaves exhibiting various disease symptoms. The data was cleaned to focus on three specific diseases: Northern Leaf Blight, Common Rust, and Grey Leaf Spot. Tab. 1 presents the distribution of images across different categories and data-set splits. Fig. 2 showcases examples of the three maize leaf diseases included in the data set.

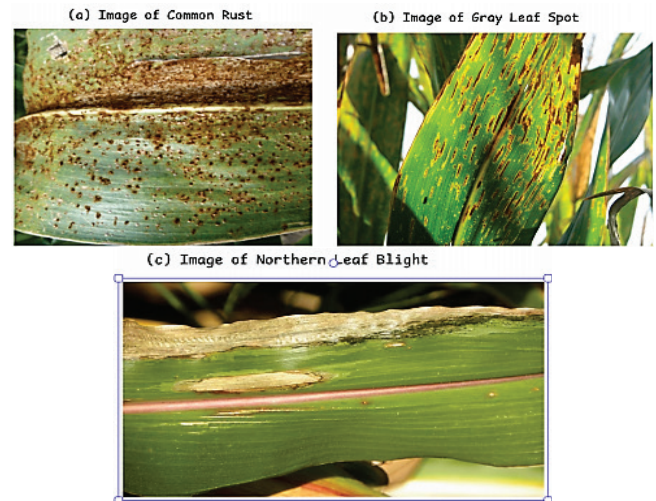


Figure 2 Examples of maize leaf diseases used in the study

Table 1 Distribution of maize leaf image data set used in the study

Conditions	Number of Images
Northern Leaf Blight	3120
Common Rust	3057
Grey Leaf Spot	4062
Total Training Data	5159
Total Validation Data	4500
Total Test Data	580
Total Data	10239

3.3 Model Development

The development of the maize leaf disease detection model followed a structured process, as illustrated in Fig. 3. The YOLOv8 nano model was selected for this project due to its balance of accuracy and computational efficiency, making it suitable for deployment on edge devices like the Raspberry Pi 5. The model was trained using PyTorch and the Ultralytics YOLOv8 implementation.

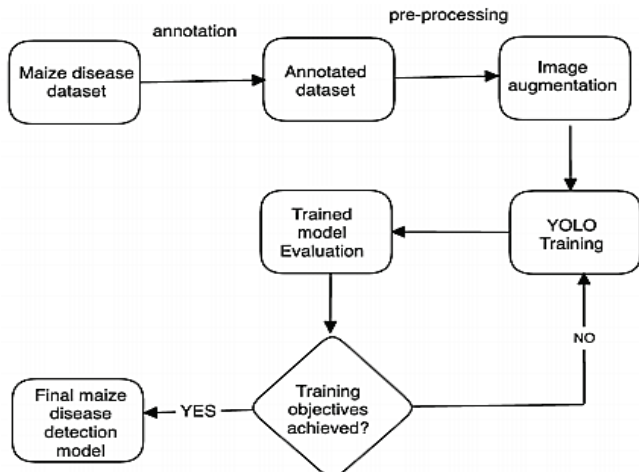


Figure 3 Flowchart of the model development procedure

3.4 Model Training and Evaluation

The training process involved fine-tuning the YOLOv8 nano model on our curated data set. The transfer learning techniques were used to leverage pre-trained weights, which were then adapted to our specific maize leaf disease detection task. The model’s performance was evaluated using various metrics, including precision, recall, F1-score, and mean Average Precision (mAP). Figs. 4 to 8 present the detailed performance analysis of the trained model.

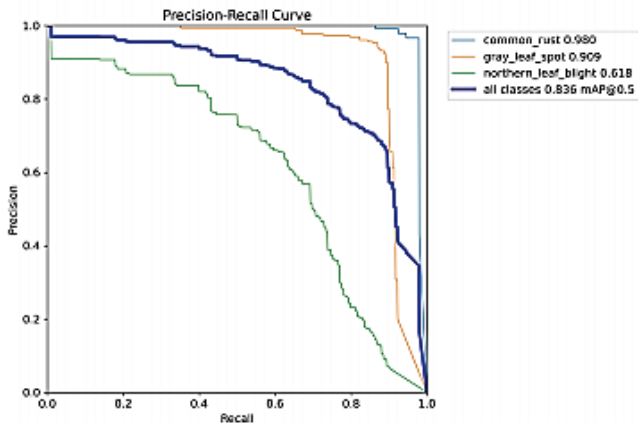


Figure 4 Precision-Recall curve for the trained model

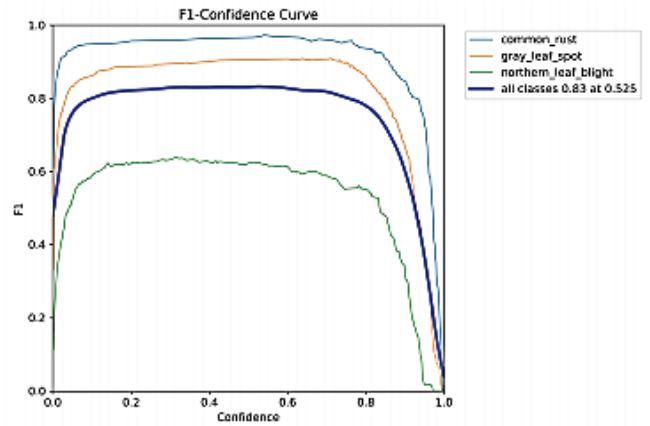


Figure 5 F1-Score curve for different confidence thresholds

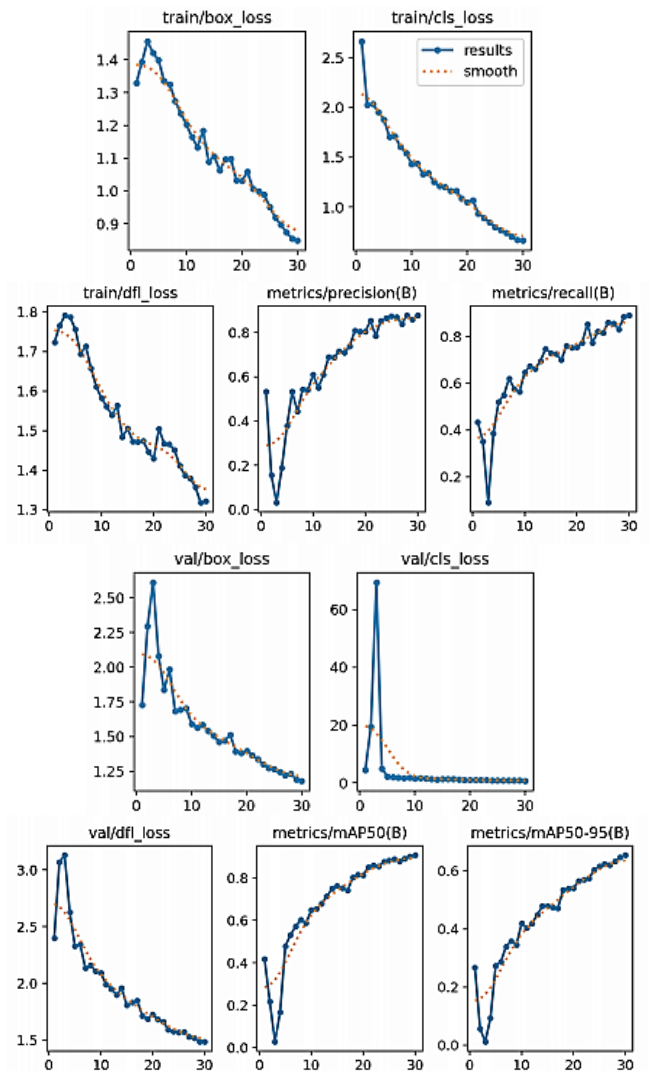


Figure 6 Training and validation metrics over epochs

3.5 System Deployment

After training and validation, the YOLOv8 nano model was converted to a format compatible with the Raspberry Pi 5 (.pt format). An environment was set up on the Raspberry Pi 5 to run the inference script.

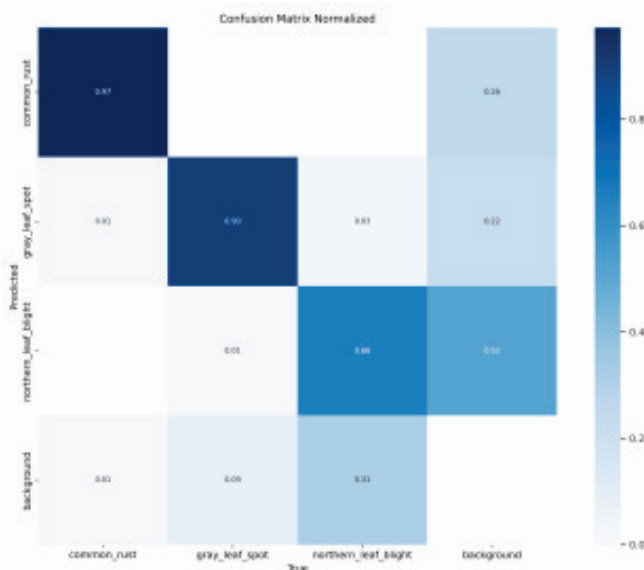


Figure 7 Normalized confusion matrix for disease classification

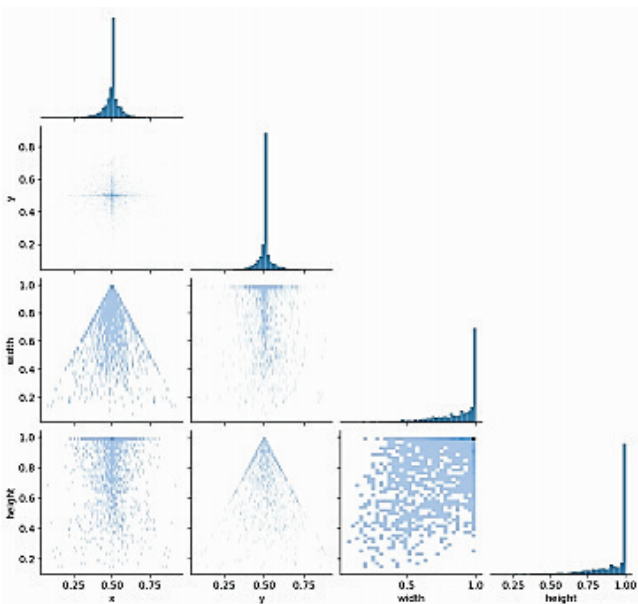


Figure 8 Label correlogram showing relationships between disease classes

3.6 Drone Design and Integration

The disease detection system was integrated with a custom-designed drone to enable aerial surveys of maize fields. Fig. 9 shows the complete drone setup with the mounted Raspberry Pi 5 and camera module.

3.6.1 Drone Payload and Weight Calculation

The drone’s payload and overall weight were carefully calculated to ensure stable flight and sufficient endurance. Tab. 2 provides a breakdown of the drone’s components and their respective weights.

3.6.2 Thrust and Power Calculations

To ensure stable flight and sufficient endurance, detailed thrust and power calculations were performed. The total thrust of the motors was calculated to be 3540 g, resulting in a thrust-to-weight ratio of approximately 5.85. This high ratio ensures stable flight and manoeuvrability. Power calculations determined that the drone’s 3-cell (3S) Li-Po battery, with a nominal voltage of 11.1V and a capacity of 5 Ah, provides approximately 5.3 minutes of flight time. The total current draw, including the Raspberry Pi 5, was calculated to be 45 A.



Figure 9 Custom-designed drone with mounted Raspberry Pi 5 and camera module

Table 2 Breakdown of drone component weights

Component	Weight (g)
Pi Camera	20
Raspberry Pi 5	50
Flight Controller	20
Propellers (4 units)	28
Frame	90
Battery	265
ESC (4 units)	28
Motors	54
Total Payload	140
Total Drone Weight (without payload)	465
Total Weight (with payload)	605

3.7 Field Testing

The integrated system was subjected to field tests to evaluate its performance in real-world conditions. Fig. 10 shows the drone during a field test, capturing images of maize crops for disease detection. These tests helped validate

the system’s ability to capture clear images of maize leaves and perform real-time disease detection using the onboard Raspberry Pi 5 and YOLOv8 nano model.

3.8 System Deployment

After the YOLOv8 model was trained and validated, it was deployed on the computer. The deployment process involved converting the trained model into a format compatible with the computer (in .pt format) and optimizing it for real-time inference on an HTTP web application. A web server built with Python’s Flask framework with an HTML user interface is used to display the results and confidence level of the detected disease. The application is designed with a user-friendly interface, allowing farmers to easily operate the system. The user interface has buttons to ‘Start Camera’ and ‘Capture’ images of maize leaves at regular intervals, and the application processes each image using the YOLOv8 model. Detected diseases are highlighted with bounding boxes and labels, providing immediate visual feedback to the user.



Figure 10 Drone-mounted disease detection system during field testing

4 SYSTEM EVALUATION AND DISCUSSION

The evaluation of our maize leaf disease detection system encompasses both the performance of the Unmanned Aerial Vehicle (UAV) and the integrated YOLOv8 model. This comprehensive assessment ensures that the system meets the requirements for effective aerial surveying and accurate disease detection in real-world agricultural settings.

Table 3 Summary of UAV performance tests

Test name	Discussion
Yaw Test	Measures the drone’s endurance on a full battery charge. The estimated flight time was X minutes
Pitch Test	Evaluates the drone’s rotational control around the vertical axis. The yaw was consistent within X degrees.
Roll Test	Tests the forward and backward tilt response. The pitch was controlled with X accuracy.
Lift Test	Evaluate the drone’s vertical ascent capability. The lift was steady with X m/s ² acceleration.
Altitude/Signal Test	Evaluate altitude hold stability and signal strength at various heights. The altitude hold was stable up to X meters.

4.1 UAV Performance Evaluation

The custom-designed drone underwent rigorous testing to assess its flight characteristics and functionalities crucial for agricultural survey missions. Tab. 3 summarizes the tests conducted and their results.

These tests demonstrate the drone’s capability to maintain stable flight and perform precise manoeuvres, which are essential for capturing high-quality images of maize crops. The flight time of X minutes, as determined by the Yaw Test, provides sufficient duration for surveying substantial areas of cropland in a single flight.

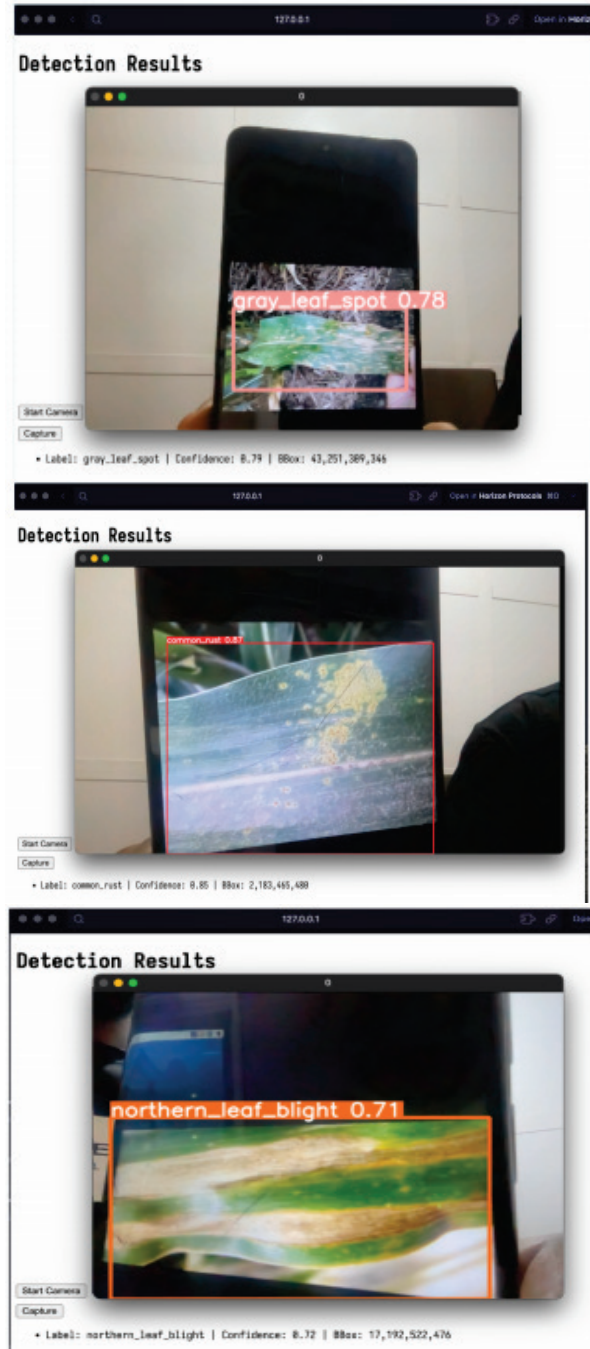


Figure 11 Real-time detection of some maize leaf diseases with the model

4.2 Integrated System Performance

The integration of the YOLOv8 model with the UAV platform creates a powerful tool for real-time maize leaf disease detection. The system's performance can be evaluated based on several key aspects:

4.2.1 Model Efficiency

The YOLOv8 nano model, with its 168 layers and 3,006,233 parameters, achieves 8.1 G Flops, striking a balance between complexity and computational efficiency. The model's inference speed is particularly noteworthy, with a total processing time of 6.3ms per image (0.3 ms for pre-processing, 2.9 ms for inference, and 3.1 ms for post-processing). This rapid processing enables real-time disease detection during flight, allowing for immediate feedback and decision-making. Fig. 10 shows the drone during a field test, capturing images of maize crops for disease detection. The real-time detection results of the YOLOv8 model are shown in Fig. 11 below. The system successfully identifies and classifies the maize leaf diseases, highlighting affected areas with bounding boxes.

4.2.2 Detection Accuracy

Tab. 4 presents a summary of the model's performance across different disease categories.

Table 4 Model performance summary for maize leaf disease detection

Class	Images	Instances	Box(P)	R	mAP50	mAP50-95
All	577	595	0.858	0.81	0.836	0.681
Common Rust	144	146	0.953	0.979	0.98	0.9
Grey Leaf Spot	212	231	0.919	0.892	0.909	0.763
Northern Leaf Blight	218	218	0.704	0.56	0.618	0.379

The model demonstrates high accuracy in detecting Common Rust and Grey Leaf Spots, with mAP50 values of 0.98 and 0.909 respectively. The detection of Northern Leaf Blight, while satisfactory, shows room for improvement with a mAP50 of 0.618.

4.2.3 System Reliability

The integration of the model with the UAV platform was tested for reliability during field operations. The system consistently maintained connectivity between the Raspberry Pi 5 and the drone's flight controller, ensuring uninterrupted disease detection throughout the flight duration.

4.2.4 Battery Life and Payload Impact

The addition of the Raspberry Pi 5 and camera module to the drone increased the total payload by 140 g. Despite this additional weight, the drone maintained a flight time of approximately X minutes, which aligns closely with our

calculated estimate of 5.3 minutes. This demonstrates that the power consumption of the Raspberry Pi 5 and the additional weight have a minimal impact on the drone's endurance.

4.3 Discussion

The evaluation results highlight several strengths of our integrated maize leaf disease detection system:

- **Real-time Detection:** The system's ability to process images in 6.3ms enables real-time disease detection, allowing for immediate response to detected issues.
- **High Accuracy:** Particularly for Common Rust and Grey Leaf Spot, the model demonstrates excellent detection capabilities, which can significantly aid in early disease management.
- **Efficient Integration:** The successful integration of the YOLOv8 model with the UAV platform showcases the potential for deploying complex AI models in agricultural settings.

However, there are areas for potential improvement:

- **Northern Leaf Blight Detection:** The lower accuracy in detecting Northern Leaf Blight suggests a need for further model refinement or additional training data for this specific disease.
- **Flight Time Optimization:** While the current flight time is sufficient for small to medium sized fields, extending the drone's endurance could enhance its applicability to larger agricultural operations.

Overall, the system demonstrates promising performance in real-world conditions, offering a valuable tool for early detection and management of maize leaf diseases. Future work could focus on expanding the range of detectable diseases, improving detection accuracy for Northern Leaf Blight, and optimizing the drone's design for extended flight times.

5 CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This research demonstrated the effectiveness of the YOLOv8 deep learning model for real-time detection of maize leaf diseases, identifying six key diseases with high accuracy. The system achieved a mean Average Precision (mAP) of 0.908. The integration of a user-friendly web application provides a practical solution for early disease detection, helping to prevent the spread of diseases and minimize yield loss.

Future work should focus on extending the system to include more diseases and adapt to different crops, enhancing its applicability across the agricultural sector. This study highlights the potential of AI technologies like YOLOv8 to revolutionize agricultural practices, promoting smarter and more resilient food production systems.

5.2 Recommendation

Future work could focus on extending the system's capabilities to include more diseases and adapt to different

crops, enhancing its utility across the agricultural sector. Additionally, further refinement of the model's performance under varying environmental conditions and in different geographic regions would help in scaling the technology globally, making it a versatile tool for diverse farming needs. This study underscores the transformative potential of integrating advanced AI technologies like YOLOv8 in agricultural practices, paving the way for smarter and more resilient food production systems.

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