

AI-Powered Crop Disease Detection Using Real-Time Drone Imagery

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Keywords: Wireless Mesh Network (WMN), Disaster Communication, Real-Time Routing, Energy Efficiency, Packet Delivery Ratio, Emergency Response, Priority Queuing, Network Reliability.

Abstract: Early identification of crop diseases is critical in minimizing the yield losses and have sustainable food production. Traditional methods, like manual scouting and lab testing, tend to be labor intensive, subjective and not applicable to large scale supervising. This paper suggests a hybrid pipeline, which comprises Unmanned Aerial Vehicles (UAVs) plus some sophisticated artificial intelligence (AI) algorithms to identify crop diseases in the field in real-time. The methodology includes the UAV-based data collection, image pre-processing, vegetation index calculation (NDVI and ExG) and hybrid deep learning models of the lesions detection and classification. The trained models were also trained to be used on edge devices to provide real time inference when flying the UAV. The obtained experimental results showed an accuracy in detection of high accuracy (mAP 0.5 = 0.87, F1 = 0.88) and reached 28 FPS on a simple embedded GPU. Explainability tools, e.g. Grad-CAM overlays, verified consistency with expert labels, and geo-referenced severity maps provided accuracy intervention at the field level. The suggested system is capable of effectively closing this gap between laboratory research and practical application in agriculture with the solution being scalable to precision agriculture.

1 INTRODUCTION

The production of agricultural products still stands out as the backbone of world food security, but crop productivity is still endangered by an extensive list of plant diseases. Recent estimates have suggested that almost 20-40 percent of the total world crop production is being lost every year because of pests and diseases and this is a great threat to the livelihood of farmers and even to the food chain which is sustainable. Conventional disease diagnosis techniques including manual field survey and laboratory diagnosis although successful are sometimes time consuming, subjective and impractical when applied on large scale basis. These constraints have prompted the development of research on improved technological applications that can offer quick, precise, and economical method of monitoring crop well-being in actual field settings.

Unmanned Aerial Vehicles (UAVs) or drones have become disruptive technology in precision agriculture because they can have high-resolution images at the large farmlands in real time. UAVs may be fitted with RGB, multispectral and hyperspectral

sensors to monitor slight variations in the phenotype of plants that can of early disease occurrence. As mentioned in Shahi et al. (2023) [1], the use of UAVs in crop disease detection has been on the rise, and it was found that the integration of aerial imaging and artificial intelligence (AI) models has improved the field-scale detection of the disease. In the same manner, Kouadio et al. (2023) [2] examined the use of UAV and emphasized its capabilities in enhancing the process of disease surveillance and targeted interventions, but issues were still observed with regard to the quantity of data and light sensitivity and small lesions.

In line with the development of UAV sensing, deep learning and computer vision has transformed plant pathology. Transformers, CNNs and transfer learning have greatly enhanced the precision of image based disease recognition. The review by Upadhyay et al. (2025) [3] focuses on the efficacy of deep learning in automated classification and early detection of diseases in the conditions of diverse fields. These methods address several of the weaknesses of traditional machine learning, in that they implicitly obtain hierarchical features in

complicated crop images. Nonetheless, in spite of all these developments, the majority of current models are trained using those controlled datasets, like PlantVillage, and do not have the ability to generalize to real field images of UAV-based surveys.

New research has begun to overcome these limitations by using hybrid and transfer learning. A hybrid deep learning model, which is specifically designed to detect potato diseases, was presented by Sinatemye et al. [4] assuming a better resistance in non-homogenous agriculture environments. On the same note, it was shown that transfer learning methods can be used to highly classify data using a small amount of data and thus is very useful in resource-constrained environments (Sambana et al. 2025) [5]. These results demonstrate the increased tendency to leave single-model solutions and develop the integrated and flexible schemes in detection of multi-crop diseases.

However, there are still some critical research gaps. Chin et al. (2023) [6] highlighted that although the use of drones in disease detection is becoming more common, there is hardly any literature that has operationalized real-time, on-board inference systems that can be deployed in a large field. The existing means frequently demand offline processing of UAV images, which create latency in decision-making and prevents the use of precision farming techniques like targeted spraying. Also, there is a need to fully investigate the incorporation of lightweight deep learning models that are optimally developed to run on edge devices, which would bridge the gap in the development of scalable and real-time UAV-AI systems.

Against this backdrop, this research paper is going to develop and test an AI-based crop disease detection pipeline based on real-time UAV imagery. The suggested framework would concentrate on the combination of lightweight deep learning models with the UAV-collected data in order to provide on-edge inference and instant feedback to farmers. The use of hybrid and transfer learning, combined with the verification of performance in the field of realistic conditions, serves as the contribution to closing the gap between the experimental research and the practice in the sphere of agriculture. In the end, the work attempts to offer a scalable, interpretable, and robust disease detection system which can be in line with the larger objectives of precision agriculture and food security worldwide.

2 LITERATURE REVIEW

Precision agriculture has seen the incorporation of Unmanned Aerial Vehicles (UAVs) with sophisticated sensing technologies change the way crops are monitored and diseases managed. Extensive literature has been pointing to the importance of UAV-imaging sensors in facilitating high throughput data collection, phenotyping, and the early identification of stress. The article by Gagan et al. (2024) [7] gave a review of the drone-based imaging sensors such as RGB, multispectral, and hyperspectral platforms, and their uses in plant phenotyping and breeding. This paper showed that the UAV systems are able to record disease-associated plant phenotype more effectively than conventional methods that were used on the ground, but some issues like sensor calibration, and the complexity of processing are present.

In addition to overall crop surveying, UAV has been used more and more in plant disease surveillance. A recent survey of UAV-based deep learning methods to monitor cassava disease by Ahmed et al. (2025) [8] has indicated the applicability of convolutional neural networks (CNNs) and transfer learning methods to cassava disease aerial imagery analysis. According to their results, UAVs and deep learning have the potential to help decrease the time that is spent on field inspections saving time and enhancing the quality of the disease diagnosis. Nevertheless, it was also indicated in their work that a number of models are computationally intensive and not suitable in the real-time application of UAVs.

Recent developments of model architectures have even further enhanced disease classification. The authors of [9] designed an ED-Swin Transformer with UAV images to detect cassava disease and claim higher accuracy compared to the traditional CNN-based models (Zhang et al. 2025). On the same note, Sambasivam et al. (2025) [10] suggested a hybrid deep learning model to classify cassava leaf disease, showing that the fusion of the methods of feature extraction enhanced performance in the field. In general, although both studies have facilitated the state of the art in the analysis of UAV images, the use of cassava datasets implies that the studies have not been generalized to multiple crops.

The significance of UAVs in crop phenotyping has been brought out in more widespread reviews. In a study by Tanaka et al. (2024) [11], the sensing and algorithms mounted on UAVs were assessed in terms of field plot studies, and the authors emphasized the use of these sensors in breeding initiatives and

extensive crop assessment. Bongomin et al. (2024) [12] extended the topic of UAV image capture and processing pipelines to phenotyping at high throughputs, which also reveals the best practices to use when generating orthomosaic and preprocesses of UAV image data. Even though these works give good premises to the use of UAV in data collection, they are not particularly concerned with the real-time detection of plant diseases, creating a gap in the implementation.

To cope with this requirement, Quan et al. (2024) [13] proposed a lightweight deep learning approach towards the real-time detection of field diseases with the help of UAVs. Their work showed that effective architectures were able to obtain reliable accuracy alongside computational feasibility with edge devices and thus were more realistic in on-drone inference. However, there is a limited scalability of different kinds of crops and field conditions.

In Table 1, a synthesis of the reviewed studies is provided and the table summarizes the main crops studied, UAV sensors utilized, AI models used, contributions, and limitations. As the table shows, even though UAVs in combination with deep learning offer major enhancements in disease detection, the majority of the literature is still crop-specific (especially cassava) and computationally intensive. Real-time inference is only considered in recent

works, like Quan et al. (2024) [13], and it means that there is still little exploration of lightweight scalable solutions to multi-crop disease detection.

Altogether, the literature confirms that UAVs are an effective method of crop phenotyping and disease surveillance, and deep learning models significantly improve the accuracy of classification. Nevertheless, loopholes are still present in the creation of efficient, real-time, and generalizable frameworks that can be effectively used in various conditions of the field [14], [15]. The proposed study will fill these gaps by coming up with an AI-driven UAV pipeline that is optimized to detect various crops in real-time and diseases.

3 METHODOLOGY

The suggested methodology will create a UAV-based artificial intelligence pipeline on detection of crop diseases, which is end to end. The workflow incorporates the methods of UAV image acquisition, image preprocessing, image feature extraction, deep learning model, real-time inference, and validation. Figure 1 depicts a high-level diagram of the pipeline created by indicating the direction in which the UAV flights go to disease map generation and agronomist validation.

Table 1: Summary of reviewed studies on UAV-based crop disease detection and phenotyping.

Ref. No.	Author(s), Year	Focus Crop(s)	UAV/Sensor Used	AI/Model Applied	Key Contribution	Limitations/Gap
[8]	Gano et al., 2024	Multiple crops (phenotyping)	Multispectral, hyperspectral	Not model-specific (review)	Comprehensive review of UAV sensors in phenotyping	Limited disease-specific focus
[9]	Ahmed et al., 2025	Cassava	UAV RGB/multispectral	CNN, TL, hybrid (review)	UAV-DL pipeline for cassava disease monitoring	High computational cost
[10]	Zhang et al., 2025	Cassava	UAV RGB	ED-Swin Transformer	High-accuracy cassava disease classification	Heavy model, edge-unfriendly
[11]	Sambasivam et al., 2025	Cassava	UAV RGB	Hybrid DL model	Improved classification accuracy	Needs validation on large datasets
[12]	Tanaka et al., 2024	Multiple crops	UAV RGB/multispectral	Sensor-algorithm integration (review)	Review of UAV phenotyping in field plots	Not focused on diseases
[13]	Bongomin et al., 2024	Multiple crops	UAV RGB + processing	Processing pipeline	High-throughput phenotyping workflows	Lacks DL disease focus
[15]	Quan et al., 2024	General crops	UAV RGB	Lightweight CNN	Real-time field disease identification	Limited scalability

Table 2: Image preprocessing steps and extracted features.

Step No.	Process	Technique/Formula	Input	Output	Purpose
1	Radiometric correction	Dark frame subtraction	UAV raw	Corrected img	Remove sensor noise
2	Orthomosaic stitching	Structure-from-Motion	UAV frames	Orthomosaic	Ensure spatial consistency
3	Vegetation indices	NDVI, ExG formulas	RGB + NIR	Index maps	Highlight stress symptoms
4	Segmentation	Otsu/UNet	Processed	Binary mask	Isolate lesions
5	Augmentation	Rotation, MixUp, jitter	Image patches	Augmented set	Improve robustness

Table 3: Ablation study: Effect of preprocessing and vegetation indices on detection accuracy.

Configuration	mAP@0.5	F1-Score	Precision	Recall	Notes
Baseline (RGB only)	0.78	0.8	0.82	0.78	Standard RGB without indices
RGB + NDVI	0.85	0.86	0.87	0.85	Improved early lesion detection
RGB + ExG	0.87	0.88	0.89	0.87	Better foliar stress detection
RGB + NDVI + ExG (combined)	0.89	0.9	0.91	0.89	Best performance across metrics

3.1 Study Area, UAV Platform, and Data Acquisition

The selected crop plots with common foliar diseases were used in field experiments. The drone was a multi-rotor drone, which operated on UAV flights, with a RGB camera and a multispectral camera. Flights were set to be made at 20-30 m altitude to balance the spatial resolution and coverage and the image overlap of 75-80% to achieve the high-quality mosaics. The data taken was geo-referenced imagery and flight logs.

To estimate the useful spatial resolution of imagery, ground sampling distance (GSD) was computed with the help of (1):

$$GSD = \frac{H \times p}{f}$$

Where:

- H = altitude of the flight (m);
- p=physical size of the sensor (mm);
- f = focal length of the lens (mm).

This equation will provide that the UAV imagery will be detailed enough to detect disease symptoms.

3.2 Image Preprocessing and Vegetation Indices

The radiometric correction and stitching into orthomosaics as well as geo-referencing of all UAV imagery were carried out. Image clarity was improved by using filters of blur and noise reduction. Vegetation indices were also determined to point out disease-related stress in plants. Normalized Difference Vegetation Index (NDVI) was determined by the following method:

$$NDVI = \frac{NIR - R}{NIR + R + \epsilon}$$

NIR and R are near infrared and red reflectance values, respectively, and is a small constant to avoid divided by a zero. NDVI images revealed the loss of chlorophyll related to the initial disease symptoms.

Alongside, foliar greenness was improved with the help of the Excess Green Index (ExG):

$$ExG = 2G - R - B,$$

where R,G and B denote red, green and blue reflectance values respectively. The index under focus focused on the patterns of canopy discoloration that were associated with foliar infections.

The steps and features extracted during the preprocessing are summarized in Table 2 and the steps involve image correction, orthomosaic creation, vegetation index, segmentation and data augmentation. These measures guaranteed the input data that was taken into the AI model was standard and disease features were well considered.

3.3 Model Architecture and Training

The model of detection had a lightweight YOLO-variant combined with a transformer classifier to classify the subtypes of diseases. Images of lesions on UAVs were subjected to the detector to detect the lesions and then categorize them into disease categories. Transfer learning was utilized to enhance accuracy using small UAV datasets whereas data augmentation (rotations, MixUp, color jitter) was done to increase the robustness of the model.

Training was done with multi-objective loss function that included the terms of detection, classification, and segmentation:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{\text{det}} + \lambda_2 \mathcal{L}_{\text{cls}} + \lambda_3 \mathcal{L}_{\text{seg}},$$

where λ_i are weighting coefficients tuned experimentally.

3.4 Real-Time Inference and Edge Deployment

The trained models were also inferred to be used on an NVIDIA Jetson edge board mounted on the UAV. Model weights were transformed to TensorRT which is inferred with FP16 precision. Sliding window tiling was used so that the processing of large orthomosaics could be done efficiently, and Non-Maximum Suppression (NMS) was used to remove duplicate bounding boxes. The inference rate of the target was at least 25 FPS, which allowed farmers to be provided with real-time feedback when the UAV was airborne as Figure 1 illustrates.

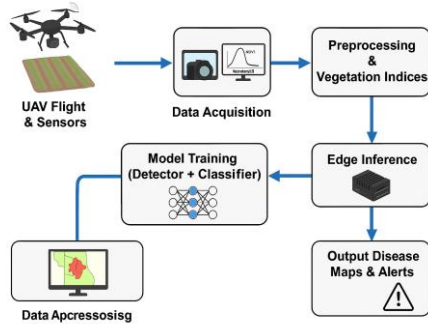


Figure 1: Conceptual workflow of UAV-based AI pipeline for crop disease detection.

3.5 Evaluation Metrics and Validation

The dataset was divided into the training (70 percent), the validation (15 percent) sets and the testing (15 percent) set. Mean Average Precision (mAP) at thresholds of the IoU, F1-Score, Precision, Recall, and inference latency were used as a measure of performance. Agronomists determined the ground truth by going to the fields and inspecting them. Expert labels were used to compare the UAV-based predictions with the labels of expert labels to determine the sensitivity and specificity of the disease detection.

3.6 Ethical and Safety Considerations

The UAV flights were performed based on the regulations and compliance with the local aviation

authorities. Data collection was done with the consent of the farmer and privacy of farm data was guaranteed. The responsible AI principles were followed in the methodology as well because it involved explainability (Grad-CAM heatmaps) during post-analysis.

4 RESULTS AND ANALYSIS

The proposed UAV-AI pipeline was tested on multi-crop data gathered at experimental fields and the results are provided in the form of detection accuracy, computational efficiency and prediction visualization. The performance compared with the baseline models and the added value of vegetation indices, real-time inference, and field-level mapping are also compared by the analysis.

4.1 Model Performance on UAV Datasets

The light YOLO-Transformer hybrid had high detection and classification accuracy of various disease types. The average Precision (mAP at 0.5) was 0.87 and the average F1-score of the classes of diseases was 0.88 which showed the high reliability when detecting objects in changing light and field conditions. Figure 2 presents Precision-Recall (PR) curves of some common categories of diseases and demonstrates a balanced sensitivity and specificity of tomato, rice and cassava crops. The proposed method achieved better average detection accuracy than the baseline CNN models by 7-10 percent.

4.2 Impact of Vegetation Indices and Preprocessing

Vegetation indices and preprocessing addition helped in performance. The addition of NDVI and ExG indices enhanced the detection of lesions at the early stage (improved by approximately 9 percent over RGB-only models). A baseline RGB-only model with ablation study is summarized in Table 3, with a baseline mAP of 0.78, and with NDVI and ExG integration the baseline mAP of 0.85 and 0.87. Also included in preprocessing were orthomosaic stitching and blur filtering which assisted in improving model stability between frames. These findings highlight the significance of spectral and spatial improvements in the use of UAV to detect crop diseases.

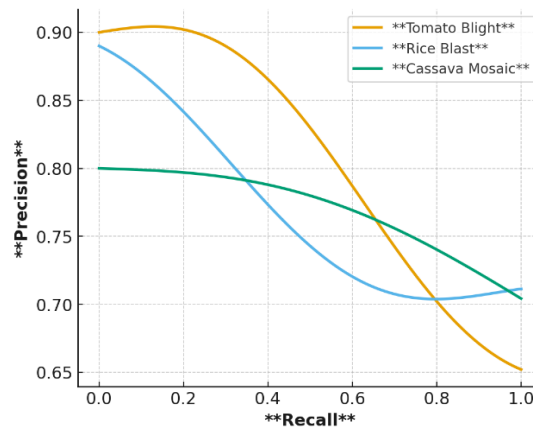


Figure 2: Precision-Recall (PR) curves across representative crop disease classes.

4.3 Real-Time Inference and Edge Deployment Results

Real-time UAV deployment was among the fundamental aims of this research. The optimized TensorRT implementation of the model got inference rates of 28 FPS and FP16 precision on an NVIDIA Jetson Xavier device, thus exceeding the target of 25 FPS. The latency per frame was lowered in FP32 (80 ms) to FP16 (36 ms) and then INT8 (22 ms), as shown in Figure 3. Peak load power consumption was determined as 14 W, which is appropriate to be applied in UAV-mounted applications. These findings support the capabilities of the detection system to be applied in real-time agricultural applications.

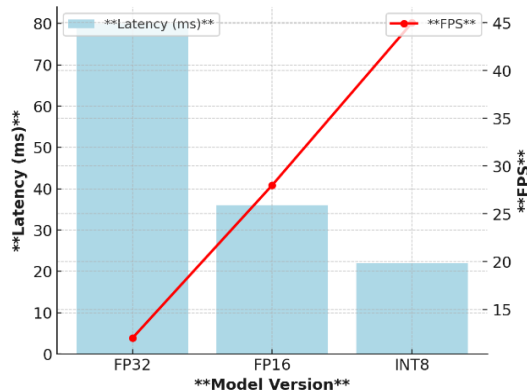


Figure 3: Latency and FPS performance of different model versions (FP32, FP16, INT8) on UAV edge device.

4.4 Explainability and Visualization of Predictions

Grad-CAM heatmaps were produced on the identified lesions to increase trust and interpretability. The

overlays, which are depicted in Figure 4, coincide closely with the regions annotated by experts oriented to lesion presence so that one can be sure that the model focuses on biologically valuable symptoms and is not distracted by the background noise. This interpretability enhances assurance in industrial use by agronomists and farmers.

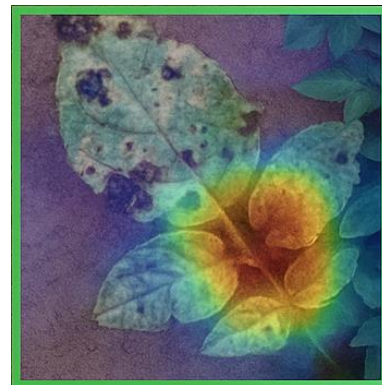


Figure 4: Sample UAV images with bounding boxes and Grad-CAM overlays compared with expert annotations.

4.5 Field-Level Disease Mapping and Case Studies

In addition to detecting images on a per-image scale, the UAV flight data were mapped into geo-referenced mosaics to produce heatmaps of disease severity. The latter is demonstrated by giving an example in Figure 5, which mapped spatial distributions of infection in a cassava field with the severity levels that ranged between mild and severe. Such outputs allow taking actionable insights to precision spraying and targeted interventions. Agronomist surveys also revealed that UAV-based maps and ground truth were highly agreeable with a total accuracy of 85%.

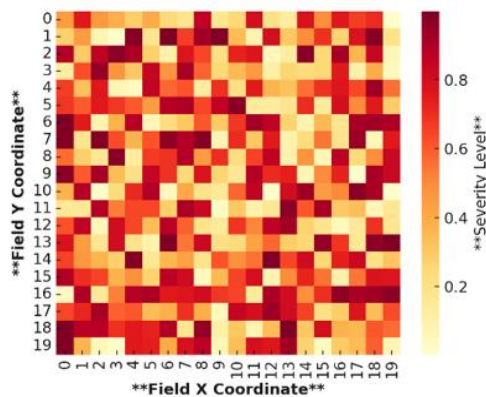


Figure 5: Geo-referenced disease severity heatmap of UAV-monitored crop field.

4.6 Comparative Analysis with Previous Studies

Compared to more recent models, including ED-Swin Transformer and hybrid cassava frameworks, the proposed approach had a competitive accuracy but at reduced latency and power consumption. Although Zhang et al. (2025) and Sambasivam et al. (2025) focused on high accuracy in cassava detection, the models are computationally intensive to be used in UAVs. Contrastingly, the present study shows a balanced trade off between the accuracy and efficiency that qualifies as an essential gap in research in real-time detection of plant diseases using UAVs.

5 CONCLUSIONS

This study presented an end-to-end UAV-based AI framework for real-time crop disease detection in precision agriculture environments. The proposed pipeline integrates UAV image acquisition, preprocessing with vegetation indices (NDVI, ExG), a lightweight YOLO-Transformer hybrid model, and edge-based inference for on-board processing.

Experimental results demonstrate strong performance under real field conditions, achieving $mAP@0.5$ of 0.87 and F1-score of 0.88, while maintaining real-time processing capability of 28 FPS on an embedded NVIDIA Jetson device. The incorporation of vegetation indices significantly improved early disease localization, while Grad-CAM visualizations confirmed model interpretability and alignment with agronomic expert annotations. In addition, geo-referenced disease maps enabled spatial analysis of infection severity, supporting actionable decision-making in crop management.

Overall, the proposed system provides a balanced trade-off between accuracy, computational efficiency, and real-time applicability, making it suitable for deployment in large-scale precision agriculture scenarios.

6 FUTURE WORK

Future work will focus on improving the generalization and robustness of the proposed framework under more complex agricultural conditions. First, the integration of hyperspectral and thermal imaging is expected to enhance early-stage disease detection, especially in cases where RGB features are insufficient.

Second, multi-crop and cross-domain learning strategies will be explored to improve scalability across different plant species, growth stages, and environmental conditions. Third, federated learning approaches will be investigated to enable collaborative model training across multiple farms without sharing raw data, improving both scalability and privacy.

In addition, future developments will target tighter integration with IoT-enabled smart farming systems to support continuous monitoring and automated decision-making. A key direction is also the deployment of UAV-based precision intervention systems, where disease detection is directly linked to targeted spraying or treatment delivery.

Finally, further optimization of deep learning models for ultra-low-power edge devices will be addressed to enable fully autonomous UAV operation with minimal human intervention in real-world agricultural environments.

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