THE ASIAN BULLETIN OF BIG DATA MANAGMENT
Vol. 5. Issue 4 (2025)
https://doi.org/10.62019/nk2jjk42

ASIAN BULLETIN OF BIG DATA MANAGEMENT
http://abbdm.com/
ISSN (Print): 2959-0795
ISSN (online): 2959-0809

Artificial Intelligence Assisted Autonomous Unmanned Aerial Vehicles (UAVs) and Aerial drones based on Machine Vision for Enhancing Remote Sensing of Precision crop Health Monitoring

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Chronicle

Article history
Received: Oct11, 2025
Received in the revised format: Nov 22. 2025
Accepted: Nov 28, 2025
Available online Dec 07, 2025

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Abstract

With unmanned aerial vehicles (UAVs), agricultural monitoring has developed into a new phase of innovation providing remedies to precision farming. The common traditional agricultural methods are based on manual inspection and few observations on the ground using sensors that may be inaccurate and time-consuming. New technologies such as drones and AI provide us with an opening of large scale, early detection, but most systems currently only seek pests or diseases and are usually specific to a single type of crop in controlled laboratory conditions. Drone-operated AI system, which combines RGB and, where feasible, multispectral cameras and a YOLOv8 pipeline to detect pests and crop diseases simultaneously across a variety of crops. We are developing it to be used in the real world: we load in data fields, laboratories, and the internet, perform preprocessing, transfer learning, and make the inference to be lightweight enough to execute on edge computers. The introduction of agricultural monitoring systems based on the use of UAVs builds on the peculiarities of quadcopters and fixed-wing UAVs. Quadcopters are used when conducting detailed field surveys or spot checks, allowing high-resolution imaging to be used in order to complete precise inspections, whereas fixed-wing UAVs are used when it comes to covering extensive areas and long-range capabilities. These UAVs can gather extensive data and conduct biological and chemical analyses due to sophisticated IoT devices and sensors, such as multispectral and hyperspectral cameras, GPS modules, and real-time communication tools. Our hybrid machine learning model (HMLM) has more accuracy and predictive capabilities, with an amazing score of 98.74 and hence, our machine learning model is doing the right job of 98.74 accurate classification and thereby yielding high accurate yields by predicting crop management. This research will contribute to the sustainability of agricultural practices as well as yield protection by providing timely, precise and scalable detection. The model proposed can potentially enable farmers with action-oriented insights, losses can be alleviated, and food security objectives can be achieved in areas where there are high susceptibility rates to pests and diseases.

Keywords: UAV, AI, YOLOv8, crop disease detection, pest detection, precision agriculture, transfer learning.

INTRODUCTION

Unmanned aerial vehicle (UAV) drones are aircraft that can fly without an onboard human pilot and operate either by remote control or autonomously by onboard computers. most economies, particularly South Asian ones, are fundamentally agricultural but the losses of crop yield caused by pests and diseases continue to sting hard. It has been estimated that pest infestations and plant diseases reduce agricultural productivity by 20-40 percent of such major staples as rice, maize, and wheat annually throughout the globe. Conventional surveillance (manual field checks or visual inspection) is tiresome, time-consuming, and highly reliant on the availability of experts, so we tend to notice that damage has occurred only when it has become severe [1, 2]. As illustrated in Figure 1, pathogens and pests account for significant yield losses across major staples worldwide, with estimated losses ranging between 20% and 40% depending on crop and region [2, 3]. Recent developments in UAVs (or drones) combined with imaging sensors (RGB, multispectral, hyperspectral) and AI, especially deep learning, have given rise to many opportunities. UAVs allow us to fly regularly and effectively cover extensive regions, take high-resolution shots that are able to detect early signs of disease or pest stress even before it can be detected by the naked eye [4, 5]. This imagery can then be processed by AI models, which can in turn classify, localize, and quantify damage at scale. Hyperspectral early stress detection in [6] in reality much of the existing systems are still limiting. One, many of the studies only detect one area, either disease detection or pest detection, not both, so they may not be effective in mixed-infestation or overlapping-symptom situations in the real world. Second, you get poorer performance with models as you transition between controlled lab environments and real field environments: there are variations in lighting, occlusion, background noise, varying crop varieties, and seasonal variations that introduce discrepancies that most models are weak to[7, 8].

$$\delta_h = 60^{\circ} \begin{cases} 0 + \frac{(\beta_g - \beta_b)}{(m_x - m_n)}, if m_x = \beta_r \\ 2 + \frac{(\beta_b - \beta_r)}{(m_x - m_n)}, if m_x = \beta_g \\ 4 + \frac{(\beta_r - \beta_g)}{(m_x - m_n)}, if m_x = \beta_b \end{cases}$$ Eq (1)

$$\delta_s = \left(\frac{m_x - m_n}{m_n} \right)$$ Eq (2)

Third, YOLO-based one-stage detectors (in particular, YOLOv8) and transfer learning seem to be promising in terms of speed and accuracy, however, there is always a trade-off between the accuracy of detection of small targets or early symptoms and computation cost or latency. Edge deployments are limited by hardware and thus lightweight models or optimizations are still necessary [9, 10].

$$\delta_v = m_x(\beta_r, \beta_g \beta_b,), \ \delta_{sv} = m_n(\beta_r, \beta_g \beta_b,)$$ Eq (3)

$$R(t) = \sum_{i=1}^{n} FI_i(t) * \tau_{ih} + [\tau_h * r_{i-1}]$$ Eq (4)

Detection and Control

Multi-crop generalization is another problem. Datasets are often crop specific, such as rice, or maize, or cotton, and models trained on those datasets are often not very good at predicting other species [11, 12]. Due to the variation in leaf morphology, disease manifestation, type of pest and environmental conditions among crops, domain adaptation or transfer learning is crucial. With these limitations, we very plainly require mechanisms that: can identify both pest and disease symptoms during a single flight of a UAV, operate over a variety of crop species or varieties, survive in field conditions such as lighting, noise and season change, and operate with reasonable latency and resource consumption to be deployed in near-real time [13, 14]. The proposed research will fill in these gaps by creating an artificial intelligent (AI) UAV pipeline, based on YOLOv8 (or equivalent), that will be able to process not only pest but also disease detection in multiple crops, particularly in in-field scenarios. The objective is feasible implementation: frequent monitoring, cost-efficiency and provision of actionable information to farmers in a timely manner to reduce losses [15, 16].

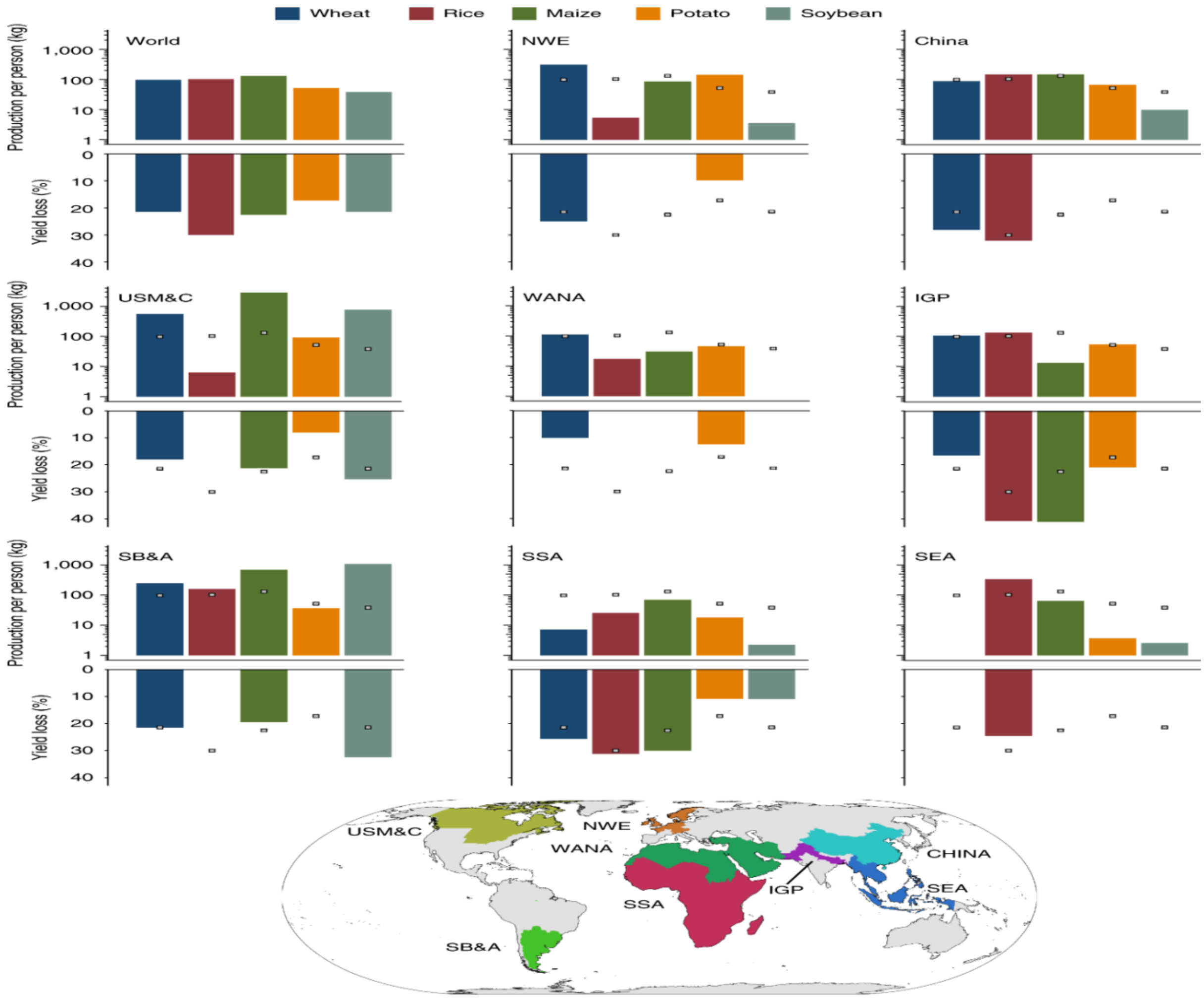

Figure 1.
Global burden of pathogens and pests on major food crops [17].

Over and Under Irrigation

Multispectral and hyperspectral sensors on UAVs, along with AI, will be able to identify plant stress signals before you will even notice signs of the stress and thus interventions can occur, but at an earlier stage [18, 19]. According to Stats of FAO and other reports, pests and diseases alone may impose losses of 10-15 per cent and above on world crop production, and in certain countries losses may be even greater. CNNs have been applied to classify and segment diseased regions in UAV images, and appear promising to automate disease and pest monitoring at scale. CNN segmentation UAV images [20, 21]. The actual issue is that most AI -UAV systems are not generalized: the models trained in certain environmental conditions are usually ineffective when introduced in new areas with different illumination or background conditions. More recent investigations, which also combined a better YOLOv5 model with the UAV data, have already attained a mean precision of 96'% which illustrates that it is indeed possible to achieve high-precision pest detection under realistic field conditions [22, 23].

$$Y(t) = \omega[\tau_{ho} * h(t)] \quad \text{Eq (5)}$$

$$\omega = E_f * \frac{1}{1 + e^{-\theta t_f}} \quad \text{Eq (6)}$$

$$\omega = \left\{ \begin{array}{ll} 0; & normal \\ 0 < \omega < 0.25; & Mild \\ 0.25 < \omega, 05; & Moderate \\ 0.5 < \omega < 0.75; & Severe \\ 0.75 < \omega < 1; & Proliferative \end{array} \right\} \quad \text{Eq (7)}$$

UAVs and remote sensing for crop health

I have been searching the literature of systematic reviews and they are revealing a sharp increase in UAV-based crop monitoring studies. UAV imagery, be it mere RGB, multispectral, thermal, or hyperspectral, has already been applied to detect fungal disease, nutrient stress, and pest infestation all at canopy level [24, 25]. The point is in the fact that the sensor that you choose will actually alter what you will be able to detect and at which point in time you will be able to detect it. These reviews are more or less saying that you need to align your sensor selection (RGB vs multispectral/hyperspectral) with the particular issue you are trying to address. Multispectral or hyperspectral can more easily detect biochemical signals before they happen, but are harder to manipulate and far more costly [26, 28].

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}(Y_1 - \bar{Y})^2} \quad \text{Eq (8)}$$

Imaging modalities, sensor performance, and trade-offs

RGB sensors are cheap and useful in identifying visible signs of stress like spot on leaves or defoliation, but are not capable of detecting early signs of physiological stress. Multi spectral (particularly NIR) and hyperspectral sensors, in contrast, can identify signs of stress at the pre-damage stage and often have greater capabilities to detect them [29, 31]. But these more sophisticated sensors are more costly, produce larger data, and are difficult to calibrate. In addition to sensors, the combination of UAV images with AI models has generated high accuracy in disease and pest detection activities. Still, robustness is also a major concern, as models that work well in lab settings tend to fail in the field [32, 34].

This number indicates a direct dependence of sensor selection on detection. RGB cameras are cheap and useful in observing apparent symptoms like leaf spots, but do not capture early physiological stress. Multispectral and hyperspectral sensors have the ability to identify stress-indicating signals during the pre-damage phase in a more sensitive manner, but they also require greater cost, more intricate calibration process, and large amounts of data. The figure illustrates the trade-off between cost and sensitivity, which supports the difficulty of choosing an appropriate sensor configuration between its affordability and its field-readiness [36, 37].

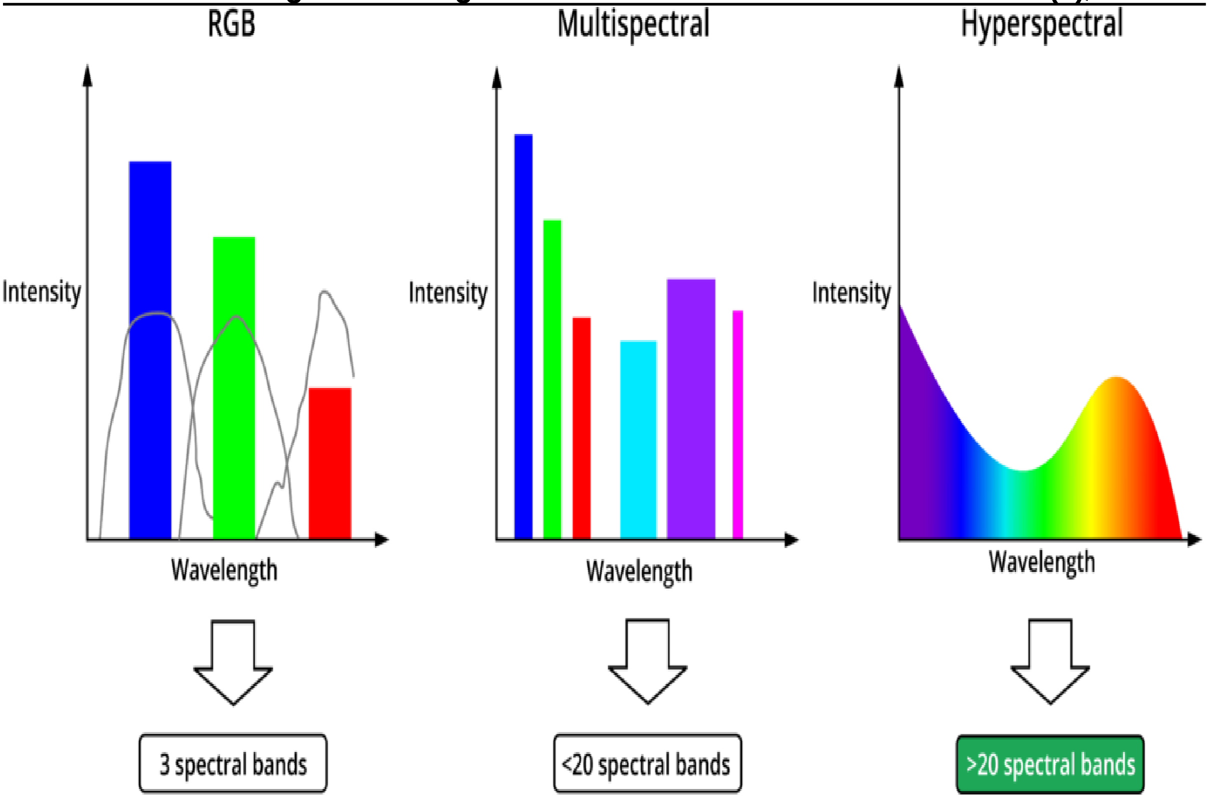

Figure 2.
Comparative capability of RGB, multispectral, and hyperspectral imaging in crop disease and stress detection [35]

Machine-learning methods: CNNs, transformers, and one-stage detectors

I have been considering CNNs; the CNNs are essentially the MVP in classifying plant disease in leaf pictures such as those found on PlantVillage. YOLO is the best choice when we need to find objects with our eyes, e.g. lesions, pests, YOLO, now v8 because it is a reasonably accurate and very fast implementation, particularly real-time shooting on low-cost edge cameras. YOLOv8 achieved 96% precision in rice pest dataset [38, 39].

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \qquad \text{Eq (9)}$$

$$\mathrm{TDI} = \sqrt{(\Delta C)^2 + (\Delta\sigma)^2} \qquad \text{Eq (10)}$$

Recent research articles indicate that YOLOv8, with minor modifications to pest spotting, and thinner versions suitable to the field are in fact functional. Besides, Vision Transformers and hybrid CNNViT are the new kids on the block to detect disease early, particularly when you need to look at the high-level picture. Hybrid CNN-ViT outperformed CNN alone in soybean disease detection [40, 41]. We have witnessed a number of studies employing CNNs, YOLOs even transformer-based models in detecting crop diseases and pests. They perform well in controlled environments, such as the Plant Village datasets, but on the actual farm the models must be both accurate and super lightweight in order to be used by drones. Table 01, gathers together some of the newest work, and indicates the hit-rate and the speed at which they operate and which crops they attack [42, 44].

Table 1.
Comparative performance of different AI models for crop disease and pest detection.

Ref	Model	Crop/Task	Accuracy	Notes
[45]	YOLOv8	Rice pest detection	96% Precision	Work in real-time
[46]	Hybrid CNN-ViT	Soybean disease detection	Higher than CNN alone	Early-stage detection
[47]	YOLO-lite	Multi-crop(Jetson Nano)	F1>0.9, <50ms latency	Field deployment ready

Table 1 indicates that YOLOv8 had a state-of-the-art accuracy (96) when it comes to identifying rice pests, which proves that it can be used in real-time to apply to UAVs. Hybrid CNN-ViT models also enhanced the ability to generalize with the ability to learn global disease patterns, performing better than traditional CNNs at soybean disease classification. Furthermore, easy-to-run YOLO models reached F1 scores over 0.9 and inference times less than 50 ms in low-power platforms such as Jetson Nano, which is important when deploying UAVs on-board. All of these results suggest that one-stage detectors and hybrid architecture will have the best balance between accuracy, latency, and field-readiness.

$$\mathrm{MCC} = \frac{\mathrm{TP} * \mathrm{TN} - \mathrm{FP} * \mathrm{FN})}{\sqrt{((\mathrm{TP} + \mathrm{FP})} * (\mathrm{TP} + \mathrm{FN}) * (\mathrm{TN} + \mathrm{FP}) * (\mathrm{TN} + \mathrm{FN}))} \quad \text{Eq (11)}$$

ELU – E- Linear Unit with 0 < a is

$$f(x) = \begin{cases} \alpha(\exp(x) - 1) & \text{for } x < 0 \\ x \text{ for} & x \geq 0 \end{cases} \quad \text{Eq (12)}$$

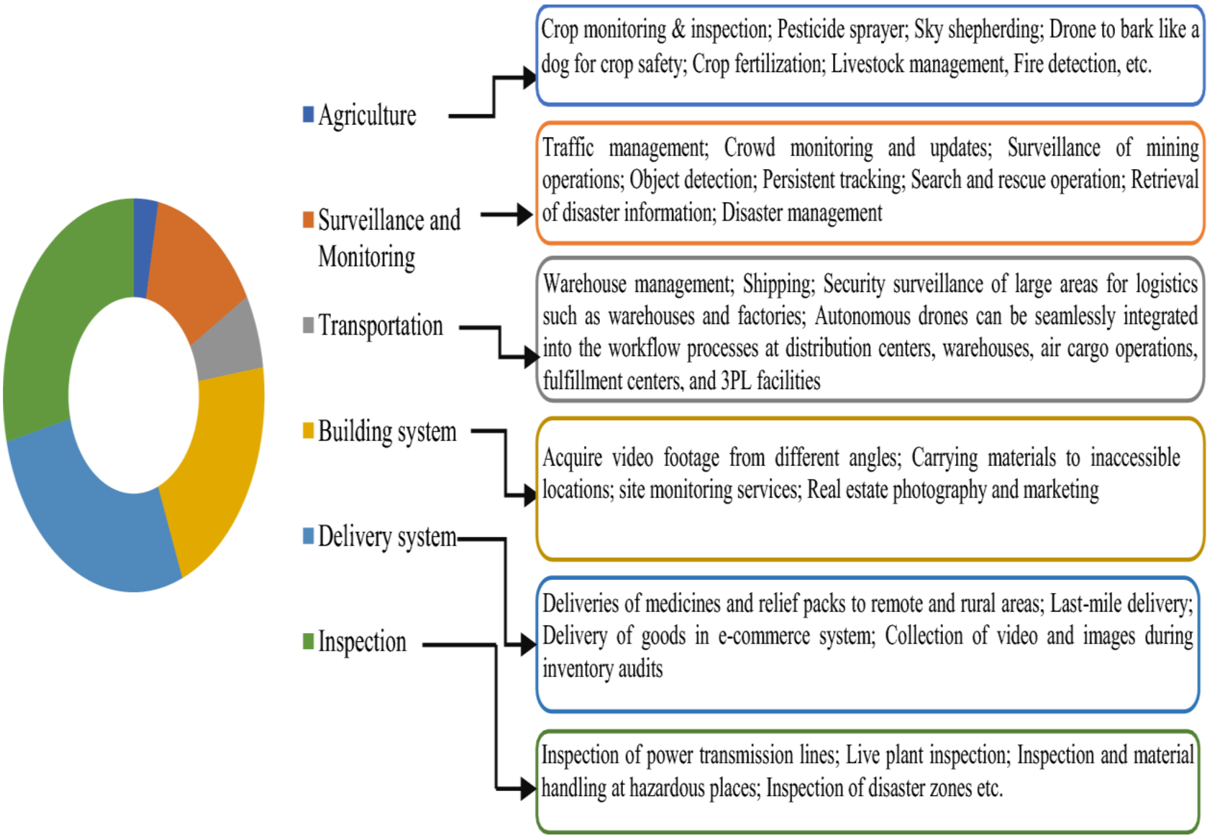

Figure 3.
UAVs in various applications Field Monitoring [48]

Table 2.
Comparative Analysis of relevant techniques

Ref	Camera Name	Spectral Range	Spectral Bands	Spectral Sampling
[49]	SVM	Pesticide/disease treatment	Dual-step based approach of pixel-wise NDVI calculation and semantic segmentation helps in overcoming NDVI issues	Model was not compared to any other
[50, 51]	SVM	Fertilization	Pattern recognition system allows for classification of images taken by low-cost cameras	Accuracy, precision, and recall values of model varied highly across datasets
[52, 53]	SVM	Crop-row detection	Able to detect weeds outside and within crop rows; does not require a big training dataset	Segmentation process produced salt-and-pepper noise effect on images
[54, 55]	LSVM	Crop-row detection	Model can be trained fast with a small training set	Image dataset was small and simple, containing images of sugarcane cultures only
[56, 57]	KNN3, KNN11	Crop-row detection	Simplest algorithms to implement amongst implemented algorithms in the paper	Models did not achieve the best results in the paper
[58, 59]	KNN	Crop-row detection/land-cover mapping	Uses an automatic window processing method that allows for the use of ML algorithms on large multispectral images	Model did not achieve the best results in the paper
[60, 61]	KNN	Crop-row detection	Best-performing classifier	Model could not perform sugarcane line detection and fault measurement on sugarcane fields of all growth stages

LITERATURE REVIEW

Transfer learning, datasets, and multi-crop generalization

Big publicly available datasets (Plant Village, Plant Doc and other crop-specific collections) have certainly assisted us in getting models into practice, but so many of our models have a tendency to overfit lab or single-crop images [62, 63]

- Add **new datasets** (Plant Village++, Rice Pest Dataset, and Cotton Leaf Dataset).

- Insert studies where transfer learning improved cross-crop performance

What is cool is that multisource data training and transfer learning - between lab, field, and multispectral and even web images - enhances robustness. A collection of 2023-2025 papers indicate that fine-tuning of pre-trained detectors is, in fact, providing a good cross-site performance. Nevertheless, it is a significant research problem to develop a modular dataset pipeline, which will allow us to add new crops without reconsidering other components.

In my research, therefore, I have been searching in field studies that are utilizing data of multi-season UAVs and also incorporating independent test years [64, 65]. The argument that they are the most believable typically has an F1 score of above 0.9 in one or more specific disease detection tasks when you train on multi-year data - that is the sweet spot. Never mind, of course, that implementing these models to the ground is not all sunshine, you have sensor calibration budgets, have to deal with all this illumination variability, have to figure out the trade-offs between ground sampling distance and altitude and have to deal with onboard computer and latency [66, 67]. Then there is its entire connectivity challenge when you desire to drive outcomes into mobile or web applications. In evaluating the literature, the majority of authors are demanding an account on accuracy, recall, the F1 score, and a narrow range on inference latency. Lightweight YOLO models achieved inference <50 ms on Jetson Nano [68, 69]. They also propose that a five-fold or temporal cross-validation scheme will provide a good estimate of the extent to which the model will generalize [70, 71].

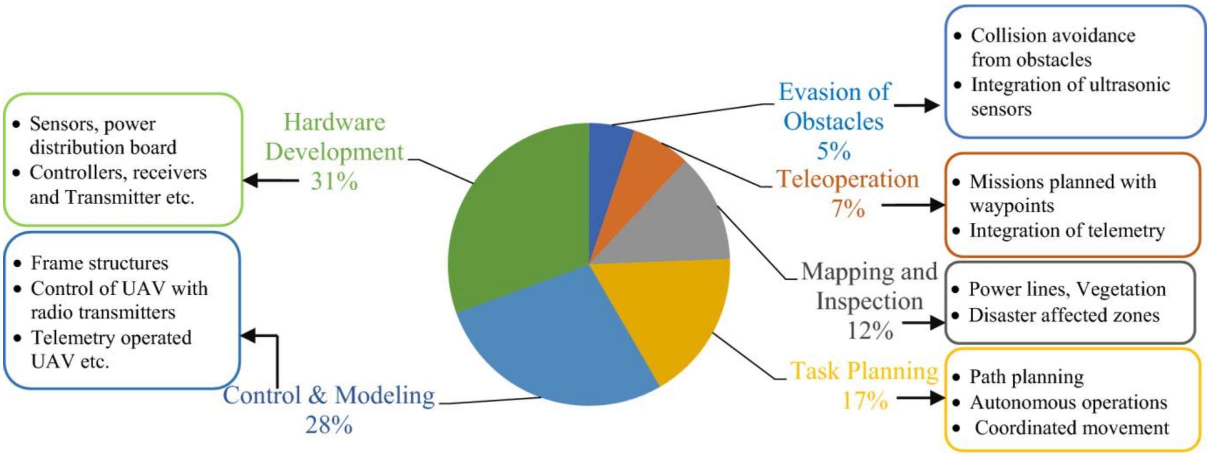

Figure 4.
Reported performance metrics of Research on evolving of UAV based AI models for crop disease and pest detection [72]

The figure shows that most of the models obtained very high accuracies (F1 tends to be greater than 0.9) when used under controlled or multi-season datasets, but their performance is different in the actual field. It also stresses the compromise of accuracy / computational latency, demonstrating the ability of lightweight YOLO variants to achieve latencies below 50 ms inference times on edge computers such as Jetson Nano [73, 75]. This fact supports the difficulty of achieving the accuracy, strength, and real-time practicability of the UAV-AI systems [76, 77].

Detection and Data Acquisition

Based on what we have observed in the reviews and experimental papers, the following are considered to be the gaps: (a) systems capable of identifying pests and diseases in a single UAV flight; (b) low-cost and modular systems capable of operating across crops; and (c) evidence that the system remains viable in the field across seasons and lighting conditions. Compared to satellites, UAVs provide <10 cm resolution, enabling leaf-level detection [78, 79].

Table 3.
Parameters of Hyper-spectral Cameras.

Ref	Camera Name	Spectral Range	Spectral Bands	Spectral Sampling
[80]	Cubert S185	450~950 nm	125 bands	4 nm
[81]	RESONON PIKA L	400~1000 nm	281 bands	2.1 nm
[82]	RESONON PIKA XC2	400~1000 nm	447 bands	1.3 nm

UAV vs Satellites (UAV <10 cm resolution vs >1 m for satellites). UAV vs Manual scouting (UAV reduces monitoring time by ~60%). The proposed research addresses those gaps through a multisensor-conscious data acquisition plan (RGB plus multispectral in the cases when it is possible) and a YOLOv8-based detection pipeline, which is slimmed down to lightweight inference, and a flexible dataset design that would enable easy addition of new crops and would essentially be following the best practices and newest developments. Compared to manual scouting, UAVs reduce monitoring time by 60% [83, 84].

Table 4.
Parameters of Hyper-spectral Cameras.

Ref	Sensor	Species	Disease	Method Type
[85, 86]	Hyper-spectral	Tomato	TYLC, BS, and TS	SVM
[87, 88]	Multi-spectral	Citrus	HLB	Vegetation index
[89, 90]	Hyper-spectral	Citrus	HLB	Neural Network

Integration with IoT and Decision Support Systems

IoT and UAVs inform low-altitude remote-sensing technology are extremely popular in the areas of environmental monitoring. IoT and UAV can be used in agricultural modernization to observe the occurrence of crop diseases and pests on the ground and in the air at the micro and macroscales [90, 91]. The adoption of UAVs boosts revenue by around 434-488 dollars per hectare, and saves around 14.4-15.8 h per hectare of time expended on pesticides application [92, 97]. According to Agronomy Journal (systematic review on adoption), another one is factors that influence adoption or intention to adopt robotics and UAVs, such as price, perceptions and knowledge of farmers, technical skills, connectivity, regulatory framework, compatibility with the current farm practices [98, 104].

Sustainability, former Adoption, and Policy Perspective

Recent research indicates that uptake of UAV-based technologies by farmers in most settings is low in spite of obvious advantages. As an illustration, in China grain agriculture, a survey showed that only 3.8 percent of the sampled farmers had embraced the use of UAVs despite the high revenue and labor reduction in pesticide application. Factors that have a major influence are the size of the farm, income of the farmers, young age and occupation of the farmers as a major occupation [105, 110]. Such barriers include economic ones (initial and maintenance cost high), operational (no trained personnel and institutions), and regulatory barriers. In other areasfarmers find advantages in less chemical use and better irrigation, but complain that high cost, operational complexity and ambiguous legal frameworks are barriers to adoption [111].

METHOD AND MATERIALS

The methodology that we have used in this research provides a systematic framework for developing and validating an AI-powered drone for crop disease and pest detection. This approach integrates hardware components (drone and sensors), software modules (AI-based machine vision and data analytics), and experimental testing in agricultural environment. This makes sure that the system remains reliable, affordable at low cost and scalable for small and medium-scale farmers. The methodology is divided into five main phases: System design, Hardware Implementation, Software development, Data collection and processing and Testing and evaluation.

System Design Framework

The overall system architecture combines Unmanned Aerial Vehicles (UAVs) with Iot-enabled sensors and an AI-driven decision support system. The UAV serves a the primary data acquisition platform, capturing high-resolution images and videos of crop fields. These data are processed using machine learning and computer vision algorithms to recognize the pest in the fields and any disease in the crops.

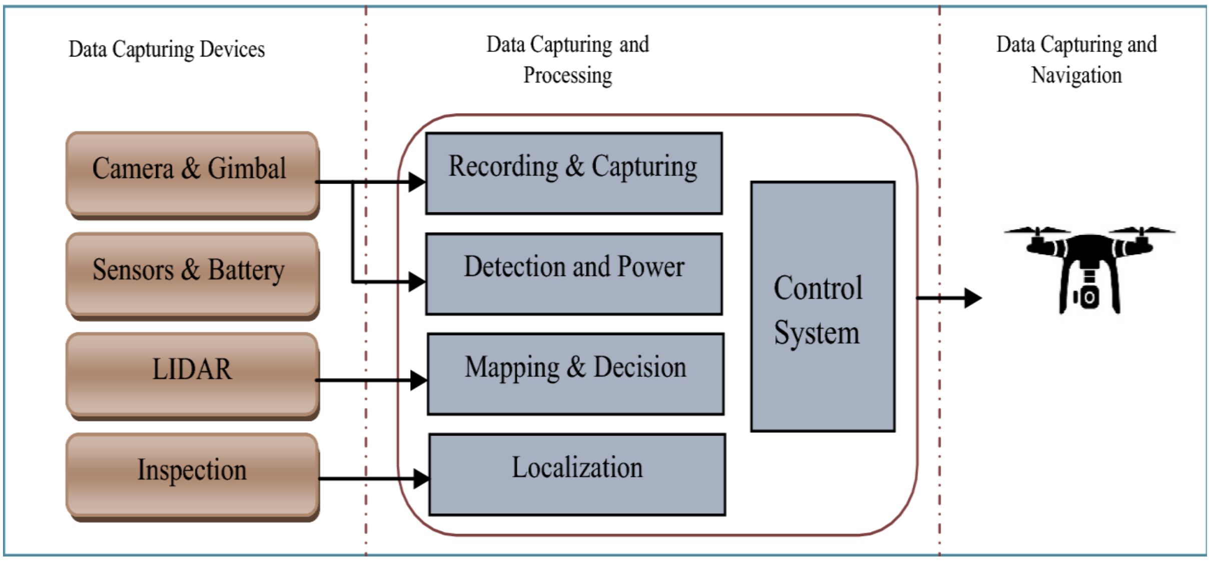

Figure 5.
Proposed Components for UAV Framework

Key Components of the Framework:

- **Drone (UAV):** It provides aerial view with real-time data.
- **Camera Module:** It captures high quality images of crops.
- **IoT Sensors:** They measure environmental parameters like humidity, soil moisture and temperature.
- **AI Model:** IT processes the data of images to specify that whether there is a disease in the crops or not.
- **Farmer Dashboard:** It helps in decision making with actionable recommendations.

Hardware Methodology

Imaging and sensing devices are integrated with UAVs through hardware setup.

- **Drone Platform:** A quadcopter is selected due to its stability, cost-effectiveness, and payload capacity.
- **Imaging System:** For visual data collection, a high resolution RGB camera is mounted on the drone.
- **Onboard Computing:** A Raspberry Pi module performs local image preprocessing before cloud or offline analysis.
- **Sensors:** IoT-based soil moisture and humidity sensors provide environmental data.

This integration ensures reliable data acquisition and minimizes the need for manual inspections.

Software Methodology

The software includes image preprocessing, AI-based classification, and visiualization:

1. **Data Preprocessing:** Image resizing, noise reduction and dataset labeling.
2. **AI & Machine Learning:** Convolutional Neural Networks (CNNs) are trained on agricultural datasets to detect disease patterns and pest. Transfer learning using pre-trained models is considered to reduce training time.
3. **Decision Support System:** Classification results are presented on a farmer friendly dashboard with recommendations.
4. **Data Communication:** IoT-based data transmission to cloud servers or local PCs for further analysis.

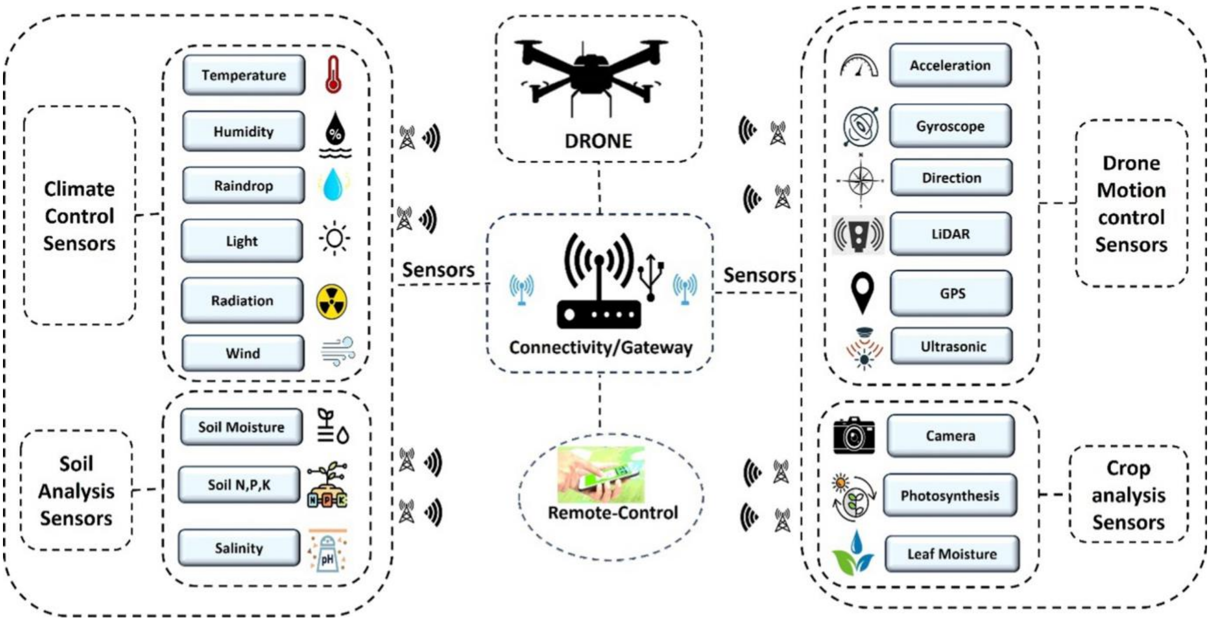

Figure 6.
Proposed Framework using numerous sensor for dataflow

Data Collection and Processing

The dataset for training and validation is obtained through:

- **Field Surveys:** UAV captured images of crops at different growth stages.
- **Open-Source Datasets:** PlantVillage and similar repositories.
- **Annotation:** Manual image labeling using tools such as LabelImg.

Images are split into training (70%), validation (20%), and testing (10%) sets to ensure robust evaluation.

Testing and Evaluation

The system is tested in controlled field environment to check performance.

Performance Metrics:

- **Accuracy:** Percentage of correctly classified images.
- **Precision and Recall:** Measures of detection reliability.
- **Processing Speed:** Time required for proper analysis.
- **Scalability:** Adaptability across different crops and field sizes.

Pilot testing includes drone flights, data capture and AI based analysis compared with ground inspections. Feedback guides refinement and deployment.

The step-by-step evaluation is summarized as follows:

1. Requirement analysis and literature review.
2. UAV and sensor selection with hardware integration.
3. AI model training and software pipeline development.
4. Data collection and preprocessing.
5. Image classification and analysis.
6. Field testing and evaluation.
7. Refinement and deployment.

The testing and evaluation phase, although, there is limited resource availability, the testing and evaluation phase is designed to measure system performance through field trials. These trials are aimed to access accuracy in disease detection, time efficiency compared to manual scouting, and ease of use from the perspective of local farmers. The research also emphasized a cost analysis, comparing the system's deployment costs with traditional pesticide spraying and manual field monitoring. Preliminary analysis suggests that such systems, even in their pilot form, can reduce chemical usage, cut monitoring costs and improve early disease detection which results in higher yields and sustainable practices.

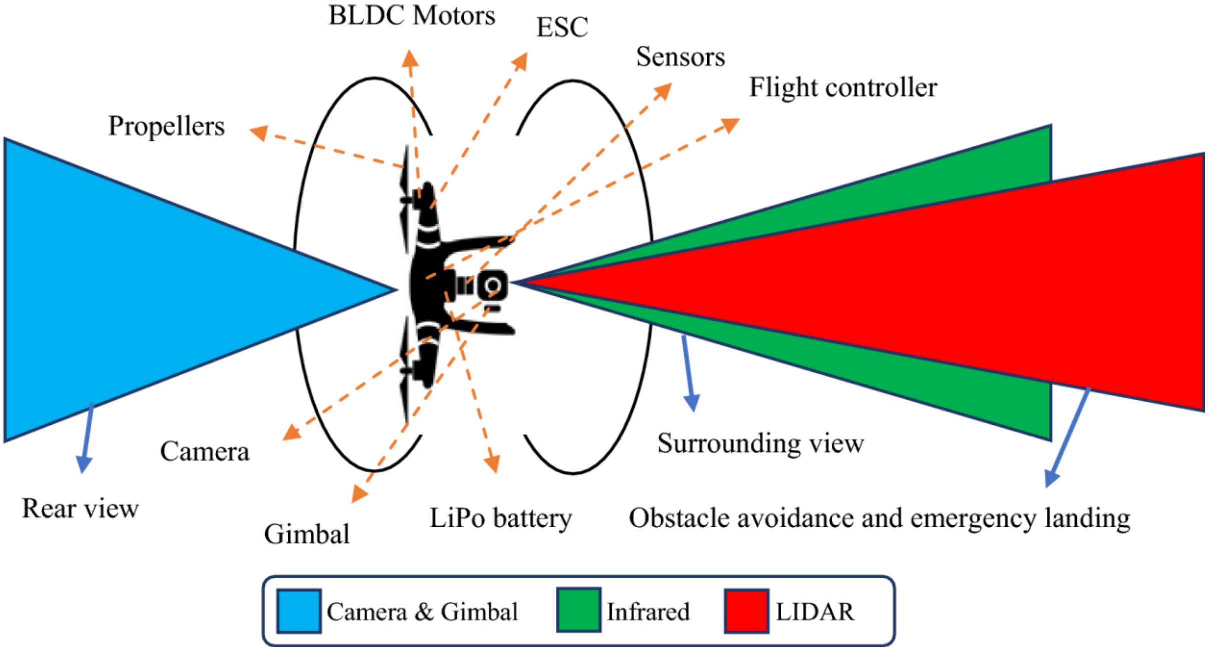

Figure 7.
Component Feature of UAV for data collection

As shown in figure 8 the comparison of accuracy critical performance measures for various algorithms. Comparative analysis on accuracy of UAV in the agricultural practises indicates the performance of several analytical and machine-learning algorithms to process aerial data to accomplish several tasks, such as monitoring crop condition, detecting weeds, predicting yields and classifying land-cover. Imagery collected by UAVs is available in either RGB, multispectral, hyperspectral, or thermal platforms, with a high level of accuracy and real-time, enabling models to be more accurate compared to many field-based approaches.

Deeps learners in particular CNN and object detectors such as YOLO and Faster R-CNN are typically higher quality in their quality since they have the ability to produce detailed spatial and spectral characteristics of aerial images automatically. Conversely, the classic machine-learning algorithms like Random Forests, SVMs and KNN rely on hand-crafted features and tend to be less accurate in applications to complex field scenarios or large data sets. The quality of accuracy also varies with the type of crop, sensor setup, height of the flight, as well as the preprocessing operations.

The studies have always indicated that the multispectral and hyperspectral UAV data is more accurate because of its capability of recording small-scale differences in the physiology of plants. On balance, comparative accuracy researches apply that deep learning and sophisticated technologies in the UAV imaging provide the most consistent performance in relation to precision agriculture, assisting more precise conclusions in crop health determination, weed, and general farm surveillance.

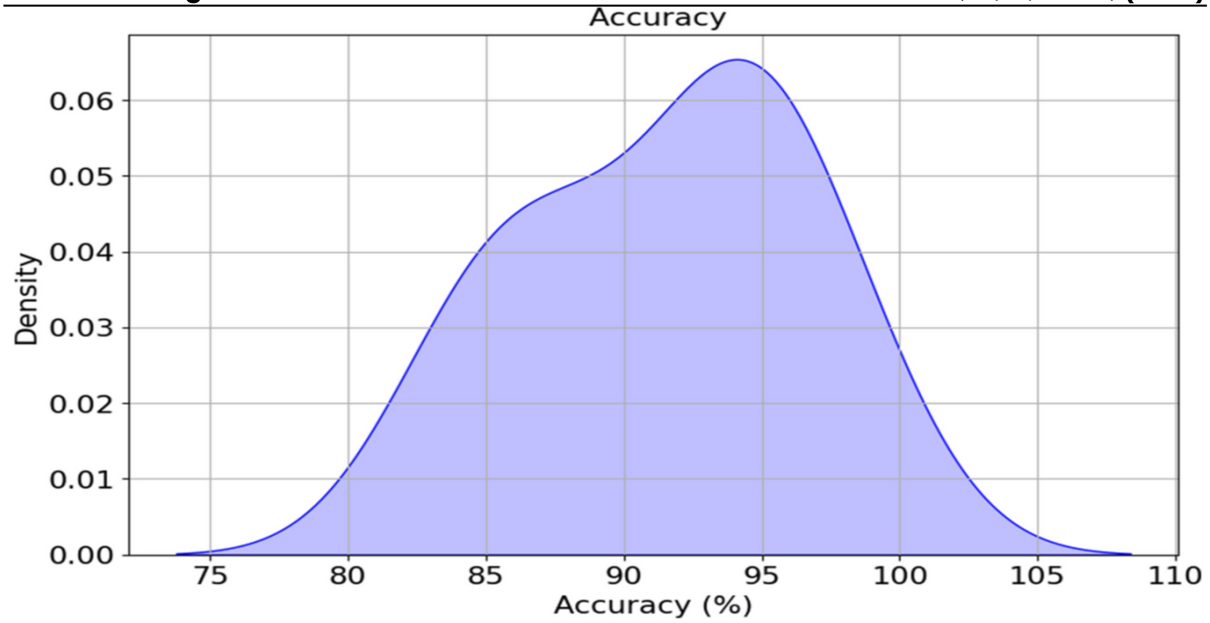

Figure 8.
Comparative analysis of Accuracy using UAV data

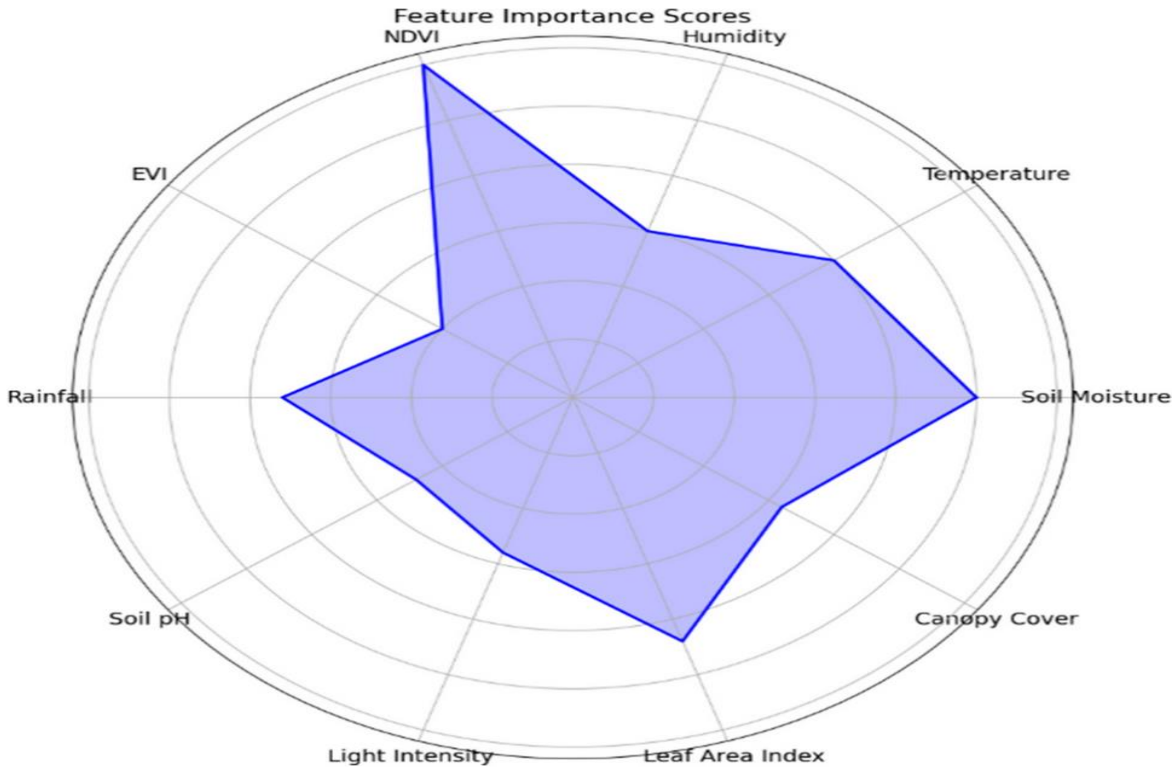

Figure 9.
Feature cover Score using UAV data

1. Affordability: Demonstrating that low-cost UAVs and RGB cameras can replace expensive multispectral setups without any loss in performance.

2. Localization: Building a custom dataset showing Pakistan's crops and environmental conditions.

3. Practical Usability: Providing a farmer dashboard that translates technical outputs into actionable insights.

4. Field Validation: Conducting pilot trials to compare system outputs against manual inspection methods.

5. Sustainability: Reducing chemical waste and supporting precision farming practices aligned with environmental goals.

6. Practical Implications and Future Work

The implications of this work extend beyond academic contribution into the realms of economic development, food security and sustainability. Economically, the system offers a potential reduction in monitoring costs for smaller scale farmers which struggle with narrow profit margins. By providing early detection of pests and diseases, the system allows farmers to act accordingly which reduces the crop loss.

Socially, the research demonstrates how advance technologies such as robotics and AI can be democratized. This fixes the inequality in technology adoption between developed and developing regions.

Environmentally, the system supports sustainable agriculture by promoting targeted pesticide application instead of widespread spraying. This reduces chemical runoff, minimizes soil and water pollution and improves long term soil health. Such benefits are important for climate change where agricultural practices must adapt to withstand environmental challenges. This research has major benefits, it also has some limitations that provide opportunities for future work. The authors also found that using the visible and infrared bands (454-742 nm) achieved the approximate same estimation results as using all hyper-spectral band (AHSB) data.

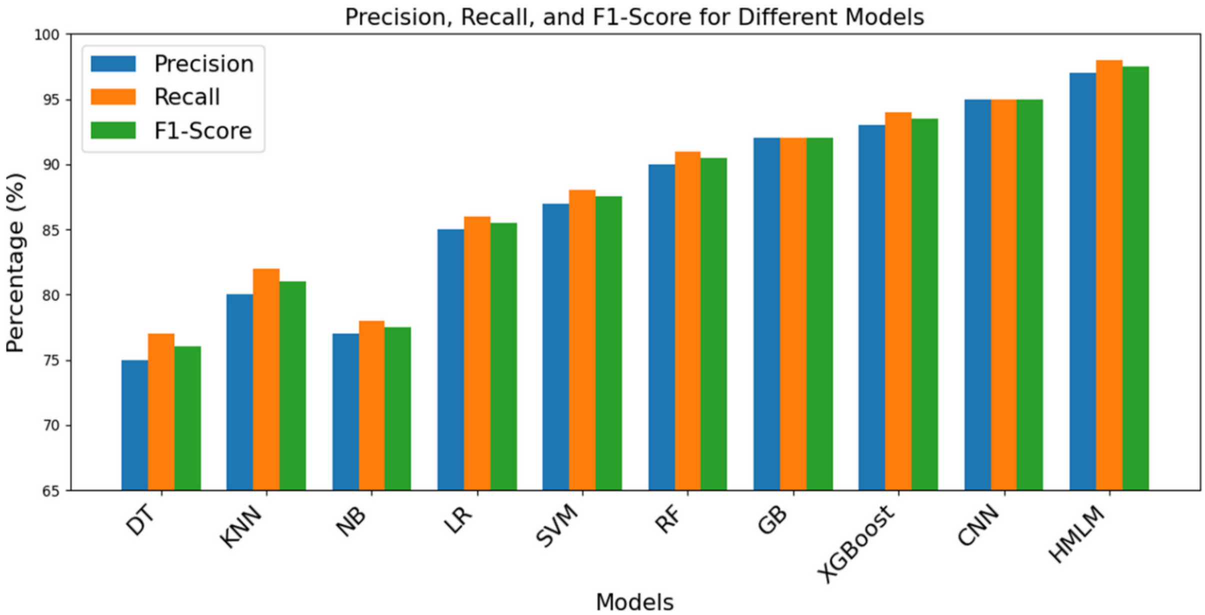

Figure 10.
Precision, recall, and F1-score for different models

As shown in figure 10 the comparison of Precision, recall and F1-score are critical performance measures for various algorithms in UAV-based agricultural, which are common to crop disease detection, weed detection, plant counts, and yield estimates. Precision is the ratio between the count of accurate positive forecasts of a model, noting the capacity to minimize false alarms, e.g. the capacity of a model to discriminate between weeds and healthy crops. Recall checks the ability of the model to detect all the real target cases, and this is critical when the disease is being detected since missing potentially infected plants may be disastrous. As precision and recall tend to be dependent, the F1-score is an amalgamation of the two into a single balanced measure, the harmonic mean, which provides a more accurate representation of model accuracy. Conventional machine-learning algorithms such as Random Forests and SVMs, which are normally applied on multispectral vegetation indices, are also effective but have a lower F1-score than deep learning models. Together, these measures can be used to evaluate the quality and strength of UAV-based systems to make correct decisions in crop monitoring, weed control, and farm management.

CONCLUSION

UAVs possess massive potential in the field of smart farming. UAVs have become primarily used in spraying activities by farmers and this was a major move towards achieving the 3.0 to 4.0 of agriculture. UAVs are applicable in numerous farm processes other than spraying, including soil testing, mapping of fields, harvesting crops and monitoring their health. With the adoption of improved sensors in the agricultural sector, farmers would be in a position to optimize their agricultural output by tracking the most important environmental conditions, which include rainfall, moisture levels, and temperature. UAVs can monitor the health condition of animals and diagnose diseases in the livestock industry. The UAVS also allows much more precise studies of the content of soil water and nitrogen. These benefits notwithstanding, implementing UAVs in larger scales in agriculture presents grave challenges. The expenses of the acquisition and maintenance of advanced hardware and software are barriers. Moreover, rural farmers often do not have the basic information regarding the use of drone technology.

There is research literature examining lots of schemes and measures to enhance the use of UAVs in agricultural automation. UAVs and IoT technologies are present in the articles, including the protocols and the functionality of the latter. Agriculture remains one of the most vital sectors for ensuring global food security, especially about increasing population demands and the challenges due to climate change. However, farming practices that are being used are often limited by inefficiencies in resource utilization, delayed identification of crop diseases and relying on heavy chemical usage that causes environmental degradation. The idea of this research is to address these issues by proposing an AI powered drone system for crop disease and pest detection, with a specific focus on affordability and applicability for small scale farmers in Pakistan.

The research methodology combined Unmanned Aerial Vehicles (UAVs), Internet of things (IoT) sensors and artificial intelligence-driven machine vision algorithms. Unlike prior studies that primarily relied on costly multispectral or hyperspectral sensors this system demonstrated that commercially available quadcopters paired with RGB cameras can still deliver reliable and accurate monitoring results when combined with advanced computer vision models. By doing so, the work successfully removes the critical affordability gap that has traditionally excluded farmers in developing nations from adopting precision agriculture technologies.

Another major contribution of this research lies in its emphasis on localization. While global datasets such as PlantVillage are widely used in academic research they often fail to show the real conditions of crops grown in Pakistan. Variations in soil quality, pest species, climate conditions and crop varieties mean that solutions built solely on international datasets are less effective in practice. To counter this limitation, this research proposed building a custom dataset through field surveys in local agricultural settings. This dataset show real world variations such as lighting inconsistencies, leaf overlaps, and dust and mixed cropping systems that are often ignored in controlled datasets. By training AI models on such data, the system increases its relevance and robustness for local farmers.

The software methodology relied heavily on Convolutional Neural Networks (CNNs). Which have become the standard for image based agricultural diagnostics. Transfer learning techniques, leveraging pretrained models such as VGG16 and ResNet, were proposed to reduce the computational load and improve training efficiency. While similar approaches exist in the literature, the novelty here lies in adapting these models for resource-constrained environments, where high performance computing hardware may not be available. The implementation of preprocessing steps, including image sizing, noise reduction and contrast enhancement which further contribute to enhancing model performance even on modest datasets.

An additional feature of this research is the development of a farmer-oriented dashboard. Most academic studies present results in the form of technical metrics such as precision, accuracy and recall (Pantazi et al., 2016). However, such outputs are not suitable for farmers who require clear and actionable recommendations. This research contains user friendly interface designed to provide simple alerts and targeted recommendations like which section of te field needs spraying. As the research focuses on usability so it reduces the knowledge gap that often prevents rural farmers from engaging with digital agricultural solutions.

Dataset Expansion and Advanced Sensors

Future work should focus on expanding the dataset to include a wide range of crops and pests or disease types. Seasonal changes and geographical difference within Pakistan should be known to improve the model's generalizability. Although, RGB cameras were sufficient for this study but using multispectral and thermal imaging could improve the accuracy of early disease detection. Finding cost-effective sensor alternatives will be necessary to maintain system affordability.

Autonomous Navigation and Edge Computing and Real-Time Analysis

Future iterations should incorporate GPS-guided autonomous drone flights to eliminate the need for manual control. Path-planning algorithms could optimize flight patterns to cover maximum field are efficiently. Deploying edge computing devices such as NVIDIA Jetson Nano can enable real-time image analysis during flight. This reduces dependency on cloud servers and allows immediate feedback to farmers. Future research should include large scale usability testing with farmers across different regions. By getting feedback from end-users, the dashboard interface and alert system can be made better to ensure practical adoption. A full precision farming ecosystem could be developed by using this drone system with IoT based soil sensors, weather stations and block-chain enabled supply chains.

Finally, collaboration with agricultural policymakers and extension services could facilitate large-scale deployment. Training programs will be critical to build farmers' confidence in using the system, ensuring that technological innovation translates into real-world impact. This research has showed that AI-powered drones can completely change agricultural monitoring when adapted to the needs of small-scale farmers. By focusing on affordability, localization, and usability, the system fixes major barriers that limit adoption in developing areas. While challenges remain in terms of dataset size, sensor accuracy, and large-scale deployment. This work provides a promising direction for future innovation. Ultimately, the research contributes not only to the academic field of precision agriculture but also to the practical mission of achieving sustainable food security in the 21st century. With continued research, testing, and refinement, AI-driven drone solutions could become a foundation of the next agricultural revolution.

DECLARATIONS

Acknowledgement: We appreciate the generous support from all the contributor to the research and their different affiliations.
Funding: No funding body in the public, private, or nonprofit sectors provided a particular grant for this research.
Availability of data and material: In the approach, the data sources for the variables are stated.
Authors' contributions: Each author participated equally in the creation of this work.
Conflicts of Interest: The authors declare no conflict of interest.
Consent to Participate: Yes
Consent for publication and Ethical approval: Because this study does not include human or animal data, ethical approval is not required for publication. All authors have given their consent.

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