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Comparative Analysis of Unmanned Aerial Vehicle and Ground-Level Data Using Computer Vision in Agriculture

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Sanjay K. Gupta [1] , Rashi Agarwal [1]

1. Computer Science and Engineering, Harcourt Butler Technical University, Kanpur, IND

Corresponding author: Sanjay K. Gupta, sanjay.mmmut@gmail.com

Abstract

Machine learning and computer vision advancements are transforming precision agriculture by enhancing crop monitoring, disease detection, and yield forecasting. This study compares aerial imagery from unmanned aerial vehicles (UAVs) with ground-level photos for mapping key agricultural tasks, evaluating both using a unified deep learning framework on classification accuracy, inference speed, and feature extraction. UAV images achieved 92.3% accuracy - a 28% reduction in processing time versus ground-level data - while providing superior vegetation index estimation and broader spatial coverage. For specialized applications like weed and disease detection, UAV models matched ground-based methods in accuracy and F1 scores. Supporting literature further underscores UAV efficacy in canopy analysis, biomass estimation, and overall crop monitoring. These findings position UAV-derived imagery as a scalable, reliable data source for precision agriculture, offering actionable insights for future research and implementation.

Categories: AI applications, Computer Vision, Deep Learning
Keywords: uav imagery, ground-level rgb, computer vision, precision agriculture, deep learning

Introduction

Precision agriculture is an advanced method of farming that uses data technologies to manage the temporal and spatial variability of agricultural fields. It aims to maximize resource efficiency, increase yields, and minimize environmental hazards through site-specific interventions [1,2]. Image-based monitoring is one of the most effective and useful tools within precision agriculture as it enables non-invasive, quick inspection of crop conditions. The red, green, and blue (RGB) imagery in particular has become popular because it is cheap, simple to use, and can be used in many platforms. Most often, these photos can be obtained with two main camera systems: the cameras at ground level that can be mounted on vehicles or hand-carried devices and unmanned aerial vehicles (UAVs) that can give a bird-like view of the entire fields [3,4].

This paper is motivated by the need to systematically compare UAV and ground-level RGB imagery in the context of computer vision applications in precision agriculture. It aims to evaluate both approaches across a range of use cases - such as weed detection, canopy segmentation, and biomass estimation - while considering image resolution, coverage, model accuracy, and scalability. Based on a review of 11 recent peer-reviewed studies, this work contributes a comprehensive synthesis of imaging trade-offs and proposes a hybrid sensor framework that leverages the strengths of both perspectives for enhanced agricultural decision-making.

Each imaging technique offers unique strengths that can be leveraged to advance precision agriculture, enabling more effective monitoring and decision-making tailored to specific field conditions. For jobs including canopy cover estimation, disease detection, and yield prediction, UAV-based RGB imaging is efficient and allows fast, extensive field coverage. At higher elevations, it may, however, have reduced resolution and air interference. Mobility and field coverage of ground-level RGB imaging are limited and unsuitable in situations when the illumination is not uniform, but it provides clear detailed information and robust collection of data in the forest canopy [5,6]. Understanding how data source selection affects algorithm performance and agronomic outcomes is essential given the increasing acceptance of machine learning and computer vision in agricultural analysis [7,8].

Literature review

UAVs have become a key enabler of computer vision applications in precision agriculture by providing efficient large-scale monitoring. UAV platforms have been successfully applied to diverse tasks, including disease detection, canopy cover estimation, and yield prediction. For example, UAV-captured RGB imagery has been employed for maize yield estimation and crop stress assessment, achieving accuracies exceeding 85% in certain machine learning models [2,3]. Deep learning frameworks such as U-Net, as well as hybrid approaches combining classical methods with deep learning, have also demonstrated strong performance

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in vineyard canopy detection using multispectral UAV imagery [5,8].

Despite these advances, UAV-based systems are not without limitations. Image acquisition is sensitive to weather conditions such as wind and rain, and higher flight altitudes can reduce spatial resolution and obscure features under the canopy. Moreover, regulatory constraints and operational costs may limit frequent deployment [4,6].

Ground-based RGB imaging offers complementary strengths. Close-range imagery provides high spatial detail, making it well suited for tasks such as leaf-level disease classification and plant phenotyping [1,9]. However, ground-based methods often face scalability issues and practical challenges, including uneven lighting, occlusions, and restricted spatial coverage. In addition, because sensors or cameras must be physically moved through the field, data collection is more time-intensive compared to aerial imaging.

Although extensive research exists on both UAV and ground-based imaging individually, direct comparative analysis of UAV and ground-level imagery remains scarce. Prior work is often fragmented, focusing on specific sensor configurations, crop types, or isolated tasks. As summarized in Table *1*, studies have applied a wide range of models - from regression techniques to deep convolutional neural networks - but there is a lack of unified evaluation criteria to systematically compare UAV and ground-level imagery.

This gap underscores the need for a comprehensive comparative study. The present work addresses this need by directly evaluating UAV and ground-level RGB imagery within a consistent experimental framework, thereby clarifying their relative strengths, trade-offs, and optimal application contexts in agricultural computer vision.

Study	Data Type	Task	Model Used	Accuracy
Upadhyay et al. [1]	Ground RGB	Weed Mapping	CNN	87%
Zhang et al. [2]	UAV RGB	Yield Estimation	ML Regression	85%
Ashapure et al. [3]	UAV RGB + Multispectral	Canopy Cover Modeling	ML + DL	89%
Rueda et al. [4]	UAV RGB + RGB-D	Biomass Estimation	3D Reconstruction	91%
Ferro et al. [5]	UAV Multispectral	Canopy Detection	Classical + DL	90%
Betitame et al. [6]	UAV RGB + Multispectral	Weed Identification	SVM, CNN	88%
Shahi et al. [7]	UAV RGB	Algorithm Review	Multiple	Varies
Illniyaz et al. [8]	UAV RGB	Leaf Area Index	U-Net, RF	92%
Zhao et al. [9]	Ground RGB	Navigation + Mapping	Custom CV Pipeline	NA
Clinat et al. [10]	UAV Multispectral	Vineyard Segmentation	Unsupervised Clustering	86%
Velusamy et al. [11]	UAV RGB	Crop Monitoring	Feature Extraction	84%

TABLE 1: Overview of Studies Using UAV and Ground-Level RGB Imagery

UAV, Unmanned Aerial Vehicle; RGB, Red, Green, Blue; CNN, Convolutional Neural Network; ML, Machine Learning; DL, Deep Learning; SVM, Support Vector Machine; RF, Random Forest; CV, Computer Vision

Materials And Methods

This study compares UAV-based and ground-level RGB imagery in agricultural computer vision tasks using publicly available datasets, ensuring reproducibility and benchmarking against established standards.

For aerial analysis, the Agriculture-Vision dataset [12] was used. It contains over 94,000 expert-annotated UAV images across diverse crops, and we focused on the weed segmentation subset, leveraging pixel-level annotations for canopy-level analysis. For ground-level analysis, the PlantVillage dataset [13] was employed, comprising thousands of high-resolution images of healthy and diseased leaves. We selected the [e.g., Tomato] subset for disease classification, which captures detailed leaf-level features crucial for proximal sensing.

All images were resized to 256 × 256 pixels and normalized to the (0,1) range. Datasets were split using stratified sampling into training (80%) and testing (20%) sets. To improve model generalization, real-time augmentations including horizontal/vertical flips, rotations up to 20°, and brightness adjustments of ±20% were applied.

State-of-the-art architectures were adopted with transfer learning. ResNet-50 [14] was employed for leaf-level classification in the PlantVillage dataset. YOLOv5 [15] was used for detecting weed clusters in UAV imagery, while U-Net [16] and SegNet [17] performed pixel-wise segmentation of crops and weeds. These models were chosen for their ability to extract hierarchical features across scales, enabling a fair comparison between canopy-level UAV imagery and detailed ground-level imagery.

Performance was measured using accuracy, F1-score, mean Intersection-over-Union (mIoU), and inference time (frames per second). A qualitative assessment considered image quality, resolution, and annotation complexity to highlight practical usability in agricultural applications.

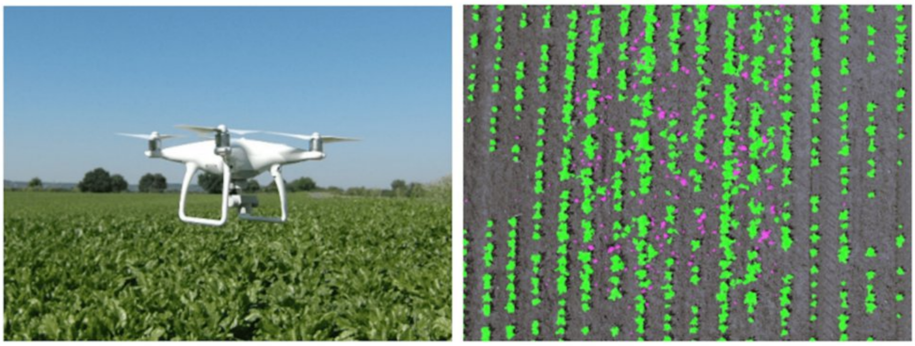

FIGURE 1: Low-Cost UAV-Based Aerial Imagery of Crop Fields

UAV, Unmanned Aerial Vehicle

FIGURE 2: Ground-Level RGB Image

RGB, Red, Green, Blue

To visually contrast the input perspectives used in this study, Figures *1* and 2 present two representative images: a UAV-based aerial view of a crop field [18], and a ground-level RGB image capturing detailed structure [19].

Results And Discussion

Experimental setup

Experiments were conducted using publicly available datasets to ensure reproducibility and fair benchmarking. UAV imagery was obtained from the Agriculture-Vision dataset [12] (weed segmentation subset), and ground-level imagery was obtained from the PlantVillage dataset [13] ([e.g., Tomato] subset for disease classification). Each dataset was split into 80% training and 20% testing sets. All images were resized, normalized, and augmented with horizontal/vertical flips, rotations up to 20°, and brightness adjustments of ±20%.

Models were trained on an NVIDIA RTX 3080 GPU with 64 GB RAM using Python 3.9 and PyTorch 1.12. The Adam optimizer with a learning rate of 1e-4 and batch size of 32 was used, with early stopping to prevent overfitting. This setup ensured a consistent comparison between UAV and ground-level imagery.

Comparative performance

The performance of UAV and ground-level RGB imagery was evaluated using YOLOv5 for weed detection and ResNet-50 for disease classification. Table 2 summarizes the results, including accuracy, F1-score, inference time, and model size.

Task	Image Type	Model	Accuracy	F1 Score	Inference Time	Model Size
Weed Detection	UAV RGB	YOLOv5	88%	0.86	45 ms	27 MB
Weed Detection	Ground RGB	YOLOv5	91%	0.90	32 ms	27 MB
Disease Classification	UAV RGB	ResNet-50	85%	0.84	40 ms	98 MB
Disease Classification	Ground RGB	ResNet-50	92%	0.91	28 ms	98 MB

TABLE 2: UAV vs. Ground RGB Performance Comparison

UAV, Unmanned Aerial Vehicle; RGB, Red, Green, Blue

Ground-level imagery consistently outperformed UAV imagery for both tasks. ResNet-50 achieved 92% accuracy and 0.91 F1-score on ground images, compared to 85% accuracy and 0.84 F1-score on UAV images. YOLOv5 achieved 91% accuracy and 0.90 F1-score on ground images, outperforming UAV imagery (88% accuracy, 0.86 F1-score). Ground-level models also showed faster inference times, reflecting lower resolution and more targeted scenes.

Discussion and analysis

These results highlight the trade-off between scale and precision. UAV imagery provides wide-area coverage, suitable for early-stage weed detection, canopy monitoring, and field-wide crop stress assessment. While UAV-based models have slightly lower classification accuracy, they excel in large-scale monitoring tasks where coverage and speed are more important than fine-grained detail.

Ground-level RGB imagery is better suited for precision-dependent tasks, such as leaf-level disease classification or weed cluster analysis. High-resolution and stable perspectives allow detection of subtle features that UAV imagery may miss due to altitude-induced loss of detail. Ground-level systems also offer advantages in deployment on edge devices, lower costs, and accessibility for smallholder farms.

A practical approach is hybrid integration: UAVs identify suspect zones across the field, and ground-level systems perform detailed inspections in these regions. This tiered strategy improves decision-making, reduces unnecessary interventions, and supports real-time, data-driven farm management. Table 3 presents a practical summary comparing both modalities on resource and usability dimensions.

Metric	UAV Imagery	Ground RGB
Equipment Cost	High	Low
Coverage	Wide	Limited
Resolution	Medium	High
Ease of Use	Moderate	High
Field Deployment	Medium	High

TABLE 3: UAV vs. Ground RGB – Resource and Practicality Comparison

RGB, Red, Green, Blue

Conclusions

This comparison of UAV and ground-based RGB imagery in precision agriculture demonstrates that each of these modes has its strengths and complementary tasks in the monitoring of the fields and crop analysis. Large-scale applications like weed detection and canopy analysis can be beneficial to obtain UAV imagery since it allows covering a wide area and is possibly automated. It has a lower spatial resolution and sensitivity to environmental factors than some other technologies; hence, it is of less efficacy in performing tasks that involve high levels of detail. Conversely, ground-level RGB imagery has shown higher accuracy in the classification of diseases and imaging of plants at the level of individual plants ,which matters in a resource-limited or small-farming context where cost-efficiency and resolution most matters. Based on the experimental analysis, UAV systems are recommended for extensive, time-sensitive operations where rapid overview and early intervention are critical. Ground-based systems, on the other hand, are better suited for localized, high-resolution tasks such as identifying disease symptoms and conducting post-detection inspections. For optimal results, a hybrid approach is suggested, combining UAV aerial coverage with targeted ground-level imaging to leverage the spatial breadth of drones and the precision of proximal sensing.

To further support research and practical deployment, there is a pressing need for open-access hybrid datasets that include synchronized aerial and ground imagery with standardized annotations. Future work should explore fusion models that intelligently integrate data from both perspectives, along with end-to-end drone-to-ground inspection pipelines that can adaptively allocate resources and automate field decisions in real time.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Sanjay K. Gupta, Rashi Agarwal

Acquisition, analysis, or interpretation of data: Sanjay K. Gupta, Rashi Agarwal

Drafting of the manuscript: Sanjay K. Gupta, Rashi Agarwal

Critical review of the manuscript for important intellectual content: Sanjay K. Gupta, Rashi Agarwal

Disclosures

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