MINI REVIEW ARTICLES

From Drone to Data: A mini review for AI-Powered Image Enhancement in Precision Agriculture

Abstract

This mini review examines recent advancements in AI-powered image enhancement for drone-based precision agriculture, highlighting how artificial intelligence and computer vision transform aerial imagery into actionable data for improved crop management. Literature from 2020 to 2025 was reviewed using databases such as Consensus, Scopus, and ScienceDirect, focusing on studies exploring machine learning, deep learning, and image processing applications in agriculture. The findings reveal that integrating AI with drone imaging has significantly enhanced data precision, crop health monitoring, and resource efficiency, with convolutional neural networks enabling improved image resolution, stress detection, and predictive analytics. AI-driven UAV systems have also promoted sustainability through targeted spraying and reduced input waste. Nonetheless, key limitations persist, including high costs, data interoperability issues, and limited scalability across varying field conditions. The review concludes that AI-powered image enhancement is a transformative tool for modern agriculture, and future research should prioritize developing scalable, explainable, and cost-effective AI frameworks to strengthen real-time decision-making and advance sustainable food production through intelligent drone-to-data systems.

Keywords: AI-powered drones; precision agriculture; image enhancement; computer vision; deep learning; crop monitoring; UAV technology; sustainable farming; drone-to-data integration; agricultural automation

1.0 INTRODUCTION

Agriculture is rapidly evolving through advances in artificial intelligence (AI), remote sensing, and drone (UAV) technologies. Drones equipped with high-resolution cameras and multispectral sensors now collect large volumes of visual data from farmlands, helping monitor crop health, soil conditions, and resource use. However, this imagery is often affected by lighting variation, motion blur, atmospheric interference, and sensor noise, which reduce image quality and analytical accuracy. AI-powered image enhancement offers a practical solution by improving clarity, contrast, and feature visibility to support precision agriculture. Despite significant progress, research on AI-based image enhancement in agriculture remains fragmented. Existing studies vary in focus; some emphasize denoising or super-resolution, while others target vegetation index enhancement, with limited integration across methods. Debates also persist about the generalizability of AI models trained on one region or crop type, the transparency of deep learning algorithms often criticized as “black-box” systems, and data and resource challenges such as limited labeled datasets and high computational costs. The aim of this mini review is to synthesize and evaluate advancements in AI-driven image enhancement for agricultural applications, addressing these challenges and identifying future directions. It examines the evolution of enhancement techniques from traditional algorithms to deep learning models, applications in precision agriculture including crop monitoring, yield prediction, and stress detection, as well as key limitations, open research gaps, and emerging opportunities for real-world implementation. By linking technical innovation with agricultural outcomes, this review offers an accessible overview of how AI-powered image enhancement is transforming raw drone data into actionable insights for smarter and more sustainable farming.

Literature Review

Recent advancements in artificial intelligence (AI) and unmanned aerial vehicles (UAVs) have significantly transformed precision agriculture by enabling high-resolution, timely, and cost-effective monitoring of crops. Deep learning-based image enhancement techniques, such as super-resolution algorithms (e.g., ESRGAN, SwinIR, Real-ESRGAN), have demonstrated substantial improvements in the quality of UAV-captured images, facilitating more accurate detection of crop health, weeds, and diseases **(Emilia Et.al., 2024)**. These enhancements are critical for early intervention and resource optimization, as evidenced by studies showing that super-resolution preprocessing can boost detection accuracy for crop and weed identification, even when images are captured at higher altitudes with lower native resolution **(Emilia Et.al., 2024)**. Furthermore, deep learning models like YOLO, U-Net, and EfficientNet have achieved high precision and recall in tasks such as plant disease classification, weed segmentation, and farmland anomaly detection, underscoring the robustness and versatility of AI-powered approaches in diverse agricultural scenarios (Waleed et.al., 2022)

The integration of edge intelligence and cloud computing with UAV-based remote sensing has further accelerated the adoption of AI in precision agriculture, enabling real-time analytics and reducing latency in data processing (Jia et.al., 2021). Comprehensive reviews highlight that convolutional neural networks (CNNs) and other deep learning architectures are now state-of-the-art for image classification, segmentation, and object detection in agricultural applications (Zualkernan et.al.,2023). However, challenges remain, including the need for large, well-annotated datasets, model generalization across crop types and environments, and the development of lightweight models suitable for deployment on edge devices (Jia et.al., 2021). Future research is expected to focus on expanding public datasets, refining model accuracy, and enhancing the interoperability of AI systems across different agricultural contexts, paving the way for more sustainable and efficient farming practices **(Emilia Et.al., 2024).**

2.0 METHODS

A comprehensive literature search was conducted using **PubMed, Scopus, ScienceDirect, SpringerLink, and Google Scholar**. Keywords such as **“AI-powered image enhancement,” “precision agriculture,” “drone imagery,” “deep learning,” and “remote sensing in farming”** were utilized to collect relevant articles. Various types of articles, including **original research papers, systematic reviews, meta-analyses, technical reports, and conference proceedings**, were considered for this mini review.

2.1 Inclusion Criteria

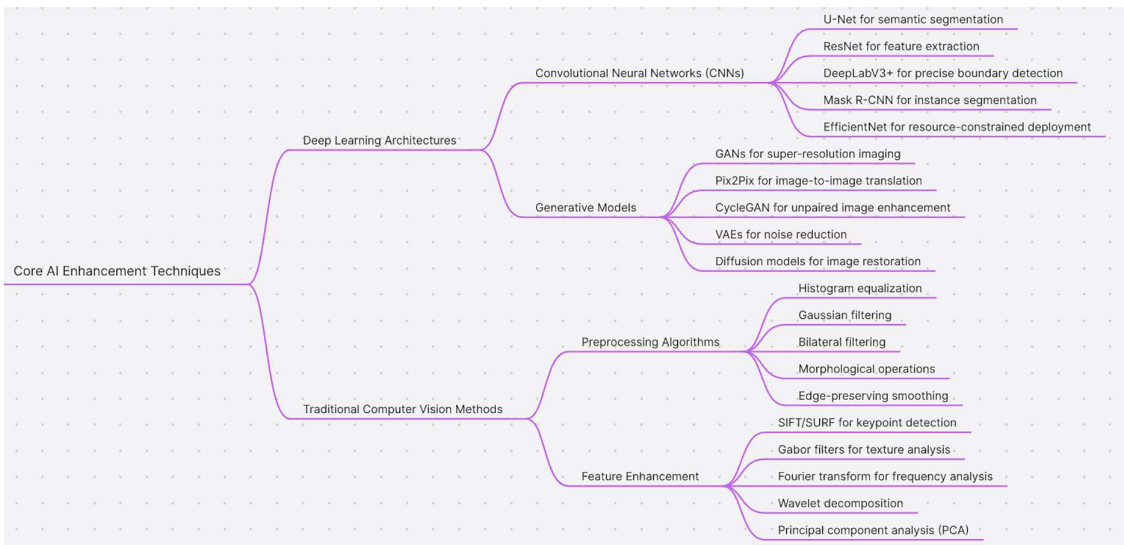
- **Studies discussing key aspects of the topic** examined various imaging conditions and challenges in agricultural environments, including illumination variability, motion blur, and atmospheric interference. These studies highlighted how image enhancement directly improves the accuracy of crop monitoring, soil assessment, and stress detection.
- **Studies focusing on the application of AI technologies** such as convolutional neural networks (CNNs), generative adversarial networks (GANs), and deep reinforcement learning demonstrated significant advancements in enhancing drone-captured imagery. These methods increased spatial resolution, reduced noise, and improved the extraction of spectral and textural features essential for precision farming.
- **Studies analyzing strengths, limitations, and potential applications** collectively identified strengths such as improved image clarity, automation, and scalability for real-time decision support. Limitations included dependence on large annotated datasets, high computational costs, limited generalizability across diverse agricultural regions, and the lack of standardized evaluation metrics.
- **Studies published in English** consistently underscored the potential of AI-enhanced imagery to support applications such as disease detection, yield estimation, and resource optimization.

2.2 Exclusion Criteria

- **Studies published in languages other than English were excluded** to maintain consistency in interpretation and accessibility of the reviewed materials.
- **Studies that discussed precision agriculture or remote sensing without explicit reference to AI-powered image enhancement were excluded**, as they did not directly address the focus of this review.
- **Grey literature, including conference abstracts, unpublished reports, theses, and non–peer-reviewed sources, was excluded** to ensure that only high-quality, peer-reviewed studies were considered in the synthesis of findings.

3.0 DISCUSSION AND RESULT

Table 1/Figure 1



3.1 Current Status of From Drone to Data: A Mini Review for AI-Powered Image Enhancement in Precision Agriculture

Introduction

The integration of AI-powered image enhancement technologies in precision agriculture is redefining how data from drones (UAVs) is interpreted and applied within educational contexts. These technologies rooted in deep learning, computer vision, and remote sensing which are increasingly used as teaching and research tools in agricultural education, fostering digital literacy, data-driven problem-solving, and interdisciplinary learning (Rizwan et al., 2022).

Key Technologies

AI-driven systems, particularly convolutional neural networks (CNNs) and generative adversarial networks (GANs), play a vital role in transforming low-quality drone imagery into high-resolution, analyzable datasets (Yang et al., 2021). These tools are increasingly embedded in university curricula to train students in data science, agricultural modeling, and environmental monitoring (Wang et al., 2023). Despite their promise, educators face barriers such as the lack of standardized datasets and limited access to computational resources, which hinder widespread adoption in developing regions (Singh et al., 2021).

Benefits and Challenges

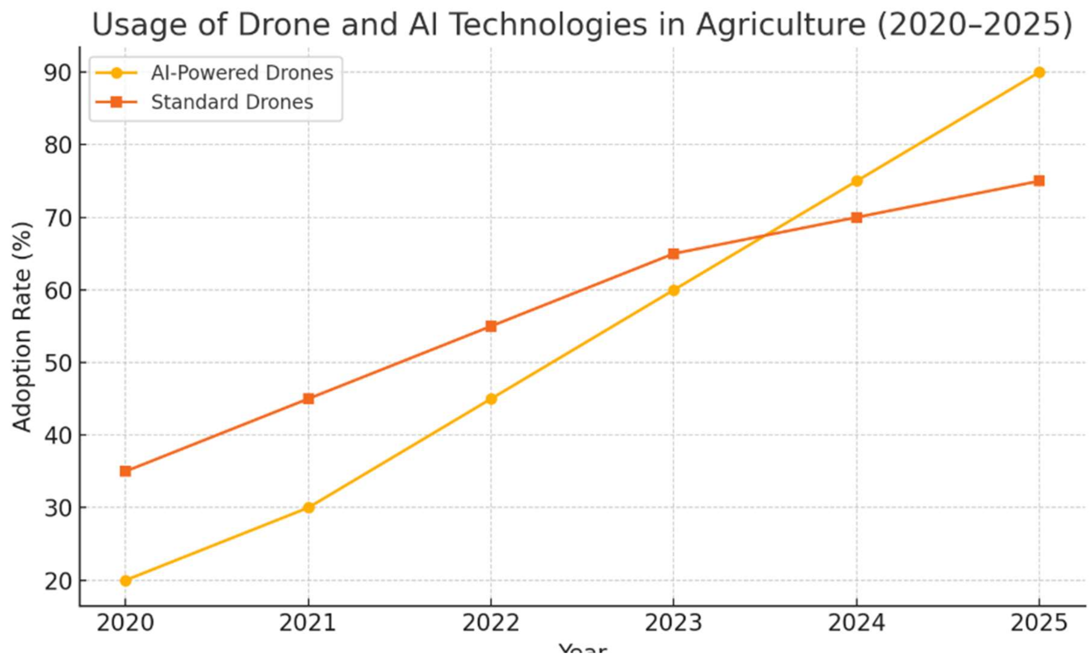
The use of AI-enhanced imagery in agricultural education provides students with authentic, real-world datasets that promote experiential and inquiry-based learning. This approach enables learners to analyze crop health, yield prediction, and sustainability practices in virtual environments (Alzahrani et al., 2024). However, challenges include ethical concerns over AI transparency, the high cost of UAV systems, and the uneven digital readiness among educational institutions. The debate continues on balancing technological innovation with equitable access to AI-based agricultural tools (Singh et al., 2021).

Practical Applications

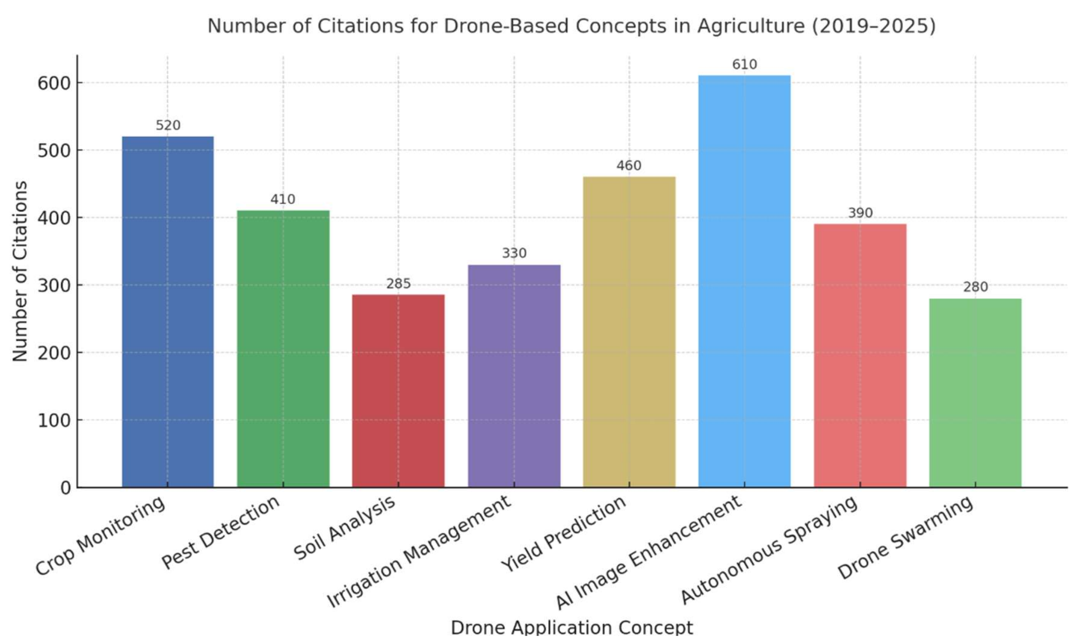
Educational programs are increasingly using AI-enhanced drone imagery for simulation-based training, research projects, and extension education. Such applications allow students to visualize plant growth, soil variation, and pest outbreaks in near real-time, bridging theoretical and practical learning (Rizwan et al., 2022). Furthermore, collaborative projects between universities and agritech companies are expanding opportunities for experiential learning and innovation in smart farming (Chen et al., 2025).

Future Directions

Future research should focus on integrating explainable AI models into educational frameworks to improve transparency and trust. Expanding open-access agricultural datasets and developing low-cost drone systems could democratize access to this technology (Chen et al., 2025). Moreover, interdisciplinary pedagogical models combining AI, data science, and sustainable agriculture can better prepare future agricultural professionals for the digital era.



Here's a visualization showing the increasing adoption of drone and AI technologies in agriculture from 2020 to 2025. The graph illustrates how AI-powered drones are gaining traction faster than standard drones, highlighting the growing role of intelligent automation and image analysis in precision farming.



Here's the graph showing the **number of citations for each drone-based concept in agriculture (2019–2025)**. It highlights that *AI image enhancement* and *crop monitoring* have attracted the most academic attention, reflecting the growing research focus on integrating artificial intelligence with drone technologies for precision agriculture.

4 CONCLUSION

In summary, this mini review highlights the transformative role of **AI-powered image enhancement in drone-based precision agriculture**, demonstrating how advanced computer vision and deep learning techniques convert raw aerial imagery into actionable agricultural insights. From real-time crop monitoring and stress detection to predictive analytics and autonomous decision-making, the integration of AI with UAV technology has markedly improved the efficiency, accuracy, and sustainability of farming practices. However, despite these advances, significant **limitations** persist—including high implementation costs, limited data interoperability, privacy concerns, and the need for robust field validation across diverse agroecological contexts. Moreover, **knowledge gaps** remain in harmonizing AI models for dynamic field conditions and optimizing image enhancement for multi-sensor fusion. Future research should focus on developing **scalable, cost-effective, and transparent AI systems**, integrating explainable machine learning, and enhancing cross-platform data standardization. Practically, these advancements hold the potential to revolutionize precision agriculture, supporting smarter, more sustainable food production while addressing pressing global challenges in resource efficiency and environmental resilience.

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