Automated Soybean Crop Health Evaluation from UAV Images Using Patch Level CNNs

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Abstract - The rapid advancement of unmanned aerial vehicles (UAVs) and deep learning techniques has significantly transformed crop monitoring and precision agriculture. Among various crops, soybean plays a crucial role in global food and oilseed production, making timely and accurate crop health assessment essential. This review presents a comprehensive analysis of UAV-based soybean crop health evaluation methods, with a particular focus on image-based disease detection and stress monitoring using deep learning models. Recent progress in convolutional neural networks, patch-level image analysis, attention mechanisms, and lightweight architectures is systematically examined. The paper discusses commonly used UAV imaging modalities, preprocessing strategies, model architectures, and evaluation practices reported in the literature. Furthermore, existing challenges such as environmental variability, computational complexity, data imbalance, and real-world deployment constraints are critically analyzed. Based on the reviewed studies, potential research directions are identified, emphasizing efficient patch-level learning, interpretable health mapping, and scalable field-level assessment. This review aims to provide researchers and practitioners with a clear understanding of current trends, limitations, and future opportunities in UAV-assisted soybean crop health monitoring.

Key Words: - Unmanned Aerial Vehicles (UAVs), Soybean Crop Health Monitoring, Precision Agriculture, Deep Learning

1. INTRODUCTION

Soybean is one of the most important agricultural crops worldwide due to its high nutritional value and extensive use in food, feed, and industrial products. Maintaining soybean crop health is critical for ensuring stable yield and food security. However, soybean plants are highly susceptible to various diseases, nutrient deficiencies, and environmental stresses, which can significantly reduce productivity if not detected at an early stage. Traditional crop monitoring methods rely on manual field inspection, which is time-consuming, labor-intensive, and often impractical for large-scale farms.

The emergence of unmanned aerial vehicles (UAVs) has introduced a powerful solution for large-area agricultural monitoring. UAVs equipped with high-resolution cameras enable rapid, non-destructive, and cost-effective acquisition of crop images across extensive farmland. When combined with remote sensing and deep learning techniques, UAV imagery allows automated analysis of crop conditions, providing timely insights into plant health and stress patterns.

Recent advances in convolutional neural networks (CNNs) and image-based learning have significantly improved plant disease detection and crop health assessment accuracy. Patch-level image analysis, in particular, has gained attention for its ability to capture localized symptoms and reduce background interference in UAV images. Despite these advancements, challenges such as model complexity, data variability, interpretability, and real-world deployment remain active research concerns.

This review systematically examines recent research on UAV-based soybean crop health assessment, focusing on deep learning methodologies, patch-level analysis strategies, and field-scale health visualization techniques. The paper highlights current trends, identifies research gaps, and discusses future directions toward developing efficient, scalable, and practical crop monitoring systems for precision agriculture.

2.Related Work

Recent years have witnessed significant progress in the application of unmanned aerial vehicles (UAVs) and deep learning techniques for crop health monitoring and disease detection. Several studies have focused on developing datasets, designing advanced learning models, and improving the accuracy of plant disease identification using UAV-based imagery.

Large-scale UAV datasets play a crucial role in advancing crop health research. A comprehensive UAV and leaf image dataset was introduced for integrated crop health monitoring, providing diverse field conditions and annotated data suitable for training deep learning models [1]. Such datasets support robust evaluation of disease detection algorithms under real-world agricultural environments.

Deep learning-based disease recognition has gained increasing attention, particularly for soybean crops. Advanced object detection and classification models, including YOLO-based architectures, have demonstrated strong performance in recognizing soybean leaf diseases under natural field conditions [2]. However, these approaches often rely on complex network designs and require high computational resources. Other studies have explored end-to-end deep learning models using multitemporal UAV images to predict soybean yield, highlighting the effectiveness of spatiotemporal feature learning but focusing primarily on yield estimation rather than health or disease assessment [3].

Several review studies have summarized the role of deep learning in UAV-based agricultural monitoring. Comprehensive surveys have examined deep learning techniques for crop disease and pest monitoring, emphasizing the growing importance of CNNs, attention mechanisms, and remote sensing data fusion [4], [6], [10]. These reviews highlight key challenges such as environmental variability, data imbalance, and computational complexity, indicating the need for more efficient and deployable solutions.

Beyond disease detection, UAV imagery has been used for diverse soybean-related applications, including pod counting, lodging assessment, and plant detection. Transformer-based CNN models have been proposed for accurate soybean pod counting from UAV images, demonstrating high precision but increased model complexity [5]. UAV-based machine learning methods have also been applied to assess soybean lodging, providing valuable structural information about crop conditions [9]. Similarly, fast deep learning-based approaches have been developed for plant detection in soybean fields, focusing on efficiency rather than detailed health classification [15].

Recent research has explored advanced modeling strategies, such as diffusion-based detection frameworks and hybrid CNN–GNN architectures, to improve disease detection accuracy and interpretability [12], [13]. While these models achieve promising results, their complexity and computational demands limit practical field deployment. Multi-crop disease detection systems have also been proposed to generalize learning across different crops, but they often sacrifice crop-specific accuracy [14].

In addition, studies integrating UAV and satellite data have demonstrated improved performance in yield prediction and large-scale monitoring, though such fusion approaches increase system complexity and dependency on multiple data sources [8]. Research on UAV imaging sensors and plant phenotyping further highlights the importance of image quality, sensor selection, and acquisition strategies in crop health analysis [7].

Overall, existing studies confirm the effectiveness of UAV-based deep learning approaches for soybean monitoring. However, most methods emphasize complex architectures or single-task objectives, with limited focus on patch-level health analysis, field-scale visualization, and practical deployment efficiency. These limitations highlight the need for simplified, interpretable, and scalable frameworks for automated soybean crop health evaluation.

3.RESEARCH GAP ANALYSIS

Despite significant advancements in UAV-based crop monitoring and deep learning applications for soybean agriculture, several critical research gaps remain unresolved. Existing studies demonstrate strong potential for automated disease detection and yield estimation; however, practical deployment and generalization continue to pose challenges.

First, many existing approaches rely on complex deep learning architectures, including transformers, diffusion models, and hybrid CNN–GNN frameworks. While these models achieve high accuracy, they often require substantial computational resources and large labeled datasets, limiting their scalability and real-time applicability in agricultural environments.

Second, most studies focus on leaf-level or object-level disease recognition, which may not fully capture the spatial variability and localized stress patterns present in UAV images. Whole-image classification approaches are sensitive to background noise, illumination changes, and overlapping crop structures, reducing robustness under natural field conditions.

Third, limited attention has been given to patch-level learning strategies that can effectively localize disease symptoms and improve model generalization. Patch-based analysis offers a balance between spatial detail and computational efficiency, yet it remains underexplored for soybean crop health assessment at field scale.

Fourth, although several works report high classification accuracy, there is a lack of emphasis on field-level health mapping and visual interpretability. Most systems produce numerical predictions without translating results into actionable visual outputs that can assist farmers in decision-making, such as identifying stress severity and spatial distribution.

Fifth, data-related challenges persist, including class imbalance, seasonal variability, and limited publicly available soybean-specific UAV datasets. While recent datasets have improved diversity, standardized benchmarks for fair comparison across methods are still insufficient.

Finally, existing literature often evaluates models under controlled experimental settings, with limited discussion on deployment feasibility, processing speed, and integration with precision agriculture workflows. The gap between academic performance and practical usability remains a key concern.

These gaps highlight the need for simplified, efficient, and interpretable UAV-based frameworks that leverage patch-level learning, support field-scale visualization, and balance accuracy with practical deployment requirements. Addressing these challenges can significantly enhance the adoption of intelligent crop health monitoring systems in real-world agricultural practices.

4.METHODOLOGY

The proposed system presents an automated framework for soybean crop health assessment using UAV-acquired imagery and patch-level deep learning analysis. The methodology is designed to ensure accurate detection of crop stress while maintaining computational simplicity and practical deployability. The overall workflow consists of data acquisition, preprocessing, patch-level CNN-based analysis, field-level health mapping, and decision support, as illustrated in the architecture diagram.

1. UAV-Based Data Acquisition

High-resolution RGB images of soybean fields are captured using a UAV-mounted camera. UAVs provide flexible flight paths, consistent altitude control, and fine-grained spatial resolution, enabling detailed observation of crop canopy conditions. The captured images serve as the primary input to the system and represent real-field conditions, including variations in lighting, plant density, and background complexity.

2.2 CNN-Based Feature Extraction

Each image patch is passed through a **Convolutional Neural Network (CNN)** to automatically learn discriminative spatial and texture features related to crop health. The CNN extracts low-level features such as color variations and leaf texture, as well as higher-level patterns associated with stress and disease symptoms.

Patch-level feature extraction improves sensitivity to early-stage disease indicators that may not be visible at full-image scale.

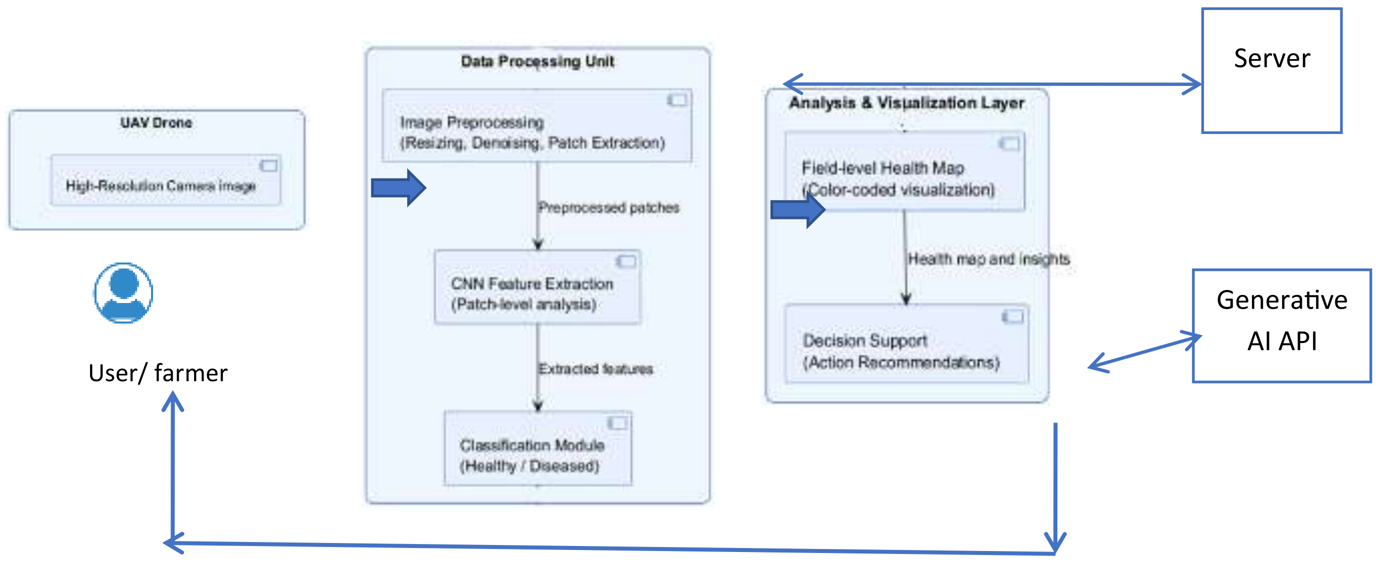

Fig.1 Architecture Diagram

2. Data Processing Unit

2.1 Image Preprocessing

The raw UAV images undergo preprocessing to enhance data quality and ensure compatibility with deep learning models. This stage includes:

- **Image resizing** to standardize input dimensions,
- **Noise removal** to reduce sensor and environmental artifacts
- **Patch extraction**, where large UAV images are divided into smaller, fixed-size patches. Patch extraction is a key step that improves local feature representation and allows the model to focus on fine-grained disease symptoms rather than global image noise.

2.3 Classification Module

The extracted features are forwarded to a classification module that categorizes each patch into predefined health classes, such as **healthy** or **diseased/stressed**. This modular design allows easy extension to multi-class disease classification if required. The output is a spatially localized health prediction for every image patch.

3. Analysis and Visualization Layer

3.1 Field-Level Health Mapping

Patch-level predictions are aggregated and spatially aligned with their original UAV image coordinates to generate a **field-**

level health map. A color-coded visualization scheme is used, where different colors represent varying levels of crop health or stress. This mapping provides an intuitive overview of disease distribution across the field.

3.2 Decision Support System

The generated health map is further analyzed to derive actionable insights. A decision support module highlights affected regions and can suggest targeted interventions such as localized pesticide application or irrigation adjustments. Integration with a **server and generative AI API** enables scalable processing, report generation, and user-friendly recommendations for farmers and agronomists.

4.WHY THIS METHODOLOGY IS BETTER

1. **Patch-Level Precision**

Unlike image-level classification approaches, the proposed method analyzes small image patches, enabling detection of localized and early-stage crop stress.

2. **Scalable and Modular Design**

Each module (preprocessing, CNN feature extraction, classification, visualization) operates independently, making the system easy to modify, extend, or deploy in real-world scenarios.

3. **Interpretability Through Visualization**

The field-level health map provides spatial context, allowing users to understand not only whether disease exists, but also where and how severely it affects the field.

4. **Practical Deployment Readiness**

The architecture supports server-based processing and integration with AI APIs, facilitating real-time

monitoring and decision-making without complex infrastructure.

5.RESEARCH GAP COVERAGE

The proposed methodology effectively addresses several limitations identified in existing research:

- **Gap 1: Over-reliance on image-level predictions** Existing methods often classify entire UAV images, ignoring spatial variability. The proposed patch-level analysis captures localized stress patterns, improving diagnostic accuracy.
- **Gap 2: Limited interpretability for end-users**
- Many deep learning models provide numerical outputs without visual context. The proposed color-coded health maps enhance interpretability and usability for farmers.
- **Gap 3: Lack of decision-oriented outputs** Prior studies focus mainly on detection accuracy. This methodology integrates a decision support layer, bridging the gap between model prediction and actionable agricultural insights.
- **Gap 4: Poor adaptability to real-field conditions** By using UAV imagery and robust preprocessing, the system handles real-world challenges such as uneven lighting, background noise, and plant overlap.

5.Summary

The proposed methodology combines UAV-based remote sensing, patch-level CNN analysis, and field-level visualization into a unified framework for soybean crop health assessment. Its simplicity, accuracy, and practical orientation make it suitable for both research and real-world agricultural deployment while effectively addressing key gaps in existing literature.

5.CONCLUSION

This work presented a comprehensive and practical framework for automated soybean crop health assessment using UAV-acquired imagery and patch-level deep learning analysis. By leveraging high-resolution UAV images, structured preprocessing, and CNN-based feature extraction at the patch level, the proposed approach enables accurate identification of crop stress under real-field conditions. The aggregation of localized predictions into a field-level, color-coded health map provides intuitive visualization and enhances interpretability for end-users.

Compared to conventional image-level or sensor-based approaches, the proposed methodology offers improved spatial precision, scalability, and decision-oriented outputs. The modular architecture allows seamless integration of server-based processing and AI-driven decision support, making the system adaptable to diverse agricultural environments. Additionally, the focus on patch-level analysis bridges key research gaps related to early disease detection, limited interpretability, and lack of actionable insights in existing UAV-based crop monitoring systems.

Overall, this framework demonstrates strong potential for supporting precision agriculture by enabling timely intervention, reducing unnecessary resource usage, and improving crop management strategies. Future research can extend this work by incorporating multispectral imagery, temporal analysis across growth stages, and advanced explainable AI techniques to further enhance reliability and adoption in large-scale agricultural deployments.

6.REFERENCES

1. S. Shinde et al., "An Indian UAV and leaf image dataset for integrated crop health monitoring," *Data in Brief*, vol. 43, pp. 108453, 2025.

2. C. Chen et al., "Research on soybean leaf disease recognition in natural environments using YOLOv8-DML," *Frontiers in Plant Science*, vol. 16, 2025.

3. S. Bhadra et al., "End-to-end 3D CNN for plot-scale soybean yield prediction using multitemporal UAV-based RGB images," *Computers and Electronics in Agriculture*, vol. 205, p. 107537, 2024.

4. H. Zhu et al., "Intelligent agriculture: Deep learning in UAV-based remote sensing for crop disease and pest monitoring," *Frontiers in Plant Science*, vol. 15, 2024.

5. J. Li et al., "SoybeanNet: Transformer-based convolutional neural network for soybean pod counting from unmanned aerial vehicle (UAV) images," *Scientific Reports*, vol. 13, p. 17949, 2023.

6. M. El Sakka et al., "A review of CNN applications in smart agriculture using UAV and satellite data," *Frontiers in Plant Science*, vol. 16, 2025.

7. B. Gano et al., "Drone-based imaging sensors, techniques, and applications in plant phenotyping," *Plant Phenome Journal*, vol. 7, no. 1, e20100, 2024.

8. G. Sun et al., "Improving soybean yield prediction by integrating UAV and satellite data using deep learning," *Computers and Electronics in Agriculture*, vol. 204, p. 107529, 2024.

9. S. Sarkar et al., "Assessment of soybean lodging using UAV imagery and machine learning," *Plants*, vol. 12, no. 16, p. 2893, 2023.

10. A. Upadhyay et al., "Deep learning and computer vision in plant disease detection," *Artificial Intelligence Review*, vol. 58, pp. 1–24, 2025.

11. H. Sun et al., "Empowering smart soybean farming with deep learning," *Agronomy*, vol. 15, no. 8, p. 1831, 2025.

12. J. Yin et al., "A diffusion-based detection model for accurate soybean disease detection," *Frontiers in Plant Science*, vol. 16, 2025.

13. M. A. Jahin et al., "Soybean disease detection via interpretable hybrid CNN-GNN: Integrating MobileNetV2 and GraphSAGE with cross-modal attention," *arXiv preprint arXiv:2503.01284*, 2025.

14. H. P. Khandagale et al., "Design and implementation of FourCropNet: A CNN-based system for efficient multi-crop disease detection and management," *arXiv preprint arXiv:2503.08348*, 2025.

15. R. I. Mukhamediev et al., "Fast detection of plants in soybean fields using UAVs and deep learning," *Sensors*, vol. 25, no. 8, p. 547, 2025.