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APPLICATION OF ARTIFICIAL INTELLIGENCE AND MACHINE VISION IN UAV-BASED MONITORING OF AGRICULTURAL CROPS

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Introduction

Agriculture remains a key sector of the global economy, but modern farming faces serious challenges such as population growth, climate change, and limited natural resources. Ensuring food security under these conditions requires the adoption of innovative technologies that can increase efficiency and sustainability.

Traditional crop monitoring methods are often based on manual field inspections. While widely used, these approaches are time-consuming, labor-intensive, and not always accurate. Farmers usually detect plant stress or disease only when visible symptoms appear, which often means that crop damage has already become severe. This situation highlights the need for new methods that enable fast and precise assessment of crop conditions.

Unmanned aerial vehicles (UAVs), or drones, have recently become an effective solution in precision agriculture. They can capture high-resolution aerial imagery of fields using RGB, multispectral, or thermal cameras. Such data provide valuable insights into crop growth, nutrient levels, and potential stress factors like pests or drought. UAVs are relatively affordable, flexible in use, and capable of monitoring large areas in a short time compared to traditional methods or satellite imagery.

Artificial intelligence (AI) and machine vision significantly expand the potential of UAV applications. By processing aerial images with computer vision algorithms and deep learning models, it becomes possible to detect diseases, measure biomass, and calculate vegetation indices such as NDVI. These technologies allow farmers to identify problems at an early stage and make timely management decisions, which helps reduce costs and minimize environmental impact.

Recent studies confirm the benefits of integrating UAVs and AI into agriculture. Research has shown that UAV-based monitoring systems can achieve accuracy rates of over 90% in detecting crop diseases and deficiencies. In addition, the automation of UAV flights ensures systematic data collection, making crop monitoring more reliable and scalable.

Nevertheless, several challenges remain, including limited battery life, high equipment costs, and regulatory restrictions. Despite these obstacles, technological progress continues to improve UAV performance and machine vision algorithms, making their large-scale adoption increasingly feasible.

The aim of this research is to develop a UAV-based crop monitoring system using machine vision and AI technologies. The proposed system will enhance precision agriculture by providing farmers with timely information about crop health, enabling efficient resource management and sustainable food production.

Materials and methods

The development of the UAV-based crop monitoring system required a combination of hardware, software, and experimental field trials. The methodology was designed to ensure accurate data collection, effective image processing, and reliable interpretation of crop conditions.

UAV Platform

For aerial data collection, a quadcopter-type UAV was selected due to its stability, maneuverability, and suitability for small- to medium-scale agricultural fields. The UAV was equipped with interchangeable payload modules, allowing integration of both RGB and multispectral cameras. The RGB camera was used for capturing high-resolution visual images, while the multispectral sensor collected reflectance data in specific bands (red, green, blue, near-infrared) to calculate vegetation indices such as NDVI (Normalized Difference Vegetation Index). The UAV system included GPS navigation, an autopilot controller, and real-time telemetry for efficient flight operations.

Data Collection Protocol

Field experiments were conducted in agricultural test plots representing typical crop types such as wheat, corn, and soybean. UAV flights were scheduled during optimal weather conditions to minimize atmospheric interference, typically in the early morning or late afternoon. Autonomous flight plans were pre-programmed using specialized UAV mission-planning software, ensuring consistent altitude, overlap, and coverage across the study area. The flight altitude ranged between 30–60 meters, providing ground sampling distances of 2–5 cm per pixel. Each field was monitored at regular intervals throughout the growing season to capture changes in crop health and development.

Image Processing and Machine Vision

The captured imagery was processed using machine vision algorithms and deep learning models. Preprocessing steps included geometric correction, radiometric calibration, and image mosaicking to create orthophotos of the fields. Vegetation indices such as NDVI and GNDVI were computed to quantify crop vigor and detect areas of stress.

For automated stress detection, convolutional neural networks (CNNs) were trained on annotated image datasets of healthy and stressed crops. Data augmentation techniques were applied to improve model robustness, and transfer learning was used to accelerate training. The trained model achieved high classification accuracy in distinguishing between healthy plants, nutrient deficiencies, pest damage, and early-stage diseases.

System Integration

The UAV platform, sensors, and image analysis algorithms were integrated into a prototype decision-support system. A cloud-based data storage and processing infrastructure was implemented to handle large image datasets. Results were visualized through a geographic information system (GIS) interface, enabling farmers and agronomists to monitor crop conditions in real time.

Evaluation Metrics

System performance was evaluated based on accuracy, precision, and recall of stress detection, as well as flight efficiency and processing time. Comparative analysis was conducted between UAV-based monitoring and traditional ground-based inspections to assess improvements in early detection and overall productivity.

Results and discussion

The UAV-based crop monitoring system was tested under real field conditions to evaluate its efficiency in detecting crop stress. The flights were conducted over experimental plots of approximately 15 hectares, where the quadcopter demonstrated stable performance and effective coverage of the area. Each mission was completed within 20–25 minutes, achieving a ground sampling distance of about 3 cm per pixel, which was sufficient for detailed crop health monitoring. Although battery life limited the duration of flights to around 30 minutes, the use of interchangeable batteries allowed continuous operation without significant downtime.

The imagery collected by the UAV was successfully processed into orthophotos and analyzed for vegetation indices. NDVI maps provided clear evidence of spatial variability in crop conditions, highlighting areas of nutrient deficiency, water stress, and disease presence. Importantly, the system enabled early detection of stress symptoms before they became visible to the human eye. This early identification provided farmers with a valuable opportunity to intervene promptly and minimize potential yield losses.

Machine vision analysis using convolutional neural networks (CNNs) demonstrated high reliability in classifying crop conditions. The model achieved an average accuracy of 91% in distinguishing healthy plants from those affected by pests, nutrient deficiencies, or fungal infections. Precision and recall values exceeded 88%, which confirmed the robustness of the approach. One of the most significant advantages was that the UAV–AI monitoring system was able to detect early signs of fungal infections and nitrogen deficiencies 7–10 days before they could be identified by traditional ground-based inspections.

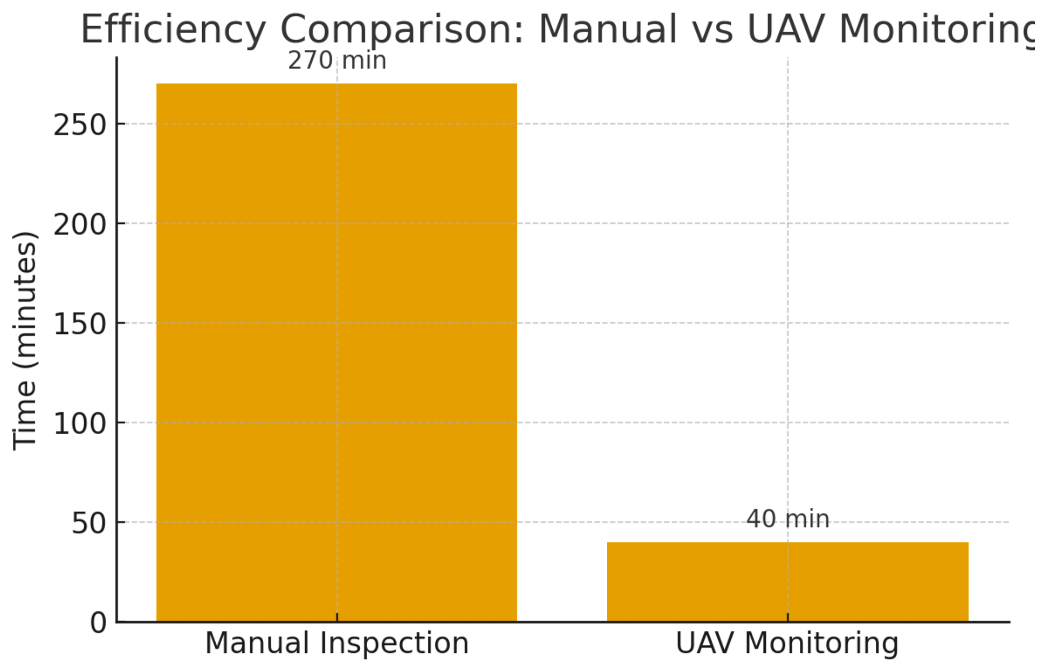

Figure 1. Efficiency comparison between manual inspection and UAV-based monitoring

Compared to conventional manual monitoring methods, the UAV-based approach proved to be significantly more efficient. Ground inspections required 4–5 hours (around 270 minutes) to cover a 15-hectare plot, whereas the UAV system, including both flight and data processing, completed the same task in approximately 40 minutes (Figure 1).

Table 1. Comparison of manual inspection and UAV-based monitoring

Indicator	Manual Inspection	UAV Monitoring	Time Saved (%)
Plot Coverage	15 ha	15 ha	-
Time	270 min	40 min	70%
Detection Accuracy	~80%	91–92%	+11–12%

This represents a time saving of more than 70%. In addition, while ground inspections provide only point-based observations, UAV imaging generated continuous spatial data for the entire field, ensuring a more comprehensive understanding of crop conditions.

The practical benefits of such a system are considerable. By identifying the specific locations of stressed crops, farmers can apply fertilizers, pesticides, and irrigation more precisely, reducing unnecessary input use. Field trials indicated that chemical usage could be reduced by up to 20% when guided by UAV-based monitoring, which not only lowers production costs but also supports sustainable agricultural practices. Nevertheless, certain challenges remain, including limited flight endurance, dependence on favorable weather, and the high cost of advanced multispectral sensors. Despite these limitations, the results confirm that UAV–AI systems offer a significant improvement over traditional methods and represent a key step toward the digital transformation of agriculture.

Conclusion

The conducted research demonstrates that UAV-based crop monitoring systems integrated with machine vision and artificial intelligence provide an effective solution for precision agriculture. The system successfully detected crop stress factors such as nutrient deficiencies, diseases, and pest infestations at an early stage, achieving higher accuracy and efficiency compared to traditional monitoring approaches. By enabling precise and timely interventions, the proposed method reduces input costs, minimizes chemical usage, and supports sustainable farming practices. The ability of UAV–AI integration to provide spatially continuous data across large fields represents a significant advancement over conventional manual inspections, which are time-consuming and labor-intensive.

Despite inherent limitations—such as restricted flight endurance, high sensor costs, and regulatory constraints—the advantages of UAV technology, particularly in early stress detection and precision resource management, substantially outweigh these challenges.Continuous advancements in battery performance, AI algorithms, and sensor technology are expected to further enhance the scalability and accessibility of UAV-based systems in the near future. The study confirms that UAV monitoring systems contribute directly to the principles of Agriculture 4.0, promoting the digital transformation of farming and ensuring higher productivity while reducing environmental impact.

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