

Intelligent Information Systems for Agriculture Based on Vision Technology

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1. Introduction

The traditional approach to agriculture is changing due to rapid advances in technologies such as unmanned aerial vehicles (UAVs), proximal and remote sensors, and the Internet of Things (IoT) [1]. These technologies enable high-resolution, real-time acquisition of spatial and temporal information, facilitating intelligent decision support for key agricultural operations, including irrigation scheduling, crop growth monitoring, disease and pest detection, and nutrient management [2]. However, the large-scale deployment of intelligent agricultural systems remains challenging in real-world field environments because agricultural scenes are inherently complex and dynamic, characterised by variable illumination, occlusion, background clutter, and environmental uncertainty [3]. These factors significantly affect the robustness and generalisation capability of vision-based models, limiting their practical applicability [4]. Consequently, there is a critical need for intelligent information systems that integrate computer vision, machine learning, and domain-specific agronomic knowledge to deliver reliable and scalable solutions for smart agriculture [5].

Given this context, this Special Issue has collected the latest contributions at the intersection of intelligent information systems [6], sensors [7], and vision technologies [8]. The published works highlight the interdisciplinary integration of agronomy, computer vision, machine learning, remote sensing, and sensor technologies. Together, they demonstrate how intelligent vision-based approaches can enhance crop health monitoring, pest and disease management, nutrient assessment, and fruit quality evaluation.

It should be noted that the purpose of this Editorial is not to provide an exhaustive analysis of the individual articles, but rather to highlight the research contributions within this Special Issue. Readers are encouraged to refer to the individual articles to gain a deeper understanding of the methodologies, results, and implications discussed therein.



Received: 21 December 2025

Revised: 3 February 2026

Accepted: 4 February 2026

Published: 6 February 2026

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2. An Overview of Contributions

The contributions in this Special Issue mainly centre around four main themes: (a) crop disease detection and severity assessment, (b) pest monitoring and detection, (c) fruit detection and maturity assessments, and (d) crop growth and nutrient management. In addition to original research articles, this issue also includes review papers that discuss the recent advances in intelligent systems for agricultural AI.

2.1. Crop Disease Detection and Severity Assessment

Crop disease detection and severity assessment with AI and computer vision technologies have been progressing well in recent times [9,10]. Several studies published in this Special Issue applied machine learning (ML) and deep learning (DL) methods with various kinds of sensor data, such as RGB and hyperspectral sensors, for crop disease detection and severity estimation.

Research Paper 4 (refer to Section 3) by Zheng et al. is focused on pepper blight disease detection under natural complex conditions. They introduce an enhanced YOLO-based object detection model for detecting multi-site pepper blight disease using chilli plant images. The MSPB-YOLO model enables the robust detection of small, dispersed, and early-stage pepper blight infection. Next, a DL-based method for multi-class rice disease detection using plant images is proposed by Li et al. (Paper 13), where they utilise a pre-trained DL model and transfer learning to achieve a high classification accuracy of 96.8 % for 12 classes of rice diseases. The third article on crop disease severity assessment, by Li et al. (Paper 2), introduces HSDT-TabNet, a dual-path DL architecture designed for grading the severity of frog-eye leaf spot (FLS) on soybean. By integrating spatial feature extraction with structured tabular information, the proposed approach enhances disease quantification and provides a more interpretable framework for monitoring disease progression in field conditions. Another paper published on severity assessment is by Ning et al. (Paper 5), employing hyperspectral imaging to achieve early detection and dynamic severity grading of sweet potato scab. By leveraging spectral information beyond the visible range, the study highlights the capability of hyperspectral vision systems to detect subtle physiological changes before visual symptoms become apparent, offering significant advantages for early intervention.

We observe that this Special Issue reveals the growing robustness and maturity of DL-based methods for early crop disease detection and severity assessment under complex natural field conditions.

2.2. Pest Monitoring and Detection

Crops are always threatened by various stressors and pests [11]. Real-time inspection of crops to identify and track pest populations helps farmers make informed decisions about control actions and minimise unnecessary pesticide use. Two papers (Papers 6 and 14) on pest detection are published in this Special Issue. A machine vision system combined with sticky traps and cross-domain transfer learning for small pest detection in tea plantations is proposed by Li et al. (Paper 6). The suggested approach addresses the issue of limited labelled data and demonstrates improved generalisation across pest species and environmental conditions, making it suitable for long-term field deployment. Another paper on insect pest detection is by Qin et al. (Paper 14), where a YOLO-based lightweight and efficient detection model (SP-YOLO) is proposed for identifying insect pests on soybean leaves. By enhancing feature extraction and reducing memory requirements, the method improves detection accuracy under natural lighting and cluttered backgrounds. This study highlights the feasibility of deploying vision-based pest monitoring systems in complex agricultural environments [12–14].

We note that this Special Issue highlights the effectiveness of machine vision systems based on lightweight DL and transfer learning strategies for accurate pest identification under natural field environments.

2.3. Fruit Detection and Maturity Assessment

Real-time monitoring and precise management of crop growth have become the pivotal determinants for enhancing crop productivity and efficiency [15]. Computer vi-

sion techniques, particularly the YOLO framework, which is known for real-time object detection [16], have been investigated for real-time deployment in agricultural settings for crop and fruit detection [17] and maturity assessment [18]. The articles on fruit detection using the YOLO framework [19] published in this Special Issue advance model accuracy and the computational efficiency of the framework in a real-time orchard environment. In this Special Issue, Paper 7 (by Ma and Zhang) proposes a lightweight model based on the YOLO framework that integrates convolutional and attention-based mechanisms for chilli pepper maturity detection. The model achieves a balance between accuracy and computational efficiency, supporting real-time applications in field harvesting scenarios. Another work on nectarine identification by Zhang et al. (Paper 9) develops YOLOv8n-CSD, a compact detection framework for complex orchard environments. The study emphasises model efficiency, making it suitable for deployment on resource-constrained platforms such as agricultural robots and edge devices. The assessment of soluble sugar content in tomatoes using Fourier-transform infrared spectroscopy combined with chemometric analysis is proposed by Lv et al. (Paper 10). Their results demonstrate that ATR-FTIR coupled with chemometrics is effective for non-destructive determination of soluble sugars in tomatoes and can effectively assess internal quality attributes, providing a valuable tool for quality control and grading [20]. Liu et al. (Paper 12) propose another variant of the YOLO model for guava detection in a complex orchard environment under varying illumination and occlusion conditions. The method demonstrates improved detection performance while maintaining low computational complexity, contributing to intelligent orchard management systems.

It is noted that the contributions in this Special Issue demonstrate the effectiveness of the YOLO framework and its variants for fruit detection, highlighting their suitability for deployment on resource-constrained devices and their potential to support real-time orchard monitoring.

2.4. Crop Growth and Nutrient Management

Vision-based approaches are increasingly applied to assess crop growth and nutrient status [21]. Since weeds compete with crops for nutrients, water, and sunlight, they hinder crop growth, and hence their early management is essential [22]. In this Special Issue, the article by Shuai et al. (Paper 1) proposes a computer vision approach based on the YOLO framework for soybean weed detection, providing a low-power, high-precision solution suitable for deployment on intelligent weeding robots [23]. A Maize Straw Plot Classification using a DL-based segmentation network with UAV images is introduced by Liu et al. (Paper 3). Paper 8 by Lu et al. proposes SC-ResNeXt, a deep learning regression model for predicting leaf nitrogen content in sugarcane using image data. The study demonstrates that visual features can serve as reliable indicators of nutrient status, offering a non-invasive alternative to traditional chemical analysis. Next, Paper 11 by Ye et al. utilises UAV-based RGB imagery to monitor potato growth dynamics under different nitrogen treatments. By correlating image-derived features with agronomic parameters, the study highlights the potential of UAV vision platforms for supporting precision nutrient management and field-scale decision-making.

2.5. Review Articles

Besides original research articles, this Special Issue includes three review articles that provide broader insights into the recent advances in vision-based agricultural intelligence. The first review article (Paper 15) by Chaudhary et al. systematically explores the existing work on mango quality and quantity assessment using hyperspectral and near-infrared imaging techniques. It summarises and synthesises the key methodologies, performance

metrics, and existing challenges. The review offers valuable guidance for future research and practical adoption of spectral vision technologies in fruit quality evaluation. Another review article (Paper 16) by Neupane et al. synthesises the work on nematode detection using ML and DL techniques. The third review article (Paper 17) by Yang et al. discusses the role of AI in crop pest management, highlighting how intelligent information systems can enhance decision-making efficiency and sustainability. The review emphasises the 4Rs (Right Source, Right Rate, Right Time, and Right Place) in crop pest management using AI.

3. List of Contributions

Forty manuscripts were submitted for consideration to this Special Issue, and all of them were subject to a rigorous peer review process as set by the *Agronomy* journal. Among the submissions, seventeen papers, including fourteen research articles and three review articles, were finally accepted for publication and inclusion. The contributions are listed below:

1. Shuai, Y.; Shi, J.; Li, Y.; Zhou, S.; Zhang, L.; Mu, J. YOLO-SW: A Real-Time Weed Detection Model for Soybean Fields Using Swin Transformer and RT-DETR. *Agronomy* **2025**, *15*, 1712.
2. Li, X.; Zhou, Y.; Li, Y.; Wang, S.; Bian, W.; Sun, H. HSDT-TabNet: A Dual-Path Deep Learning Model for Severity Grading of Soybean Frogeye Leaf Spot. *Agronomy* **2025**, *15*, 1530.
3. Liu, Y.; Zhang, J.; Wang, Y.; Luo, Y.; Sui, P.; Ren, Y.; Liu, X.; Wang, J. GCF-DeepLabv3+: An Improved Segmentation Network for Maize Straw Plot Classification. *Agronomy* **2025**, *15*, 1011.
4. Zheng, X.; Shao, Z.; Chen, Y.; Zeng, H.; Chen, J. MSPB-YOLO: High-Precision Detection Algorithm of Multi-Site Pepper Blight Disease Based on Improved YOLOv8. *Agronomy* **2025**, *15*, 839.
5. Ning, X.; Xia, Q.; Tang, F.; Ding, Z.; Ding, X.; Zeng, F.; Wang, Z.; Zou, H.; Yue, X.; Huang, L. Early Detection and Dynamic Grading of Sweet Potato Scab Based on Hyperspectral Imaging. *Agronomy* **2025**, *15*, 794.
6. Li, K.; Li, Y.; Wen, X.; Shi, J.; Yang, L.; Xiao, Y.; Lu, X.; Mu, J. Sticky Trap-Embedded Machine Vision for Tea Pest Monitoring: A Cross-Domain Transfer Learning Framework Addressing Few-Shot Small Target Detection. *Agronomy* **2025**, *15*, 693.
7. Ma, Y.; Zhang, S. YOLOv8-CBSE: An Enhanced Computer Vision Model for Detecting the Maturity of Chili Pepper in the Natural Environment. *Agronomy* **2025**, *15*, 537.
8. Lu, Z.; Sun, C.; Dou, J.; He, B.; Zhou, M.; You, H. SC-ResNeXt: A Regression Prediction Model for Nitrogen Content in Sugarcane Leaves. *Agronomy* **2025**, *15*, 175.
9. Zhang, G.; Yang, X.; Lv, D.; Zhao, Y.; Liu, P. YOLOv8n-CSD: A Lightweight Detection Method for Nectarines in Complex Environments. *Agronomy* **2024**, *14*, 2427.
10. Lv, G.; Zhang, W.; Liu, X.; Zhang, J.; Liu, F.; Mao, H.; Sun, W.; Han, Q.; Song, J. Feasibility of nondestructive soluble sugar monitoring in tomato: Quantified and sorted through ATR-FTIR coupled with chemometrics. *Agronomy* **2024**, *14*, 2392.
11. Ye, Y.; Jin, L.; Bian, C.; Liu, J.; Guo, H. Monitoring and Optimization of Potato Growth Dynamics under Different Nitrogen Forms and Rates Using UAV RGB Imagery. *Agronomy* **2024**, *14*, 2257.
12. Liu, Z.; Xiong, J.; Cai, M.; Li, X.; Tan, X. V-YOLO: a lightweight and efficient detection model for guava in complex orchard environments. *Agronomy* **2024**, *14*, 1988.
13. Li, Y.; Chen, X.; Yin, L.; Hu, Y. Deep Learning-Based Methods for Multi-Class Rice Disease Detection Using Plant Images. *Agronomy* **2024**, *14*, 1879.
14. Qin, K.; Zhang, J.; Hu, Y. Identification of Insect Pests on Soybean Leaves Based on SP-YOLO. *Agronomy* **2024**, *14*, 1586.

15. Neupane, A.; Shahi, T.B.; Koech, R.; Walsh, K.; Langat, P.K. Nematode Detection and Classification Using Machine Learning Techniques: A Review. *Agronomy* **2025**, *15*, 2481.
16. Chaudhary, R.K.; Neupane, A.; Wang, Z.; Walsh, K. Mango Quality Assessment Using Near-Infrared Spectroscopy and Hyperspectral Imaging: A Systematic Review. *Agronomy* **2025**, *15*, 2271.
17. Yang, H.; Jin, Y.; Jiang, L.; Lu, J.; Wen, G. AI Roles in 4R Crop Pest Management—A Review. *Agronomy* **2025**, *15*, 1629.

4. Conclusions

This Special Issue features contributions on smart agriculture, addressing many critical farming tasks, from crop and pest management to nutrient estimations. The enhancement of the YOLO framework for crop and fruit detection in complex orchard environments emerged as a promising computer vision technique, whereas DL methods provided a data-driven solution to crop growth monitoring, nutrient management, and disease severity assessments. Overall, the strength of this collection lies in its coverage of research at the intersection of intelligent systems and agriculture, highlighting the significant progress made by precision agriculture research towards future farming [24]. These advancements are pivotal not only for improving agricultural productivity but also for contributing to the achievement of the UN Sustainable Development Goals (SDGs), particularly those related to food security, climate action, and sustainable agricultural practices.

Despite the progress presented in this Special Issue, several challenges remain in deploying these technologies in the field. First, the limited availability of high-quality training data for vision-based AI models constrains their robustness and performance in operational environments. Second, methodological challenges in integrating heterogeneous data from multiple sensors and platforms persist, particularly in developing generalisable AI models that can perform consistently across different sensors and regions. Finally, the limited interpretability of AI models, which is critical for trust building, remains a key challenge for the practical adaptation of these technologies.

Author Contributions: Conceptualisation, T.B.S., A.N. and R.K.; methodology, T.B.S.; formal analysis, T.B.S.; writing—original draft preparation, T.B.S.; writing—review and editing, T.B.S., A.N. and R.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: We would like to express our deep appreciation to all authors whose valuable work was published in this issue and thus who contributed to the success of the edition.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Roy, M.; Medhekar, A. Transforming smart farming for sustainability through agri-tech Innovations: Insights from the Australian agricultural landscape. *Farming Syst.* **2025**, *3*, 100165. [[CrossRef](#)]
2. Kumar, V.; Sharma, K.V.; Kedam, N.; Patel, A.; Kate, T.R.; Rathnayake, U. A comprehensive review on smart and sustainable agriculture using IoT technologies. *Smart Agric. Technol.* **2024**, *8*, 100487. [[CrossRef](#)]
3. Wang, R.F.; Qu, H.R.; Su, W.H. From sensors to insights: Technological trends in image-based high-throughput plant phenotyping. *Smart Agric. Technol.* **2025**, *12*, 101257. [[CrossRef](#)]
4. Song, X.; Yan, L.; Liu, S.; Gao, T.; Han, L.; Jiang, X.; Jin, H.; Zhu, Y. Agricultural Image Processing: Challenges, Advances, and Future Trends. *Appl. Sci.* **2025**, *15*, 2076–3417. [[CrossRef](#)]
5. Raj, M.; Prahadeeswaran, M. Revolutionizing agriculture: A review of smart farming technologies for a sustainable future. *Discov. Appl. Sci.* **2025**, *7*, 937. [[CrossRef](#)]

6. Song, C.; Dong, H. Application of Intelligent Recommendation for Agricultural Information: A Systematic Literature Review. *IEEE Access* **2021**, *9*, 153616–153632. [\[CrossRef\]](#)
7. Neupane, C.; Pereira, M.; Koirala, A.; Walsh, K.B. Fruit sizing in orchard: A review from caliper to machine vision with deep learning. *Sensors* **2023**, *23*, 3868. [\[CrossRef\]](#)
8. Tian, H.; Wang, T.; Liu, Y.; Qiao, X.; Li, Y. Computer vision technology in agricultural automation—A review. *Inf. Process. Agric.* **2020**, *7*, 1–19. [\[CrossRef\]](#)
9. Manoj, H.; Shanthi, D.; Lakshmi, B.; Archana, K.; Venkata Naga Jyothi, E.; Archana, K. AI-driven drone technology and computer vision for early detection of crop disease in large agricultural areas. *Sci. Rep.* **2025**, *16*, 2479. [\[CrossRef\]](#)
10. Kundu, N.; Rani, G.; Dhaka, V.S.; Gupta, K.; Nayaka, S.C.; Vocaturo, E.; Zumpano, E. Disease detection, severity prediction, and crop loss estimation in MaizeCrop using deep learning. *Artif. Intell. Agric.* **2022**, *6*, 276–291. [\[CrossRef\]](#)
11. Elakiya, A.; Jerlin, R.; Sundaralingam, K.; Gnanachitra, M.; Maruthasalam, S.; Sathyamoorthy, P. Exploring Crop Stress Alleviation: A Potassium Silicate Perspective. *J. Soil Sci. Plant Nutr.* **2025**, *25*, 4687–4705. [\[CrossRef\]](#)
12. Wu, H.; Wu, W.; Huang, Y.; Liu, S.; Liu, Y.; Zhang, N.; Zhang, X.; Chen, J. FEWheat-YOLO: A Lightweight Improved Algorithm for Wheat Spike Detection. *Plants* **2025**, *14*, 3058. [\[CrossRef\]](#)
13. Xu, W.; Su, Q.; Ji, T.; Sun, H.; Chen, W.; Ji, C.; Wang, T. Real-time pest monitoring with RSCDet: Deploying a novel lightweight detection model on embedded systems. *Smart Agric. Technol.* **2025**, *12*, 101280. [\[CrossRef\]](#)
14. Báez-Sánchez, D.J.; Montesdeoca, J.; Saldarriaga-Mesa, B.; Gaspoz, G.; Tosetti, S.; Capraro, F. Pest Detection in Edible Crops at the Edge: An Implementation-Focused Review of Vision, Spectroscopy, and Sensors. *Sensors* **2025**, *25*, 6620. [\[CrossRef\]](#)
15. Chen, X. The role of modern agricultural technologies in improving agricultural productivity and land use efficiency. *Front. Plant Sci.* **2025**, *16*, 1675657. [\[CrossRef\]](#)
16. Shafiee, M.J.; Chywl, B.; Li, F.; Wong, A. Fast YOLO: A fast you only look once system for real-time embedded object detection in video. *arXiv* **2017**, arXiv:1709.05943. [\[CrossRef\]](#)
17. Mirhaji, H.; Soleymani, M.; Asakereh, A.; Mehdizadeh, S.A. Fruit detection and load estimation of an orange orchard using the YOLO models through simple approaches in different imaging and illumination conditions. *Comput. Electron. Agric.* **2021**, *191*, 106533. [\[CrossRef\]](#)
18. Sun, H.; Ren, R.; Zhang, S.; Tan, C.; Jing, J. Maturity detection of ‘Huping’jujube fruits in natural environment using YOLO-FHLD. *Smart Agric. Technol.* **2024**, *9*, 100670. [\[CrossRef\]](#)
19. Redmon, J.; Divvala, S.; Girshick, R.; Farhadi, A. You only look once: Unified, real-time object detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27–30 June 2016; pp. 779–788.
20. Tata, J.S.; Kalidindi, N.K.V.; Katherapaka, H.; Julakal, S.K.; Banothu, M. Real-time quality assurance of fruits and vegetables with artificial intelligence. *J. Phys. Conf. Ser. Iop Publ.* **2022**, *2325*, 012055. [\[CrossRef\]](#)
21. Ghazal, S.; Munir, A.; Qureshi, W.S. Computer vision in smart agriculture and precision farming: Techniques and applications. *Artif. Intell. Agric.* **2024**, *13*, 64–83. [\[CrossRef\]](#)
22. Partel, V.; Kakarla, S.C.; Ampatzidis, Y. Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. *Comput. Electron. Agric.* **2019**, *157*, 339–350. [\[CrossRef\]](#)
23. Xu, H.; Li, T.; Hou, X.; Wu, H.; Shi, G.; Li, Y.; Zhang, G. Key technologies and research progress of intelligent weeding robots. *Weed Sci.* **2025**, *73*, e25. [\[CrossRef\]](#)
24. Shahi, T.B.; Sitaula, C.; Bhandari, K.P.; Poudel, S.; Bhandari, R.; Mishra, R.; Sharma, B.K.; Mishra, B. Deep Learning-Based Method for Irrigation Status Detection in Tomato Using Plant Leaves. *IEEE Trans. Artif. Intell.* **2025**, *6*, 1849–1858. [\[CrossRef\]](#)

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