Plant Archives Vol. 26, No. 1, 2026 pp. 823-830 e-ISSN:2581-6063 (online), ISSN:0972-5210

Plant Archives

Journal homepage: http://www.plantarchives.org
DOI Url : https://doi.org/10.51470/PLANTARCHIVES.2026.v26.no.1.112

APPLICATION OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN FRUIT CROP MANAGEMENT: A REVIEW

Ashish Kumar[1*], Naval Kishore Meena[1], Chiranjit Mazumder[2], Pujarani Rath[3], Fatima Inamdar[4], Ankit Singh[5], Posham Raghuram[6] and Gaurav Kant[7]

[1]Department of Horticulture (Fruit Science), Rajasthan College of Agriculture, MPUAT, Udaipur-313001, Rajasthan, India
[2]Scientist, Division of Agricultural Economics, ICAR-IARI, New Delhi, India
[3]Department of Fruit Science and Horticulture Technology, College of Agriculture, OUAT, Bhubaneswar, Odisha, India
[4]Department of Computer Engineering, Vishwakarma Institute of Technology, Pune, Maharashtra, India
[5]Department of Horticulture, Udai Pratap Autonomous College, Varanasi, U.P., India
[6]Department of Sericulture, Dr. Ganta Gopal Reddy Horticulture Polytechnic, Gaddipally, Telangana, India
[7]Subject Matter Specialist, Department of Horticulture, Government of Haryana, India
*Corresponding author E-mail: ashishchoudhary1528@gmail.com

(Date of Receiving : 01-01-2026; Date of Revision : 26-02-2026; Date of Acceptance : 08-03-2026)

ABSTRACT

Artificial Intelligence (AI) and Machine Learning (ML) are becoming potent tools in agriculture where they are considered as promoters for decision transforming making, automation, and precision control of crop production systems. Fruit crops, which are highly vulnerable to climatic fluctuations, pest and outbreaks, soil conditions, and management practices, were among those disease tech most impacted by the adoption of AI-based technologies. These high solutions bring fresh approaches to boosting productivity, quality and sustainability in horticultural production systems. In fruit crop production, AI can be applied to yield prediction, early disease and pest detection, harvest, and quality assessment precision irrigation and fertilization, robotic of fruits. Combining technologies, such as remote sensing, Internet of Things (IoT), robotics, and big data analysis, AI systems enable farmers and crop health, manage resources efficiently, and make scientists to track informed decisions. The recent studies reveal that AI-enabled technologies resource use efficiency, and facilitate better crop monitoring, increase promote sustainable agriculture. Nevertheless, there are multiple challenges to the adoption of AI and ML in fruit crop management despite their potential opportunities, such as high cost of implementation, limited availability of technology, and lack of awareness of high quality data, the complexity of the AI in horticulture is the high potential among growers. The adoption of expected to be boosted by continuous development of digital technologies, enhanced data availability, and enabling policy environment. In this review, we thoroughly discuss the applications, techniques, merits, demerits and future opportunities of AI and ML in fruit crop management with a special focus on generation of sustainable horticulture. their contribution in building the next

***Keywords* :** Artificial Intelligence, Machine Learning, Fruit Crops, IoT, Remote Sensing, Big Data, Sustainable Horticulture

Introduction

Despite fruit crops being essential for global food security, nutrition, and rural livelihoods, their production is under growing threat from climate change, biotic and resource use (Kutyauripo abiotic stresses, labor shortages, and poor *et al*., empirical, can be 2023). Traditional management methods, which tend to be insufficient in a rapidly changing environment (Yang and Xu, 2021). Artificial Intelligence (AI), Machine Learning (ML), and other novel techniques provide new approaches for analyzing various big data generated by sensors, satellites, drones, and weather stations to model crop growth and make predictions about practices (Gul and

Banday, 2024; Arogundade crop yields and management and Njoku, 2024). These are now the cornerstone of precision agriculture with a capacity for real-time monitoring and predictive decision-making (Bandla *et al.*, 2024).

In fruit production, AI applications in pest and disease detection, yield prediction, soil fertility evaluation, and quality assessment have greatly enhanced productivity, sustainability (Keskes, 2025; Corceiro resource-use efficiency, and *et al.*, techniques are being developed as key instruments 2023). Therefore, AI-based for fostering robust and sustainable fruit production systems (Manonmani *et al.*, 2025; Ajith *et al.*, 2025).

Concept of Artificial Intelligence and Machine Learning in Agriculture

Artificial Intelligence

Artificial Intelligence tasks associated (AI) is a computational system that can be used for performing with human intelligence, such as perceiving, learning, reasoning, and thinking apple production, AI facilitates data-driven and (Russell and Norvig, 2016). In automated orchard management based on the processing of multidimensional biological and environmental data (Russell and Norvig, 2016; Liakos *et al.*, fruit crops, AI serves as a combination of machine learning, sensors, 2018). In robotics, computer vision, remote sensing, and Internet of Things (IOT) that allows managers to monitor and manage orchards in real time and with precision (Kamilaris and Prenafeta-Boldu, 2018; Dhal *et al.*, 2022).

AI applications in fruit crops have been extended to predicting yield, detecting pest and disease, assessing soil fertility, scheduling irrigation, and evaluating fruit quality and field sensors (Yang with information collected from drones, satellites *et al.*, 2017; Xu *et al.*, 2023). AI enhances the productivity, resource-use efficiency, and sustainability of fruit production systems by enabling precision agriculture, and thus signifies the transition from orchard experience-based growers practices to intelligent, data driven management (Sharma and Gawade, 2025; Arora *et al.*, 2025).

Machine Learning

Machine learning is a subset of artificial intelligence that involves computers learning (ML) from data rather than being explicitly programmed. In fruit crops cultiva- tion, ML methods are becoming widely applied to perform an analysis of large datasets related to climate, soil, plant health, and orchard management (Mohanty *et al.*, 2016; Sladojevic *et al.*, 2016). ML techniques Vector Machines (SVM), including Artificial Neural Networks (ANN), Support Random Forest (RF), Gradient Boosting and deep learning models have found widespread application in horticulture for classification, regression and decision making applications. These models facilitate precision and robust solutions to tackle the complexity of fruit production systems (Chlingaryan *et al.*, 2022).

In fruit crops, deep learning methods, especially CNN, achieved high performance for detection of on image-based pests and diseases, fruit detection, and ripeness prediction early detection, and reduce the loss of yield data. These approaches facilitate caused by biotic stresses (Ferentinos, 2018; Too *et al.*, 2019). ML models also find their application in yield prediction, climate risk modeling and crop growth simulation by considering weather, soil and remote information. Such predictive analytics enable proactive decisions in sensing management. Thus, the use of ML in fruit crop management is a shift orchard toward intelligent, data-driven orchard systems instead of traditional experience-based systems. Owing to issues such as data availability, technical complexity and infrastructure, it is expected that ML-based approaches will have a significant impact on the future of smart and sustainable fruit production (Saiz-Rubio and Rovira-Mas, 2020).

AI and ML Techniques Used in Fruit Crop Management

Machine Learning Algorithms

The management of fruit crops through machine learning encompasses a broad range of methods, supervised, unsupervised, deep learningand reinforcement learning. Including among the most popular supervised learning algorithms used for SVM, ANN, RF are detection of diseases, prediction of yield, and quality evaluation. Component Analysis Unsupervised techniques, such as clustering and Principal (PCA) are used for identifying patterns and reducing the dimension of data learn features (Jolliffe and Cadima, 2016). Deep learning models are able to from the data itself, which consists of the raw sensor readings. Convolutional Neural Networks (CNNs) are commonly used for crop disease and fruit quality are suitable for time series grading whereas Recurrent Neural Networks (RNNs) prediction. Vision Transformers bring nontrivial gain in accuracy but need resources (Stein significantly more computing *et al.*, 2016; Majdalawieh *et al.*, 2025). Reinforcement learning can be applied also for dynamic irrigation, management,robotic harvesting systems (Chang greenhouse *et al*., 2025; Wang *et al*., 2025).

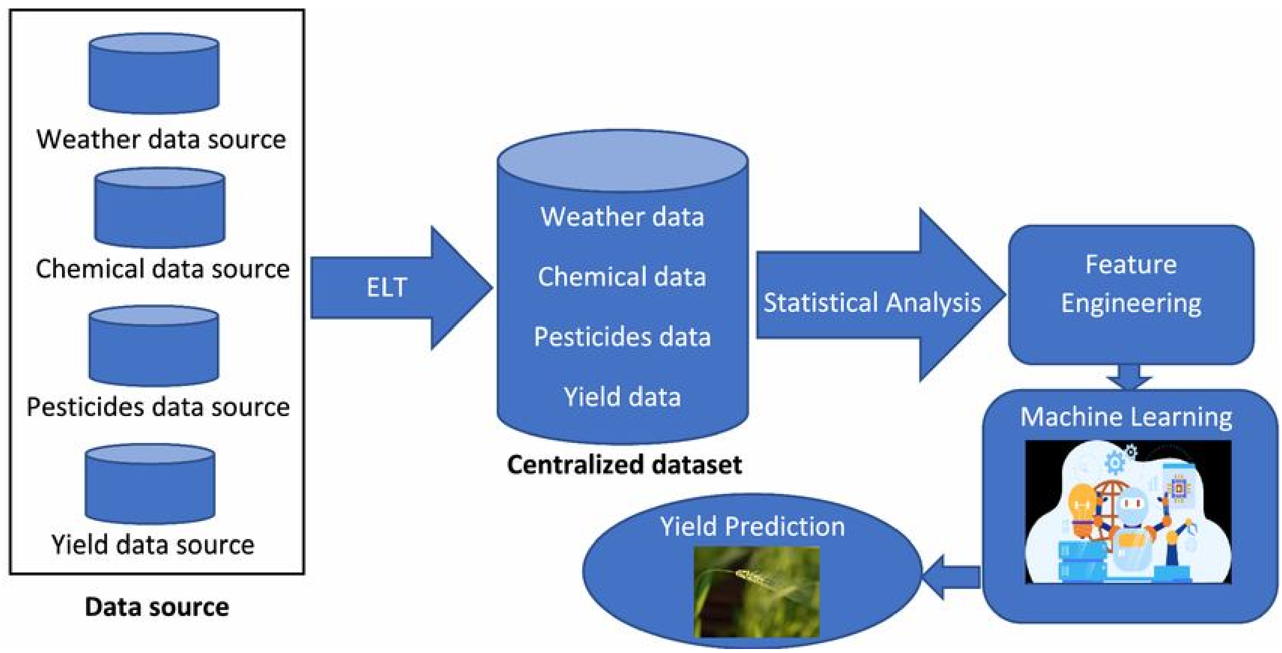
Data Sources for AI in Fruit Crops

Applications of in the management of fruit crops are based on artificial intelligence heterogeneous and multidimensional data. Remote sensing-related data such as satellite, UAV images can provide orchard canopies, disease status, nutrient (Zhang status information at spatial level *et al*., 2021; Sun *et al*., 2023). IoT enabled sensors monitor soil moisture, temperature, humidity, and stress detection (Rao nutrients real time and help in precision irrigation and and Kulkarni, 2023; Zhang *et al*., 2017; Garcia *et al*., 2020). Climatic information, being the critical input for yield forecasting, phenology risk analysis, is provided by automated weather stations and modeling and pest prediction models (Hoque *et al*., 2024). Genomic and phenotypic datasets are increasingly combined through AI approaches to associate genetic with traits such as disease resistance and fruit quality, variation facilitating data-driven breeding and rootstock selection (Liao *et al*., 2025; Cembrowska-Lech *et al*., 2023; Farooq *et al*., 2024). conjunction, these multi-source data establish the basis for intelligent and In precision fruit crop systems.

Applications of AI and ML in Fruit Crop Management

Yield Prediction

are used to AI models process historical weather data, soil conditions, and crop growth signals to forecast fruit yield (Malashin *et al*., 2024; Liu *et al*., 2025; Goel and Pandey, 2024). ML-based yield predictions allow the farmers to refine their economics (Ajith input usage and to better plan *et al*., 2025; Mishra and Srivastava, 2025).



Source : Talaat, 2023

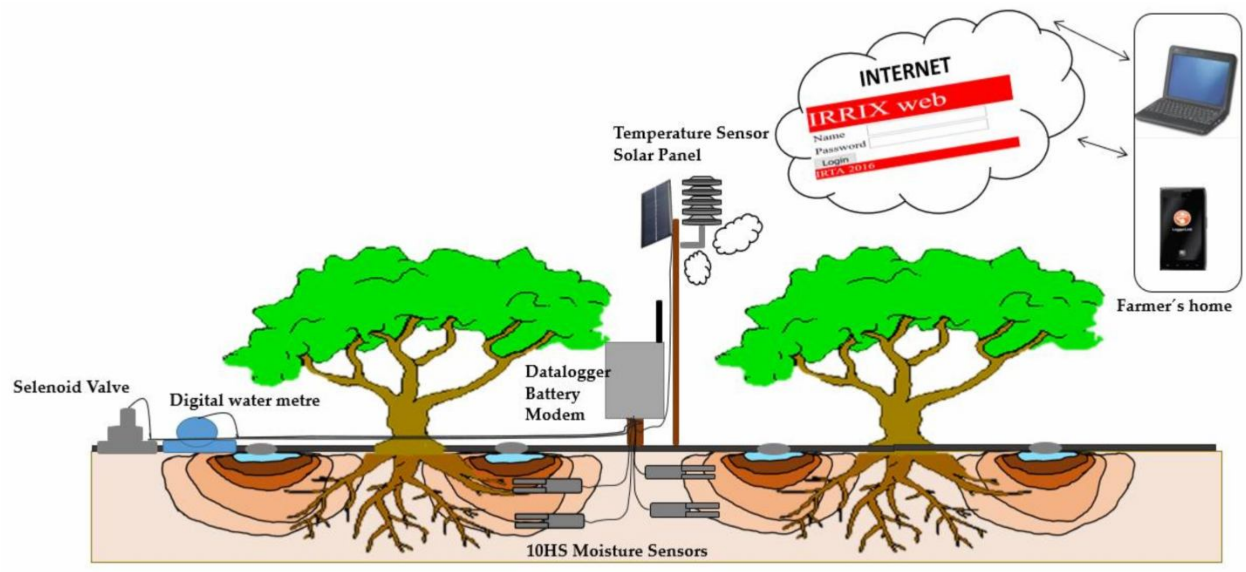
Fig. 1 : AI/Machine Learning based yield prediction framework showing integration of weather, soil, and crop data to forecast agricultural yield.

Pest and Disease Detection

detection is Disease one of the best employments of AI-based techniques in fruit crops. Deep learning models have been shown to achieve high accuracy in detecting diseases from leaf images (Reddy and Kumari, 2026; Khan *et al*., 2022; Khattak *et al*., 2021). For instance, computer vision-based AI systems have been detection in orchards to decrease crop losses by introduced for in situ pest early intervention (Singh and Butail, 2026; Albanese *et al*., 2021).

Precision Irrigation and Nutrient Management

Deficit irrigation scheduling and nutrient application are optimized using AI models with soil moisture and weather data, leading to enhancement of resource use efficiency (Adeyemi and crop yield *et al*., 2018; Navarro-Hellin *et al*., 2016; Dominguez-Nino *et al*., 2020).



Source : Millan *et al.*, 2019

Fig. 2 : AI-Based Smart Irrigation and Soil Moisture Monitoring System for Precision Orchard Management

Crop Monitoring and Phenotyping

Remote sensing and AI (Furuya can be used for continuous monitoring of crop growth and stress *et al.*, 2024; Omia *et al.*, 2023). AI-based image analysis has been in applied to evaluate fruit maturity, canopy health and harvesting maturity mango, apple and lemon (Ma *et al.*, 2024; Zhao *et al.*, 2025).

Robotics and Automation in Orchards

AI-enabled robotic systems for pruning, harvesting, and orchard management are under development (Ahmed *et al.*, 2025; Navone *et al.*, 2025; Mortazavi *et al.*, 2025). Autonomous pruning robots have demonstrated the potential significantly reduce labor costs and increase precision in orchard to operations (Li and Ma, 2023).

Source: Bac *et al.* (2014)

Fig. 3 : Application of Artificial Intelligence in Automated Apple Harvesting

Climate Risk and Stress Management

Systems are in place allow the prediction of environmental stresses including drought and heat that stress, making possible the implementation of management strategies in advance. development of AI-based crop risk monitoring systems for fruit crops (cranberry) The with high prediction performance has been reported (Akiva *et al.*, 2021; Ahmad, 2025; Patra *et al.*, 2025).

Table 1: Recent Applications of AI and Machine Learning in Fruit Crop Management

Application Area	AI / ML Techniques Used	Data Sources	Key Outcomes in Fruit Crops	References
Yield prediction	Deep Learning, Random Forest, Neural Networks	Weather data, UAV imagery, crop growth parameters	Predicting accurately enables improvement of inputs, harvest planning, and fruit yield marketing	Van Klompenburg *et al.*, 2020
Pest and disease detection	CNN, Vision Transformers, YOLO, Deep Learning	Leaf images, UAV images, smartphone images	The disease is detected early with an accuracy of >95%, thus minimizing losses and pesticide misapplication crop	Liu *et al.*, 2025; Zainab and Mahum, 2025
Fruit detection and maturity assessment	Computer Vision, CNN, YOLOv8	RGB images, drone imagery	Precise maturity detection for harvesting automation fruit counting, grading, and	Zhao *et al.*, 2024
Precision irrigation and stress monitoring	Machine Learning, IoT-based predictive models	Soil moisture sensors, weather stations	Improved water-use efficiency and reduced drought stress in orchards	Elshaikh *et al.*, 2024; Dong *et al.*, 2024
Orchard monitoring and phenotyping	Deep Learning, Remote sensing, Image segmentation	Satellite imagery, UAV, multispectral images	Monitoring growth, and nutrient status on-line of plant health, canopy	Popescu *et al.*, 2023; Huang *et al.*, 2024
Autonomous harvesting and orchard automation	Robotics integrated with AI, Computer vision	Vision sensors, robotics cameras	Reduced labour dependency and increased harvesting precision	Bac *et al.*, 2014
Climate stress and risk prediction	Machine learning, predictive analytics	Weather, soil, environmental data	Advance orchard hardiness notice of heat, drought, and stress enhances	Hobart *et al.*, 2024; Ali *et al.*, 2024; Geli *et al.*, 2025

Benefits of AI and ML in Fruit Crop Management

Advantages of AI-based devices include the following:

- Increased productivity and yield (Sudha and Loret, 2026)
- water and fertiliser use Reduction in (Soussi *et al.*, 2024)
- Pests and diseases can be detected at an and Prenafeta-Boldu, 2018) early stage (Kamilaris
- Decrease in labour dependence
- market price Improved fruit quality and (Koirala *et al.*, 2019)
- farming Environmentally friendly

AI tools contribute decisions and data-based farm management (decision also to support real-time making process) and, hence, digital agriculture (Wolfert *et al.*, 2017).

Socio-Economic and Practical Implications

New programmes and interest in applying AI in agriculture. As an activities show the increasing crop example, we have an outline of what AI-based tools for real-time monitoring and pest detection are going to allow us do that are going to help us to better optimize our resources and minimize losses. Nevertheless, the reluctant because of the high costs, shortage of technical adoption is still expertise and data (Geng *et al.*, 2024; Das and Nayak, 2024).

Challenges and Limitations

Technical Challenges

- Data and poor data quality Lack of
- Model generalization Cross-region
- Expensive Computationally

Economic Challenges

- High initial investment
- Limited access for smallholder farmers

Ethical and Social Issues

- Data privacy concerns
- Digital divide between farmers
- Dependence on technology

Future Perspectives

Emerging technologies like diffusion models and generative AI will benefit smart agriculture with image processing, data augmentation, and predictive analytics.Future enhanced research should consider:

- Integration of AI with genomics and phenomics
- of cost-effective AI tools Design for farmers
- AI models that integrate Hybrid diverse data sources
- guidelines and capacity Policy enhancement.

Conclusion

The AI and ML tools are the management of fruit crops. They improve now proven to be game changers in sustainability and resilience of fruit production systems the productivity, through enabling precision agriculture and predictive decision-making. current barriers, rising technological advancements and supportive Despite policies could foster the growth of AI adoption in hort. Management of fruit to crops using AI, therefore, marks a paradigm shift from traditional farming smart, data-driven agriculture.

References

Adeyemi, O., Grove, I., Peets, S., Domun, Y. and Norton, T. (2018). Dynamic neural network modelling of soil moisture content for predictive irrigation scheduling. *Sensors*, **18**(10), 3408.

Ahmad, S. (2025). Temporal vegetation index-based unsupervised crop stress detection via eigenvector-guided contrastive learning. *arXiv preprint*, arXiv:2506.03394.

Ahmed, D., Imran, B. M., Churuvija, M. and Karkee, M. (2025). An integrated visual servoing framework for precise robotic pruning operations in modern commercial orchard. *IFAC-PapersOnLine*, **59**(23), 28–33.

Ajith, S., Vijayakumar, S. and Elakkiya, N. (2025). Yield prediction, pest and disease diagnosis, soil fertility mapping, precision irrigation scheduling, and food quality assessment using machine learning and deep learning algorithms. *Discover Food*, **5**(1), 1–23.

Akiva, P., Planche, B., Roy, A., Dana, K., Oudemans, P. and Mars, M. (2021). AI on the bog: Monitoring and evaluating cranberry crop risk. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision* (pp. 2493–2502).

Albanese, A., Nardello, M. and Brunelli, D. (2021). Automated pest detection with DNN on the edge for precision agriculture. *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, **11**(3), 458–467.

Ali, T., Rehman, S. U., Ali, S., Mahmood, K., Obregon, S. A., Iglesias, R. C. and Ashraf, I. (2024). Smart agriculture: Utilizing machine learning and deep learning for drought stress identification in crops. *Scientific Reports*, **14**(1), 30062.

Arogundade, J. B. and Njoku, T. K. (2024). Maximizing crop yields through AI-driven precision agriculture and machine learning. *International Research Journal of Modern Engineering, Technology and Science*.

Arora, G., Kumar, S. and Singh, A. (2025). Smart agriculture and water governance. In *Recent trends in intelligent computing and communication* (pp. 146–153). CRC Press.

Bac, C. W., Van Henten, E. J., Hemming, J. and Edan, Y. (2014). Harvesting robots for high-value crops: State-of-the-art review and challenges ahead. *Journal of Field Robotics*, **31**(6), 888–911.

Bandla, A. K., Nagireddy, N. R., Ch, S., Shaik, A. B. and Vanitha, T. (2024). AI in agriculture: Precision farming and crop monitoring. *Journal of Computational Analysis & Applications*, **33**(4).

Bock, C. H., Chiang, K. S. and Del Ponte, E. M. (2022). Plant disease severity estimated visually: A century of research, best practices, and opportunities for improving methods and practices to maximize accuracy. *Tropical Plant Pathology*, **47**(1), 25–42.

Cembrowska-Lech, D., Krzemińska, A., Miller, T., Nowakowska, A., Adamski, C., Radaczyńska, M. and Mikiciuk, M. (2023). An integrated multi-omics and artificial intelligence framework for advanced plant phenotyping in horticulture. *Biology*, **12**(10), 1298.

Chang, Q., Peiqin, Z., Qian, Y., Yang, G., Xingyao, H., Xin, M. and He, J. (2025). A comprehensive review of big data intelligent decision-making models for smart farms. *Agronomy*, **15**(12), 2898.

Chlingaryan, A., Sukkarieh, S. and Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Computers and Electronics in Agriculture*, **151**, 61–69.

Corceiro, A., Alibabaei, K., Assunção, E., Gaspar, P. D. and Pereira, N. (2023). Methods for detecting and classifying weeds, diseases and fruits using AI to improve sustainability of agricultural crops: A review. *Processes*, **11**(4), 1263.

Das, S. K. and Nayak, P. (2024). Integration of IoT-AI powered local weather forecasting: A game-changer for agriculture. *arXiv preprint*, arXiv:2501.14754.

Dhal, S. B., Bagavathiannan, M., Braga-Neto, U. and Kalafatis, S. (2022). Artificial intelligence in agriculture. *Artificial Intelligence in Agriculture*.

Dominguez-Nino, J. M., Oliver-Manera, J., Girona, J. and Casadesús, J. (2020). Differential irrigation scheduling by an automated algorithm of water balance tuned by capacitance-type soil moisture sensors. *Agricultural Water Management*, **228**, 105880.

Dong, Y., Werling, B., Cao, Z. and Li, G. (2024). Implementation of an in-field IoT system for precision irrigation management. *Frontiers in Water*, **6**, 1353597.

Elshaikh, A., Elsheikh, E. and Mabrouki, J. (2024). Applications of artificial intelligence in precision irrigation. *Journal of Environmental and Earth Science*, **6**.

Farooq, M. A., Gao, S., Hassan, M. A., Huang, Z., Rasheed, A., Hearne, S. and Li, H. (2024). Artificial intelligence in plant breeding. *Trends in Genetics*, **40**(10), 891–908.

Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, **145**, 311–318.

Furuya, D. E. G., Bolfe, E. L., Parreiras, T. C., Barbedo, J. G. A., Santos, T. T. and Gebler, L. (2024). Combination of remote sensing and artificial intelligence in fruit growing: Progress, challenges, and potential applications. *Remote Sensing*, **16**(24), 4805.

Garcia, L., Parra, L., Jimenez, J. M., Lloret, J. and Lorenz, P. (2020). IoT-based smart irrigation systems: An overview on recent trends. *Sensors*, **20**(4), 1042.

Geli, H. M., Omar, I., Elshinawy, M. Y., DuBois, D. W., Prehodko, L., Smith, K. H. and Badawy, A. H. A. (2025). Prediction and forecast of short-term drought impacts using machine learning. *arXiv preprint*, arXiv:2512.18522.

Geng, W., Liu, L., Zhao, J., Kang, X. and Wang, W. (2024). Digital technologies adoption and economic benefits in agriculture. *Sustainability*, **16**(11), 4431.

Goel, M. and Pandey, M. (2024). Crop yield prediction using AI: A review. In *Proceedings of the 2nd International Conference on Disruptive Technologies (ICDT)* (pp. 1547–1553). IEEE.

Gul, D. and Banday, R. U. Z. (2024). Transforming crop management through advanced AI and machine learning. *AI, Computer Science and Robotics Technology*.

Hobart, M., Schirrmann, M., Abubakari, A. H., Badu-Marfo, G., Kraatz, S. and Zare, M. (2024). Drought monitoring and prediction in agriculture using earth observation data. *Remote Sensing*, **16**(11), 1942.

Hoque, M. J., Islam, M. S., Uddin, J., Samad, M. A., De Abajo, B. S., Vargas, D. L. R. and Ashraf, I. (2024). Forecasting crop yields using machine learning. *IEEE Access*, **12**, 47768–47786.

Huang, Y., Li, D., Liu, X. and Ren, Z. (2024). Monitoring canopy SPAD using UAV and multispectral imaging. *Frontiers in Plant Science*, **15**, 1435613.

Jolliffe, I. T. and Cadima, J. (2016). Principal component analysis: A review. *Philosophical Transactions of the Royal Society A*, **374**(2065), 20150202.

Kamilaris, A. and Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, **147**, 70–90.

Keskes, M. I. (2025). *Artificial intelligence in sustainable fruit growing: Innovations, applications, and future prospects*.

Khan, A. I., Quadri, S. M. K., Banday, S. and Shah, J. L. (2022). Deep diagnosis: A real-time apple leaf disease detection system. *Computers and Electronics in Agriculture*, **198**, 107093.

Khattak, A., Asghar, M. U., Batool, U., Asghar, M. Z., Ullah, H., Al-Rakhami, M. and Gumaei, A. (2021). Automatic detection of citrus diseases using deep learning. *IEEE Access*, **9**, 112942–112954.

Koirala, A., Walsh, K. B., Wang, Z. and McCarthy, C. (2019). Deep learning for fruit detection and yield estimation. *Computers and Electronics in Agriculture*, **162**, 219–234.

Kutyauripo, I., Rushambwa, M. and Chiwazi, L. (2023). Artificial intelligence applications in agrifood sectors. *Journal of Agriculture and Food Research*, **11**, 100502.

Li, Y. and Ma, S. (2023). Navigation of apple tree pruning robot based on improved RRT-connect algorithm. *Agriculture*, **13**(8), 1495.

Liakos, K. G., Busato, P., Moshou, D., Pearson, S. and Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, **18**(8), 2674.

Liao, L., Xie, M., Zheng, X., Zhou, Z., Deng, Z. and Gao, J. (2025). Molecular insights fast-tracked: AI in biosynthetic pathway research. *Natural Product Reports*.

Liu, J., Wang, X., Chen, Q., Yan, P. and Guo, D. (2025). Intelligent deep learning architecture for precision vegetable disease detection advancing agricultural new quality productive forces. *Frontiers in Plant Science*, **16**, 1611865.

Liu, S., Ampatzidis, Y., Zhou, C. and Lee, W. S. (2025). AI-driven time series analysis for predicting strawberry weekly yields integrating fruit monitoring and weather data. *Computers and Electronics in Agriculture*, **233**, 110212.

Ma, J., Li, M., Fan, W. and Liu, J. (2024). State-of-the-art techniques for fruit maturity detection. *Agronomy*, **14**(12), 2783.

Majdalawieh, M., Martins, C., Radi, M., Alaraj, M. and Khan, S. (2025). Precision agriculture in the age of AI: A systematic review. *Smart Agricultural Technology*, 101491.

Malashin, I., Tynchenko, V., Gantimurov, A., Nelyub, V., Borodulin, A. and Tynchenko, Y. (2024). Predicting sustainable crop yields using deep learning and explainable AI tools. *Sustainability*, **16**(21), 9437.

Manonmani, S., Senthilkumar, S., Govind, U. S. and Manivannan, S. (2024). Application of artificial intelligence in fruit production: A review. *Agricultural Science Digest*, **44**(1), 1–5.

Millan, S., Casadesús, J., Campillo, C., Monino, M. J. and Prieto, M. H. (2019). Using soil moisture sensors for automated irrigation scheduling in a plum crop. *Water*, **11**(10), 2061.

Mishra, H. and Srivastava, A. B. (2025). Sustainable agriculture: Economic perspectives on AI and ML in crop yield estimation. In *Artificial intelligence and computer vision for ecological informatics* (pp. 348–392). CRC Press.

Mohanty, S. P., Hughes, D. P. and Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, **7**, 215232.

Mortazavi, M., Cappelleri, D. J. and Ehsani, R. (2025). RoMu4o: A robotic manipulation unit for orchard operations automating proximal hyperspectral leaf sensing. *arXiv preprint*, arXiv:2501.10621.

Navarro-Hellín, H., Martinez-del-Rincon, J., Domingo-Miguel, R., Soto-Valles, F. and Torres-Sánchez, R. (2016). A decision support system for managing irrigation in agriculture. *Computers and Electronics in Agriculture*, **124**, 121–131.

Navone, A., Martini, M. and Chiaberge, M. (2025). Autonomous robotic pruning in orchards and vineyards: A review. *Smart Agricultural Technology*, 101283.

Norvig, P. and Russell, S. (2016). *Artificial intelligence: A modern approach* (3rd ed.). Pearson Education.

Omia, E., Bae, H., Park, E., Kim, M. S., Baek, I., Kabenge, I. and Cho, B. K. (2023). Remote sensing in field crop monitoring: A comprehensive review. *Remote Sensing*, **15**(2), 354.

Patra, A. K., Varshney, A. and Sahoo, L. (2025). An explainable vision transformer with transfer learning-based efficient drought stress identification. *Plant Molecular Biology*, **115**(4), 98.

Popescu, D., Ichim, L. and Stoican, F. (2023). Orchard monitoring using UAV and AI: A systematic review. *Frontiers in Plant Science*, **14**, 1237695.

Rao, A. and Kulkarni, S. B. (2023). RETRACTED: A hybrid approach for plant leaf disease detection and classification. *International Journal of Electrical Engineering & Education*, **60**(1_suppl), 3428–3446.

Reddy, K. S. and Kumari, K. P. (2026). Fruit disease detection using AI: A review of classical and deep learning approaches. *Indian Journal of Agricultural Research*.

Saiz-Rubio, V. and Rovira-Más, F. (2020). From smart farming towards agriculture 5.0: A review on crop data management. *Agronomy*, **10**(2), 207.

Sharma, R. D. and Gawade, S. (2025). Advancements in precision agriculture: A literature review of machine learning applications. *Environmental Claims Journal*, 1–45.

Singh, G. and Butail, V. (2026). Artificial intelligence: A real-time detector to detect diseases and pests in crops. In *Handbook of agricultural technologies* (pp. 1–20). Springer Nature.

Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D. and Stefanovic, D. (2016). Deep neural networks-based recognition of plant diseases by leaf image classification. *Computational Intelligence and Neuroscience*, **2016**(1), 3289801.

Soussi, A., Zero, E., Sacile, R., Trinchero, D. and Fossa, M. (2024). Smart sensors and smart data for precision agriculture: A review. *Sensors*, **24**(8), 2647.

Stein, M., Bargoti, S. and Underwood, J. (2016). Image-based mango fruit detection and yield estimation. *Sensors*, **16**(11), 1915.

Sudha, S. P. and Loret, J. B. (2026). A review on machine learning-based precision agriculture techniques for crop farming monitoring with IoT. *Discover Environment*, **4**(1), 10.

Sun, G., Hu, T., Chen, S., Sun, J., Zhang, J., Ye, R. and Liu, J. (2023). UAV-based multispectral imagery for diagnosing leaf nitrogen status. *Precision Agriculture*, **24**(6), 2522–2548.

Talaat, F. M. (2023). Crop yield prediction algorithm (CYPA) in precision agriculture. *Neural Computing and Applications*, **35**(23), 17281–17292.

Too, E. C., Yujian, L., Njuki, S. and Yingchun, L. (2019). Comparative study of deep learning models for plant disease identification. *Computers and Electronics in Agriculture*, **161**, 272–279.

Van Klompenburg, T., Kassahun, A. and Catal, C. (2020). Crop yield prediction using machine learning: A systematic review. *Computers and Electronics in Agriculture*, **177**, 105709.

Wang, Z., Jang, W., Ruan, B., Wang, J. and Xiao, S. (2025). Developing and integrating trust modeling into reinforcement learning for agriculture. *arXiv preprint*, arXiv:2505.10803.

Wolfert, S., Ge, L., Verdouw, C. and Bogaardt, M. J. (2017). Big data in smart farming: A review. *Agricultural Systems*, **153**, 69–80.

Xu, S., Zhang, Y., Dong, W., Bie, Z., Peng, C. and Huang, Y. (2023). Early identification of weak seedlings using machine learning. *Agriculture*, **13**(1), 212.

Yang, B. and Xu, Y. (2021). Applications of deep learning in horticultural research: A review. *Horticulture Research*, **8**.

Yang, G., Liu, J., Zhao, C., Li, Z., Huang, Y., Yu, H. and Yang, H. (2017). UAV remote sensing for crop phenotyping. *Frontiers in Plant Science*, **8**, 1111.

Zainab, Z. and Mahum, R. (2025). Plant disease detection using deep learning techniques. *ICCK Journal of Image Analysis and Processing*, **1**(1), 36–44.

Zhang, C., Valente, J., Kooistra, L., Guo, L. and Wang, W. (2021). Orchard management using UAVs: A survey. *Precision Agriculture*, **22**(6), 2007–2052.

Zhang, X., Zhang, J., Li, L., Zhang, Y. and Yang, G. (2017). Monitoring citrus soil moisture using IoT systems. *Sensors*, **17**(3), 447.

Zhao, F., He, Y., Song, J., Wang, J., Xi, D., Shao, X. and Mizuno, K. (2025). Smart UAV-assisted blueberry maturity monitoring. *Precision Agriculture*, **26**(4), 56.

Zhao, M., Lu, H., You, Z., Chen, H., Wang, X., Zhang, Y. and Wang, Y. (2024). Olfactory sensing array for predicting fruit ripeness using deep learning. *ACS Applied Materials & Interfaces*, **16**(42), 56623–56633.

.