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Review Paper

Review on Role of Artificial Intelligence in Fruit Crop Cultivation

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ABSTRACT

The growing global demand for nutritious food, alongside environmental and economic constraints, has intensified the need for sustainable agricultural practices, particularly in fruit production. Artificial Intelligence (AI) has emerged as a transformative tool for enhancing the sustainability, productivity, and efficiency of fruit cultivation. This review examines the current landscape of AI applications in sustainable fruit growing, emphasizing technological innovations, practical implementations, and future directions. Core AI technologies, including machine learning, computer vision, robotics, and data analytics are analyzed for their roles in precision agriculture, pest and disease management, yield prediction, and automated orchard operations. Notable advancements include AI-based models achieving over 98% accuracy in detecting pomegranate diseases and robotics reducing labor costs by up to 95%. These developments contribute to environmental sustainability by minimizing chemical usage and resource waste while improving economic viability and social well-being. However, barriers such as high implementation costs, extensive data requirements, and limited technical expertise continue to hinder large-scale adoption. Future research should focus on developing robust, interpretable AI systems, integrating them with emerging technologies such as the Internet of Things (IoT) and block chain, and addressing challenges related to climate change and resource management. Overall, this review underscores AI's potential to revolutionize sustainable fruit production, paving the way for resilient, efficient, and environmentally responsible food systems.

Key Words: Artificial intelligence, Fruit farming, Machine learning, Yield prediction.

INTRODUCTION

The word artificial in AI portray non-biological and the word intelligence denotes ability to achieve complex tasks. Artificial Intelligence (AI) represents a transformative technological approach that enables machines to perform complex tasks traditionally requiring human intelligence. (Jani *et al,* 2019; Parekh *et al,* 2020). Human brain remains as most complex organ which contains billions of neurons that are connected to each other in a neural network. Meanwhile, AI is a technology to develop human brain in digital format by employing various complex algorithms (Joseph *et al,* 2020). This technology execute the function of human brain in several way *viz.,* educating itself like humans, finding the reason and solution for problems and on critical decision making times act like human. In other words, AI refers to computer-based systems designed to simulate aspects of human intelligence, such as learning, reasoning, and decision-making.

AI is defining as the study of computer system and software which strive to be a model with artificial mind similar to human intelligence. It simulates the intelligent behaviour of human beings think and act (and in times to come, better than them), accomplish the thought process of human in all sensible tasks (Saxena *et al,* 2020). AI based technologies helps to govern the challenges in agriculture such as crop establishment and protection, soil nutrient and moisture sensing, improvement of yield with good quality. It aids in field management and enhance the field efficiency on the whole (Kim *et al,* 2008).

UN FAO (Food and Agriculture Organization) proclaims that the availability of land area for the crop cultivation will be 4% in 2050 with additional population of 2 billion to the existing global population. This context creates a strong pressure over agricultural production, where there will be more demand for food. The food production obtained from these traditional methods of cultivation which have been followed by farmers right now were not sufficient

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or may fail to feed this growing global population. Adaptation of new and latest technological solutions for the improvement of farming might be the only possible way to meet out the food requirement in future. While Artificial Intelligence (AI) proved to support all sectors of agriculture to boost the productivity and also helps to control uninvited natural condition. The solution is to create a shift in agriculture and to assist us to overcome the challenges in agriculture and its application.

AI-supported solution makes the farmers to produce more with less in addition quality improvement in products. AI technology helps to achieve competitive advantage in market. In recent years AI powered systems aids the farmers in all process of fruit production such as in irrigation scheduling through smart irrigation systems, detection and diagnosis of pest and diseases, weed management, precise predictions, etc. AI technology not only improves the farming efficiency, it facilitate precise and accurate farming of fruit crops.

Artificial intelligence (AI) stands out as a transformative technology with the potential to instigate a profound revolution across various facets of fruit growing (Liakos *et al,* 2018). Its capacity to analyze extensive datasets, discern intricate patterns, and automate complex tasks offers considerable advantages for optimizing the inherently complex systems involved in agricultural production, particularly fruit cultivation (Kamilaris and Prenafeta-Boldu, 2018). Key AI domains, including machine learning, computer vision, robotics, and advanced data analytics, hold immense promise for addressing the challenges and advancing the goals of sustainable fruit growing (Jha *et al,* 2019). The ability of AI to process large volumes of information from diverse sources, ranging from satellite imagery to ground-based sensors, and to derive actionable insights from this data, positions it as a powerful tool for enhancing efficiency, reducing environmental impact, and improving the overall sustainability of fruit production (Benos *et al,* 2021).

This review endeavors to explore the current landscape of AI applications within the context of sustainable fruit growing. It aims to elucidate the key innovations in AI technologies and methodologies that are being applied in this domain, to examine the specific applications of AI across the entire life cycle of fruit production, and to discuss the future prospects and potential of AI to further transform fruit growing practices towards greater sustainability and resilience. The subsequent sections of this report will delve into the materials and methods used for this review, followed by a detailed discussion of the results, encompassing innovations, applications, and the contribution of AI to sustainability goals, as well as the challenges and future directions. Finally, a conclusion will synthesize the key findings and offer a perspective on the future role of AI in shaping sustainable fruit production.

Application of AI in fruit production

The automation is essential key area of interest in case of precision farming. Artificial intelligence possesses various functional works in agriculture. The most important and few examples of AI application in production of fruit crops are given below.

Prediction through AI

Presently artificial intelligence systems were utilized for developing predictive models for many agriculture practices and monitoring of yield (Panda *et al,* 2010). Though the current methodologies focus on post-harvest yield prediction, it is preferable to focus on pre-harvest yield prediction methods for fruit crops. Most of the fruit growers estimate their yield by counting fruits during the early fruit drop. Since conventional yield estimation methods, such as manual counting or weight-based calculations, are time-consuming and often inaccurate, AI-powered predictive models offer a reliable and efficient alternative. In case of cherry fruit, prediction of two most important disease-causing pathogens namely Monilinia laxa and Coccomyces hiemalis were done using data mining. Gobasco (an artificial intelligence-based platform) offers locating, optimization and yield prediction for the agricultural produces.

Another interesting method of yield prediction as developed by the Robotics Vision lab of Northwest Nazarene University that estimates fruit yield by counting the blossoms (Braun *et al,* 2018). It was found that during the blossom period photosynthetic activity tends to increase, which positively correlates with the fruiting process. Hence, the fruit yield can be estimated by counting the blossoms by using the correlation between the blossoms detected in an image with the actual number of fruits in the tree. This system of early yield prediction is successfully implanted in Pink Lady Apple cultivars (Braddock *et al,* 2019). In Kiwi, firmness of the fruit was measured by predicting N and Ca concentrations, including their ratio in fruit at the time of harvest using Artificial Neural Networks (Torkashvand *et al,* 2017).

AI-driven yield prediction and crop monitoring are transforming sustainable arborial fruit growing by integrating historical yield data, weather patterns, real-time sensor information, and drone imagery. A citrus orchard study in Morocco uses five years of field data (climate, irrigation, fertilization) and Sentinel-2/Landsat imagery, achieving high accuracy with Random Forest models for yield forecasting, enabling optimized resource allocation (Mokhtar *et al,*, 2022). In apple orchards, a drone-based system employs Faster R-CNN to detect fruits, reporting an R^2 of 0.86, supporting precise harvest planning and market strategies (Apolo-Apolo *et al,* 2020). UAV imagery facilitates fruit detection, growth stage monitoring, and stress identification (e.g., pests, nutrient deficiencies) in citrus, apples, and grapes, enhancing early interventions (Reis *et al,* 2023). Another citrus study combines ground-based sensors and drone imagery with Random Forest, reducing labor costs and improving yield predictions.

A strawberry yield prediction model, adaptable to arborial fruits, uses drone imagery and deep neural networks, integrating weather and sensor data for accurate forecasts. These AI approaches enable proactive stress detection, optimized harvesting schedules, and economic sustainability in orchards by minimizing losses and improving resource use. However, challenges include high equipment costs for drones and sensors, which may limit adoption by small-scale farmers, and environmental variability (e.g., cloud cover, terrain) that can affect imagery quality. Robust validation across diverse orchards is needed to ensure real-world reliability.

AI in Variety selection

This is one area where farmers can make decisions just by selecting the right crop/variety for the region. In the future, AI will also be able to evaluate conditions and suggest, which varieties of the crops can be grown in a particular region. This is especially important given the climatic differences of the country. For instance, the red-pulp guava 'Lalit' can grow in some high-altitude regions as AI could identify more regions where it can grow and develops red colour on the peel also.

AI in crop health monitor

The crop health monitoring is a critical factor to ensure productivity of crops. Early detection of crop infestation with pest, nutrient deficiencies and stress due to climate change are needed to mitigate the problems of low productivity. This can be achieved by means of high resolution weather data, remote sensing data, AI technologies and AI platform. All these provisions make crop monitoring process easy, accurate and provide additional insights to the farmers on time. Soilsens technology is a low cost smart soil monitoring system to help farmers who facing farming decisions predicament. Soilsens system consist of various sensors that includes soil moisture, soil temperature, ambient humidity and ambient temperature sensor to make a decision on optimum irrigation using mobile app in order to increase the water use efficiency. The plantix application is used to determine the potential defects and nutrient deficiencies in soil. The analysis is conducted by software algorithms which correlate particular foliage patterns with certain soil defects, plant pest and disease. This application also detects crop diseases and offers advice regarding respective treatment measures for the detected disease by the app. In banana, *Fusarium* wilt (the most common and serious diseases of banana) can be mass diagnosed early by using E-Nose integrated autonomous rover system which is fabricated with MOS sensors (Sanjay and Kalpana, 2017).In case of examining the crop maturity in the fruit orchard, most of the time manual prediction leads to inaccurate decision. Hence precise monitoring equipment that is capable of rapid detection of produce quality is desirable, together with a low marketing cost. The E-Nose would be the potential tool in this regard, as it monitors the production of volatile organic compounds in the crop with specific situation. Thus indirectly monitor and evaluating the crop growth at real time (Voss *et al,* 2019).

AI in crop protection

Plant protection is crucial in crop production because of its complexity in understanding the cause and lagging tools for detection of specific infections as well for the prediction of condition that were favorable for infections. A cost-effective automated system comprising AI and machine vision are used to recognize, differentiate and geo-locate citrus psyllid (*Diaphornia citri*) in orchard of citrus (Partela *et al,* 2019). Utilizing deep learning models in image processing and recognition system is a latest technology to spot diseases of different crops through visible symptoms captured in précised manner. Several banana pest and disease are identifiable even by the persons who lack knowledge on symptoms produced due to infection of various pest and diseases of banana with the help of detection model developed using artificial intelligence with deep learning systems (Selvaraj *et al,* 2019).

A knowledge-based system for apple diseases helps the farmers to identify the symptoms and cause of various diseases and treats the disease whenever possible (Shawwa and Naser, 2019). Similarly, in pineapple knowledge- based expert system for detection of various diseases and recommendation of disease management method for pineapple diseases (Shawwa and Naser, 2018). Likewise, in banana a knowledge based expert system was developed to manage banana diseases to have insights on to the diagnosis and treatment of various diseases in banana (Almadhoun and Naser, 2018). The most common postharvest disease of Golden Delicious apple was able to identify with aid of an electronic nose (E-Nose) technology during processing and packing of apples (Jia *et al,* 2019).

Several studies highlight AI's effectiveness in detecting pomegranate fruit diseases, consistently achieving accuracies above 98%. PomeNetV1 and PomeNetV2, convolutional neural networks, attained 99.80% and 99.02% accuracy, respectively, in classifying Bacterial blight, Anthracnose, Cercospora, and Alternaria using a 5,099-image dataset (Pakruddin and Hemavathy 2024). DenseNet and other transfer learning models reached 99% accuracy, though the 99.21% for DenseNet-201 lacks direct confirmation. A hybrid CNN with the Honey Badger Algorithm and a capsule network (Hybrid OACapsNet) also showed high accuracy for similar diseases (Deshpande, 2023; Kumar and Sharma, 2023). A leaf-focused study reported 98.07% accuracy using machine learning for the same diseases (Bhange and Hingoliwala, 2020), while image processing targeted Bacterial blight (Akhilesh and Kumar, 2019). These findings underscore AI's potential to transform orchard disease management, though real-world variability requires caution (Pakruddin and Hemavathy, 2024). Specialized datasets are critical for advancing AI-driven disease detection in agriculture. PomeNetV1 and PomeNetV2 use a dataset of 5,099 pomegranate fruit images (Pakruddin and Hemavathy, 2024). Another dataset with 5,857 images of pomegranate growth stages aids crop health monitoring (Li *et al,* 2024). The FruitNet dataset, containing 12,000 images of Indian fruits including pomegranates, facilitates disease and quality assessment (Meshram and Patil, 2021). A 1,500-image soybean dataset targets bacterial blight detection (Kotwal *et al,* 2024), while a pomegranate quality dataset supports machine vision applications (Kumar *et al*, 2021). These farm-sourced, expertly annotated datasets enable robust computer vision systems, promoting timely disease interventions to enhance crop yields, though challenges like environmental variability persist.

Studies on AI-driven fruit disease detection emphasize systematic image processing techniques: image acquisition, preprocessing, segmentation, feature extraction, and classification. K-means clustering is widely used for segmentation, isolating diseased regions in fruits like apples and grapes, while SVM classifiers deliver 93– 97% accuracy (Khan *et al,* 2021; Sharif *et al,* 2023). Image acquisition under controlled conditions, preprocessing for noise removal, and feature extraction (color, texture, HOG) enhance precision (Kumar and Kumar, 2023; Sivakumar *et al,* 2022). Hybrid k-means and graph-based segmentation refines defect detection (Nguyen *et al,* 2014). Leaf disease studies using k-means and SVM are adaptable to fruits (Rani *et al,* 2019). These methodologies enable accurate, timely disease interventions, though challenges include equipment costs and environmental variability.

Automation system in Irrigation

The Internet of Things (IoT)-based smart irrigation system is a device that can automate the irrigation process by monitoring the soil's moisture content and meteorological conditions. Irrigation is one of the most labor-intensive processes in farming which can be avoided by artificial intelligence because it is aware of historical weather patterns, soil quality, and the type of crops to be grown.

AI in Weed Control

An estimated 250 kinds of weeds have developed resistance to herbicides, controlling weeds is one of farmers' main priorities. A startup business in California created a robot named See & Spray that purportedly uses computer vision to track and precisely spray on weeds. Herbicide resistance can be avoided with precise spraying. It accurately sprays fertilizers where they are needed, on the plant. This might reduce the amount of herbicide needed to spray the entire field by around 90%.

Produce maturity identification

Identifying the stage of fruit ripeness requires taking pictures of various crops under white/UV-A light. Particularly in the case of extremely perishable horticultural products, farmers might develop multiple maturity grades based on the crop/fruit category and place them into separate stacks before delivering them to the market. Harvesting at the right maturity would also increase post-harvest shelf life (Vipin Kumar *et al,* 2023)

AI in harvesting of fruits

AI powered solution for ease of harvest lower the cost of man power utilize for harvest as well harvest the produce at right time. Mechanical vibration harvester is used to harvest walnut. This harvester comprises two mechanism namely clamping and exciting mechanism. Here mechanical force used to create vibration at definite frequency and amplitude which makes fruits fall off from branches and are collected on loading device (Yang, 2020). In other words, the vibration accelerated to weaken the binding force of fruits to branches which facilitates harvest of walnuts precisely (Rapur and Tiwari, 2018).

AI-driven robotics in fruit orchards significantly enhance sustainability by automating labor-intensive tasks like harvesting, pruning, and weeding. A study on apple harvesting robots using computer vision reports a 21% CAGR in robotics markets, reducing labor costs and chemical use through precise operations (Gammanpila *et al,* 2024). Drone-based apple yield estimation with Faster R-CNN achieves an R^2 of 0.86, optimizing harvest timing and minimizing labour dependency (Apolo-Apolo *et al,* 2020). UAVs with YOLO algorithms enable fruit detection, pruning, and weed control in citrus, apples, and grapes, promoting efficiency and reducing herbicide reliance (Reis *et al,* 2023). Robotic systems such as Weed Spider and Harvest CROO have demonstrated substantial reductions in labour requirements under experimental and commercial orchard conditions, addressing shortages while cutting chemical inputs (Bilal *et al,* 2024). Robotics' apple harvester, part of Western Growers' initiative, uses AI for precise picking, boosting efficiency in Washington orchards. These systems leverage sensors and computer vision to identify ripe fruits and weeds, ensuring precision and supporting economic sustainability.

It has reportedly resulted in millions of dollars' worth of income losses due to a labour shortage. To assist strawberry growers with picking and packing their products, Florida-based Wish Farms stated that they would use a Harvest CROO Robotics strawberry harvester in the summer of 2017 (Vipin Kumar, 2023).

AI driven robotics for Selective harvesting

This is a selective method of harvesting by the robotic systems that use robotic manipulators equipped with an end-effector for grasping the fruits. They are usually installed on a mobile platform with machine vision technology for vision and the end-effector selectively separates mature fruit (Bac *et al,* 2014) as shown in Figure 4 and 5. Since robotic systems can combine machine efficiency with long-term goal line (Shevfelt *et al,* 2014), an automated harvesting technique is thought to have the potential to completely substitute the human pickers (Sanders, 2005). Therefore, this method of selective harvesting has received widespread attention from both academia and industrial sectors and emerged as the ideal method of harvesting horticultural crops among fruit growers. The rapid development in artificial intelligence (AI) and robotics technologies has paved the way for commercial automated techniques for selective harvesting.

AI driven robotics for Bulk harvesting

The bulk harvesting method is based on the principle of using oscillation or vibration force on fruit trees to force the fruits from the trees (Mehta, 2016) as shown in Figure 6. This type of harvesting method is implemented by many apples and cherries fruit growers (De Kleine and Karkee, 2015; Zhou *et al,* 2022). Although large-scale bulk harvesting systems are highly efficient (Sola-Guirado *et al,* 2020), there are significant drawbacks. Farmers have expressed concern about extreme damage to canopies and fruit caused by mechanisms (Moseley *et al,* 2012). The research studies to reduce bulk harvest damage remains active as fruit spoilage affects its market acceptance (Pu *et al,* 2018; Wang *et al,* 2019). Another big disadvantage of the bulk harvesting method is that the quality of the harvested fruits can change dramatically since less mature fruits are also harvested with mature fruits.

Fruit recognition, end effector, and detachment

The first step in automated robotic harvesting is to spot the fruits and estimate their 3D location in the canopy of the tree so that the end effector can grasp the target fruit and separate it from the tree. Extensive research studies on the detection of fruits and obstacles using precise features such as shape, colour, edge, size, and texture, including different thresholds and classification techniques such as neural networks and Bayesian classifiers (Silwal *et al,* 2014, Tabb *et al,* 2006). However, these technologies based on the precise feature techniques, have limited success due to issues such as clogging, fruit gathering, unstructured, variable lighting conditions, various uncertainty conditions, and crop and canopy variability. To meet the challenge of fruit gathering, the convex hull technique is being used for the identification of individual citrus fruits and their center in the images with overlapping bunches of fruits with an assumption that the shape of the fruit is round in images (Changhui *et al,* 2017). This is particularly useful when dealing with images where multiple fruits are closely packed together, making it difficult to distinguish between them. The convex hull technique helps in accurately identifying and locating each fruit's center, which is essential for various applications such as fruit grading, yield estimation, and quality assessment. Similarly, Wang *et al* (2019) developed an image enhancement technology that involved the Retinex principle and wave conversion to reduce problems related to fruit identification under changing lighting conditions.

Artificial intelligence for sustainable fruit growing

The field of sustainable fruit growing is witnessing a surge of innovation driven by advancements in artificial intelligence (Liakos *et al,* 2018). Key AI technologies and methodologies are increasingly being adopted to address the complex challenges associated with fruit production while minimizing environmental impact (Kamilaris and Prenafeta-Boldu, 2018). A notable trend is the growing application of machine learning and deep learning algorithms to tackle sophisticated agricultural tasks (Patricio and Rieder, 2018). These advanced techniques enable the development of predictive models for yield estimation, optimization strategies for resource allocation, and sophisticated systems for pest and disease management (Jha *et al,* 2019). The ability of these algorithms to learn from vast amounts of data and identify subtle patterns that may be imperceptible to humans is proving invaluable in enhancing the efficiency and sustainability of fruit cultivation (Benos *et al,* 2021).

Computer vision stands out as another critical AI domain that is significantly contributing to sustainable fruit growing (Tian *et al,* 2020). This technology empowers systems to "see" and interpret visual information from orchards, enabling a wide range of applications such as the early and accurate detection of fruit diseases, the assessment of fruit maturity for optimal harvesting, and the monitoring of overall plant health (Patricio and Rieder, 2018). By processing images captured by drones, robots, or fixed cameras, computer vision algorithms can identify anomalies and provide timely alerts, facilitating targeted interventions and reducing the need for broad-scale treatments (Barbedo, 2019). Furthermore, the integration of AI with robotics is paving the way for automation in various labor-intensive tasks within fruit orchards (Zhang *et al,* 2020). AI powered robots are being developed for automated harvesting, precise pruning, and efficient weed management (Bac *et al,* 2014). These robots can work continuously, improving efficiency and potentially reducing the reliance on manual labor, which can be particularly beneficial in regions facing labor shortages (Marinoudi *et al,* 2019). The development and deployment of such intelligent robotic systems represent a significant step towards more sustainable and economically viable fruit production (Fountas *et al,* 2020).

AI contributes to sustainability in fruit production by improving resource-use efficiency, enhancing economic returns, and reducing the physical burden of labour, thereby addressing environmental, economic, and social dimensions simultaneously. Precision agriculture minimizes water and fertilizer use by up to 20%, reducing pollution, as seen in tomato farming with AI-driven irrigation and pest detection (Pakruddin and Hemavathy*,* 2024). In citrus orchards, Random Forest models optimize resource use, enhancing yields and profitability while conserving resources (Mokhtar *et al,* 2022). AI-powered pest management in apple orchards cuts pesticide use by 30%, promoting biodiversity and human health through robotic precision (Gammanpila *et al,* 2024). For grapes, Sentinel-2 imagery and CNNs achieve 90% yield prediction accuracy, reducing chemical inputs and boosting economic viability (Patel *et al,* 2024). A pomegranate disease dataset enables 99% accurate detection, minimizing pesticide reliance and supporting reliable production (Pakruddin and Hemavathy, 2024). Economically, AI enhances productivity through automation and accurate forecasting, with robots reducing labor costs by up to 95%. Socially, automation alleviates strenuous labor and enhances food security by ensuring consistent fruit supply, though job displacement risks for seasonal workers require retraining solutions (Gammanpila *et al,* 2024).

Table.1 Artificial intelligence (AI)-based opportunities in Fruit Crops.

AI-based opportunities	Description
Agronomic decisions	Imlementation of AI in farming decisions such as soil management, pest and weed management, disease management, crop management, and water-use optimization.
Economic performance	Cost-benefit assessment to improve profits based on local/tacit farming knowledge and recommendation actualized through digital platforms. Predictions and recommendations driven by AI models can help farmers reduce fertilizer overuse, forecast uncertainties such as plant and livestock-based diseases, and monitor soil conditions to prevent yield loss.
Alpha Supporting inclusive growth in developing economies	AI-based agricultural technologies can prevent market and information asymmetries in food value chains at the local and global level if data is shared transparently and responsibly.
Social mobility	AI-based agriculture can benefit from availability and development of skilled workforce in the domains of computer science, agronomy and plant science, animal science, and social sciences.
Social and environmental impact	Sustainability of food and water systems, food -security for global population, and resource optimization.

Table 2. Comparative analysis of four common AI techniques.

Method	Typical algorithms	Applications	Pros	Cons	Model complexity
Machine learning	Linear Reg., Log. Reg., DT, RF, SVM, KNN, etc.	Classification, Regression, Clustering, Rec. Systems, etc.	Algorithm simplicity, interpretability	Limited handling of high-dimensional and non-linear problems	Low
Deep learning	CNN, RNN, LSTM, GAN, etc.	Image Recognition, NLP, Speech Recognition, Video Analysis, etc.	Automatic feature extraction, effective for high-dimensional and non-linear problems	Requires large datasets and computational power, complex models	Very high
Computer vision	Edge Detection, SIFT, SURF, YOLO, SSD, Mask R-CNN, etc.	Image Classification, Object Detection, Segmentation, Face Recognition, etc.	Specialized for image processing, strong algorithmic focus	Relies on manually designed features, limited generalization	Medium
Image learning	Image Enhancement, Repair, Generation (e.g., GAN), Super-Resolution, etc.	Image Enhancement, Repair, Generation, Medical Image Analysis, etc.	Focuses on image data, generates high-quality images	Requires large datasets, high computational complexity	High

AI across the fruit growing lifecycle

AI is revolutionizing sustainable fruit growing by optimizing key stages of the production lifecycle, from resource management to harvest. By leveraging technologies such as Machine Learning, Computer Vision, and Robotics, AI enables precision in irrigation, early disease detection, accurate yield prediction, and efficient harvesting, all while advancing environmental, economic, and social sustainability goals

Challenges and future directions:

Despite the significant advancements and promising applications of AI in sustainable fruit growing, several challenges need to be addressed to ensure its widespread and successful adoption. One major challenge is the requirement for large and high-quality datasets to train and validate AI models, particularly deep learning algorithms (Keskes and Nita, 2025). The performance of these models heavily depends on the availability of representative and accurately labeled data, which can be a limitation in certain agricultural contexts (Benos *et al,* 2021). The cost associated with the adoption of AI technologies, including sensors, drones, robots, and software platforms, can also be a barrier for many farmers, especially small scale producers (Garske *et al,* 2021). Furthermore, the lack of technical expertise and digital literacy among some farmers poses a challenge to the effective implementation and utilization of AI-powered tools (Marques *et al,* 2024). Addressing the need for data standardization and interoperability is crucial for facilitating the effective application of AI in agriculture. Standardized data formats and protocols would enable seamless integration of data from various sources and platforms, enhancing the capabilities of AI models and promoting collaboration across the agricultural research and development community (Tzounis *et al,* 2017). Future research directions in this field are manifold. There is a need for the development of more robust and interpretable AI models that can perform reliably under diverse and real-world agricultural conditions (Neethirajan, 2023). The integration of AI with other emerging technologies, such as the Internet of Things (IoT) and block chain, holds the potential to create even more powerful and transparent solutions for sustainable fruit growing (Chen *et al,* 2019; Kamilaris *et al,* 2019). Additionally, future research should focus on applying AI to address new and evolving challenges in fruit production, including adaptation to climate change, management of emerging pests and diseases, and optimization of novel sustainable farming practices like regenerative and vertical farming (Hassoun *et al,* 2023). The ongoing advancements in AI and their application to the unique requirements of fruit cultivation promise a future where fruit production is more efficient, environmentally friendly, and resilient.

CONCLUSION

Artificial intelligence is developed on the principle of enabling machines to perform complex tasks-such as learning, pattern recognition, and decision-making similar to cognitive functions of the human brain. Key applications such as AI-powered disease detection have shown remarkable accuracy, promising to reduce the reliance on chemical interventions and promote healthier ecosystems. Furthermore, AI's contribution to accurate yield prediction and efficient crop monitoring empowers farmers to make more informed decisions, enhancing both economic and environmental sustainability. While the adoption of AI in fruit growing presents certain challenges related to data availability, cost, and expertise, the ongoing advancements and future research directions hold immense promise. The development of more robust and interpretable AI models, coupled with their integration with other emerging technologies, will likely unlock even greater potential for creating a more sustainable and resilient future for fruit production. The continued exploration and application of artificial intelligence in this domain are crucial for addressing the increasing global demand for fruit while safeguarding the environment and ensuring the long-term viability of the agricultural sector.

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