Review

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Review

Artificial Intelligence in Sustainable Fruit Growing: Innovations, Applications, and Future Prospects

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Abstract: The global demand for nutritious food, coupled with environmental and economic constraints, has driven the need for sustainable agricultural practices, particularly in fruit growing. Artificial intelligence (AI) has emerged as a transformative technology to enhance the sustainability and efficiency of fruit production. This review explores the current landscape of AI applications in sustainable fruit growing, focusing on innovations, practical applications, and future prospects. Key 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 management. Notable advancements include AI models achieving over 98% accuracy in detecting pomegranate fruit diseases and robotics reducing labor costs by up to 95%. These applications contribute to environmental sustainability by minimizing resource waste and chemical use, while also improving economic viability and social well-being. However, challenges such as high costs, data requirements, and technical expertise gaps hinder widespread adoption. Future directions involve developing robust, interpretable AI models, integrating with emerging technologies like IoT and blockchain, and addressing climate change and evolving agricultural challenges. This review underscores AI's potential to revolutionize sustainable fruit growing, ensuring resilient and environmentally friendly fruit production to meet global food demands.

Keywords: artificial intelligence; sustainable fruit growing; precision agriculture; machine learning

1. Introduction

The escalating global population and its increasing demand for nutritious food sources (United Nations, 2019), coupled with the growing awareness of the environmental and economic limitations of conventional agricultural practices (Tilman et al., 2011), have necessitated a significant paradigm shift towards sustainable agriculture. Within this context, sustainable fruit growing has emerged as a critical area of focus due to the high nutritional value of fruits (FAO, 2020) and the significant environmental impact of their production (Notarnicola et al., 2017). The importance of sustainable fruit growing extends beyond mere production volume, encompassing the preservation of environmental health, the support of biodiversity (Power, 2010), and the assurance of long-term food security (Godfray et al., 2010). Practices that reduce carbon footprints, support ecological balance, and promote resource efficiency are becoming increasingly vital in ensuring the resilience and longevity of fruit production systems (Pretty et al., 2018). The convergence of rising global food demand and the imperative for environmental stewardship underscores the need to explore innovative solutions that can enhance both the productivity and the sustainability of fruit cultivation (Foley et al., 2011).

Sustainability in the realm of agriculture is not a monolithic concept but rather a multifaceted endeavor that requires solutions addressing ecological integrity, economic viability for producers, and social well-being of communities (Pretty et al., 2006). Any technological intervention aimed at fostering sustainable fruit growing must be evaluated based on its impact across these three interconnected dimensions to achieve truly sustainable outcomes (Elkington, 1997). Solutions that focus solely on increasing yields without considering environmental consequences or the livelihoods of farmers may fall short of achieving long-term sustainability (Tilman et al., 2011).

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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 & Prenafeta-Boldú, 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 lifecycle 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.

2. Materials and Methods

The compilation of this review involved a systematic strategy for identifying and analyzing relevant research material. The initial phase focused on conducting a comprehensive literature search utilizing specific keywords and search terms pertinent to the topic, such as “artificial intelligence,” “fruit growing,” and “sustainable agriculture”. Academic databases and platforms, including Google Scholar, ResearchGate, and PubMed, served as primary sources for identifying scholarly articles, conference papers, and other relevant publications. This approach aimed to capture a broad spectrum of research activities and findings related to the application of AI in the context of fruit production and sustainability.

The selection of research snippets for inclusion in this review was guided by specific criteria to ensure relevance and focus. The primary inclusion criterion was the direct relevance of the material to the intersection of artificial intelligence, fruit growing, and sustainability. Studies that specifically explored the application of AI techniques in enhancing the sustainability of fruit production, or those that detailed AI innovations and applications within the fruit growing sector, were prioritized. The publication date was also considered to ensure that the review reflects recent advancements and current trends in the field. No specific exclusion criteria were applied based on study type or methodology, as the aim was to provide a comprehensive overview of the existing research landscape.

The synthesis and analysis of the information extracted from the selected research snippets were conducted using a thematic analysis approach. This involved identifying recurring themes and patterns related to AI innovations, specific applications across the fruit growing lifecycle, and future prospects in sustainable fruit production. The performance metrics of different AI models, particularly those related to fruit disease detection, were also compared and analyzed to assess the current state of the art in specific application areas. This structured approach to data synthesis allowed for the identification of key trends, the extraction of meaningful insights, and the development of a comprehensive understanding of the role of AI in promoting sustainability in fruit growing.

3. Results and Discussions

3.1. Innovations in 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 & Prenafeta-Boldú, 2018). A notable trend is the growing application of machine learning and deep learning algorithms to tackle sophisticated agricultural tasks (Patricio & 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 & 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).

3.2. Applications of 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 (Figure 1).

3.2.1. Precision Agriculture and Resource Management

AI plays a pivotal role in enabling precision agriculture practices that are crucial for sustainable fruit growing (Liakos et al., 2018). By leveraging sensor data and sophisticated algorithms, AI facilitates site-specific management of essential resources such as water and fertilizers (Chlingaryan et al., 2018). This targeted approach ensures that resources are applied only when and where they are needed, optimizing their use and minimizing waste, thereby contributing significantly to environmental sustainability (Basso & Antle, 2020). AI algorithms can analyze data from soil moisture sensors, weather forecasts, and plant health indicators to provide farmers with informed recommendations on irrigation schedules and fertilizer application rates (Mohamed et al., 2024; Keskes et al.,2025; Kamilaris & Prenafeta-Boldú, 2018). This data-driven decision-making process leads to more efficient resource utilization, reduces the risk of environmental pollution from excessive nutrient runoff, and ultimately enhances the overall sustainability of fruit production (Talaviya et al., 2020).

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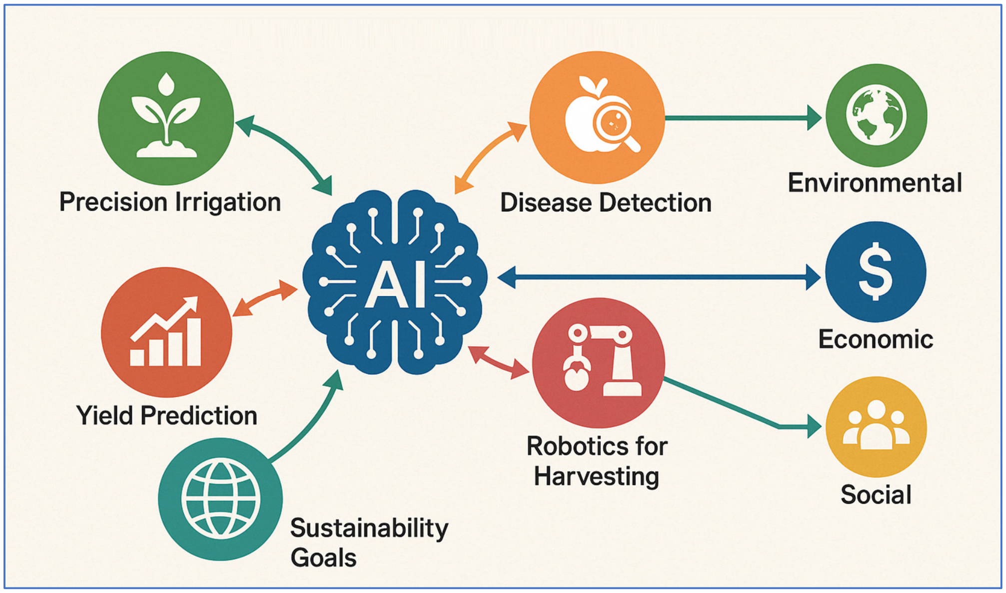

Figure 1. AI Applications in Sustainable Fruit Growing.

3.2.2. Pest and Disease Management

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 et al., 2024a; Shreyas et al., 2024). DenseNet and other transfer learning models reached 99% accuracy, though the 99.21% for DenseNet-201 lacks direct confirmation (Shreyas et al., 2024). A hybrid CNN with the Honey Badger Algorithm and a capsule network (Hybrid OACapsNet) also showed high accuracy for similar diseases (Bhange & Gavali, 2023; Kumar & Sharma, 2023). A leaf-focused study reported 98.07% accuracy using machine learning for the same diseases (Bhange & Hingoliwala, 2020), while image processing targeted Bacterial blight (Akhilesh & Kumar, 2019). These findings underscore AI's potential to transform orchard disease management, though real-world variability requires caution (Pakruddin et al., 2024b).

Specialized datasets are critical for advancing AI-driven disease detection in agriculture. PomeNetV1 and PomeNetV2 uses A dataset of 5,099 pomegranate fruit images (Pakruddin et al., 2024b). 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 & 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 & 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.

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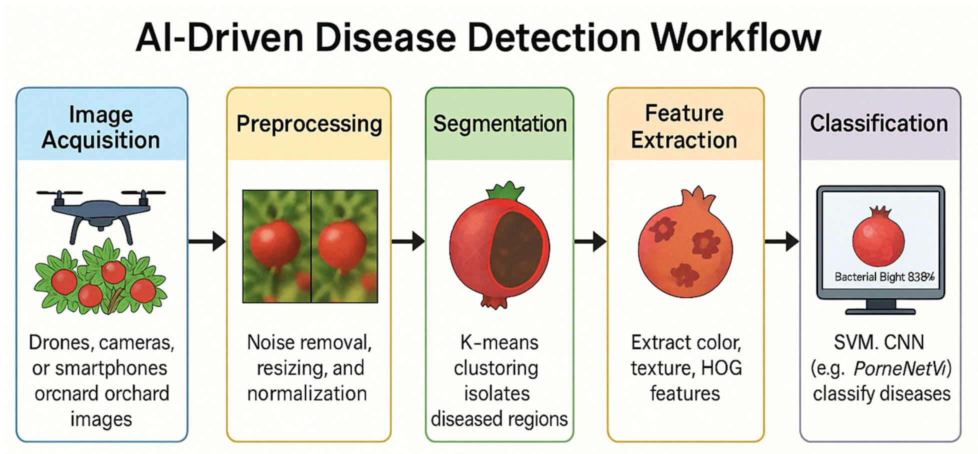

Figure 2. Workflow of AI-driven disease detection in fruit orchards, illustrating the pipeline from image acquisition to classification for timely interventions (adapted from Pakruddin et al., 2024; Khan et al., 2021).

3.2.3. Yield Prediction and Crop Monitoring

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 (Vijayakumar et al., 2021). A strawberry yield prediction model, adaptable to arborial fruits, uses drone imagery and deep neural networks, integrating weather and sensor data for accurate forecasts (Lee et al., 2020). 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.

3.2.4. Robotics and Automation in Harvesting and Orchard Management

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 labor 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). Robots like WeedSpider and Harvest CROO achieve up to 95% labor cost savings in orchards, addressing shortages while cutting chemical inputs (Bilal et al., 2024). FFRobotics' apple harvester, part of Western Growers' initiative, uses AI for precise picking, boosting efficiency in Washington orchards (Good Fruit Grower, 2021). These systems leverage sensors and computer vision to identify ripe fruits and weeds, ensuring precision and supporting economic sustainability.

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3.3. Contribution of AI to Sustainability Goals

AI significantly advances sustainability in fruit growing across environmental, economic, and social dimensions. 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 (Numalis, 2025). 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 et al., 2024b). 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).

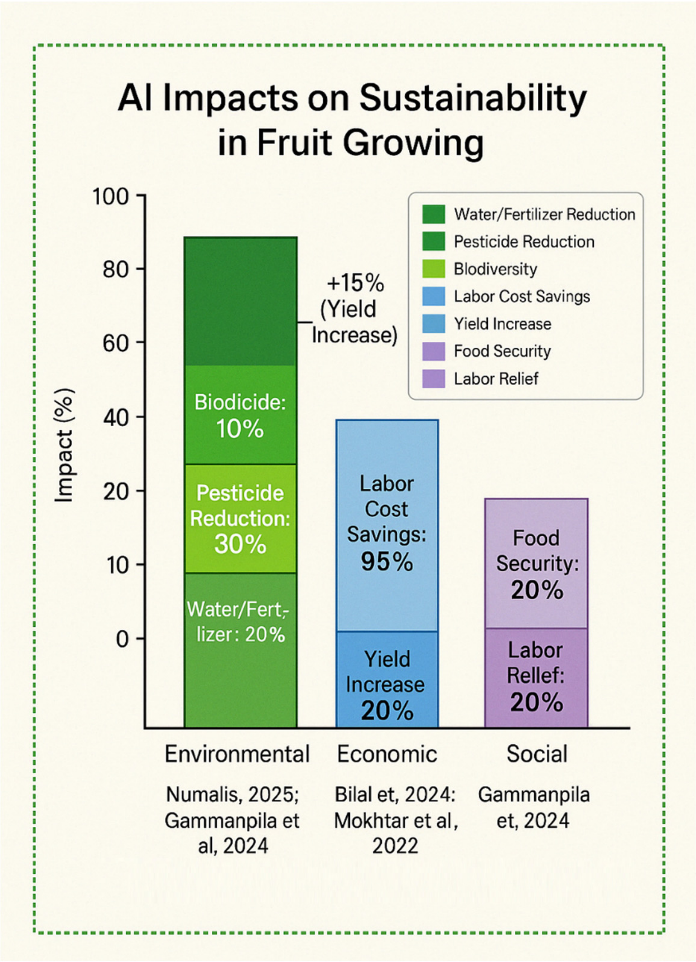

Figure 3. Impact of AI on Sustainability Metrics in Fruit Growing Purpose.

3.4. 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 (Mohamed, 2025; keskes and Nita, 2025). The

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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 blockchain, 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.

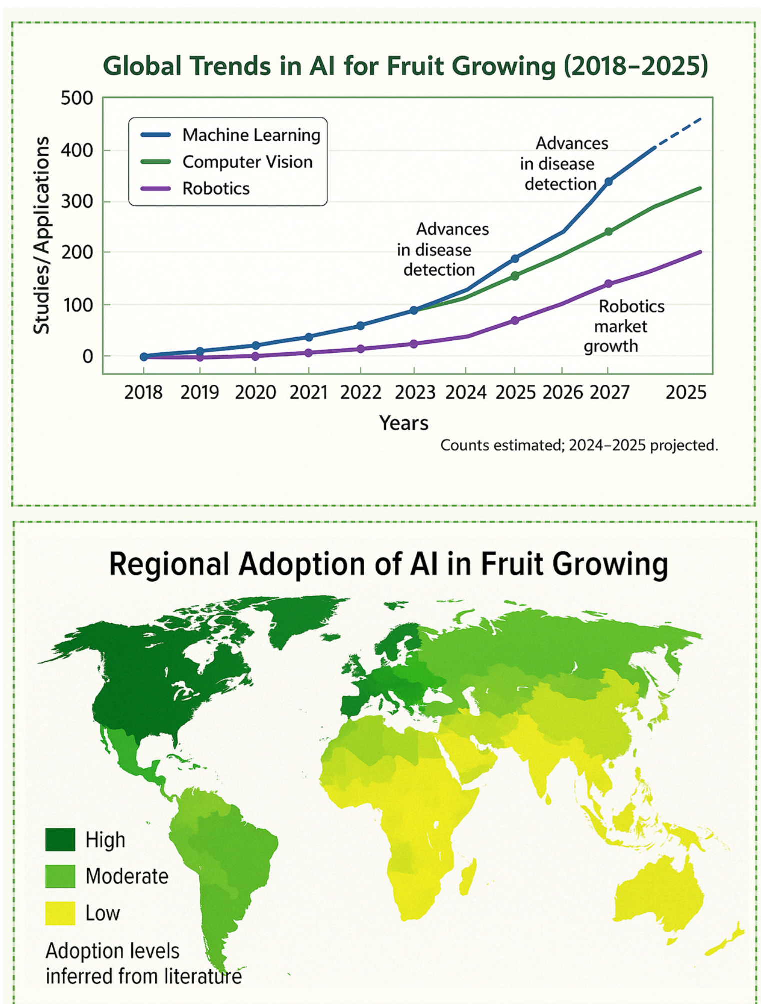

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Figure 4. Global Trends in AI Research and Applications for Fruit Growing (2018–2025).

4. Conclusions

This review has highlighted the significant and growing role of artificial intelligence in advancing sustainable fruit growing practices. The integration of AI innovations across various stages of fruit production, from precision resource management to automated harvesting, demonstrates the transformative potential of this technology. 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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