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A Review of Solar-Powered, Robotic, and AI-Driven Agricultural Machinery for Smart and Sustainable Farming

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ABSTRACT

The transition from conventional mechanization to intelligent and sustainable farming is increasingly driven by clean energy and automation. This review synthesizes recent advances in solar-powered agricultural machinery, robotics, and artificial intelligence (AI) within the broader context of biosystems engineering. Solar-powered tractors, autonomous ground vehicles, and unmanned aerial systems reduce reliance on fossil fuels, lower labor demands, and enhance precision in seeding, irrigation, and harvesting. At the same time, AI, machine vision, IoT, and big data enable real-time monitoring and decision-making, contributing to resource-efficient and climate-resilient farming systems. Despite progress, challenges such as high initial costs, limited battery capacity, and insufficient charging infrastructure hinder large-scale adoption. Promising solutions include next-generation batteries, modular energy storage, hybrid renewable energy platforms, and advances in robotic perception and deep learning. This review highlights the synergistic role of bioenergy integration, digital automation, and mechanical innovation in shaping future agricultural machinery. By outlining research priorities in energy storage, robotics, and data-driven farm management, the article provides a roadmap for accelerating smart agriculture toward financially viable, climate-smart, and digitally integrated biosystems.

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INTRODUCTION

The agricultural sector has undergone extraordinary technological transformations in recent decades, driven by global population growth and shifting consumer demands. Traditional methods have been increasingly replaced with intelligent technologies, including the Internet of Things (IoT), robotics, and precision navigation systems significantly enhancing agricultural practices' efficiency, productivity, and sustainability. A central aspect of smart agriculture involves autonomous and robotic machinery for sowing, growing, and harvesting (Waleed et al., 2021). Modern tractors and combines can efficiently operate in fields while avoiding obstacles by integrating sensors, machine vision, and LiDAR with navigation algorithms (Saleem et al., 2021). In areas with limited telecommunications and satellite infrastructure, researchers have emphasized the combination of deep-learning cameras and multiple sensor inputs to reduce positional errors.

(Figure 1) presents a schematic flowchart of integrated smart agricultural technologies, including solar-powered mechanization, robotics, IoT-based data systems, and their adoption challenges and opportunities. This roadmap reflects the ongoing evolution toward more advanced and efficient agricultural systems.

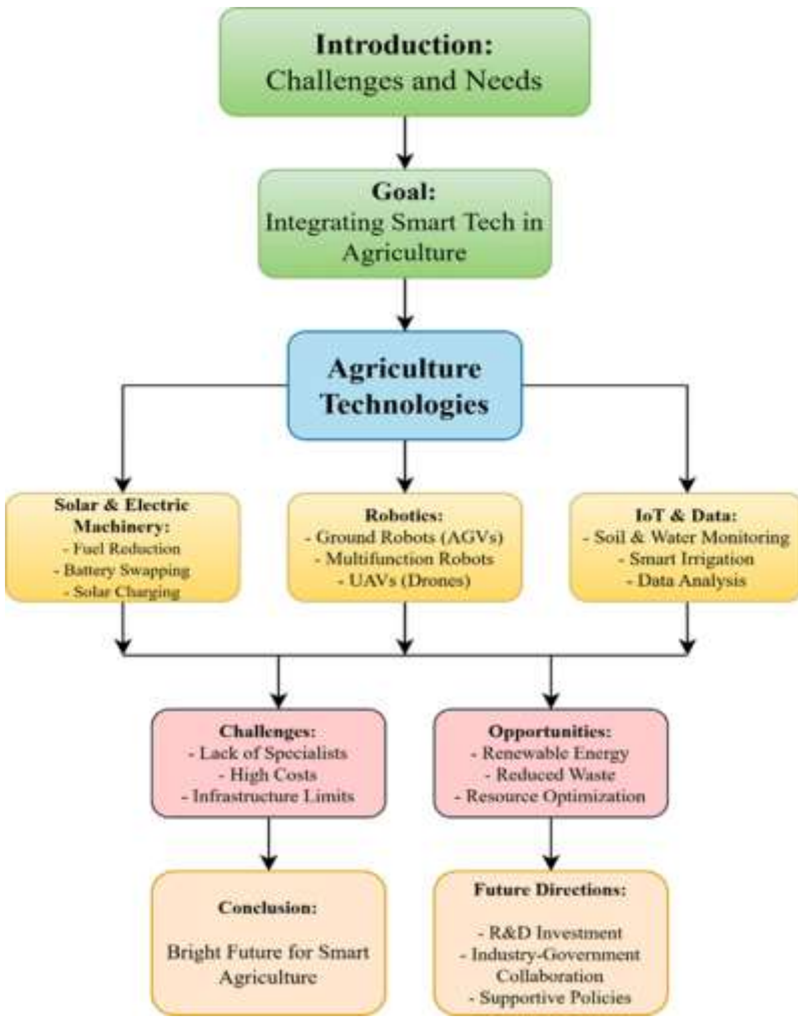

Figure 1. Flowchart illustrating the integration of smart technologies in agriculture, highlighting key components, challenges, and future directions.

Apart from navigation, dedicated farm robots have automated processes such as weeding, pesticide spraying, and harvesting fruits (Kokieva et al., 2024). These robots identify weeds based on machine vision algorithms and spray only the targeted area, significantly reducing pesticide input and environmental costs (Saleem et al., 2021).

Besides speed and precision, this system decreases dependence on the workforce and provides considerable profits for farmers who adopt these technologies (Gorjian et al., 2021; Scolaro et al., 2021). Keyword cluster analysis was conducted using a word cloud (as shown in Figure 2) to examine key trends in smart agriculture. In this word cloud, high-frequency terms are visually highlighted, representing important technologies and concepts emphasized in the relevant literature. (Figure 2) illustrates how emerging technologies, such as Sustainable Management, Artificial Intelligence, Big Data, and Autonomous Systems, have become focal points in the digital transformation of modern agriculture.

Figure 2. Word cloud illustrating the most prominent concepts in smart agricultural machinery and digital farming technologies.

Soil moisture sensors and machine learning models have led to the automation of irrigation systems, which has been a significant development in recent years. These smart systems can accurately sense irrigation timing and amounts, reducing up to 75% of the water used while improving crop yield (Saiful Azimi Mahmud et al., 2020). Furthermore, small robots with tailormade cameras are used for periodic inspection of plant pests and diseases (Barnes et al., 2021). These robots can detect early signs of biological stress or contamination on the leaves and help mitigate the damage before it spreads (Kokieva et al., 2024). The data-driven development of risk assessment systems and human-detection sensors will also aid in preventing accidents and injuries when working with autonomous machinery (Zhang et al., 2019). To implement precision agriculture and management, integrating data analysis, diverse sensors, and autonomous farming equipment with IoT systems is essential (Rizvi et al., 2024). This way, parameters like ambient temperature, soil moisture, wind speed, fertilizer use, and machinery data are uploaded to a cloud platform (Marinoudi et al., 2024). The data enables timely decisions on water, fertilizer, or pesticide usage through intelligent analyses while allowing remote monitoring and control (Vij et al., 2020).

Moreover, combining this information with optimization algorithms supports efficient machinery route planning, reducing fuel consumption and operational time (Waleed et al., 2021). IoT in smart agriculture covers real-time data collection, communication, and processing to optimize farm operations. (Figure 3) illustrates two key aspects: (a) the architecture of IoT systems including sensors, data storage, and machine learning for fast decision-making; and (b) the operational procedures of IoT-based agriculture, such as real-time monitoring, data analysis, and farmer interaction.

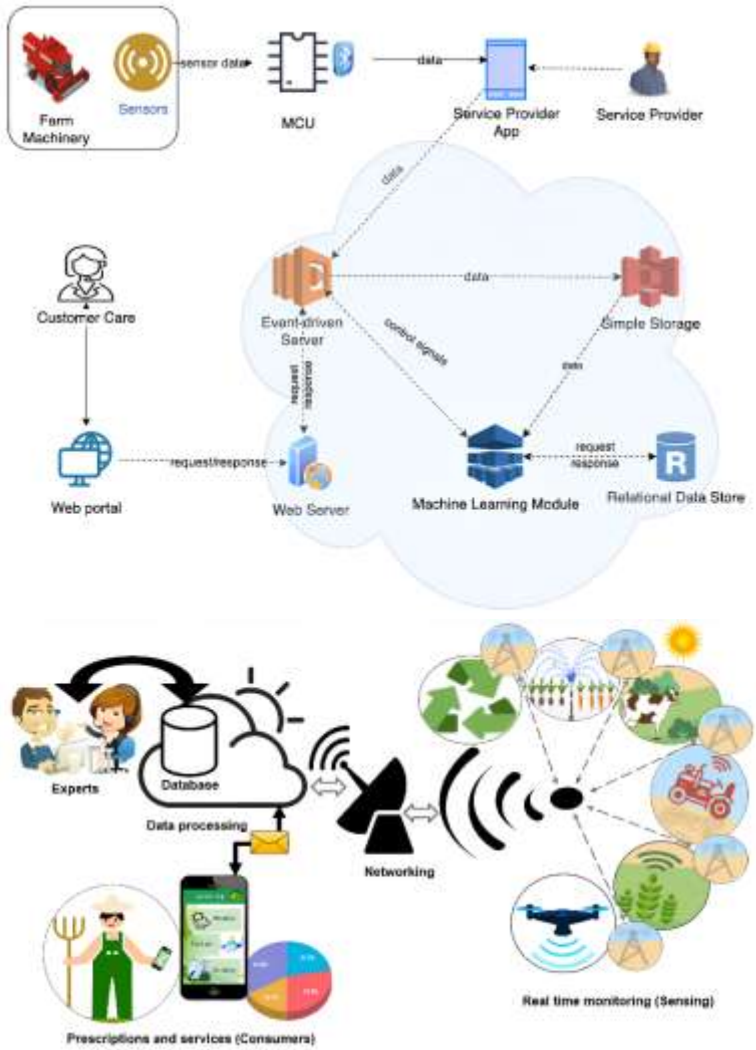

Figure 3. (a) IoT's System architecture illustrates the integration of devices, communication gateways, and data processing modules (Waleed et al., 2021). (b) Procedures of IoT in agriculture, including real-time monitoring, data analysis, and consumer interaction (Kim et al., 2020).

With increasing restrictions on fossil fuels and global initiatives to reduce greenhouse gas emissions, the development of electric tractors, hybrid vehicles, and solar-powered systems has received significant attention (Rifky et al., 2024). Although initial challenges such as high battery costs, limited charging infrastructure, and battery lifespan exist, studies show that these technologies significantly lower operating costs, extend machine life, and improve overall performance. Simultaneously, intelligent energy analytics platforms are being introduced to optimize fuel usage based on field and soil conditions (Kokieva et al., 2024). The advancement of intelligent agricultural machinery requires strong collaboration between academia, industry, and policymakers. This collaboration may include funding programs, joint laboratories, and accelerated patent processes (Danda, 2022).

Additionally, educating and training skilled personnel to operate and maintain autonomous and robotic farming systems is vital (Barnes et al., 2021). Governmental support such as financial aid, reducing production costs, and improving telecommunications infrastructure can accelerate the transition from traditional to smart machinery, thereby enhancing productivity and operational efficiency throughout the agricultural sector (Scolaro et al., 2021). Despite promising progress, certain barriers remain: high initial investment, complexity of digital integration, and lack of skilled labor (Kokieva et al., 2024; Danda, 2022; Scolaro et al., 2021). However, these challenges can be mitigated through interdisciplinary cooperation and increased investment in R&D initiatives.

Ultimately, modern agriculture empowered by intelligent and robotic machinery offers significant advantages, including increased productivity, labor cost reduction, optimized resource utilization, and enhanced safety (Waleed et al., 2021; Saleem et al., 2021; Scolaro et al., 2021). Integrating digital tools, AI-based analytics, and clean energy sources marks a transformative shift toward sustainable and efficient agricultural systems that can meet the demands of future generations. Despite growing interest in smart agriculture, existing literature reviews often focus on isolated technologies or specific applications without offering a comprehensive analysis of how solar-powered machinery, robotics, and AI-based decision systems collectively contribute to sustainable, climate-resilient farming. This review aims to bridge that gap by systematically examining the integration of clean energy systems, autonomous agricultural machinery, and digital tools within the broader context of precision agriculture. The article identifies current challenges, explores emerging technological and infrastructural innovations, and outlines future research directions needed to scale intelligent farming practices. Unlike prior reviews, this work highlights the synergistic potential of combining solar electrification, AI-driven automation, and IoT-based platforms to reshape agricultural operations providing a timely, multidisciplinary perspective aligned with the goals of climate-smart and resource-efficient farming.

Despite the rapid growth of smart agriculture research, most existing reviews concentrate on isolated technologies such as robotics, renewable energy, or AI-based systems without providing an integrated perspective on how these domains collectively contribute to advancing biosystems engineering. The novelty of this review lies in its comprehensive synthesis of solar-powered machinery, agricultural robotics, and AI-driven digital platforms, framed within the broader goals of sustainable and climate-resilient farming. By systematically highlighting synergies across clean energy utilization, mechanical innovation, and data-driven management, this article offers fresh insights into scaling intelligent agricultural systems. The objective is to guide researchers, policymakers, and industry stakeholders toward innovative strategies that accelerate the transition from conventional mechanization to digitally integrated, resource-efficient farming systems.

Solar, Electric, and Robotic Agricultural Machinery

Due to the increasing global population and the urgent food supply, agriculture faces many challenges, such as water scarcity, climate change, increased energy costs, and the need for higher efficiency. Within this context, increasing focus on sustainability and renewable energies has created a space for popularizing novel technologies on farms, mainly photovoltaic (PV) systems (Yao et al., 2024). However, alongside the technological advancement of clean energy, there are emerging trends of decreasing fossil fuel utilization and improving precision and velocity of field operations through solar-powered electric machinery systems and robotic systems (Kokieva et al., 2024; Saleem et al., 2021). One distinctive feature of this new paradigm is the development of solar-electric agri-chemical equipment that can wholly or partially satisfy its energy needs through photovoltaic panels (Gorjian et al., 2021). Such solar-electric tractors have, in particular, been deployed in regions aiming to reduce fuel costs and improve farm management precision (Scolaro et al., 2021). At the same time, agricultural robots with applications that include harvesting and precision spraying have become an integral part of the future of global agriculture due to the proliferation of the Internet of Things (IoT) and remote-control systems (Barnes et al., 2021; Saiful Azimi Mahmud et al., 2020). As (Zhang et al., 2019) illustrated in recent studies, adopting technologies such as solar-powered electric tractors and fully autonomous robots can significantly reduce labor costs, energy consumption, and pollution. However, future research and policies must resolve difficulties like high upfront investment, inadequate battery storage, and infrastructural bottlenecks (Aby & Issa, 2023). We summarize the different applications of PV in agriculture, show the shift towards solar-electric tractors and other agricultural robots, and end with challenges and potential research directions (Gorjian et al., 2021; Saleem et al., 2021).

Applications of Solar (PV) Technology in Agriculture

The solar module, the central part of the PV system, consists of semiconductor cells, which convert solar radiation into direct electric current (Rizvi et al., 2024). The module technologies are divided into two main classes: silicon-based-crystalline, polycrystalline, and mono-crystalline-and thin-film. Monocrystalline silicon cells exhibit higher efficiency than polycrystalline types. However, these are more expensive (Gorjian et al., 2021; Kim et al., 2020) Researchers have tried many different approaches to cut costs during production, increase efficiency, and lengthen the lifecycle of solar cells, from improvements in wafer formation steps to emerging materials such as perovskite in hybrid cells (Saleem et al., 2021). However, silicon-based modules are still the most popular option in agriculture thanks to their robust stability, long service life, and established manufacturing technologies (Waleed et al., 2021). Frame structure, protective glass, and back sheet material, beyond cell type, can also have a substantial impact on module efficiency and longevity (Marinoudi et al., 2024)

Incentives and Motivations for Using PV in Agriculture

As a result, many governments worldwide provide support packages and incentives for solar energy adoption, such as low-interest loans for installing solar systems in agriculture or feed-in tariff programs for excess electricity generated by farm-based PV systems (Kim et al., 2020). Governments use other policy tools, such as tax incentives and preferential tariffs, to promote PV in the agricultural sector (Vij et al., 2020). Farmers have increasingly embraced PV for a variety of advantages. For example, using solar energy to power irrigation pumps can significantly reduce fuel costs (Rifky et al., 2024). Solar systems enable farmers to be energy self-sufficient in remote farms or regions with limited access to public power grid (Saleem et al., 2021). In addition, enhancing environmental sustainability and minimizing emissions of greenhouse gases are significant reasons to use solar energy in agricultural producers' units (Gorjian et al., 2021; Yao et al., 2024).

Transition to Solar-Electric Tractors on Farms

The Emergence of Electric Tractors in Agricultural Applications

The rapid development of power electronics and the evolution of energy storage technologies have sparked the concept of substituting diesel engines for electric ones in tractors (Scolaro et al., 2021). Initially, electric tractors were mainly confined to light-duty tasks or smaller acreage, where reduced pollution, lower noise, and greater precision were beneficial (Marinoudi et al., 2024). Advancements added the ability to use electric tractors for more demanding tasks, including deep plowing, land leveling, and heavy implement hauling (Zhang & Wang, 2024). In addition to environmental benefits, the primary driver for farm operations to implement electric tractors is the potential reduction in fuel and maintenance costs in the longer term (Kokieva et al., 2024). Even though the upfront cost may be higher, the reduced operating costs throughout the equipment's lifecycle can compensate for such differences (Saleem et al., 2021). In addition, being more compatible with remote-control and IoT-based systems, electric tractors have become a suitably efficient method for implementing precision agriculture strategies (Aby & Issa, 2023).

New Trends in Electric Tractor Propulsion Systems

In contemporary electric drivetrains, high-efficiency AC motors (e.g., permanent magnet synchronous or induction motors) are often used

(Scolaro et al., 2021). The continuous control of speed and torque allows the tractor to adapt dynamically to farm conditions and, thus, better optimize energy consumption (Danda, 2022). Some new models also have regenerative braking, which recaptures kinetic energy during downhill travel or deceleration (Saleem et al., 2021). Researchers proposed hybrid electric-hydraulic power transmission systems to lower total costs. These systems utilize electric power not only for the main propulsion of the tractor but also for the hydraulic operation of auxiliary devices (e.g., hydraulic steering or hydraulic arms) (Yao et al., 2024). The hybrid configuration boosts operational flexibility. It reduces the energy losses in power transmission (Rizvi et al., 2024).

Solar Charging Methods for Electric Tractors

Electric tractors can be charged from the grid or local generators. Still, using solar panels is especially attractive (Gorjian et al., 2021). Large farms can set aside some land for a solar charging station with optimally angled PV panels. The tractor can park under these panels during downtime or scheduled intervals to recharge (Scolaro et al., 2021). Another approach uses lightweight and flexible panels that can be mounted on the tractor body or fixed implements to complement the continuous partial supply of energy needed (Saleem et al., 2021). Despite their limited output, these portable solar panels can cover some base load of the tractor during sunny hours (Marinoudi et al., 2024). In addition, studies suggest that solar tracking systems or canopies designed around fields may enhance performance during planting and harvesting seasons (Kim et al., 2020).

Battery Storage Technologies

Electric tractors need batteries with high energy density, long life, and comparatively short charging time (Rifky et al., 2024). Lithium-ion batteries are the preferred technology today; however, next generations, like solid-state or metal-air batteries, are also under development (Saleem et al., 2021). Overcoming safety hazards (such as the risk of fire or thermal runaway), alongside ensuring reliable performance across diverse temperature and humidity ranges, remains a principal challenge for battery manufacturers (Kokieva et al., 2024). Several companies have suggested swappable or modular battery packs to combat prolonged charging outages. In this approach, it is possible to quickly swap out a depleted pack for a fully charged one (Scolaro et al., 2021). This solution is flexible. Still, it requires a complex infrastructure to store spare modules and manage charging cycles (Zhang & Wang, 2024).

Review of Research Studies and Commercial Examples

According to numerous studies, electric tractors integrated with solar on medium-to-large farms can be cost-effective, especially when factoring in long-term fossil fuel and environmental costs (Gorjian et al., 2021). Some European pilot projects have reduced the operational costs of electric tractors by up to 50% compared to diesel equivalents (Scolaro et al., 2021). Small-scale commercially viable models have also been implemented in Asia, particularly for rice or vegetable farms, reducing air pollution and fuel savings (Kokieva et al., 2024). Some research projects target software development for farm management and Artificial Intelligence (AI)-based controls for electric tractors (Danda, 2022). These systems can process sensor data in real-time and determine the best speed, routing, or battery charging schedules (Rizvi et al., 2024). The integration of such systems with cloud infrastructure, as well as the IoT, can pave the way for full automation in farm operations (Saleem et al., 2021). (Figure 4) illustrates the historical development of hybrid tractors, showcasing how new designs and technologies have contributed to improved efficiency and sustainability.

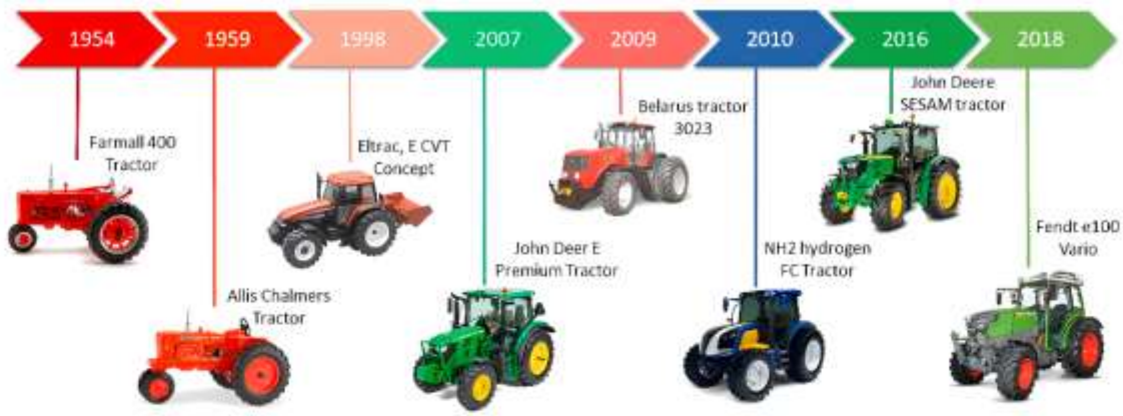

Figure 4. Historical development of hybrid tractors, adapted from (Ghobadpour et al., 2019)

Agricultural Robots

Mechanical Manipulators

One of the first robots created for agriculture was robotic arms designed for the precise harvest of crops, including tomatoes, cucumbers, and strawberries in greenhouses (Saiful Azimi Mahmud et al., 2020). These arms use colorful or multispectral cameras and machine vision algorithms to identify and pick ripe fruit without damage (Saleem et al., 2021). Some may even have basic tactile sensors to regulate grip strength and avoid bruising (Barnes et al., 2021). (Figure 5) illustrates examples of robotic end-effectors designed for precise cotton harvesting. These tools include one-finger and three-finger models.

Figure 5. Agricultural robotic end-effectors: (1) One-finger end-effector, (2) One-finger end-effector in the field, (3 and 4) Three-finger end-effector (Gharakhani & Thomasson, n.d.).

Robotic arms are also used for specific tasks such as pruning, grafting, and, if possible, even automated packaging (Danda, 2022). With advances in deep learning, it is possible to identify more complex patterns, such as early-stage pest infestations on leaves or defective produce (Saleem et al., 2021). (Figure 6) presents examples of agricultural robots and machinery used in smart farming operations.

Figure 6. Examples of agricultural robots and machinery: (a) BoniRob robot (Ruckelshausen et al., 2009), (b) Shrimp robot (Stein et al., 2016), (c) Chisel cultivator (Roca et al., 2019), (d) DJI AGRAS MG-1S Drone Sprayer (Robotics and Automation in Agriculture: Present and Future Applications | Applications of Modelling and Simulation, n.d.), (e) Combined Harvester (Chaab et al., 2020)

Autonomous Ground Vehicles (AGVs)

AGVs are self-driving machines (ground robots) that transport loads (Barnes et al., 2021). These robots are equipped with LiDAR sensors, stereo cameras, or advanced GNSS, allowing them to move through fields while steering clear of obstacles or crops (Rizvi et al., 2024). In advanced weeding applications, autonomous ground vehicles (AGVs) use deep learning algorithms to identify the weeds from the primary crops and eliminate them selectively (Saleem et al., 2021). This method reduces the use of herbicides. It ensures greater weed removal accuracy (Yao et al., 2024). (Figure 7) illustrates the overall structure of the automatic driving system for agricultural machinery, which includes various modules such as environmental perception, autonomous navigation, path planning, and control systems (adapted from Yao et al., 2024). (Figure 8) depicts the overall structure of an agricultural robotic system based on machine learning (ML) and deep learning (DL) algorithms. The system includes data collection, robotic platforms, and performance evaluation for plant disease detection, weed discrimination, and other smart agricultural operations (Saleem et al., 2021).

Unmanned Aerial Vehicles (UAVs)

Drones or UAVs offer a wide range of applications in agriculture, from multispectral imaging for plant health and nutrient deficiency detection to targeted spraying in inaccessible areas (Saleem et al., 2021). Thermal and infrared sensors on drones provide valuable information on soil surface temperature, crop water stress, and even weed density (Marinoudi et al., 2024). Moreover, small tanks are fitted on some drones that spray pesticides or liquid fertilizers precisely where sensors detect the need for this application (Aby & Issa, 2023). (Figure 9) shows examples of agricultural drones used for mapping and spraying.

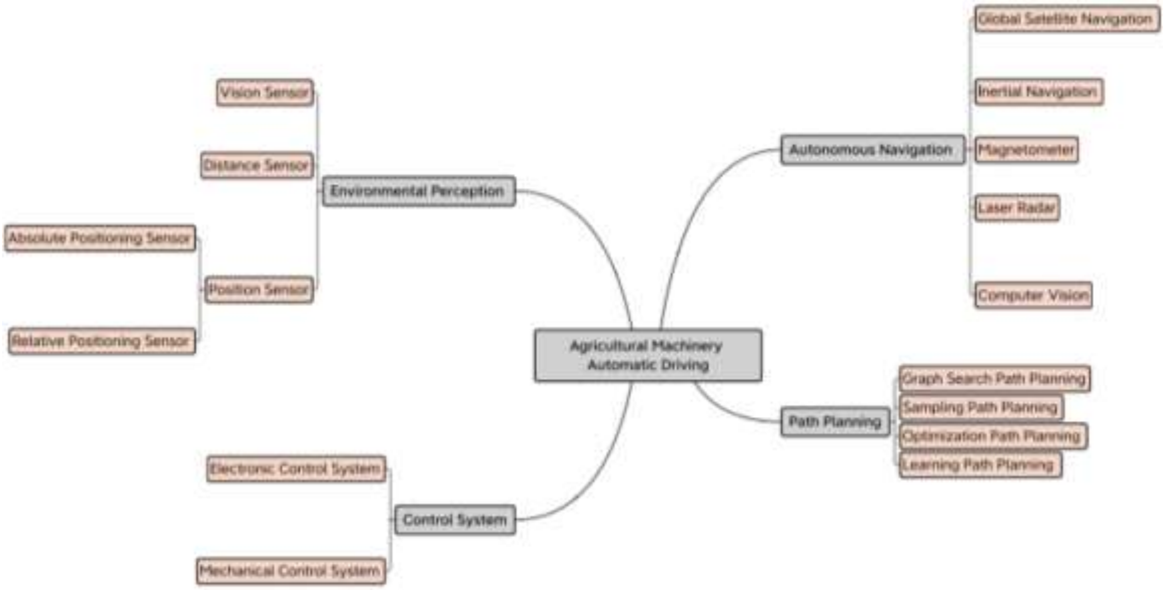

Figure 7. The Automatic driving system for agricultural machinery and its main components include sensors, control systems, and path planning modules (Yao et al., 2024)

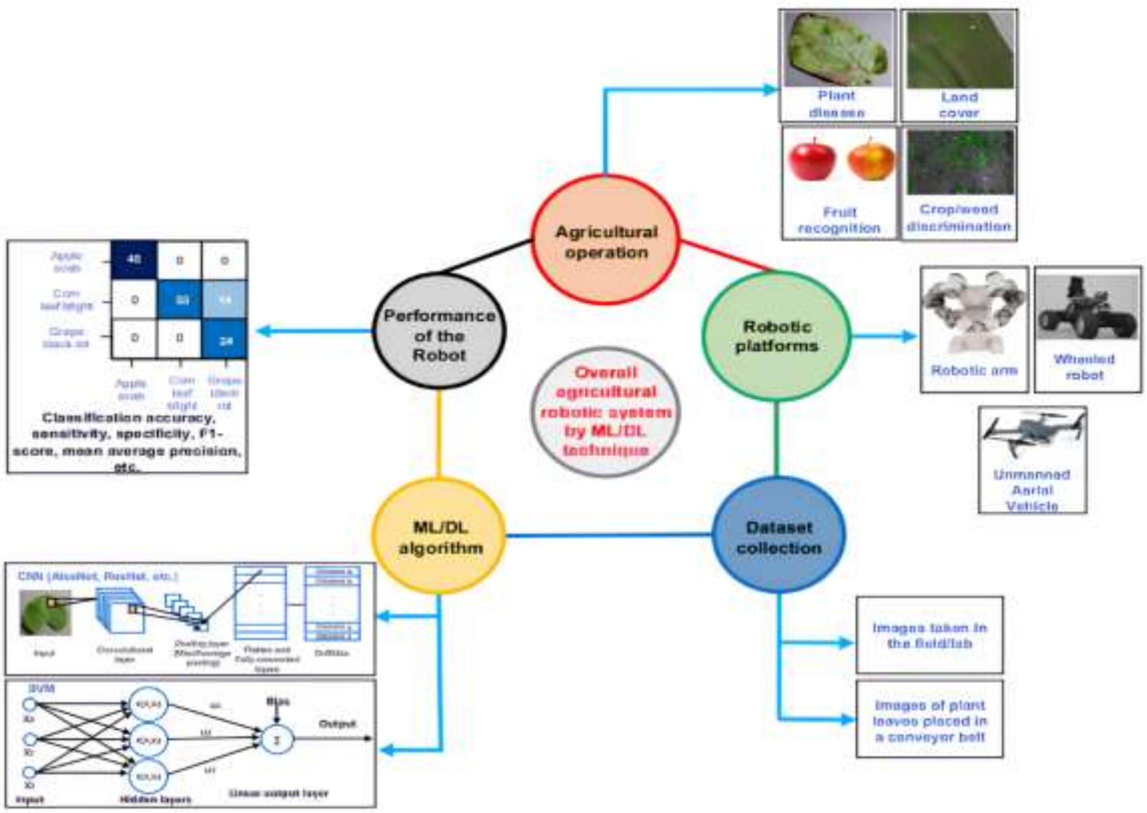

Figure 8. Block diagram of implementing an agricultural robotic system through ML/DL algorithms (Saleem et al., 2021).

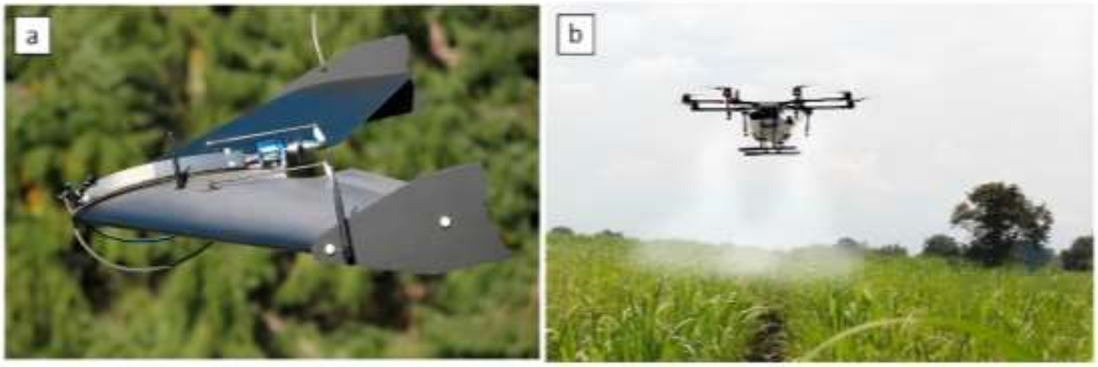

Figure 9. (a) The AgDrone developed by HoneyComb, (b) A spraying drone flying over a farm (Gorjian et al., 2021)

Solar-Powered Farm Robots

Small and light robots with solar panels are ubiquitous on organic farms and small orchards (Kokieva et al., 2024). Common tasks performed by these robots include monitoring soil conditions, measuring moisture levels, collecting weather data, and caring for young plants (Danda, 2022). They can operate independently because they collect solar energy daily, requiring only occasional grid charging (Gorjian et al., 2021). Despite their low power, these robots are an excellent solution for innovative and sustainable agriculture where high power is unnecessary (Saleem et al., 2021).

However, significant barriers remain before widespread adoption of electric tractors, solar systems, and agricultural robots becomes possible. For instance, the high up-front cost of solar-electric tractors and on-farm solar arrays is a major challenge for small-scale farmers (Rifky et al., 2024). Additionally, battery capacity limitations can reduce operational effectiveness during extended tasks or emergencies, such as extreme weather conditions (Saleem et al., 2021). Rural settings often lack rapid-charging infrastructure or dedicated maintenance services for such machines, making it difficult to find spare parts or expert mechanics (Kim et al., 2020). Data security, wireless communication reliability, and farmers' privacy in agricultural robotics add complexities (Aby & Issa, 2023). Additionally, a shortage of skilled labor for operating and maintaining smart devices slows their adoption in some areas (Danda, 2022). (Figure 10) illustrates modular robotic applications in various domains.

Figure 10. Modular robotic applications: (a) Window cleaning robot (Vega-Heredia et al., 2019), (b) Underwater robotic arm (Barbieri et al., 2018), (c) Mobile robotic platform (Tkáčik et al., 2019)

Despite these challenges, a review of recent studies indicates that combining solar technology, electric machines, and robotic approaches has already transformed agriculture (Saleem et al., 2021). These advancements from producing clean and cost-effective energy to precisely managing planting, tending, and harvesting with minimal human intervention represent a fundamental shift from traditional agricultural practices (Gorjian et al., 2021; Kokieva et al., 2024). Realizing this vision depends on overcoming key technical, financial, and infrastructural issues. High-capacity, fast-charging batteries remain a top research priority for large-scale farming applications (Rifky et al., 2024).

Intelligent energy management systems are also essential to optimize consumption patterns and schedule daily charging (Scolaro et al., 2021). In robotics, efforts should improve pest and weed detection accuracy, stable navigation algorithms, and multi-robot coordination (Barnes et al., 2021). Governmental policies and structural support are crucial in accelerating the transition toward solar-electric agriculture (Danda, 2022; Kokieva et al., 2024). Financial incentives, assistance for small-scale farmers, and favorable regulations for electric vehicles in agriculture can expand the adoption of these technologies. With continued progress and structural support, agriculture can become brighter, cleaner, and more productive a future where solar energy and autonomous robotics power the green economy (Gorjian et al., 2021; Saleem et al., 2021).

To provide a comprehensive and accurate comparison of the key and significant studies in agricultural machinery automation, (Table 1) examines and contrasts 19 prominent studies. This table includes information regarding the main applications, type of article, key findings, limitations, and advantages of each study. The selection of these 19 studies is based on their importance and impact in advancing knowledge and technologies related to smart agriculture. Analyzing this comparison allows for a clearer understanding of research trends, strengths and weaknesses, and potential opportunities within this domain. This table serves as a primary reference source in the current review article, enabling readers to familiarize themselves with a comprehensive and comparative view of the conducted research.

Table 1. Comparison of 19 Key Studies on Agricultural Machinery Automation Focusing on Applications, Article Type, Key Findings, Limitations, and Advantages.

Main Applications	Key Findings	Limitations	Advantages	Ref.
Automatic navigation path planning in agricultural machinery	• A review of GNSS, machine vision, and LiDAR methods for autonomous navigation • Introduction of four path planning algorithm categories (graph search, sampling, optimization, and learning) • Emphasis on sensor fusion and integration with deep learning to increase accuracy	• Slow progress in remote rural areas • Weak GNSS signals in some regions • Deep learning-based research is still in the early stages	• Creation of accurate and autonomous navigation • Reduction of labor time and costs • Potential for multi-sensory fusion and combining methods to achieve better performance	(Yao et al., 2024)
Machine efficiency in automating agricultural operations	• Provides analysis for refined estimation of resource needs (labor, materials, etc.) at different planning levels • Emphasis on systematic methods to improve operational management • Suggests ways to minimize intra-shift downtime	• Requires precise local data for better forecasting • Challenges in large-scale implementation across diverse farms • Lack of complete computational infrastructure for applying accurate predictive methods	• Improved accuracy and efficiency in operational planning • Reduction of unnecessary machine downtime • A framework for comprehensive resource management at various scales	(Kokieva et al., 2024)
Unmanned systems in the sky, land, and water for agriculture	• Emphasis on the development of autonomous systems on land, air, and water • Examines pest detection algorithms, optimized irrigation, and machine vision applications • Introduces drones, ground robots, and underwater robots for planting, cultivation, and harvesting	• Instability of some sensors under different weather conditions • Challenges in simultaneous implementation of multi-layered systems (control, communication, cloud processing) • Limited training data for deep learning	• Improves precision and speed of agricultural operations • Reduces the need for human labor • Potential to reduce pesticides and fertilizers with intelligent control	(Zhang & Wang, 2024)
The impact of robotics and automation on the agricultural job market	• Presents a two-dimensional model of “cognitive/manual vs. routine/non-routine” to classify jobs at risk of robotization • Analyzes skill requirements for the future of agriculture • Highlights the combined role of STEM, management, and soft skills for workforce success	• Uncertainty in the rapid adoption of robots across all sub-sectors of agriculture • A digital gap among the traditional rural workforce • Need for transparent and long-term policymaking	• Identification of future skill requirements • Possibility to plan training and upskilling of human resources • Emergence of new employment and entrepreneurship routes in the robotic equipment sector	(Marinoudi et al., 2024)

Main Applications	Key Findings	Limitations	Advantages	Ref.
Safety of autonomous agricultural machines	• Categorizes safety studies into three areas: environmental perception, risk assessment, and human factors • Recommends the use of standard frameworks (ISO 18497) alongside real-time risk assessment • Emphasizes understanding predictable human activities and safe human-robot interaction	• Lack of prior data on emerging technologies • Current standards do not cover all scenarios of repair, transport, and rural road driving • Challenges in designing human-robot models that account for diversity in human dimensions	• Enhances safety in autonomous agricultural machines • Reduces accidents and costs from collisions • Identifies research needs in the human-machine interaction phase	(Aby & Issa, 2023)
Automated irrigation system based on soil moisture sensors	• Designed and implemented a system using two electrodes for soil moisture measurement • Improved plant performance (height and leaf area) and maize yield with automated irrigation • Significant savings in water and electricity consumption	• Needs precise calibration of sensors in different soil types • Unavailability or instability of electrical supply in some rural areas • Sudden climatic factors affecting automated control	• Reduces water and energy costs • Better crop growth and yield improvement • Easy implementation with simple, low-cost equipment	(Rifky et al., 2024)
Use of ML and DL in weed detection and improving crop quality	• Introduces various machine vision methods (GLCM, LBP, ResNet, DenseNet, etc.) for weed classification • High accuracy and detection speed using deep neural networks • Mentions data augmentation approaches in cases of limited data	• Requires large and diverse datasets • Algorithm sensitivity to lighting variations and imaging angle • Hardware cost for powerful real-time processing	• Significant reduction in pesticide usage • Improvement in product quality and yield • Potential implementation on mobile devices and drones for quick field coverage	(Rizvi et al., 2024)
A review of IoT applications in agricultural automation	• Classifies IoT in agriculture into management, monitoring, control, and unmanned machinery • Examines wireless communication technologies (Wi-Fi, LoRa, 4G, ZigBee) • Emphasizes stable integration and security in open agricultural environments	• Challenge in integrating various sensors and communication protocols • Risk of wireless interference with other systems • Security vulnerabilities in open data networks	• Improves farm management and cost reduction • Provides data-driven basis for precision agriculture • Enables remote control and monitoring of equipment and environment	(Kim et al., 2020)
AI, computer vision, and deep learning in agriculture	• Demonstrates the superiority of DL over traditional ML in disease and weed detection • Reviews CNN, RCNN, ResNet, FCN algorithms • Stresses the need for extensive data to improve accuracy	• Weakness in low-light scenarios or high plant density • Processing cost and need for powerful hardware • Lack of a comprehensive and standardized dataset	• Enhanced speed and accuracy in disease and weed identification • Better management and reduced pesticide use • Potential integration with on-farm robots and drones for quick field coverage	(Saleem et al., 2021)

Main Applications	Key Findings	Limitations	Advantages	Ref.
The use of robotics and automation in planting, spraying, harvesting	• Classify robotic applications by task type (planting, inspection, harvesting, etc.) • Emphasizes higher accuracy and efficiency of automated methods • Examines technical challenges in uneven environments	• High costs of development and maintenance • Complexity in integrating different subsystems (sensors, mechanical, software) • Systemic failure risks in open-field conditions	• Reduced labor costs and improved speed • Increased productivity and reduced human error • Broader range of applications across different stages of production	(Saiful Azimi Mahmud et al., 2020)
A review of computer vision in agricultural automation	• Examines image processing methods in disease detection, growth measurement, and automatic harvesting • Analyzes recent computer vision algorithms in small-field farming • Points out the necessity of building large-scale, standardized datasets	• Challenges of complex farm environments (lighting, uneven backgrounds, overlapping leaves) • Lack of skilled personnel for developing advanced systems • Need for stronger links with deep learning and more capable hardware	• Higher accuracy in detection and tracking • Improves decision-making in farm management based on visual data • Potential to reduce resource use and time	(Tian et al., 2020)
Remote detection and classification of farm machinery	• Uses accelerometer and gyroscope sensors to record vibration and tilt • Employs KNN, SVM, Decision Tree, RF, and Gradient Boosting for machinery classification • Higher accuracy achieved by combining vibration and tilt data	• Requires stable IoT infrastructure in rural areas • Possible fraud or misuse of data if not combined with geographical positioning systems • Limited potential for expansion if network coverage is poor	• Automated remote monitoring of machinery • Prevention of misuse and incorrect machinery replacement • Possible integration with farm management systems	(Waleed et al., 2021)
Electric agricultural machinery powered by solar energy	• Discusses replacing fossil fuels with solar in tractors and robots • Analyzes early commercial models and challenges of cost, batteries, and maintenance • Emphasizes infrastructure reform and financial incentives for solar adoption	• High initial cost for installing panels and batteries • Dependence on weather and solar radiation • Need for specialized charging and maintenance infrastructure	• Reduced environmental pollution and fuel costs • Energy independence in remote farms • Improved sustainability and alignment with green agriculture approaches	(Gorjian et al., 2021)
Electrifying agricultural machinery and tractors	• Examines various hybrid and electric tractor configurations • Reviews industrial examples and proposed prototypes • Discusses considerations for torque control, power distribution, and energy management in electric agricultural vehicles	• High R&D costs • Challenges in integrating with traditional farming implements • Battery capacity limits for heavy, long-duration operations	• Improved energy efficiency and reduced pollution • More precise control of motion and output power • Higher efficiency in maintenance and repair	(Scolaro et al., 2021)

Main Applications	Key Findings	Limitations	Advantages	Ref.
Smart irrigation using IoT and machine learning	• Presents an economical approach to irrigation automation and prediction using SVR and Random Forest • Investigates distributed sensor nodes for climate and moisture data • Enables real-time prediction of water consumption and intelligent control	• Model sensitivity to SVR kernel type and amount of training data • Needs stable server or network storage • Sensors may fail or be damaged by animals	• Reduced water use and optimized irrigation • Better prediction of crop water requirements • Capable of integrating with farm robots for quick response to water stress	(Vij et al., 2020)
Examining the role of ML/DL in agricultural automation	• Focus on CNN, RCNN, ResNet, FCN in disease detection, fruit counting, weed differentiation, etc. • Introduces some datasets and the challenges of data collection • Suggests integration of AI with harvesting and spraying robots	• Lack of suitable sensors for real-time data • Problem of insufficient standardized datasets in all regions • Complexity in training deep models	• Increased speed and accuracy in pest and disease detection • Reduced reliance on human labor for repetitive tasks • Improved decision-making with real-time and analytical data	(Saleem et al., 2021)
Innovation in agricultural machinery and their effect on efficiency	• Analyzes macro trends such as Big Data, robotics, and IoT • Highlights the interplay among market, innovative companies, and government research • Investigates patent registration and the role of cross-sector collaboration in accelerating technology	• No standardized classification system for innovations • Difficulty in long-term evaluation of technologies' impact on market structure • Need for precise cost-benefit data for policy decisions	• Clarifies main trends and research gaps • Provides insights for long-term policy and investment • Potential to mobilize national and international collaborations in technology development	(Danda, 2022)
Testing innovative methods for agricultural machinery evaluation	• Introduces accelerometer and gyroscope sensor systems for assessing the dynamics and energy of agricultural units • Enables continuous performance evaluation without halting agricultural operations • Evolved from a simple system to a multi-purpose system for power and fuel consumption parameters measurement	• Requires precise equipment and high expertise in sensor installation • High sensitivity of data to environmental conditions and uneven terrain • High cost and complexity of measurement tools for widespread use in small farms	• Provides uninterrupted and real-time assessment of machinery performance • Reduces human error in measurement • Improves early detection and troubleshooting in machinery	(Artiomov et al., 2021)
Application of robotic systems and automation in cotton production	• Examines automated cotton harvesting methods and weed detection via machine vision • Points to opportunities for using drones and AGVs for spraying and continuous monitoring Analyzes cost hurdles, harvesting speed, and complexity of transport operations	• High cost of purchasing and maintaining robotic equipment • Current technology weakness in multiple harvests (due to uneven plant maturity) • Limited data on fully autonomous methods in diverse climatic conditions	• Increases harvest speed and reduces manual labor • Improves cotton quality and reduces waste • Potential to enhance organic methods and reduce pesticide use	(Barnes et al., 2021)

Challenges, Barriers, and Opportunities in Smart Agriculture

Integrating intelligent technologies into agriculture particularly solar-powered machinery and robotic systems has introduced significant improvements in efficiency, energy use, and sustainable practices. However, despite these promising advancements, the large-scale adoption of these technologies is still limited due to several challenges. This section analyzes key barriers and emerging opportunities in transitioning toward smart agricultural machinery systems.

One of the primary obstacles lies in the high initial investment required to develop and implement solar-powered electric tractors and intelligent robotic machinery (Saiful Azimi Mahmud et al., 2020). The costs associated with photovoltaic panel manufacturing, battery systems, and autonomous platforms with embedded sensors are substantial (Zhang et al., 2019). Nonetheless, advancements in solar cell production and scalability offer the potential to lower costs shortly (Rifky et al., 2024). These conditions present promising opportunities for manufacturers to innovate and enter competitive markets through cost-optimized solutions (Kokieva et al., 2024).

Current battery technologies used in electric tractors and robots face energy density and durability limitations, particularly under harsh agricultural environments (Scolaro et al., 2021). Extended operation in high-temperature, high-dust, or high-humidity conditions can degrade battery performance. However, research in solid-state batteries, supercapacitors, and metal-air storage systems has shown great promise for higher efficiency, longer lifespan, and reduced maintenance requirements (Kokieva et al., 2024).

Rural areas often lack fast-charging infrastructure and specialized maintenance facilities, hindering the implementation of electric machinery (Aby & Issa, 2023). Nonetheless, field-based solar charging systems such as mobile PV arrays or stationary solar canopies are increasingly used to reduce grid dependency (Rifky et al., 2024). Furthermore, workforce development programs supported by governmental institutions can help train technicians in robotics and power electronics, filling the gap in technical expertise (Danda, 2022).

Solar-electric systems are weather-dependent and reduced solar radiation during overcast or winter seasons can limit performance (Scolaro et al., 2021). Yet, innovations in solar tracking systems and high-efficiency panels help mitigate these issues by maximizing exposure and energy output across diverse climates (Kokieva et al., 2024). Integrating complementary sources like wind or bioenergy may also enhance overall system resilience.

The transition to intelligent agricultural systems is sometimes slowed by traditional mindsets or resistance to change in rural communities (Zhang et al., 2019). Bridging this gap requires targeted training programs and awareness-building efforts involving universities, governments, and the private sector. Long-term partnerships and demonstration projects on farms can foster hands-on experience and build trust in smart technologies (Rizvi et al., 2024).

Growing global interest in sustainable and organic agricultural practices is opening new markets for clean-energy technologies and autonomous robots (Kokieva et al., 2024). Investors and funding agencies are increasingly supporting infrastructure for electric machinery, especially in emerging economies. This trend presents fertile ground for startups and technology firms focused on developing AI-powered agricultural equipment and smart energy management systems.

The synergy between solar-electric machinery and digital technologies such as IoT, big data, and AI offers immense benefits (Zhang et al., 2019). Real-time sensor feedback enables precise decision-making for route planning, energy allocation, and task execution. These integrations enhance productivity while reducing inputs like fuel, labor, and fertilizers. Moreover, predictive analytics help respond swiftly to climate variability or pest outbreaks (Barnes et al., 2021). This cross-domain fusion creates high-value opportunities for innovation in the agricultural technology ecosystem (Danda, 2022).

Although technological, infrastructural, and cultural constraints pose adoption barriers, the long-term prospects for intelligent agricultural machinery are increasingly favorable. Policy support, declining costs, and global emphasis on sustainability are converging to accelerate the transition toward cleaner and smarter farming systems (Rifky et al., 2024).

In comparison with prior reviews, this article extends the discussion by integrating solar-powered machinery, robotics, and AI-driven platforms into a single framework of smart farming. Earlier studies have typically examined these technologies in isolation, whereas this review emphasizes their synergies and cross-domain interactions. By doing so, it highlights how the convergence of clean energy and digital automation can reshape biosystems engineering, creating more resilient, efficient, and adaptable farming systems. This integrative perspective is essential not only for advancing technical research but also for informing policies and investment strategies that support the widespread adoption of intelligent agriculture.

CONCLUSION AND DIRECTIONS FOR FUTURE RESEARCH

The adoption of solar-powered machinery, autonomous robotics, and artificial intelligence is steadily transforming traditional agriculture into a more efficient, sustainable, and economically viable system. This transition reduces dependency on fossil fuels, mitigates greenhouse gas emissions, and improves the precision of core operations such as planting, irrigation, pest control, and harvesting. The convergence of smart technologies with clean energy marks a pivotal step toward climate-resilient and data-driven farming models.

Despite these advancements, significant barriers including high initial costs, limited battery capacity, and insufficient rural infrastructure still constrain large-scale deployment. Promising directions to overcome these obstacles include next-generation energy storage technologies, modular charging systems, hybrid renewable platforms, and advanced robotic perception powered by deep learning. To accelerate progress, future research should emphasize:

i. **Next-Generation Energy Storage:** improving efficiency, durability, and scalability of solid-state, metal-air, and hybrid batteries;

ii. **Advanced Agricultural Robotics:** enhancing machine vision, adaptive perception, and autonomous decision-making;

iii. **Cost-Benefit and Environmental Assessment:** integrating economic viability with long-term sustainability metrics;

iv. **Infrastructure and Workforce Development:** fostering rural innovation hubs and specialized training programs;

v. **Hybrid Renewable Energy Platforms:** merging solar power with wind, biomass, or micro-hydro solutions.

Ultimately, the full realization of intelligent, electrified agriculture requires coordinated contributions from academia, industry, and policymakers. The novelty of this review lies in presenting a holistic synthesis that connects renewable energy integration, mechanical innovation, and AI-driven automation as mutually reinforcing pillars of agricultural transformation. Beyond its academic value, the insights provided here offer practical pathways for policymakers, industry leaders, and farmers to accelerate the transition toward climate-smart, digitally integrated, and financially viable farming systems.

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The authors declare no conflict of interest.

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Abbreviations

FCN	Fully Convolutional Network
LBP	Local Binary Patterns
AGVs	Autonomous Ground Vehicles
UAV	Unmanned Aerial Vehicle
MEMS	Micro-Electro-Mechanical Systems
NDT	Non-Destructive Technologies
GNSS	Global Navigation Satellite System
IoT	Internet of Things
ML	Machine Learning
DL	Deep Learning
CNNs	Convolutional Neural Networks
GPS	Global Positioning System
AEF	Agricultural Industry Electronics Foundation
ISE	Institute for Solar Energy Systems
ANNs	Artificial Neural Networks
NIR	Near Infrared
PV	Photovoltaic
ResNet	Residual Network