



Artificial Intelligence in Electric Agricultural Machinery: A Comprehensive Review of Technologies, Applications, Challenges and Future Directions

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ABSTRACT

The global agricultural sector faces mounting pressures from population growth climate change labor shortages and rising fossil-fuel expenses necessitating a transition toward sustainable efficient and intelligent farming systems. This review comprehensively synthesizes the convergence of artificial intelligence AI and electrification in modern agricultural machinery. Conventional diesel-powered machinery while reliable contributes significantly to greenhouse gas emissions pollution and high operational costs. The electrification of agricultural equipment ranging from tractors and sprayers to weeders reapers and autonomous robots offers high drivetrain efficiency reduced local emissions and compatibility with renewable energy sources. However challenges such as limited battery capacity charging infrastructure and variable operational loads require advanced control strategies. By integrating AI technologies such as machine learning deep learning computer vision reinforcement learning and fuzzy logic electric agricultural machinery can achieve autonomous navigation smart energy management predictive maintenance and precise site-specific operations. This review highlights current technological applications key sensor integrations existing technical and environmental challenges future research directions including edge AI digital twins and swarm robotics and essential research gaps to facilitate the widespread commercialization of next-generation smart agricultural machinery.

Keywords: Artificial Intelligence; Electric Agricultural Machinery; Sustainable Agriculture; Autonomous Navigation; Energy Management; Precision Farming; Computer Vision; Predictive Maintenance

1. Introduction

The global agricultural sector is facing unprecedented challenges arising from rapid population growth, climate change, shrinking natural resources and increasing demand for sustainable food production. According to the United Nations, the global population is expected to reach approximately 9.7 billion by 2050, requiring agricultural production to increase substantially while minimizing environmental impacts (United Nations, 2022). Consequently, sustainable agriculture has become a central objective worldwide, emphasizing efficient utilization of energy, water, land and other agricultural inputs while simultaneously reducing greenhouse gas (GHG) emissions and preserving ecosystem health (FAO, 2022).

Agricultural mechanization has significantly improved farm productivity over the last century; however, most agricultural machinery still relies on diesel-powered internal combustion engines. Although diesel machinery provides high power and reliability, it contributes considerably to greenhouse gas emissions, particulate matter (PM), nitrogen oxides (NO_x) and noise pollution, thereby adversely affecting both environmental sustainability and human health (Scolaro et al., 2021). Furthermore, the agricultural sector remains highly dependent on fossil fuels, making farming operations vulnerable to fuel price fluctuations and increasing operational costs.

The continuous rise in diesel prices has become another major concern for modern agriculture. Fuel expenses constitute a substantial portion of the operational costs of tractors, harvesters, sprayers and other farm equipment, particularly in developing countries where smallholder farmers dominate agricultural production. Increasing fuel costs directly reduce farm profitability and encourage the search for cleaner and more economical alternatives. Electrification of agricultural machinery has therefore emerged as a promising solution due to its potential for higher energy efficiency, lower maintenance requirements, quieter operation and reduced greenhouse gas emissions compared with conventional diesel-powered systems (Malik and Kohli, 2020; Scolaro et al., 2021).

In addition to environmental and economic challenges, agriculture is experiencing an increasing shortage of skilled labor. Rapid urbanization, migration from rural areas and an aging farming population have significantly reduced the availability of agricultural workers in many countries. Timely execution of field operations such as sowing, spraying, harvesting and transportation has consequently become more difficult, affecting both productivity and crop quality. These challenges have accelerated the adoption of automation and autonomous agricultural machinery capable of performing repetitive and labor-intensive tasks with minimal human intervention (Walter et al., 2017).

Recent advances in sensing technologies, Global Navigation Satellite Systems (GNSS), Internet of Things (IoT), robotics, wireless communication and embedded systems have enabled the development of intelligent agricultural machinery capable of precise, efficient and autonomous operation. Automation not only reduces labor dependency but also improves operational accuracy, minimizes input wastage and enhances overall farm productivity through precision agriculture practices.

The transition from diesel-powered agricultural machinery to electrically driven equipment represents one of the most significant technological shifts toward sustainable farming. Battery-electric tractors, autonomous electric robots, electric sprayers, electric weeders and electric harvesting systems have attracted increasing research attention because of their superior drivetrain efficiency, lower maintenance costs, reduced operating noise and compatibility with renewable energy sources. Continuous advancements in lithium-ion battery technology, electric motor drives, power electronics and battery management systems have further accelerated the development of electric agricultural machinery. Nevertheless, challenges such as limited battery capacity, charging infrastructure, energy optimization and operational efficiency remain barriers to widespread commercialization (Malik and Kohli, 2020; Scolaro et al., 2021).

Artificial Intelligence (AI) has emerged as a transformative technology capable of addressing many of these limitations. AI techniques, including machine learning (ML), deep learning (DL), computer vision, reinforcement learning and intelligent decision-support systems, enable agricultural machines to analyze sensor data, recognize crops and weeds, estimate battery state-of-charge, optimize energy consumption, predict component failures and perform autonomous navigation in complex field environments. The integration of AI with electric agricultural machinery facilitates intelligent energy management, predictive maintenance, precision operation, obstacle detection and adaptive decision-making, thereby improving machine efficiency, productivity and sustainability. AI-driven systems are expected to play a pivotal role in the next generation of autonomous electric agricultural machinery by combining electrification with intelligent control and data-driven optimization.

Although substantial progress has been made in the fields of agricultural automation, electric mobility, robotics and artificial intelligence, the available literature is generally dispersed across multiple research domains. Comprehensive reviews specifically focusing on AI-based systems integrated with electric agricultural machinery remain limited. Therefore, a systematic synthesis of recent developments is necessary to provide researchers, engineers and policymakers with a holistic understanding of this rapidly evolving field.

The primary objective of this review is to comprehensively examine the application of artificial intelligence in electric agricultural machinery. The review discusses the latest developments in AI algorithms, intelligent energy management systems, battery management, autonomous navigation, computer vision, predictive maintenance and precision farming applications associated with electrically powered agricultural equipment. Furthermore, it identifies current technological challenges, research gaps and future research directions to support the development of sustainable, intelligent and autonomous agricultural machinery. The scope of this review encompasses AI-enabled electric tractors, autonomous field robots, electric harvesting systems, electric spraying and weeding machines, battery management systems and related intelligent technologies that contribute to next-generation smart agriculture.

2. Evolution of Agricultural Machinery

Agricultural machinery has undergone significant technological development in response to increasing food demand, shortage of agricultural labour, rising energy costs and the need for sustainable and efficient farming systems. The evolution of agricultural machinery can broadly be categorized into five major stages: traditional machinery, mechanized machinery, precision agriculture, electric agricultural machinery and AI-powered autonomous machinery. Each stage introduced technological advancements that addressed important limitations associated with the preceding agricultural production system.

2.1 Traditional Agricultural Machinery

Early agricultural production was predominantly dependent on human labour and animal power. Operations such as soil preparation, sowing, weeding, harvesting and transportation were performed using simple hand tools and animal-drawn implements. Although these systems required relatively low capital investment and were suitable for small-scale farming, they were labour-intensive and characterized by low field capacity. The dependence on human and animal power also restricted the area that could be cultivated within a given period. The transition from traditional farming toward mechanization was therefore driven largely by the need to increase labour productivity and overcome power bottlenecks in agricultural operations (Pingali, 2007).

2.2 Mechanization of Agriculture

The introduction and widespread adoption of internal combustion engines and tractors represented a major transformation in agricultural production. Agricultural mechanization enabled human and animal power to be replaced or supplemented by engine-powered machinery, substantially increasing field capacity and reducing labour requirements. Tractors, combine harvesters, mechanical seeders, sprayers and other powered implements enabled farmers to cultivate larger areas and perform field operations more rapidly and uniformly (Pingali, 2007).

Mechanization has consequently played an important role in increasing agricultural productivity and reducing the physical drudgery associated with farm operations. However, conventional agricultural machinery has predominantly relied on diesel-powered internal combustion engines. This dependence has resulted in considerable fossil-fuel consumption and associated environmental emissions. Fuel consumption, engine maintenance and dependence on

fossil fuels have therefore become important considerations in the economic and environmental performance of modern mechanized agriculture (Scolaro et al., 2021).

2.3 Emergence of Precision Agriculture

The subsequent integration of Global Positioning System (GPS)/Global Navigation Satellite System (GNSS), geographic information systems (GIS), remote sensing, sensors, yield monitoring and variable-rate technologies resulted in the emergence of precision agriculture. Unlike conventional mechanization, precision agriculture enables agricultural operations to account for spatial and temporal variability within fields rather than applying inputs uniformly across an entire field (Gebbers and Adamchuk, 2010).

GPS/GNSS-based guidance systems can improve machinery positioning and reduce overlaps and skips during field operations, while sensors and remote-sensing technologies provide information regarding crop and soil conditions. Variable-rate technologies can subsequently adjust the application of seeds, fertilizers, pesticides and other inputs according to field variability. Consequently, agricultural machinery began transitioning from equipment primarily designed for power delivery toward data-driven systems capable of site-specific operation and informed decision-making (Gebbers and Adamchuk, 2010).

The development of precision agriculture also established important technological foundations for modern intelligent machinery. Positioning systems, field sensors, digital maps, data acquisition systems and electronic controllers developed for precision agriculture are increasingly being integrated with artificial intelligence, robotics and autonomous control systems. These developments have contributed to the transition from conventional mechanization toward increasingly automated and intelligent agricultural systems (Liakos et al., 2018).

2.4 Transition Toward Electric Agricultural Machinery

Increasing concerns regarding fossil-fuel consumption, greenhouse-gas emissions, operating costs and environmental sustainability have encouraged research into the electrification of agricultural machinery. Advances in lithium-ion batteries, electric motors, power electronics and battery-management systems have increased the feasibility of using electric powertrains in agricultural applications (Scolaro et al., 2021).

Electric tractors, autonomous field robots, electric sprayers, electric weeders and electrically powered harvesting machinery are being investigated as alternatives to conventional diesel-powered equipment. Electric powertrains offer several potential advantages, including high drivetrain efficiency, reduced local emissions, lower noise, reduced maintenance requirements and compatibility with renewable energy sources (Scolaro et al., 2021). Furthermore, electric motors provide precise electronic control of speed and torque, which can be advantageous for agricultural operations requiring variable operating conditions.

Despite these advantages, the electrification of agricultural machinery continues to face several challenges. Battery energy density and capacity can limit operating time, while charging duration, battery degradation, thermal management, initial battery cost and inadequate charging infrastructure can restrict practical field applications. The high and variable energy requirements of agricultural operations also make effective battery sizing and energy management essential for the successful deployment of electric agricultural machinery (Scolaro et al., 2021).

2.5 AI-Powered Autonomous Agricultural Machinery

The latest stage in the evolution of agricultural machinery involves the integration of Artificial Intelligence (AI), machine learning (ML), deep learning (DL), computer vision, robotics, Internet of Things (IoT) and autonomous control systems. These technologies enable agricultural machinery to move beyond conventional mechanization and predetermined automation toward systems capable of sensing their environment, interpreting information, making decisions and adapting their operation to changing field conditions (Liakos et al., 2018).

Machine learning techniques have been applied to a wide range of agricultural problems, including crop monitoring, yield prediction, disease detection, machinery control and decision support. Deep learning, particularly convolutional neural networks, has demonstrated considerable potential for image-based agricultural applications such as crop and weed identification, plant classification and disease recognition (Kamilaris and Prenafeta-Boldú, 2018). The increasing availability of sensors and computational technologies has further enabled these algorithms to be integrated into agricultural machinery for real-time perception and decision-making.

AI-powered agricultural machinery can employ cameras, LiDAR, GNSS, inertial measurement units (IMUs), ultrasonic sensors and other sensing technologies to identify crops, detect weeds and obstacles, estimate field conditions and navigate autonomously. Such systems can potentially improve operational accuracy while reducing human intervention and enabling agricultural machines to operate more effectively in complex and variable field environments (Liakos et al., 2018).

AI can also play an important role in the management of electric agricultural machinery. Machine-learning models can be employed for battery state-of-charge (SOC) estimation, state-of-health (SOH) prediction, energy-consumption forecasting, fault diagnosis, predictive maintenance and intelligent energy management. AI-based control systems can optimize machine speed, motor operation and power distribution according to field conditions and available battery energy. These capabilities are particularly important for electric agricultural machinery because efficient energy utilization directly influences operating time, field capacity and overall machine performance.

The convergence of electrification and artificial intelligence therefore represents an important development in modern agricultural machinery. Electrification provides an efficient and controllable powertrain, whereas AI provides the intelligence required for perception, decision-making, optimization and autonomous operation. The integration of these technologies has the potential to produce agricultural machines that can perform field operations with reduced human intervention while simultaneously optimizing energy consumption and operational performance.

Thus, the evolution of agricultural machinery can be viewed as a transition from human- and animal-powered tools to engine-powered machinery, followed by data-driven precision machinery, electrically powered machinery and finally intelligent autonomous machinery. This technological progression provides the foundation for next-generation agricultural systems in which electric powertrains, advanced sensing, artificial intelligence and autonomous control are integrated into a single platform.

3. Electric Agricultural Machinery

The increasing demand for sustainable agricultural production, reduction of fossil-fuel dependence and improvement in energy efficiency has accelerated the development of electrically powered agricultural machinery. Electrification involves replacing conventional internal combustion engine (ICE)-based powertrains with electric motors powered primarily by batteries or other electrical energy sources. Unlike conventional machinery, electric agricultural machines can combine high-efficiency electric drives with electronic control systems, renewable energy sources and intelligent energy-management technologies. Recent developments in battery technology, electric motors, power electronics and autonomous systems have further increased the potential of electrification across a wide range of agricultural operations (Scolaro et al., 2021; Gade et al., 2025).

Electric agricultural machinery encompasses a broad range of equipment, including tractors, reapers, seeders, sprayers, harvesters, weeders, unmanned aerial vehicles (UAVs) and electrically powered irrigation systems. The level of electrification varies among machines depending on their power requirements, operating duration, field conditions and the nature of the agricultural operation.

3.1 Electric Tractors

Electric tractors are among the most significant developments in the electrification of agricultural machinery. They generally consist of a battery pack, electric motor(s), motor controller, transmission or reduction system, power electronics and auxiliary electrical systems. Electric tractors can provide high torque at low speeds and allow precise control of speed and torque. Their regenerative braking capability, reduced drivetrain losses and potential integration with renewable energy sources make them attractive alternatives to conventional diesel tractors (Scolaro et al., 2021).

Electric tractors can be particularly suitable for low- and medium-power operations such as seedbed preparation, sowing, spraying, inter-row cultivation and transportation. However, high-power operations such as deep tillage and heavy-duty soil preparation require substantial energy, making battery capacity and operating range important considerations. Recent research has therefore focused on appropriate battery sizing, energy management, hybrid powertrains and charging strategies for agricultural tractors (Malik and Kohli, 2020; Gade et al., 2025).

3.2 Electric Reapers

Electric reapers use electric motors to power one or more functions such as cutting, conveying and machine propulsion. Compared with conventional engine-powered reapers, electric reapers can have a simpler drivetrain and lower maintenance requirements because electric motors contain fewer mechanically moving components. Battery-powered operation can also reduce noise and local exhaust emissions, making electric reapers potentially suitable for small and medium-sized farms.

The power requirement of an electric reaper depends on crop characteristics, cutter-bar dimensions, forward speed, conveyor requirements and field conditions. Effective energy management is therefore important for maintaining sufficient battery energy throughout harvesting operations. Integration of sensors and intelligent controllers can further enable real-time adjustment of cutting and propulsion parameters according to crop and field conditions.

3.3 Electric Seeders and Planters

Electrification of seeders and planters can improve the control and precision of seed metering systems. Electric motors can independently drive seed-metering mechanisms, enabling accurate control of seed rate, spacing and planting speed. Compared with mechanically driven seed-metering systems, electric drives can provide greater flexibility because the metering speed can be electronically controlled according to travel speed and prescribed planting rates.

Electric seeders can also be integrated with GNSS, sensors and variable-rate technologies to enable site-specific seeding. This creates opportunities for integrating AI-based systems for real-time adjustment of seed rate according to soil and crop conditions. Such integration represents an important connection between agricultural electrification, precision agriculture and intelligent machinery (Gebbers and Adamchuk, 2010; Liakos et al., 2018).

3.4 Electric Sprayers

Electric sprayers utilize batteries and electric motors to operate pumps, fans, control valves, or propulsion systems. Electrically driven pumps allow precise regulation of spray pressure and application rate and can be controlled independently from the propulsion system. This can improve the accuracy of chemical application and reduce unnecessary energy consumption.

The integration of sensors, GNSS, machine vision and AI can further transform electric sprayers into intelligent application systems. For example, computer-vision algorithms can identify weeds or crop conditions, after which an electronically controlled spraying system can selectively apply chemicals. Such systems have the potential to reduce chemical consumption while improving application efficiency (Liakos et al., 2018).

3.5 Electric Harvesters

Harvesting machinery generally has high and variable power requirements because several functions may operate simultaneously, including cutting, threshing, separating, conveying and cleaning. Electrification of harvesters therefore presents greater challenges than electrification of relatively low-power agricultural equipment. However, individual subsystems such as conveyors, fans, cutting mechanisms and auxiliary drives can be electrified even when the primary power source remains hybrid or engine-based.

Modular electric drives can provide independent control of individual harvesting functions and potentially improve overall energy efficiency. In the long term, improvements in battery energy density and rapid-charging technology could increase the feasibility of fully electric harvesting machinery (Scolaro et al., 2021).

3.6 Electric Weeders

Electric weeders include battery-powered mechanical weeders, robotic weeders and electrically actuated precision-weeding systems. Electric motors can drive wheels, cutting mechanisms, rotary weeders, or other weed-removal components. Their relatively low energy requirements compared with large tractors make electric propulsion particularly attractive for small autonomous field robots.

The integration of computer vision and machine learning can further enable intelligent weed detection. A camera can acquire images of the field, while an AI model identifies weeds and crops. The electric actuator can then selectively remove or target the detected weeds. Consequently, electric weeding systems represent an important application area where electrification and AI can be directly integrated to achieve precision field operations (Bechar and Vigneault, 2016; Kamilaris and Prenafeta-Boldú, 2018).

3.7 Electric Agricultural Drones

Electric unmanned aerial vehicles (UAVs), commonly referred to as agricultural drones, have become increasingly important in precision agriculture. Multicopter and fixed-wing UAVs generally use rechargeable batteries to power their electric motors and onboard electronic systems. Agricultural drones can carry RGB, multispectral, thermal, or other sensors to collect information about crop health, plant density, water stress, disease and field variability.

The combination of electric propulsion, advanced sensors, wireless communication and AI-based image analysis enables UAVs to perform tasks such as crop monitoring, disease detection, weed identification, field mapping and precision spraying. Deep-learning techniques have increasingly been applied to agricultural images acquired from UAVs and other sensing platforms (Kamilaris and Prenafeta-Boldú, 2018; Liakos et al., 2018).

However, battery capacity remains a major limitation because UAV flight time is strongly dependent on battery energy, payload mass, flight conditions and propulsion efficiency. Therefore, energy-efficient flight planning and intelligent mission management are important areas for further research.

3.8 Electric Irrigation Systems

Electrification is also being applied to agricultural irrigation systems through electrically driven pumps, automated valves and sensor-based irrigation controllers. Electric pumps can be powered from grid electricity, batteries, or renewable energy systems such as photovoltaic panels. Solar-powered irrigation systems are particularly attractive in areas with high solar energy availability because they can reduce dependence on diesel-powered pumps and provide access to irrigation in remote agricultural areas.

The integration of soil-moisture sensors, weather information, IoT and AI can further improve the efficiency of electrically powered irrigation systems. Intelligent controllers can estimate crop water requirements and determine when irrigation should be initiated and how much water should be supplied. Thus, electric irrigation systems can evolve from simple electrically powered pumps toward intelligent, sensor-driven water-management systems.

3.9 Major Components of Electric Agricultural Machinery

Although the configuration varies according to machine type and power requirement, most electric agricultural machines consist of several fundamental subsystems: battery, electric motor, motor controller, transmission or mechanical power-transfer system and sensors.

3.9.1 Battery

The battery acts as the primary energy-storage system in battery-electric agricultural machinery. Lithium-ion batteries are currently among the most promising technologies because of their relatively high energy density, efficiency, cycle life and declining cost. Battery capacity directly affects the operating duration and field capacity of an electric machine.

Important battery parameters include:

- Nominal voltage
- Capacity (Ah)
- Energy capacity (kWh)
- State of charge (SOC)
- State of health (SOH)
- Charging rate
- Cycle life
- Operating temperature

Battery-management systems (BMS) are required to monitor voltage, current, temperature, SOC and other operating parameters to ensure safe and efficient battery operation (Scolaro et al., 2021).

3.9.2 Electric Motor

The electric motor converts electrical energy into mechanical power for propulsion or operation of agricultural implements. Different motor types, including permanent-magnet synchronous motors (PMSM), induction motors and brushless DC motors (BLDC), may be employed depending on the power requirement and application. Electric motors offer high efficiency and precise speed and torque control. They can also deliver high torque at low rotational speeds, which is beneficial for agricultural machinery operating under variable loads.

3.9.3 Motor Controller

The motor controller regulates the electrical power supplied to the motor according to the required speed and torque. It receives commands from the operator or higher-level control system and adjusts motor operation accordingly. In an AI-enabled electric machine, the controller can also receive information from sensors and AI-based decision systems. This allows motor speed, torque and power consumption to be dynamically adjusted according to operating conditions.

3.9.4 Transmission and Power-Transfer System

Electric agricultural machines may employ conventional mechanical transmissions, reduction gearboxes, belt drives, chain drives, or direct-drive configurations. Because electric motors can operate efficiently over a relatively wide speed range and provide high starting torque, some electric machines can use simplified transmissions or direct-drive arrangements. Reducing the number of mechanical components can potentially decrease mechanical losses, maintenance requirements and system complexity.

3.9.5 Sensors

Sensors provide information required for monitoring, control, automation and AI-based decision-making. Common sensors include: GNSS/GPS, IMU, Camera/RGB camera, LiDAR, Soil-moisture sensor, Current sensor, Voltage sensor, Temperature sensor, Wheel-speed sensor and Load/torque sensor. The increasing integration of sensors with AI algorithms allows electric agricultural machinery to move from simple automated operation toward adaptive and autonomous operation.

3.10 Advantages of Electric Agricultural Machinery

Lower emissions: Electric machines produce no direct exhaust emissions during operation.

Reduced maintenance: Electric motors generally contain fewer moving mechanical components than internal combustion engines.

Lower noise: Electric motors generally produce considerably less mechanical and combustion noise.

Higher drivetrain efficiency: Electric motors can achieve high conversion efficiency over appropriate operating ranges. Precise electronic control of motor speed and torque also provides opportunities for optimizing power consumption (Scolaro et al., 2021).

Compatibility with renewable energy: Electric agricultural machinery can be coupled with renewable energy systems, particularly photovoltaic generation.

3.11 Limitations and Challenges

Limited battery capacity: High-power agricultural operations can require substantial energy, resulting in large and heavy battery packs.

Charging time: Compared with conventional refueling, battery charging generally requires more time.

High initial cost: Electric agricultural machinery can involve substantial initial investment.

Limited operating hours: The operating duration of a battery-electric machine is constrained by available battery energy.

Table 1. Major electric agricultural machinery and their applications

Machine	Primary electric application	Potential AI integration
Electric tractor	Propulsion and implement operation	Energy management, autonomous navigation, predictive maintenance
Electric reaper	Cutting, conveying, propulsion	Crop detection, speed optimization, energy management
Electric seeder	Seed metering and propulsion	Variable-rate seeding, crop/soil sensing
Electric sprayer	Pumping and spraying	Weed detection, variable-rate spraying
Electric harvester	Cutting, conveying, auxiliary systems	Crop recognition, yield estimation, energy optimization
Electric weeder	Propulsion and weed-removal mechanism	Weed detection, autonomous navigation
Electric drone/UAV	Flight and sensing	Crop monitoring, disease/weed detection, route optimization
Electric irrigation system	Pumping and water control	Soil-moisture prediction, irrigation scheduling

Overall, electric agricultural machinery represents an important transition from fossil-fuel-dependent mechanization toward cleaner and more efficient agricultural power systems. However, electrification alone does not guarantee optimal machine performance. Limitations associated with battery capacity, charging time, operating range and energy management highlight the need for intelligent control strategies. The integration of AI with electric agricultural machinery can address these challenges by enabling accurate energy prediction, adaptive control, autonomous operation, predictive maintenance and intelligent decision-making.

4. Artificial Intelligence Technologies in Electric Agricultural Machinery

Artificial Intelligence (AI) has emerged as an important enabling technology for the development of intelligent and autonomous agricultural machinery. AI allows machines to process information obtained from sensors, identify patterns, make decisions and adapt their operation according to changing environmental and operational conditions. In agricultural applications, AI has been employed for crop and weed identification, yield prediction, disease detection, autonomous navigation, machinery control, energy management and predictive maintenance (Liakos et al., 2018; Benos et al., 2021).

The integration of AI with electric agricultural machinery is particularly significant because electric machines contain electronically controllable powertrains and generate large quantities of operational data from batteries, motors, controllers and sensors. These characteristics provide opportunities for AI algorithms to simultaneously optimize machine performance, energy consumption, battery utilization and autonomous operation. The major AI technologies relevant to electric agricultural machinery include machine learning, deep learning, computer vision, reinforcement learning, fuzzy logic and expert systems.

4.1 Machine Learning

Machine Learning (ML) is a branch of AI in which computational algorithms learn relationships and patterns from data without requiring explicit programming for every individual task. In agricultural applications, supervised learning methods such as artificial neural networks (ANN), support vector machines (SVM), decision trees, random forests and gradient-boosting algorithms have been widely used for prediction and classification tasks (Liakos et al., 2018).

Machine learning is particularly relevant to electric agricultural machinery because the performance of batteries, motors and agricultural operations is strongly influenced by variable operating conditions.

4.1.1 Yield Prediction: Machine-learning models can estimate crop yield using information obtained from soil sensors, weather data, satellite imagery, UAVs, crop characteristics and historical yield records.

4.1.2 Energy Prediction: Energy prediction is particularly important for battery-powered agricultural machinery because available battery energy directly determines operating duration. ML models can estimate energy consumption based on parameters such as machine speed, soil resistance, implement load, terrain, crop condition, battery SOC and environmental conditions.

4.1.3 Battery Health Estimation: ML models can estimate state of charge (SOC), state of health (SOH), remaining useful life (RUL) and degradation rate using voltage, current, temperature, charging history and operating-cycle data.

4.2 Deep Learning

Deep Learning (DL) is a subset of machine learning that uses multi-layer artificial neural networks to learn complex representations from large datasets. Convolutional Neural Networks (CNNs), recurrent neural networks (RNNs) and more recently transformer-based architectures have been applied extensively to agricultural image and sensor-data analysis (Kamilaris and Prenafeta-Boldú, 2018).

4.2.1 Crop Detection: Deep-learning models can identify crops from images acquired by cameras mounted on tractors, robots, UAVs and harvesting machinery.

4.2.2 Disease Detection: DL-based image classification models can identify visual symptoms associated with crop diseases.

4.2.3 Obstacle Recognition: Autonomous electric agricultural machines must detect obstacles such as humans, animals, trees, rocks, farm equipment and other vehicles. Deep-learning-based object-detection algorithms can identify and classify these objects.

4.2.4 Image Classification: Deep-learning models can classify agricultural images according to crop type, plant condition, weed species, disease status, fruit maturity, or other characteristics.

4.3 Computer Vision

Computer Vision (CV) enables machines to obtain useful information from images and video. It involves image acquisition, preprocessing, segmentation, feature extraction, object detection, tracking and image interpretation.

4.3.1 Row Guidance: Camera-based row detection can identify crop rows and provide information about the machine's position relative to the crop.

4.3.2 Weed Detection: Weed detection is one of the most important applications of computer vision in precision agriculture. Cameras can capture field images, while image-processing and AI algorithms distinguish weeds from crop plants (Kamilaris and Prenafeta-Boldú, 2018).

4.3.3 Fruit Detection: Computer vision can identify and locate fruits on plants based on their colour, shape, texture and spatial characteristics.

4.3.4 Automated Harvesting: Computer vision forms an important component of autonomous harvesting systems. Cameras can detect crop plants, fruits, stems and other relevant structures, while AI algorithms determine their position and characteristics.

4.4 Reinforcement Learning

Reinforcement Learning (RL) is an AI approach in which an agent learns an optimal decision-making strategy through interaction with its environment.

4.4.1 Path Planning: Reinforcement-learning algorithms can learn path-planning policies that minimize travel distance or energy consumption while maximizing field coverage.

4.4.2 Autonomous Navigation: RL can be used to develop navigation policies for electric agricultural robots and autonomous tractors.

4.4.3 Energy Optimization: One of the most promising applications of RL in electric agricultural machinery is intelligent energy management. An RL-based controller can learn how machine speed, motor torque, implement load and battery conditions influence energy consumption.

4.5 Fuzzy Logic

Fuzzy Logic is an AI-based decision-making technique designed to handle uncertainty and imprecise information.

4.5.1 Motor Control: Fuzzy logic can be used to control motor speed and torque under varying load conditions.

4.5.2 Steering Control: Fuzzy controllers can determine steering corrections based on parameters such as lateral deviation, heading error and vehicle speed.

4.5.3 Speed Control: A fuzzy controller can adjust machine speed according to load and operating conditions rather than maintaining a fixed speed.

4.6 Expert Systems

Expert systems are knowledge-based AI systems that use a collection of rules and domain-specific knowledge to provide recommendations or decisions.

4.6.1 Decision Support: Expert systems can assist operators in making decisions regarding machinery operation, crop management, irrigation, pest control and maintenance.

4.6.2 Farm Management: Expert systems can combine information concerning weather, soil, crop conditions, machinery availability and farm operations to support farm-management decisions.

Table 2. AI Technologies and their relevance to electric agricultural machinery

AI technology	Major applications	Relevance to electric agricultural machinery
Machine Learning	Yield prediction, energy prediction, battery SOC/SOH estimation, predictive maintenance	Energy management and machine-health monitoring
Deep Learning	Crop detection, disease detection, obstacle recognition, image classification	Autonomous perception and decision-making
Computer Vision	Row guidance, weed detection, fruit detection, harvesting	Machine perception and precision operation
Reinforcement Learning	Path planning, autonomous navigation, energy optimization	Autonomous control and energy-efficient operation
Fuzzy Logic	Motor control, steering control, speed control	Adaptive machine and powertrain control
Expert Systems	Decision support, farm management, maintenance recommendations	Knowledge-based operational decisions

4.7 Integration of AI Technologies

The individual AI technologies described above are not necessarily used independently. Advanced electric agricultural machinery can combine several AI techniques to perform complex tasks. For example, an autonomous electric weeder may use computer vision and deep learning for weed detection, reinforcement learning for path planning, GNSS for localization and an electric motor controller for precise actuation. This integration creates a multi-layer intelligent architecture in which sensors provide data, AI algorithms interpret the data, decision-making systems generate commands and electric actuators execute those commands.

5. AI Applications in Electric Agricultural Machinery

The integration of artificial intelligence (AI) with electric agricultural machinery represents a major step toward intelligent, autonomous and energy-efficient farming systems. AI applications in electric agricultural machinery can broadly be categorized into autonomous navigation, smart energy management, intelligent motor control, predictive maintenance, precision farming operations, computer vision and swarm robotics (Liakos et al., 2018; Koirala et al., 2022).

5.1 Autonomous Navigation

Autonomous navigation is one of the most important applications of AI in electric agricultural machinery. Autonomous tractors, robotic weeders, electric harvesters and other field robots must determine their position, understand their surroundings, plan a suitable path and continuously control their movement. A typical autonomous navigation system combines GNSS/GPS, Real-Time Kinematic GPS (RTK-GPS), LiDAR, cameras, inertial measurement units (IMUs), wheel encoders and AI-based algorithms (Bechar and Vigneault, 2016; Shamshiri et al., 2018).

- **GPS and RTK-GPS:** Provides metre-level or centimetre-level geographical positioning.
- **LiDAR:** Generates three-dimensional representations of the environment, useful for obstacle detection and field mapping.
- **Cameras:** Provide visual information about crops, soil, weeds, obstacles and field boundaries.
- **IMU:** Measures acceleration and angular velocity to estimate orientation and motion.
- **AI Algorithms for Autonomous Navigation:** Convolutional Neural Networks (CNNs), You Only Look Once (YOLO), Simultaneous Localization and Mapping (SLAM) and Deep Reinforcement Learning (DRL) can be integrated to enable perception, route planning and control.

5.2 Smart Energy Management

Energy management is one of the most critical applications of AI in electric agricultural machinery because battery capacity directly determines machine operating time.

- **Battery State-of-Charge Estimation:** AI models (ANNs, LSTMs, SVMs) can estimate SOC using battery voltage, current, temperature, charging history and operating conditions.
- **Battery State-of-Health Estimation:** AI-based SOH estimation can identify degradation patterns using historical charging and operating data.
- **Charging Optimization:** AI can optimize battery charging by considering battery SOC, temperature, degradation characteristics, electricity availability and expected machine operation.
- **Intelligent Power Distribution:** AI-based systems can dynamically distribute available power among traction motors, implement motors, hydraulic systems and sensors according to their priority.
- **Energy Prediction:** Machine-learning models (ANN, LSTM, Random Forest, XGBoost) can predict energy consumption using variables such as machine speed, soil resistance, implement load and terrain slope.

5.3 Intelligent Motor Control

Electric motors can be controlled electronically with high precision, creating opportunities for AI-based systems that dynamically adjust motor speed, torque and power.

- **Torque Optimization:** AI-based controllers can estimate the required torque and adjust motor operation accordingly, reducing unnecessary energy consumption.
- **Speed Control:** AI-based systems can dynamically adjust machine speed according to soil resistance, crop condition and implement load.
- **Efficiency Optimization:** AI algorithms can identify operating regions associated with high motor efficiency and select appropriate speed–torque combinations.
- **Predictive Control:** Future operating conditions can be estimated and control actions selected before the machine encounters changing loads.

5.4 Predictive Maintenance

Predictive maintenance uses sensor data and AI algorithms to estimate the condition of components and identify potential failures before they occur.

- **Fault Diagnosis:** AI models can identify abnormal operating patterns using measurements such as motor current, temperature and vibration.
- **Bearing Monitoring:** Machine-learning models can classify vibration patterns and identify conditions such as wear or misalignment.
- **Motor Health Monitoring:** AI models can provide early warnings of electrical and mechanical motor faults.
- **Battery Degradation:** AI can analyze charging cycles, temperature, current and voltage data to estimate remaining useful life.
- **Sensor Failure:** AI-based anomaly-detection systems can identify inconsistent sensor outputs.

5.5 Precision Farming Operations

The combination of AI decision-making and electrically controlled actuators enables agricultural machinery to transition from uniform field operations toward site-specific and variable-rate operations.

- **Electric Spraying:** AI-based computer vision identifies weeds or diseased plants, transferring info to electrically controlled pumps and valves.
- **Variable-Rate Fertilizer Application:** Electrically driven metering systems adjust fertilizer rates based on AI-estimated crop nutrient requirements.
- **Electric Seeding:** Electric seed-metering systems provide precise control of seed rate and spacing based on soil properties and historical yield data.
- **Harvesting:** AI-based crop recognition can be integrated with electric harvesting systems to control the harvesting mechanism.
- **Weeding:** Electric robotic weeders combine computer vision with electrically actuated mechanisms to remove or target weeds.

5.6 Computer Vision Applications

- **Crop Recognition:** Image-processing systems distinguish crops from soil, weeds and other vegetation.
- **Weed Detection:** Deep-learning models identify weeds based on visual characteristics.
- **Fruit Counting:** AI detects and counts fruits for yield estimation and harvesting planning.
- **Disease Detection:** Deep-learning models classify diseased and healthy plants based on visual symptoms.
- **Obstacle Avoidance:** Object-detection algorithms identify people, animals, trees and other vehicles in real time.

5.7 Swarm Robotics

Swarm robotics involves multiple relatively small and autonomous agricultural robots cooperating to perform tasks.

- **Electric Agricultural Robots:** Small robots can perform tasks like weeding, seeding, crop monitoring and spraying.
- **Collaborative Robots:** Robots share information regarding crop conditions, obstacles and task progress.
- **Multi-Agent Systems:** AI algorithms assign tasks, plan paths, avoid collisions and manage energy across the fleet.

Table 3. AI applications in electric agricultural machinery

Application	AI techniques	Sensors/data	Electric machinery	Expected benefit
Autonomous navigation	CNN, YOLO, SLAM, DRL	GNSS, RTK-GNSS, LiDAR, camera, IMU	Electric tractor, robot, harvester	Autonomous and safer operation
SOC estimation	ANN, LSTM, SVM	Voltage, current, temperature	All battery-electric machines	Accurate remaining-energy estimation
SOH estimation	ANN, LSTM, RF, XGBoost	Battery cycle, voltage, current, temperature	Electric tractor, robot, UAV	Battery-life prediction
Energy prediction	ANN, LSTM, RF, XGBoost	Load, speed, terrain, SOC	Electric tractor, reaper, harvester	Extended operating range
Motor control	Fuzzy logic, ANN, MPC	Speed, torque, current	Electric tractor, reaper, robot	Improved efficiency and control
Predictive maintenance	SVM, ANN, decision tree	Vibration, temperature, current	Motors, batteries, actuators	Reduced downtime
Weed detection	CNN, YOLO	RGB/multispectral camera	Electric weeder/sprayer	Reduced chemical use
Crop recognition	CNN, YOLO	RGB/multispectral images	Tractor, robot, harvester	Precision operation
Fruit detection	CNN, YOLO	RGB/depth camera	Electric harvester	Automated harvesting
Precision spraying	CNN, ML	Camera, crop sensors	Electric sprayer	Variable-rate application
Swarm coordination	DRL, multi-agent learning	GNSS, LiDAR, communication	Multiple electric robots	Cooperative field operation

5.8 Overall Integration of AI with Electric Agricultural Machinery

A typical AI-enabled electric machine can be represented as a five-layer architecture:

Sensing: GNSS + RTK-GNSS + cameras + LiDAR + IMU + machine sensors



Data-processing: Data acquisition + filtering + sensor fusion



AI: ML + DL + computer vision + RL + fuzzy logic



Decision/control: Navigation + energy management + motor control + implement control



Actuation: Electric motors + steering actuators + pumps + cutters + seed meters

6. Sensors Used in AI-Based Electric Agricultural Machinery

Sensors are the primary data-acquisition components of AI-based electric agricultural machinery. They provide information about the field environment, machine position, motion, battery condition, motor performance and operating conditions. The data collected by these sensors are processed by AI algorithms to support autonomous navigation, precision farming, energy management, machine control and predictive maintenance. The selection and integration of appropriate sensors are therefore essential for reliable operation of intelligent agricultural machinery.

Table 4. Sensors used in AI-based electric agricultural machinery

Sensor	Primary application	AI-based application in electric agricultural machinery
Camera (RGB/Multispectral)	Crop and object detection	Crop recognition, weed detection, disease detection, fruit detection, obstacle recognition, autonomous harvesting
LiDAR	Navigation and environmental mapping	Obstacle detection, 3D mapping, autonomous navigation, SLAM and path planning
IMU	Motion and orientation estimation	Vehicle localization, attitude estimation, navigation, sensor fusion and autonomous control
GPS/GNSS	Positioning	Field navigation, route tracking, autonomous operation and precision field operations
RTK-GPS/GNSS	High-accuracy positioning	Row guidance, precision seeding, spraying, weeding and autonomous tractor navigation
Ultrasonic sensor	Short-range obstacle detection	Collision avoidance, obstacle detection and proximity sensing
Current sensor	Current measurement	Battery monitoring, motor-load estimation, energy-consumption estimation and fault detection
Voltage sensor	Battery-voltage measurement	SOC estimation, battery monitoring, power-management and fault diagnosis
Temperature sensor	Thermal monitoring	Battery health, motor health, controller monitoring and overheating protection
Wheel encoder	Wheel speed and rotation measurement	Vehicle speed estimation, odometry, traction control and navigation
Torque sensor	Motor/shaft torque measurement	Load estimation, torque optimization, motor control and energy prediction
Vibration sensor/accelerometer	Mechanical condition monitoring	Bearing fault detection, motor-health monitoring and predictive maintenance

Sensor	Primary application	AI-based application in electric agricultural machinery
Soil-moisture sensor	Soil condition measurement	Irrigation control, field-condition assessment and precision operations
Soil electrical-conductivity sensor	Soil variability assessment	Precision agriculture, variable-rate input application and field mapping

6.1 Camera

Cameras are among the most important sensors for AI-based agricultural machinery because they provide rich visual information. RGB cameras can be used for crop detection, weed identification, disease recognition, fruit detection and obstacle recognition.

6.2 LiDAR

LiDAR provides distance measurements and three-dimensional information about the surrounding environment. It is particularly useful for autonomous navigation, obstacle detection, mapping and SLAM.

6.3 IMU

An IMU measures linear acceleration and angular velocity and can therefore provide information about machine motion and orientation. IMUs are commonly combined with GNSS and other sensors through sensor-fusion techniques.

6.4 GPS/GNSS and RTK-GNSS

GPS/GNSS provides the geographical position of the machine and is widely used for field navigation. RTK-GNSS provides substantially higher positioning accuracy and is particularly useful for row guidance, precision seeding, spraying, weeding and autonomous tractor operation.

6.5 Ultrasonic Sensor

Ultrasonic sensors determine the distance to nearby objects using ultrasonic waves. They are relatively simple and can be used as supplementary sensors for short-range obstacle detection and collision avoidance.

6.6 Current Sensor

Current sensors measure the electrical current flowing through the battery, motor, or other electrical components. Current data are important for battery monitoring, energy-consumption estimation, motor-load estimation, SOC estimation and fault diagnosis.

6.7 Voltage Sensor

Voltage sensors measure battery voltage and are essential components of battery-management systems. Voltage measurements, particularly when combined with current and temperature data, can be used by AI models for SOC and SOH estimation, battery monitoring and energy-management applications.

6.8 Temperature Sensor

Temperature sensors are important for monitoring both battery and motor health. Excessive battery temperature can accelerate degradation and create safety concerns, while high motor temperature can indicate excessive loading or inadequate cooling.

6.9 Sensor Fusion

No individual sensor can provide complete information about an agricultural machine and its environment under all operating conditions. Therefore, sensor fusion is an important component of intelligent agricultural machinery.

- Camera + LiDAR → Environmental perception
- GPS/RTK-GPS + IMU → Accurate localization
- Voltage + Current + Temperature → Battery condition

- Current + Torque + Vibration + Temperature → Motor health

7. AI Algorithms Used in Electric Agricultural Machinery

Different AI algorithms offer different capabilities depending on the type of data, computational resources and application requirements of electric agricultural machinery. Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, Random Forest (RF), Support Vector Machines (SVM), Reinforcement Learning (RL) and Fuzzy Logic are among the techniques that can be applied to battery management, computer vision, energy prediction, fault diagnosis, autonomous navigation and motor control (Liakos et al., 2018; Kamilaris and Prenafeta-Boldú, 2018).

Table 5. Comparison of AI algorithms used in electric agricultural machinery

Algorithm	Advantages	Limitations	Applications in electric agricultural machinery
Artificial Neural Network (ANN)	Capable of modelling complex nonlinear relationships; adaptable to different input variables	Requires suitable training data; can require considerable computational resources during training; model interpretability can be limited	Battery SOC/SOH estimation, energy consumption prediction, motor performance prediction, fault diagnosis
Convolutional Neural Network (CNN)	High performance in image and spatial-feature recognition; automatically extracts relevant features	Computationally intensive; requires substantial labelled image data; performance can be affected by changes in lighting and field conditions	Crop recognition, weed detection, disease detection, fruit detection, obstacle recognition
Long Short-Term Memory (LSTM)	Effective for sequential and time-series data; can learn long-term temporal dependencies	Training can be computationally demanding; requires sequential datasets; model complexity can make interpretation difficult	Battery SOC/SOH estimation, battery degradation prediction, energy-consumption prediction, machine-condition monitoring
Random Forest (RF)	Robust to noise and nonlinear relationships; handles multiple input variables; relatively easy to implement	Large ensembles can require considerable memory; less transparent than simple decision trees	Energy prediction, battery-health estimation, fault classification, crop and weed classification
Support Vector Machine (SVM)	Effective with small and medium-sized datasets; performs well in high-dimensional feature spaces	Computational cost can increase with dataset size; requires appropriate kernel and parameter selection	Motor fault diagnosis, bearing-fault detection, crop classification, disease classification
Reinforcement Learning (RL)	Learns decision-making policies through interaction with the environment; suitable for sequential decision problems	Training can be computationally expensive; reward-function design is important; safety during real-world learning can be challenging	Autonomous navigation, path planning, energy optimization, adaptive speed control
Fuzzy Logic	Handles uncertainty and imprecise information; does not require a large training dataset; suitable for real-time control	Requires appropriate rule-base and membership-function design; performance depends strongly on expert knowledge	Motor control, speed control, steering control, battery-management systems

Source: Adapted and synthesized from Liakos et al. (2018), Kamilaris and Prenafeta-Boldú (2018), Lei et al. (2018) and Shamshiri et al. (2018).

7.1 Artificial Neural Networks

Artificial Neural Networks are computational models inspired by the structure of biological neural networks. In agricultural applications, ANN models have been used for prediction, classification and decision-making tasks (Liakos et al., 2018). For electric agricultural machinery, ANN can be applied to battery SOC/SOH estimation, energy-consumption prediction, motor-performance prediction and fault diagnosis.

7.2 Convolutional Neural Networks

CNNs are deep-learning architectures particularly suited to image and spatial data. They can automatically learn hierarchical visual features from images, reducing the need for manual feature extraction (Kamilaris and Prenafeta-Boldú, 2018). In electric agricultural machinery, CNNs can be used for crop recognition, weed detection, disease identification, fruit detection and obstacle recognition.

7.3 Long Short-Term Memory Networks

LSTM networks are a type of recurrent neural network designed to process sequential data and retain information over longer time periods. In electric agricultural machinery, LSTM models can be used for battery SOC/SOH estimation, degradation prediction, energy-consumption prediction and machine-condition monitoring.

7.4 Random Forest

Random Forest is an ensemble machine-learning algorithm that combines multiple decision trees to perform classification or regression. It can handle nonlinear relationships and multiple input variables and is relatively robust to noise (Liakos et al., 2018). Potential applications in electric agricultural machinery include energy-consumption prediction, battery-health estimation, fault classification and agricultural-image classification.

7.5 Support Vector Machine

Support Vector Machine is a supervised-learning algorithm commonly used for classification and regression. SVM can be particularly useful when the available dataset is relatively small but contains informative features. In electric agricultural machinery, SVM can be applied to motor and bearing fault diagnosis, battery-condition classification, crop classification and disease detection.

7.6 Reinforcement Learning

Reinforcement Learning differs from conventional supervised learning because an agent learns by interacting with an environment and receiving rewards or penalties for its actions. For electric agricultural machinery, RL can be used for autonomous navigation, path planning, adaptive speed control and energy optimization.

7.7 Fuzzy Logic

Fuzzy Logic is particularly useful when agricultural-machine operation involves uncertainty, imprecise information, or nonlinear relationships that are difficult to describe mathematically. Fuzzy-logic controllers can therefore be applied to motor speed control, torque control, steering control and battery-management systems.

8. Current Challenges

Although the integration of artificial intelligence (AI) with electric agricultural machinery offers considerable potential for improving automation, energy efficiency, precision and operational performance, several technical and practical challenges continue to limit large-scale adoption. These challenges are associated with the energy limitations of electric powertrains, computational requirements of AI, sensor reliability, data availability, communication infrastructure, cost, cybersecurity and the variability of agricultural environments (Bechar and Vigneault, 2016; Liakos et al., 2018; Scolaro et al., 2021).

8.1 Battery Limitations

Battery performance remains one of the major constraints of electric agricultural machinery. Agricultural operations such as tillage, harvesting and field transportation can require substantial power, while currently available batteries have limited energy density compared with conventional liquid fuels. Consequently, battery-electric machines may have limited operating duration and may require frequent charging or battery replacement. Battery weight, degradation, charging time and thermal management further influence machine performance (Scolaro et al., 2021).

8.2 High AI Computational Requirements

Advanced AI models, particularly deep-learning architectures such as CNNs, LSTMs and object-detection networks, can require considerable computational resources. Agricultural machines often operate under constraints related to processor capacity, memory, energy consumption and heat generation. Deploying complex AI models directly on-board an electric machine can therefore increase computational load and electrical energy consumption. Model compression, pruning, quantization, edge computing and efficient AI architectures can help address this challenge (Kamilaris and Prenafeta-Boldú, 2018).

8.3 Poor Internet Connectivity

Many agricultural fields are located in rural areas where high-speed and reliable internet connectivity may not be available. AI-based agricultural systems that depend on cloud computing or continuous data transmission may therefore experience communication delays or interruptions. For safety-critical applications such as autonomous navigation, dependence on continuous internet connectivity can be particularly problematic.

8.4 Sensor Errors

AI systems depend heavily on the quality of sensor data. Cameras can be affected by poor illumination, dust, rain, shadows and occlusion, while LiDAR performance can be influenced by environmental conditions. GNSS positioning may be affected by signal obstruction and multipath effects. Similarly, current, voltage, temperature and vibration sensors may experience noise, calibration errors, or sensor drift. Incorrect sensor information can consequently result in incorrect AI predictions or machine-control decisions (Bechar and Vigneault, 2016; Shamshiri et al., 2018).

8.5 High Initial Cost

Electric agricultural machinery requires batteries, electric motors, power electronics, controllers, sensors, communication systems and potentially high-performance computing hardware. The addition of AI-based perception and control systems can further increase the initial cost. Although lower operating and maintenance costs may provide economic benefits over the machine's lifetime, the high initial investment can remain a barrier, particularly for small and marginal farmers (Scolaro et al., 2021).

8.6 Data Availability

AI algorithms require appropriate datasets for training, validation and testing. However, agricultural data are highly variable and depend on crop type, soil characteristics, geographical location, weather, machine configuration and operating conditions. Large, standardized datasets containing synchronized information from batteries, motors, implements, sensors and field conditions are still relatively limited. The absence of representative datasets can reduce the generalization capability of AI models (Liakos et al., 2018).

8.7 Cybersecurity

The increasing connectivity of intelligent agricultural machinery creates cybersecurity risks. Autonomous machines may exchange information through wireless communication, cloud platforms, GNSS systems and farm-management networks. Unauthorized access or manipulation of machine data could potentially affect navigation, operation, or safety.

8.8 Lack of Standardization

There is currently considerable variation in sensor configurations, data formats, communication protocols, AI models, evaluation metrics and testing procedures among agricultural machinery research studies. This makes direct comparison between different AI systems difficult.

8.9 Weather Dependency

Agricultural machinery operates in highly variable environmental conditions. Rain, fog, dust, sunlight intensity, temperature, humidity and soil moisture can significantly affect sensor performance and machine operation. For example, camera-based AI models trained under clear daylight conditions may perform poorly under low-light or rainy conditions. Therefore, AI models need to be trained and validated under diverse environmental conditions to achieve reliable field performance (Shamshiri et al., 2018).

8.10 Real-Time Processing Challenges

Agricultural machines often require decisions within milliseconds or seconds. Autonomous navigation, obstacle avoidance, weed detection, motor control and battery management therefore require low-latency processing. A highly accurate AI model is not necessarily suitable if it cannot provide predictions quickly enough for real-time machine control.

Summary of Current Challenges

Overall, the major challenges can be grouped into four interconnected areas:

- **Energy-related:** Battery capacity → charging time → battery degradation → thermal management
- **AI-related:** Computational requirements → training data → model complexity → real-time processing
- **Environmental:** Weather → dust → illumination → soil variability → sensor errors
- **System-level:** Cost → cybersecurity → connectivity → standardization → safety

These challenges demonstrate that the development of AI-based electric agricultural machinery requires an integrated approach involving battery technology, efficient AI algorithms, reliable sensors, edge computing, secure communication and robust machine design.

9. Future Research Directions

The integration of artificial intelligence (AI) with electric agricultural machinery is still an emerging research area. Future developments are expected to focus not only on improving individual AI algorithms but also on developing connected, autonomous, energy-efficient, explainable and collaborative agricultural machines. The following areas represent important research directions for advancing AI-based electric agricultural machinery.

9.1 Edge AI

Edge AI refers to processing AI algorithms directly on the agricultural machine or on nearby edge-computing hardware rather than relying entirely on cloud servers. This approach can reduce communication latency, improve data privacy and enable autonomous operation in areas with poor internet connectivity. Future research should focus on developing lightweight CNN, object-detection and machine-learning models that can operate on low-power embedded processors without significantly increasing the energy consumption of electric machinery.

9.2 Digital Twin

Digital Twin technology can create a virtual representation of an electric agricultural machine and its operating environment. The digital model can incorporate information from sensors, battery systems, motors, implements and field conditions. AI can then be used to predict machine behaviour, energy consumption, component degradation and maintenance requirements.

9.3 AI + IoT

The combination of AI and the Internet of Things (IoT) can enable agricultural machines to continuously exchange information with sensors, farm-management systems, weather stations, cloud platforms and other machines. IoT-generated data can provide information about machine condition, crop status, soil conditions, weather and energy availability.

9.4 Federated Learning

Agricultural datasets are often distributed among different farms, research institutes, machinery manufacturers and agricultural organizations. Sharing raw data may be difficult because of privacy, ownership and commercial concerns. Federated Learning provides a potential approach in which AI models are trained using distributed datasets without requiring all raw data to be transferred to a central server.

9.5 Generative AI

Generative AI represents an emerging research opportunity for agricultural machinery. Future systems could potentially use generative models to create synthetic agricultural images for training computer-vision systems, generate simulated field conditions, assist in machine diagnostics and support human-machine interaction.

9.6 Explainable AI

Many advanced AI models, particularly deep-learning models, operate as complex black-box systems. In agricultural machinery, understanding why an AI system has made a particular decision can be important for operator confidence, safety, troubleshooting and regulatory acceptance. Explainable AI (XAI) can provide information about the factors influencing a prediction or decision.

9.7 AI-Powered Battery Management

Battery performance is one of the most important factors limiting electric agricultural machinery. AI can improve battery-management systems by predicting SOC, SOH, remaining useful life, energy consumption, temperature behaviour and degradation. Future research should develop integrated AI-based battery-management systems capable of considering battery condition, machine load, field requirements, ambient temperature and planned operations simultaneously.

9.8 Vehicle-to-Grid (V2G)

Electric agricultural machinery contains substantial stored electrical energy that could potentially be integrated with electrical grids. Vehicle-to-Grid technology allows compatible electric vehicles to exchange energy with the grid. AI could optimize charging and discharging schedules by considering battery SOC, battery degradation, electricity prices, agricultural operation schedules and renewable-energy availability.

9.9 Swarm Electric Robots

Future agricultural operations may increasingly involve multiple small electric robots working collaboratively rather than relying exclusively on a single large machine. Swarm robots could perform tasks such as weeding, crop monitoring, seeding, spraying and harvesting. AI-based multi-agent systems can coordinate robot movement, allocate tasks, avoid collisions and optimize overall field coverage.

9.10 Human–Robot Collaboration

Fully autonomous agricultural machinery may not always be appropriate or economically feasible. A more practical approach could involve collaboration between human operators and intelligent machines. Human–robot collaboration can allow the operator to provide high-level instructions while AI handles repetitive or computationally intensive tasks.

9.11 AI-Assisted Autonomous Harvesting

Harvesting is one of the most challenging agricultural operations because crops can vary considerably in size, maturity, location and orientation. AI-based computer vision can identify suitable harvesting targets, while autonomous electric machinery can control the harvesting mechanism. Future research should focus on improving fruit/crop detection, maturity estimation, grasping, path planning, damage prevention and real-time harvesting decisions under changing field conditions.

9.12 Renewable Energy Integration

The integration of renewable energy with electric agricultural machinery is another important research direction. Solar photovoltaic systems, farm-based renewable-energy systems and energy-storage systems can potentially provide electricity for charging agricultural machinery. AI can optimize the interaction between renewable-energy generation, battery storage, machinery operation and grid electricity.

9.13 Integrated Future Architecture

A major future direction is the development of an integrated agricultural machinery ecosystem in which these technologies operate together:

Renewable Energy → Smart Charging → AI Battery Management → Electric Powertrain → Sensors → Edge AI → Autonomous Control → IoT/Cloud → Farm Management

Such an architecture could enable electric agricultural machines to become self-monitoring, energy-aware, connected, autonomous and collaborative systems. The future research focus should therefore move from developing isolated AI applications toward integrated AI–electric machinery platforms capable of simultaneously optimizing machine performance, energy consumption, reliability, safety and agricultural productivity.

10. Research Gaps

Despite significant advances in artificial intelligence, agricultural robotics and electric powertrains, the integration of these technologies into practical agricultural machinery remains at an emerging stage. The literature indicates that AI applications have been extensively investigated for crop recognition, weed detection, autonomous navigation, prediction and agricultural robotics; however, comparatively less attention has been given to their integrated application in battery-powered agricultural machinery, particularly machinery designed for small and fragmented farms (Liakos et al., 2018; Bechar and Vigneault, 2016).

10.1 Limited AI Integration in Electric Reapers and Small Farm Machinery

A significant research gap exists in the application of AI to electric reapers, weeders, seeders, sprayers and other small-scale agricultural machines. Much of the existing research on autonomous agricultural machinery focuses on tractors, robotic platforms, UAVs and high-value crops. Electric reapers and other compact machines used by small and marginal farmers have received comparatively limited attention. Future studies should investigate AI-based navigation, crop detection, energy management and adaptive machine control specifically for these machines.

10.2 Lack of Standardized Datasets

The development of reliable AI systems requires large and representative datasets. However, agricultural datasets differ substantially in terms of crop, soil, environmental conditions, sensors, machine configuration and geographical location. There is a lack of standardized datasets specifically containing synchronized battery, motor, sensor, implement-load, field-condition and operational data from electric agricultural machinery. This makes comparison between AI models and reproduction of published results difficult (Liakos et al., 2018).

10.3 Limited Integration of AI-Based Battery Management with Field Operations

Battery-management research and autonomous agricultural-machinery research are often conducted as separate research areas. Relatively limited work has investigated systems in which battery SOC/SOH, machine load, field conditions, travel speed, implement operation and remaining field workload are considered simultaneously. Integrating these variables could allow AI systems to optimize machine operation according to available battery energy and expected field requirements.

10.4 Limited Long-Term Field Validation

Many AI-based agricultural systems are evaluated using laboratory experiments, controlled environments, simulation, or relatively small field datasets. Agricultural machinery, however, operates under continuously changing conditions involving soil variability, crop density, weather, terrain, dust, vibration and illumination. Therefore, long-term field validation across multiple seasons, crops, locations and operating conditions remains necessary (Shamshiri et al., 2018).

10.5 High Computational Requirements for Embedded Deployment

Deep-learning models can achieve high prediction and classification performance but may require substantial computational resources. Deploying such models on embedded controllers used in agricultural machinery creates challenges related to processing speed, memory, power consumption, heat generation and system cost. Research is therefore needed on lightweight AI models, model compression, quantization, edge AI and hardware–software co-design for agricultural machinery.

10.6 Limited Low-Cost AI Solutions for Smallholder Farmers

The economic feasibility of AI-based electric agricultural machinery is particularly important for smallholder farming systems. High costs associated with batteries, sensors, processors, cameras, LiDAR, communication systems and AI-enabled controllers can restrict adoption. Future research should therefore prioritize low-cost sensors, lightweight AI algorithms, modular electric powertrains, open-source platforms and affordable edge-computing solutions.

10.7 Integration Gap Between Individual AI Technologies

Another important gap is that many studies focus on a single application—for example, weed detection, battery prediction, or autonomous navigation—rather than integrating multiple AI functions into a single agricultural machine. Future research should investigate integrated systems in which computer vision, autonomous navigation, energy management, predictive maintenance and implement control operate together.

10.8 Lack of Common Evaluation Standards

Different studies use different datasets, experimental conditions, performance metrics and validation procedures. Consequently, it is difficult to determine which AI technique is most suitable for a particular agricultural-machinery application. Standardized benchmarks should be developed for evaluating AI systems based on accuracy, computational requirements, energy consumption, response time, robustness, reliability and economic feasibility.

10.9 Research Gap Summary

The major research gaps identified from the literature can therefore be summarized as:

Limited application of AI to small electric agricultural machinery → lack of standardized machine datasets → insufficient integration of AI and battery management → inadequate long-term field validation → high computational requirements → limited low-cost solutions → lack of integrated and standardized AI platforms. Addressing these gaps can help move AI-based electric agricultural machinery from experimental research toward practical, affordable, reliable and scalable field applications.

11. Conclusion

The integration of artificial intelligence with electric agricultural machinery represents a promising pathway toward the development of autonomous, precise, energy-efficient and intelligent farming systems. AI enables agricultural machines to process information from cameras, GNSS, LiDAR, IMUs and machine-condition sensors and use this information for navigation, crop and weed recognition, energy management, predictive maintenance and precision field operations (Liakos et al., 2018; Shamshiri et al., 2018).

Electric agricultural machinery provides several potential advantages over conventional internal-combustion-powered machinery, including lower direct emissions, reduced noise, high drivetrain efficiency and the possibility of integration with renewable energy systems. AI further enhances these advantages by enabling intelligent control of machine operation, battery utilization, motor performance and agricultural inputs (Scolaro et al., 2021).

However, the widespread adoption of AI-based electric agricultural machinery is still constrained by battery capacity, charging requirements, high initial cost, sensor reliability, availability of representative datasets, computational requirements, real-time processing, connectivity and the variability of agricultural environments. These challenges become particularly important for smallholder farming systems, where affordability and simplicity are essential.

Future research should therefore move toward integrated AI–electric agricultural machinery platforms rather than isolated AI applications. Particular attention should be given to AI-powered battery management, edge AI, autonomous navigation, computer vision, predictive maintenance, renewable-energy integration, human–robot collaboration and swarm electric robots. The development of low-cost and energy-efficient AI systems that can operate reliably under real field conditions will be essential for practical adoption.

Overall, the convergence of artificial intelligence, electric powertrains, IoT, autonomous robotics and renewable energy has the potential to transform agricultural machinery from conventional mechanically controlled equipment into intelligent and adaptive systems. Future research should focus on making these technologies affordable, reliable, energy-efficient, safe and scalable across different crops, farming systems and farm sizes.

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