Smart Agricultural Technology 7 (2024) 100416

Contents lists available at ScienceDirect

Smart Agricultural Technology

journal homepage: www.journals.elsevier.com/smart-agricultural-technology

Sustainable AI-based production agriculture: Exploring AI applications and implications in agricultural practices

A.A. Mana [a], A. Allouhi [a], A. Hamrani [b,*], S. Rehman [c], I. el Jamaoui [d], K. Jayachandran [e]

[a] Ecole Supérieure de Technologie de Fès, U.S.M.B.A, Route d'Imouzzer, BP 242 Fez, Morocco
[b] Department of Mechanical and Materials Engineering, Florida International University, Miami, FL 33174, USA
[c] Interdisciplinary Research Center for Renewable Energy and Power Systems (IRC-REPS), King Fahd University of Petroleum and Minerals (KFUPM), Dhahran 31261, Saudi Arabia
[d] Department of Agricultural Chemistry, Geology and Pedology, Faculty of Chemistry, University of Murcia, 30100 Murcia, Spain
[e] Agroecology Program, Department of Earth and Environment, Florida International University, Miami, FL 33199, USA

ARTICLE INFO

Editor: Stephen Symons

Keywords:
Artificial intelligence
Precision agriculture
Energy
Sustainability

ABSTRACT

In general, agriculture plays a crucial role in human survival as a primary source of food, alongside other sources such as fishing. Unfortunately, global warming and other environmental issues, particularly in less privileged nations, hamper the Agricultural sector. It is estimated that a range of 720 to 811 million individuals experienced food insecurity. Today's agriculture faced significant difficulties and obstacles, as do the surveillance and monitoring systems (climate, energy, water, fields, works, cost, fertilizers, diseases, etc.). The COVID-19 pandemic has exacerbated the susceptibilities and insufficiencies inherent in worldwide food systems. Current agricultural practices tend to prioritize productivity and profitability over environmental conservation and long-term sustainability. To establish sustainable agriculture capable of meeting the needs of a projected ten billion people in the next 30 years, substantial structural and automation changes are required. However, these obstacles can be overcome by employing smart technologies and advancing Artificial Intelligence (AI) in agricultural operations. AI is believed to contribute to global sustainability goals in multiple sectors, particularly in the incorporation of renewable energy. It is anticipated that AI will revitalize both existing and new agricultural fields by retrofitting, installing and integrating automatic devices and instruments. This paper presents a comprehensive review of the most promising and novel applications of AI in the agriculture industry. Furthermore, the role of AI in the transition to sustainability and precision agriculture is investigated.

Introduction

Background

Currently, agriculture faces critical challenges, including climate change, water scarcity, environmental degradation, and dependence on conventional energy sources. Intensive transformation and landscaping can reduce biodiversity, pollute air and water sources, and put human and animal health at risk [1,2]. As such, a worldwide agricultural mutation is needed to switch from conventional to modern automated approaches [3]. Such approaches consider the agriculture farms as factories and plants and animals as production units [4,5]. The development of sustainable agriculture has attracted the attention of several countries focusses on economic, social, and environmental sustainability [6,7]. Smart innovations will be necessary to transition to a smarter and more sustainable agricultural sector [8]. Artificial intelligence (AI) seeks to develop technologies and systems capable of performing like human intelligence [9,10]. Recently, AI has been shown to be essential for information and services in the fields of health [11], education [12], trade [13], and others.

Moreover, AI holds significant potential to enhance the sustainability of the agricultural industry through various applications. For instance, it can contribute to identifying the optimal time for harvesting fruits and vegetables, reducing waste, and monitoring the health of soil and crops. Using AI, real-time monitoring of crop production can be improved, enabling more effective and supervised processing. Additionally, the integration can lead to efficient water use, conserving this valuable resource while maximising crop yields [14]. Additionally, the deployment of robots and drones in agricultural farms can detect weeds, pests and diseases, nutrient-deficient spots, monitor crop yield and quality, and other applications.

* Corresponding author.
E-mail address: ahamrani@fiu.edu (A. Hamrani).

https://doi.org/10.1016/j.atech.2024.100416
Received 9 May 2023; Received in revised form 13 January 2024; Accepted 16 February 2024
Available online 17 February 2024

Nomenclature

ADM	Agricultural Decision-Making
AI	Artificial intelligence
ANNs	Artificial Neural Networks
BMBF	Federal Ministry of Education and Research
CNNs	Convolutional Neural Networks
DT	Digital twin
DL	Deep Learning
EC	Edge Computing
FAO	Food and Agriculture Organization
IPCC	The Intergovernmental Panel on Climate Change
IOT	Internet of things
ML	Machine learning
MLP	Multi-layer perceptron
M2M	Machine to Machine
NDVI	Normalized Difference Vegetation Index
PA	Precision Agriculture
PLF	Precision Livestock Farming
PWM	Precision Water Management
SSCM	Site-specific crop management
SSSA	Secured Smart Sustainable Agriculture
RPAS	Remotely Piloted Aircraft System
UAV	Unmanned Aerial Vehicle

Benos et al. [15] delved into the use of AI and machine learning in agriculture, covering aspects like crop, water, soil, and livestock optimization. The study highlighted crop management as the most prominent area, with a focus on maize, wheat, and sheep. To foster smart and sustainable farming, key elements include ecosystem conservation, adopting modern technologies, effective resource management, and providing robust services in AI-based agriculture [16]. To ensure agricultural sustainability and maximise crop productivity while preserving the environment [17], it is imperative to improve, optimize, and modernize farming practises. Machine learning techniques have found applications in various aspects of sustainable agriculture, including crop recognition [18,19], crop disease identification [20,21], weed detection [22,23], water management [24,25], animal health [26,27], and livestock production [28,29]. AI has contributed a lot to agriculture and has protected crops from adverse weather changes and provided food security. Talaviya et al. [30] presented the analysis of some applications of AI in agriculture that included irrigation, weeding, and spraying using robots, sensors, and drones. Such AI-based techniques and equipment conserve water, pesticides, and, herbicide consumption and at the same time, maintain soil fertility, manage efficient use of manpower, and enhance the production quality [30]. The promising AI technologies being used or under various stages of technological development for sustainable agriculture, practices can be summarized as follows:

- Crop and soil health monitoring
- Automated weeding
- Intelligent spraying
- Insect and Plant Disease Detection
- Livestock Health Monitoring
- Harvesting, plowing, and pruning
- Produce grading and sorting
- Energy security

However, smart agriculture is a practical and promising alternative to satisfy global food demand while maintaining a balance between the agricultural industry and the environmental ecosystem. The concept of smart agriculture refers to all management practices that use AI, machine learning, data-driven, and recent technologies to ensure the quality and quantity of agricultural products. This concept is one of the major elements in the 4.0 revolution. AI can help farmers at every step, from soil preparation for seeding to harvesting with robots and computer-assisted engines. In 2017, the total estimated value of investments in the AI technologies in agricultural sector was 518.7 million dollars and is expected to reach 2.6 billion by 2025, with an annual increase of 16.2 % [31].

Scope and motivation of the study

The aim of this review article is to analyse the existing practices and technologies that are used and are sustainable for the ecological and digital transition in the agriculture sector. Preliminary understanding is that AI and machine-learning techniques have the potential to provide solution to improve agriculture and sustain the agro-production. The present scope of work defines sustainable agriculture's dimensions and provides a comprehensive review of AI utilization in the agriculture industry. The review also aims at providing a useful discussion on the most promising applications of AI in agriculture sector. Specifically, this review paper is intended to propose answers to the following research questions.

- How can AI promote agriculture practices and accelerate sustainability.
- To what extent the use of can AI promote the sustainability of agriculture in developing countries with agriculture-based economies?
- What are the limitations and challenges transitioning to smart agricultural practices?
- The future of AI in Agriculture: Farmers as AI engineers?

AI applications in agriculture

Sustainable agriculture is a fundamental approach to meeting society's food and rural needs while safeguarding the ability of future generations to meet their own needs. To achieve this, it is based on understanding of ecosystem services. Artificial intelligence emerges as a powerful tool for promoting sustainable agriculture, optimizing various farming aspects such as water and energy management, precision agriculture and smart farming techniques [32].

AI-driven agriculture plays a vital role in improving precision and contributing to overall sustainable farming practices. Through AI algorithms, farmers can gain insight to efficiently manage irrigation and conserve water resources. In addition, AI facilitates automating labor-intensive tasks, such as crop harvesting, pruning, and plowing in agriculture, with the aid of autonomous tractors and harvesters guided by AI technologies, thus reducing the need for extensive human intervention.

However, the world faces a twofold challenge: an ever-growing population and widespread hunger. To address these critical issues, an integrated approach is necessary to address the challenges related to soil fertility, water scarcity, energy insecurity, pests, and diseases that affect crops and animals. Sustainable agriculture is defined by a set of methods that ensure food production in harmony with ecological, economic, and social limits [33].

In the realm of agriculture, the concept of "secured smart sustainable agriculture (SSSA)" embodies an integrated framework that amalgamates several essential branches to catalyze a revolution, ensuring the sustainability, efficiency, and security of the agricultural sector. Picture this framework as a dynamic ecosystem, vividly illustrated in Fig. 1, where each branch assumes a pivotal role in sculpting the future of agriculture. Sustainable Agriculture encompasses practices such as crop rotation and organic farming, augmenting yields while concurrently minimizing the environmental footprint. On the other hand Data

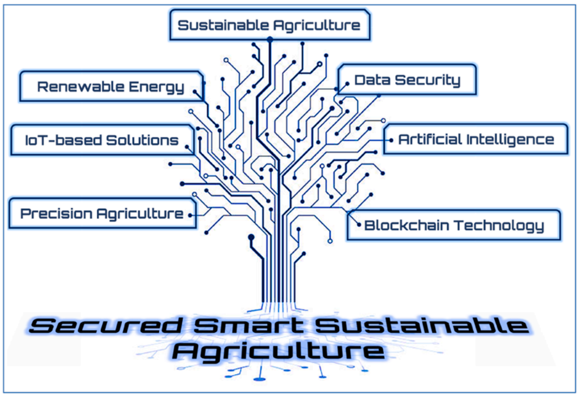

Fig. 1. Main pillars of Secured Smart Sustainable Agriculture.

Security stands as a pivotal facet, diligently safeguarding sensitive agricultural data garnered through the deployment of sensors, drones, and IoT devices.

Furthermore, blockchain Technology, with its decentralized and immutable ledgers, bestows transparency and traceability advantages, thus guaranteeing the unassailable integrity of supply chains and financial transactions. Precision Agriculture harnesses cutting-edge technology, including GPS, sensors, and analytics, to facilitate real-time decision-making, thereby mitigating resource wastage and elevating crop yields. In this perspective, renewable Energies are integrally woven into this framework, enabling the assimilation of clean energy sources such as solar panels and wind turbines into farming operations, thereby curtailing carbon emissions and energy expenditure.

IoT-Based Solutions (Internet of Things) intricately connect an array of devices and sensors, delivering real-time monitoring and fostering data-driven decision-making for a more resource-efficient and secure agricultural practice.

On another front, AI was defined in 1956, as ‘the science and engineering of making intelligent machines.’ The main notion was to create a technology able to perform like a human intelligence [9]. This was achieved by studying human brain processes to develop intelligent software and systems capable of offering the optimal result for all valid input [10]. The field of AI is rapidly expanding, including Machine Learning and Deep learning. The main objective of machine learning is to obtain computational models of complex non-linear relationships or complex models in the data, whereas AI can be described as a tool of decision making and advanced analytics [34]. MLs are often used to trace models in data,as well as to achieve high performance [35].

ML algorithms are trained using three prominent methods commonly recognised as ‘supervised’ where the system learns from labelled data; ‘unsupervised’ where the unlabelled system finds patterns in the data; and ‘reinforcement’ learning from new situations using a trial-and-error method [36]. Fig. 2 shows the different ML used in literatures. However, it’s important to note that the representation of ML in Fig. 2 lacks the inclusion of reinforcement learning, a significant omission that deserves acknowledgment. Reinforcement learning holds particular significance as it involves learning optimal decision-making strategies through interactions with an environment, receiving feedback in the form of rewards or penalties [37]. This method overlooks a crucial aspect of ML algorithms, as reinforcement learning plays a vital role in various AI applications, such as robotics, gaming, and autonomous systems [38].

Fig. 2. Artificial intelligence dimensions.

Its ability to learn from experiences and optimize decisions based on feedback distinguishes it as a key paradigm within ML.

AI has significantly contributed towards improving the efficiencies of many engineering and social led to problems of different industries. These technologies have even been introduced in the agricultural value chain from production to transport, to distribution, and to marketing. Agricultural robots have added a high value of AI and help in several stages of agricultural production such as increasing crop yield, optimising irrigation, detecting soil content, monitoring crops, and weeding. From another point of view, intelligent systems can process information, provide complex reports, and serve farmers in decision making and complying efficiently with quality requirements. Consequently, AI has the potential to provide essential solutions to address different challenges in this industry and will make it possible to produce better results more effectively. The diverse form, in which AI can intervene in the agriculture sector, operates through the usage of new information, communication technologies, and internet of things.

Precision water management

Precision water management (PWM) is a data-driven approach in agriculture that optimizes water usage by applying water precisely at the right time, place, and crop growth stage. By leveraging technology and data analysis, PWM aims to conserve water resources, promote sustainability, and enhance overall farming efficiency [39]. This approach involves sensible use of water to achieve sustainable water consumption. In agriculture, PWM refers to accurate and appropriate application of high-quality water at the proper time, place, and crop growth stage. Due to numerous technologies and instruments, several ways have been proposed to achieve such objective.

Therefore, AI is pivotal role in revolutionizing water precision management in agriculture lies in its ability to conduct data analysis and real-time monitoring, thus optimizing irrigation practices for sustainable farming. The transformative power of AI in this domain can be attributed to the following key aspects:

- Insights from Geospatial Data: AI and big data technologies analyses geospatial data to offer valuable information on soil moisture levels, weather patterns, and crop water requirements [40].
- Real-time Sensor Data and Weather Forecasts: By integrating geospatial data with real-time sensor data and weather forecasts, AI enables more accurate and efficient irrigation scheduling [41]. Farmers can rely on AI's analysis to determine optimal irrigation schedules and amounts, avoiding over- or under-watering their crops.
- Identifying Areas of Inefficiency: AI-powered sensors monitor water usage on farms, detecting inefficiencies and patterns. This helps farmers identify areas where water is wasted or used inefficiently, allowing corrective measures to be taken [42].
- Reducing Water Wastage: AI fine-tunes irrigation practices to minimize water wastage. By precisely controlling the application of water, AI enables farmers to maximize crop yields while minimizing water usage, which is particularly crucial in regions with limited water resources or unpredictable weather patterns [43,44].

Many technologies have been developed to control the communication between machines and different nodes settled in agricultural farms. These Machine to Machine technologies are efficient for monitoring soil moisture content and temperature at periodic intervals to automate the irrigation with precise requirement [45]. Remotely controlled sensors can be used to observe both biological and climatic conditions [46,47].

Furthermore, ML becomes a valuable tool, with the aid of measured real time data from the agriculture farm, for making right decisions for

Table 1
Literature survey on water management models.

Ref.	Inputs	Algorithms	Method model	Technology	Performance
Choudhary et al. [61]	Climatic conditions, soil moisture content	Partial Least Square Regression (PLSR)	Evapotranspiration model	Economic hardware, sensors, (IoT).	Increased efficiency and economic feasibility
Anand et al. [62]	Temperature, soil humidity	Fuzzy Logic Controller	Penman–Monteith model	Wireless Sensor Networks (Sensor nodes, hub, and control unit)	Automated drip irrigation water conservation
Subathra et al. [63]	Climatic conditions, soil moisture content topography	ANN method	Soil moisture model	____	Precision and Robustness of soil moisture prediction, water saving
Chen et al. [64]	Soil water content and meteorological data	Convolutional neural network-)	Pearson correlation, soil water content autocorrelation	Deep learning Near-infrared (NIR) spectroscopy	Prediction accuracy ninety-three %
Arvind et al. [65]	Moisture, weather forecast and water level	Machine Learning algorithm –	______	IoT, ZigBee technology, Arduino microcontroller	Drought prediction
Poblete et al. [66]	Meteorological data, soil composition	Artificial neural network (ANN) Machine learning techniques	Evapotranspiration model	Unmanned aerial vehicle (UAV) remote sensing platforms	Performance to predict water stress
Melit and manghanem [67]. Melit and Benghanem[68]	Different conditions	ANN networks	Optimal model sizing	Hybrid intelligent systems (HIS)	Sizing of optimal stand-alone photovoltaic systems
Richards and Cnibeer. [69]	Different conditions	Regression comparison	Optimal model sizing	Standalone power supply (SAPS)	Seasonal Variability of Solar Insolation (PV) panels with H2 storage
Hernandez and Medina [70]	Different conditions and inputs	Genetic algorithms	Optimal model sizing	Sizing grid-connected PV-system	Stability voltage distribution
Ammmar and Oualha [71]	Climatic data	Feed Forward Neural Network Adaptive Neuro Fuzzy Inference System	Optimal model sizing	Solar pumping systems	Photovoltaic power forecast
Achite et al. [72]	meteorological and hydrological	ANN, ANFIS, SVM, and DT	Hydrological Drought Modeling	machine learning techniques	ML accurately predicted drought, with SVM outperforming
Chandel et al. [73]	Crop data and images	AlexNet, GoogLeNet and Inception V3	Water stress modeling	Deep learning	GoogLeNet achieved remarkable accuracy

improving water usage efficiency and managing evapotranspiration process. As summarised in Table 1, ML allows for a correct and effective use of resources. One of the essential aspects of digitalization is the large-scale use of wireless sensor networks centrally controlled by ML. Furthermore, the commercialization of thermal cameras, facilitated by advancements in graphics and high-speed real-time computer processing, has opened new opportunities for estimating soil hydraulic conditions through the acquisition of thermal indices [48]. With recent advances, AI-based reasoning about soil water balance and forecasting can optimise hydraulic variables and protect land against erratic climatic conditions and disasters [49,50].

Furthermore, solar photovoltaic water pumping has become technologically mature and commercially acceptable for water pumping in the agricultural sector in rural areas. A great advantage of using solar PV based water pumping is that the water requirement and sunshine availability timings coincide. However, due to the intermittent nature of solar radiation, more than one energy sources can be integrated to assure continuous energy availability for irrigating the crops. Moyo [51] presented a comprehensive AI-based modelling of a solar/diesel hybrid water pumping system with the objective of optimizing its performance. The results revealed that the ANFIS-based MPPT system was able to generate maximum energy from PV modules under prevailing weather conditions [51]. Furthermore, hybrid power systems reduce life cycle costs relative to standalone power systems and also provide continuous and reliable energy [52]. Karar et al. [53] used the internet of things to minimise water wastage in irrigation process based on meteorological data measured through sensors (ambient temperature, relative humidity, soil moisture, etc.) and the multilayer perceptron neural network approach. The proposed model could manage sensor data to automatically control the operation of the water pump. For sustainable irrigation, the management information system along with the online adaptation of climatic conditions help improve crop productivity and reducing the overall cost [54]. Abidin et al. [55] used moisture content data in the soil with an intelligent irrigation control system to reduce the use of water usage for cultivation. The technology of wireless sensor networks was used in the agriculture sector to promote Precision Agriculture (PA) [56]. Wireless sensors with fuzzy controllers [57] have been recommended for the automation of the irrigation system [58]. Xiao and Liu [59] proposed the use of microcontroller units to facilitate a smart irrigation system. Karar et al. [53] used a smart controller based on MLP neural networks for water irrigation system [60].

Integrated food safety

Conventionally, agricultural productivity and crop diversification is strongly linked to protection against weeds and diseases or infestation by pests and insects. In the face of these risks, food security becomes crucial [74]. Thereby, the faster the detection, better will be the implementation of security parameters and the measures necessary for the preservation of crops [75]. In recent years, ML and DL have been applied to protect through insect pest monitoring [76], weed detection [77], and identification of plant diseases [78].

Machine learning, using remote sensing to recognise species and diseases [79], is applied using decision trees, random forests, and neural networks to extract features and object classification. Deep learning has emerged as useful method with big data and visual technologies. Convolutional neural networks are the easiest type of DL to process 2D images with fewer errors but depend on high volumes of measured and expert data sets (Fig. 3). The AI-based disease detection process involves image collection, image labelling, data splitting and storage, and dividing the data set into training, validation, and testing data subsets. The model is trained and validated using the data subsets, as defined, and then the model results are tested against the third data set to provide the decision on whether the disease exists in the crop or not.Deep CNNs have gained the interest of researchers in intelligent integrated management. CNN based on deep learning, coupled with remote sensing and big data, is faster and more dependable [80,81]. Details of input data, algorithm, performance, and limitations, of using ML approaches for weed and disease detection are summarized in Table 2. It is observed from the Table that imagery data along with appropriate ML method provides the most accurate detection of the presence of weeds in the crops.

Precision livestock farming

Monitoring the health of livestock plays an important role in modern agriculture by ensuring the welfare of animals and producing high-quality products. Advanced artificial intelligence techniques can use sensors and cameras to monitor animal health in real time, dropping the need for traditional training. Compared to conventional methods, AI-based systems have several advantages, such as identifying patterns and potential health problems before they become serious. [94,95]. These systems can be based on various models and technologies such as IoT, edge computing, and Distributed Ledger Technologies [96]. However, the implementation of such a system comes with several potential concerns, including initial cost, technical expertise and requirements for specialised equipment, ethical concerns, and doubts about job relocation of jobs [97]. Despite these challenges, leveraging AI for Precision livestock farming systems can significantly enhance animal welfare and decision-making process. By providing information on animal

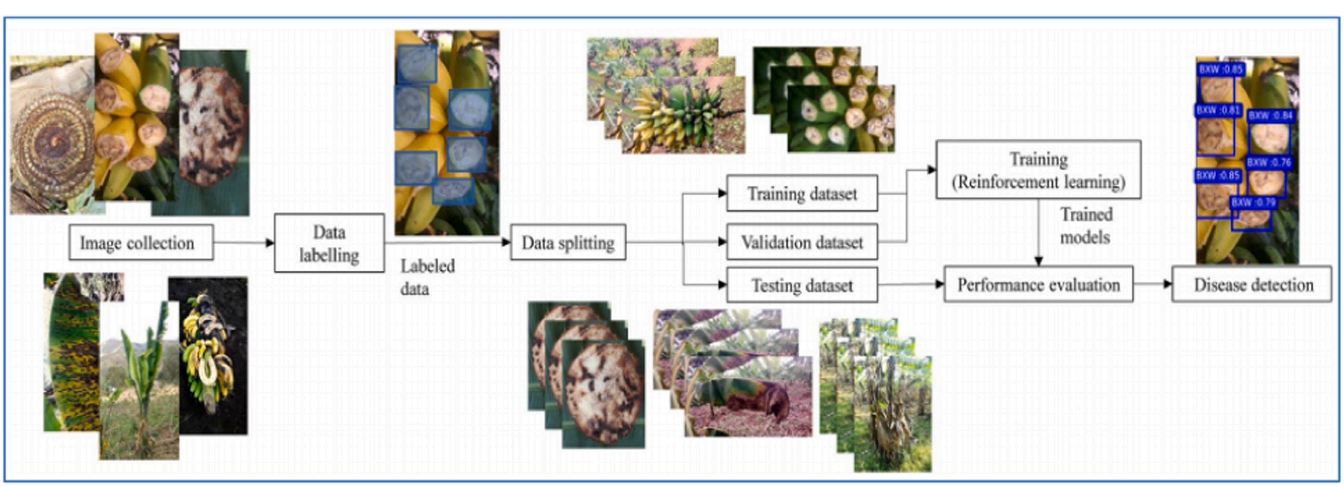

Fig. 3. Banana disease detection using intelligent algorithms [82].

Table 2
AI performance and limitations for weed and disease detection.

Application	Inputs	Method/algorithms	Performance	Limitations	Ref
Weed detection	UAV images	Fully Convolutional Network (FCN) method	Weed mapping: 94 % weed recognition: 88 %	Requires vast human expertise	H. Huang et al. [83]
Weed prevention	multispectral, hyperspectral cameras, and GPS data	ROBOTs. Sensor machine learning	Saves time and removes resistant weeds.	Expensive and affect soils	Brazo. [84]
Weed prevention	Yield sensing and imagery data	Colour-based and Texture Based algorithms;	High accuracy 92.9 %	Expensive	Sujaritha et al. [85].
Weed detection	(RGB)/ hyper spectral images	Deep Convolutional neural networks	High accuracy 98.23 %	Requires big data.	Assad and Bais. [86]
Disease detection	UAV images (RGB)	CNN	Overall accuracy 89 %,94 %	Requires big data and human expertise	Bah and Canals. [87]
Disease detection	Multispectral Imaging and sensing data	Phenotyping technology, remote sensing methods	Early season detection and performance	Require big data	Ampatzidis and Partel [88]
Disease detection	Expert systems	Web-Based Expert System	High performance	Internet dependence	Beiranvand . [89]
Disease detection	UAS images Data Base	CNN	an average accuracy of 93.75 %	Image segmentation affect CNN acuraccy	Junde Chen et al. [90]
Weed detection	Digital Image	Remote sensing methods	real-time, submeter- or even decimeter-level accuracy	–	Perez-Ruiz el al [91].
Weed detection	Hyper spectral images	SVM, ANN, and CNN	Quick detection.	Accepted accuracy	Che'Ya [92]
Weed detection	Thermal images,Big data	ANNs	Performance. Reduces trial and error.	Requires big data, expensive	Zamani and el. [93]

behaviour, feeding, and environment, AI helps farmers optimize their livestock management systems.

In recent years, the need of establishing comparable standards in large-scale livestock farming systems has been discussed to improve decision-making and data interchange. Both farmers and farm-integrated approaches were advocated for adoption, along with a consensus on the requirements for data exchange [98]. This would allow farmers and regional stakeholders to realize the benefits of sharing data effectively.

Studies on energy usage in dairy farms have been explored, highlighting the significance of prediction models to analyse energy consumption and evaluate the effects of modifications in infrastructure equipment and management practices. The literature commonly reports a reduction of 35 % in energy usage with the adoption of grazing-based dairy systems [99]. Various methods have been used to forecast energy consumption in dairy farming, including the CART decision tree, the random forest ensemble, artificial neural networks, and support vector machine [99,100].

Furthermore, animal health is also a key aspect of livestock production. The monitoring can focus on sound analysis that have the potential to be automated for large-scale farming, thus providing an efficient and cost-effective way to track animal well-being [101]. The use of machine learning algorithms, including face-face recognition through convolutional neural networks became widely used. For example, the review [102] identified relevant sensors to measure animal health, such as cameras (2D and 3D), microphones, thermistors and accelerometers, and highlighted how these technologies can be used to improve pig health, leading to better outcomes for both animals and the industry. In summary, these studies prove the potential of advanced technology in promoting animal welfare and improving the efficiency of livestock farming.

Crop productivity and fertility

Precision agriculture or site-specific crop management is defined as an agricultural system that uses technology, satellite and aerial images, climate forecasts, and prediction applications to improve the productivity and the profitability indicators of the fields. Based on collected data, AI could foster agro-technologies and increase crops quality, productivity, and hence the profitability. ML makes it more achievable by learning from the analysis of measured data and performing agricultural production with a high degree of accuracy (Fig. 4)

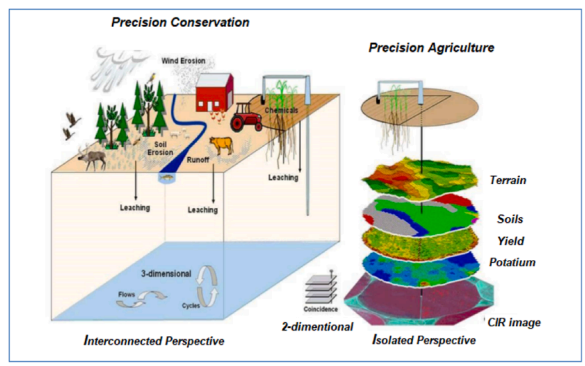

Fig. 4. Site-specific crop management based on a three-dimensional approach that assesses inputs and outputs from fields to watersheds and regional scales [8].

For example, AI may response to crop health issues or soil nutrient deficiencies based on the measured data [103]. AI techniques can examine photo-sanitary models, soil health, and the amount of fertilisers required [104]. Therefore, the risks of plant and the soil degradation may reduce, and yields can cope with the market trends, maximize the income from different farms [105], and ensure better crop mapping for decision-making (Fig. 5) [106]. Under the recent Soil monitoring scenarios, once farmers submit a sample of their agricultural soil to the monitoring agency, they will receive a detailed summary of their field soil contents. Based on the results obtained, an appropriate decision/action is taken and communicated to the farmer about the presence and type of bacteria, fungi and wide-ranging microbial progression [107].

AI for harvesting, pruning and ploughing

AI-based robots have revolutionized agricultural tasks, offering advanced capabilities in areas such as harvesting, pruning, and plowing. These robots have brought significant improvements to farming operations, resulting in increased productivity and efficiency. One remarkable example is the development of a sowing, pruning, and harvesting robot designed to work efficiently in dense vegetation. This small and flexible robot minimizes its impact on the environment and exhibits impressive obstacle avoidance capabilities, reducing operating time by 49 %

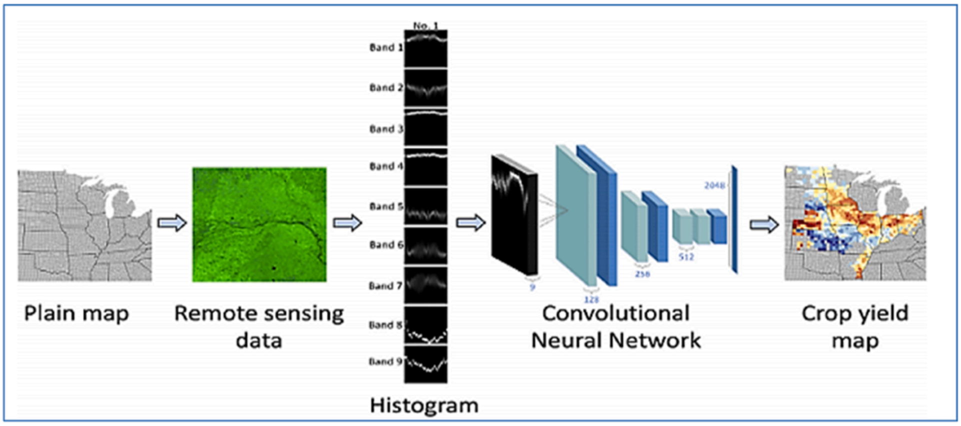

Fig. 5. Crop yield map using machine intelligence algorithms [106].

compared to traditional controllers [108]. Precision farming, which uses appropriate technology and practices to produce high-quality agricultural products, is one area where AI can be applied. Here are some examples of how AI can be used for harvesting, pruning, and plowing:

- Smart Spectrometer: This is a spectrometer with integrated artificial intelligence that can estimate properties such as substance concentrations and compositions. It can be integrated into a harvesting vehicle, where quality is determined by predicting sugar and acid in grapes in the field [109].
- Complexity-Driven CNN Compression: This is a type of model compression that can accelerate Convolutional Neural Networks (CNNs) on low-power devices. It can be used for pruning CNNs for resource-constrained edge AI [110].
- Selective Harvesting Robotics: This is an area of research that aims to develop robots for selective harvesting. The task of selective harvesting is not easy for robots, but it allows for improved farm management and can optimize the food-production chain [111].
- Pruning and Harvesting Manipulators: These are manipulators used in the agricultural robotics field. They can be used for pruning grapevines and apple trees, as well as harvesting strawberries, tomatoes, apples, sweet-peppers, and iceberg lettuce [112].
- Plant Counting with UAV RGB Images and Deep Learning Networks: Utilizing Unmanned Aerial Vehicles (UAVs) equipped with RGB cameras and deep learning networks, AI demonstrates its capability in accurately counting plants within agricultural fields, such as rice paddies. The methodologies employed—image processing and deep learning algorithms—form the foundational technology that extends beyond plant counting. These methodologies serve as the basis for various AI-driven agricultural tasks like harvesting, pruning, and plowing, leveraging similar data processing, decision-making algorithms, and precision achieved through advanced image analysis [113,114].

These are just a few examples of how AI can be used for harvesting, pruning, and plowing in agriculture. As AI technology continues to advance, we can expect to see even more innovative applications in this field.

Sustainable AI based agriculture

Predictive analytics for smart energy planning

Predictive analytics is a powerful tool that empowers farmers to optimize their energy usage and make informed decisions in agriculture. By analyzing data from diverse sources, predictive analytics offers valuable insights on crop selection, optimal planting times, appropriate fertilizers, irrigation schedules, and pest or disease management. One application of predictive analytics in agriculture is smart energy planning, promoting the use of renewable energy sources and energy conservation techniques to enhance sustainability and decrease fossil fuel dependency. Smart agriculture further leverages predictive analysis, integrating Agro IoT systems, renewable energy sources, and vertical farming techniques to increase yields while minimizing water and energy consumption, resulting in more sustainable farming practices.

The integration of AI-driven energy management and IoT-based weather forecasting holds immense potential in transforming agriculture practices for greater efficiency and sustainability. Utilizing machine-learning algorithms, AI accurately predicts energy demands, detecting potential inefficiencies in energy usage. With historical data analysis, farmers can proactively allocate energy resources, minimizing environmental impact. The coupling of IoT with meteorological sensors enhances weather forecasts, surpassing conventional methods' limitations and providing predictions that are more precise. Proposed solutions incorporate deep neural networks and CNNs, supported by meteorological satellite data, to bolster weather forecasting. Recurrent neural networks improve long-term climate modeling with short-term memory capabilities [115]. Managed through CPU or cloud platforms, the collected data ensures precise results, accessible via mobile applications for real-time monitoring and decision-making in agricultural activities [116]. This fusion of AI-driven energy management and IoT-based weather forecasting presents a transformative approach to sustainable and efficient agriculture practices. Hybrid models combining CNN with RNN architectures may enhance accuracy in managing both spatial and temporal data [117]. Table 3 summarizes diverse energy predictive solutions.

AI-based energy management for agriculture products

To modernise the agriculture sector, electrification may be an effective approach and can result in environmental and economic benefits [126]. In the present times, the agricultural energy internet (AEI) concept is getting popular in developing relevant agriculture technologies. AEI is relatively a recent development and was derived from Energy Internet to accomplish clean energy generation for isolated places. AEI is a multi-energy system realized by combining power networks, heating, gas and requires agricultural information sharing by the people [126]. AEI supports new energy industries, smart agriculture solutions, and rural revival, Fu et al. [127]. The intelligent management and control systems adopt standard methods for collecting the current, voltage, electrical fault, and power classification data to carry out the real-time safety analysis and issue warning, if any for the safety of agriculture production, Song et al. [128]. Fu and Yang [129] provided guidelines for protecting crops and trees from low temperatures and agricultural deficiency. The multi-source data fusion concept is useful for monitoring, positioning, and navigating the greenhouse environment to

Table 3
Performances and limitations of AI on predictability.

applications	Technologies	Inputs	Performance	Limitations	Ref
Energy modelling	AI and ANFIS	Energy, climatic and agricultural data	High accuracy using Hybrid learning method	_	Ashkan et al. [118]
Smart energy inputs	,Smart energy pacages,ANN	Nitrogen,fuel,manure, and electricity	Reducing 17.3 % of energy and 23 % of GHG emissions	_	Elahi et al. [119]
Agrivoltaics energy prediction	Regression, ANOVA	Weather and crop data	Predicted LER value of 2.17 relies on the proper arrangement of PV panels and crops in the research region.	Low accuracy	Abidi et al. [120]
energy consumption in greenhouses	Baysian model	Climatic data and greenhouse dimensions	The CBMA model outperformed BMA, MLP-SEOA, MLP-SCA, MLP-BA, MLP-PSO, and MLP models.	_	Ehteram et al. [121]
Early warning systems	IoT and ML	Climatic data	Reduce the number of tasks and data completeness of routing in a larger coverage agricultural greenhouses.	Data collection	Liu et al. [122]
Weather forecasting	ANN	Metrological parameters	Acceptable error percentage, fast prediction. prediction results till 2050	Increasing of the percentage predicted errors with time.	Yahya and Seker. [123]
Load forecasting	ML, IoT	Different parameters	Acceptable errors, Fast prediction.	Short term load prediction	Raju and Laxmi. [124]
Load forecasting	Multi Linear Regression (MLR)	Different parameters	Higher accuracy	Short term	Kim et al. [125]

optimize and improve agriculture produce. For risk assessment, it is essential to predict the meteorological variables to safeguard the growth level of agricultural products. Mancipe and Gutiérrez [130] proposed a data fusion strategy to predict meteorological parameters to precisely monitor the growth of agriculture products.

Sparrow et al. [131] provided proper strategies may be needed when AI begins to affect the agriculture sector. The study pointed out some of the consequences which may arise due to the implementation of AI technology in agriculture sector. According to the authors, AI may be beneficial for farmers, end users and the environment but may present unknown risks and suggested some alternative designs and regulatory procedures have been suggested to the risks. The civil and principled impacts of using AI in the farming were studied to find out how are they correlated with AI ethics [132]based on sustainability, trust, privacy, benefits, transparency, freedom, responsibility, justice, morality, and unanimity.

Vincent et al. [133] mentioned that currently some of the farmers are using automated equipment fed through huge data collected by meteorological sensors and satellite imagery. These farmers act in accordance with the advice provided by sophisticated computer applications. Existing investment on precision agriculture assures an important role of AI in agriculture [134,135]. The ML methods are expected to address key research topics in agriculture sector, which include meteorological parameter prediction ahead of time, economic modelling, and plant and animal breeding. Furthermore, AI and ML methods have the potential to improve distribution, balance energy consumption loads, and manage fluctuations in renewable energy production. The energy transition can incorporate AI into their system for more opportunities to improve the efficiency of production and consumption.

Moreover, it is agreed that improving the efficiency of biomass processing could help agricultural regions to produce bioenergy and addressing the challenges that hinder biomass-based energy development [136]. Practically, agricultural biomass can feed large scale of bioplants (100 MW and more) [137,33]. Thus, pyrolysis and gasification technologies been widely developed [138], explaining the reason for huge AI studies coupled with these systems [139,140]. Combined heat and power (CHP) technology can be widely adopted for waste management and energy production [141]. CHPs are identified for their promising efficiency in modern greenhouses, compared to biogas plants [142]. Considering the progress of cogeneration systems, if integrated with AI methods, can be an effective and potential solution to compensate for the different energy demands of agricultural greenhouses [143,144]. Furthermore, bioenergy systems have proven performance, as well as combined and hybrid with other green technologies [145,146]. Generally, the potential benefit of AI is to simultaneously supply electricity by controlling and monitoring main equipment, input, and output parameters [147].

Nanotechnologies utilization for agricultural management

The exponentially increasing population, adverse effects of climate change, growing biofuel demands, and deteriorating soil condition are some of the alarming international food security issues. Exploring new and sustainable options requires modern techniques to emulate information from materials science and automation [148]. Emergence of precision agriculture with nanotechnology and AI, offers excellent avenues for sustainable food production. The third Green Revolution of the 1950s and 1960s improved agriculture production and minimized the scarcity of food and spread of malnutrition. Since then, the global population has crossed 6 billion mark and has compelled an increase in agriculture production. Today, this sector is facing challenges such as decreased yields, soil quality, freshwater availability for irrigation, fertility, and excessive use of pesticides and fertilizers [149].

For the development of the precise and sustainable agriculture sector development, nanotechnology can offer excellent opportunities, discussed in review articles covering strategies to improve crop nutrition and develop smart plant sensors [150,151] . Nanotechnology can facilitate the delivery of fertilisers to tissues and organisms in a controlled way [152], which would be beneficial for plant growth and optimal use of fertilizers and pesticides and minimise adverse effect on soil condition [153,154]. Furthermore, nanotechnology applications in agriculture include the plant sensor development through which the plants can itself sense abiotic stress depending on the directed delivery of nanomaterials [155]. Four main areas in which nanotechnology is progressing include improving production yield, soil conditions, and efficiency of materials usage, Fig. 6 [148].

Additionally, the integration of nanotechnologies with AI-driven methodologies amplifies these advancements in agriculture. AI complements nanotechnologies by providing intelligent data analysis, predictive modeling, and autonomous decision-making capabilities. The fusion of nanotechnology and AI promises novel opportunities in precision farming, allowing for real-time monitoring, precise resource management, and informed decision support systems. This collaboration aims to revolutionize agricultural practices, enhancing productivity, sustainability, and efficiency in the face of global agricultural challenges

Discussions: issues and challenges related to the use of AI

As perceived before, AI can change our traditional view of the agricultural sector and enable farmers to be agents of change, especially in rural areas. However, AI remains a vast field that operates in a way

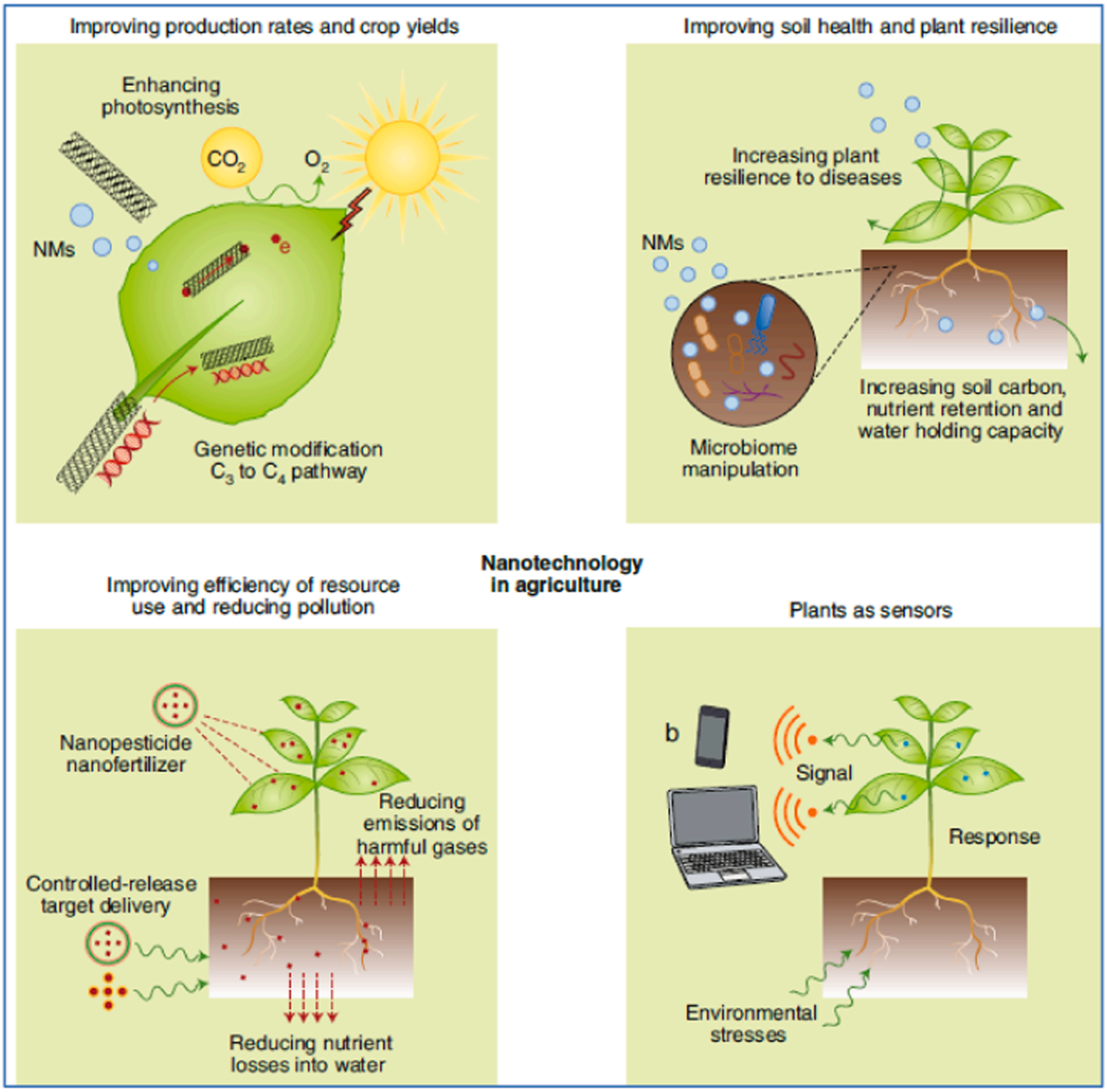

Fig. 6. Nanotechnology Applications in agriculture [148].

that is dependent on several factors relating to the nature and quantity of data collected, modelling, design, type of algorithm used, and is highly dependent on the way in which is all applied. All these elements can be a hindrance to the development of AI in the agricultural sector. However, the advantages of AI are unavoidably accompanied by several risks. Currently, the issues and difficulties raised by using AI in agriculture are still not inevitable. In this section, the relevant challenges of AI applications in agriculture are highlighted.

Lack of trust

The question of whether we are capable of placing the total trust in agricultural and food processing machines is the subject of a long debate [156–158]. Today, agriculture industry is undergoing a digital revolution, but lacks the intelligence to delegate all agricultural tasks to technology and robots.

Today, intelligent systems may help to optimize performance, manage risks at all levels and if possible, innovate. From a security perspective, agriculture may be at risk of conflict and war due to these systems' susceptibility to hacking and cyber assaults. This raises the question of entrusting decision making to algorithms based on meteorological, biological, or energetic data.

Thus, experience has shown that AI has disrupted the processes of many fields such as banking, industry, and medicine. Relying on machines and decision support systems can pose major ethical and problems and programs may have a "cold" logic. The limitations of trusting these algorithms in agriculture can be seen as the emerging self-driving car technology. It will be difficult to define ethics for insurance to cover liability in case of fatal decisions and accidents. The need for normative rules for these innovations is the next step soon.

Impact of artificial intelligence on the workforce

The ability of AI to replace humans in performing cognitive tasks is one of the critical issues. Digitalization of agriculture will make it possible to our production-related tasks at a lower cost and in a shorter time, which will change the function of farmers and reduce their numbers to the minimum possible. The digitalization of activities and relationships creates new dangers for occupational health and safety (OHS), such as an increase in mental load and a blurring of personal and professional boundaries. These significant technical advancements cause people, especially older workers, to doubt their knowledge, which can put them in situations where they are incompetent and cause significant personal destabilization. As a result, learning new technologies or procedures through training can be challenging, and this can lead to feelings of frustration and failure that may demotivate people, creating a vicious cycle of professional disinsertion. Good change management will consist of anticipating these psychosocial risks, defining, and implementing an approach that allows the project to be implemented without significant disruption to new working contexts, tasks/responsibilities, and skills.

AI application in the workplace creates new concerns about occupational dangers and safeguarding farmers from the effects of the changes in labor [159–161]. Psychological dangers, such as emotions of reliance, loss of autonomy and identity, and extra mental load, are linked to human-machine interaction, in addition to the physical risks brought on by malfunctioning robot/s. With legal, ethical, social, and regulatory issues at stake, such as the emergence of technostress, the exploitation of personal data in the workplace, the security and decision-making latitude dimensions of human-machine interactions, the transparency of monitoring algorithms, etc., there is growing concern about the risks of artificial intelligence and machine learning in the workplace. This concern comes from its integration to automated machines and in farmer monitoring.

The question of data-driven algorithms

The future of smart agriculture lies in the efficient collection and analysis of data. Data are not readily available, particularly at a local farm scale [162], and if available could contain uncertainty. The measured data contains information and trends about weather, soil, crops, water resources and more could be extracted and used as decision support for farmers, researchers, agricultural advisors, and market services. Development of an open-source database, at a global and local scale, will serve as the baseline for scientists, economist, and farmers. This database will contain satellite imagery, Internet of Things (IoT) sensors data, soil, crops, water, tillage and surface temperature data [39,163]. At the data collection stage, IoT network can help collect data measured from sensors located in the field, in the soil probes, tower-mounted devices on tractors, providing real-time accessibility.

The next stage concerns the integration of collected information with data from cloud-based systems (soil types, present and future weather conditions, cost models, etc.) to extract insights and patterns by machine learning models. These predictive models help farmers and scientists to detect existing and future issues. The challenge now lies in promoting global efforts for the availability, accessibility and usability of data in agriculture. Integrating these stochastic algorithms in deterministic approaches such as biophysical models is a hot topic that research is working on. Scientists are actively working on the integration of the physical aspect in the ML algorithms for making the whole system more realistic application. There is also significant legal ambiguity around machine learning in general, as with any breakthrough. Although there are still standards that must be followed, the sector is evolving, concerning the concepts of ethics and accountability.

The question of interpretability

Good design may be able to reduce some of the hazards mentioned above, making them important considerations for those who develop AI for agriculture. The characteristics of AI, such as its proneness to bias and algorithms nature, are linked to several the problems involved with its application in agriculture. In fact, concerns about interpretability have recently arisen in response to the emergence of machine learning. Some machine learning algorithms operate in a very opaque manner and their conclusions are still not fully explicable or justified [164,165]. Therefore, interpretability may also be of an instrumental relevance for several reasons, including the right to explanation of stakeholders who may be impacted by an ML decision in agriculture.

AI and ML models, however powerful it may be, but still considered mysterious and black boxes. Now, it is difficult to measure and justify their results or outcomes. Interpretability is the inherent issue with the use of AI. There are two distinct levels of interpretability in machine learning models.

1) Low interpretability: This includes ML models such as support vector machine (SVM), neural networks, and deep learning. The lack of interpretability is justified by using structure of multiple interconnected layers containing different types of neurones; in the case of deep learning or complex geometrical foundations; in the case of SVM.
2) High interpretability: This level includes the classical regression algorithms such as linear, multiple linear, decision trees, Ridge and least absolute shrinkage and selection operator Lasso regressions. Although these models are inherently interpretable but there is a limited relationship between explain ability and the accuracy of the predictability in the future.

To this end, it is essential to avoid technological determinism while considering the future of agriculture. This is not meant to ignore the possibility of agricultural uses being facilitated by technology, but rather to improve intelligent systems and adapt them in the agro-food sector.

Explainable AI (XAI) is a branch of AI that has been specifically developed to ensure transparency and comprehensibility. This is particularly important in fields such as agriculture, where decisions made by AI systems can have significant impacts on crop yields, water usage, and overall sustainability [166]. The use of XAI in smart agriculture can help build trust in AI-based technologies, identify potential biases or errors, and ensure that these technologies are transparent, accountable, and in compliance with relevant regulations and standards.

Specific issues of use of AI in agriculture sector in developing countries

The agriculture sector has gone through several transformational revolutions throughout history that have significantly affected production and efficiency. From the first agricultural revolution, which enabled people to settle down around 10,000 years ago, to the most recent agricultural revolution called "digital agricultural revolution". This revolution is characterized by the integration of IoT technologies and the emergence of Big Data to connect agricultural systems, resulting in unprecedented levels of efficiency and productivity. All These changes have played a critical role in the development of agriculture. However, the development and adoption of smart agricultural technologies in developing countries is significantly lagging and varies depending on the country and region. The main obstacles to the adoption and use of intelligent agricultural technologies in developing countries include a lack of financing (initial investment), low awareness of modern agricultural technologies and processes, limited technical capabilities, and restricted access to information sources on agricultural technologies. Cultural factors, biases, and traditional agricultural practices also play a role in resistance to the adoption of intelligent agricultural technologies.

Furthermore, the lack of coherent policies and legal frameworks to support the use and adoption of intelligent agricultural technologies is a significant obstacle. Developing countries do not have the same resources or expertise as developed countries to support research and innovation in intelligent agricultural technologies. In addition, farmers may be limited by low-income levels, which hinder their ability to invest in agricultural technologies.

In this section, a roadmap is presented which outlines the crucial issues surrounding AI and agriculture in developing countries. The aim is to provide a thorough understanding of the questions being posed and their relevance for researchers, businesses, and policymakers who are not well versed in agriculture and rural realities. It should be noted that while the section highlights important issues and provides an overview, it does not explore specific case studies for each country.

Logistic issues

From a logistical point of view, the provision of low-cost agricultural machinery by AI-based platforms enables farmers to access on-demand tractor services and optimise their resources [167,168]. Several technologies can help farmers who cannot afford to buy equipment to respond to the uncertainty caused by climate change in a faster and more cost-effective way.

In addition, AI and algorithmic decision-making systems used in agriculture can be applied to improve efficiency in various sectors and have been used in the implementation of complex public procurement. These systems can also help reduce fraud and corruption and remove excessive and burdensome bureaucracy. Developing countries can therefore build on decision-making systems in agricultural administration, logistics and supply chains, including input programmes, to improve efficiency and accountability [169].

To conduct a comprehensive study on improving agricultural logistics, it is essential to gather data on various aspects such as the number and locations of logistical services, their capabilities, challenges, and benefits. Additionally, the research must explore opportunities for scaling these services and examine the government's role in enabling them.

It is also crucial to review existing regulatory frameworks that apply to public infrastructures like satellites and advanced technologies. These frameworks need to address not only the capacity benefits but also safety and security challenges posed by these systems. Furthermore, the study should assess how Agricultural Decision-Making (ADMs) can enhance the efficiency of logistics operations, minimize corruption, and contribute to more inclusive and equitable schemes. This analysis would help identify areas where ADMs could be implemented to streamline logistics operations and improve their overall effectiveness in supporting agricultural production. By giving smallholder farmers access to market data, pricing, and demand, ADMs can aid in the creation of more inclusive and equitable programmes. This can assist farmers in more profitably planning their produce. ADMs may also be used to identify farmers who may be facing food insecurity, enabling policymakers to provide these farmers specialised assistance. This may result in more just and environmentally friendly agriculture systems that are advantageous to both farmers and consumers.

Gender inequalities

The challenges faced by women in agriculture are multiple and complex and they are particularly widespread in developing countries. Women farmers face numerous obstacles that limit their productivity and potential, including unequal land ownership, limited access to capital, training, and agricultural inputs, as well as cultural discrimination based on gender [170].

One of the most significant challenges faced by women farmers is the lack of access to land ownership. In many countries, women are not allowed to own or inherit land. This limits their ability to invest in their farms, make long-term plans, and access financing. Access to capital and financial services is another major challenge for women farmers. Women are often excluded from formal financial services such as loans and credit due to their lack of collateral and limited financial knowledge. This limits their ability to invest in their farms, purchase inputs, and access markets.

The use of AI algorithms in agriculture can potentially exacerbate these inequalities. AI algorithms are often trained on biased datasets, which can perpetuate existing gender discrimination in agriculture. However, responsible use of AI can also help to mitigate some of these inequalities and make agriculture more accessible to women.

To promote gender parity in agriculture participation, intentional policies are needed to address discriminatory anomalies and use AI technologies to include women in new forms of work, entrepreneurship, and innovation. This could include policies aimed at increasing women's land ownership, improving access to financial services, providing training and inputs, and promoting the use of AI to connect women farmers with markets and buyers.

Overall, it is essential to address the challenges faced by women in agriculture to promote sustainable development and reduce poverty. By encouraging gender parity in agriculture participation and using AI technologies responsibly, we can help to ensure that women farmers have the resources, income, and control over their own projects that they need to succeed.

Innovation and data access

The agricultural sector has been transformed by the emergence of technology and the improvement of analytical tools. These advancements have opened new opportunities for innovation, which are already being observed and are likely to multiply. The use of cutting-edge technology is not always necessary, as innovation can be achieved by increasing yields to generate data, digitizing physical assets, integrating data across industries, exchanging data, and encoding unique capabilities. However, the use of large and valuable data faces constraints, including limited access and capacity in emerging economies and contractual rules that restrict public access to data [171].

In agriculture, increasing yields is the most relevant approach to generating data, with sensors installed on the equipment to improve accuracy and inputs. These data can be used to improve the design, operation, maintenance, and repair of assets, creating new and better services and business models. However, the use of big data and AI technology raises concerns about user privacy, which must be resolved before these innovations can be implemented on a large scale, particularly in Africa.

In the context of AI in agriculture, the exclusive property rights of data and their implications are illustrated using digital information on sequences. Although these advancements have transformed genomics and gene editing, the implications for agriculture and livestock have not received enough attention. At the macroeconomic level, the circulation of information and the governance of information on digital sequences are a current issue.

Taking the example of Africa, the use of AI in agricultural infrastructure raises several crucial questions [172,173]. These include how to promote the use of data for African agricultural innovations, how farmers and agricultural businesses can create value for their customers using data and analytical tools they own or could have access to, and who should own the data collected on farms. It is essential to address these questions to successfully implement AI in flourishing countries and develop new and innovative services and agricultural models.

Climate change

Global energy consumption and greenhouse gas emissions have skyrocketed due to the widespread and extensive use of digital technology, which is a major factor in climate change. Digital technology alone is predicted to use 20 % of global power by 2025 and produce 14 % of greenhouse gas emissions by 2040, therefore this trend is projected to continue [174] . Huge volumes of data storage demand a lot of power, which greatly contributes to climate change, the effects of which are already disproportionately felt in developing nations.

It is critical to investigate how AI and data initiatives could help developing countries cope with the consequences of climate change to solve this issue. However, it is significant to emphasise that, compared to other nations, flourishing nations are more consumed with pressing problems such as famine, drought, and political instability, and therefore measures to ameliorate the consequences of climate change generally take longer to develop and are less important. Investigating alternate data compression techniques might help eliminate the need for expensive, power-guzzling machines and data farms.

Furthermore, it is important to focus on raising awareness and promoting sustainable practices. This can be achieved by developing AI and data projects that are tailored to the specific needs and circumstances of these countries. For example, AI algorithms can be developed to help familial farmers optimise their crops and reduce water usage, or to help local communities had better manage natural resources such as forests and rivers. In addition, shifting to renewable energy sources such as solar, wind, and hydropower is an alternative approach to mitigate the environmental impact of digital technology. The extensive use of fossil fuels to power data centres and computer facilities has led to an enormous increase in greenhouse gas emissions. The utilization of renewable energy can significantly reduce the carbon footprint of digital technology. Additionally, the implementation of AI and data initiatives can substantially help monitor and predicting the effects of climate change. AI algorithms can collect and analyse data on environmental factors such as weather patterns and soil moisture, helping us to understand the impact of climate change on agriculture, animals, and habitats [175]. Data obtained from these initiatives can be used to help communities plan and adapt to changing climate and inform policy decisions.

Conclusion

Considering the challenge posed by global warming, taking tangible measures toward more inclusive and ecologically sustainable models has become a global priority.

The evolution of agriculture towards the new agro-food 4.0 will encourage businesses and farmers to invest in automation and artificial intelligence. Integration of green energy, slowly introduced into agriculture, will find technological support based on DL and other approaches to improve production and improve agricultural security. The current article proposes the use of computer vision technologies and artificial intelligence in the agricultural sector based on the globally used AI technologies reported in the literature. Importantly, this review provides a detailed understanding of promising applications in agriculture. The positive impacts of the use of AI in agriculture sector include:

- The strength of AI methods in detecting, analysing, and estimating data surpasses that of traditional techniques, especially when utilizing deep learning algorithms such as CNNs, RNNs, or other computational networks.
- Wireless technology and IoT may use the latest communication protocols and sensors to better manage water resources and avoid excessive irrigation losses or lack of water.
- Different integrated methods can be expended to create a sustainable environment and increased production. Applications include planting, fertilising, crop weeding, spraying, and harvesting.
- AI can be implemented for distant meteorological monitoring and control of agricultural practises.
- The use of AI algorithms in agriculture can potentially exacerbate gender inequalities, but responsible use of AI can also help mitigate some of these inequalities and make agriculture more accessible to women.
- Innovation can be accomplished with the use of cutting-edge technology by encoding special talents, digitising physical assets, integrating data throughout agriculture, improving yields to create data, and exchanging data.
- Renewable energy sources and AI offer a promising solution for reducing the carbon footprint of agriculture.

CRediT authorship contribution statement

A.A. Mana: Investigation, Writing – original draft, Writing – review & editing. **A. Allouhi:** Conceptualization, Investigation, Methodology, Supervision, Validation, Writing – review & editing. **A. Hamrani:** Investigation, Methodology, Writing – review & editing. **S. Rehman:** Writing – review & editing. **I. el Jamaoui:** Writing – review & editing. **K. Jayachandran:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.atech.2024.100416.

References

[1] M.G. Betts, et al., Global forest loss disproportionately erodes biodiversity in intact landscapes, Nature 547 (7664) (2017) 441–444.
[2] X. Qi, Y. Fu, R.Y. Wang, C.N. Ng, H. Dang, Y. He, Improving the sustainability of agricultural land use: an integrated framework for the conflict between food security and environmental deterioration, Appl. Geogr. 90 (2018) 214–223.
[3] H.C.J. Godfray, T. Garnett, Food security and sustainable intensification, Philos. Trans. R. Soc. B Biol. Sci. 369 (1639) (2014) 20120273.
[4] S. Juhola, N. Klein, J. Käyhkö, T.S.S. Neset, Climate change transformations in Nordic agriculture? J. Rural Stud. 51 (2017) 28–36.
[5] P.G. Pardey, J.M. Beddow, T.M. Hurley, T.K.M. Beatty, V.R. Eidman, A bounds analysis of world food futures: global agriculture through to 2050, Aust. J. Agric. Resour. Econ. 58 (4) (2014) 571–589.
[6] Y. Lu, N. Nakicenovic, M. Visbeck, A.S. Stevance, Policy: Five priorities for the UN sustainable development goals, Nature 520 (7548) (2015) 432–433.
[7] C.A. Helander, K. Delin, Evaluation of farming systems according to valuation indices developed within a European network on integrated and ecological arable farming systems, Eur. J. Agron. 21 (1) (2004) 53–67.
[8] A.A. Mana, A. Allouhi, A. Hamrani, A. Jamil, K.O.A. Barrahmoune, D. Daffa, Survey Review on Artificial Intelligence and Embedded Systems for Agriculture Safety: A proposed IoT Agro-meteorology System for Local Farmers in Morocco, Smart Embed. Syst. Appl. (2023) 211.
[9] H. Lu, Y. Li, M. Chen, H. Kim, S. Serikawa, Brain intelligence: go beyond artificial intelligence, Mob. Networks Appl. 23 (2) (2018) 368–375.
[10] V. Parekh, D. Shah, M. Shah, Fatigue detection using artificial intelligence framework, Augment. Hum. Res. 5 (1) (2020) 5.
[11] I. Keshta, AI-driven IoT for smart health care: Security and privacy issues, Informatics Med. Unlocked 30 (2022) 100903.
[12] L. Zheng, C. Wang, X. Chen, Y. Song, Z. Meng, R. Zhang, Evolutionary machine learning builds smart education big data platform: Data-driven higher education, Appl. Soft Comput. 136 (2023) 110114.
[13] Y. Zhou, P.D. Lund, Peer-to-peer energy sharing and trading of renewable energy in smart communities - trading pricing models, decision-making and agent-based collaboration, Renew. Energy (2023).
[14] S.A. Nikolidakis, D. Kandris, D.D. Vergados, C. Douligeris, Energy efficient automated control of irrigation in agriculture by using wireless sensor networks, Comput. Electron. Agric. 113 (2015) 154–163.
[15] L. Benos, A.C. Tagarakis, G. Dolias, R. Berruto, D. Kateris, D. Bochtis, Machine learning in agriculture: A comprehensive updated review, Sensors 21 (11) (2021) 3758.
[16] M.G. Lampridi, C.G. Sørensen, D. Bochtis, Agricultural sustainability: A review of concepts and methods, Sustainability 11 (18) (2019) 5120.
[17] F. Zecca, The Use of Internet of Things for the Sustainability of the Agricultural Sector: The Case of Climate Smart Agriculture, Int. J. Civ. Eng. Technol. 10 (3) (2019).
[18] J. Wäldchen, M. Rzanny, M. Seeland, P. Mäder, Automated plant species identification—Trends and future directions, PLoS Comput. Biol. 14 (4) (2018) e1005993.
[19] K. Pushpanathan, M. Hanafi, S. Mashohor, W.F. Fazlil Ilahi, Machine learning in medicinal plants recognition: a review, Artif. Intell. Rev. 54 (1) (2021) 305–327.
[20] A. Abade, P.A. Ferreira, F. de Barros Vidal, Plant diseases recognition on images using convolutional neural networks: A systematic review, Comput. Electron. Agric. 185 (2021) 106125.
[21] Y. Yuan, L. Chen, H. Wu, L. Li, Advanced agricultural disease image recognition technologies: A review, Inf. Process. Agric. (2021).
[22] A. Wang, W. Zhang, X. Wei, A review on weed detection using ground-based machine vision and image processing techniques, Comput. Electron. Agric. 158 (2019) 226–240.
[23] W.H. Su, Advanced Machine Learning in Point Spectroscopy, RGB-and hyperspectral-imaging for automatic discriminations of crops and weeds: A review, Smart Cities 3 (3) (2020) 767–792.
[24] S.S. Virnodkar, V.K. Pachghare, V.C. Patil, S.K. Jha, Remote sensing and machine learning for crop water stress determination in various crops: a critical review, Precis. Agric. 21 (5) (2020) 1121–1155.

[25] A.Y. Sun, B.R. Scanlon, How can Big Data and machine learning benefit environment and water management: a survey of methods, applications, and future directions, Environ. Res. Lett. 14 (7) (2019) 73001.
[26] R. Garcia, J. Aguilar, M. Toro, A. Pinto, P. Rodriguez, A systematic literature review on the use of machine learning in precision livestock farming, Comput. Electron. Agric. 179 (2020) 105826.
[27] N. Li, Z. Ren, D. Li, L. Zeng, Automated techniques for monitoring the behaviour and welfare of broilers and laying hens: towards the goal of precision livestock farming, animal 14 (3) (2020) 617–625.
[28] J.L. Ellis, et al., Synergy between mechanistic modelling and data-driven models for modern animal production systems in the era of big data, animal 14 (S2) (2020) s223–s237.
[29] D. Lovarelli, J. Bacenetti, M. Guarino, A review on dairy cattle farming: Is precision livestock farming the compromise for an environmental, economic and social sustainable production? J. Clean. Prod. 262 (2020) 121409.
[30] T. Talaviya, D. Shah, N. Patel, H. Yagnik, M. Shah, Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides, Artif. Intell. Agric. (2020).
[31] "AI in Agriculture Market by Technology (Machine Learning, Computer Vision, Predictive Analytics), Offering, Application (Precision Farming, Drone Analytics, Agriculture Robots, Livestock Monitoring), Offering, and Geography - Global Forecast to 2025," 2019.
[32] A.K. Kar, S.K. Choudhary, V.K. Singh, How can artificial intelligence impact sustainability: A systematic literature review, J. Clean. Prod. (2022) 134120.
[33] A.A. Mana, A. Allouhi, K. Ouazzani, A. Jamil, Feasibility of agriculture biomass power generation in Morocco: Techno-economic analysis, J. Clean. Prod. (2021) 126293.
[34] D.M. Dimiduk, E.A. Holm, S.R. Niezgoda, Perspectives on the impact of machine learning, deep learning, and artificial intelligence on materials, processes, and structures engineering, Integr. Mater. Manuf. Innov. 7 (3) (2018) 157–172.
[35] M. Schmidt, H. Lipson, Distilling free-form natural laws from experimental data, Science (80-.) 324 (5923) (2009) 81–85.
[36] S.S. Mousavi, M. Schukat, E. Howley, Deep reinforcement learning: an overview, in: Proceedings of SAI Intelligent Systems Conference, 2016, pp. 426–440.
[37] Z. Zhang, J. Boubin, C. Stewart, S. Khanal, Whole-field reinforcement learning: A fully autonomous aerial scouting method for precision agriculture, Sensors 20 (22) (2020) 6585.
[38] R. Gautron, O.A. Maillard, P. Preux, M. Corbeels, R. Sabbadin, Reinforcement learning for crop management support: Review, prospects and challenges, Comput. Electron. Agric. 200 (2022) 107182.
[39] M.T. Linaza, et al., Data-Driven Artificial Intelligence Applications for Sustainable Precision Agriculture, Agron. 2021 11 (6) (Jun. 2021) 1227, https://doi.org/10.3390/AGRONOMY11061227. Vol. 11, Page 1227.
[40] G.P. Obi Reddy, B.S. Dwivedi, G. Ravindra Chary, Applications of geospatial and big data technologies in smart farming. Smart Agriculture for Developing Nations: Status, Perspectives and Challenges, Springer, 2023, pp. 15–31.
[41] L. Gong, et al., An IoT-based intelligent irrigation system with data fusion and a self-powered wide-area network, J. Ind. Inf. Integr. 29 (2022) 100367.
[42] K. Kudashkina, M.G. Corradini, P. Thirunathan, R.Y. Yada, E.D.G. Fraser, Artificial Intelligence technology in food safety: A behavioral approach, Trends Food Sci. Technol. 123 (2022) 376–381.
[43] Z.H. Kok, A.R. Mohamed Shariff, M.S.M. Alfatni, S. Khairunniza-Bejo, Support Vector Machine in Precision Agriculture: A review, Comput. Electron. Agric. 191 (Dec. 2021) 106546, https://doi.org/10.1016/J.COMPAG.2021.106546.
[44] S. Bitla, S. Santhan, S. Bhagat, A. Pandey, V. Nath, Smart irrigation system: A review, in: International Conference on Nanoelectronics, Circuits and Communication Systems, 2018, pp. 569–578.
[45] Y. Shekhar, E. Dagur, S. Mishra, S. Sankaranarayanan, Intelligent IoT based automated irrigation system, Int. J. Appl. Eng. Res. 12 (18) (2017) 7306–7320.
[46] J. Muangprathub, N. Boonnam, S. Kajornkasirat, N. Lekbangpong, A. Wanichsombat, P. Nillaor, IoT and agriculture data analysis for smart farm, Comput. Electron. Agric. 156 (2019) 467–474.
[47] K. Jha, A. Doshi, P. Patel, M. Shah, A comprehensive review on automation in agriculture using artificial intelligence, Artif. Intell. Agric. 2 (2019) 1–12.
[48] S. Fuentes, R. De Bei, J. Pech, S. Tyerman, Computational water stress indices obtained from thermal image analysis of grapevine canopies, Irrig. Sci. 30 (6) (2012) 523–536.
[49] K.E. Adikari, S. Shrestha, D.T. Ratnayake, A. Budhathoki, S. Mohanasundaram, M. N. Dailey, Evaluation of artificial intelligence models for flood and drought forecasting in arid and tropical regions, Environ. Model. Softw. 144 (2021) 105136.
[50] F.A. Prodhan, et al., Deep learning for monitoring agricultural drought in South Asia using remote sensing data, Remote Sens 13 (9) (2021) 1715.
[51] R.T. Moyo, "Artificial intelligence based solar/diesel hybrid water pumping system." 2021.
[52] M. Fadaee, M.A.M. Radzi, Multi-objective optimization of a stand-alone hybrid renewable energy system by using evolutionary algorithms: A review, Renew. Sustain. energy Rev. 16 (5) (2012) 3364–3369.
[53] M.E. Karar, M.F. Al-Rasheed, A.F. Al-Rasheed, O. Reyad, IoT and neural network-based water pumping control system for smart irrigation, arXiv Prepr. arXiv2005.04158 (2020).
[54] F. Khan, O. Reyad, Application of intelligent multi agent based systems for E-healthcare security, arXiv Prepr. arXiv2004.01256 (2020).
[55] M.S.B.Z. Abidin, S. Shibusawa, S. Buyamin, Z. Mohamed, Intelligent control of capillary irrigation system for water-saving cultivation, in: 2015 10th Asian Control Conference (ASCC), 2015, pp. 1–5.
[56] P.J. Kia, A.T. Far, M. Omid, R. Alimardani, L. Naderloo, Intelligent control based fuzzy logic for automation of greenhouse irrigation system and evaluation in relation to conventional systems, World Appl. Sci. J. 6 (1) (2009) 16–23.
[57] M.E. Karar, A simulation study of adaptive force controller for medical robotic liver ultrasound guidance," Arab, J. Sci. Eng. 43 (8) (2018) 4229–4238.
[58] P. Patil, B.L. Desai, Intelligent irrigation control system by employing wireless sensor networks, Int. J. Comput. Appl. 79 (11) (2013).
[59] J. Xiao, D. Liu, Water-saving irrigation intelligent control system based on STC89C52 MCU. Future Control and Automation, Springer, 2012, pp. 223–230.
[60] B.A. El-Rahiem, M.A.O. Ahmed, O. Reyad, H.A. El-Rahaman, M. Amin, F.A. El-Samie, An efficient deep convolutional neural network for visual image classification, in: International conference on advanced machine learning technologies and applications, 2019, pp. 23–31.
[61] S. Choudhary, V. Gaurav, A. Singh, S. Agarwal, Autonomous Crop Irrigation System using Artificial Intelligence, Int. J. Eng. Adv. Technol. 8 (5S) (2019) 46–51.
[62] K. Anand, C. Jayakumar, M. Muthu, S. Amirneni, Automatic drip irrigation system using fuzzy logic and mobile technology, in: 2015 IEEE Technological Innovation in ICT for Agriculture and Rural Development (TIAR), 2015, pp. 54–58.
[63] M.S.P. Subathra, C.J. Blessing, S.T. George, A. Thomas, A.D. Raj, V. Ewards, Automated Intelligent Wireless Drip Irrigation Using ANN Techniques. Advances in Big Data and Cloud Computing, Springer, 2019, pp. 555–568.
[64] H. Chen, et al., A deep learning CNN architecture applied in smart near-infrared analysis of water pollution for agricultural irrigation resources, Agric. Water Manag. 240 (2020) 106303.
[65] G. Arvind, V.G. Athira, H. Haripriya, R.A. Rani, S. Aravind, Automated irrigation with advanced seed germination and pest control, in: 2017 IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR), 2017, pp. 64–67.
[66] T. Poblete, S. Ortega-Farías, M.A. Moreno, M. Bardeen, Artificial neural network to predict vine water status spatial variability using multispectral information obtained from an unmanned aerial vehicle (UAV), Sensors 17 (11) (2017) 2488.
[67] A. Mellit, M. Menghanem, M. Bendekhis, Artificial neural network model for prediction solar radiation data: application for sizing stand-alone photovoltaic power system, IEEE Power Engineering Society General Meeting 2005 (2005) 40–44.
[68] A. Mellit, M. Benghanem, Sizing of stand-alone photovoltaic systems using neural network adaptive model, Desalination 209 (1–3) (2007) 64–72.
[69] B.S. Richards, G.J. Conibeer, A comparison of hydrogen storage technologies for solar-powered stand-alone power supplies: A photovoltaic system sizing approach, Int. J. Hydrogen Energy 32 (14) (2007) 2712–2718.
[70] J.C. Hernández, A. Medina, F. Jurado, Optimal allocation and sizing for profitability and voltage enhancement of PV systems on feeders, Renew. Energy 32 (10) (2007) 1768–1789.
[71] R. Ben Ammar, M. Ben Ammar, A. Oualha, Photovoltaic power forecast using empirical models and artificial intelligence approaches for water pumping systems, Renew. Energy 153 (2020) 1016–1028.
[72] M. Achite, M. Jehanzaib, N. Elshaboury, T.W. Kim, Evaluation of machine learning techniques for hydrological drought modeling: A case study of the Wadi Ouahrane basin in Algeria, Water 14 (3) (2022) 431.
[73] N.S. Chandel, S.K. Chakraborty, Y.A. Rajwade, K. Dubey, M.K. Tiwari, D. Jat, Identifying crop water stress using deep learning models, Neural Comput. Appl. 33 (2021) 5353–5367.
[74] E. Skotadis, et al., A sensing approach for automated and real-time pesticide detection in the scope of smart-farming, Comput. Electron. Agric. 178 (2020) 105759.
[75] C.L. Chung, K.J. Huang, S.Y. Chen, M.H. Lai, Y.C. Chen, Y.F. Kuo, Detecting Bakanae disease in rice seedlings by machine vision, Comput. Electron. Agric. 121 (2016) 404–411.
[76] A.N. Alves, W.S.R. Souza, D.L. Borges, Cotton pests classification in field-based images using deep residual networks, Comput. Electron. Agric. 174 (2020) 105488.
[77] L. Nanni, G. Maguolo, F. Pancino, Insect pest image detection and recognition based on bio-inspired methods, Ecol. Inform. 57 (2020) 101089.
[78] S. Shrivastava, S.K. Singh, D.S. Hooda, Soybean plant foliar disease detection using image retrieval approaches, Multimed. Tools Appl. 76 (24) (2017) 26647–26674.
[79] M. Zomeni, J. Tzanopoulos, J.D. Pantis, Historical analysis of landscape change using remote sensing techniques: An explanatory tool for agricultural transformation in Greek rural areas, Landsc. Urban Plan. 86 (1) (2008) 38–46.
[80] M.E. Karar, F. Alsunaydi, S. Albusaymi, S. Alotaibi, A new mobile application of agricultural pests recognition using deep learning in cloud computing system, Alexandria Eng. J. 60 (5) (2021) 4423–4432.
[81] G. Pattnaik, V.K. Shrivastava, K. Parvathi, Transfer learning-based framework for classification of pest in tomato plants, Appl. Artif. Intell. 34 (13) (2020) 981–993.
[82] M.G. Selvaraj, et al., AI-powered banana diseases and pest detection, Plant Methods 15 (1) (2019) 92.
[83] H. Huang, J. Deng, Y. Lan, A. Yang, X. Deng, L. Zhang, A fully convolutional network for weed mapping of unmanned aerial vehicle (UAV) imagery, PLoS One 13 (4) (2018) e0196302.
[84] "Fighting weeds: Can we reduce, or even eliminate, herbicides by utilizing robotics and AI? | Genetic".
[85] M. Sujaritha, S. Annadurai, J. Satheeshkumar, S.K. Sharan, L. Mahesh, Weed detecting robot in sugarcane fields using fuzzy real time classifier, Comput. Electron. Agric. 134 (2017) 160–171.

[86] M.H. Asad, A. Bais, Weed detection in canola fields using maximum likelihood classification and deep convolutional neural network, Inf. Process. Agric. (2019).
[87] M.D. Bah, A. Hafiane, R. Canals, Deep learning with unsupervised data labeling for weed detection in line crops in UAV images, Remote Sens 10 (11) (2018) 1690.
[88] Y. Ampatzidis, V. Partel, UAV-based high throughput phenotyping in citrus utilizing multispectral imaging and artificial intelligence, Remote Sens 11 (4) (2019) 410.
[89] Z. Beiranvand, Integration of expert system and fuzzy theory for diagnosis wheat plant diseases, QUID Investig. Cienc. y Tecnol. (1) (2017) 1924–1930.
[90] J. Chen, J. Chen, D. Zhang, Y.A. Nanehkaran, Y. Sun, A cognitive vision method for the detection of plant disease images, Mach. Vis. Appl. 32 (2021) 1–18.
[91] M. Perez-Ruiz, J. Martínez-Guanter, S.K. Upadhyaya, High-precision GNSS for agricultural operations. GPS and GNSS Technology in Geosciences, Elsevier, 2021, pp. 299–335.
[92] N.N. Che'Ya, E. Dunwoody, M. Gupta, Assessment of weed classification using hyperspectral reflectance and optimal multispectral UAV imagery, Agronomy 11 (7) (2021) 1435.
[93] S.A. Zamani, Y. Baleghi, Early/late fusion structures with optimized feature selection for weed detection using visible and thermal images of paddy fields, Precis. Agric. 24 (2) (2023) 482–510.
[94] C. Aquilani, A. Confessore, R. Bozzi, F. Sirtori, C. Pugliese, Precision Livestock Farming technologies in pasture-based livestock systems, Animal 16 (1) (2022) 100429.
[95] V.R. Pathmudi, N. Khatri, S. Kumar, A.S.H. Abdul-Qawy, A.K. Vyas, A systematic review of IoT technologies and their constituents for smart and sustainable agriculture applications, Sci. African 19 (Mar. 2023) e01577, https://doi.org/10.1016/J.SCIAF.2023.E01577.
[96] R.S. Alonso, I. Sittón-Candanedo, Ó. García, J. Prieto, S. Rodríguez-González, An intelligent Edge-IoT platform for monitoring livestock and crops in a dairy farming scenario, Ad Hoc Networks 98 (Mar. 2020) 102047, https://doi.org/10.1016/J.ADHOC.2019.102047.
[97] B.C. Stahl, Artificial Intelligence For a Better future: an Ecosystem Perspective On the Ethics of AI and Emerging Digital Technologies, Springer Nature, 2021.
[98] C. Bahlo, P. Dahlhaus, H. Thompson, M. Trotter, The role of interoperable data standards in precision livestock farming in extensive livestock systems: A review, Comput. Electron. Agric. 156 (Jan. 2019) 459–466, https://doi.org/10.1016/J.COMPAG.2018.12.007.
[99] P. Shine, J. Upton, P. Sefeedpari, M.D. Murphy, Energy Consumption on Dairy Farms: A Review of Monitoring, Prediction Modelling, and Analyses, Energies 2020 13 (5) (Mar. 2020) 1288, https://doi.org/10.3390/EN13051288. Vol. 13, Page 1288.
[100] P. Shine, T. Scully, J. Upton, M.D. Murphy, Annual electricity consumption prediction and future expansion analysis on dairy farms using a support vector machine, Appl. Energy 250 (2019) 1110–1119.
[101] M.P. Mcloughlin, R. Stewart, A.G. McElligott, Automated bioacoustics: methods in ecology and conservation and their potential for animal welfare monitoring, J. R. Soc. Interface 16 (155) (2019) 20190225.
[102] M. Benjamin, S. Yik, Precision livestock farming in swine welfare: a review for swine practitioners, Animals 9 (4) (2019) 133.
[103] A. Hamrani, A. Akbarzadeh, C.A. Madramootoo, Machine learning for predicting greenhouse gas emissions from agricultural soils, Sci. Total Environ. 741 (2020) 140338.
[104] A.K. Mahlein, Plant disease detection by imaging sensors–parallels and specific demands for precision agriculture and plant phenotyping, Plant Dis 100 (2) (2016) 241–251.
[105] D.I. Patrício, R. Rieder, Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review, Comput. Electron. Agric. 153 (2018) 69–81.
[106] "Crop yield analysis — Sustainability and artificial intelligence lab." http://sustain.stanford.edu/crop-yield-analysis (accessed Jan. 02, 2021).
[107] I. Kumar, J. Rawat, N. Mohd, S. Husain, Opportunities of artificial intelligence and machine learning in the food industry, J. Food Qual. 2021 (2021).
[108] T. Otani, et al., Agricultural Robot under Solar Panels for Sowing, Pruning, and Harvesting in a Synecoculture Environment, Agriculture 13 (1) (2022) 18.
[109] J. Krause, et al., SmartSpectrometer—Embedded optical spectroscopy for applications in agriculture and industry, Sensors 21 (13) (2021) 4476.
[110] M. Zawish, S. Davy, L. Abraham, Complexity-driven cnn compression for resource-constrained edge ai, arXiv Prepr. arXiv2208.12816 (2022).
[111] G. Kootstra, X. Wang, P.M. Blok, J. Hemming, E. Van Henten, Selective harvesting robotics: current research, trends, and future directions, Curr. Robot. Reports 2 (2021) 95–104.
[112] V. Tinoco, M.F. Silva, F.N. Santos, L.F. Rocha, S. Magalhães, L.C. Santos, A review of pruning and harvesting manipulators, in: 2021 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC), 2021, pp. 155–160.
[113] X. Bai, et al., RPNet: Rice plant counting after tillering stage based on plant attention and multiple supervision network, Crop J (2023).
[114] X. Bai, et al., Rice Plant Counting, Locating, and Sizing Method Based on High-Throughput UAV RGB Images, Plant Phenomics 5 (2023) 20.
[115] X. Ren, et al., Deep learning-based weather prediction: a survey, Big Data Res 23 (2021) 100178.
[116] D.K. Krishnappa, D. Irwin, E. Lyons, M. Zink, CloudCast: Cloud computing for short-term mobile weather forecasts, in: 2012 IEEE 31st International Performance Computing and Communications Conference (IPCCC), 2012, pp. 61–70.
[117] R. Castro, Y.M. Souto, E. Ogasawara, F. Porto, E. Bezerra, STConvS2S: Spatiotemporal Convolutional Sequence to Sequence Network for weather forecasting, Neurocomputing 426 (Feb. 2021) 285–298, https://doi.org/10.1016/j.neucom.2020.09.060.
[118] A. Nabavi-Pelesaraei, S. Rafiee, F. Hosseini-Fashami, K. Chau, Artificial neural networks and adaptive neuro-fuzzy inference system in energy modeling of agricultural products. Predictive Modelling For Energy Management and Power Systems Engineering, Elsevier, 2021, pp. 299–334.
[119] E. Elahi, Z. Khalid, Estimating smart energy inputs packages using hybrid optimisation technique to mitigate environmental emissions of commercial fish farms, Appl. Energy 326 (2022) 119602.
[120] M.A.Z. Abidin, M.N. Mahyuddin, M.A.A.M. Zainuri, Optimal efficient energy production by PV module tilt-orientation prediction without compromising crop-light demands in Agrivoltaic systems, IEEE Access (2023).
[121] M. Ehteram, A.N. Ahmed, P. Kumar, M. Sherif, A. El-Shafie, Predicting freshwater production and energy consumption in a seawater greenhouse based on ensemble frameworks using optimized multi-layer perceptron, Energy Reports 7 (2021) 6308–6326.
[122] Y. Liu, Intelligent analysis platform of agricultural sustainable development based on the Internet of Things and machine learning, Acta Agric. Scand. Sect. B—Soil Plant Sci 71 (8) (2021) 718–731.
[123] B.M. Yahya, D.Z. Seker, Designing weather forecasting model using computational intelligence tools, Appl. Artif. Intell. 33 (2) (2019) 137–151.
[124] M.P. Raju, A.J. Laxmi, IoT based online load forecasting using machine learning algorithms, Procedia Comput. Sci. 171 (2020) 551–560.
[125] J. Kim, S. Cho, K. Ko, R.R. Rao, Short-term electric load prediction using multiple linear regression method, in: 2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), 2018, pp. 1–6.
[126] X. Fu, F. Yang, Viewpoints on the Theory of Agricultural Energy Internet. Front, Energy Res 10 (2022) 871772.
[127] X. Fu, et al., A review of key technologies and trends in the development of integrated heating and power systems in agriculture, Entropy 23 (2) (2021) 260.
[128] I.K. Song, S.Y. Yun, S.C. Kwon, N.H. Kwak, Design of smart distribution management system for obtaining real-time security analysis and predictive operation in Korea, IEEE Trans. Smart Grid 4 (1) (2012) 375–382.
[129] X. Fu, F. Yang, Artificial Intelligence Early Warnings of Agricultural Energy Internet, Front. Energy Res. (2022) 594.
[130] L. Mancipe-Castro, R.E. Gutiérrez-Carvajal, Prediction of environment variables in precision agriculture using a sparse model as data fusion strategy, Inf. Process. Agric. 9 (2) (2022) 171–183.
[131] R. Sparrow, M. Howard, C. Degeling, Managing the risks of artificial intelligence in agriculture, NJAS Impact Agric. Life Sci. 93 (1) (2021) 172–196.
[132] M. Ryan, The social and ethical impacts of artificial intelligence in agriculture: mapping the agricultural AI literature, AI Soc. (2022) 1–13.
[133] D.R. Vincent, N. Deepa, D. Elavarasan, K. Srinivasan, S.H. Chauhdary, C. Iwendi, Sensors driven AI-based agriculture recommendation model for assessing land suitability, Sensors 19 (17) (2019) 3667.
[134] M.J. Smith, Getting value from artificial intelligence in agriculture, Anim. Prod. Sci. 60 (1) (2018) 46–54.
[135] X. Pham, M. Stack, How data analytics is transforming agriculture, Bus. Horiz. 61 (1) (2018) 125–133.
[136] M. Liao, Y. Yao, Applications of artificial intelligence-based modeling for bioenergy systems: A review, GCB Bioenergy 13 (5) (2021) 774–802.
[137] C. Bibbiani, F. Fantozzi, C. Gargari, C.A. Campiotti, E. Schettini, G. Vox, Wood biomass as sustainable energy for greenhouses heating in Italy, Agric. Agric. Sci. procedia 8 (2016) 637–645.
[138] A. Aslani, T. Mazzuca-Sobczuk, S. Eivazi, K. Bekhrad, Analysis of bioenergy technologies development based on life cycle and adaptation trends, Renew. energy 127 (2018) 1076–1086.
[139] J. Chen, et al., Investigation of co-combustion characteristics of sewage sludge and coffee grounds mixtures using thermogravimetric analysis coupled to artificial neural networks modeling, Bioresour. Technol. 225 (2017) 234–245.
[140] L.M. Romeo, R. Gareta, Neural network for evaluating boiler behaviour, Appl. Therm. Eng. 26 (14–15) (2006) 1530–1536.
[141] H. Lund, Renewable energy strategies for sustainable development, Energy 32 (6) (2007) 912–919.
[142] T. Compernolle, N. Witters, S. Van Passel, T. Thewys, Analyzing a self-managed CHP system for greenhouse cultivation as a profitable way to reduce CO2-emissions, Energy 36 (4) (2011) 1940–1947.
[143] J. Chen, J. Zhao, F. Xu, H. Hu, Q. Ai, J. Yang, Modeling of energy demand in the greenhouse using PSO-GA hybrid algorithms, Math. Probl. Eng. 2015 (2015).
[144] S.S. Clair, J. Hillier, P. Smith, Estimating the pre-harvest greenhouse gas costs of energy crop production, Biomass and bioenergy 32 (5) (2008) 442–452.
[145] A.A. Mana, "opportunities to Integration of renewable energies in Moroccan agriculture," Oct. 2021, Accessed: Apr. 06, 2023. [Online]. Available: https://hal.science/tel-04025164.
[146] J. Wang, Z. Han, Z. Guan, Hybrid solar-assisted combined cooling, heating, and power systems: A review, Renew. Sustain. Energy Rev. 133 (2020) 110256.
[147] D. Wu, R. Wang, Combined cooling, heating and power: A review, Prog. energy Combust. Sci. 32 (5–6) (2006) 459–495.
[148] P. Zhang, Z. Guo, S. Ullah, G. Melagraki, A. Afantitis, I. Lynch, Nanotechnology and artificial intelligence to enable sustainable and precision agriculture, Nat. Plants 7 (7) (2021) 864–876.

[149] A.N. Shahzad, M.K. Qureshi, A. Wakeel, T. Misselbrook, Crop production in Pakistan and low nitrogen use efficiencies, Nat. Sustain. 2 (12) (2019) 1106–1114.
[150] G.V. Lowry, A. Avellan, L.M. Gilbertson, Opportunities and challenges for nanotechnology in the agri-tech revolution, Nat. Nanotechnol. 14 (6) (2019) 517–522.
[151] J.P. Giraldo, H. Wu, G.M. Newkirk, S. Kruss, Nanobiotechnology approaches for engineering smart plant sensors, Nat. Nanotechnol. 14 (6) (2019) 541–553.
[152] N. Kottegoda, et al., Urea-hydroxyapatite nanohybrids for slow release of nitrogen, ACS Nano 11 (2) (2017) 1214–1221.
[153] S. Kabiri, F. Degryse, D.N.H. Tran, R.C. da Silva, M.J. McLaughlin, D. Losic, Graphene oxide: A new carrier for slow release of plant micronutrients, ACS Appl. Mater. Interfaces 9 (49) (2017) 43325–43335.
[154] B. Huang, et al., Advances in targeted pesticides with environmentally responsive controlled release by nanotechnology, Nanomaterials 8 (2) (2018) 102.
[155] J.P. Giraldo, et al., Plant nanobionics approach to augment photosynthesis and biochemical sensing, Nat. Mater. 13 (4) (2014) 400–408.
[156] M. Cubric, Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study, Technol. Soc. 62 (Aug. 2020) 101257, https://doi.org/10.1016/J.TECHSOC.2020.101257.
[157] C.D. Alupo, D. Omeiza, D. Vernon, Realizing the Potential of AI in Africa: It All Turns on Trust, Intell. Syst. Control Autom. Sci. Eng. 102 (2022) 179–192, https://doi.org/10.1007/978-3-031-09823-9_13/COVER.
[158] M. Gardezi, R. Stock, Growing algorithmic governmentality: Interrogating the social construction of trust in precision agriculture, J. Rural Stud. 84 (May 2021) 1–11, https://doi.org/10.1016/J.JRURSTUD.2021.03.004.
[159] S. Munnisunker, L. Nel, D. Diederichs, The Impact of Artificial Intelligence on Agricultural Labour in Europe, J. Agric. Informatics 13 (1) (Mar. 2022) 46–54, https://doi.org/10.17700/JAI.2022.13.1.638.
[160] S. Makridakis, The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms, Futures 90 (Jun. 2017) 46–60, https://doi.org/10.1016/J.FUTURES.2017.03.006.
[161] M. Javaid, A. Haleem, I.H. Khan, R. Suman, Understanding the potential applications of Artificial Intelligence in Agriculture Sector, Adv. Agrochem 2 (1) (Mar. 2023) 15–30, https://doi.org/10.1016/J.AAC.2022.10.001.
[162] D. Jiménez, et al., A scalable scheme to implement data-driven agriculture for small-scale farmers, Glob. Food Sec. 23 (Dec. 2019) 256–266, https://doi.org/10.1016/J.GFS.2019.08.004.
[163] N. Tantalaki, S. Souravlas, and M. Roumeliotis, “Data-Driven Decision Making in Precision Agriculture: The Rise of Big Data in Agricultural Systems,” https://doi.org/10.1080/10496505.2019.1638264, vol. 20, no. 4, pp. 344–380, Oct. 2019, 10.1080/10496505.2019.1638264.
[164] N. Ranasinghe, et al., Interpretability and accessibility of machine learning in selected food processing, agriculture and health applications, J. Natl. Sci. Found. Sri Lanka 50 (Nov. 2022) 263–276, https://doi.org/10.4038/jnsfsr.v50i0.11249, no. Special Issue.
[165] M. Ryo, Explainable artificial intelligence and interpretable machine learning for agricultural data analysis, Artif. Intell. Agric. 6 (Jan. 2022) 257–265, https://doi.org/10.1016/J.AIIA.2022.11.003.
[166] N.L. Tsakiridis, et al., Versatile Internet of Things for Agriculture: An eXplainable AI Approach, IFIP Adv. Inf. Commun. Technol. 584 (2020) 180–191, https://doi.org/10.1007/978-3-030-49186-4_16/FIGURES/5. IFIP.
[167] J.G.A.J. van der Vorst, J. Snels, Developments and Needs for Sustainable Agro-Logistics in Developing Countries, World Bank, Washington, DC, 2014.
[168] R. Mazhar, A. Ghafoor, B. Xuehao, Z. Wei, Fostering sustainable agriculture: Do institutional factors impact the adoption of multiple climate-smart agricultural practices among new entry organic farmers in Pakistan? J. Clean. Prod. 283 (Feb. 2021) 124620 https://doi.org/10.1016/J.JCLEPRO.2020.124620.
[169] S.W. Anuga, C. Gordon, E. Boon, J.M.I. Surugu, Determinants of Climate Smart Agriculture (CSA) Adoption among Smallholder Food Crop Farmers in the Techiman Municipality, Ghana, Ghana J. Geogr. 11 (1) (May 2019) 124–139, https://doi.org/10.4314/gjg.v11i1.
[170] M. Tsige, G. Synnevåg, J.B. Aune, Gendered constraints for adopting climate-smart agriculture amongst smallholder Ethiopian women farmers, Sci. African 7 (Mar. 2020) e00250, https://doi.org/10.1016/J.SCIAF.2019.E00250.
[171] D.M. Nyariki, Household Data Collection for Socio-Economic Research in Agriculture: Approaches and Challenges in Developing Countries, Kamla Raj Enterp 19 (2) (May 2017) 91–99, https://doi.org/10.1080/09718923.2009.11892696.
[172] H. Baumüller, Towards Smart Farming? Mobile technology trends and their potential for developing country agriculture, Handb. ICT Dev. Ctries. 5 G Perspect. English (Aug. 2017) 191–210, https://doi.org/10.1201/9781003338376-9/Towards-smart-farming-mobile-technology-trends-potential-developing-country-agriculture-Heike-Baum.
[173] U. Deichmann, A. Goyal, D. Mishra, Will digital technologies transform agriculture in developing countries? Agric. Econ. 47 (S1) (Nov. 2016) 21–33, https://doi.org/10.1111/AGEC.12300.
[174] F.N. Tubiello, et al., Estimating greenhouse gas emissions in agriculture: a manual to address data requirements for developing countries, Estim. Greenh. gas Emiss. Agric. a Man. to address data Requir. Dev. countries. (2015).
[175] G. Grenon, A. Hamrani, C.A. Madramootoo, B. Singh, C. von Sperber, Neural network model predictions for phosphorus management strategies on tile-drained organic soils, Hydrol. Res. 53 (6) (Jun. 2022) 825–839, https://doi.org/10.2166/NH.2022.127/1060151/NH2022127.PDF.