Artificial Intelligence in the Agriculture

Subjects: Agronomy

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Artificial intelligence (AI) involves the development of algorithms and computational models that enable machines to process and analyze large amounts of data, identify patterns and relationships, and make predictions or decisions based on that analysis. AI has become increasingly pervasive across a wide range of industries and sectors, with healthcare, finance, transportation, manufacturing, retail, education, and agriculture are a few examples to mention. As AI technology continues to advance, it is expected to have an even greater impact on industries in the future. For instance, AI is being increasingly used in the agri-food sector to improve productivity, efficiency, and sustainability.

machine learning smart farming internet of things sustainable management

1. Introduction

The world's population is rapidly growing and is expected to reach around 9.7 billion by 2050 [1]. As a result, there is a growing concern about how to meet the increasing demand for food while also ensuring food security and sustainability. In this regard, the use of artificial intelligence (AI) applications in the agri-food sector has the potential to revolutionize the industry and increase sustainability in several ways. It can help farmers, food manufacturers, and distributors make more informed decisions, improve efficiency, reduce waste, and improve food security and sustainability.

The Nobel-prize-winning economist Herbert Simon in 1965 said, "Machines will be capable of doing any work a man can do". His visionary perspective has come true today through the remarkable achievements that occurred through AI applications [2]. AI refers to the ability of machines or computer programs to perform tasks that normally require human intelligence, such as learning, reasoning, problem-solving, and decision-making. There are various subfields of AI, including machine learning (ML), deep learning, natural language processing, computer vision, robotics, and cognitive computing. There are several algorithms, for instance, reinforcement learning [3], swarm intelligence, cognitive science, expert system, fuzzy logic (FL), Artificial Neural Networks (ANN), and Logic Programming, that can be used in AI technology [4]. Each of these algorithms has its own unique advantages and limitations, and the choice of algorithm will depend on the specific task or problem at hand. AI is being used in a wide range of applications, such as speech recognition, image and video analysis [5], autonomous vehicles [6], medical diagnosis, financial forecasting, and many others [7]. Similar to any other industry, AI can also be used in the agri-food sector to improve efficiency [8] and develop new, more nutritious crops [9], reduce waste [10], and ensure safety [11]. AI can be used to optimize crop yields [12] and improve distribution and logistics [13]. **Table 1** presents summary of the equipment and product' developed by various AI technologies and their domains.

Table 1. Summary of the equipment and product' developed by various AI technologies and their domains.

Domain/Sector	Technology	Equipment/Products Developed	References
Smart farming	- Soil monitoring: IoT - Robocrop: SVM - Predictive analysis: ML algorithms	NPK soil sensors, temperature sensors, moisture sensors, etc.; Adaptive Robotic Chassis (ARC), dual arm harvesting robot; Learning models are constructed to follow and forecast several environmental effects such as climate variation during crop production	[8][9]
Supply chain quality data integration method	- Blockchain technology	Logistics of agriculture products raising water availability	[12][13]
Product sorting/packaging	- Sensor-based sorting system - Tensor flow ML-based system	TOMRA	[14][15]
Fruit safety and quality	- Gaussian Mixture Mode and IR vision sensor - Fourier Based separation model - Multi-resolution Wavelet transform and AI (classifier)of SVM and BPNN - FNN and SVM	Smart refrigerator; Intelligent refrigerator	[15][16][17]
Food Quality	ANN	Forecast the quality loss as weight loss of frozen dough using ANN	[18]
Quality control	- X-ray detection - MRI	X-ray imaging detects defects and contaminants in agricultural commodities	[19]
Image processing	- CNN - Hyperspectral imaging - PCANet	Food tray packaging system; Food tray sealing fault detection	[20][21]
Forecasting of food production	- Fuzzy logic - ML	Predict the production and consumption of rice using ANN, SVM, GP, and GPR to predict future milk yield	[22][23]
Supply chain optimization	- Evolutionary ML	Scheduled transportation; reduced held inventory; cost in supply chain	[24][25]

Domain/Sector	Technology	Equipment/Products Developed	References
Preparing and dispensing food	- Robotics	Food applications, drone and robotic deliveries, and autonomous cars	[26]
New food product development	- ML - Deep learning algorithms	Self-service soft drink corner	[27]
Identification of taste characteristics	- Convolutional Neural Networks (CNN) - Multi-layer perceptron (MLP)-Descriptor - MLP Fingerprint	MLP-Fingerprint model showed the best prediction results for bitterant/non-bitterant, sweetener/non-sweetener, and bitterant/sweetener	[28]

e farming osts, and reduced environmental impact [29][30]. In crop monitoring, AI-powered cameras and sensors can monitor crops in real-time, detecting diseases, pests, and nutrient deficiencies. This allows farmers to take action quickly and prevent crop loss [31][32]. AI algorithms can analyze weather patterns, soil conditions, and historical data to predict crop yields and market demand. This can help farmers plan their planting and harvesting schedules and optimize their pricing strategies [33]. During supply chain optimization, AI can help streamline the supply chain by predicting demand, optimizing logistics, and reducing waste. For example, AI algorithms can be used to predict the optimal time to harvest crops and route trucks, and optimize inventory levels [34][35].

In the food processing industry, AI can be used to optimize food processing operations, such as sorting and grading, and to detect defects or contaminants in food products [30][36]. AI can also be used to identify and sort fruits and vegetables based on their size, color, and other attributes [37]. This can help improve the quality and consistency of food products and reduce waste. AI can be used to monitor food safety by analyzing data from sensors and cameras to detect potential contaminants or other hazards. This can help prevent foodborne illness and improve public health [38][39]. In addition, AI can be used to analyze individual consumer data, such as age, gender, and activity level, to provide personalized nutritional recommendations. This can help consumers make more informed choices about their diet and improve their overall health [40].

2. Role of AI in the Agriculture

The food industry has always been dependent on the agriculture sector since its inception. An increase in food production by the agriculture sector can lead to a larger supply of raw materials for the Fast-Moving Consumer Goods (FMCG) industries, which rely on these raw materials for processing and manufacturing products [26]. The COVID-19 pandemic has significantly affected innumerable lives and the supply of these industries pessimistically [41][42]. The government's decision to declare a state of emergency led to the closure of numerous industries worldwide, which had an effect on the entire supply chain, from the farmer to the consumer [43]. The unexpected decline in output and income, the drop in oil prices, the drop in tourism receipts, the issues with climate change, and other reasons are all connected to the COVID-19 pandemic [44]. According to the FAO, the number of people suffering from hunger and malnutrition has been on the rise in recent years [45]. However, by introducing AI and ML in crop management and using high-tech automated systems, the agriculture industry can tackle many of the problems that affect crop production and improve the quality and quantity of raw materials available to the food industry. **Figure 1** depicts the impact of AI on the Argo food sector and FMCG.

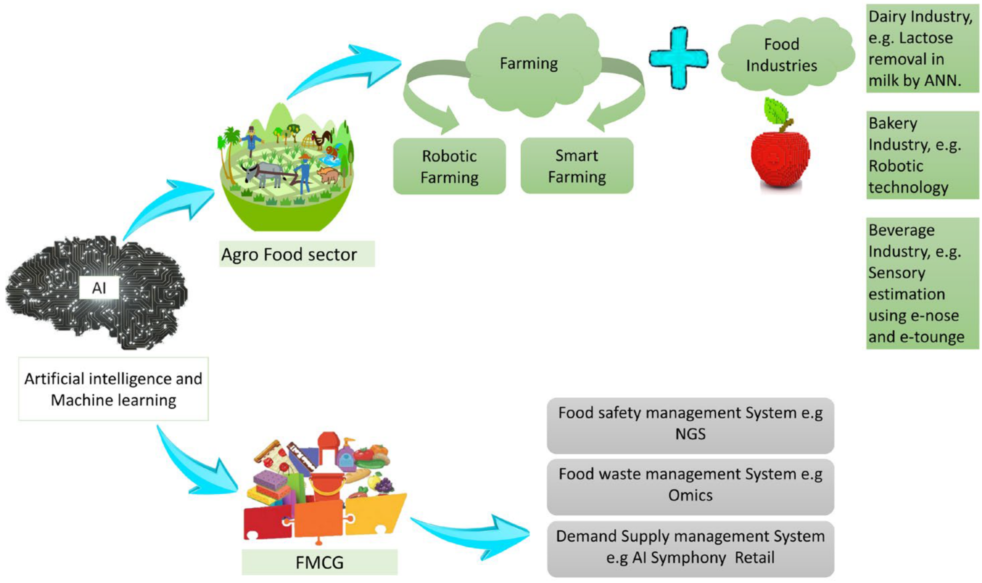

Figure 1. Impact of artificial intelligence (AI) and machine learning (ML) in the Agrofood and FMCG sector.

2.1. Grain Quality

Manual grain inspection is a time-consuming process and is prone to human error, which can result in the selection of lower-quality grains. This is because manual inspection relies on human visual acuity and can be affected by factors, such as fatigue, distractions, or variability in lighting conditions. Therefore, the use of computer vision systems in grain inspection is becoming increasingly popular. These systems use advanced imaging techniques and ML algorithms to analyze images of grains and identify defects or impurities, such as broken kernels, foreign materials, or fungal infestations [46]. ANN, dense scale-invariant feature transform (DSIFT) algorithm, and support vector machines (SVM) are ML techniques that have been successfully applied in the agriculture sector for the classification and identification of grains and other agricultural products.

ANNs are used to classify different wheat species based on their visual characteristics, such as shape, size, and color [47]. DSIFT algorithm is a computer vision technique that can identify features, such as the size, shape, and texture of the wheat grains, and use them to classify the grains into different categories [48]. SVM is another ML technique that is used for the categorization of wheat grains, identification of fungal species in rice, germinated wheat grains, and analysis of milled rice grains.

Some technologies apply computer vision systems for the inspection of grains in the agricultural sector: (i) examination of milled rice grains using SVM, (ii) computerized wheat quality assessment system, and (iii) development of a method using hyperspectral imaging system for the detection of Fusarium infected wheat grains [49][50]. Computer vision systems can help in the accurate and automated monitoring of various plant phenology stages, such as seedling emergence, leaf unfolding, flowering, and fruit ripening. They can also aid in the early detection of plant stress and diseases, allowing for timely interventions and preventing crop losses. In 2015, researchers proposed a computer vision system that uses disease-specific image processing algorithms to identify the presence and severity of leaf spot diseases in rice plants [51]. Backpropagation neural networks (BPNN) have been used in conjunction with other technologies, such as wavelets and fuzzy inference systems, for crop disease detection and classification [52]. In 2017, a study was conducted to investigate the risks of chlorosis due to iron deficiency in soybean plants using real-time phenotyping and ML techniques [53]. This approach allowed for the early detection and monitoring of iron deficiency stress in soybean plants, enabling researchers to optimize iron fertilization strategies and improve crop yields [54][55][56][57].

2.2. Pest Detection and Weed Management

Accurate identification of insect species, size variation, and stage of development is crucial for effective pest management in agriculture. By identifying the type and number of insects present in a crop field, farmers can take appropriate measures to control the pest population and prevent damage to their crops. Several AI and ML technologies are being developed and tested for insect detection and counting. Some of these technologies use computer vision algorithms, while others rely on ML algorithms to identify and classify different insect species [58][59]. However, it is important to note that these technologies are still in their testing stages and have not yet been widely adopted in the agricultural industry.

Similarly, herbicides have been widely used by farmers for many years to control weeds and improve crop yields. However, the overuse or improper application of herbicides can have negative impacts on both human health and the environment. To minimize the negative impacts of herbicides, there is a growing need for more precise and accurate application methods [60]. Precision agriculture techniques, such as site-specific application, can help farmers apply herbicides only where they are needed, reducing the amount of chemicals used and minimizing the risk of contamination. The development of AI-based technologies which use ML algorithms and computer vision techniques to detect and classify different types of weeds in crop fields has the potential to improve the efficiency and sustainability of agriculture while also reducing the need for herbicides and improving crop yields [61].

Unmanned aircraft systems (UAS) and counter propagation-artificial neural networks (CP-ANN) were used for the detection of the weed *Silybum marianum* [62]. The use of ANN and Multispectral/Hyperspectral imaging technologies can be very effective in detecting and recognizing weed species in crop fields. CP-ANN and multispectral imaging captured by UAS were used to detect the weed *Silybum marianum* [63]. CP-ANN is a type of artificial neural network that can be used for pattern recognition tasks, while multispectral imaging involves capturing images of crop fields at different wavelengths of light. The combination of these technologies allowed the researchers to identify the presence of the weed with high accuracy and precision. In another research, hyperspectral imaging and ML techniques were used to develop a method for crop and weed species recognition [3]. Hyperspectral imaging involves capturing images of crop fields at many different wavelengths of light, which can provide more detailed information about the spectral properties of different plant species. ML algorithms were then used to analyze these images and classify different plant species, including both crops and weeds. Researchers have also developed SVM based algorithm for the classification of different types of weeds in grassland cropping systems based on images captured by unmanned aerial vehicles (UAVs) [64].

Robotic weed control is also an emerging technology that shows great promise for the future of agriculture. Robotic weed control systems typically use computer vision and ML algorithms to detect and identify weeds in crop fields, then use robotic arms or other mechanical tools to remove or destroy the weeds. These systems can operate in a wide range of crop environments, including greenhouses, where traditional weed control methods, such as herbicides, may not be effective or appropriate [65]. There is the possibility of cultivars being equipped with finger weeders or elastic tines for both inter and intra-row types of weed control [66]. For analyzing site-specific weed control, precision weed management as a part of precision farming is grounded on the utilization of information technology [67]. Although intelligent mechanical weed control would be more felicitous than weeding devices with cutting action, contrary to time-based weed removal [68], it is possible to remotely regulate the tendency of tines of spring-tine harrow prototype systems based on the conditions of soil, the density of weed, and crop production [69].

2.3. Crop Selection and Yield Improvement

Agricultural planning performs an important role in food security around the world, especially in countries with the agro-based sector. The challenge in selection of suitable crops with improved yield is critical as this could be varied depending on numerous conditions, such as weather, soil quality, water access, and pests and diseases [8]. AI and ML technologies are being increasingly used in crop selection and yield improvement in agriculture. These technologies are particularly useful in crop breeding and genetic improvement. By analyzing genetic data from different crop varieties and using ML algorithms to identify key traits associated with yield and other desirable characteristics, plant breeders can develop new crop varieties that are better adapted to specific environmental conditions and produce higher yields. Automation technologies, such as robots, are being increasingly used to improve crop yields by reducing labor costs and improving efficiency in various agricultural tasks, including spraying herbicides, removing weeds, and harvesting fruits and vegetables [4][7][8]. Robots, such as the Berry 5 Robot from Harvest Croo Robotics (Tampa, FL, USA), are designed to automate the harvesting of strawberries, which is a labor-intensive and time-consuming process [12]. The robot uses computer vision and ML algorithms to identify and pick ripe strawberries at a faster rate than humans can. This can help farmers to reduce labor costs and improve their yields by ensuring that more strawberries are harvested at the optimal time.

Similarly, robots, such as the “Robocrop”, are being developed for specific agricultural tasks, such as pruning flowers on strawberry plants. Furthermore, the image-processing robot being developed for picking ripened strawberries uses computer vision and ML algorithms to identify and pick the strawberries, reducing labor costs and improving the speed and efficiency of the harvesting process [70]. The National Physical Laboratory (NPL) in London is developing robots that use computer vision and ML to identify water and nutrient levels, control weeds, and perform sorting and packaging [71]. Researchers have developed a method for measuring plant water retention using image processing techniques in combination with software, such as Adobe Photoshop CC 2021 (version 22.0.0.) and MATLAB (version R2022b (9.13)). For the purpose of using X-ray CT to study unsaturated Hostun sand and its water retention behavior, a complete configuration and setup were created. A “step-by-step” technique for obtaining sufficiently high-quality reconstructions that allow the three phases of the material (grain, water, and air) to be differentiated was also provided. The visualization and characterization of the three stages inside the specimen were made easier using picture post-processing. This made it easier to create a measuring map that encompasses the full specimen field [72]. Robotic chassis are developed for robot software where they are assigned their specific tasks. This robot system includes navigation through a field, robotic arms to eliminate unwanted flowers, and image capturing [70]. Similarly, Agboka et al. [73] applied Agroecological breeding methods, such as maize–legume intercropping (MLI) and push-pull technology (PPT), that have been found to be effective in minimizing the losses due to insects. Two simple and explainable models, namely, the hybrid fuzzy logic combined with the genetic algorithm and symbolic regression, are used to forecast maize production. This study also reported that the scale-up of MLI and PPT systems improved productivity in sustainable farming.

2.4. Big Data and IoT in Smart Farming

With the use of modern technology called the Internet of Things (IoT), gadgets may link remotely to enable smart farming. To improve efficiency and performance across all sectors, the IoT has started to have an impact on a wide variety of businesses, including those in health, trade, communications, energy, and agriculture [8]. The adoption of modernized technologies in agriculture has led to the emergence of “smart farming”, which is a revolutionary approach that leverages advanced technologies to increase the quality and quantity of agricultural production. AI encourages smart farming, a sustainable technique that helps to avoid resource waste (such as fertilizers and pesticides) and achieve sustainable development, to replace conventional agricultural practices and methodologies [62]. By providing farmers with detailed information on specific crops, such as soil nutritional deficiencies, and moisture levels, and hyper-spectral data to prevent damage, smart farming enables farmers to make more informed decisions about their crops and to optimize their production processes [9]. According to research, the Supply Chain Big Data Analytics Market will climb to $9.28 billion by 2026 [74]. The Agri-IoT framework has the potential to significantly benefit farmers by providing them with real-time data and alerts. By integrating social media trends, farm council alerts, and automatic reasoning, the platform can help farmers to make informed decisions and take action to mitigate the impact of climatic conditions on their crops [75].

Another aspect of smart farming is climate condition-based irrigation. The Specialty Crop Research Initiative-Managing Irrigation and Nutrients with Distributed Sensing (SCRI-MINDS) project is a great initiative aimed at improving plant production. It has been developed to increase efficiency in plant production while controlling the excessive use of irrigation water and nutrients [8]. Microsoft (Redmond, WA, USA) has also developed an AI-based sowing application that provides recommendations, such as the optimal period for sowing seeds, preparing land for cultivation, etc. The model by mobile phone app uses remote sensing data from geo-stationary satellite images to predict crop yields through every stage of farming. To determine the optimal sowing period, the moisture adequacy index was calculated. The input data include historical sowing area, production, yield, and weather. The app sends sowing advisories to participating farmers on the optimal date to sow. The farmers do not need to install any sensors in their fields or incur any capital expenditure; they just need a feature phone capable of receiving text messages [76]. It is thus imperative that smart solutions are being developed for global food safety and security, sustainability of food consumption, and the well-being of society. Likewise, environmentally friendly strategies could reduce the use of resources (water, fertilizers, herbicides, etc.) for agriculture, reduce losses, and shelf-life extension of food products for global food security [77]. Low altitude spectral imaging for identifying pest infestation, nutrient or moisture deficiency, and many more computer-aided systems are being introduced for the protection of natural resources and sustainable agriculture. The use of sensors deployed to monitor farm conditions and low-altitude air-borne hyperspectral imaging is an example of smart farming [78].

Smart farming is one of the biggest methods or systems of precision farming. Precision farming involves the precise number of inputs, such as soil, water, fertilizer, etc., to be distributed in an accurate time and at an accurate place, such as weed control [79]. Trimble Agriculture (Westminster, CO, USA), an industrial technology company, has developed a system called WeedSeeker spot spray which is an innovative solution for efficient and targeted weed control. By using sensors to detect the presence of weeds and a spray nozzle to deliver a precise amount of chemicals, the system can help reduce the use of herbicides and minimize the environmental impact of weed control [65][66]. This system can be mounted even on traditional spraying machines with some modifications and is most effective in areas with intermittent growth of weeds. Precision Agriculture (PA) can be described as a management concept having the ability to recognize variability within the soil environment and maximize agricultural production while minimizing environmental concussion, i.e., temperature and humidity changes, for a particular location. Yield Technology (Carrollton, MO, USA) and Bosch (Stuttgart, Germany) have developed a range of technologies that can be used in precision agriculture to optimize crop yield and reduce resource waste. These technologies include drones, computers, data analytics, and robots, among others [77].

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