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Review

Artificial Intelligence: Implications for the Agri-Food Sector

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Abstract: 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. It has the potential to revolutionize the agri-food sector in several ways, including but not limited to precision agriculture, crop monitoring, predictive analytics, supply chain optimization, food processing, quality control, personalized nutrition, and food safety. This review emphasizes how recent developments in AI technology have transformed the agri-food sector by improving efficiency, reducing waste, and enhancing food safety and quality, providing particular examples. Furthermore, the challenges, limitations, and future prospects of AI in the field of food and agriculture are summarized.

Keywords: machine learning; smart farming; internet of things; sustainable management; food quality; food safety

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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	[15–17]
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]
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]

In precision agriculture, AI can be used to analyze data from sensors, drones, and satellites to optimize farming practices, such as irrigation, fertilization, and pest management.

This can lead to higher yields, lower costs, 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]. While these studies provide some valuable insights into AI applications in the agri-food sector, a detailed review is still needed to understand the current advancements of AI technology in the agri-food sector. Therefore, the objective of this review is to highlight the recent developments in the food and agriculture sector along with the application of AI technology, providing specific examples by the databases during 2010–2023. The review also summarizes the future prospects, challenges, and limitations in the field.

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. Some of the ML technologies introduced in the agriculture sector that have contributed to improving crop management are discussed in this section.

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.

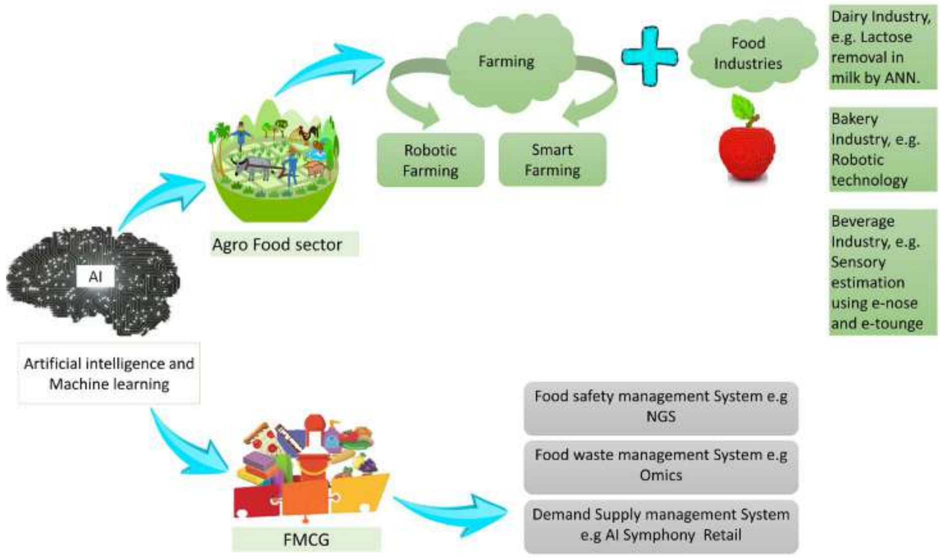

Figure 1. Impact of artificial intelligence (AI) and machine learning (ML) in the Agrofood and FMCG sector.

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 [54–57].

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].

3. Role of AI in the Food Processing

AI and ML technologies are being increasingly adopted in the food processing industry. These technologies are helping to optimize various processes and improve overall efficiency and quality control. The capabilities of the intelligent systems in various tasks, such as intelligent food packaging, product sorting, foreign object detection, new food product development, equipment cleaning, and supply chain management, are elucidated along with the equipment and products developed by various AI technologies.

3.1. Intelligent Food Packaging

The proper arrangement and packing of food products are among the challenging tasks and time-consuming processes in the manufacturing sections of the food industry. Food packing has four vital roles—protecting the food, displaying the product, sanitation, and transportation ability [80]. It protects the food from damage caused by biological, chemical, and physiological reasons during the complete food logistic system. The visual appearance of the package helps consumers to judge the quality of the food and is the first impression about the product. Therefore, effective packaging is an essential part of the food manufacturing sector [81].

AI and ML are increasingly being used in the food packaging industry to improve the design, production, and functionality of packaging materials. AI and ML technologies are being used in the food packaging industry to improve packaging design. Liu [82] applied a packaging design model based on deep convolution generative adversarial networks (DC-GAN). A packaging design image can be enhanced using visual communication technology, resulting in better visual communication ability, a higher degree of image information fusion, and an improved packaging design effect. However, the development of AI-based systems is a tedious task in the fruits and vegetables sector owing to the inconsistency in shape, color, and size [83]. Thus, a copious quantity of data is required to train the system properly and perform the task in a structured manner.

Intelligent tools, such as robotics and drones, can also perform a critical role in reducing the packaging cost significantly [14,84]. For instance, robotics can be used to automate the packaging process, reducing the need for human labor and improving the speed and efficiency of the process. Robots can be used to sort and inspect food products to ensure that they are properly packaged and meet quality standards. Robotics can be used to manage inventory, ensuring that packaging materials are available when needed and reducing the risk of shortages or excess inventory. In addition, drones can be used to deliver food products directly to consumers, reducing the need for packaging and transportation [85].

3.2. Product Sorting

AI-based systems can incorporate a variety of technologies, such as laser technology, X-ray systems, high-resolution cameras, and infrared (IR) spectroscopy, to evaluate the parameters of products at the input level [86]. These technologies can help identify defects, contaminants, and inconsistencies in the products, enabling intelligent decision-making and improving the overall quality of the products. However, the inconsistent product homogeneity can be a major drawback for sorting methods that rely on input-level evaluation. Inhomogeneous products may result in inaccurate sorting decisions, leading to increased waste or lower product quality [15]. To overcome this challenge, some sorting systems use multiple sensors or technologies to assess product quality and identify defects from multiple perspectives. Additionally, ML algorithms can be trained to recognize patterns and variations in product properties, helping to improve accuracy and consistency in sorting decisions. TOMRA (Asker Municipality, Norway), the global provider of advanced collection and sorting systems, has developed an AI system that can efficiently perform the sorting task with 90% efficiency. Industries, by utilizing such systems, have gained some advantages, such as increased production, high-quality yielding, and reduced labor cost. It has been reported that the segregation and arrangement issues can be enhanced by 5–10% in the case of potatoes [14].

In the apple processing industry, deep learning, a subdivision of ML, and a sub-field of AI help to categorize the apples with the help of datasets through pattern recognition and decision-making. Similarly, Deep Convolutional Neural Network (CNN) assists in identifying the type of apple with the support of CVS (Concurrent Versions System). The deep learning model was processed by the data from image processing, apple detection, and ripeness classification. The classifiers are able to achieve the best result, i.e., the ripeness class of an apple from a given digital image [15]. In addition, coffee beans are classified based on the standards, category, defects, and nature of the beverage produced. The types of Arabic espresso are numbered from the grouping by type or imperfection, from two to eight [87].

3.3. Foreign Object Detection

Contamination by foreign objects causes major issues, including food recalls, rejection by consumers, harm to customers, and leads to a fall in brand reliability. Foreign matter, including insects, glass, metal, or rubber, may accidentally enter the food or packing material during food processing, handling, or preparation. Although the magnitude of risks associated with foreign matter depends on the size, type, clarity, and hardness of the object, the consumption of food contaminated with such objects could lead to choking or other complications [88]. As identification of such contaminants with the unaided eye is tough, AI and ML technologies can perform an important role in their detection by analyzing images of the food products to identify any foreign objects that may be present [47]. One approach to foreign object detection using AI and ML is to use image recognition algorithms that are trained on large datasets of images of contaminated and uncontaminated food products. The algorithm can then analyze images of the food products in real-time and identify any foreign objects that may be present [89].

Shimonomura et al. [90] applied a cylindrical tactile image sensor for detecting foreign objects in food based on differences in hardness. Small, hard foreign bodies that were sub-millimeter in size and mixed in with soft food could be successfully detected by using a reflective membrane-type sensor surface with high sensitivity. Through investigations to find shell pieces left on the surface of raw shrimp and bones left in fish fillets, the effectiveness of the suggested method was confirmed.

3.4. New Food Product Development

As new product development in the food industry completely relies on the consumer's perspectives, the data collected by the various decision-making systems are useful in the launch of new products. By analyzing the data gathered by the system, the ML-based module could answer the question "what exactly the consumers are looking for" and make proper decisions. One of the multinational companies has installed automatic vending machines throughout the USA for delivering soft drinks, and consumers have thousands of options to select their favorite flavors. The information stored by the machine could be analyzed by the ML module and deep learning algorithms for the development of a new product; one such example is Cherry Sprite, launched by the company. It has also been proposed that, in the upcoming decades, many of the food industries will benefit from the ML-based decision-making system for the launch of new food products [91].

A biotechnology company has launched the world's first bioactive peptide through AI technology. A sports nutrition ingredient is a unique peptide network derived from rice protein for alleviating inflammation via modulating cytokine responses and for improving immune activity. The company has become the world's first company to demonstrate the potential of AI in improving human health [92]. Another US-based IoT-focused technology company has introduced AI-powdered 'home cooking sidekick', a web and mobile application that integrates with smart kitchen assistant Hello Egg to fully automate kitchen needs. The home assistant is powered through voice technology to recommend a diet plan based on the preferences of an individual. This can also manage the pantry, categorize shopping cart, exhibits video recipes, and assists in the delivery of groceries [93]. The role of sensory panelists employed in food and beverage industries aim to sensory evaluate the new products based on the flavor preferences of consumers. Unfortunately, it is difficult to predict the perception and preferences of the target group. This led industries to develop a robust methodology for measuring and predicting consumer preferences through an AI-based Gastrograph system which uses ML and predictive algorithms to understand market preference [94].

3.5. Equipment Cleaning and Maintenance

Pieces of machinery and processing tools used in food processing industries must be cleaned regularly for proper maintenance. AI-based systems, such as Cleaning in place (CIP) and Clean-out-of-place (COP) systems, assist the food industry to ensure hygiene and maintain product quality at high standards. For its implementation, various cameras and sensors are installed to carry out the tasks. Currently, a European company specializing in providing cleaning solutions has introduced SOCIP, a Self-Optimizing-Clean-In-Place system to autonomously optimize the cleaning process for food manufacturing equipment using AI technology. SOCIP employs ultrasonic sensing imaging methods and optical fluorescence methods to assess the number of food particles and microbial debris that is present inside the equipment. The SOCIP system works by using sensors to scan the inside of the equipment and create a real-time image of the surface. This information is then used to determine how much cleaning is necessary to achieve the desired level of cleanliness [36,74].

3.6. Demand-Supply Chain Management

Presently, food industries are concerned about food safety policies, which are necessary for the transparent execution of all food logistic activities [2,62]. To monitor every stage of the process, for instance, from cost regulation to resource management, AI is being employed. It manages and predicts the passage of possessions from where they are grown to the place where consumers gather them [95].

One company provides integrated AI-enabled solutions for the retail industry. Their solutions can help to optimize various aspects of retail operations, including transportation, billing, resource management, and inventory control. The system can improve the retail industry using AI algorithms to optimize packaging and improve shelf life [96].

By analyzing data on product characteristics, environmental conditions, and other factors, AI algorithms can help to identify the optimal packaging materials and designs to improve product quality and extend shelf life. Additionally, AI can help to improve food safety by providing greater transparency and visibility into the logistics and supply chain process. By tracking products from farm to table, retailers can identify and address potential food safety issues before they become a problem. There will be a need for more contributions that make use of a variety of data sources in order to realize the goal of an expanded agri-food supply chain that involves more stakeholders and the whole supply chain lifetime. Additionally, to complete the loop in sustainable agri-food, the extended AI support for agri-food needs to increase the use of contextual information, food consumption, and food waste reduction [97].

3.7. 3D/4D Food Printing-Extrusion Technology

AI can be of particular interest when combined with 3D and 4D printing technologies. By integrating AI into 3D/4D printing process, it is possible to increase the performance of the printers, reduce the risk of errors, and facilitate automated production. The combination of AI and 3D/4D printing technologies can lead to the establishment of start-ups and research projects that integrate AI into 3D/4D printing products and services [98,99]. The food processing sectors worldwide are now adopting 3D food printing technology to engender operations more systematically and independently. This technology can cause active food value chains more client-friendly and viable by delivering on-demand food manufacturing, empowering computerized food customization, and reducing food wastage.

A 3D/4D food printer operates in a similar way to a regular 3D printer, with the primary difference being the printing medium used. Instead of using melted plastic, a 3D/4D food printer uses a food material as the printing medium. Consumers can materialize designs from an e-commerce platform via websites or mobile applications, and this would minimize warehousing, packaging, and delivery charges [100]. The effectiveness of printing food is improved while food processing expenses and time are minimized, and time is saved by refining 3D printing techniques and equipment [101]. An additional aspect is that personalized products will be delivered very quickly using 3D printing technology than regular food processing technology. As the products are delivered much faster, the need for synthetic polymer-based packing materials and chemical preservatives could be eliminated, and this will also improve food safety. Furthermore, multiphase processing of food products could be minimized to a single stage [102].

4. Role of AI in Food Quality and Food Safety

AI's captivating capability has made it an extremely appealing technology to use in industries not only for decision-making, process estimation, cost savings, and high profitability but also for overall quality improvement [103]. AI, combined with data science, has the potential to improve the quality of food and service offered by cafes, restaurants, online food delivery systems, and food stores, leading to increased sales, profitability, and customer satisfaction. By analyzing data and applying algorithms, AI can help to improve sales prediction, menu optimization, personalized recommendations, and supply chain optimization [16]. AI has made significant contributions to various aspects of the food industry, and these contributions can be broadly classified into three main categories, food quality management, food security management, and food waste management [74]. AI has significant roles and potential applications in several food sectors, including dairy, beverage, and bakery, and are presented in Figure 2.

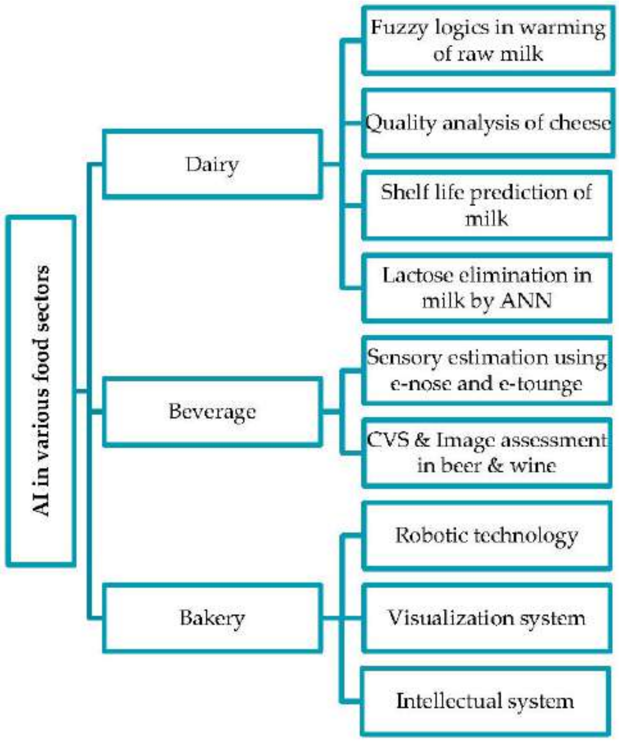

Figure 2. The layout of the functions of AI in several food sectors.

AI can be used to analyze large amounts of data from dairy production processes to identify patterns and make predictions that can optimize production and improve product quality. By using AI tools, such as fuzzy logic and ANN, dairy producers can make more accurate predictions and adjust their processes accordingly, leading to more efficient and higher-quality production. Similarly, AI tools, such as e-nose, e-tongue, CVS, and image analysis, can help producers optimize their production processes and understand consumer preferences in the beverage industry. AI can also help the bakery industry to improve product quality, increase productivity, and by using AI-powered tools, such as robots and visualization, bakeries can create more innovative products and optimize their production processes [85].

4.1. Food Quality Management

Fresh fruits and vegetables are highly perishable and can quickly spoil if not stored and monitored properly. In the past, many vendors did not have access to the necessary tools to monitor the real-time condition of fruits in storage, which resulted in significant food waste. However, with the advancements in technology, there are now several solutions available that can help vendors to monitor the condition of fresh fruits and vegetables in real-time [104].

Digital twin (DT) technology is a promising tool for monitoring the quality and condition of fresh fruits and vegetables throughout the cold chain. The extent of tissue damage that occurs in fruits depends on several factors, including physical and biochemical properties, and environmental factors, such as temperature, humidity, and postharvest treatments. By using DT technology to monitor these factors, it is possible to identify potential issues early on and take corrective action to prevent further damage [17].

In addition to monitoring the cold chain, DT technology can also be used to optimize the storage and transportation of fresh fruits and vegetables [17,105]. Thermal imaging is a non-contact and emerging technology that is becoming increasingly popular for fruit quality examination in the fruit and food industry. It offers a non-destructive way to examine a product without the need for extraction, which could cause permanent damage. Infrared thermal imaging detects the presence of damage or defects in fresh fruits and vegetables by measuring the change in temperature between undamaged and damaged tissues, which is caused by the variation in thermal diffusion coefficients [105]. Likewise, CVS technologies are increasingly being used in the food industry to examine the quality of different kinds of food products. By using different types of CVS, including traditional CVS, hyperspectral CVS, and multispectral CVS to examine the exterior quality of food products, it is possible to identify potential issues early on and take corrective action to prevent further deterioration or contamination [106].

Electric noses (Ens) and electric tongues (Ets) are among the most promising inventions of AI in the food industry [107]. EN is an instrument that consists of an array of electronic chemical sensors with an appropriate pattern recognition system and partial specificity, capable of recognizing complex or simple odors and Ets are multisensory systems for liquid analysis based on chemical sensor arrays and pattern recognition [108]. The sensors used in Ens are able to collect data on the different smells and flavors present in the food or beverage being analyzed. This data is then transferred to a data center, where it can be accessed by ML algorithms [109]. These algorithms are able to analyze the data and make decisions based on the information gathered. In addition, EN technology can also be used to improve the overall quality of food products. By detecting subtle differences in the smells and flavors of different batches of food products, companies can make adjustments to their production processes to ensure that their products are consistent and of the highest quality [110]. The coffee cupping method was developed by the Specialty Coffee Association of America (SCAA). It is a well-established process for assessing the quality of roasted coffee, and it involves steeping ground coffee beans in boiling water and evaluating the aroma, flavor, and other sensory characteristics of the resulting brew. In recent years, AI technologies, such as Ens and ANNs, have been used to enhance the coffee cupping process. E-noses can be used to detect and analyze the volatile organic compounds (VOCs) that are responsible for the aroma of coffee. By using an EN in combination with an ANN, it is possible to predict the quality and flavor of roasted coffee with a high degree of accuracy [111].

Ets are another promising technology in the food industry that can be used to assess the qualities of various types of beverages, including dairy and alcoholic beverages. Ets can detect different taste characteristics, such as sweetness, saltiness, sourness, and bitterness, which can be important factors in determining the overall quality of a product. For example, in the case of tea, there are certain flavor compounds, such as theaflavin (TF) and thearubigin (TR), which can vary in concentration depending on the age of the tea. By using a pulse voltametric ET in combination with a UV-VIS spectrophotometer-based analysis, these compounds can be measured and used to identify the type of tea being analyzed [112,113].

One of the key advantages of the e-tongue is its ability to detect dissolved solids and volatile compounds that are responsible for the aroma and can give off odors after evaporation. This makes it a useful tool for analyzing the overall flavor profile of a sample, and its aroma [114]. The use of Ets for food recognition has been studied extensively, including for the differentiation of liquid and flesh foods. In a study by Rudnitskaya et al. [113], an ET was used to analyze a range of liquid and flesh food samples, including juices, wines, and meat products. The results of the study showed that the ET was able to successfully differentiate between different types of liquid and flesh foods based on their taste profiles. The study conducted by Tan and Xu [114] reviewed the applications of electronic noses (e-noses) and electronic tongues (e-tongues) in the determination of food quality-related properties. The study found that e-noses and e-tongues are increasingly being used in the food industry due to their ability to detect and identify various volatile and non-volatile compounds that contribute to food aroma and taste.

4.2. Food Safety Management

Food safety ensures the absence of any harmful/toxic substances in it and fulfills the obligatory nutritional requirements. A multidisciplinary approach is necessary to ensure food safety and good hygiene during food processing, storage, and sale, and to eliminate the risk of biotic and abiotic contaminants, which causes food poisoning.

Image processing techniques can be used to analyze various characteristics of food products, including size, shape, color, and texture. By estimating the projected area and perimeter of food items, one can quantify their size and shape, which can be useful for quality control purposes [115]. However, it is worth noting that image processing techniques alone cannot detect the presence of harmful microorganisms or other potential food safety hazards. That is where next-generation sequencing (NGS) comes into perform by the determination of the whole genome sequence of a single cultured isolate (e.g., a bacterial colony, a virus, or any other organism), also known as "whole genome sequencing" (WGS), and "metagenomics", in which NGS is used to generate sequences of several microorganisms in a biological sample [11]. Furthermore, the use of AI and automation can greatly speed up the analysis of NGS data, allowing for more rapid identification of potential food safety hazards. This can help prevent widespread illness by allowing for quick intervention before contaminated products reach consumers [116].

4.3. Food Waste Management

Food waste is a significant issue that affects not only the environment but also food security and financial sustainability. It is estimated that 1.6 billion tons of food are wasted annually, and most of this waste (81%) is made up of inedible by-products of food production practices. There is a growing recognition within the food industry that food waste is not just an unavoidable cost of doing business but also a significant sustainability issue and an underutilized resource [85]. According to McKinsey & Company (New York, NY, USA), a consulting firm that has been at the forefront of researching and implementing AI in various industries, AI could offer a $127 billion opportunity by reducing food waste by 2030 [74]. Modern techniques, such as omics, can be exploited to overcome food waste reduction and management challenges. For example, metagenomics, proteomics, transcriptomics, waste omics, and disease omics can be used to understand the biochemical processes that occur during food waste decomposition and identify potential hazards and contaminants in food waste [10].

There have been various conglomerate concepts and solutions developed and tested by researchers and government organizations to mitigate and manage food waste issues. For instance, Black Soldier Fly (BSF) farming is a promising practice for its versatility and multi-roles in various applications, such as sustainable food production and food waste management. The implementation of Internet of Things (IoT) technology in BSF farming can offer significant benefits in terms of efficient production and waste management. By integrating sensors and devices with software and mobile applications, farmers can remotely monitor and control various parameters of BSF farming. This allows for more precise and customized control over the growing conditions of the BSF larvae, leading to higher yields and better-quality biomass [117,118].

4.4. Predicting Shelf Life

AI and ML techniques, including ANNs, have been widely applied to predict the shelf life of foods. These techniques use mathematical models and data from various physicochemical and sensory parameters of the food product to develop predictive models that can estimate the expected shelf life [18,119]. A research study conducted by Goyal and Goyal [120] proposed the use of time-delayed neural network (TDNN) models for predicting the shelf life of processed cheese. The study aimed to develop a model that could accurately predict the shelf life of processed cheese and reduce the need for time-consuming physical testing. The results of the study showed that the TDNN model was able to accurately predict the shelf life of processed cheese. AI models for shelf-life prediction of mangoes stored under different conditions were developed based on respiration rate and ripeness levels under different supply chain scenarios. A deep-CNN was fine-tuned on 1524 image data of mangoes that can classify the ripeness levels of mangoes [121].

5. Role of AI in the Personalized Nutrition

Nutrition can be a complex and individualized aspect of life, and what works for one person may not work for another. Personalized nutrition is an approach that considers an individual's unique nutritional needs, preferences, and health goals. Advancements in technology, such as AI and ML, are enabling the development of personalized nutrition solutions. These solutions use data about an individual's genetics, microbiome, lifestyle, and dietary habits to provide personalized nutrition recommendations [122].

One example of a personalized nutrition solution is a digital health company that offers personalized nutrition solutions for individuals and healthcare organizations, which uses ML to analyze an individual's dietary habits and provide personalized food recommendations. Another example is a biotechnology company that offers personalized nutrition solutions based on an individual's microbiome. The company uses AI and ML to analyze an individual's gut microbiome and provide personalized dietary recommendations based on the types and amounts of gut bacteria present [123]. Similarly, another digital health company offers a range of personalized health coaching solutions, including personalized nutrition coaching, weight management, diabetes management, and hypertension management. This company uses speech recognition and voice AI technologies to provide personalized health coaching to individuals. The company's mobile app uses speech recognition technology to analyze an individual's voice and provide personalized coaching based on their responses.

One is a mobile app and website that allows individuals to track their daily food intake and monitor their nutrition goals. The app provides users with access to a database of over 800,000 food items, allowing them to easily log their meals and track their calories, macronutrients, and micronutrients. Im2Calories uses a combination of computer vision algorithms and deep learning to analyze the visual features of food images and estimate the number of calories in the food [124].

6. Conclusions and Future Perspectives

AI has the potential to revolutionize the food and agriculture sector by improving efficiency, increasing productivity, and promoting sustainability. However, the future of AI in the food and agriculture sector also raises some concerns. For example, there are concerns about the potential for AI to increase inequality and reduce jobs in rural areas. A major constraint is the high cost of implementing AI systems. AI requires significant investment in hardware, software, and training, which can be prohibitively expensive for small and medium-sized businesses. Additionally, there are concerns about the reliability and accuracy of AI systems, particularly when it comes to making decisions about crop management and food safety.

Smart, robotic farming and factories are just some of the ways in which AI and ML are being used to improve efficiency, productivity, and sustainability in the Agri-food industry. The future of the agriculture and food industry is likely to be shaped by AI and ML technologies with a range of potential applications across farming, pest management, food processing, packaging, quality control, shelf-life extension, and supply chain management. While there is a lot of potential for AI to revolutionize the agri-food sector, making it more efficient, sustainable, and innovative, it also raises important ethical, legal, and social implications that need to be carefully considered and addressed. It is important to ensure that these technologies are developed and used in a sustainable and ethical manner to ensure their long-term benefits.

The sustainability of AI will depend on a range of factors, including the development and deployment of AI technologies, the policies and regulations that govern their use, and the way in which society adapts to the changes that AI brings. The sustainability of AI encompasses a range of environmental, social, and economic factors. There are several key considerations that need to be considered when it comes to the sustainability and future of AI. There is a need to address the skills gap and to ensure that there is a sufficient pool of talent to develop and deploy AI systems in a sustainable and responsible manner. This requires investment in education and training programs that can equip individuals with the skills and knowledge needed to work in the field of AI. While there are still challenges to be overcome, such as data privacy concerns, high cost, ethical issues, and the need for specialized training, the future looks promising for AI in this industry. As more and more farmers adopt AI-powered technologies, one can expect to see significant improvements in food production and distribution in the years to come. Future works could include a comparison of different ML algorithms in terms of predictive performance on operational processes in the agri-food sector.

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