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Review

Artificial intelligence on the agro-industry in the United States of America

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Abstract: Integrating artificial intelligence (AI) into agriculture is a pivotal solution to address the pressing challenges posed by rapid population growth and escalating food demand. Traditional farming methods, unable to cope with this surge, often resort to harmful pesticides, deteriorating soil health. However, the advent of AI promises a transformative shift toward sustainable agricultural practices. In the context of the United States, AI's historical trajectory within the agricultural sector showcases a remarkable evolution from rudimentary applications to sophisticated systems focused on optimizing production and quality. The future of American agriculture lies in AI-driven innovations, spanning various facets such as image sensing for yield mapping, labor management, yield optimization, and decision support for farmers. Despite its numerous advantages, the deployment of AI in agriculture does not come without challenges. This paper delved into both the benefits and drawbacks of AI adoption in the agricultural domain, examining its impact on the agro-industry and the environment. It scrutinized the emergence of robot farmers and AI's role in reshaping farming practices while acknowledging the inherent problems associated with AI implementation, including accessibility, data privacy, and potential job displacement. Moreover, the study explored how AI tools can catalyze the development of agribusiness, offering insights into overcoming existing challenges through innovative solutions. By comprehensively understanding the opportunities and obstacles entailed in AI integration, stakeholders can navigate the agricultural landscape adeptly, fostering a more sustainable and resilient food system for future generations.

Keywords: artificial intelligence; agro-industry; image sensing; robot farmers; sustainable agriculture

1. Introduction

Over the 20th century, the United States has witnessed a remarkable evolution in its agricultural landscape, marked by a substantial increase in population alongside significant shifts in land use patterns [1]. Despite a population surge of approximately 255 million since the early 1900s, data from authoritative sources like the Economic Research Service (ERS), the National Agricultural Statistics Service (NASS), and the National Land Cover Database (NLCD) reveal a decline of around 3% in the proportion of cropland relative to the total national land area since the 1970s [2]. This reduction, primarily occurring over the past four decades, underscores a pivotal transformation in agricultural practices. Paradoxically, while the nation's cropland has diminished, overall agricultural production has more than doubled since 1948, a parallel growth mirrored by the exponential rise in the U.S. population. The capacity of the agricultural industry to sustainably feed a significantly larger populace today, despite utilizing less farmland compared to sixty years ago, owes much to relentless advancements in agricultural productivity [3]. Embracing cutting-edge technology like AI, from historical to contemporary times, the United States remains at the forefront of agricultural innovation, fortifying its agricultural sector for present and future challenges [4].

AI is a dynamic discipline within computer science that delves into algorithms to mimic various aspects of nature and human cognition, physiology, and evolutionary processes. Unlike traditional problem-solving approaches, AI does not rely on predetermined paths for resolving issues; rather, it harnesses the power of data, solution examples, and their interrelationships to tackle diverse challenges. Through its capacity to exhibit intelligent behaviors akin to those of human experts in certain tasks, AI has evolved into a powerful tool for constructing solutions to problems characterized by large, evolving datasets prone to inaccuracies and contradictions [4]. Presently, the predominant techniques within AI, namely machine learning and deep learning, leverage iterative methods and interconnected neural network architectures to address complex problems [5–7]. This redirection of focus within AI has broadened its applications, with a common thread being the analysis of voluminous and temporally dependent datasets with inherent uncertainties. As a multidisciplinary field encompassing science, engineering, and economic dimensions, AI has not overlooked agriculture. Numerous studies have been dedicated to leveraging AI techniques to enhance various aspects of agricultural practices, marking its integration into this vital sector [8,9].

The application of AI in precision agriculture presents a promising avenue for transforming farming practices and enhancing sustainability. By harnessing data from sensors, drones, and satellites, AI can optimize various facets of agriculture, such as irrigation, fertilization, and pest management, leading to increased yields, cost reduction, and minimized environmental impact [10,11]. Additionally, AI-powered cameras and sensors enable real-time crop monitoring, facilitating the early detection of diseases, pests, and nutrient deficiencies, thereby averting potential crop losses [12,13]. Additionally, AI systems can predict agricultural yields and market demand by using historical data, soil conditions, and weather patterns. This allows farmers to plan planting and harvesting timetables and adjust pricing tactics appropriately [14]. In the realm of supply chain optimization, AI aids in predicting demand, optimizing logistics, and reducing waste, exemplified through the optimal timing of crop harvests, efficient truck routing, and inventory management [15,16]. Despite the significant potential benefits, the adoption and implementation of AI in agriculture face challenges and potential issues that necessitate careful consideration and mitigation strategies to ensure its effective and sustainable integration.

Therefore, the review aims to outline the benefits and drawbacks of integrating AI in agriculture, highlighting its potential to enhance productivity and sustainability while addressing challenges such as infrastructure requirements and ethical concerns. Despite obstacles, AI holds promise for revolutionizing farming practices and addressing food security issues, provided efforts are made to overcome limitations and ensure equitable access to technology. A notable research gap identified in the literature is the limited exploration of AI applications tailored specifically for small-scale and resource-constrained farmers. Most existing studies primarily focus on large-scale, technologically advanced farming operations, often overlooking the unique challenges faced by smaller farms, such as limited access to high-quality data, inadequate technological infrastructure, and financial constraints. This gap suggests a need for more inclusive research that develops AI solutions accessible to all farming scales and explores how tailored AI innovations can be effectively implemented in diverse agricultural contexts, particularly in developing regions.

This paper is organized as follows: Section 2 provides a comprehensive review of the background and current state of the agro-industry in the United States. Section 3 delves into the integration and impact of AI within this sector. In Section 4, we explore the concepts of robotic farming and other AI-driven innovations. Section 5 presents real-world case studies that illustrate the application of advanced AI technologies in U.S. agriculture. Section 6 discusses the advantages and disadvantages of incorporating AI into agricultural practices. Finally, Section 7 concludes the paper with a summary of our findings and outlines potential directions for future research in this field.

2. Background of the agro-industry in the USA

The agricultural industry in the USA has undergone significant transformation with the integration of AI. Historically reliant on manual labor and traditional methods, AI technologies have revolutionized farming practices. AI-driven solutions enhance efficiency, productivity, and sustainability by enabling data-driven decision-making. Further progress in AI promises even greater advancements, ensuring resilience and food security amidst evolving challenges [17].

2.1. Past conditions without AI

Before the advent of AI, the agro-industry in the USA was heavily reliant on manual labor, making farming labor-intensive and often inefficient. Tasks such as planting, harvesting, and pest control required significant human effort, resulting in limited precision and efficiency. Fertilizers and pesticides were typically applied by hand or with basic machinery, leading to uneven distribution, potential crop damage, and resource wastage [18]. This reliance on manual processes introduced constant risks of human error and made achieving uniformity in agricultural practices challenging. Predicting weather patterns, pest outbreaks, and crop yields relied on rudimentary methods and guesswork, leaving crops vulnerable to adverse conditions [19].

Resource utilization was inefficient, with water, fertilizers, and pesticides often used in suboptimal quantities due to the lack of precise control and monitoring, increasing costs and causing environmental harm. Agricultural data was fragmented and difficult to integrate, with crucial information scattered across various sources, hindering data-driven practices and comprehensive analysis. Consequently, farmers' decision-making was less informed and more error-prone, impacting productivity and sustainability. Traditional farming methods did not adequately leverage technological advancements, leading to slower innovation and adaptation. Farmers relied on generational knowledge and experience rather than scientific data, which, while valuable, could not match the precision and efficiency of modern technology [20]. As a result, the agro-industry faced significant challenges in maximizing crop yields, ensuring food security, and maintaining environmental sustainability [21]. The transition to AI and advanced technologies has since transformed these practices, making farming more efficient, precise, and sustainable.

2.2. Present conditions with AI

The agro-industry is transforming significantly by integrating AI technologies, fundamentally enhancing various aspects of agricultural practices. Precision agriculture leverages AI tools such as drones, sensors, and satellite imagery to monitor crops in real-time. This allows for optimized resource usage and data-driven decision-making, thereby increasing efficiency and reducing input costs [22].

Predictive analytics further revolutionize decision-making by analyzing extensive data on weather patterns, soil health, and crop characteristics. These predictive insights help farmers anticipate risks and refine planting, irrigation, and pest control strategies. Akkem et al. [23] provided a comprehensive overview of machine learning and deep learning approaches. They proposed that crop datasets be utilized to classify soil fertility, crop selection, and a variety of other factors using machine learning algorithms. Deep learning algorithms can be used on farming data to do time series analysis and crop selection. Jha et al. [24] discussed various automation practices, including the Internet of Things (IoT), wireless communications, machine learning, artificial intelligence, and deep learning, which address advancements in the agriculture field. These advancements help manage crop diseases, improve storage management, control pesticide use, manage weeds, and enhance irrigation and water management. Additionally, automation and robotics are streamlining labor-intensive tasks like planting, weeding, and harvesting. This reduces reliance on manual labor and addresses labor shortages. Shamshiri [25] worked with robotic harvesting, developing an autonomous framework with several simple-axis manipulators and claimed it can be faster and more efficient than the currently adapted professional, expensive manipulators. Nath et al. [26] investigated cutting-edge AI methods, focusing on machine learning, neural networks, and deep learning. The implementation of AI in the agri-food business, as well as quality assurance throughout the production process, is comprehensively examined, with a focus on existing scientific knowledge and future prospects.

AI-driven supply chain optimization is transforming the logistics of food distribution by increasing transportation efficiency and reducing waste. Beyond logistics, AI is advancing genetic improvement techniques, enabling the creation of crop varieties with enhanced traits such as drought resistance, pest resistance, and higher nutritional value. Jung et al. [27] highlighted the use of sensing and AI to bolster the resilience of agricultural production systems, resulting in improved output. Rejeb et al. [28] discussed developing developments in the link between AI and the agricultural economy. The study found three unique growth periods and the most common AI techniques in the sector. Javaid et al. [29] determined and evaluated significant papers on AI in agriculture. Farmers may now use AI to gain access to advanced data and analytics tools that will promote better farming, increase efficiency, and minimize waste in biofuel and food production, all while minimizing negative environmental impacts.

These technological advancements collectively contribute to more sustainable and resilient agricultural systems, ultimately boosting productivity and ensuring food security. The integration of AI in agriculture not only leads to higher yields and cost savings but also plays a vital role in tackling global challenges like food scarcity and environmental sustainability. Embracing AI in agriculture is essential for securing a sustainable and abundant food supply for the future. Table 1 summarizes the domains and equipment created by different AI methods.

The growth of AI in the U.S. agricultural sector has been remarkable, with the global AI in the agriculture market valued at approximately $1.1 billion in 2021 and expected to grow at a CAGR of 25.5% from 2022 to 2030. About 15–20% of large U.S. farms have adopted AI technologies like precision agriculture, autonomous machinery, and predictive analytics. AI-driven precision farming increases crop yields by up to 30% through optimized resource use. Robotics and automation are projected to reduce labor needs by 20% in the coming decade, addressing labor shortages, while predictive analytics can cut input costs by 15–20% [30,31]. Venture capital investment in agri-tech startups, particularly those focusing on AI, exceeded $6 billion in 2022, highlighting the strong financial backing and growing confidence in AI's transformative impact on agriculture, driving efficiency, sustainability, and profitability [32].

Table 1. Advanced products and equipment created by different AI technologies.

References	Sector	Technology	Equipment
1. Chukkapalli et al. & Dhanaraju et al. [33,34]	Smart farming	• Soil monitoring: IoT • Robocrop: SVM • Predictive analysis: ML algorithms	Learning models are developed to track and predict various environmental impacts like climate variation during crop production, utilizing NPK soil sensors, temperature sensors, moisture sensors, and an adaptive robotic chassis (ARC) equipped with a dual-arm harvesting robot
2. Wang et al. & Xiong et al. [35,36]	Supply chain quality data integration method	• Blockchain technology	Logistics of agriculture products raising water availability
3. Dewi et al. & Kumar et al. [37,38]	Product sorting/packaging	• Sensor-based sorting system • Tensor flow ML-based system	TOMRA
4. Pérez-Gomariz et al. & Sobuz et al. [39,40]	Fruit safety and quality	• Gaussian mixture mode and IR vision sensor • Fourier separation model • Multi-resolution wavelet transform and AI (classifier) of SVM and BPNN • FNN and SVM	Smart refrigerator; Intelligent refrigerator

Continued on the next page

References	Sector	Technology	Equipment
5. Phimolsiripol et al. [41]	Food quality	• ANN	Use ANN to predict the quality loss of frozen dough by measuring its weight loss.
6. Haff & Toyofuku [42]	Quality control	• X-ray detection • MRI	X-ray imaging identifies defects and contaminants in agricultural commodities.
7. Benouis et al. & Medus et al. [43,44]	Image processing	• NN • Hyperspectral imaging • PCANet	Food tray packaging system with integrated food tray sealing fault detection.
8. Sharma and Patil & Sobuz et al. [45,46]	Forecasting of food production	• Fuzzy logic • ML	Use ANN, SVM, GP, and GPR to predict the future production and consumption of rice as well as milk yield.
9. Cheraghalipour et al. & Ketsripongsa et al. [47,48]	Supply chain optimization	• Evolutionary ML	Scheduled transportation helps reduce held inventory and lower costs in the supply chain.
10. Sharma et al. [49]	Preparing and dispensing food	• Robotics	Food applications, drone and robotic deliveries, and autonomous cars are all innovative technologies transforming modern life.
11. Wardah et al. [50]	New food product development	• ML • Deep learning algorithms	Self-serve soda station.
12. Bo et al. [51]	Identification of taste characteristics	• Convolutional neural networks (CNN) • Multi-layer perceptron (MLP)-descriptor • MLP fingerprint	The MLP-fingerprint model demonstrated the best prediction results for distinguishing between bitterant and non-bitterant, sweetener and non-sweetener, as well as bitterant and sweetener.

2.3. Potential future development with AI

The agro-industry stands on the brink of a transformative revolution with the integration of AI technologies, promising to enhance efficiency and sustainability. AI-driven predictive analytics can maximize crop yields and guide precision farming methods by examining past data, soil conditions, and weather patterns. Artificial intelligence-equipped autonomous drones and robots can do jobs like planting, watering, and harvesting, saving labor and raising output. Furthermore, AI-powered monitoring systems can detect diseases and pests early, enabling timely interventions that minimize crop damage and reduce reliance on chemical pesticides [52]. By harnessing AI, the agro-industry can not only boost food production to meet the growing global demand but also do so in an environmentally responsible and economically viable way. Enhanced automation, such as AI-powered robotics and autonomous machinery, will continue to evolve, enabling fully automated farming operations. This includes tasks such as planting, harvesting, and even crop monitoring and management, leading to increased efficiency and reduced labor costs.

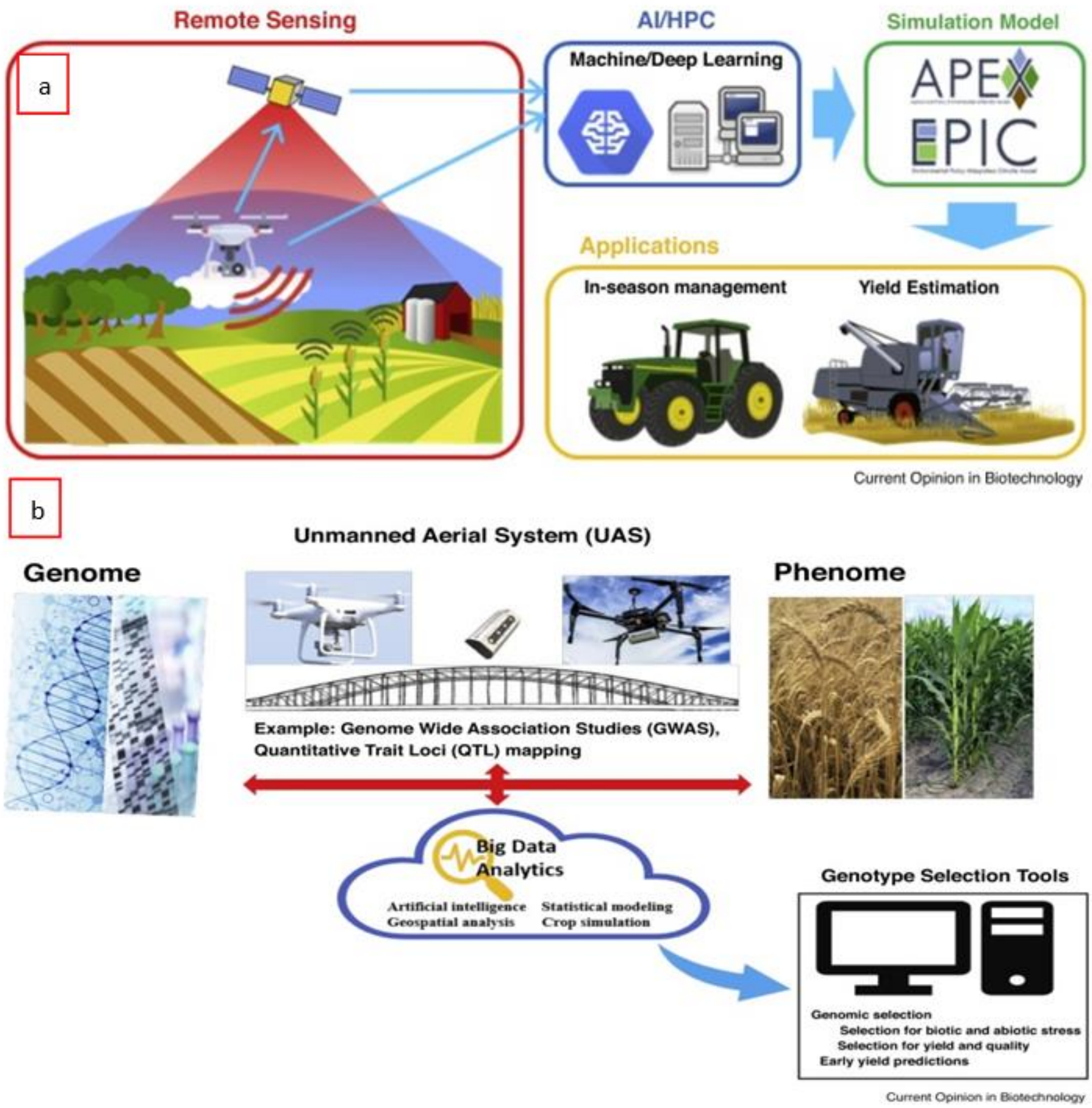

Figure 1. (a) Advanced AI technology used in modern technology; (b) Concept of genetic research using AI technology [27].

Advances in AI and sensor technology will enable even greater precision in farming practices, giving rise to hyper-precision farming. Farmers will have access to highly detailed data about soil health, crop conditions, and environmental factors, allowing for precise and targeted interventions to optimize yields while minimizing resource usage and environmental impact. Future AI systems will offer more sophisticated decision support capabilities, leveraging vast amounts of data from multiple sources to provide actionable insights in real-time. By combining AI and remote sensing, Jung et al. [27] strengthened agricultural systems and opened the door to new possibilities for the prescription tools that will be necessary to solve the food security and farming problems of the coming decade (see Figure 1(a)). AI will also accelerate genetic research and crop breeding programs, developing more resilient and nutritious crop varieties tailored to specific environmental conditions. Figure 1(b) illustrates the concept behind cutting-edge AI-based genetic research. Additionally, AI-powered supply chain management systems will optimize the entire agricultural value chain, from production to distribution. Predictive analytics and machine learning algorithms will streamline logistics, minimize waste, and ensure the efficient allocation of resources, ultimately improving food security and affordability [53,54]. As AI advances, emerging technologies such as quantum computing and synthetic biology will further revolutionize agriculture, heralding a new era of innovation and sustainability.

3. Role of AI in the agriculture industry

AI integration in crop management has transformed US agriculture through sensors, drones, robots, and advanced algorithms, optimizing farming practices. Real-time monitoring, resource efficiency, and predictive analytics enhance productivity and sustainability while improving raw material quality for the food industry. AI's role in agriculture addresses key challenges and positively impacts the agro-industry, shaping its future with innovation and efficiency as follows.

3.1. Seeding and weeding

The new era of efficiency and precision has been brought about by agricultural technology developments, which is especially noticeable in the field of seed and weed management. Robots and autonomous tractors powered by AI algorithms and equipped with sophisticated seeding and weeding mechanisms are revolutionizing farming practices. Through the integration of computer vision and machine learning, these machines can accurately identify crops and weeds, facilitating targeted seed placement and weed control without human intervention. Modern methods, including counter propagation-artificial neural networks (CP-ANN) and unmanned aircraft systems (UAS), make it possible to precisely identify weed species like Silybum marianum, guaranteeing successful eradication [28]. Similarly, the fusion of multispectral and hyperspectral imaging technologies with ML algorithms enables the recognition and classification of various plant species, enhancing the efficacy of weed management strategies [55]. Further potential options, even in demanding settings like greenhouses, are emerging technologies like robotic weed management systems, which utilize computer vision and machine learning algorithms to identify and eradicate weeds [56,57]. Additionally, the prospect of equipping cultivars with specialized tools for intra- and inter-row weed control highlights the potential for tailored, site-specific weed management within the framework of precision farming. The capacity to remotely change weed removal procedures depending on soil conditions, weed density, and crop output highlights the dynamic character of contemporary agricultural practices as intelligent mechanical weed management continues to develop.

3.2. Precision farming

A paradigm change in contemporary agricultural methods, precision agriculture, is typified by smart farming methods. This approach harnesses cutting-edge technologies such as sensors and drones, which gather intricate data on various aspects, including crop health, soil moisture levels, and environmental conditions [58]. Through sophisticated AI analysis, this data is transformed into detailed field maps, empowering farmers with actionable insights to optimize input utilization and tailor farming practices to individual field segments. By strategically deploying resources like water, fertilizer, and weed control, precision agriculture maximizes yields and minimizes resource wastage, thus promoting sustainability. Industry leaders like Yield Technology and Bosch have been instrumental in advancing this field, developing a suite of technologies ranging from drones to data analytics tools [59]. Ultimately, precision agriculture enhances agricultural productivity and minimizes environmental impact, heralding a more sustainable future for global food production.

3.3. Crop monitoring and disease detection

In the realm of agricultural innovation, the integration of AI-powered drones and sensors has revolutionized crop management practices. These sophisticated drones take high-resolution photos of crops and use multispectral cameras and sensors to do real-time analysis to find indications of stress, illness, or pest infestation [60]. Leveraging machine learning algorithms trained on extensive datasets, these technologies can accurately identify disease symptoms and provide early warnings to farmers, facilitating timely interventions to prevent crop loss [35]. Furthermore, the application of AI and ML technologies goes beyond the identification of pests to tackle important issues in crop selection and increase output. Especially helpful in agricultural planning, these technologies help choose appropriate crops with higher yield potential by considering various variables like weather patterns, soil quality, water availability, and the frequency of pests and diseases. Through the use of machine learning (ML) algorithms and genetic data from different crop varieties, plant breeders can create new crop varieties that are more suited to particular environmental conditions, thus increasing agricultural productivity and promoting global food security.

3.4. Autonomous farming

Advancements in AI and automation technologies are revolutionizing the agricultural sector, particularly in the realm of autonomous machinery and robotics. Sophisticated navigation and control systems on autonomous tractors and harvesters are revolutionizing farming methods by remarkably, accurately, and efficiently carrying out chores like plowing, harvesting, and transportation. This integration of AI-driven automation is streamlining operations and significantly reducing labor costs while boosting productivity levels. In addition, specialized robots like Harvest Croo Robotics' Berry 5 Robot are designed to tackle complex and time-consuming jobs, such as strawberry harvesting. Leveraging computer vision and machine learning algorithms, these robots can swiftly identify and pick ripe produce at a pace surpassing human capabilities. The "Robocrop" is just one example of how technological advancements have met niche demands in farming, such as the requirement to remove strawberry blossoms [61]. By harnessing image-processing technology, these robots enhance agricultural processes' speed, efficiency, and cost-effectiveness, offering farmers the opportunity to optimize yields and operational efficiency while minimizing labor expenses.

3.5. Supply chain optimization

Smart logistics and inventory management in agriculture are revolutionized by AI, leveraging advanced data analytics to optimize supply chain operations [62]. By scrutinizing variables such as inventory levels, market demand, and transportation routes, machine learning algorithms forecast demand fluctuations and adjust inventory stocking levels accordingly. Simultaneously, route optimization algorithms minimize transportation costs and enhance delivery efficiency, facilitating the seamless flow of agricultural products from farm to market. Further improving product quality and prolonging shelf life are AI algorithms' analysis of product characteristics, environmental conditions, and other relevant elements to identify the best packaging materials and designs. Moreover, by improving transparency and traceability throughout the supply chain, AI makes a substantial contribution to food safety. Retailers can proactively handle possible food safety issues by following products from their farm of origin to their consumption at the table. However, more contributions leveraging various data sources are urgently needed to realize the potential of an expanded agri-food supply chain that encompasses several stakeholders throughout its whole lifecycle. Additionally, to achieve a sustainable agri-food ecosystem, AI support must intensify its utilization of contextual information, focusing on food consumption patterns and devising strategies for minimizing food waste [63].

3.6. Smart irrigation and resource management

Smart farming leverages the integration of AI with sensor networks and IoT devices to revolutionize agricultural practices. Machine learning algorithms optimize irrigation scheduling and resource management by combining data from soil and crop canopy sensors with weather forecasts and historical climate data [33]. Initiatives like the Specialty Crop Research Initiative-Managing Irrigation and Nutrients with Distributed Sensing (SCRI-MINDS) project focus on enhancing plant production efficiency while curbing excessive water and nutrient usage [64]. Microsoft has also created an AI-based sowing program that forecasts crop yields and identifies the best times to sow using imagery gathered using geostationary satellite photos. This application, accessible through feature phones, eliminates the need for farmers to install sensors, thereby reducing capital expenditure. Such innovations optimize resource usage and contribute to global food safety, sustainability, and societal well-being. Moreover, eco-friendly techniques that highlight the dedication to protecting natural resources and promoting sustainable agriculture include minimal elevation spectrum photography to diagnose insect infestations and nutrient shortages. With sensors monitoring farm conditions and airborne hyperspectral imaging, smart farming epitomizes a proactive approach toward agricultural sustainability and food security [65].

3.7. Farm management software

AI-powered farm management software is transforming agriculture by giving farmers sophisticated analytics and decision-support capabilities. These systems combine information from gadgets, drones, and climate predictions, among other sources, to provide useful insights for raising output and profitability. London's National Physical Laboratory (NPL) is advancing this cause by creating robotics with machine learning and computational sensing skills [64]. These robots can manage weeds, detect the levels of water and nutrients, and carry out autonomous sorting and packaging jobs. Furthermore, scientists have developed novel approaches, such as image processing technologies integrated with MATLAB and Adobe Photoshop CC 2021, to use X-ray CT to evaluate plant water retention and investigate soil behavior. Moreover, robotic chassis are being designed with specific tasks in mind, such as navigation through fields and robotic arms for weed elimination, showcasing the integration of hardware and software in agricultural automation. Moreover, research like those by Agboka et al. [66] demonstrated how well agroecological breeding techniques like push-pull technology (PPT) and maize-legume intercropping (MLI) may lower insect-related losses and increase productivity. These approaches, coupled with the utilization of hybrid fuzzy logic and genetic algorithms for forecasting maize production, demonstrate the multifaceted approach to sustainable farming enabled by AI and advanced technologies.

3.8. Productivity improvement

AI technology has revolutionized the agricultural landscape by empowering farmers with data-driven decision-making capabilities. Various agricultural data are gathered and analyzed through the integration of sensors, drones, and various data collection sources. Leveraging sophisticated machine learning algorithms, farmers can discern patterns and correlations within this data, leading to optimized farming practices and enhanced productivity. By harnessing AI insights, farmers can mitigate risks associated with unpredictable weather patterns, soil conditions, and pest infestations, enabling them to make proactive adjustments and maximize yields. This data-driven approach fosters sustainability and cultivates a more efficient and resilient agricultural sector poised for future challenges.

3.9. Climate resilience

In the face of escalating climate challenges, integrating AI tools offers a transformative solution for enhancing climate resilience in agriculture. Farmers gain access to invaluable real-time weather forecasts and predictive analytics through AI-driven platforms, enabling them to make informed decisions crucial for adapting to changing environmental conditions. For instance, platforms like Climate Corporation's Climate FieldView utilize AI algorithms to analyze vast amounts of weather data, providing farmers with actionable insights tailored to their specific locations [67]. These insights empower farmers to adjust planting schedules, optimize irrigation practices, and even diversify crop selection based on projected climate trends. Moreover, drones and other AI-driven precision agriculture technology enable fine-grained monitoring of crop health, soil moisture levels, and insect infestations, enabling prompt actions to reduce the dangers linked to severe climate like heatwaves, floods, and droughts. By leveraging AI, farmers are better equipped to navigate the uncertainties of climate change and poised to enhance the sustainability and productivity of their operations in the long run.

4. Robot farmers and AI

Robot farmers and AI are catalyzing a profound transformation in agriculture across multiple fronts. Primarily, they expedite labor-intensive tasks like growing, cleaning up, and picking through automation. These sophisticated devices, including robotic arms and AI-driven vision systems, reduce the need for human labor, resolving labor shortages and greatly increasing farm productivity and efficiency [68]. This automation boosts operational speed and accuracy and reduces operational costs, making farming more sustainable and economically viable.

Moreover, AI algorithms harness data from an array of sources, including sensors, drones, and satellites, to offer profound insights into soil health, crop growth dynamics, and environmental conditions. This facilitates the adoption of precision farming methodologies, enabling farmers to optimize resource allocation such as water, fertilizers, and pesticides to maximize yields while minimizing ecological footprints [69]. Using quickly identifying symptoms of anxiety, illness, or insect infestation, real-time crop monitoring using AI-powered systems further improves agricultural resilience and enables prompt interventions, hence preventing possible production loss. By synthesizing predictive analytics with actionable insights, AI equips farmers with the foresight needed to navigate climatic variability, market dynamics, and pest outbreaks, ensuring informed decision-making and bolstering agricultural sustainability in the face of evolving challenges.

5. Case studies

5.1. An artificial neural network (ANN)-based crop predictor using smartphones

Ravichandran and Koteeshwari [70] pioneered a groundbreaking method for crop prediction using artificial neural networks (ANN) tailored specifically for smartphones (Figure 2). Their innovative approach culminated in the development of a prediction model comprising three distinct layers, the efficacy of which was contingent upon the judicious selection of hidden layers. Employing an array of algorithms, including Silva and Almeida's Delta-bar-delta and Rprop, alongside diligent trial and error, researchers sought to optimize the model's configuration. Central to their investigation was the critical role of hidden layers in dictating the system's predictive accuracy. Through meticulous experimentation, it became evident that augmenting the number of hidden layers corresponded to enhanced prediction precision. Figure 2 is a firm representation of step by step artificial neural network based crop estimator using smartphone.

To ensure widespread accessibility among farmers, the system was meticulously crafted for the APK platform, featuring a user-friendly interface for seamless smartphone integration. The researchers meticulously orchestrated the system's architecture by leveraging Java codes within Eclipse and harnessing the power of MATLAB and the ANN toolbox for algorithm development. The resultant amalgamation of cutting-edge technology and agricultural expertise yielded a multifaceted tool capable of recommending suitable crops and providing invaluable guidance on fertilizer selection. This holistic approach underscores the system's potential to revolutionize farming practices, empowering growers with actionable insights at their fingertips.

5.2. Automated harvester

The integration of automation and AI technologies has revolutionized the agricultural industry, particularly in crop harvesting. Let us consider the case of lettuce farming, where the Vegebot developed by the University of Cambridge showcases the transformative potential of automated harvesters [71]. Traditionally, harvesting iceberg lettuce requires significant manual labor due to the delicate nature of the crop. However, Vegebot's sophisticated computer vision capabilities enable it to accurately identify ripe lettuce heads amidst foliage. Leveraging machine learning algorithms, Vegebot can distinguish between ripe and unripe lettuce based on various factors, ensuring precise harvesting while minimizing damage to the produce. By automating lettuce harvesting, Vegebot addresses labor shortages and enhances overall efficiency in lettuce farming, marking a significant advancement in modern agriculture.

Another compelling example is the development of strawberry-picking robots by companies like Harvest CROO Robotics and Octinion [72]. Harvesting strawberries manually is labor-intensive and requires careful handling due to the fruit's delicate nature. However, these robots utilize advanced technologies such as high-resolution cameras and sensors to identify ripe strawberries accurately. With gentle suction or gripping mechanisms, the robotic arms harvest strawberries without causing damage, significantly reducing labor costs associated with this task. By automating strawberry harvesting, these robots ensure consistent quality in harvested fruits while improving overall efficiency in strawberry farming operations. This case illustrates how automated harvesters are reshaping agricultural practices, offering scalability, precision, and sustainability to meet the growing demands of modern food production.

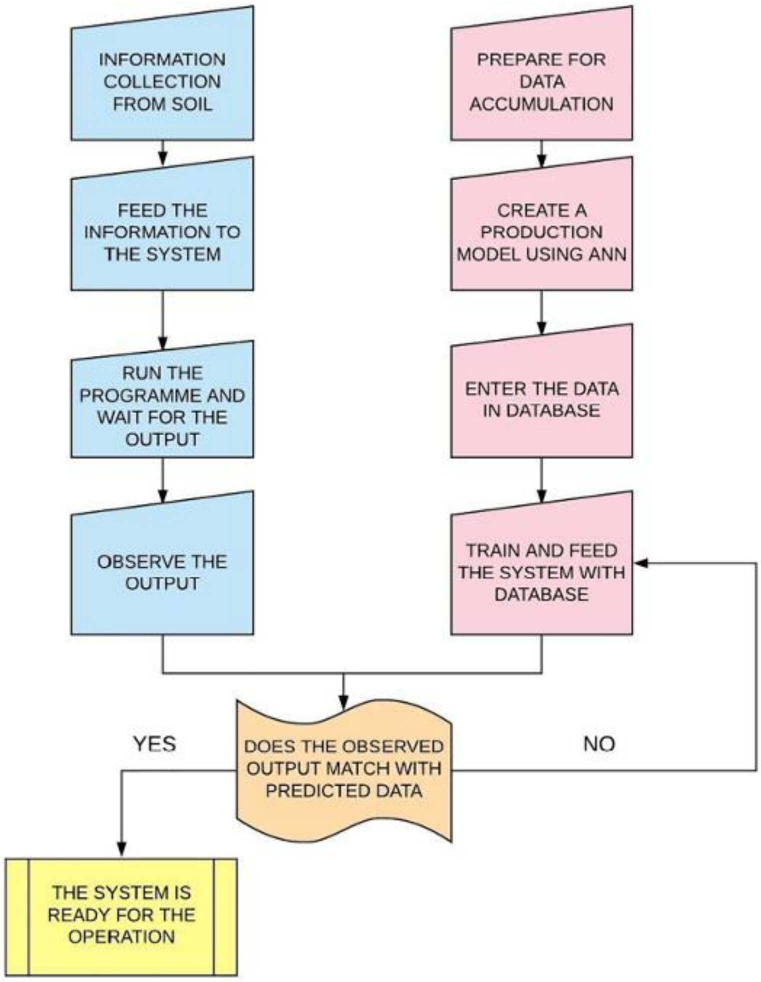

Figure 2. ANN-based crop estimator employing smartphones [70].

5.3. Grape disease detection with ML

In 2016, amidst the pivotal socio-economic landscape of Indian agriculture, researchers Patil and Thorat [73] pioneered a groundbreaking system aimed at bolstering the vitality of grape cultivation (Figure 3). Recognizing the detrimental impact of disease outbreaks on vineyards, they devised an innovative predictive tool capable of preempting grape afflictions. The system, meticulously crafted, integrated a network of advanced sensors strategically positioned throughout the vineyard. These sensors, including temperature gauges, leaf wetness detectors, and humidity monitors, operated in tandem to continuously collect crucial data. A brief diagram for Grape disease detection with Machine Learning is shown in Figure 3. This data was swiftly transmitted to a central repository housed within a Zigbee server, leveraging the open global standards established by the Zigbee Alliance. Comprising four distinct layers—physical, medium access control, network, and application—Zigbee compliance ensured seamless integration and interoperability. Within this wireless sensor network (WSN) framework, three key devices played pivotal roles: the Zigbee Coordinator (ZC), responsible for orchestrating communication among all devices; the Zigbee Router (ZR), facilitating data transmission across the network; and the Zigbee End Device (ZED), tasked with sensing and relaying critical environmental metrics. Through the harmonious synergy of cutting-edge technology and agricultural expertise, Patil and Thorat's visionary system not only averted potential crop devastation but also heralded a new era of precision farming in India's agricultural landscape.

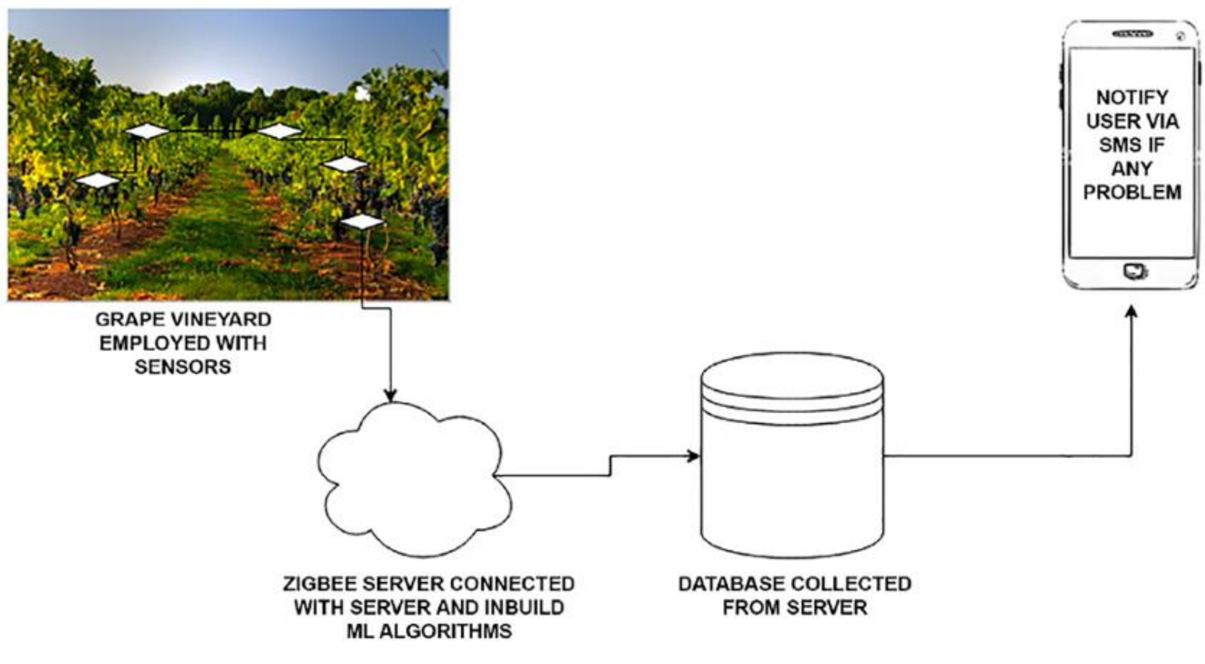

Figure 3. Machine learning-based approach for detecting grape diseases [73].

6. Advances and disadvantages of AI in agriculture

There are environmental benefits and drawbacks to incorporating AI into farming. Sustainable practices can be advanced through AI-driven precision farming by increasing resource efficiency and protecting biodiversity [74]. Energy usage, digital inequality, and the loss of traditional knowledge are some of the worries that have emerged. Balancing these factors is crucial to realizing AI's potential for environmentally sustainable farming.

6.1. Positive effects

Precision agriculture methods driven by AI have completely changed resource management in agriculture, bringing in a sustainable and efficient period. By harnessing data from sensors and drones, AI algorithms meticulously analyze factors such as soil moisture levels, crop health indicators, and pest threats. This granular analysis allows for precise targeting of inputs like water, fertilizers, and pesticides, minimizing waste and environmental impact. Moreover, by detecting early signs of pest infestation or disease, AI-enabled monitoring systems enable farmers to intervene swiftly with targeted treatments, reducing reliance on broad-spectrum chemical pesticides and fungicides. Consequently, this approach leads to reduced chemical usage and environmental contamination fostering healthier ecosystems and promoting biodiversity conservation through precision land management practices.

In addition to resource efficiency and environmental benefits, AI in agriculture significantly enhances operational cost-effectiveness through automation and optimization. By automating labor-intensive tasks such as planting, harvesting, and crop health monitoring, farmers can streamline operations and reduce their dependency on human labor; a major component of operational expenses. Moreover, AI-driven predictive analytics optimize resource management by providing real-time insights into soil conditions, weather patterns, and crop health, enabling farmers to make data-driven decisions that maximize yields and profitability. Furthermore, AI's role extends beyond the field, facilitating predictive maintenance of machinery and equipment, thereby minimizing downtime and maintenance costs. Additionally, AI-powered data analysis offers invaluable market insights and risk management strategies, empowering farmers to make informed decisions about crop selection, timing, and marketing, ultimately reducing the risk of financial losses and ensuring long-term sustainability in agriculture.

6.2. Negative effects

In the realm of agriculture, the integration of AI technologies presents both promising opportunities and significant challenges. One of the foremost concerns revolves around data privacy and security. The sheer volume of agricultural data being collected and analyzed raises apprehensions among farmers regarding potential breaches or misuse by third parties. This hesitancy to share sensitive operational data can hinder the development and implementation of AI solutions. Furthermore, obstacles are created by the availability and cost of AI technologies, especially for modest and resource-limited farmers, which exacerbate inequality in the agricultural industry. These difficulties emphasize the need to resolve problems with data confidentiality, availability, and cost to provide fair utilization of AI-driven agricultural developments.

Furthermore, the complexity and technical expertise required to deploy and operate AI systems present additional hurdles. Many farmers lack the necessary skills and resources to effectively harness the potential of AI technologies, limiting their adoption and impact. Additionally, concerns regarding the reliability and accuracy of AI algorithms loom large. Biases or inaccuracies within training data can compromise the trust and confidence of farmers in AI-powered solutions, highlighting the necessity for rigorous validation and transparency measures. Addressing these challenges calls for collaborative efforts among policymakers, stakeholders, and agricultural practitioners to develop regulatory frameworks, enhance technical capabilities, and promote ethical standards that facilitate the responsible integration of AI in agriculture while safeguarding privacy, equity, and sustainability.

7. Conclusions and future work

With so many uses in cultivation, control of pests, processing food, presentation, control of quality, shelf-life implication, and logistic system management, AI technology is about to transform the agriculture sector completely. These innovations promise to enhance efficiency, productivity, and sustainability, ushering in a new era of agricultural practices. However, the possible advantages must be carefully balanced with important legal, moral, and economic ramifications. Concerns include the potential exacerbation of inequality, job displacement in rural areas, and the high cost of implementing AI systems, which may pose challenges for smaller businesses. Furthermore, there are legitimate worries about the precision and dependability of AI systems, especially in crucial decision-making procedures linked to food safety and crop management. Therefore, even if AI has a lot of potential to revolutionize the agriculture industry, its creation and application must be carried out ethically, inclusively, and sustainably, putting the long-term interests of all those engaged first.

The sustainability of AI hinges on a multifaceted framework encompassing technological advancement, regulatory frameworks, and societal adaptation. Essential to this sustainability is the cultivation of a skilled workforce capable of responsibly developing and deploying AI solutions. This necessitates substantial investments in educational initiatives to equip individuals with the requisite expertise. Though data security issues, moral quandaries, and the need for specialized training remain obstacles, AI's future looks bright. As evidenced by the increasing adoption of AI technologies in agriculture, there is potential for substantial improvements in food production and distribution. Future research could focus on comparing the predictive performance of various machine learning algorithms within the agriculture sector, facilitating informed decision-making and enhancing operational efficiency.

AI-driven precision agriculture techniques, such as soil monitoring and crop health analysis, are being widely adopted in states like California and Iowa, where optimizing water usage and increasing crop yields are critical. Furthermore, the U.S. faces distinct challenges like labor shortages and the need for sustainable farming practices, which have led to the development of AI-powered solutions such as automated harvesting robots and predictive analytics for resource management. Additionally, U.S. government initiatives, like the USDA’s investments in smart farming technologies, provide a supportive framework that accelerates AI adoption in the agricultural sector. By focusing on these U.S.-specific dynamics, the manuscript can better articulate how AI shapes the future of agriculture in the United States, distinguishing it from broader, more generic discussions of AI in agriculture.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

None of the authors have any conflicts of interest to declare.

Author contributions

Jahanara Akter, Sadia Islam Nilima, Rakibul Hasan were equally involved in literature review and original drafting of the manuscript. Anamika Tiwari, Md Wali Ullah, and Md Kamruzzaman were equally involved in literature review, and editing of the manuscript.

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