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Towards sustainable agriculture: Harnessing AI for global food security

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ABSTRACT

The issue of food security continues to be a prominent global concern, affecting a significant number of individuals who experience the adverse effects of hunger and malnutrition. The finding of a solution of this intricate issue necessitates the implementation of novel and paradigm-shifting methodologies in agriculture and food sector. In recent times, the domain of artificial intelligence (AI) has emerged as a potent tool capable of instigating a profound influence on the agriculture and food sectors. AI technologies provide significant advantages by optimizing crop cultivation practices, enabling the use of predictive modelling and precision agriculture techniques, and aiding efficient crop monitoring and disease identification. Additionally, AI has the potential to optimize supply chain operations, storage management, transportation systems, and quality assurance processes. It also tackles the problem of food loss and waste through post-harvest loss reduction, predictive analytics, and smart inventory management. This study highlights that how by utilizing the power of AI, we could transform the way we produce, distribute, and manage food, ultimately creating a more secure and sustainable future for all.

1. Introduction

Ensuring global food security is a complex task, particularly within the agricultural sector, which forms the foundation of food production. There are certain key challenges faced in the agricultural field concerning global food security (Hossain et al., 2020).

The steady growth of the global population, coupled with changing dietary preferences, places significant pressure on agricultural systems to produce more food. Sustaining high levels of productivity and meeting the increasing demand for diverse and nutritious crops pose substantial challenges. The impact of increasing temperatures, modified precipitation patterns, and the occurrence of severe weather events has resulted in the disruption of agricultural practices, leading to adverse effects on crop yields, animal production, and the general viability of the agricultural sector (Mahato, 2014). Environmental concerns, such as soil degradation, deforestation, and water scarcity, further strain agricultural systems. On the other hand, limited availability of arable land and water resources poses significant challenges to agricultural production (Fitton et al., 2019). Urbanization, soil erosion, and degradation reduce the amount of cultivable land, while water scarcity and inefficient irrigation practices hinder optimal crop growth and productivity. Pests, diseases, and invasive species pose substantial threats to crop and livestock health (Ristaino et al., 2021). The emergence of new pests and diseases and the spread of existing ones due to globalization and climate change contribute to the complexity of this challenge (Singh et al., 2023). Limited availability and affordability of quality seeds, fertilizers, pesticides, and machinery hamper the ability of farmers to increase productivity and crop quality. Farmers, particularly in developing regions, may lack information on modern farming practices, sustainable technologies, and market trends, limiting their potential to optimize production and improve resilience (Smidt and Jokonya, 2022). To effectively tackle these difficulties, it is imperative to implement collaborative endeavors aimed at promoting sustainable agricultural practices, facilitating the transfer and use of technology, increasing research and extension services, and improving farmers' access to markets and resources. Artificial intelligence has emerged as a disruptive technology with significant potential in diverse domains, encompassing agriculture and the critical issue of ensuring food security (How et al., 2020). The field of study involves a variety of methodologies and computational models that facilitate the ability of computers to perceive, engage in logical reasoning, acquire knowledge, and independently generate decisions. The fundamental elements of artificial intelligence encompass machine learning, natural language processing, computer vision, robotics, and expert systems (Collins et al., 2021). In the agricultural domain, artificial intelligence exhibits significant potential for transforming the methods by which food is generated, supervised, and disseminated (Ahmad and Nabi, 2021). The utilization of AI technologies might be an opportunity to address current constraints, optimize the allocation of resources, increase production, and enhance the resilience and

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sustainability of agricultural systems. Precision agriculture is a prominent utilization of artificial intelligence within the agricultural sector (Ahmad and Nabi, 2021). Through the collection and analysis of extensive datasets encompassing satellite imagery, weather patterns, and soil conditions, artificial intelligence systems possess the capability to offer farmers significant and important insights (Javaid et al., 2023). This allows individuals to make well-informed decisions pertaining to the most suitable periods for planting, the application of nutrients, the scheduling of irrigation, and the management of pests and diseases. The targeted interventions have been shown to effectively optimize crop yields while simultaneously reducing input waste (Ayoub Shaikh et al., 2022). Artificial intelligence also assumes a pivotal role in the monitoring of crops and the detection of diseases. Sophisticated computer vision algorithms possess the capability to examine photos obtained from drones or similar imaging devices in order to detect crop health concerns, deficits in nutrients, and the existence of pests or diseases (Javaid et al., 2023). Early detection and timely intervention based on AI-driven analysis allow farmers to take preventive measures, minimizing yield losses and reducing the reliance on agrochemicals. In addition to on-farm applications, AI contributes to supply chain management and logistics in the food industry (Bačiulienė et al., 2023). By integrating AI-powered systems, stakeholders can optimize inventory management, enhance transportation and distribution efficiency, and reduce post-harvest losses. Predictive analytics algorithms enable accurate demand forecasting, improving market access and reducing food waste along the entire value chain (Seyedan and Mafakheri, 2020). Furthermore, AI supports sustainable resource management in agriculture. AI-driven systems can analyze real-time data on soil moisture levels, weather conditions, and plant stress indicators to optimize water usage and irrigation practices (Javaid et al., 2023). This ensures efficient water allocation, reduces water waste, and promotes sustainable farming practices. Through the utilization of artificial intelligence technologies, it is possible to optimize agricultural practices, thereby increasing production, enhancing resource management, mitigating post-harvest losses, and fostering the development of more sustainable and resilient food systems (Ayoub Shaikh et al., 2022; Bhardwaj et al., 2022; Javaid et al., 2023; Linaza et al., 2021). This paper dives deep into the transformative potential of AI in agriculture, exploring its applications in various domains and outlining the future trajectory of this critical partnership.

2. Understanding global food security

Food security is a complex and broad idea that involves various dimensions, including the availability, accessibility, utilization, and stability of food (Clapp et al., 2022). It also pertains to the state whereby every individual has the necessary physical, social, and economic means to obtain an adequate supply of food that is both safe and nutritious, in accordance with their dietary requirements and preferences. The global food security encompasses six fundamental elements, namely *availability, accessibility, utilization, stability, resilience, and sustainability* (Fig. 1).

The concept of "*Availability*" pertains to the abundance, excellence, and variety of food resources (Misselhorn et al., 2012) The primary objective is to guarantee the production or importation of sufficient quantities of food to fulfil the nutritional needs of the population. '*Accessibility*' refers to the ability of individuals to obtain food economically and physically(Gibson, 2012). It ensures equitable access to food, particularly for vulnerable populations, is crucial for achieving food security. Another dimension of global food security '*utilization*' emphasizes the quality, safety, and nutritional value of food. It pertains to the ability of individuals to use and benefit from the food they consume (Clapp et al., 2022). Food security also necessitates '*stability*' in food availability, access, and utilization over time. Stable food systems ensure long-term resilience and the ability to

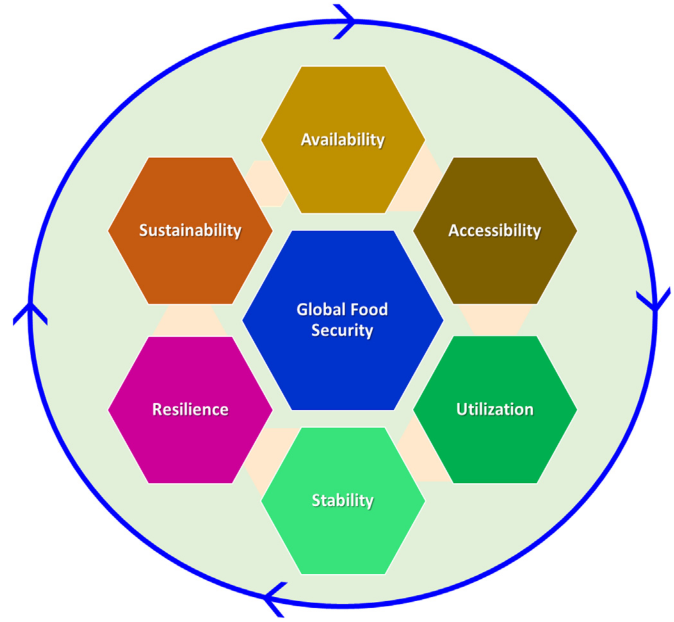

Fig. 1. The essential components of global food security.

meet future food needs (de Guiné et al., 2021). '*Resilience*' is a crucial dimension that emphasizes the capacity of food systems to withstand and recover from shocks and stresses (Tendall et al., 2015). Resilient food systems are adaptable, diversified, and sustainable, enabling communities to maintain food security in the face of challenges, including climate change, pests, diseases, and market volatility (Béné, 2020). While '*sustainability*' focuses on the long-term viability of food production and consumption systems (de Guiné et al., 2021). Sustainable food systems promote responsible resource management, biodiversity conservation, and equitable distribution. Understanding and addressing these key dimensions of food security is vital for developing comprehensive strategies and policies to tackle global hunger and malnutrition. In order to achieve enduring food security for individuals, communities, and nations, it is imperative to use a comprehensive approach that takes into account important factors such as availability, accessibility, utilization, stability, resilience, and sustainability. The issue of global food insecurity is shaped by a multifaceted interplay of diverse forces that operate at several scales, including local, regional, and global levels (Table 1).

Different countries and global institutions have launched agricultural development initiatives with the objective of expanding agricultural productivity, bolstering rural livelihoods, and advocating for the adoption of sustainable farming methodologies (Bizikova et al., 2015; Woodhill et al., 2022).

Due to the growing awareness of the implications of climate change for food security, there has been a heightened emphasis on the development and implementation of climate change adaptation methods within the agricultural sector.

3. Role of artificial intelligence in agriculture

The utilization of Artificial Intelligence possesses the capacity to bring forth a transformative impact within the agricultural sector by enhancing its productivity, sustainability, and resilience (Liakos et al., 2018) (Table 2). AI is playing a substantial role in the advancement of precision agriculture and the integration of this technology with existing agricultural practices can contribute to a more secure and sustainable food future (Javaid et al., 2023).

Table 1
Factors contributing to global food insecurities.

S.N.	Key Factors	Contribution in global food insecurities
1	Lack of Agricultural Investment and Infrastructure	Insufficient investment in agricultural research and development, inadequate rural infrastructure, and limited extension services hinder agricultural productivity improvements. Inadequate storage and transportation facilities, inefficient value chains, and limited access to markets constrain farmers' ability to maximize productivity and access profitable markets.
2	Climate Change and Environmental Degradation	Climate change poses significant threats to agricultural productivity and food security. Rising temperatures, changing precipitation patterns, and increased frequency of extreme weather events impact crop yields, water availability, and livestock health. Environmental degradation, including deforestation, soil erosion, and degradation, further undermines agricultural sustainability.
3	Poverty and Income Inequality	Poverty is a significant driver of food insecurity. Limited financial resources and low income levels restrict individuals' ability to access and afford sufficient, nutritious food. Income inequality exacerbates this issue, as marginalized and disadvantaged populations often face greater challenges in meeting their food needs.
4	Market Volatility and Trade Policies	Fluctuations in global food prices, influenced by market speculation, trade policies, and supply and demand imbalances, affect food access and affordability. Price volatility can lead to food price shocks, particularly in vulnerable populations that rely heavily on imported food or have limited purchasing power.
5	Food Loss and Waste	Significant amounts of food are lost or wasted throughout the food supply chain, from production to consumption. Inadequate storage facilities, inefficient transportation, and poor post-harvest practices contribute to food loss. Consumer behavior, including excessive food purchasing and improper disposal, leads to food waste. Food loss and waste strain resources and exacerbate global food insecurity.
6	Limited Access to Resources and Technology	Unequal access to productive resources, such as land, water, seeds, and credit, hampers agricultural productivity and resilience. Smallholder farmers, particularly in developing countries, often lack access to modern agricultural technologies, infrastructure, and markets, limiting their ability to improve productivity and overcome food insecurity.
7	Population Growth and Rapid Urbanization	The world's growing population, coupled with rapid urbanization, places pressure on agricultural systems to produce more food. Urban expansion leads to the conversion of agricultural land into built-up areas, reducing the availability of arable land. Moreover, rural-to-urban migration can strain urban food systems and livelihoods, exacerbating food insecurity.
8	Conflict and Political Instability	Armed conflicts, civil unrest, and political instability disrupt food production, distribution, and access. Displacement of populations, damage to infrastructure, and disruption of market systems contribute to food insecurity in conflict-affected regions. Fragile and unstable governance structures also hinder effective food security policies and interventions.

Table 2
AI Models and Algorithms used in Agriculture.

S. N.	AI Component (Algorithm/Model)	Application	Reference
1	Convolutional Neural Networks (CNN)	Crop Disease Detection: Image classification for identifying crop diseases and pests.	(Singla et al., 2024)
2	Long Short-Term Memory (LSTM)	Crop Growth Prediction: Forecasting to predict crop growth and yield based on historical data and environmental factors.	(Bhimavarapu et al., 2023)
3	Random Forest	Weed Detection and Management: Classification for distinguishing between crops and weeds using image data from drones or cameras.	(Gao et al., 2018)
4	Support Vector Machines (SVM)	Livestock Monitoring: Analyzing sensor data from livestock to monitor health, behavior, and productivity.	(Satoła and Satoła, 2024)
5	Deep Q-Networks (DQN)	Autonomous Farming Robots: decision-making in autonomous robots for tasks like planting, weeding, and harvesting.	(Escobar-Naranjo et al., 2023)
6	K-Means Clustering	Precision Farming: Segmenting fields based on soil characteristics to optimize irrigation and fertilization strategies.	(Hassan Hayatu et al., 2020)
7	Recurrent Neural Networks (RNN)	Climate Prediction: Sequence modelling for weather forecasting and climate prediction.	(Nketiah et al., 2023)
8	Genetic Algorithms	Crop Breeding: Genetic Algorithms for optimizing crop breeding programs by selecting desirable genetic traits.	(Gao et al., 2023)
9	Markov Decision Processes (MDP)	Irrigation Management: Decision-making in optimizing irrigation scheduling based on crop water requirements and soil moisture levels.	(Huong et al., 2018)
10	Principal Component Analysis (PCA)	Soil Nutrient Analysis: Dimensionality reduction and analysis of soil nutrient data to recommend fertilization strategies.	(Abdel-Fattah et al., 2021)
11	Reinforcement Learning (RL)	Autonomous machine Navigation: Training autonomous machine to navigate fields, avoiding obstacles and optimizing path planning.	(Gautron et al., 2022)
12	Linear Regression	Market Price Prediction: Predicting commodity prices based on market data and supply-demand dynamics.	(Rani et al., 2022)
13	Fuzzy Logic	Irrigation Control Systems: Decision-making in automated irrigation systems based on soil moisture levels, weather forecasts, and crop water requirements.	(Neugebauer et al., 2023)
14	Decision Trees	Pest Management: Identifying pest infestation patterns and recommending appropriate pest control strategies based on environmental factors and crop	(Teixeira et al., 2023)
15	Bayesian Networks	Crop Risk Assessment: Analyzing multiple factors such as weather conditions, soil quality, and historical data to assess and predict risks related to crop failure or disease outbreaks.	(Mentzel et al., 2022)
16	Ensemble Learning	Yield Prediction: Combining predictions from multiple models to improve accuracy in forecasting crop yields based on multiple parameters.	(Hasan et al., 2023)
17	Deep Belief Networks (DBN)	Pest Identification in plant: Analyzing images and identifying pests in plants including stored grains, helping to prevent post-harvest losses.	(Shoaib et al., 2023)
18	Naive Bayes Classifier	Crop Variety Recommendation: Analyzing soil and climate data to recommend suitable crop varieties that are likely to thrive in specific environmental conditions.	(Priya et al., 2018)
19	Self-Organizing Maps (SOM)	Crop Yield Mapping: Clustering and visualizing spatial patterns in crop yield data collected from fields, facilitating targeted interventions and management practices.	(Ruß et al., 2009)
20	Deep Reinforcement Learning	Autonomous Crop Spraying Drones: Training drones to autonomously detect and spray herbicides or pesticides in targeted areas, minimizing chemical usage and environmental impact.	(Azar et al., 2021)
21	Logistic Regression	Disease Spread Prediction: Modelling the probability of disease outbreaks based on factors such as weather conditions, crop types, and historical incidence data.	(Tadelo et al., 2022)

3.1. AI models in agriculture

Multiple artificial intelligence models and algorithms have been developed in recent years to enhance the efficiency of farming (Table 3). *Supervised learning models* in the field of crop and soil management function as intelligent aides, examining extensive quantities of agricultural data, weather predictions, and soil investigations (Bhullar et al., 2023). *Regression models* are advanced tools that employ comprehensive agricultural data, weather forecasts, and soil assessments to produce precise predictions. Their predictive skills provide precise forecasts of agricultural yield, aiding farmers in making well-informed choices on crop selection and optimizing land and resource allocation (Panigrahi et al., 2023). AI models utilize advanced algorithms to assess soil nutrient levels and crop requirements, providing precise recommendations for fertilizer dosages too (Table 3). This approach effectively reduces wastage and minimizes the environmental impact. By leveraging data on crop maturity and weather patterns, these models predict the optimal timeframe for harvesting, resulting in enhanced crop quality and more profitability (Sharma et al., 2023).

Predictive modelling encompasses the utilization of both historical and real-time data in order to construct models that can effectively anticipate and project future results (Nti et al., 2023). Within the field of agriculture, AI algorithms possess the capability to analyses a wide range of information encompassing climatic data, soil properties, crop performance, and insect incidence (Linaza et al., 2021). By leveraging these datasets, AI algorithms may construct predictive models that aid in forecasting future outcomes and trends within the agricultural field (Table 3). These models offer valuable insights into various aspects of crop cultivation, including growth patterns, potential yield, occurrences of insect outbreaks, and the most favorable periods for planting and harvesting activities (Fig. 2).

Classification models utilize field imagery taken by drones, which is comparable to observations made from the air. By employing enormous databases of annotated visuals, they exhibit great expertise in identifying diseases such as scab and rust (Bohnenkamp et al., 2019; Zhu et al., 2022). This allows for targeted interventions, effectively preventing significant damage to crops. These algorithms accurately identify the presence of various insects, including aphids and locusts, allowing farmers to take preemptive measures and minimize losses (Kiobia et al., 2023). Furthermore, these models accurately detect weeds, allowing for proper administration of herbicides, reducing chemical use, and safeguarding beneficial insects. *Clustering models*, akin to effective organizers, categories crops based on their specific requirements. They have remarkable expertise in identifying areas with similar irrigation needs, and this optimization improves water management by reducing both overwatering and under watering. Additionally, it has the ability to classify crops according to their similar nutrient needs. This strategic approach enables accurate fertilizer application, optimizing resource utilization and minimizing any imbalances (Rivera et al., 2022; Vani and Rathi, 2021).

Computer vision models have a crucial role in livestock management as they serve as continuous monitors, assuring the welfare of animals. Their extraordinary expertise in promptly identifying lameness or injuries allows for immediate veterinary care, hence enhancing the well-being and production of animals (Koger et al., 2023). By analyzing animal activity, posture, and facial expressions, one can identify illnesses like as mastitis or lameness, which allows for timely medical intervention (McLennan and Mahmoud, 2019). *Reinforcement learning models* are being employed to automate agricultural operations in innovative manners. Robots have the ability to independently remove unwanted plants from fields by using computer vision and artificial intelligence. This cutting-edge technology allows for precise identification and eradication of weeds, hence minimizing the requirement for manual work and the use of pesticides (Javaid et al., 2023). Robots equipped with advanced image recognition capabilities are employed for targeted harvesting, efficiently gathering fully grown crops while minimizing any harm or wastage.

3.2. Application of AI in crop breeding

Conventional crop breeding has depended on careful observation and selection, but advancements are frequently sluggish and require significant resources. Artificial intelligence offers a significant chance to expedite the creation of enhanced cultivars that possess desirable characteristics. Within the domain of crop breeding, artificial intelligence assumes a crucial role by means of various fundamental applications that includes,

Genomic Selection: Artificial intelligence systems utilize genetic data to forecast the efficacy of breeding lines, hastening the process of selecting desired traits. By employing this approach, they circumvent the necessity for large field tests, therefore decreasing the time of breeding cycles and improving the efficiency of resource allocation (Bhat et al., 2023; Budhlakoti et al., 2022; Sinha et al., 2023).

Phenomics Analysis: The use of advanced sensors and digital photography, along with artificial intelligence, enables thorough examination of intricate plant features. AI is highly proficient in detecting subtle variations in growth patterns, nutrition absorption, and stress reactions, which is essential for customizing breeding strategies to specific environmental circumstances (Nabwire et al., 2021).

Precision Agriculture: AI efficiently combines data from several sources, including soil sensors, weather forecasts, and satellite imaging, to enhance agricultural practices such as planting, irrigation, and fertilization. This optimization results in enhanced efficiency, decreased resource consumption, and mitigated environmental footprint (Javaid et al., 2023; Yousaf et al., 2023).

Through the analysis of comprehensive data, which includes genomic information and environmental parameters, artificial intelligence reveals traits that are associated with a high capacity for producing crops, thereby assisting in the development of cultivars that are well-suited for different agroecological situations (Akkem et al., 2023). Utilizing AI-powered breeding techniques, it is possible to improve the nutritional composition of crops by specifically targeting genes that regulate the levels of vitamins and minerals (Ferrão et al., 2023). This method tackles the issue of malnutrition and encourages the adoption of healthier eating habits by finding genes linked to increased nutrient content in foods. Additionally, AI-powered breeding tackles the issue of climate change by developing plant varieties that can withstand environmental stressors like drought, high temperatures, and diseases (Rai, 2022). By utilizing genomic analysis, artificial intelligence detects the genes associated with characteristics like as drought tolerance and disease resistance (Khan et al., 2022). This allows for the creation of robust cultivars that can flourish under varying climatic situations. Moreover, artificial intelligence simplifies labor-intensive procedures in breeding programs, enabling breeders to concentrate on strategic decision-making and innovation. Machine learning techniques improve the analysis of large datasets, making it easier to identify suitable breeding targets with higher precision (Xu et al., 2022; Yoosefzadeh Najafabadi et al., 2023). Predictive modelling facilitates the assessment of cultivar performance in various conditions, hastening the identification of good candidates for future evaluation.

Therefore, the utilization of AI in breeding has the capacity to transform agriculture by increasing productivity, improving nutritional value, strengthening resilience to climate conditions, and optimizing breeding efforts. It serves as a stimulus for innovation, drastically altering current methods and introducing a period of efficiency and ecological sustainability in agriculture.

3.3. AI in development of improved cultivars

The integration of artificial intelligence in the development of improved cultivars represents a cutting-edge approach to revolutionize

Table 3
Role of AI in smart agriculture.

Area of Impact	Application	Description	Benefits	Example AI Models/Algorithms	References
Precision Agriculture & Resource Management	Crop & Soil Monitoring	Sensors, drones, satellites analyze soil health, moisture, nutrients, growth.	Optimizes resource use, improves yield, reduces waste.	Convolutional Neural Networks (CNNs) for image analysis of soil and crops.	(Mendoza-Bernal et al., 2024)
	Predictive Analytics	Analyzes historical data & weather to predict yields, pests, market trends.	Enables informed decisions on planting, harvesting, resource allocation.	Long Short-Term Memory (LSTM) networks for time series analysis. Random Forests for multi-variable prediction.	(Rani et al., 2023)
	Variable Rate Technology	AI adjusts fertilizer, water, pesticide application based on real-time data.	Minimizes waste, reduces costs, protects environment.	Supervised learning algorithms like Support Vector Machines (SVMs) or Random Forests. Reinforcement learning for dynamic decision-making.	(Sarker, 2021)
	Precision Irrigation	Sensors & AI models track soil moisture & weather for optimal irrigation.	Reduces water consumption, increases yield, promotes sustainability.	Markov Decision Processes (MDPs) for optimizing irrigation schedules. Deep Reinforcement Learning for complex decision-making.	(Abioye et al., 2022)
Pest & Disease Management	Insect & Disease Detection	AI analyzes images from drones, satellites, sensors to detect issues early.	Enables timely interventions, minimizes crop losses, reduces pesticide use.	YOLO (You Only Look Once) or Faster R-CNN for object detection in images. Deep learning models for disease classification.	(Ahmad et al., 2022)
	Predictive Pest Management	AI models predict outbreaks based on data, weather, crop type.	Allows proactive pest control, minimizes damage, reduces pesticide dependence.	Time series analysis models like ARIMA or SARIMA. Causal inference models to identify pest-influencing factors.	(Pacheco-Sánchez et al., 2023)
	Automated Spraying	Robots & drones with AI & computer vision target & spray pesticides precisely.	Reduces pesticide use, improves safety, increases efficiency.	Path planning algorithms for autonomous robots. Object detection and tracking algorithms for precise spraying.	(Talaviya et al., 2020)
Automation & Robotics	Autonomous Vehicles/Robots & Farm Machinery	AI-powered robots perform tasks like planting, weeding, harvesting.	Increases productivity, reduces labor costs, improves safety.	Deep Q-learning for robot decision-making and navigation. Computer vision for obstacle detection and path planning.	(Puente-Castro et al., 2024)
	Livestock Monitoring	Sensors & AI track animal health, behavior, productivity.	Enables early disease detection, optimizes feeding & breeding, improves animal welfare.	Anomaly detection algorithms for identifying abnormal behavior. Recurrent Neural Networks (RNNs) for analyzing activity patterns.	(Park et al., 2021)
	Automated Milking & Sorting	Robotic systems milk cows & sort fruits/vegetables based on size, quality, ripeness.	Reduces labor costs, improves efficiency, ensures consistent product quality.	Computer vision for object recognition and quality assessment. Robotic arm control algorithms for precise manipulation.	(Xie et al., 2022)
Market & Supply Chain Management	Demand Forecasting	AI predicts market demand for crops, helping farmers make informed planting decisions.	Minimizes overproduction risk, maximizes profitability, optimizes resource allocation.	Prophet or Facebook's AutoML for time series forecasting.	(Yoo and Oh, 2020)
	Dynamic Pricing	AI adjusts prices based on real-time market data.	Improves market efficiency, reduces waste, increases farmer income.	Reinforcement learning for dynamic pricing optimization. - Market simulation models for predicting price trends.	(Rana and Oliveira, 2015)
	Traceability & Food Safety	AI-powered systems track food from farm to fork.	Builds consumer trust, reduces foodborne illnesses, improves brand reputation.	Blockchain technology for secure data tracking. - AI-powered anomaly detection for identifying potential food safety risks.	(Chen et al., 2021)
Personalized Farm Management	Smart Guidance	AI analyzes farm data and provides personalized recommendations for planting, irrigation, pest control, *etc.*	Increased yield, reduced costs, improved decision-making.	Decision trees or rule-based systems for generating recommendations. - Reinforcement learning for adapting recommendations to specific contexts.	(Shams et al., 2024)
Greenhouse climate control	Controlled Climate Optimization	AI optimizes temperature, humidity, and CO2 levels for optimal plant growth.	Increased yield, reduced energy consumption, improved resource efficiency.	Deep Reinforcement Learning for complex environment control. - Fuzzy logic systems for handling uncertain sensor data.	(Bersani et al., 2022)
Crop breeding and genomics	New cultivar Development	AI analyzes genetic data to identify desirable traits and develop improved crop varieties.	Faster development of resilient and high-yielding crops, improved food security.	Deep learning models for image analysis of plant phenotypes. Genome-Wide Association Studies (GWAS) for identifying genetic markers linked to desired traits. Genetic algorithm- genetic algorithms in agriculture optimize crop breeding by mimicking natural selection, utilizing iterative Processes to select and evolve desirable traits, enhancing crop yield, resilience, and adaptability to environmental challenges.	(Yoosefzadeh Najafabadi et al., 2023)
Food waste reduction	Demand & Supply Management	AI predicts food demand and optimizes logistics to minimize waste throughout the supply chain.	Reduced food waste, improved resource utilization, increased food security.	Time series forecasting models for demand prediction. - Optimization algorithms for route planning and resource allocation.	(Taneja et al., 2023)

Fig. 2. The importance of artificial intelligence (AI) is highlighted in relation to sustainable agriculture to solve the problems associated with global food security. The image shows the range of agricultural applications for artificial intelligence (AI) technologies. Additionally, the effectiveness of AI-powered interventions has been demonstrated in the areas of inventory control, logistics, and supply chain management, and food waste management.

traditional breeding practices in agriculture. By employing AI techniques, such as machine learning and genetic algorithms, researchers can expedite the breeding process, enhance precision, and unlock genetic potential that may otherwise remain untapped. One of the key applications of AI in cultivar development is genotype-phenotype prediction (Danilevicz et al., 2022). AI algorithms analyze vast genomic datasets to identify genetic markers associated with desirable traits, such as yield, disease resistance, and stress tolerance (Anilkumar et al., 2023). By correlating genomic information with phenotypic data collected from field trials and experimental plots, AI models can predict the performance of different genetic combinations with unprecedented accuracy (Yoosefzadeh Najafabadi et al., 2023). This enables breeders to prioritize promising candidates for further evaluation and streamline the selection process, ultimately accelerating the development of superior cultivars. Furthermore, AI facilitates the optimization of breeding strategies through virtual screening and simulation. By simulating breeding scenarios *in silico*, AI algorithms can explore vast genetic landscapes and identify optimal crossing combinations to achieve desired breeding objectives (Degen and Müller, 2023). This computational approach allows breeders to overcome traditional constraints, such as long breeding cycles and limited resources, by identifying potential cultivar improvements more efficiently and cost-effectively. In addition to genotype-driven approaches, AI contributes to phenotype-based breeding strategies by analyzing high-dimensional phenotypic data (Choi et al., 2023). Advanced imaging techniques, such as drones equipped with multispectral cameras and hyperspectral sensors, capture detailed phenotypic information at scale. AI algorithms process and analyze these data to extract meaningful insights about plant morphology, physiology, and performance under varying environmental conditions (Chen et al., 2023b). By integrating phenomics data with genomic information, AI enables breeders to make informed decisions and select cultivars with superior agronomic traits and resilience to biotic and abiotic stresses (Danilevicz et al., 2022; Shams et al., 2024).

It is evident that, AI is poised to revolutionize cultivar development by enhancing breeding efficiency, accelerating genetic gain, and expanding the genetic diversity of crop plants. However, ongoing research and collaboration are essential to harness the full potential of AI in agriculture and ensure its accessibility to breeders worldwide.

3.4. Application of AI in disease identification, monitoring and pest management

The integration of artificial intelligence technology has revolutionized disease identification, monitoring, and pest management in agriculture (González-Rodríguez et al., 2024). AI has unmatched processing capacity and advanced abilities in recognizing patterns, hence transforming conventional methods of agriculture management (Biswas et al., 2023).

AI algorithms in disease identification utilize a range of data sources such as multispectral photography, spectral reflectance, and environmental sensor data (Jung et al., 2023; Shoaib et al., 2023). These algorithms utilize sophisticated machine learning methodologies, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to identify subtle disease-related patterns and anomalies (Sarkar et al., 2023; Shoaib et al., 2023). Through the utilization of extensive datasets comprising annotated instances of diseased and healthy crops or livestock, AI models may proficiently identify and categories diseases with exceptional swiftness and accuracy (Table 2).

AI-driven solutions in the field of monitoring offer continuous surveillance and analysis of environmental conditions, pest populations, and crop health indices. Different advanced algorithms utilize sensor networks, unmanned aerial vehicles (UAVs), and satellite data to continuously monitor changing agricultural environments (Mohsan et al., 2023; Rajak et al., 2023). These algorithms utilize patterns in spatiotemporal data to detect departures from predicted norms, allowing for the early identification of disease outbreaks or pest infestations. Furthermore, AI-driven prediction algorithms leverage past data and environmental factors to predict disease and pest patterns, equipping farmers with proactive ways for managing them (Lee and Yun, 2023).

The utilization of AI technologies greatly improves pest management tactics by optimizing the use of control measures and minimizing their environmental impact. AI-powered decision support systems take into account many elements such as pest life cycles, habitat preferences, weather conditions, and ecological interactions (Shoaib et al., 2023). AI algorithms combine expert knowledge and data-driven insights to recommend precise interventions that target specific pest concerns. This approach minimizes the need for broad-spectrum insecticides and reduces harm to non-target creatures (Javaid et al., 2023; Mesías-Ruiz et al., 2023).

3.5. Robotics, automation, and IoT in agriculture

The integration of AI-driven robotic systems with advanced computer vision capabilities has revolutionized agricultural practices, leading to increased efficiency and cost savings by automating tasks previously reliant on labor. These systems excel at identifying and harvesting mature produce, ensuring consistent quality, and reducing labor expenses (Eli-Chukwu, 2019).

Similarly, the concept of the Internet of Things (IoT) has transformed agriculture by providing real-time data on environmental conditions and crop status through interconnected devices like weather stations and soil moisture sensors (Dhanaraju et al., 2022). AI algorithms analyze this data to optimize irrigation schedules and resource management, facilitating precision farming practices (Table 2).

The adoption of robotics and automation technologies continues to grow in agriculture, offering enhanced efficiency across various operations such as planting, harvesting, and weed control (Marinoudi et al., 2019). These AI-driven robots are capable of navigating fields, distinguishing between crops and weeds, and executing tasks with precision, ultimately improving overall efficiency.

Furthermore, advancements in Natural Language Processing (NLP) contribute to the development of computational models that enable machines to understand and interpret human language, further enhancing communication and interaction in agricultural settings (Chowdhary, 2020).

Robotics play a crucial role in automating labor-intensive tasks, addressing labor shortages, and improving operational efficiency in agriculture. Agricultural robots are designed for various tasks including planting, weed control, and harvesting, utilizing vision systems and mechanical tools to optimize processes and minimize environmental impact (Balaska et al., 2023; Rafi et al., 2022).

Automation extends beyond robotics to encompass technologies like automated milking systems, irrigation systems, and greenhouses, all of which enhance efficiency and resource management in agricultural production. IoT serves as the backbone of these automated systems, enabling real-time data collection and analysis for precision agriculture, remote monitoring, and predictive maintenance (Dhanaraju et al., 2022). Therefore, the integration of robotics, automation, and IoT represents a significant shift in agriculture, offering solutions to global challenges and promoting sustainable food production. By empowering farmers with data-driven insights and efficient technologies, these advancements contribute to a more resilient and secure food system for future generations.

4. Sustainable water-resource management

The agriculture industry and global food security face considerable problems due to water scarcity and the need for appropriate water management (Mancosu et al., 2015). Nevertheless, artificial intelligence offers potential answers for enhancing water management strategies, enhancing irrigation effectiveness, and preserving water supplies (Jenny et al., 2020). By leveraging AI technologies such as machine learning, data analytics, and remote sensing, the attainment of intelligent decision-making and accurate water allocation can be realized (Krishnan et al., 2022). Artificial intelligence algorithms possess the capability to analyses a wide range of data sources, encompassing weather patterns, soil moisture levels, and crop properties. This analytical process enables the determination of plants' precise water requirements (Folorunso et al., 2023; Javaid et al., 2023). Through the consideration of these elements, AI-driven systems have the capability to enhance irrigation schedules, durations, and application rates. This enables the provision of an optimal amount of water to crops at the precise moment it is required. The implementation of this precision irrigation methodology effectively mitigates water wastage, diminishes runoff, and optimizes crop health and productivity (Liang et al., 2020).

Artificial intelligence enabled systems, integrated with Internet of Things (IoT) sensors and satellite data, have the capability to continuously monitor and assess soil moisture levels. This technology offers the advantage of giving up-to-date and accurate information regarding moisture conditions across various agricultural fields (Table 2). Subsequently, farmers possess the ability to modify their irrigation practices in a manner that mitigates the risks associated with excessive or insufficient irrigation. The implementation of meticulous monitoring techniques serves to mitigate water stress in plants, enhance water-use efficiency, and diminish the likelihood of waterlogging or soil damage. In addition, artificial intelligence has the potential to contribute to water resource management through its ability to analyses data pertaining to water availability, patterns of usage, and meteorological conditions (El Hachimi et al., 2022; Krishnan et al., 2022). Artificial intelligence algorithms have the capability to forecast water demand, optimize techniques for water allocation, and offer suggestions for implementing water conservation practices (Yi, 2022). AI-driven systems optimize water allocation decisions by combining data from several sources, such as weather forecasts, sensor networks, and historical usage data. This integration enables the reduction of water waste and ensures the implementation of sustainable water management practices. AI technologies, such as remote sensing and image analysis, have the capability to identify initial indications of crop water stress. By utilizing satellite images or drone data, artificial intelligence systems have the capability to detect regions of agricultural fields that are undergoing water stress. This detection is achieved by examining various indications such as leaf temperature, vegetation indices, and color fluctuations. This allows farmers to promptly respond by modifying irrigation systems or applying specific treatments to alleviate water stress, minimize reductions in crop output, and optimize water use (Akkem et al., 2023; Junaid et al., 2021). Artificial intelligence algorithms possess the capacity to evaluate sensor data for the purpose of identifying variations from acceptable limits of indicators, hence facilitating the detection of water quality problems. These algorithms can generate alerts to promptly notify relevant stakeholders about the occurrence of such issues. The prompt highlights the significance of promptly detecting water quality issues, as it enables farmers to proactively address these concerns. AI algorithms utilize data from many sources, such as weather forecasts, soil moisture sensors, and crop models, to integrate and develop tailored irrigation plans, anticipate crop water needs, and provide up-to-date recommendations (Elbasi et al., 2023; Javaid et al., 2023). These technologies facilitate farmers in making well-informed decisions, optimizing water utilization, and enhancing total water yield. The incorporation of artificial intelligence technologies into water management practices yields enhanced efficiency and sustainability in agricultural operations. This integration plays a crucial role in safeguarding water resources for future generations and concurrently bolstering global food security.

5. Improving supply chain efficiency

Artificial intelligence exhibits significant promise for revolutionizing and enhancing multiple facets of the food supply chain, encompassing the entire spectrum from production to consumption (Table 2). By utilizing artificial intelligence algorithms, companies have the capability to analyses historical data and market patterns in order to make precise predictions about consumer demand. This allows them to effectively manage inventory levels and devise efficient distribution plans. The utilization of real-time data analysis enables the optimization of inventory management, transportation routing, fleet operations, and warehousing procedures, leading to enhanced efficiency and cost reduction (Ganeshkumar et al., 2023; Khadem et al., 2023). The integration of IoT sensors and blockchain technology facilitates the continuous monitoring, traceability, and visibility across the whole supply chain, consequently augmenting the level of food safety (Qian et al., 2023). Artificial intelligence based predictive analytics play a crucial role in facilitating risk management and contingency planning. By conducting an examination of data pertaining to demand patterns, inventory levels, transportation routes, and market circumstances, artificial intelligence facilitates the optimization of supply chains and the reduction of food waste (Dora et al., 2022). Artificial intelligence additionally facilitates the advancement of food safety initiatives, offers tailored recommendations, and empowers customers to make well-informed decisions (Sharma et al., 2021). Furthermore, it plays a crucial role in mitigating the issue of food waste through its ability to optimize inventory management and provide support for redistribution initiatives (Onyeaka et al., 2023). The potential ramifications of artificial intelligence on the food supply chain are transformative, since it has the capacity to significantly enhance productivity, quality control, waste management, and sustainability. Through the optimization of storage, transportation, and distribution processes, artificial intelligence contributes to the improvement of product handling, waste reduction, and overall efficiency enhancement (Onyeaka et al., 2023). Artificial intelligence algorithms are employed to continuously monitor the temperature and humidity levels in real-time by utilizing IoT sensors (Fig. 2). This implementation guarantees the maintenance of ideal storage conditions and effectively mitigates the risk of rotting. Artificial intelligence plays a crucial role in the transportation industry by enhancing the efficiency of scheduling and routing for refrigerated vehicles, so ensuring the maintenance of optimal temperature conditions throughout the whole voyage (Li et al., 2023b). The application of computer vision and machine learning techniques contributes to the improvement of quality control processes by facilitating the identification of product flaws and enabling the monitoring of various parameters, including moisture levels and air quality. AI-driven automation plays a crucial role in enhancing warehouse operations by facilitating various processes, including sorting and picking, hence optimizing overall efficiency and productivity. Real-time tracking systems facilitate the ongoing monitoring of product movement, hence allowing for prompt detection of any deviations that may occur. AI technologies, including computer vision, machine learning, and blockchain, contribute to the enhancement of quality control and traceability (Lu and Wang, 2016). Artificial intelligence is utilized to automate inspection procedures, identify deviations from normal patterns, and deliver immediate notifications. The system examines sensor data in order to discover variables that influence the quality of a product and uses predictive analytics to proactively mitigate the occurrence of errors. The utilization of artificial intelligence in conjunction with blockchain technology serves to guarantee the authentication and traceability of products, hence augmenting transparency and impeding counterfeiting efforts. AI-powered traceability solutions enable the effective tracking of product movement from the source to the consumer, hence helping the prompt detection of any issues that may arise. The examination of data from the quality control and traceability system yields significant insights that may be utilized to optimize processes and improve the quality of products. In general, the incorporation of artificial intelligence into quality control and traceability processes enhances the provision of food items that are of superior quality, safe for consumption, and genuine in nature (Katiyar et al., 2021). This development brings advantages to both consumers and stakeholders involved in various stages of the food supply chain.

6. Addressing food loss and waste

Post-harvest losses pose a significant obstacle in the pursuit of global food security and the promotion of sustainable agriculture. Losses in the food supply chain manifest at the stages of storage, transportation, and distribution, hence giving rise to notable economic, nutritional, and environmental ramifications (Wunderlich and Martinez, 2018). Nevertheless, artificial intelligence presents novel approaches for addressing the issue of post-harvest losses through the facilitation of effective monitoring, prediction, and decision-making procedures (Singh et al., 2022). AI-driven solutions have the capability to offer instantaneous surveillance of storage facilities, encompassing warehouses and cold storage units, among others. Through the integration of IoT sensors, artificial intelligence algorithms are able to analyze various environmental characteristics, such as temperature, humidity, and gas concentrations (Rajak et al., 2023). Alerts are triggered in the event of any deviations from optimal circumstances, facilitating the implementation of fast corrective actions. Furthermore, computer vision techniques based on artificial intelligence can be employed to evaluate the integrity of stored merchandise by identifying indications of deterioration or impairment (Matsuzaka and Yashiro, 2023). The implementation of real-time monitoring and quality assessment measures serves to mitigate spoilage, minimize losses, and guarantee the market's exclusive access to products of superior quality (da Costa et al., 2022). In addition, artificial intelligence algorithms have the capability to analyze historical data pertaining to crop attributes, storage conditions, and environmental variables in order to construct prediction models aimed at determining the duration of product viability on shelves (Taneja et al., 2023). These models take into account variables such as temperature, humidity, and handling protocols in order to predict the anticipated duration of storage for perishable items. Such information enables stakeholders to enhance the efficiency of storage and distribution processes, hence reducing losses caused by product deterioration and maximizing the utilization of resources. AI-powered systems have the capability to enhance storage and inventory management procedures, resulting in a decrease in post-harvest losses. Through the examination of several elements like supply and demand dynamics, market conditions, and product features, artificial intelligence algorithms are capable of producing suggestions pertaining to inventory levels, storage capacity, and rotation tactics (Praveen et al., 2019). Furthermore, the implementation of artificial intelligence technology has the potential to augment packaging and preservation methods, hence prolonging the longevity of perishable commodities (Li et al., 2023a). AI algorithms are utilized to analyses several parameters, including moisture levels, gas concentrations, and product respiration rates, with the aim of optimizing packing materials, designs, and storage conditions. Intelligent packaging systems, which are equipped with sensors and artificial intelligence (AI) capabilities, have the ability to actively monitor and regulate the environmental conditions within the package. This functionality serves to maintain the quality of the product and minimize instances of spoilage (Li et al., 2023a). AI algorithms produce optimal delivery schedules and routing strategies by taking into account several aspects, including traffic conditions, weather forecasts, and product attributes (Zuo et al., 2022). The implementation of this approach leads to a reduction in transit durations, mitigates the risk of product deterioration, and enhances the overall effectiveness of the supply chain, thereby diminishing losses incurred after the harvesting process (Katiyar et al., 2021; Toorajipour et al., 2021). AI-based technologies facilitate stakeholders in making well-informed decisions, hence minimizing losses, optimizing resource utilization, and augmenting overall efficiency in post-harvest management. The utilization of artificial intelligence systems to mitigate post-harvest losses presents notable advantages, encompassing enhanced food accessibility, optimized resource utilization, and diminished ecological ramifications (Fadiji et al., 2023). The incorporation of artificial intelligence into post-harvest management practices plays a significant role in fostering a sustainable and resilient food supply chain, thereby bolstering global food security and mitigating the issue of food waste (Onyeaka et al., 2023). This strategy signifies a paradigm shift in tackling the issues surrounding post-harvest losses, with the aim of fostering a more effective and environmentally conscious trajectory for the agriculture and food sector.

7. Challenges

The use of artificial intelligence technology in the context of tackling worldwide food security concerns has notable advantages, as well as ethical, social, and economic concerns. The increasing prevalence of artificial intelligence in the agriculture and food industries necessitates a thorough examination and resolution of the associated ramifications. Three primary areas give birth to ethical, social, and economic concerns. First and foremost, artificial intelligence heavily depends on vast quantities of data, encompassing personal and sensitive information (Aldoseri et al., 2023). Hence, safeguarding the privacy of persons and implementing robust protocols for secure data management are crucial. It is imperative to establish explicit protocols and regulatory measures to ensure the protection of data privacy and mitigate the risk of potential misuse or unauthorized intrusion into individuals' personal information. Ensuring the accessibility of AI solutions to small-scale farmers, marginalized groups, and emerging regions is of utmost importance. It is quite important to priorities initiatives aimed at narrowing the digital divide and facilitating equitable access to AI-driven tools and resources, in order to prevent the amplification of pre-existing disparities. Furthermore, the utilization of artificial intelligence technology has the potential to automate specific operations within the agriculture industry, hence potentially affecting the labor force. It is also imperative to acknowledge the social ramifications associated with the displacement of jobs, and to proactively address the necessity for implementing reskilling and upskilling initiatives. This approach is crucial in facilitating a seamless transition and mitigating the adverse effects experienced by workers. Moreover, the availability of dependable internet connectivity and robust digital infrastructure is crucial for the use of artificial intelligence technology. In addition, the implementation of AI technology might incur substantial expenses, encompassing infrastructure, hardware, software, and maintenance. Ensuring the accessibility and cost-effectiveness of AI solutions is of paramount importance in order to make them available to farmers and stakeholders along the food supply chain, with a particular emphasis on small-scale farmers and regions with limited resources. The implementation of artificial intelligence inside the food business has the potential to result in market concentration and consolidation, wherein prominent corporations have significant control over the sector (Kler et al., 2022). The maintenance of power dynamics equilibrium and the promotion of competition are essential in order to prevent monopolistic behaviors and establish a marketplace that is characterized by diversity and inclusivity. In order to effectively tackle the ethical, social, and economic ramifications at hand, it is important to establish collaborative initiatives including policymakers, industrial players, researchers, and civil society organizations. Furthermore, the promotion of inclusive and transparent communication, active involvement of relevant parties, and ongoing assessment and analysis of the effects of AI systems may effectively ensure the successful application of the benefits associated with AI in the context of food security, while simultaneously addressing and limiting potential risks and barriers.

8. Future-prospects

The field of artificial intelligence is advancing at a rapid pace, presenting new opportunities and innovations in the realm of food security. As technology evolves, several emerging trends and future prospects are shaping the application of AI in addressing global food security challenges. AI is increasingly being integrated with other cutting-edge technologies, amplifying its impact on food security. For instance, the convergence of AI with remote sensing, satellite imagery, and IoT devices enables real-time monitoring and data-driven decision-making in agriculture (Pechlivani et al., 2023). This integration enhances precision farming practices, resource allocation, and crop management. Machine learning (ML) and deep learning (DL) techniques are continuously evolving, allowing for more accurate and sophisticated analysis of agricultural data (Benos et al., 2021). The advancement of neural networks, reinforcement learning algorithms, and generative models enhances the prediction capacities and facilitates the ability of artificial intelligence systems to acquire knowledge from extensive datasets (Durai and Shamili, 2022). These technological improvements create opportunities for enhanced forecasts of crop yields, identification of diseases, and management of pests (Durai and Shamili, 2022). The concept of edge computing, which involves the handling of data in close proximity to its origin rather than depending on servers located in the cloud, is increasingly gaining recognition within the agricultural sector (Kalyani and Collier, 2021). On-farm artificial intelligence systems utilize edge computing devices, such as smart sensors and drones, to facilitate instantaneous data analysis and decision-making at the farm level (O'Grady et al., 2019). This phenomenon decreases dependence on internet connectivity, improves responsiveness, and empowers farmers with practical information. The utilization of robotics and autonomous systems within the agricultural sector is experiencing a notable increase, mostly propelled by breakthroughs in artificial intelligence technology. Robotic systems, integrated with artificial intelligence algorithms, have the capability to execute many activities, including but not limited to harvesting, sorting, and precision spraying, with exceptional levels of accuracy and efficiency (Wakchaure et al., 2023). Autonomous vehicles and drones play a vital role in enabling field monitoring, crop analysis, and targeted interventions. The incorporation of AI-enabled robotics and autonomous systems in agricultural practices serves to optimize operational efficiency and mitigate the challenges posed by labor scarcity. The increasing prevalence of data gathering technologies in the agricultural sector, in conjunction with the integration of artificial intelligence capabilities, facilitates the utilization of big data analytics and predictive modelling (Subeesh and Mehta, 2021). The analysis of extensive datasets that incorporate weather patterns, soil conditions, crop characteristics, and market trends has the potential to yield practical and implementable insights (Linaza et al., 2021). AI-powered predictive models play a crucial role in enhancing resource allocation, forecasting crop yields, and facilitating decision-making across the whole food supply chain (Fig. 2). Blockchain technology provides a transparent and unalterable documentation of transactions and supply chain operations. When integrated with artificial intelligence, the food system can see improved traceability and accountability (Ellahi et al., 2023). AI-enabled algorithms possess the capability to examine blockchain data in order to monitor and authenticate the source, caliber, and safety of agricultural commodities (Taherdoost, 2022). The advancement of artificial intelligence in the domain of food security is contingent upon the establishment of collaborative efforts among many stakeholders, including researchers, policymakers, farmers, and technology specialists. The utilization of AI-driven advanced analytics and machine learning techniques has brought about a significant transformation in the processing and interpretation of intricate data sets within the food industry. These technological advancements provide enhanced precision in forecasting, continuous monitoring in real-time, and the adoption of decision-making processes based on data analysis. With the increasing sophistication of AI algorithms, there is a growing capability to unveil patterns, discern correlations, and provide valuable insights that help enhance crop management, optimize supply chains, and analyze risks. The amalgamation of artificial intelligence with the Internet of Things engenders a potent symbiosis within the domain of food security (Misra et al., 2022). The Internet of Things encompasses a range of devices, such as sensors, drones, and smart agricultural equipment, which have the ability to collect and analyze real-time data on important variables like soil moisture levels, weather conditions, and crop health, among others (Akhter and Sofi, 2022; Rehman et al., 2022). AI algorithms have the capability to analyze the aforementioned data in order to offer accurate recommendations for the scheduling of irrigation, control of pests, and allocation of resources. This optimization of agricultural practices by AI can lead to increased productivity. The integration of blockchain technology and artificial intelligence holds the capacity to revolutionize supply chain management, thereby guaranteeing enhanced levels of transparency, traceability, and authenticity within the food system (Fig. 2). Through the utilization of decentralized and irreversible ledgers, blockchain technology has the potential to facilitate the secure and efficient monitoring of food items along the whole supply chain, from their origin on the farm to their consumption by end-users. Artificial intelligence algorithms possess the capability to examine the data held on the blockchain for the purpose of validating the origins of products, identifying instances of fraudulent activity, and improving the safety of food products. The progress made in the field of robotics and automation has created opportunities for the integration of artificial intelligence within the food industry. Robots endowed with artificial intelligence capabilities have the ability to execute labor-intensive activities, such as harvesting, sorting, and packaging, with heightened levels of accuracy and productivity (Fountas et al., 2020; Zhou et al., 2023). AI-driven robotic systems have the potential to augment efficiency, diminish expenditures on labour, and mitigate labour scarcities, particularly in areas grappling with workforce difficulties (Balaska et al., 2023; Subeesh and Mehta, 2021). The integration of artificial intelligence with genomics and precision breeding techniques presents significant opportunities for enhancing agricultural improvement and the management of genetic resources (Biswas et al., 2023; Mishra and Pandey, 2021). Artificial intelligence systems possess the capability to effectively analyze extensive genomic datasets, hence expediting the process of identifying advantageous characteristics, disease resistance, and crop resilience. This facilitates the advancement of climate-resilient crops, augmenting food output in response to evolving environmental circumstances (Chen et al., 2023a; Harfouche et al., 2019; Javaid et al., 2023). AI models have the capability to analyze many sources of information such as climate data, satellite images, and historical records. By leveraging these data sources, AI models may make predictions and take actions to minimize the negative consequences associated with climate-related risks. This includes optimizing the timing of planting activities, effectively managing water resources, and establishing early warning systems to limit the impact of pests and diseases. By adopting these emerging patterns and leveraging the revolutionary capabilities of artificial intelligence, we may make significant strides towards achieving worldwide food security.

9. Conclusion

The task of ensuring food security for an expanding global population in conjunction with climate change and limited resources necessitates the use of inventive and revolutionary measures. This study has examined the potential of artificial intelligence as a promising mechanism to tackle these difficulties and improve global food security. Artificial intelligence offers unparalleled prospects for optimizing agricultural practices, enhancing decision-making processes, and improving overall efficiency within the food system. By employing predictive modelling, precision farming techniques, and AI-based crop monitoring and disease detection systems, farmers are able to utilize data-driven approaches to make informed decisions that effectively allocate resources, reduce wastage, and enhance crop yields. The utilization of artificial intelligence in supply chain management and logistics solutions facilitates the optimization of inventory control, traceability, and quality control processes. This implementation effectively mitigates food loss and guarantees the punctual delivery of products. The potential advantages of artificial intelligence in the context of food security are extensive. It possesses the capacity to augment productivity, optimize resource allocation, facilitate tailored nutritional approaches, and fortify resistance in the context of climate change. Nevertheless, it is crucial to recognize and confront the ethical, societal, and economic ramifications linked to the use of artificial intelligence technology. In summary, AI has emerged as a potentially effective approach for enhancing global food security. By employing strategic planning, fostering collaboration, and prioritizing fairness and sustainability, artificial intelligence has the potential to make substantial contributions towards the attainment of global food security objectives and the realization of a world devoid of hunger and malnutrition.

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Dhananjay K. Pandey: Conceptualization, Writing – original draft, Writing – review & editing, Supervision. **Richa Mishra:** Writing – original draft, Writing – review & editing.

Data availability

Not applicable for this study.

Declaration of competing interest

The authors declare that they have no known competing interests.

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