Review Article

Frontiers of Artificial Intelligence in Agricultural Sector: Trends and Transformations

Abstract

Artificial intelligence (AI) in agriculture is transforming the sector by improving resources efficiency, sustainability and productivity.Our study examined a number of AI-related applications such as pest control, crop monitoring, precision farming and soil health evaluation. AI powered devices enables automated fertilization, harvesting and irrigation, and therefore, cutting down the labour expenses and resource waste. Predictive analytics in AI helps with crop yield and weather forecasts which ultimately improves the planning and risk management. The paper also discusses the challenges and limitations of AI adoption in agriculture, such as the need for reliable data, technical expertise and infrastructure investment. Ultimately, the findings highlightsthe AI can have positive transformative potential in creating resilient agricultural practices that can meet the demands of a growing global population while minimizing environmental impact.However, one of the biggest uses of AI is precision farming, which uses the technology to optimize inputs like water, fertilizer and pesticides by adjusting them to the unique requirements of the crop and the field. AI techniques also make it possible to detect the pests and diseases through picture recognition and predictive analytics, which ultimately minimizes the crop loss and allows for prompt interventions.Widespread use may be hampered by issues with data quality, model interpretability, expensive prices and system integration. Furthermore, issues with labour impact, regulatory frameworks and scalability complicate its adoption. In order to fully utilize AI in agriculture, researchers, farmers and policymakers must work together to overcome these challenges and develop workable and accessible solutions that are suited to a variety of agricultural environments.Present review also highlighted how AI involvement has the ability to revolutionize agricultural sector by developing resilient methods that can both minimize environmental effects and meet the needs of an expanding global population. The agriculture industry can set the path for a sustainable future by adopting AI advances and guaranteeing the environmental stewardship and goals of food safety and security.

Keywords: Artificial intelligence, agriculture, crop security, smart agriculture, sustainability

Introduction

In agricultural sector, one of the main topics in present is artificial intelligence (AI). These daysAIhas permeated many industries, including healthcare, finance and education, due to its ability to solve issues that people are not well suited to handle.In India, agriculture is primary source of income to most of the countrymen. The advancements in AI have been changing the methods used in modern farming(Banerjee *et al.*, 2019). Switched reluctance motors (SRM's) are becoming an increasingly popular drive unit for a variety of applications, including high-speed aircraft and modern electrical vehicles. This is because of their straightforward and durable motor construction, potential low production costs(Kamalakannan *et al.,*2011). Agriculture used to be restricted to the production of crops and food. However, over the past 20 years, it has changed to include the production, distribution, marketing, and processing of agricultural and livestock goods. Nowadays, agriculture provides the primary means of subsistence and boosts the GDP (Fam*et al.*,2012; Thakur *et al.,* 2023), facilitates national trade, lowers unemployment, supplies raw materials for other industries production, and advances the economy as a whole.One of the biggest issues at the moment is agriculture, which is crucial for any nation. More than 800 million people worldwide are estimated to be undernourished. Furthermore, 70 per cent more food needs to be produced because the world's population is increasing day by day(Shubham *et al.*, 2023). Therefore, more funding for agriculture will be required in addition to the predicted amounts, as without it, many people would go hungry in future. Robotics, big data analytics and other technological advancements will make it possible to apply AI to agriculture. The availability of inexpensive sensors the internet of things (IoT) and cameras, unmanned aerial vehicles and even widespread internet covering of fields that are spread geographically. Artificial Intelligence (AI) systems examine soil management data sources, including temperature, weather, soil analysis, moisture and past crop performance (Smriti *et al.*, 2024). Thus, it will be able to offer forecasts regarding which crop to plant in a particular year, when the best times to sow and harvest are concentrated in a certain region, enhancing agricultural yields and reduce the number of herbicides, fertilizers, and water used. Additionally, it assesses the urgent problems facing this sector, such as the predicted unequal distribution of mechanization in various domains, concerns about security and privacy, and the adaptability of algorithms in real-world applications when plants are physically diverse. Processing of huge data sets and more variables is required.

Presentscenarioof AI in agriculture

1. **AI for soil Management:**A crucial component of farming operations is soil management. Having a solid understanding of the many kinds and conditions of soil will improve agricultural productivity and preserve soil resources. It involves using procedures, methods, and therapies toenhance the soil quality. Pollutants that might cause contamination in urban soils be examined using a conventional method for soil survey. Compost and manure promote soil aggregation and porosity; an alternate tillage strategy can prevent soil physical degradation. These methods can improve soil condition. Negative elements, like as contaminants and soil-borne diseases, could be reduced, for instance, by proper soil management (Eli-chkwu and Ogwugwam, 2019). The evaluation of thesustainability of land management systems implicitly takes soil degradation sensitivity into account, with recognition given that different soil has different capacities to withstand changes and recuperate. The various layers and proportions of soil beneath the surface, as well as the relationships between the soil and landscape, can be shown on soil maps created with AI (Elijah*et al.*,2018). Soil texture (sand, clay and silt concentrations) is predicted by an artificial neural network (ANN) model using characteristics gleaned from current coarse hydro-graphic characteristics in combination with high-resolution soil maps obtained by using a digital elevation model (DEM) (Zhao*et al.,* 2009) The characteristics and estimation of soil moisture dynamics are

provided via a remote sensing device integrated into a higher-order neural (HONN) network (Anonymous, 2020; Elshorbagy*et al.*,2008).

2. **AI for weed management:** AI plays crucial role in controlling the infestation of weeds in agricultural field through its smart applications (Table. 1).One of the factors that most lowers a farmer's predicted profit is weeds. For instance, if weed invasion is allowed to spread, dried bean and maize harvests may lose 50 per cent of their yield and wheat output may be reduced by 48per cent due to weed competition. Crops and weeds compete for resources like water nutrientsand sunlight, even if some of them are toxic and potentially pose a risk to public health (Eli-chkwu and Ogwugwam, 2019). A report verifies that if weed infestations are not controlled, the production of corn and dry beans will be reduced by 50 per cent (Harker,2001). Although spray is frequently used to suppress weeds, excessive use of it can contaminate the environment and have a detrimental effect on human health. Thus, tests have been conducted on artificial intelligence weed identification systemsin labs to determine the correct dosage to be used and to spray the intended area precisely, which reduces expenses and the possibility of causing crop damage (Partal,2019).

Table 1. AI involvement in weed management

Sr. No.	Technique	Strength	Limitation	Source
1.	ANN, GA	High performance. Reduces trial and error	Big data is required	Tobaland Mokhtar, 2014
2.	Optimization using invasive weed optimization (IVO), ANN	Cost effective & Potentially high performance	Adaptation challenge with new data	Brazeau, 2018
3.	Saloma: expert system for evaluation, prediction & weed management	High adaptation rate and prediction level	Need big data and usage expertise	Moallem and Razmjooy, 2012
4.	Support Vector Machine (SVM), ANN	Detection of stress in crop that will prompt timely site-specific remedies	Detects only low levels of nitrogen.	Brazeau, 2018.
5.	Digital Image Analysis (DIA), GPS	Has above 60% accuracy and success rate	Time consuming	Stigliani and Resina, 1993
6.	UAV & GA	Can quickly and efficiently	Little control on weeds &	Ortiz*et al.*, 2016

		monitor weeds	Expensive cost	
7.	Mechanical Control of Weeds. ROBOTICS Sensor machine learning	Saves time and removes resistant weeds	Expensive cost. Continuous use of heavy machines lowers down soil productivity	Brazeau, 2018.

3. **AI for crop health management:** Crop management involves planting seeds, keeping an eye on growth, harvesting, storing, and distributing the crop. It can be summed up as the actions that enhance the expansion and productivity of agricultural goods. Comprehensive knowledge of crop classes based on their timing and a healthy soil type would undoubtedly boost crop productivity(Zhao *et al.*, 2009). A system of agricultural management is called crop management,to target soil and crop inputs in accordance with field criteria to maximize revenue and safeguard the surroundings. PCM has experienced delays due to insufficient, disseminated data on soil and agricultural conditions. Water deficits caused by poor soil, unfavourable weather, or insufficient irrigation require farmer's to use a variety of crop management techniques. Adaptable crop management techniques founded on the preference should be for decision rules. The timing, vigour and the ability to forecast droughts is a crucial factor when making adecision among cropping substitutes. One of the more complex issues in precision agriculture is predicting crop yield, and numerous models have been put forth and proven effective thus far. Several datasets must be used to solve this problem because crop output is dependent on a wide range of variables, including soil, weather, fertilizer use and seed variety. By detecting numerous soil factors and parameters relevant to the crop, crop prediction methodology is utilized to predict the appropriate crop. The atmosphere, factors include pH, phosphate, nitrogen, and type of soil sulphur, calcium, magnesium, potassium, organic carbon, and depth, temperature, rainfall, humidity, manganese, copper, and iron. Weather data, equipment capacity, labour availability, and details on approved and priority operators, tractors, and implements are all used by PROLOG for assessing a farm system's operational behaviour(Elijah *et al.*, 2018). Additionally, it calculates the overall income, net profit, and crop production for both for specific areas and the entire farm. Weather factors and rainfall data particular to each place can be used. The precision of rice yield forecasts is impacted by changing the ANN parameters. Require smaller data sets. Reduced learning rates and fewer hidden nodes in the model optimization.
4. **AI for disease management:**Plant disease has been a major factor influencing food production and human societal development over thousands of years (Palmgren *et al.*,2015). Disease control is required for agricultural harvests to have the best possible yield. Diseases of plants and animals are a significant barrier to yield growth. Numerous elements play a part in the development of these plant-attacking illnesses and animals, such as genetics, soil composition, precipitation, and arid climate temperature, wind, etc. Because of these elements as well as the shaky the cause and nature of certain diseases, controlling the impacts is a significant problem, particularly in large-scale farming.A great deal of research has been done to address these issues by creating solutions based

on artificial intelligence (AI). Crop damage can be significantly reduced by using machine learning or deep learning techniques to speed up the detecting process(Jasim and AI-Tuwaijari, 2020). For example, proposed a CNN based framework for leaf disease detection. This research achieved an accuracy of 98.02 per cent (Pawar *et al.*,2022). The system that assists in illness detection and provides has been developed using a rule-based and forward chaining inference enginetherapy recommendation (Munirah*et al.*,2013)

5. **AI for pest and insects management:**Pest control plays a crucial role in ensuring agricultural productivity and safeguarding our crops from the devastating effects of invasive species. Researchers have attempted to lessen this threat for many years by creation of electronic systems that could recognize the current pests and offer preventative strategies.Farmer's have traditionally employed chemical treatments and pesticides to keep pests in control. Increased environmental harm to soil and groundwater as well as detrimental effects on human health are the results of the growing usage of pesticides for crop protection. Conversely, yet, this also raises the possibility that pests will become resistant to pesticides (Deutsch *et al.*,2018). Therefore, to overcome these limitations automated techniques for crop forecasts and monitoring is required, itsignificantly lessens the harm done to the environment and the population by preventing the overuse of chemicals and pesticides (Kartikeyan and Shrivastava,2021).
6. **AI for irrigational management:** It is well known that an intelligent irrigation system can determine a farm's water needs by using real-time data and weather forecasts for several criteria. The yield of tomato crops (33.3 mg/ha) was similarly impacted by utilizing soil moisture sensors to monitor irrigation, thus notably greater production values were noted even with less water was used for irrigation as opposed to timed irrigation and subsurface drip irrigation (Dukes *et al.*,2015). Smart irrigation technology is designed to enhance productivity without requiring a significant amount of labour by detecting the water level, soil temperature, fertilizer content, and predicting theweather. The actuation is carried out in compliance with the micro controller by switching the irrigator pump ON or OFF. The development of machine-to-machine technology aims to facilitate the exchange of information and data between parties as well as with the server through the main network between all the nodes of the agricultural domain (Shekher*et al.*,2017).
7. **Image recognition and perception:** Applications for self-driving drones are numerous and include AI-based recognition and surveillance, human body detection and geo-tagging, search and rescue operations for missing persons, and summertime forest fire detection. Due to their adaptability, imaging capabilities, remote controller compatibility, and agility in the air, drones, also known as unmanned aerial vehicles, are growing in popularity. They are able to perform a variety of tasks and ascend higher than average humans(Palmgren *et al.*, 2015).
8. **AI for weather forecasting:** Predicting the weather is a vital and challenging task for the meteorology department. They employ Artificial Neural Network (ANN), an artificial intelligence technology, to help with this endeavour. They use probabilistic models like

Bayesian Belief Network (BBN) in addition to deterministic techniques to estimate variables like precipitation. The long-term effects of climate change on the water resources in the Zambezi Riparian Region (ZRR) basin were the subject of a recent study. The study found that there has been less precipitation upstream of ZRR, which will eventually result in less runoff to the Bukan reservoir(Meydani*et al.*,2022).

AIfostering economic performance

In agricultural economics research, digitalization has drawn more and more attention. The quantity of Businesses use of AI technologies has grown significantly during the past ten years (Davenport*et al.*,2020). Generally speaking, agriculture is limited by a number of factors, including human health and food quality, optimizing productivity while reducing the need for antibiotics, fertilizers, and pesticides, and more. Another significant obstacle for Seasonality is a feature of agriculture. Every year (and every season), the output Positions differ, weather patterns shift, and the cost of farming supplies (such as prices for seeds) change. In addition, weeds proliferate in unprepared in predictable ways, pests can cause unforeseen problems, and viruses pandemics and epidemics in animal populations(Eli-Chkwu,2019). The promotion of agricultural AI aims to tackle these issues. Consequently, AI has an effect on the agricultural sector. Agriculture-focused AI technology is anticipated to have an impact on the sector, affecting how food is generated, handled, and ingested (Dolsfma*et al.*,2021). Agricultural artificial intelligence (AI) is utilized to increase farmer's returns on investment through more productive farming that uses less resource (such as water, land, pesticides, and fertilizer). Utilizing AI has the potential to lower variable costs by using labour more effectively and resources and exact measures. Umeda (2021) and SEO have discovered cost reduction AI application in Japanese rice farming through the use of smart aerial vehicles, such as drones(Kartikeyan and Shrivastav,2021).

Beyond automation, AI eventually aspires to replace human intelligence in roles like agri-food managers, consultants, farmer's and experts. Automation is going to surely have a significant, both immediate and long-term influence on labour. But when AI issued more, new professions that call for human abilities arise like human judgment in difficult situations that are impossible for AIs to solve. Currently, labour-intensive automated actions are replaced by AI systems need to use little to no expert judgment (Clifton *et al.*,2020). Farmer's are hoping that artificial intelligence (AI) would enable them to overcome market inequalities in local and global value chains. Since farmer's in emerging economies typically have limited access to market information, this is especially important. AI for agriculture that looks outward, makes use of market trend data, agricultural costs, customer demands, specifications, and aesthetics may enable farmer'sto choose more wisely in the market(Dharamraj and Vijayanand, 2018). With the use of reservation equipment, data on livestock, food safety and conservation, and other AI-enabled mobile apps, farmer's may increase their chances of securing supply contracts and lower their risk of experiencing market failure to produce suggestions for the farmer's course of action. Applying AI allows for the tracking of volume and quality metrics across the whole supply chain. This knowledge is especially crucial for lenders and investors. Increased origin and quality traceability lowers market failures and enables farmer's to reach premium markets anytime their products meet the necessary quality standards. Credit scores are generated using machine learning systems, andrates that lessen the disparity in knowledge between value chain participants, additionally provide access to insurance and microloans.

Technological aspects of AI for agriculture

The kinds of computer science methods that are usually applied are among the traits that characterize artificial intelligence. ANN models are used in soil management, for example, to estimate soil texture (sand, clay, and silt concentrations) based on characteristics given by soil maps mixed with hydro-graphic factors (Zhao*et al.*, 2009). Artificial neural networks require massive amounts of data for training, yet they can handle unstructured data.While non-numeric data is the main emphasis of natural language processing (NLP), particularly, comprehending the structure and meaning of human language, which are able to comprehend farmer needs with effectiveness. These AI uses in farming create new opportunities (Kakani *et al.*, 2020). The application of AI in agriculture requires high-performance computers in order to deliver effective solutions. For instance, environmental and climate data are applied. Using data analytics can help vulnerable places manage water and drought (Viktor *et al.*, 2021). For artificial intelligence to be reliable and accurate, both the volume and quality of data are crucial. Large training data sources are a barrier to developing effective AI. Data is frequently scarce in the agricultural industry because farmer's are sometimes less inclined to share data with "outsiders" and have lower levels of technology literacy than professionals in other sectors (Ryan*et al.*, 2021). Both shallow machine learning (ML) and deep learning (DL) have drawn interest recently in various agricultural areas and stages. Machine learning has been used in pre-harvest, harvesting, and post-harvest farming processes (Zhong and Zho, 2020).

AI based drones and robotictechnologiesin agriculture

In agriculture, drones are being used for disaster mitigation, weed identification, crop health evaluation, herd and animal monitoring, and irrigation equipment monitoring (Ahirwar*et al.*, 2019). Remote Agriculture is being greatly impacted by sensing, which uses unmanned aerial vehicles (UAV's) to capture, interpret, and analyse images (Abdullahi*et al.*, 2015). The rural industry seems to have embraced technological innovation with gusto, using these powered tools to alter current farming practices.These might aid in overcoming the various limitations that impede agricultural output. Wireless Sensor Networks (WSN) are integrated into the UAS development process. The information retrieved by the WSN allows the UAS to improve its use, such as limiting its spraying of artificial substances to precisely designated areas. The ecological conditions are always changing thus the control circle must most likely react as quickly as is reasonably possible. Reconciliation with WSN can facilitate such direction (Costa *et al.*, 2012). UAVs are mostly used in precision agriculture for tasks like pesticide spraying, crop height estimation, crop monitoring, and soil and field analysis. In the upcoming years, the market for agricultural drones is anticipated to expand by over 38 per cent. It is anticipated that rising population numbers and shifting climatic patterns would only highlight the need for efficient agriculture (Puri *et al.*, 2017).

Robots, for instance, will help farmers deal with the problem of a shrinking workforce and enable them to operate more productively while saving money on labor. In order to increase crop yields, sophisticated robotic systems will also tend to and harvest plants as well as gather data from farms. In the agricultural sector, AI bots can perform tasks similar to those of modern combination harvesters, which can gather crops more quickly and in greater quantities than human laborers. In-vivo agriculture uses computer vision to its fullest potential to assist with spraying, weeding and monitoring.

Problems with agricultural robotics

Despite great advancements in the field of agricultural robotics research, there are still no commercially accessible robots suitable for labour in intricate agricultural environments. The primary cause was the lack of algorithms designed to handle the chaotic and unpredictably changing real-world agricultural environmentdeveloped yet, and additional elements, including the seasonality of agriculture, also contribute to the distinction between the laboratory's experimental environment and the real world. The quick-witted and the agricultural environment will always change throughout time and space, regardless of unstructured settings, as those found in space and the military or in situations where the atmosphere, like rough terrain, vision, and lighting, is essentially unpredictable. However, some autonomy will still help with technological production. The Pareto principle, which holds true for many tasks, essentially states that automation may be used for 80per cent of a task, with the remaining 20per cent being extremely challenging. To put it another way, 80per cent of the necessary physical labour can be eliminated with automation. Additionally, the 80per cent automation can help replace conventional farming methods. To fully automated farming systems and more knowledge will be gained through testinghardware and software components (Bechar*et al.*, 2016).

One important quality of any good AI system is flexibility. Although it seems that a lot of progress has been made in using AI approaches for specific, isolated jobs, the key idea. At the forefront of robotics technology powered by AI, it appears to be the subsystems' interface with integrated surroundings. This necessitates the subsystems' adaptabilityby themselves. Additionally, it ought to be expandable in order to hold additional user data from the subject matter expert. The majority of AI systems are internet-based, which limits or decreases their use, especially in isolated or rural locations. The government can help farmer’s by creating a gadget that allows them to use web services and has a reduced tariff to work specifically with agricultural AI systems. The capacity of an intelligent or expert system to complete tasks precisely and quickly is one of its main characteristics. The majority of the systems are either inaccurate or have slow response timeseven both of them. A system lag influences the task that a user chooses strategy. The selection of a strategy is thought to be based on a cost function that combines two elements:

1. The work necessary to synchronize the availability of the input system.
2. The precision degree made possible. People want to reduce work and maximize precision.

Inconsistencies between the real implementation and control attempts of AI

The fact that photos obtained under application are different from those utilized in control conditions due to various aspects including fluctuating lighting, complicated backgrounds, camera angle, etc. Furthermore, grains grown in field exhibit physical heterogeneity even within the same location. Then, in such instance, the physiological Individual features increase the number of variables that need to be taken into account when processing images, so in order to enhance the current system, a bigger and more varied set of control data was needed. However, using computer vision, algorithms such as DB (Deep Belief Network) CNN (Convolution Neural Network) notwithstanding the little quantity of case study point to exciting future uses for handling complex, large-scale data collections. Furthermore, the most pertinent data should be handled by a system in order to reduce response time. The capacity of a system to complete tasks accurately and quickly is crucial in determining its commercial worth, and it has a significant impact on users' decision-making. What buyers value most is the minimized their level of effort and the highest level of precision (Eli-Chukwu, 2019).

Potentially unequal mechanization of AI

Robot shipments are expected to expand by 9 annually on average in the United States, 12 per cent in Asia-Australian countries, and 8per cent in Europe between 2011 and 2013, according to projections for the period. This trend indicates that by 2030, robot penetration is expected to reach 15 per cent and will by 2045, reach 75 per cent. Nonethe less, there is a chance that mechanization will be dispersed unevenly with certain regions lack resources and face unchangeable circumstances despite scientific advancements and technological progress(Popa and Cosmin,2011). For example, since most AI systems are based on the Internet, their usage may be constrained in remote or rural places with the absence of a web service and expertise with handling AI activities.As a result, it is reasonable to anticipate a slower and more uneven adoption of AI in agriculture. In the interim, it is unclear if this adoption would boost food production beyond some natural land constraints.

Merits of artificial intelligence in agriculture

Artificial intelligence has shown to be a very beneficial tool for the agriculture sector, helping to solve a variety of problems such risinglabor costs, pest infestations and crop production. The food and agriculture industries have greatly benefited from the use of AI, which has made it possible to do more with regard to crop monitoring, pest identification, field management, harvesting, chemical application, weeding, weather forecasting and irrigation.

Demerits of artificial intelligence in agriculture

Significant challenges facing agriculture include the lack of an irrigation infrastructure, climate changes, groundwater density, food scarcity and waste, and many more. The outcome of growing relies heavily on the acceptance of different cognitive answers. Even though much research is still ongoing and certain applications are already on the market, the sector is still significantly under fulfilled(Davenport*et al.*,2020). The COVID-19 epidemic has brought attention to the vulnerabilities in our agri-food systems and the disparities that exist in our societies, adding to the mounting challenges in the fight against hunger and food insecurity (Shobila and Mood, 2014). Via increased food system resilience, agricultural operations can be optimized through the application of artificial intelligence (AI) approaches. A range of applied challenges are addressed by an ever-evolving group of technologies called AI and has recently seen widespread application in farming (Javaid *et al.,* 2022). But even with all benefits, there are still some issues with AI technology. The risk of unemployment is, first and foremost, the biggest social worry. Essentially, the majority of intelligent labour could take the role of repetitive tasks and labour robots and machinery; hence, there is a substantial human interference, which will result in significant issues with the standards of employment. Despite of this, there are other challenges also of AI in agriculture.

Due to the fact that physical devices, like the Internet of Things, can be left out in the open for extended periods of time without being monitored, they are first susceptible to hardware attacks. Common countermeasures for security include data encryption, altering tag frequency, implementing tag removal policies, and utilizing blocking tags, and so forth. Device capture attacks are another risk that location-based services face, so after once the device is taken over,the attacker can extract the cryptographic implementations and so have limitless availability of the device's data. While transferring from the device, data can also be compromisedto the gateway, after which the information is uploaded to additional systems, such as the cloud. The automatic processes on the farm may be un-invitedly disrupted by data manipulation on the cloud servers. Cloud infrastructures can also be interfered with by techniques like denial of service (DoS), session hijacking, and login abuse. The associated security guidelines comprise data flow control and cryptographic techniquesregulations, identification verification systems, etc. As a result, security concerns are creating major complicationsand ought to be dealt with on several levels.

Future of AI in agriculture

Just roughly 10per cent of this extra output can originate from underutilized landand existing production ought to cover the remaining costs intensification. In this instance, utilizing the most recent technical farming more effective is still one of the biggest challenges. Current agricultural production intensification strategies significant energy inputs and the market require superior food products (Panpatte, 2018; Shubham *et al.,* 2023). Global industries are poised to undergo a transformation thanks to robotics and autonomous systems (RAS). These technologies will have a significant impact on sizable economic sectors with low productivity like agro-food, or farm-produced food to the store rack). The agro-food chain in the UK produces over £108 billion annually, employing 3.7 million people in a genuinely global a sector that exported 20 billion pounds in 2016 (Shubham *et al.,* 2021; Bechar*et al.,* 2016).

Conclusion

Our present study emphasized how AI can revolutionize the agricultural industry by fostering more resilient and sustainable farming methods. With the world's population continuing to rise, creative solutions are more needed. The agricultural industry may reduce its environmental impact and increase productivity while ensuring food security by utilizing AI. To create a more sustainable agricultural ecosystem, the way forward will involve stakeholder collaboration, infrastructure investment, and a dedication to moral technology deployment methods.The use of AI in agriculture marks a substantial advancement in upgrading farming methods and tackling the urgent issues of efficiency, sustainability, and food security. Farmer’s may reduce their environmental impact, maximize crop yields, and optimize resource use by utilizing AI technology in precision agriculture, automated systems, and predictive analytics. AI enables data-driven decision-making which makes quick interventions in resource allocation and crop health management possible. As a result, farmer’s are able to adopt more sustainable techniques that support long-term ecological balance in addition to increasing output. There are obstacles in the way of a broad adoption of AI in agriculture, though. It is imperative to address concerns like data quality, accessibility and farmer’s digital literacy in order to guarantee fair advantages throughout the agricultural sector. Ethical issues pertaining to labour implications and data privacy also need to be carefully considered. In conclusion, artificial intelligence has enormous potential to revolutionize agriculture. Through the adoption of these technologies, the agriculture industry can progress towards a future that is more robust, capable of satisfying the needs of an expanding world population while preserving natural resources. Realizing the full potential of AI will need stakeholder collaboration, infrastructural investments, and a dedication to moral behaviour. This will ultimately result in a more secure and sustainable food system.

Acknowledgements

I would like to express my great appreciation and gratitude to all the authors for providing their assistance and their contribution for valuable and constructive suggestions.

Conflict of interest statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article. Author(s) hereby declare that NO generative AI technologies and text-to-image generators have been used during the writing or editing of this manuscript.

Disclaimer (Artificial intelligence)

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

Option 2:

Author(s) hereby declare that generative AI technologies such as Large Language Models, etc. have been used during the writing or editing of manuscripts. This explanation will include the name, version, model, and source of the generative AI technology and as well as all input prompts provided to the generative AI technology

Details of the AI usage are given below:

1.

2.

3.

References

Abdullahi HS, Mahieddine F and Sheriff RE. 2015. Technology Impact on Agricultural Pro ductivity: A Review of Precision Agriculture Using Unmanned Aerial Vehicles. *Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering* 388–400.

Ahirwar S, Swarnkar R, Bhukya S and Namwade G. 2019. Application of drone in agriculture. *International Journal of Current Microbiology and Applied Sciences* 8(1): 2500–2505.

Anonymous. 2020. "Hunger and Food Insecurity." *Food and Agriculture Organization of the United Nations, www.fao.org/hunger/en/.*

Banerjee G, Sarkar U, Das S and Ghosh I. 2019. Artificial Intelligence in Agriculture: A Literature Survey. *International Journal of Scientific Research in Computer Science Applications and Management Studies* 7(3):1-6.

Bechar A, Vigneault and Clement *2016*. Agricultural robots for field operations: Concepts and components. *Biosystems Engineering 149:94-111*.

Brazeau M. 2018. Fighting Weeds: Can we Reduce, or Even Eliminate, Herbicides by Utilizing Robotics and AI", available at: https://geneticliteracyproject.org/2018/12/12/fighting-weeds-can-we-reduce-or-even-eliminate-herbicide-use-through-robotics-and-ai/.

Clifton J, Glasmeier A, and Gray M. 2020. When machines think for us: The consequences for work and place. *Cambridge Journal of Regions, Economy and Society* 13(1): 3–23.

Costa FG, Ueyama J, Braun T, Pessin G, Osorio FS and Vargas PA. 2012. The use of un manned aerial vehicles and wireless sensor network in agricultural applications. *IEEE International Geoscience and Remote Sensing Symposium. https://doi. org/10.1109/igarss.2012.6352477.*

Davenport T, Guha A, Grewal D, and Bressgott T. 2020. How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science* 48(1): 24–42.

Deutsch CA, Tewksbury JJ, Tigchelaar M, Battisti DS, Merrill SC, Huey RB and Naylor RL. 2018.Increase in crop losses to insect pests in a warming climate. *Science 361: 916–919.*

Dharmaraj V and Vijayanand C. 2018. Artificial intelligence (AI) in agriculture. *International Journal of Current Microbiology and Applied Sciences* 7(12): 2122–2128.

Dolfsma W, Isakhanyan G and Wolfert J. 2021. Information exchange in supply chains: The case of agritech. *Journal of Economic Issues* 55(2): 389–396.

Dukes MD, Zotarelli L, Liu GD and Simonne EH. 2015. Principles and practices of irrigation management for vegetables. *University of Florida Institute Food and Agricultural Science Bulletin, AE* 260-277.

Eli-Chukwu N and Ogwugwam EC. 2019. *Applications of Artificial Intelligence in Agriculture: A Review. Journal of Engineering, Technology and Applied Research* 9(4):4377-4383.

Eli-Chukwu NC. 2019. Applications of artificial intelligence in agriculture: A review. *Engineering, Technology & Applied Science Research* 9(4): 4377–4383.

Elijah O, Member S, et al. 2018. An Overview of Internet of Things (IoT) and Data Analytics in Agriculture: Benefits and Challenge. *IEEE Internet of Things Journal* (99):1-19.

Elshorbagy A and Parasuraman K. 2008. On the relevance of using artificial neural networks for estimating soil moisture content. *Journal of Hydrology* 362(1-2): 1-18

Fan M, Shen J, Yuan L, Jiang R, Chen X, Davies WJ and Zhang F. 2012. Improving crop productivity and resource use efficiency to ensure food security and environmental quality in China. *Journal of experimental botany* 63(1):13-24.

Harker KN. 2001. Survey of yield losses due to weeds in central Alberta. *Canadian Journal of Plant Science* 81(2): 339–342.

Jasim MA and Al-Tuwaijari JM. 2020. Plant leaf diseases detection and classification using image processing and deep learning techniques. *International Conference on Computer Science and Software Engineering (CSASE)* 259-265.

Javaid M, Haleem A, Khan IH and Suman R.2022. Understanding the potential applications of artificial intelligence in agriculture sector. *Advanced Agrochemistry*2.

Kakani V, Nguyen VH, Kumar BP, Kim H and Pasupuleti VR. 2020. *A critical review on computer vision and artificial intelligence in food industry. Journal of Agriculture and Food Research* 2:100033.

Kamalakannan C, Kamaraj C, Paramasivam VS and Paranjothi SR. 2011, January. Switched reluctance machine in automotive applications - A technology status review. In 2011 1st International Conference on Electrical Energy Systems 187-197.

Kartikeyan P and Shrivastava G. 2021. Review on emerging trends in detection of plant diseases using image processing with machine learning. *International Journal of Computer Applications* 975: 8887.

Meydani A, Dehghanipour A, Schoups G and Tajrishy M. 2022. Daily reservoir inflow forecasting using weather forecast downscaling and rainfall-runoff modeling: Application to Urmia Lake basin, Iran. *Journal of Hydrology: Regional Studies 44: 101228*

Moallem P and Razmjooy N. 2012. A multi-layer perception neural network trained by invasive weed optimization for potato color image segmentation. Trends in Applied Sciences Research 7(6): 445-455.

Munirah MY, Rozlini M and Siti YM. 2013. An Expert System Development: Its Application on Diagnosing Oyster Mushroom Diseases. *13th International Conference on Control, Automation and Systems*, Gwangju, South Korea, 20-23.

Ortiz MP, Gutierrez PA, Pena JM, Sanchez JT, Granados FL, Martinez CH. 2016. Machine Learning Paradigms for Weed Mapping Via Unmanned Aerial Vehicles. Symposium Series on Computational Intelligence, Athens, Greece.

Palmgren MG, Edenbrandt AK, Vedel SE, Andersen MM, Landes X, Osterberg JT, Falhof J, Olsen LI, Christensen SB, Sandoe P, Gamborg C, Kappel K, Thorsen BJ and Pagh P. 2015. Are we ready for back-to-nature crop breeding? *Trends in Plant Science 20: 155–164*

Panpatte DG. 2018. Artificial Intelligence in Agriculture: An Emerging Era of Research. Anand Agricultural University 90-102.

Partel V, Charan Kakarla S and Ampatzidis Y. 2019. Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. *Computers and Electronics in Agriculture* 157:339-350.

Pawar S, Shedge S, Panigrahi N, Jyoti AP, Thorave P and Sayyad S. 2022. Leaf disease detection of multiple plants using deep learning. *International conference on machine learning, big data, cloud and parallel computing (COM-IT-CON)* 1: 241-245.

Popa and Cosmin. *2011*. Adoption of Artificial Intelligence in Agriculture. *Bulletin of the University of Agricultural Sciences & Veterinary* 3(8):17-38.

Puri V, Nayyar A, Raja L. 2017. Agriculture drones: a modern breakthrough in precision agriculture. *Journal of Statistics and Management Systems* 20(4): 507-518.

Ryan M, van der Burg S, and Bogaardt MJ. 2021. Identifying key ethical debates for autonomous robots in agri-food: A research agenda. *AI and Ethics* 2: 493-507.

Shekhar Y, Dagur E, Mishra S, Tom RJ, Veeramanikandan M and Sankaranarayanan S. 2017. Intelligent IoT based automated irrigation system. *International Journal of Applied Engineering Research* 12(18): 7306–7320. https://intellias.com/artificial-intelligence-in-agriculture/

Shobila P and Mood V. 2014. Automated irrigation system using robotics and sensors. *Internationl Journal of Scientific and Engineering Research* 3(8): 9-13.

Shubham, Sharma U and Chahal A 2021. Effect of forest fire on ammonification and nitrification: A study under Chir Pine (*Pinus roxburghii*) forest areas of Himachal Pradesh. Indian Journal of Ecology 48(2): 376-380.

Shubham, Sharma U and Kaushal R. 2023. Effect of soil applied natural and synthetic nitrification inhibitors on nitrogen transformations and nitrification inhibition in NW Himalayan region of Himachal Pradesh. *Indian Journal of Soil Conservation*51(2): 95-101.

Smriti, Rai A, Shubham and Kaushal S. 2024. Potential of Plant Based Metallophytes for Phytoremediation in Agriculture. *Journal of Experimental Agriculture International 46 (6): 154-161.*

Stigliani L and Resina C. 1993. Seloma: Expert system for weed management in herbicide intensive crops. Weed Technology 7(3): 550-559.

Thakur P, Wadhwa H, Shubham and Kaushal S. 2023.Soil Conditioners: Refinement of Soil Health for Better Tomorrow *Current Journal of Applied Science and Technology42(42): 1-9*

Tobal AM and Mokhtar SA. 2014. Weeds identification using evolutionary artificial intelligence algorithm. Journal of Computer Science 10(8): 1355-1361.

Viktor S, Tímea C and Janos A. 2021. The applicability of big data in climate change research: The importance of system of systems thinking. *Frontiers in Environmental Science 9(17) 34-48. https://doi.org/10.3389/fenvs.2021.619092.*

Zhao Z, Chow TL, Rees HW, Yang Q, Xing Z and Meng FR. 2009. Predict soil texture distributions using an artificial neural network model. *Computers and Electronics in Agriculture* 65(1): 36-48.

Zhao Z, Chow TL, ReesHW, Yang Q, Xing Z, and Meng FR. 2009. Predict soil texture distributions using an artificial neural network model. *Computers and Electronics in Agriculture,* 65(1): 36–48.

Zhong X and Zhou S. 2020. *Risk analysis method of bank microfinance based on multiple genetic artificial neural networks. Neural Computing & Applications* 32: 5367–5377.