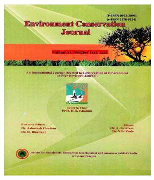
Environment Conservation Journal 25 (1):274-288, 2024

Journal homepage:https://www.environcj.in/

Environment Conservation Journal

ISSN 0972-3099 (Print) 2278-5124 (Online)



Artificial intelligence (AI) and its applications in agriculture: A Review

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ARTICLE INFO

Received : 15 June 2023
Revised : 30 September 2023
Accepted : 09 October 2023

Available online: 05 February 2024

Key Words:
Artificial intelligence
Food production
Agricultural problems
Technology

ABSTRACT

Providing food for the growing population is a challenging task, however, with historical agricultural practices, we can't meet the food requirement of the world population. We are in the need to adopt modern technology to overcome adverse climatic and cultural challenges, which are faced by current generation, that is Artificial Intelligence (AI). AI is the booming technology in the agriculture, which uses different sensors and neural networks and uses resources minimally based on need and predict the coming obstacles, which causes huge loss to crop. This review explain is, various applications of AI in the sustainable agriculture for crop managemen by overcoming realtime challenges and importance of AI in agriculture by comparing with traditional methods.

Introduction

By the 1960s, AI had already been developed in computer science. John McCarthy, who is often called the "founder" of the field, first defined artificial intelligence in 1956 as the "science and engineering of making intelligent machines" (Andresen, 2002). From the 1950s to the 1980s, most AI research focused on how to use algebra, how to prove geometric theorems, and how to learn English [Lu, 2019]. In 1983, researchers wrote about the first-time computers were used in agriculture. This marked the beginning of artificial intelligence in the field (Gouravmoy *et al.*, 2018). Since then, the agricultural sector's use of computers and other forms of technology has flourished. As of 2019, AL is being used in several fields, including medicine, business, banking, education, industry, security, and agriculture (Jha *et al.*, 2019). Primary jobs like farming often require a lot of hard effort, tenacity, and persistence despite little pay and an unpleasant way of life. Farmers put a lot of time and effort into growing good crops, and they have little choice but to rely on agriculture for their livelihood. However, they often make very little money and even lose money due to unfavourable environmental or

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Doi:https://doi.org/10.36953/ECJ.24052645

economic situations. In a similar vein, the inability to choose an appropriate secondary occupation, which needs more time and energy, is a significant factor that contributes to the problem. Farmers will have more time and energy at their disposal, thanks to the assistance of AI, to dedicate to finding and putting into action answers to the logical problems they face. AI has been used to increase productivity, boost soil quality and crop yields, and address a wide range of other problems in the agricultural industry (Alreshidi, 2019). Driverless tractors, smart irrigation systems, fertiliser and spraying systems, smart spraying, vertical farming software, and AI-based robots are all examples of AI-based agriculture. AI-based agriculture has allowed farmers to get more done without adding staff. Self-driving tractors, also known as driverless tractors or autonomous tractors, are one example of a machine that can do tasks with a level of precision and mistake prevention that is just not feasible while a human operator is in charge [Khan *et al*., 2021]. Breeding 1.0 lasted from around 10,000 to 12,000 years ago [Meyer *et al*., 2012], during which time people from all across the globe discovered and cultivated almost 7,000 different types of food plants. The discovery of inbreeding depression in the late 19th and early 20th centuries marked the beginning of breeding stage 2.0. Replicated field trials, controlled crossings, statistical analyses, formal experimental designs, hybrid breeding, pedigree-based estimates of breeding values, and precise yield measurement at scale (e.g., with multirow combines) were just some of the advances made in the science of breeding during this time [Moran and Smith 1918]. About 30 years ago, molecular markers and genomic data started to augment phenotypic data, marking the beginning of breeding 3.0 [Meuwissen *et al*., 2001]. Large amounts of omics data and the fast development of informatics technologies are ushering in Breeding 4.0 [Wallace *et al*., 2018]. Since crop domestication marked the beginning of the plant breeding process, new methodologies mediated by diverse technological revolutions have continually expanded the science to quicken the speed, raise the accuracy, and increase the precision of plant breeding [Zargar *et al*., 2015]. This research has already delivered the green revolution by generating semidwarf cultivars, nutrient-responsive cultivars, and hybrid cultivars over the course of the last decade [Bhat et al., 2021]. To generate agricultural cultivars at a faster speed with better accuracy and greater precision, however, more accurate, high-throughput techniques are needed in light of population expansion, shrinking arable land, and climatic changes. It has been proposed that the relatively new area of artificial intelligence offers amazing potential to help in the creation of climate-resilient smart crops. Artificial intelligence (AI) is the fastest-growing field in computer science at the moment because it allows programmers to make machines that are as smart as humans [Harfouche, 2019]. Modern computing is often characterised by phrases like "big data," "machine learning," and "artificial intelligence" [Cravero and Seplveda, 2021]. Massive data sets with unusually complicated structures that challenge traditional data analysis methods are at the heart of the big data movement [Supriya and Deepa, 2020]. As used here, AI programmes a machine to make decisions in complex scenarios where human effort would be inefficient due to the time and effort required [Berente *et al*., 2021]. Machine learning (ML) is a subfield of artificial intelligence in which computers learn to make inferences from large collections of examples. The collection of meteorological or Earth System-related measurements, as well as high spatial and temporal resolution Earth System Model (ESM) outputs for analysis, is what constitutes "big data" in the context of weather and environmental applications; machine learning (ML) is the refinement or discovery of new linkages between locations, times, and quantities in the datasets (such as where sea surface temperature features aid the weather prediction for months over land regions), etc [Huntingford *et al*., 2019]. This novel usage of computer memory brings computations much closer to the site where data is stored, improving both efficiency and accuracy [Huntingford *et al*., 2019]. The primary focus of using AI in breeding is to provide continuous farm monitoring, which complements the job of the breeder. Indeed, with farm automation and data standardisation, breeders may be able to devote more time to higher-value tasks by spending less time in their facilities. A significant advantage of AI is the time it saves in identifying and processing data. Gaining self-assurance and the ability to respond quickly allows breeders and technical advisers to take decisive action when it is needed [Talaviya *et al.*, 2020].

Application of AI in agriculture

Soil management

In addition to water, nitrogen, phosphorus, potassium, and proteins, which are all essential for healthy crop growth and development, the soil is one of the most significant aspects in agriculture's success [Eli-Chukwu and Ogwugwam, 2019]. Compost and manure boost soil porosity and aggregation, while a reduced tillage approach prevents soil from physically degrading. Negative influences, such as soil-borne diseases and pollutants, may be reduced with proper soil management (fig-1) [Eli-Chukwu and Ogwugwam, 2019]. Soil maps, which employ AI to highlight the interactions between soil and landscape, as well as the different layers and proportions of soil below ground, are one more example [Elijah, 2018].

Fig-1: AI in soil management

Weed management

Weeds are one of the main things that bring down a farmer's expected profit. Dried bean and corn yields may drop by half if weed invasion is not controlled, while wheat yields might drop by almost half due to weed competition. Some weeds are harmful and even pose a hazard to public health, but they nevertheless compete with crops for water, nutrients, and sunshine [Eli-Chukwu and Ogwugwam, 2019]. Although weed spray is widely used, there is concern that it may be harmful to human health and that its misuse may cause environmental damage. Therefore, lab-tested AI weed identification(fig-2) systems have been developed to determine the appropriate spray dosage and correctly spray the intended area, reducing expenses and the possibility of crop damage [Partel, 2019].

Crop production

Crop efficiency and production may be increased with the use of artificial intelligence-based technologies, as stated by Talaviya *et al.* (2020). These technologies aid in addressing difficulties related to weeding, irrigation, crop establishment, and crop monitoring. Concerns such as unpredictable climate change, a rapidly expanding population, and food poverty have pushed the adoption of artificial intelligence to assure sustainable agriculture. Ghosh and Singh (2020) claim that AI has been used throughout several subfields of agriculture, including but not limited to general crop management systems, pest and disease control, soil and irrigation management, weed management, and yield prediction. (fig-3). Drones and other robots are increasingly being used by farmers in a variety of applications around the farm.

Irrigation

It is critical that we construct an irrigation system that guarantees the correct use of water resources since 85 percent of freshwater is used on agricultural operations worldwide (Talaviya *et al.*, 2020). Soil has to be kept wet for plant development, and this is what irrigation is all about. Low crop yields are a direct consequence of inefficient irrigation systems, which may also contribute to the waste of water resources and the leaching of chemicals in the soil [Eisenhauer, 2021]. Soil and water management are obviously crucial to preventing crop failure and soil degradation. In agriculture, irrigation is often performed by farmers using antiquated irrigation technologies like watering cans or buckets. These antiquated systems should be replaced with current approaches using artificial intelligence. Artificial intelligence (AI) used in a machine-based irrigation control system guarantees effective management of both soil and water [Angelin Blessy and Kumar, 2021]. A well-designed irrigation system will boost agricultural production by boosting yields and maintaining output, whereas a poorly designed system will have the opposite effect and diminish crop productivity. In order to save water during

Fig-2: AI in weed management

Fig-3: AI in crop production

irrigation and lessen the need for farmhands, agricultural monitoring is used [Shekhar *et al.*, 2019]. Mechanical irrigation systems are now widely used in agriculture(fig-4).

Weather & price forecasting

One of the difficulties is that, as we have previously said, climate change makes it more difficult for farmers to estimate the optimal times to harvest, sow seeds, and prepare the land. Other difficulties include the fact that climate change also makes it more expensive. Farmers will be able to acquire information on weather analysis and make educated choices about the crop to produce, the seeds to sow, and the time of harvesting with the assistance of AI weather forecasting (fig-5). This will allow farmers to get information on the weather. Price forecasting allows farmers to maximize their earnings by predicting how much their products will be worth in the weeks to come. This allows farmers to budget their expenses more effectively.

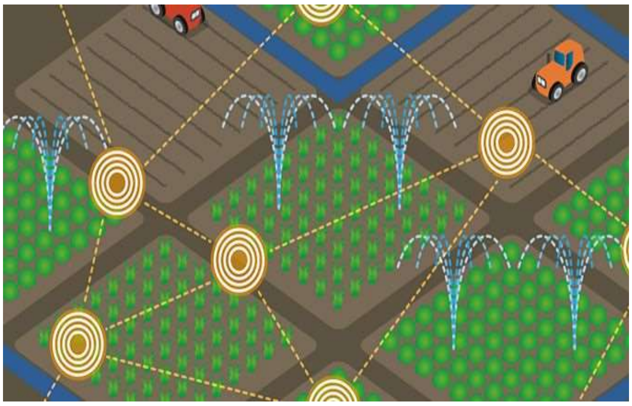

Fig-4: AI in irrigation

Pest and disease management

Farmers worry a lot about pest infestation and crop disease since they have both been related to

Fig-5: AI in weather forecasting

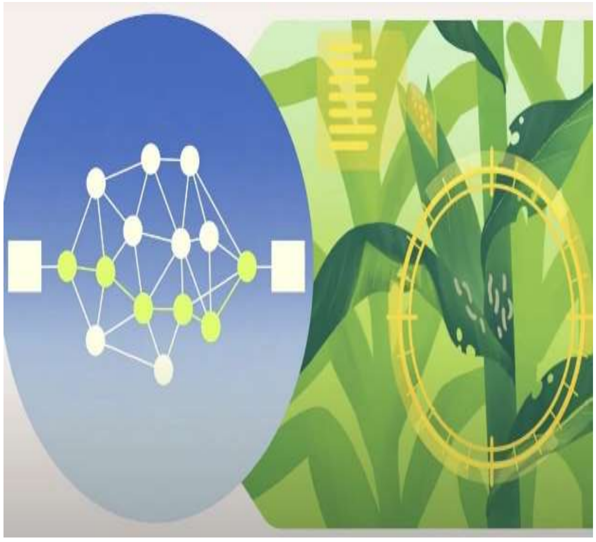

Fig-6: AI in pest and disease identification

generating a big economic loss in agriculture [Gouravmoy*et al.*, 2018]. This is one of the major challenges facing agriculture today. Pests and crop diseases not only result in monetary loss but also endanger the ecosystem and lead to food insecurity [Liu *et al.*, 2020]. Because of this, the use of artificial intelligence to identify agricultural illnesses and provide treatment recommendations [Clara, 2019). The use of AI for early identification of pests and illnesses is crucial for efficient management in agricultural settings. "AI and machine learning may help identify those places most at risk of invasions or outbreaks and help with strategies to control the spread of invasives or illnesses," Bestelmeyer *et al.* [2020] write. Conventional farmers have relied on their expertise to combat plant diseases and pests. Businesses now employ IT systems for everything from pest control to disease analysis and control recommendations [Sharma 2021]. Through this method of early identification and management, agricultural plants will suffer less damage from pests and diseases, resulting in a greater harvest(fig-6).

Phenomics

The study of plant phenotypes, or outward physical characteristics, is known as "plant phenomics" (Kumar *et al.*, 2015). With the potential for high-throughput analysis in agricultural fields, plant field phenotyping has gained a lot of interest in recent years (Selvaraj *et al.*, 2020). Improvements in quantitative agricultural characteristics evaluation may be attributed to the use of machine learning techniques and other technical advancements in the realm of picture analysis (fig-7). (Zhao and Rewald, 2016; Selvaraj *et al.*, 2020; Dobbels and Lorenz, 2019). CNN-based identification and analysis of wheat spikes utilising wheat field trials photos taken over one planting season produced an average accuracy of 88 to 94 percent across varied sets of test photographs. CNN (Convolutional Neural Networks) has shown superior performance, making it a reliable model for genome-based selection and prediction in plant breeding (Hasan *et al.*, 2018). Plant image segmentation, which required the collection and analysis of several photos of plants, also made use of the RF method (Carvalho *et al.*, 2022). Model projections led to the identification of a wide range of plant growth characteristics (Selvaraj *et al.*, 2020).

Precision farming

"Right location, right time, and right goods" sums up precision farming. The labor-intensive aspects of farming may be replaced with the considerably more precise and manageable precision farming technology. The measurement of plant stress is one example of precision farming. This may be gleaned from various plant sensor data and high-resolution

Fig-7: AI in phenomics

photos. Sensor data is used to train a machine learning model for stress detection (fig-8).

Fig-8: AI in precision farming

Plant breeding

When used in agriculture, artificial intelligence (AI) is an intriguing high-tech system that offers unlimited possibility; this, in turn, opens up new vistas for digital breeding [Montesinos-López *et al*. 2018]. High-throughput genomics and phenomics for advanced breeding are only two examples of how artificial intelligence (AI) is being used to speed up the process of developing new plant varieties [Harfouche *et al*., 2019; Esposito *et al*., 2020; Reinoso-Peláez *et al*., 2022 and Crossa *et al*., 2017]. More and more, ML methods are being used for genomic prediction, genomic selection, and marker-assisted selection (Reinoso-Peláez *et al*., 2022; Crossa *et al*., 2017). Hundreds of millions of dollars have already been spent by agricultural giants like Monsanto and John Deere in developing such technology that can use vast data on soil type, seed variety, and weather to help farmers decrease costs and increase yields (Faulkner *et al*., 2014). Both of their operations rely on data from similar sources, such as weather predictions and Google Maps. Moreover, they may obtain information from agricultural machines that have been wirelessly sent to the cloud (Stergiou *et al*., 2017). Companies such as Nippon Electric Company, Limited (NEC; headquartered in Minato, Tokyo, Japan) and Dacom (headquartered in Santa Clara, USA) used environmental sensors and massive data analytics technologies as part of a precision-farming experiment in Romania. Increased agricultural output is a direct result of modern agriculture's increased use of data and computing systems (Bilali and Allahyari 2018). The complexity of agricultural data sets presents challenges for creative architecture and frameworks, algorithms, and analytics, all of which are essential for gleaning the value and hidden information contained therein (Priya and Ramesh, 2020). Current efforts in artificial intelligence study methods including machine learning (ML), deep learning (DL), and predictive analysis (PA) have the goal of bettering our capacities for forethought, reflection, deliberation, and action (Shaw *et al.*, 2019). Breeders of plants are working on systems to help researchers learn more about how plants respond to different climates [Jeong *et al.*, 2016] (fig-9).

Fig-9: AI in Plant Breeding

Plant genomics

In order to gather massive datasets and develop novel biological hypotheses, genomics typically employs ML, the discipline of using programming to train computers to learn from data. To get fresh insights from the flood of genomics data, more expressive ML models are necessary. Deep learning's innovative use of large datasets has reshaped fields like natural language processing and computer vision. In addition, deep learning is a cutting-edge method for processing data and images that shows great promise and vast potential. Additionally, deep learning has just entered the agriculture industry after being effectively implemented in a number of other sectors (Bioshop, 2016). There has been a lot of research on the efficacy of various deep learning methods for genomic prediction in recent years. But unlike conventional statistical learning techniques, deep learning approaches are nonparametric models, meaning they can easily accommodate a wide variety of input-output relationships (Kukar *et al.*, 2007). For genomic selection, there is strong evidence that deep learning algorithms capture nonlinear patterns more successfully than conventional genome-based techniques (GS). These methods provide a meta-image of GS efficiency and show how these methods might be useful in solving challenging plant breeding challenges. Moreover, deep learning algorithms may integrate data from numerous sources, and they have shown the capacity to enhance prediction accuracy for huge plant breeding datasets, as is frequent in gene selection-assisted breeding. Therefore, it is essential to use deep learning methods on huge datasets for both training and evaluation (Bernardo, 2008).

Produce harvesting

Mechanizing crop and harvest management is essential for farmers in order to cut down on labour costs and increase agricultural output [Waleed *et al.*, 2020]. Mechanization in crop management and product harvesting is highly sought after by farmers due to the time and labour savings it provides. The use of drones for crop monitoring, robots in farming, machine learning and big data in farming, etc., have all benefited greatly from AI's contribution to mechanisation in agriculture [Mentsiev *et al.*, 2021]. Artificial intelligence has been shown to improve agricultural plant monitoring, which in turn speeds up harvesting, processing, and distribution of crops (Fig-10) [Talaviya *et al*, 2020]. Since the burden is decreased thanks to the application of AI, the issue of needing numerous people is resolved. Even nut harvesting can be done by robots and AI now [Mentsiev *et al*, 2021]. Unlike human workers, robots may be taught to work at a quicker pace while harvesting [Alreshid 2019]. Mechanized harvesting methods, such as harvesting robots equipped with sensors to detect their surroundings, have also been developed [Montoya-Cavero *et al*, 2021]. (Table-1).

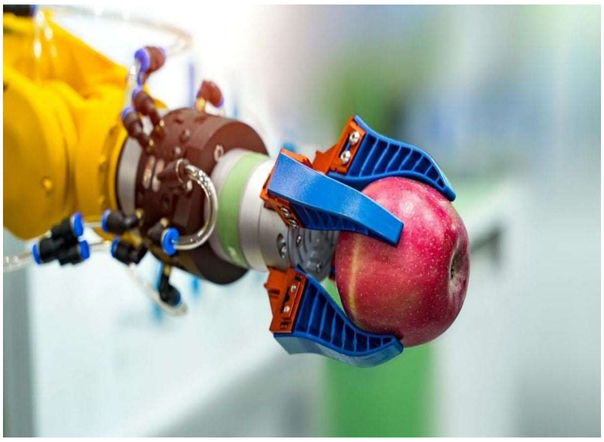

Fig-10: AI in harvesting

Table 1. Different AI techniques in agriculture management

Management	Technique	Strength	Limitation	References
Soil	MOM	Minimizes nitrate leaching, maximizes production.	Takes time. Limited only to nitrogen.	Li, 2000
	Fuzzy Logic: SRC-DSS	Can classify soil according to associated risks.	Needs big data. Only a few cases were studied.	Lopez *et al*., 2008
	DSS	Reduces erosion and sedimentary yield.	Requires big data for training.	Montas, and Madramootoo, 1992
	ANN	Can predict soil enzyme activity. Accurately predicts and classifies soil structure.	Only measures a few soil enzymes. It considers more classification than improving the performance of the soil.	Tajik *et al*., 2012
	ANN	Can predict monthly mean soil temperature	Considers only temperature as a factor for soil performance.	Levine *et al*., 1996
	ANN	It predicts soil texture	Requires big data for training. Has restriction in areas of implementation.	Bilgili, 2011
	ANN	Able to predict soil moisture.	The prediction will fail with time as weather conditions are hardly predictable.	Zhao *et al*., 2009
	ANN	Successfully reports soil texture.	It does not improve soil texture or proffers solution to bad soil texture.	Elshorbagy, and Parasuraman, 2008
	ANN	Cost-effective, saves time, has 92% accuracy	Requires big data.	Chang, and Islam, 2000
	ANN	Can estimate soil nutrients after erosion.	Its estimate is restricted to only NH_4.	Behrens *et al*., 2005
Crop	CALEX	Can formulate scheduling guidelines for crop management activities	Takes time	Plant, 1998
	PROLOG	Removes less used farm tools from the farm.	Location-specific.	Lal *et al*., 1992
	ANN	Predicts crop yeild.	Only captures weather as a factor for crop yeild.	Snehal, and Sandeep, 2014
	ROBOTICS-Demeter	Can harvest up to 40 hectares of crop	Expensive: Uses a lot of fuel.	Pilarski *et al*., 2002
	ROBOTICS	Has 80% success rate in harvesting crops	Slow picking speed and accuracy.	Henten *et al*., 2002
	ANN	Above 90% success rate in detecting crop nutrition disorder.	A little number of symptoms were considered.	Song and He, 2005

	FUZZY Cognitive Map	Predict cotton yield and improve crop for decision management.	It is relatively slow.	Papageorgiou *et al.*,2011
	ANN	Can predict the response of crops to soil moisture and salinity.	Considers only soil temperature and texture as factors.	Dai *et al.*, 2011
	ANN and Fuzzy Logic	Reduces insects that attack crops.	Shows inability to differentiate between crop and weed	Yang *et al.*, 2003
	ANN	Can accurately predict rice yield.	Time-consuming, limited to a particular climate.	Ji *et al.*, 2007
Disease	Computer vision system (CVS), genetic algorithm (GA), ANN	Works at a high speed. Can multi- task.	Dimension-based detection which may affect good species.	Balleda *et al.*, 2014
	Rule-Based Expert, Data Base (DB)	Accurate results in the tested environment.	Inefficacy of DB when implementing in large scale.	Balleda *et al.*, 2014
	Fuzzy Logic (FL), Web GIS	Cost-effective, eco-friendly.	Inefficiency due to scattered distribution. Takes time to locate and disperse data. The location of the data is determined by a mobile browser.	Jesus *et al.*, 2008
	FL Web-Based, Web-Based Intelligent Disease Diagnosis System (WIDDS)	Good accuracy. Responds swiftly to the nature of crop diseases.	Limited usage as it requires internet service. Its potency cannot be ascertained as only 4 seed crops were considered.	Kolhe *et al.*, 2011
	FL & TTS converter	Resolves plant pathological problems quickly.	Requires high speed internet. Uses a voice service as its multimedia interface.	Kolhe *et al.*, 2011
	Expert system using rule-base in disease detection	Faster treatment as diseases are diagnosed faster. Cost effective based on its preventive approach.	Time consuming. Needs constant monitoring to check if pest has built immunity to the preventive measure.	Munirah *et al.*, 2013
	ANN, GIS	95% accuracy	Internet-based. Some rural farmers will not have access.	Liu *et al.*, 2006
	FuzzyXpest provides pest information for farmers. It is also supported by internet services.	High precision in forecast.	Internet dependent.	Siraj and Arbaiy, 2006
	Web-Based Expert System	High performance.	Internet and web based.	Virparia,2007
	ANN	Has above than 90% prediction rate.	The ANN does not kill infections or reduces its effect.	Wang *et al.*, 2006
Weed	ANN, GA	High performance. Reduces trial and error.	Requires big data.	Tobal and Mokhtar, 2014
	Optimization using invasive weed optimization (IVO), ANN	Cost effective, enhanced performance.	Adaptation challenge with new data.	Moallem and Razmjooy, 2012

	Mechanical Control of Weeds. ROBOTICS. Sensor machine learning	Saves time and removes resistant weeds.	Expensive. Constant use of heavy machine will reduce soil productivity.	Brazeau, 2018
	UAV, GA	Can quickly and efficiently monitor weeds.	Has little or no control on weeds. Expensive.	Ortiz *et al.*, 2016
	Saloma expert system for evaluation, prediction & weed management.	High adaptation rate and prediction level.	Requires big data and usage expertise.	Stigliani and Resina, 1993
	Support Vector Machine (SVM), ANN	Quickly detects stress in crop that will prompt timely site–specific remedies.	Only detects low levels of nitrogen.	Karimi, 2006
	Digital Image Analysis (DIA), GPS	Has above 60% accuracy and success rate.	Its success was achieved after 4 years and as such, it is really time consuming.	Gerhards and Christensen, 2003
	UAV	High rate of weed detection within a short period of time.	It is really expensive and requires vast human expertise.	Lopez Granados, 2011
	Learning Vector Quantization (LVQ), ANN	High weed recognition rate with short processing time.	The method of data input used affected the AI's perfromance.	Yang *et al.*, 2002

Challenges of AI adoption in agriculture

1. As more farmers become aware of the ways in which artificial intelligence might make farming more sustainable, adopting this technology may seem to be the next obvious step. On the other hand, there are still certain significant difficulties that are common knowledge, and they are as follows: Lack of familiarity with ai machines
2. Lack of experience with emerging technologies
3. Privacy and security issues

Conclusion

In light of the massive growth in population and therefore high demand for food, the conventional method of farming is no longer viable. Since this poses a global crisis, immediate and extreme measures are required. To satisfy the world's need, we must immediately adopt more efficient methods of agricultural production. Artificial intelligence has shown to be a groundbreaking technology with vast applications throughout the whole agricultural value chain. Plowing, seeding, fertilising, watering, protecting, and harvesting are all made easier using AI. This has helped ensure that the agricultural system is machine-driven, which has increased output while maintaining or improving quality. The research shows that using AI to automate agricultural processes will lead to significant labour savings, lower overall production costs, and higher outputs thanks to greater input efficiency. So, there will be a lot of productivity and a good harvest. The trajectory of AI is difficult to foresee. The purpose of artificial intelligence in the 1990s was to improve R&D efforts, but will that continue to be the case in the future? Examining the differences between robots and humans is a significant focus of current study. A shift in human responsibilities is inevitable if machines begin replacing human labour. In the future, thanks to the efforts of researchers, it's possible that machines will perform most of our job and robots will accompany us wherever we go. Soon, robots will be used in agriculture, leading to increased yields of higher quality.

Acknowledgement

The authors express his/her gratitude to ICAR-Indian Agricultural Research Institute, and ICAR-National Dairy Research Institute, for providing the opportunity to pursue master's degree by providing fellowship.

Conflict of interest

The authors declare that they have no conflict of interest.

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