International Journal of Environment and Climate Change

Volume 14, Issue 4, Page 562-573, 2024; Article no.IJECC.116317
ISSN: 2581-8627
(Past name: British Journal of Environment & Climate Change, Past ISSN: 2231–4784)

A Systematic Review of Artificial Intelligence: A Future Guide to Sustainable Agriculture

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/IJECC/2024/v14i44139

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/116317

Review Article

Received: 14/02/2024
Accepted: 19/04/2024
Published: 24/04/2024

ABSTRACT

The population is expected to grow rapidly and reach 10 billion people by the year 2050. As a result, there will be a greater need for food. The conventional techniques employed by the farmers proved insufficient to meet these demands. For this, new automated techniques were unveiled. Along with other cutting-edge computer science applications, farming has long made use of technologies like artificial intelligence. The focus has shifted in recent years to consider the applications of this new technology. A significant percentage of humanity's nutrition has come from agriculture for thousands of years, with the most significant contribution being the broad adoption of efficient farming techniques for a variety of crops. The application of artificial intelligence (AI) in agriculture has sparked a revolution in the field, and AI technology has made the agro-based commercial sector operate more profitably. Artificial intelligence (AI) technologies have the power to transform the future and address problems. This will make it easier for farmers to learn about

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climate variance and pests that lower crops. The use of AI focuses on identifying damaged crops and enhancing the ability of healthy crops to provide higher yields. This paper gives a thorough analysis of AI models used in agricultural applications. It also examines the use of AI models to specify sustainable goals. This article explores the challenges and opportunities for utilizing AI to develop future generations of sustainable agriculture through this comprehensive review.

Keywords: Artificial-intelligence; automation technology; sustainable agriculture; climate change.

1. INTRODUCTION

In the current era of digital technology, humans have advanced their thinking to unprecedented levels to create several forms of artificial intelligence, which will significantly boost any system's operational efficiency. Artificial intelligence is essential to every industry, including robotics, agriculture, health, and education [1]. Agriculture plays a vital role in the economic development of every nation. With the global population projected to reach 9.7 billion by 2050 [2], it is crucial to update traditional agricultural practices to maximize yield and minimize resources. Incorporating artificial intelligence into modernization efforts is essential to meet these demands and ensure efficient and effective food production. The Industrial Revolution of the 19th century saw significant improvements in human efficiency through mechanization. Similarly, the 20th century saw the introduction of computers and AI, leading to the digitalization of mechanization. Today, AI serves as a critical safeguard for the agriculture industry [3], mitigating challenges such as population growth, climate change, labor shortages, and food safety concerns. Agriculture has reached new heights in the modern era, thanks in part to the integration of AI technology [4].

Any economy's foundation for sustainability depends on agriculture up to a certain level [5]. Although it varies by country, it is essential to long-term economic growth and structural transformation [6]. Historically, agriculture was only used to produce crops and food. However, during the past 20 years, it has changed to include the production, distribution, marketing, and processing of agricultural and animal goods in a huge industrial scale. Nowadays, agriculture provides the primary means of subsistence, boosts GDP [7], facilitates national commerce, lowers unemployment, supplies raw materials for other industries' production, and advances the economy as a whole. Agricultural methods must be evaluated to provide novel solutions for maintaining and enhancing agricultural activity, given the exponential increase in world population. AI might be quickly adapted to agriculture through a variety of farming techniques. The idea of cognitive computing, also known as interchangeably AI, is the imitation of human mental processes by computer models. This leads to intense automation in AI-introduced agriculture, which aids in situational interpretation, acquisition, and response to boost agricultural system efficiency [8]. With the recent improvements in the farming industry, farmers may now receive additional benefits by using digital platforms like as chatterbots to give answers. Microsoft Corporation now runs a structured procedure in the Indian state of Andhra Pradesh, where 175 farmers offer services and solutions for the whole cultivation process [9]. Every facet of farming for a 30% improvement in crop output per hectare has already been observed in comparison to the conventional techniques. The following section discusses the numerous areas where AI expertise may be used to improve agriculture.

Over the past few decades, climate change, rising production costs, dwindling irrigation water supplies, and a decline in the number of farm workers have all contributed to significant problems for agriculture production systems [10]. The sustainability of the ecosystem, as well as the current and future food supply chains, are threatened by these issues [11]. Staying abreast of the ongoing climate change constantly requires significant inventions. It makes sense that the issue here is how to gather enough food to feed the world's expanding population. The research experts are always using cutting-edge knowledge and coming up with fresh ideas to include them in the farming system [10].

The primary concern of this article is the important Artificial Intelligence (AI) approaches that are applied to address agricultural problems. The three fundamental AI methods are as follows: Artificial Neural Networks, Expert Systems, and Fuzzy Systems are quantified as the focused regions [12]. To track the measured development of agro-intelligent systems, this

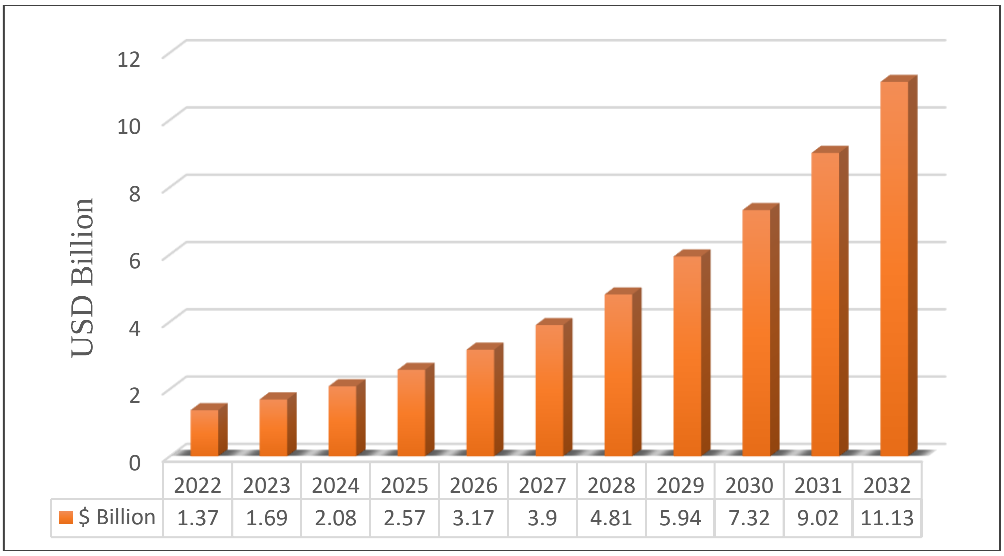

Fig. 1. Artificial intelligence market size in agriculture
(Source: www.precedenceresearch.com)

study discusses the application of artificial intelligence techniques in a wide range of farming applications.

2. OBSTACLES IN CONVENTIONAL AGRICULTURAL METHODS

Before delving more into AI and its usage in agriculture, it is important to comprehend the difficulties farmers have while utilizing conventional farming practices. These difficulties include the following:

Farming is highly dependent on weather patterns, humidity, temperature, and rainfall [13]. However, with the increasing impact of climate change, there is a possibility of abrupt changes in deforestation and pollution levels, which can make it challenging for farmers to make informed decisions about planting, tilling, harvesting, and other critical aspects of farming. This complex situation demands a careful assessment of environmental factors to ensure that the crops are healthy and productive, and the farming practices remain sustainable [14].

For a healthy and optimally yielding crop, it is essential to have productive soil that contains all the necessary nutrients that the plant needs. Nitrogen, phosphorus, and potassium are some of the essential nutrients that play a crucial role in crop growth and development. Inadequate amounts of these nutrients in the soil might result in crops of lower quality as well as deficiency symptoms, such as yellowing of leaves, stunted growth, and poor fruit or vegetable production [15]. Just like in conventional farming, understanding the nutrient requirements of the soil is crucial for successful crop production in any farming system.

The increasing scarcity of water is a critical issue that has arisen due to the overuse of both groundwater and surface water. It is estimated that around 70 percent of our freshwater supply is utilized in traditional agriculture practices [16]. However, the use of fertilizers that are high in nitrogen and pesticides has led to the seepage of these harmful chemicals into the soil, which eventually contaminates rivers, lakes, groundwater, and even seas. As a result, the presence of harmful algal blooms, fish die-offs, and contaminated drinking water for humans has become more frequent, posing a significant threat to both the environment and human health [17]. This situation calls for immediate and effective measures to be taken to ensure the responsible and sustainable management of our water resources.

The agricultural system is a complex and intricate network that requires careful attention and management. One of the most critical components of this system is weed control. If left unchecked, weeds can quickly spread and take over a field, resulting in decreased yield production and higher manufacturing costs. Moreover, weeds absorb valuable nutrients from the soil, which can lead to a shortfall in soil nutrients, ultimately resulting in a lack of plant nutrition. Unfortunately, weed detection and prevention using conventional methods have proven to be ineffective, making it crucial to explore alternative solutions to tackle this problem [18].

3. AI TECHNIQUES TO BOOST SUSTAINABLE AGRICULTURE

Farmers encounter several obstacles when using traditional agricultural practices, and artificial intelligence (AI) is being utilized extensively in the farming industry to address these issues. Artificial Intelligence has emerged as an innovative technology in agriculture, by readily providing information on healthy crop yields, soil monitoring, pest management, and improving a wide range of agriculture-related chores throughout the food supply chain, it helps farmers. The following are some significant uses of artificial intelligence in agriculture:

3.1 Weather & Price Indicating

As we previously discussed, climate change has created a challenge for farmers when it comes to deciding when to harvest, sow, and prepare their soil. However, AI-powered weather forecasting can provide farmers with crucial information regarding weather analysis [19]. This information can help farmers to plan the type of crops to grow, choose the most suitable seeds to sow and determine the optimal time for harvesting their crops. Additionally, with price forecasting, farmers can get a better idea of the potential crop prices for the upcoming season. The goal of the app 'Onesoil' is to assist farmers in making more informed choices [20]. This program employs computer vision and a machine learning algorithm to enable precision farming. Anyone can use remote crop monitoring to detect issues in the fields, determine the quantity of fertilizer needed, and check the weather prediction.

3.2 Agricultural Robotics

Robots are utilized extensively to carry out difficult tasks in a variety of industries, primarily manufacturing. Numerous AI startups are now working on creating agricultural robots. Based on AI, robots that are capable of performing a wide range of tasks in agricultural sectors are being created [21]. These robots have been instructed to harvest crops faster and in larger numbers than humans can while keeping weeds under control. These robots are programmed to gather and bundle crops while also assessing their quality and scanning the area for weeds [22]. These robots can also overcome the challenges faced by agricultural laborers. harvest and pack crops while keeping an eye out for weeds and assessing the quality of the crops. These robots can also overcome the challenges faced by agricultural laborers [23].

3.3 Intelligent Spraying

In addition to controlling weeds using herbicide sprayers, spraying robots may also be used to apply liquid fertilizers and control pests. Consequently, despite taking precautions, the farmer gets subjected to high concentrations of those hazardous active substances. Thus, the introduction of spraying robots is essential to avert any health risks. In contrast to traditional homogeneous spraying over the crop, robotic sprayers incorporate unique intelligence systems that enable selective spraying, thanks to neural networks and machine learning. By using such technology, robots might lessen the environmental effects of agriculture, reduce consumer exposure to pesticides, and stop the targeted organisms from developing a resistance to those poisons.

Table 1. Agri-robotic spraying systems

Perception	Crop	Result	Reference
Thermal infrared camera, monocular color camera	Vegetable	Taking just 68% to 77% of the time, raster approaches outperform back-to-front scheduling.	[24]
Robot controller	Cantaloupe	For the identical test scenarios, NSGA-II executed 1.5–7% faster than NSGA-III.	[25]
Ultrasonic sensors	Grapevine	Absence of performance indicators.	[26]
Bump and IR sensors	Cucumber	Run success:90%, bottom and topside leaf coverage, 95% and 95%, and 20% overspray.	[27]

3.4 Disease Diagnosis

Plant diseases pose a serious threat to the environment, farmers, consumers, and the world economy. Pests eradicate 35 percent of the crops in India. The use of pesticides without distinction poses a risk to public health as some of them are hazardous. The crop can be monitored to prevent these impacts, it may be identified, and the appropriate treatment can be administered. It takes a great deal of experience and knowledge to identify an unfit plant and then take the necessary steps to help it recover. Throughout the world, computerized systems are used to analyze the disease and then suggest ways to control it. To identify the problem, sensing, and evaluating the picture are done to make sure that the leaf images are divided into external areas such as the backdrop, the leaf's infected area, and the leaf's non-diseased area. This aids in the identification of pests and subsequently the detection of nutritional deficiencies.

Huang suggested the use of a model based on neural networks in conjunction with an image-dispensing system to classify the phalanopsis seedlings' ailments [28].

In conclusion, disease-identification robots are still in their early stages. As of right now, disease detection in robots faces three main challenges: (i) the absence of image archives for every disease; (ii) slow data processing, particularly when large volumes of images like hyperspectral are used; and (iii) irregular lighting in the field. The scarcity of picture datasets is progressively being addressed with the introduction of novel data synthesis techniques [29] and the availability of open-access agricultural databases [30].

3.5 Plant Health Monitoring

crop monitoring is the earliest technique that producers have employed to guarantee excellent production and quality. At this point, obvious signs of plant stress have been identified by looking for any abnormalities on the leaves or the plant overall, such as color changes, wilting, spots, or other abnormalities. New sensors are now available for the planter to monitor plant health and stress, even when it is invisible to the human eye, thanks to advancements in remote sensing technology. Canopy temperature is now measured using infrared thermometers and thermal cameras [31]. Additionally, several vegetation indices are used by researchers to gather relevant data regarding the health of plants, their capacity for photosynthetic activity, and other topics. These include the Ratio Vegetation Index (RVI), the Normalized Difference Vegetation Index (NDVI) [32], and others.

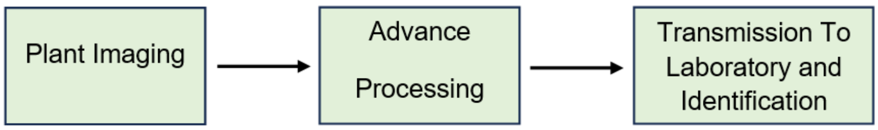

Fig. 2. Disease detection

Table 2. Plant health monitoring robotic systems

Perception	Crop	Result	Reference
NDVI, IR thermometer	Canola	Get phenotypic information. 2.5% is the maximum measurement error.	[31]
LiDAR	Orchards	Keep an eye on canopy coverage and vitality. Terrestrial Laser Scanning precision of 2 mm at a distance	[34]
IR camera, Pressure sensors	Grape	Crop surveillance. There are no performance metrics given.	[35]
Luxmeter	Orchards	Estimates volume of canopy. The system processes data quickly, is extremely dependable, and is unaffected by light fluctuations.	[36]

AI has developed a new application called Plantix. It was developed by PEAT to identify deficiencies in soil, including crop pests and diseases. With the help of this app, farmers can get an idea of how to use better fertilizer to improve crop quality. This application uses AI image recognition technology, which allows farmers to capture images of plants and get quality information [33].

In conclusion, issues including lighting, backdrop separation, and data modification present difficulties for robots that monitor plant vitality. Up until now, different lighting conditions brought on by weather patterns have been dealt with artificially and by adhering to stringent deadlines for the processing of the collected images. The reason for background separation is caused by nearby vegetation obstructing the sight sensors. Either by employing several cameras or by developing better algorithms that might catch these visual interpolations, this problem can be solved. The massive volume of data gathered is a problem that may be resolved with more powerful technology and quicker processing techniques.

3.6 Recognizing Harvest Maturity

Despite being a necessary component of every agricultural production cycle, harvesting is one of the most labor-intensive and monotonous chores. To automate this process, commercial businesses and academic institutions have created several robotic systems.

Robotic harvesters come in two varieties: bulk, which gathers all fruits and vegetables, and selective, which gathers just mature, ready-to-be-harvested produce. Since selective robotic harvesters have garnered the greatest interest in research development, this evaluation primarily focuses on them. The two primary performance measures utilized in selective robotic harvesting are picking rate and picking speed, which refers to the number of fruits that are successfully selected from the total quantity of fruit that is ready for harvesting [37].

Most harvesting robots are designed to work with strawberries, a high-value crop that has high production costs mostly because of human costs, especially during harvesting [38]. With picking speeds of 7.5 and 8.6 seconds per strawberry, respectively, the strawberry harvesting robots in [37,39] and Harvest Croo's Berry 5 robot, which claims to pick strawberries at a pace of 8 seconds per fruit, were the fastest [40].

Apples and tomatoes are two more crops that are receiving attention. The optimum picking rates demonstrated were 89% [41] and almost 90% in a dense apple orchard [42]. The fastest apple harvesting robots have recorded plucking speeds of 7.5 s per apple [43]. The most dependable tomato harvester had an 87% picking rate [44], while the quickest one picked at a rate of 23 seconds per tomato [45]. Without accounting for movement time, the picking speed for cherry tomatoes was 8 s per tomato bunch [46].

In summary, harvesting robots are not a direct competitor for human labor. Two main issues prevent harvesting robotic systems from operating as intended: first, the robot has trouble localizing the object to be gathered because leaves, fruits, and other plant components block its vision; second, the delicate nature of agricultural goods causes harm to the fruit. Harvesting robots should be able to perform on par with human labor in the future. Better software should be able to handle fruit clusters and occlusions, and hardware should be able to harvest the product consistently without causing damage.

3.7 Drone to Increase Efficiency

A recent analysis by Price Waterhouse Coopers estimates that the global market for drone-based solutions is worth $127.3 billion, and it comes to $32.4 billion for agriculture [47]. Numerous benefits flow from these drone-based solutions for the agriculture industry, including increased production, precision farming, yield management, and weather adaptation. Using the drone, a thorough 3D map of the field's topography, irrigation drainage, and soil viability might be created [48]. Drone-powered methods can also be used for soil N2 control. Drones are used to spray plant nutrients and seeds from the air, giving the plants the extra boost they need. Furthermore, the drones' programming allows them to atomize liquids by varying the distance they are from the ground surface based on the topography. One of the most significant applications of drone technology in agriculture is for crop monitoring and crop health assessment, working in conjunction with computer vision and artificial intelligence [49].

4. PRECISION FARMING

The primary objective of precision farming is "identifying the right product, at the right time, and in the right place." The labor-intensive portion of farming may be replaced with a significantly more regulated and exact process called precision farming. Plant stress level identification is one example of precision farming [50]. High-resolution photos and other data from the sensors on the plants may be used to get this, after that, a machine learning model is trained using the sensor data to identify stress [51].

autonomous mobile robots are also instruments utilized in precision agriculture for a variety of distinct jobs. Agriculture is a dynamic process, and autonomous robots with the ability to adapt and learn are crucial [52]. The majority of autonomous robots are equipped with sensors that allow the control unit to process information. Fuzzy logic may serve as the foundation for the robot control system [53]. With integrated gripper and eye-hand systems, robots may be utilized for plant inspection and treatment. [54]. Other common robot uses include robotic weed control [55]. This appears to be mostly advantageous since manually controlling weeds by hand is a labor-intensive, incredibly tedious process. Furthermore, robots are employed in agricultural phenotypic analysis to evaluate plant health. Robots that travel between rows of plants are often directed by a combination of GPS and a laptop that is handled by a human, however, various robots utilize different navigation algorithms.

Waheed et al. studied how hyperspectral satellite imagery may be used to improve crop care skills [56]. leaf nitrogen accumulation [57], intrusive weed varieties [58], and harmful insects such as leafhoppers [59]can be identified by hyperspectral image analysis [60].

5. YIELD MANAGEMENT AND RESOURCE CONSERVATION BY AI

Modern technologies like artificial intelligence, machine learning, satellite images, and sophisticated analytics are bringing about the development of an ecosystem that will support intelligent, productive, and sustainable agriculture [51]. By combining these technologies, farmers may increase their average output per hectare and have more control over grain prices, which will guarantee their profitability. The Cortana Intelligence Suite, which combines machine learning with Power BI to transform data into intelligent actions, is being used by Microsoft Corporation to engage with farmers in the Indian state of Andhra Pradesh to provide agricultural extension services [9]. The average yield per hectare has increased by 30% [61] as a result of this pilot project's use of an AI-based planting application that suggests planting dates, farmland preparation, FYM requirements [62], treatment of seeds, and optimal planting depth recommendations to farmers. forecasts for rainfall, as well as advice on when farmers should plant. Microsoft and United Phosphorus Limited are working together to develop a malware risk prediction application programming interface that will use artificial intelligence and machine learning to accurately predict the likelihood of a malware attack to predict potential malware attacks. Pest infestation levels are projected to be high, medium, or low based on meteorological factors, crop growth stage in the field, and other factors [63].

Water is one of the major resources which are deteriorating day by day. Water resources in agriculture face extra problems as a result of climate change. It modifies patterns of precipitation, resulting in erratic and unpredictable rainfall exacerbating the problem of water shortage [64]. Climate change is predicted to affect the quantity and quality of water resources in India by causing temporal and geographical fluctuations in water availability. For example, the flow of major rivers like the Ganges and the Indus, which are vital to India's agriculture, is being impacted by the retreating Himalayan glaciers, which are a key source of the country's river systems [65]. To maintain sustainability, these changes necessitate adaptive solutions in agricultural water management. To lessen the effects of climate change on agriculture, it is essential to incorporate climate-resilient agricultural practices, such as changing the dates of seeding, using water-saving irrigation methods, and utilizing climate-smart agricultural technology. The use of detectors with the Internet of Things in water management represents a major advancement in precision farming practices. Farmers may make educated judgments regarding fertilization and irrigation by using real-time data on soil moisture, temperature, and nutrient levels provided by sensors [66].

6. GOALS EXPECTED TO ACHIEVE THROUGH AI

6.1 Profitability

AI Identifies which crops to grow, sells them strategically, and projects ROI using gross profit and cost. AI-enabled precision farming technology allows farmers to grow more crops with less money and resources [67]. With the real-time knowledge AI gives farmers, they can make informed decisions at every level of farming. Making this wise choice will result in fewer product and chemical waste as well as effective use of time and funds. Furthermore, it enables farmers to pinpoint the precise regions that require pesticide treatment, fertilization, and irrigation, helping to prevent the abuse of chemicals in farming. Together, these factors lead to a decrease in the usage of herbicides, improved crop quality, and significant financial gains with fewer resources [4].

6.2 Efficiency

Using a precise algorithm makes it possible to swiftly and affordably take advantage of better farming prospects. This makes the usage of resources generally efficient. Durability Every season, further advancements for every performance metric are guaranteed by improved socioeconomic and environmental operations [14].

6.3 Reduction in Labour

In the agricultural industry, a labor deficit has long existed. AI can help with this issue of agricultural automation. A few examples of how farmers may do their tasks without hiring more workers are autonomous tractors, intelligent spraying, intelligent irrigation and fertilization systems, vertical farming software, and robotic harvesting robots. Compared to human farmers, AI-controlled machinery and gadgets are far faster and more precise [68].

7. PROBLEMS OF AI IN AGRICULTURE

Considering AI's advantages for sustainable farming, adopting this technology would seem like the right course of action for all farmers. But everyone is aware that there are still some significant obstacles, which are as follows:

In most parts of the world, people feel uncomfortable employing artificial intelligence (AI) and AI-enabled solutions and gadgets, even though AI has numerous benefits for the agricultural industry. AI businesses must first provide farmers with simple equipment so they can become accustomed to it before upgrading to more sophisticated machinery to tackle the issues [69].

For underdeveloped nations, implementing AI and innovative technology in agriculture might be difficult. Selling such technologies in places where agricultural technology is not used would be extremely challenging. Farmers in these locations require assistance to use these technologies [70].

One might raise many legal concerns with the usage of AI because there are currently unclear rules and laws in place [71]. Additionally, someone may run into privacy and security problems like cyberattacks and data breaches as a result of using software and the internet. For farmers or farm owners, any one of these issues might be quite problematic.

8. CONCLUSION

Real-time data monitoring has demonstrated the value of artificial intelligence. This has been used to control yield, weeds, pests, and crops. The Robots converse with one another to determine which crop is best for harvesting and marketing. Farmers might be guaranteed healthier crops and appropriate field management by using significant approaches. The AI provides timely information through the appropriate channels, which can help users become more resilient. This essay illustrates how artificial intelligence has been applied to farming in the past, beginning in 1983. The goal of the paper's preparation was to include as much information as possible about the various AI approaches applied to agriculture. The rule-based expert systems were extensively used from the 1980s through the 1990s, but artificial neural networks and fuzzy inference systems started to take center stage in 1990. Artificial neural networks are used in conjunction with hybrid systems, such as neuro-fuzzy or image processing, in modern times. By using AI, farmers will be able to make better judgments in the field and achieve their goal of a healthier harvest. The power of data may be more creatively applied to forecast risk, examine potential outcomes, and intervene before hunger becomes a humanitarian emergency. Since food is the most basic human need, this can contribute to the world's overall development.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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