Research Article

Artificial Intelligence in Agriculture: A Systematic Literature Review

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Abstract: In this era, AI has a key role to make revolutionary changes in the field of Agriculture. In the past agricultural work was done manually with lots of difficulties and challenges. AI removed those difficulties by introducing automated systems for this reason nowadays artificial intelligence has a great impact on agriculture. The objectives are to present and gather information about AI's use, challenges, and future. The systematic literature review is used for gathering and presenting the use of AI in agriculture. From the systematic literature review clear that the challenges and difficulties of agriculture are solved with the help of the application of artificial intelligence. Artificial intelligence automates soil management, disease management, crop monitoring, and weeding. The research helps humans to know how to use Artificial intelligence that's why removes human difficulties in agriculture, and needs less manpower in agriculture works, researcher found compact information about the use of AI in agriculture to do more research.

Keywords: Agriculture, Use of AI, Artificial intelligence, Systematic literature review, automated system.

1. Introduction

Artificial intelligence runs the modern world, and it is known as a system that works like a human being and makes revolutionary changes in the sector of agriculture that's why the economy depends on it. Country to country the economic growth has a huge difference based on agriculture [1]. The picture below shows the use of AI in agriculture.

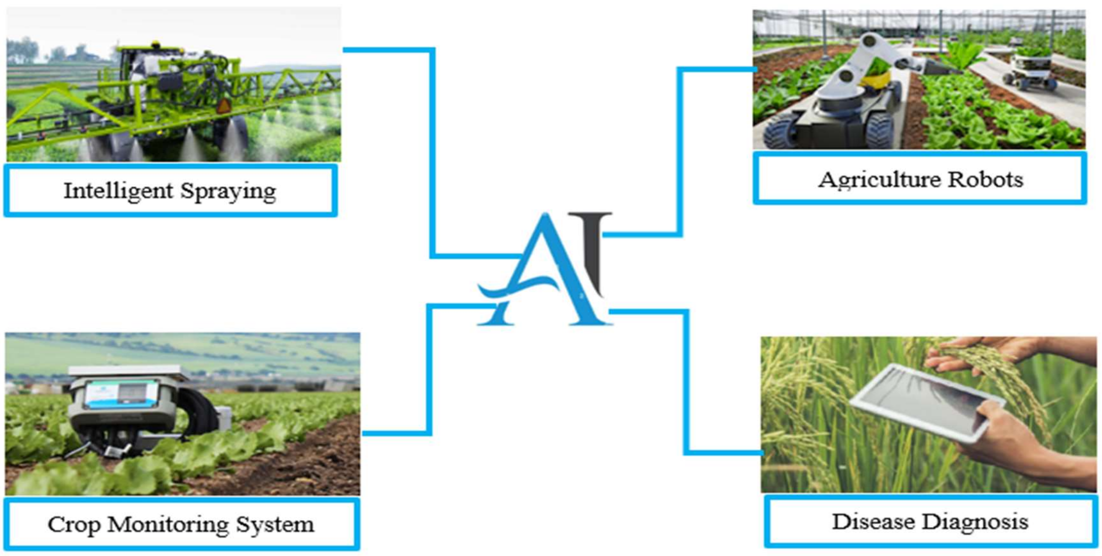

Figure.1. Use of Artificial Intelligence in agriculture.

In the past, AI is not used in the sector of agriculture that's why agriculture activities were limited to crop production and food **[1]**. Whatever, in the last two-decade crops production, processing, marketing, and distribution have evolved. Recently, the activities of agriculture were the basic source of improving GDP, livelihood, etc. [2]. The aim of agriculture practices is reviewed to sustain and enhance human life. AI is introduced in agriculture with the help of technology, robots, data analytics, IoT, cameras, cheap sensors, drones, and wide-scale internet. AI systems can predict which product is grown massively in a year and which diseases attack the crops. With the help of technology, it is proved that the natural ecosystem impacts will be reduced and the safety of workers are increased, food prices will be down and the production of food will be increasing with the needs of the population [2].

2. Consideration Overview

Cultivating poor dietary choices has many risks that can cause significant health problems. Seasonal weather changes, prices of farm inputs fluctuate, soil erosion, crop failure, pests damage crops, and climate change. Farmers have to deal with this uncertainty. Although Agricultural practices span, this research covers soil, crops, Diseases, and weeds as major contributors to agriculture The application of manufacturing AI is most important to review Agriculture related to soil, crops, diseases, and pest management.

2.1 Soil management

Soil is known as a natural resource. An indissoluble part of agriculture is soil management. Crop production will be improved and soil resources will be conserved with thorough knowledge of different soil types and conditions. It is the application of procedures, techniques, and therapies to enhance soil quality. The standard soil survey approach can be used to investigate if urban soils contain contaminants [4]. Compost and manure applications increase soil aggregation and porosity. Better aggregation shows the presence of organic components, which are crucial in preventing the formation of soil crusts. To stop the physical deterioration of soil, alternate tillage techniques can be used. To enhance soil quality, organic materials must be applied [5]. Numerous soil-borne diseases that must be controlled by soil management frequently have a substantial impact on the production of vegetables and other consumable crops [6]. Because of the difference between the capacity of soil to withstand and recover from change, soil erosion is a factor that must be taken into account when assessing the sustainability of land management strategies [7].

Using a colorimetric testing technique, IBM built a tiny soil testing system in 2018 that is capable of evaluating five indicators. On the card's microfluidic chip, chemical analysis is performed, and artificial neural networks (ANN) can forecast the moisture content of soil [8], according to research. The vision algorithm also forecasts the results of the colorimetric test [9]. A supervised AI-based machine learning algorithm is called a Support vector machine (SVM). The mean weight diameter of the soil was predicted by it [10]. AI can recognize the carbon sources and sinks in various locations. Different models were utilized as input inputs in ARIES (2018). The carbon flow model, potentially stored carbon release sink model, carbon sequestration source model, and greenhouse gas emission model are suggested by ANN [8]. MOM or management-oriented modeling is an AI-driven approach to soil management. It is a useful instrument for preventing nitrogen leaching [11]. Decision support systems are yet another crucial soil management technique (SRC-DSS). To determine soil qualities and contaminated soil, it analyses accidental risk using AI's fuzzy logic. Another benefit of using fuzzy logic in soil management is the elimination of impressions or uncertainty [12]. AI neural networks can assess the hydraulic conductivity of soil [13]. AI can predict biological parameters like soil enzyme activity as well as physical parameters [14].

2.2 Crop Monitoring

Numerous novel approaches to boost productivity and lessen crop damage have been made possible by artificial intelligence. The health of the crop is frequently dependent on selecting the ideal crop for harvest. Seed selection may benefit from the use of big data technology. On thousands of acres of agricultural land, remote sensing (RS) techniques like hyperspectral photography and 3D laser scanning may effectively create crop matrices [15]. Monitoring plant development is crucial for determining the health of crops. Crops require a total of 17 key components for growth [16]. Crop growth is measured and predicted using a variety of computer vision algorithms. Different methods have been developed to monitor various kinds of crops. For managing cotton, use COMAX and COTFLEX [17,18]. In actuality, COMAX was the very first expert system ever created in 1986. For the soybean crop, another fuzzy logic-based expert system has been developed [19]. The ANN algorithm serves as a crop counselor and predictor [20]. In this, the farmer suggests using fertilizer if the reader wishes to grow a certain crop. Utilizing software and hyperspectral frame cameras, the nitrogen content of the rice leaf is observed [21]. For the monitoring of agriculture is eventually connected to crop health monitoring, many AI-powered sensors are used. For sensing carbon monoxide and natural gas, respectively, sensors like MQ4 & MQ7 are employed [22]. The ambient temperature and humidity are measured using a DHT11 device. Crop yield may be predicted using artificial neural networks. An overview of using AI to check crop health is mentioned below in table 1.

Table.1. Using AI to check the health of crops.

Author	Application	Algorithm/Method	Result
[23]	Growth indicators of plants are measured	Machine learning, Threshold segmentation CIE	Achieved a benchmark result
[24]	Growth monitoring of Graph	Use Computer vision	Individual barriers are identified and grape bunches were accurate
[25]	Diagnosis of nitrogen content in rice leaves	MATLAB	Blade change process quantified
[26]	Observing the heading date of white	Computer vision	The method is a 10.14% absolute error per day compared to other methods
[27]	Monitoring the growth of paddy	Remote sensing	Achieved a good result

2.3 Irrigation

The automated irrigation system has replaced the conventional irrigation system. There is no need for human intervention with this kind of technology. Additionally, it not only minimizes labour but also excessive water waste. Arduino is a prime example of an automatic irrigation system [28]. Two sensors are used in this system: a soil moisture sensor that is implanted into the ground close to the plant, and a water sensor that is placed in water so the source from which irrigation water will be pumped. A microcontroller and sensors are connected to Arduino. Arduino in this system uses soil moisture sensors to read the conditions. If the soil is dry, water level sensors are used to determine whether there is any water available. The pump starts up if there is water available and shuts off automatically when there is enough water delivered. A relay-driven circuit powers the pump. If water is accessible, a sound will alert the user. Raspberry Pi 3 is another case. This system's mechanism is intricate. Nod MCUs and soil moisture sensors are dispersed uniformly over the irrigation area in this system. Wireless LAN that links the Raspberry Pi3 to the nodes [29]. Through a soil moisture sensor, it receives updates on the state of the soil's wetness. If the moisture level dropped, it activates the motor or pump and calculates the necessary amount of water using the Partial Less Square Regression (PLSR) algorithm [30]. The Raspberry Pi3 weather prediction system uses a Random Forest regressor. It can gradually adjust to the climatic conditions unique to the area. Every 30 minutes, on average, the system is updated. It is an autonomous system that requires very little or no human input. To design diverse irrigation systems, farmers use a variety of sensors, including soil moisture sensors, rain and frost sensors, air sensors, and pH meter sensors. These sensors are used to record watering practices and modify watering schedules in real-time or use prior data to demonstrate efficacy. Soil moisture sensors are one of the irrigation system's primary tools. A soil moisture sensor calculates how much water is stored in the soil horizon by measuring the water content of the soil. It aids irrigators in comprehending what goes on at a crop's root. Before the scheduled irrigation event, it provides information regarding the moisture content in the active root zone. Farmers are implementing smart irrigation systems with the aid of AI applications. This system combines nozzles and sprinklers, a cutting-edge technology. It gathers data from sensors and communicates predetermined human commands to actuators that turn sprinkles on and off [31,32]. AI, machine learning, and other technologies are needed for smart irrigation systems to operate correctly and completely. Without human involvement, this technology can determine the soil temperature and water level. Different types of irrigation systems are developed using Evapotranspiration (ET) and AI technologies [33,34]. It is the total of water evaporation and transpiration from a region of the atmosphere's surface. Temperature, wind, solar radiation, and relative humidity all play a role in it. Farmers can compute how much water is required under all conditions if they can use ET to assess how much water has entered and left plants.

2.3 Weather Forecasting

Climate change can affect crops. Crop productivity can be impacted by a variety of factors, including temperature, wind direction, sunlight, rainfall, and humidity. Climate change is causing severe weather events like hurricanes, tornadoes, and hailstorms that might cost millions of dollars, AI-driven weather predictions assist farmers with keeping current on environmental circumstances. Machine learning algorithms are the main foundation for AI-based weather forecasting. By analyzing and manipulating enormous data sets transmitted from a weather satellite, relay station, and radiosondes, the Numerical weather prediction (NWP) model, a well-known machine learning model, may deliver short-term weather forecasts and long-term climate change projections [35]. Some AI-driven methods for forecasting the weather include Artificial neural networks, Ensemble neural networks, Backpropagation networks, Radial basis Function networks, General regression neural networks, Genetic algorithms, Multilayer perception, and Fuzzy clustering. The UNET convolutional neural network is used by Google's AL forecast too to predict rain six hours in advance of precipitation (CNN). Hyper-local weather forecasts with a resolution of 0.2 to 1.2 miles are offered by IBM's deep thunder. Agricultural weather forecasts are produced by Monsanto's Climate Corporation using satellite images, hyper-local weather data, and machine learning models.

2.4 Weeding

Unwanted plants are called weeds. The expense of farming goes up and crop output decreases when weeds are present. According to a report by the Indian council for agricultural research, weeds cost India's farmers $11 billion in lost agricultural output [36]. Weeds outcompete crops in every parameter, including mineral nutrients, water, solar energy, and space. Therefore, weed management or eradication is crucial for agricultural output. Farmers can use artificial intelligence to assist them to address this issue. Herbicides are typically used by farmers to get rid of weeds. Herbicides are broadcast sprayed across farms by farmers using conventional techniques. However, this type of broad-spectrum spraying wastes pesticides and is bad for the environment. Farmers can identify and separate weeds from crops with the use of AI. The identification of weeds is done using neural networks and image pre-processing. This technique involves taking pictures of crop fields. The photos are then put through a few filtering steps. After that, crops and weeds are separated using the Deep Convolutional neural networks (DCNN) picture segmentation algorithm [37]. After weeds are discovered in a crop, farmers must remove them. Farmers can eliminate weeds with the least amount of pesticide thanks to smart spraying technology. It eventually brings down the price of weed control. This method uses AI to examine the size and age of weeds after they have been identified. Then, high-precision robotic nozzles target those weeds and spray a herbicide dose based on previously determined weed size and age [38].

Table.2. Applications of crop health monitoring.

Author	Application	Algorithm/Method	Result
[39]	Weed detection	Fuzzy time classification, texture-based algorithm, and color	Accuracy=92.9%
[40]	Precision weed management	Machine vision	Low cost and very effective
[41]	Weed estimation	Multispectral images, HOG (Histogram of Oriented Gradients).	Analyze large areas of crops in less time
[42]	Weed detection in agricultural fields	Convolution Neural Network	accuracy rate=70.5%
[43]	Weed detection in crops	SVM, Image processing	Crops and weeds are distinctions.
[44]	Identification of potato plants and three different weeds	Computer vision except system based on a neural network	The recognition rate is 98.38% and the average PC execution time of less than 0.08s

2.4 Disease and Pest Management

The quantity and quality of crop yield are both decreased by plant disease. For the control of diseases, farmers shell out enormous sums. Using AI-based disease management, farmers may find and eradicate illnesses. Accurately identifying leaf disease has been improved by a Convolutional neural network (CNN). A CNN algorithm based on picture segmentation may identify illnesses in vegetable leaves [45]. CNN is a tool used by deep learning algorithms to identify sickness. Numerous photos of healthy and diseased plants can be found in the dataset. CNN models are trained and tested using datasets in deep learning. Crop disease is also detected by computer vision (CV) technologies. To categorize and identify diseases, support vector machines (SVM) classify and analyze leaf color, texture, and form [46]. Pests of all kinds damage crops, but the most significant ones are gastropod mollusks, mites, nematodes, and insects. Pests can harm crops both internally and externally. AI is employed to eradicate pests. Pests are recognized and treated using image recognition technology, an AI-based technique. CNN is used by the YOLOv3 an AI-driven algorithm, to categorize and name the pest. CCNN uses image processing techniques to automatically count the number of pests on any plant [47]. Technologies like computer vision, machine learning, and deep learning forecast pests by assessing several meteorological conditions [48]. To keep pests out of their crops, farmers employ pesticides. The environment is harmed by pesticide overuse. An eco-friendly pest control technique is integrated pest management (IPM). In the long run, IPM effects may be superior to chemical control [49]. Biopesticides can also be used by farmers in place of chemical pesticides. Eco-friendly biopesticides manage insect infestations by using natural inhibitors. A summary of AI's use in weeding operations, disease prevention, and pest management are mentioned below.

Table.2. Applications of AI in weeding operation disease & pest management.

Author	Application	Crop	Disease/pest	Algorithm/Method
[50]	Bakanae detection	Rice	Bakanae	Machine vision
[51]	Leaf disease detection	Soyabean	Foliar	CV, SVM, KNN
[52]	Detection of Aphids in wheat fields	Wheat	Aphids	SVM, MSER (Maximally Stable Extremal Regions), HOG (Histogram of Oriented Gradients).
[53]	Leaf spot Severity	Wheat	Septoria, Yellow rust	CV, SVM
[54]	Pest detection	-	Pest	Deep convolution neural network
[55]	Detection of Fungal colonies	Rice	Mould	Deep learning, CNN, BPNN
[56]	Flying insect counting and identification	-	Insects	Raspberry PI

2.4 Drones and Robots

Agriculture is made easier by the use of drones. Unmanned aerial vehicles (UAVs), also referred to as drones, are managing and streamlining agricultural operations. It uses flight to carry out all of its work. The two basic elements of drone flight are state estimation and control. A drone's ability to govern its state and adapt to its surroundings is being improved via AI and ML [57]. Map-making is a key function of the drone. Algorithms in CV powered by AI enhance the drone's mapping capabilities. Artificial intelligence has made it possible to deploy drones for farm work such as watering, observation, identifying, disaster management, and picture collection, process, and analysis (AI). Drones can spray plants utilizing a variety of techniques. Sprinklers that are using kinetic energy, centrifugal power, gaseous energy, or hydraulic energy are a few of those [58]. Farmers should learn from drones how much sunlight their crops are getting. Applying ML, drones can inspect fields to identify which regions need watering and which have weeds and illnesses. Many companies and groups have created special drones to perform particular farming activities. Among these are the T16 from DJI, the eBEE SQ from senseFly, the Quantix Mapper from Dragonfly, and the drone4Agro V3. These drones do the required agricultural tasks using a variety of various technologies, including AI, ML, IoT, GPS, and RTK. Robots have been utilized in agriculture due to their automation, accuracy, and efficiency. Robots help farmers in finding innovative methods for increasing agricultural productivity and streamlining their work. Robots employ AI and CV technology to complete their tasks. A camera or cameras are part of the CV system, which collects data and transmits it to the robot. The robot then responds to the input by acting accordingly. Thanks to technology, tasks like harvesting, growth monitoring, picking, sorting, and packing may now be completed by robots. Intelligent robots based on machine learning and machine vision are being employed for planting [59]. Prototypes of intelligent and autonomous agricultural robots are being used in this process [60], [61]. Numerous AI-based wedding robots perform marijuana procedures. Robots may recognize weeds and then spray amounts of herbicide using image processing, CNN, SVM, and other algorithms [62], [63]. The robotic arm was created by Dogtooth Technologies to be capable of delicately plucking fruits like strawberries.

Using motion planning algorithms and machine vision, the robot can locate and identify ripe fruits. Apple harvesting robots employ mechanical hands to gather apples from trees using computer vision and deep learning [64].Vegebot is a robot created by Cambridge University. It gathers lettuce using machine vision. It analyzes the lettuce with a camera and indicates whether or not to harvest it. The picture below shows the use of drones and robots.

Figure.2. Use of drones in agriculture.

Figure.3. Use of robots in agriculture.

3. Challenges of AI in Agriculture

Despite the incredible ways that AI has transformed and advanced agriculture, there are still certain difficulties. The first and most crucial problem is a lack of expertise and knowledge in AI. A distinct degree of skill set is needed for AI technology in agriculture. Software, hardware, sensors, and other varied tools make up AI technology. To effectively use and operate these devices, farmers must receive sufficient training. However, the majority of framers lack both time and qualified instructors needed to train them. The disconnect between farmers and AI engineers is another issue that creates difficulties. IoT, ML, and AI are typically not studied by farmers. On the other side, engineers do not frequently work in the fields, research, or employ agricultural practices. In agriculture, strange circumstances occasionally happened. Time is required for AL and ML to assess, analyze, research, and come up with a solution. By that time, everything might have gotten out of hand. The price of technology is a significant additional problem. There are two different types of costs: the first is the price of the machinery, and the second is the price of upkeep. Agricultural robots and drones are not inexpensive. Farmers must spend a significant sum of money to purchase them. As a result, numerous businesses rent out these tools and technology in exchange for a share of the yield. Whatever the case, there is still work to be done to improve agricultural activities using AI because its application has several drawbacks.

3.1 Limitations

One of the important features of an intelligent or expert system is its capacity to complete tasks accurately and quickly. Many systems are either sluggish to react or erroneous or both. A system delay affects the task approaches a user selects. It is hypothesized that the basis for choosing a method is indeed a cost function that mixes the effort required to synchronize input system availability with the accurate level provided. Automatic performance, pace, and ability to monitor are three main strategies that can be used to put in the smallest amount of effort while achieving the best results [65]. Another aspect that affects how powerful an expert system is is the volume of data input. However, this should continue to react to important or unexpected events [66]. To boost the system's accuracy and speed a field expert must have a thorough awareness of the task at hand. Only extremely pertinent data must be employed. The farmers who will utilize it and a group of experts across various agricultural fields must work together to build an agricultural intelligent system [67]. The brilliance of any intelligent system lies in its implementation strategy. The lookup and training algorithms should be sufficiently defined for efficiency and accuracy because big data is employed. Since most AI systems are internet-based, their application is constrained, especially in remote or rural areas. The government may help farmers by developing a web service enabling equipment with a lower tariff to work with the AI system directly for farming. To help farmers acclimatize to the utilization of AI in agricultural farming, it is also very beneficial to provide them with "how to use" orientations (training and re-training). Any successful AI system must possess flexibility. The integration of the systems into a coherent ecosystem seems to be the main focus at the forefront of AI-based robotics technology, even though it appears that great progress has been made in applying AI methods to some discrete activities. For this, the subsystems themselves need to be adaptable [68]. It should also include a wide range of features to accept more user data from the subject matter specialist.

4. FUTURE OF AI IN AGRICULTURE

Artificial intelligence is successfully used in agriculture, with positive outcomes. Future developments may broaden the application of AI in agriculture. According to BI Intelligence Research, the market for agriculture technologies and systems, including AI and ML, is expected to triple by 2025 and reach $15.3 billion. To address agricultural issues and assure greater harvests, AI application in agriculture is necessary. For their cultivation, farmers rely on the environment and the weather. By analyzing the previously gathered data and suggesting the ideal time to sow seed, defining the crop options, and selecting hybrid seeds to increase yield, AI and machine learning act as predictive analysts. To increase yields, the ML model can also recommend adjusting cropping patterns. An AI-sowing was created by Microsoft and the International Crop Research Institute for Semi-Arid Tropics (ICRISAR). Farmers that use the app receive notifications regarding the best seeds to plant. A 30% boost in production is predicted to benefit from AI-based advice. Crop loss caused by natural disasters, especially pest invasions, is farming's biggest challenge. Microsoft is yet another project that has worked with United Phosphorus Limited to develop a Pest risk prediction API that uses Ai and ML to predict the likelihood of a pest assault in advance. Robots can be equipped with sensors and algorithms that are powered by AI to quickly collect fruits and crops. Using ML and DL, machines can make decisions at a level comparable to human n brains. These choices are based on a vast amount of data and are more precise than those made by the human brain. Variations in crop prices are among the main worries for farmers. With the aid of technologies like big data, AI and ML, it is possible to identify pest and disaster infestations, estimate crop output, and predict prices. This information can be used to advise farmers and the government on future price patterns, the level of demand, and the best kind of crop to plant to reap the greatest rewards. Technology is being developed by a tech business called Nature-Fresh, based in the USA, to forecast how long a crop would take to produce a yield. The yield that will be available for sale in the future could be estimated using this method. A farm may be optimized down to the last detail with AI, which can also make wise choices and quickly complete challenging, lengthy jobs. It is an essential tool for converting conventional agriculture to sustainable automated agriculture.

5. CONCLUSION

Day by day AI makes huge changes in the field of agriculture which are not presented together in the research paper. In this paper use of AI in agriculture is presented together. In past agriculture, work is done manually with lots of challenges and problems whereas, in the current time, most of the work is done automatically with the help of AI. In the sector of agriculture now AI is must needed thing that's why where AI is used it is needed to know. A systematic literature review helps us to find out the sector of agriculture where AI is used. From this systematic literature review, research has been seen on the use of AI in agriculture and know that how AI automated the system of agriculture. In future agriculture is mostly dependent on AI that's why future research will try to find out the farmer's limitations to using AI by using ML.

References

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

[2] Oyakhilomen, O., & Zibah, R. G. (2014). Agricultural production and economic growth in Nigeria: Implication for rural poverty alleviation. *Quarterly Journal of International Agriculture*, *53*(892-2016-65234), 207-223.

[3] Fan, M., Shen, J., Yuan, L., Jiang, R., Chen, X., Davies, W. J., & 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.

[4] De Kimpe, C. R., & Morel, J. L. (2000). Urban soil management: a growing concern. *Soil science*, *165*(1), 31-40.

[5] Pagliai, M., Vignozzi, N., & Pellegrini, S. (2004). Soil structure and the effect of management practices. *Soil and Tillage Research*, *79*(2), 131-143.

[6] Abawi, G. S., & Widmer, T. L. (2000). Impact of soil health management practices on soilborne pathogens, nematodes and root diseases of vegetable crops. *Applied soil ecology*, *15*(1), 37-47.

[7] Syers, J. K. (1997). Managing soils for long-term productivity. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, *352*(1356), 1011-1021.

[8] Sarkar, A., Maity, P. P., & Mukherjee, A. (2021). Application of AI in Soil Science. *Technology*, *62*, 131-136.

[9] Sanuade, O. A., Adetokunbo, P., Oladunjoye, M. A., & Olaojo, A. A. (2018). Predicting moisture content of soil from thermal properties using artificial neural network. *Arabian Journal of Geosciences*, *11*, 1-10.

[10] Bhattacharya, P., Maity, P. P., Ray, M., & Mridha, N. (2021). Prediction of mean weight diameter of soil using machine learning approaches. *Agronomy Journal*, *113*(2), 1303-1316.

[11] Li, M., & Yost, R. S. (2000). Management-oriented modeling: optimizing nitrogen management with artificial intelligence. *Agricultural Systems*, *65*(1), 1-27.

[12] López, E. M., García, M., Schuhmacher, M., & Domingo, J. L. (2008). A fuzzy expert system for soil characterization. *Environment International*, *34*(7), 950-958.

[13] Ghanbarian-Alavijeh, B., Liaghat, A. M., & Sohrabi, S. (2010). Estimating saturated hydraulic conductivity from soil physical properties using neural networks model. *International Journal of Environmental and Ecological Engineering*, *4*(2), 58-63.
[14] Tajik, S., Ayoubi, S., & Nourbakhsh, F. (2012). Prediction of soil enzymes activity by digital terrain analysis: comparing artificial neural network and multiple linear regression models. *Environmental Engineering Science*, *29*(8), 798-806.
[15] Thomas, J. (2020). Application of Artificial Intelligence in Thyroidology. In *Artificial Intelligence* (pp. 273-283). Productivity Press.
[16] Culman, M. A., Gomez, J. A., Talavera, J., Quiroz, L. A., Tobon, L. E., Aranda, J. M., ... & Bayona, C. J. (2017, April). A novel application for identification of nutrient deficiencies in oil palm using the internet of things. In *2017 5th IEEE International Conference on Mobile Cloud Computing, Services, and Engineering (MobileCloud)* (pp. 169-172). IEEE.
[17] Lemmon, H. (1986). COMAX: An expert system for cotton crop management. *Science*, *233*(4759), 29-33.
[18] Stone, N. D., & Toman, T. W. (1989). A dynamically linked expert-database system for decision support in Texas cotton production. *Computers and electronics in agriculture*, *4*(2), 139-148.
[19] Prakash, C., Rathor, A. S., & Thakur, G. S. M. (2013). Fuzzy-based Agriculture expert system for Soyabean. In *International Conference on Computing Sciences WILKES100-ICCS2013, Jalandhar, Punjab, India* (Vol. 113).
[20] Ravichandran, G., & Koteeshwari, R. S. (2016, February). Agricultural crop predictor and advisor using ANN for smartphones. In *2016 International Conference on Emerging Trends in Engineering, Technology, and Science (ICETETS)* (pp. 1-6). IEEE.
[21] Arias, F., Zambrano, M., Broce, K., Medina, C., Pacheco, H., & Nunez, Y. (2021). Hyperspectral imaging for rice cultivation: Applications, methods, and challenges. *AIMS Agriculture and Food*, *6*(1), 273-307.
[22] Babu, K. S., & Nagaraja, C. (2018). Calibration of MQ-7 and Detection of Hazardous Carbon Mono-oxide Concentration in Test Canister. *International Journal of Advance Research, Ideas, and Innovations in Technology*, *4*(1), 18-24.
[23] Rico-Fernández, M. P., Rios-Cabrera, R., Castelán, M., Guerrero-Reyes, H. I., & Juarez-Maldonado, A. (2019). A contextualized approach for segmentation of foliage in different crop species. *Computers and Electronics in Agriculture*, *156*, 378-386.
[24] Pérez-Zavala, R., Torres-Torriti, M., Cheein, F. A., & Troni, G. (2018). A pattern recognition strategy for visual grape bunch detection in vineyards. *Computers and Electronics in Agriculture*, *151*, 136-149.
[25] Sun, Y., Duan, H., & Xian, N. (2018). Fractional-order controllers optimized via heterogeneous comprehensive learning pigeon-inspired optimization for autonomous aerial refueling hose–drogue system. *Aerospace Science and Technology*, *81*, 1-13.
[26] Zhu, Y., Cao, Z., Lu, H., Li, Y., & Xiao, Y. (2016). In-field automatic observation of wheat heading stage using computer vision. *Biosystems Engineering*, *143*, 28-41.
[27] Ali, A. M., Savin, I., Poddubskiy, A., Abouelghar, M., Saleh, N., Abutaleb, K., ... & Dokukin, P. (2021). An integrated method for rice cultivation monitoring using Sentinel-2 data and Leaf Area Index. *The Egyptian Journal of Remote Sensing and Space Science*, *24*(3), 431-441.
[28] Okoye, F., Orji, E., & Ozor, G. (2018). Using Arduino-based automatic irrigation system to determine irrigation time for different soil types in Nigeria. *International journal of advanced research in computer and communication engineering*, *7*, 42-47.
[29] Ilakkiya, R., & Murugesan, A. (2019). Smart Agriculture Irrigation System Using Raspberry Pi. *South Asian Journal of Engineering and Technology*, *8*(1), 19-24.
[30] P Leone, A., A Viscarra-Rossel, R., Amenta, P., & Buondonno, A. (2012). Prediction of soil properties with PLSR and vis-NIR spectroscopy: Application to mediterranean soils from Southern Italy. *Current Analytical Chemistry*, *8*(2), 283-299.
[31] Mitra, A., & Saini, G. (2019, October). Automated smart irrigation system (ASIS). In *2019 international conference on computing, communication, and intelligent systems (ICCCIS)* (pp. 327-330). IEEE.
[32] Jha, K., Doshi, A., & Patel, P. (2018). Intelligent irrigation system using artificial intelligence and machine learning: a comprehensive review. *Int. J. Adv. Res*, *6*(10), 1493-1502.
[33] Arif, C., Mizoguchi, M., & Setiawan, B. I. (2013). Estimation of soil moisture in paddy field using artificial neural networks. *arXiv preprint arXiv:1303.1868*.
[34] Al-Ghobari, H. M., & Mohammad, F. S. (2011). Intelligent irrigation performance: evaluation and quantifying its ability for conserving water in arid region. *Applied Water Science*, *1*, 73-83.

[35] Al-Yahyai, S., Charabi, Y., & Gastli, A. (2010). Review of the use of numerical weather prediction (NWP) models for wind energy assessment. *Renewable and Sustainable Energy Reviews*, *14*(9), 3192-3198.
[36] Gharde, Y., Singh, P. K., Dubey, R. P., & Gupta, P. K. (2018). Assessment of yield and economic losses in agriculture due to weeds in India. *Crop Protection*, *107*, 12-18.
[37] Yu, J., Schumann, A. W., Cao, Z., Sharpe, S. M., & Boyd, N. S. (2019). Weed detection in perennial ryegrass with deep learning convolutional neural network. *Frontiers in plant science*, *10*, 1422.
[38] Sabanci, K., & Aydin, C. (2017). Smart robotic weed control system for sugar beet. *Journal of Agricultural Science and Technology*, *19*(1), 73-83.
[39] Reinecke, M., & Prinsloo, T. (2017, July). The influence of drone monitoring on crop health and harvest size. In *2017 1st International conference on next generation computing applications (NextComp)* (pp. 5-10). IEEE.
[40] Eli-Chukwu, N. C. (2019). Applications of artificial intelligence in agriculture: A review. *Engineering, Technology & Applied Science Research*, *9*(4), 4377-4383.
[41] Lara, A. E. P., Pedraza, C., & Jamaica-Tenjo, D. A. (2020). Weed estimation on lettuce crops using histograms of oriented gradients and multispectral images. In *Pattern Recognition Applications in Engineering* (pp. 204-228). IGI Global.
[42] Ngo, H. C., Hashim, U. R. A., Sek, Y. W., Kumar, Y. J., & Ke, W. S. (2019). Weeds detection in agricultural fields using convolutional neural network. *International Journal of Innovative Technology and Exploring Engineering*, *8*(11), 292-296.
[43] Pulido, C., Solaque, L., & Velasco, N. (2017). Weed recognition by SVM texture feature classification in outdoor vegetable crop images. *Ingeniería e Investigación*, *37*(1), 68-74.
[44] Sabzi, S., Abbaspour-Gilandeh, Y., & García-Mateos, G. (2018). A fast and accurate expert system for weed identification in potato crops using metaheuristic algorithms. *Computers in Industry*, *98*, 80-89.
[45] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in plant science*, *7*, 1419.
[46] Ghyar, B. S., & Birajdar, G. K. (2017, November). Computer vision based approach to detect rice leaf diseases using texture and color descriptors. In *2017 International conference on inventive computing and informatics (ICICI)* (pp. 1074-1078). IEEE.
[47] Chen, C. J., Huang, Y. Y., Li, Y. S., Chang, C. Y., & Huang, Y. M. (2020). An AIoT based smart agricultural system for pests detection. *IEEE Access*, *8*, 180750-180761.
[48] Cui, S., Ling, P., Zhu, H., & Keener, H. M. (2018). Plant pest detection using an artificial nose system: a review. *Sensors*, *18*(2), 378.
[49] Peshin, R., Jayaratne, K. S. U., & Sharma, R. (2014). IPM Extension: A global overview. *Integrated pest management*, 493-529.
[50] Patrício, D. I., & Rieder, R. (2018). Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review. *Computers and electronics in agriculture*, *153*, 69-81.
[51] Shrivastava, S., Singh, S. K., & Hooda, D. S. (2017). Soybean plant foliar disease detection using image retrieval approaches. *Multimedia Tools and Applications*, *76*, 26647-26674.
[52] Liu, T., Chen, W., Wu, W., Sun, C., Guo, W., & Zhu, X. (2016). Detection of aphids in wheat fields using a computer vision technique. *Biosystems Engineering*, *141*, 82-93.
[53] Han, L., Haleem, M. S., & Taylor, M. (2015, July). A novel computer vision-based approach to automatic detection and severity assessment of crop diseases. In *2015 Science and Information Conference (SAI)* (pp. 638-644). IEEE.
[54] Nam, N. T., & Hung, P. D. (2018, June). Pest detection on traps using deep convolutional neural networks. In *Proceedings of the 1st International Conference on Control and Computer Vision* (pp. 33-38).
[55] Sun, K., Wang, Z., Tu, K., Wang, S., & Pan, L. (2016). Recognition of mould colony on unhulled paddy based on computer vision using conventional machine-learning and deep learning techniques. *Scientific reports*, *6*(1), 1-14.
[56] Zhong, Y., Gao, J., Lei, Q., & Zhou, Y. (2018). A vision-based counting and recognition system for flying insects in intelligent agriculture. *Sensors*, *18*(5), 1489.
[57] Bini, D., Pamela, D., & Prince, S. (2020, March). Machine vision and machine learning for intelligent agrobots: A review. In *2020 5th International Conference on Devices, Circuits and Systems (ICDCS)* (pp. 12-16). IEEE.

[58] Kanade, P., Akhtar, M., David, F., & Kanade, S. (2021). Agricultural Mobile Robots in Weed Management and Control. *International Journal of Advanced Networking and Applications*, *13*(3), 5001-5006.
[59] Wu, X., Aravecchia, S., Lottes, P., Stachniss, C., & Pradalier, C. (2020). Robotic weed control using automated weed and crop classification. *Journal of Field Robotics*, *37*(2), 322-340.
[60] Johnson, F. T., & Akerele, J. (2020). ARTIFICIAL INTELLIGENCE FOR WEED DETECTION-A TECHNO-EFFICIENT APPROACH.
[61] Bogue, R. (2020). Fruit picking robots: has their time come?. *Industrial Robot: the international journal of robotics research and application*, *47*(2), 141-145.
[62] Jia, W., Zhang, Y., Lian, J., Zheng, Y., Zhao, D., & Li, C. (2020). Apple harvesting robot under information technology: A review. *International Journal of Advanced Robotic Systems*, *17*(3), 1729881420925310.
[63] Davidson, J. R., Silwal, A., Hohimer, C. J., Karkee, M., Mo, C., & Zhang, Q. (2016, October). Proof-of-concept of a robotic apple harvester. In *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (pp. 634-639). IEEE.
[64] Talaviya, T., Shah, D., Patel, N., Yagnik, H., & Shah, M. (2020). Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artificial Intelligence in Agriculture*, *4*, 58-73.
[65] Teal, S. L., & Rudnicky, A. I. (1992, June). A performance model of system delay and user strategy selection. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (pp. 295-305).
[66] Washington, R., & Hayes-Roth, B. (1989, August). Input Data Management in Real-Time AI Systems. In *IJCAI* (Vol. 89, No. 11).
[67] Rajotte, E. G., Bowser, T., Travis, J. W., Crassweller, R. M., Musser, W., Laughland, D., & Sachs, C. (1992, February). Implementation and adoption of an agricultural expert system: The Penn State Apple Orchard Consultant. In *III International Symposium on Computer Modelling in Fruit Research and Orchard Management 313* (pp. 227-232).
[68] Mowforth, P., & Bratko, I. (1987). Ai and robotics; flexibility and integration. *Robotica*, *5*(2), 93-98.