

ARTIFICIAL INTELLIGENCE IN AGRICULTURE

Abstract

In recent years, artificial intelligence (AI) has emerged as a game-changing technology across a wide range of industries, including agriculture. Technology fueled by AI helps farmers make informed choices, maximise efficiency, and boost output. Water conservation and sustained soil fertility are aided by smart irrigation systems and artificial intelligence-based soil health monitoring. By detecting pests and diseases early, AI helps farmers save a lot of money. Additionally, new forms of AI, such as robotics and drones, automate labor-intensive tasks and supply accurate field data. In order to reap the benefits of artificial intelligence (AI) and build a more resilient and productive agricultural industry as technology advances, it is crucial to address barriers and encourage its ethical integration. Focusing on soil monitoring, crop harvesting monitoring & forecasting, pest management, disease management, crop management, irrigation, soil management, and emerging AI capabilities in agriculture like drones, robotics, and automation, this paper provides an overview of the application of AI in various aspects of agriculture, highlighting its potential benefits and challenges.

Keywords: Artificial intelligence, Soil monitoring, Disease Control, Irrigation, Crop harvesting monitoring, Robotics.

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I. INTRODUCTION

Machines were created throughout the industrial revolution to replace human work in many different industries, greatly increasing output and efficiency. As the 20th century progressed, Information Technology exploded, eventually leading to the invention of computers. The development of AI-enabled machines was made possible by these technological advancements.

Machines are now capable of learning and solving problems much like humans do thanks to advancements in artificial intelligence. Critical to AI is machine learning, which trains computers to recognise, grasp, and evaluate data patterns for better decision making and efficiency. These days, machine learning is one of the most important frontiers in computer science. Rapid technological developments and widespread applicability in problems—especially those that are intractable to traditional computing systems or even humans—have propelled this field forward quickly. Increased yields and more efficient use of resources will be possible in the future of agriculture thanks to novel approaches and novel computational capabilities. Already, agricultural output and resource effectiveness are benefiting from the integration of crop models and decision-making tools. By incorporating cutting-edge technologies, artificial intelligence has the potential to dramatically alter the agricultural sector through improved yield predictions. Sustainable and productive farming practises can be achieved through the use of AI by enabling farmers to make data-driven decisions, optimise resource allocation, and improve overall agricultural practises (Dutta et al., 2020). Many methods, from databases to decision support systems, have been proposed to deal with agriculture's current problems (Thorpe et al., 1992). When comparing the effectiveness of different options, AI-based systems stand out as particularly robust and precise. Many factors, including climate change, growing production costs, a shrinking water supply for irrigation, and a dramatic decrease in the farm workforce, have combined in recent decades to pose serious problems for agricultural production systems. The COVID-19 pandemic also threatens to disrupt supply networks and food production (Outlaw et al., 2020). The stability of the environment and the security of the food supply in the future are at risk from these causes (Andersen et al., 2018). Major advances are always required to keep up with the ever-evolving climate (Hatfield et al., 2014). The use of AI is a game-changer in the agricultural industry. Today's agricultural system is at a new level thanks to the machinery and tools powered by artificial intelligence. This innovation has improved agricultural monitoring, harvesting, processing, and marketing in real time. Agricultural robots and drones are part of the latest generation of automated systems that have contributed greatly to the agro-based economy (Liakos et al., 2018). In order to boost output and decrease labour demands, farmers are increasingly turning to automated irrigation, weeding, and spraying systems (Wall and King, 2004).

II. TRACKING THE SOIL

Due to its importance in plant growth, soil health must be monitored on a field scale. Significant progress has been achieved in recent years by scientists in the creation of instruments, technologies, and equipment specifically designed for soil monitoring. As a result of their ability to evaluate water holding capacity, moisture levels, chemical composition, and physical qualities of soil, these cutting-edge resources have become important to farmers and growers.

The salinity, pH, soil organic carbon (SOC), electrical conductivity (EC), nitrogen content (N), potassium content (K), and phosphorus content (P) can all be monitored with these cutting-edge instruments. Farmers can use this data to determine how many nutrients their crops need based on soil conditions and other factors. Agro Cares' Scanner and Lab-in-a-box are notable innovations in this area. This high-tech gear functions as a whole soil laboratory, delivering essential data and services that shed light on the soil's current condition (Vgen et al., 2016). Many farmers have begun using this improved equipment, which eliminates the need for costly and time-consuming trips to the lab.

Consistent monitoring of soil moisture is a major obstacle to calculating crop water needs. Many farms lack access to reliable data on soil moisture, but this problem can be overcome by using in-situ soil moisture monitors, remote sensing technology, and other instruments. In addition, many active satellites are devoted to collecting worldwide soil moisture data. Soil moisture can also be monitored effectively on farms using in-situ wireless sensors (Ray et al., 2017).

Determine crop parameters like soil depth to improve the efficacy of sowing with the help of cutting-edge technologies like vision-based and wireless sensors. Numerous robotic equipment have been developed to increase crop yields, marking a big step forward in the field of "smart farming." FarmBot and Agribot are two examples of such agricultural robots with revolutionary potential. Agribots are a subset of agricultural robots that are designed to work in tandem with digital computers and a vehicle's visual system. Agribots are able to easily map and explore any agricultural terrain thanks to the global positioning system (GPS). In addition, remote sensors including those with light-emitting diodes (LEDs) are used to collect data on seed flow rates (Devaux et al., 2014).

III. FORECASTING AND MONITORING HARVESTS

It is crucial to keep an eye on crops as they develop. It is important to evaluate crop output not just at harvest time, but also during the growing process and before to harvest. Optimal pollination levels are one of several variables that must be tracked in order to keep an eye on crop productivity, especially as weather patterns shift. Furthermore, reliable forecasting of seed yield is crucial (Torbick et al., 2017).

Predicting crop yields in advance of harvest is called crop prediction. Farmers really benefit from these kinds of predictions since they allow them to make educated choices and plans in the near future. By assessing the crop's maturity and quality, the best time to harvest can be determined with precision. The monitoring procedure can also evaluate other aspects of the fruit, such as its colour, size, quality, and developmental stage. Improved crop prediction can lead to better disease management tactics and other aspects of crop development, including increased yield and quality. Understanding when to harvest becomes crucial for maximising yields in this context. Any type of harvesting equipment can benefit from incorporating cutting-edge technology, like the enhanced yield monitor. In addition, the yield monitor device can be synced with an app for smartphones called FarmRTX, which supplies accurate information about harvesting. In the end, this information can be analysed using the producer's web-based app (<https://www.farmtrx.com/>).

IV. ROBOTIC DISEASE AND PEST CONTROL

Infestation by infectious pests is the most problematic issue in agriculture, resulting in substantial economic losses. For a long time, researchers have been trying to find a solution to this issue by creating pest-identification computer systems.

Rule-based expert systems tend towards hesitation because of imprecise, incomplete, and unfocused data connected to agricultural management (Pasqual et al., 1988). (Saini et al., 2002) and (Siraj et al., 2006) presented a number of logic-based expert systems to deal with this ambiguity.

Ghosh and Samanta's TEAPEST rule-based expert system for tea pest management was structured using an object-oriented approach (Ghosh et al., 2003). A method of successive consultation and identification was built into the system. After that, Banerjee improved upon a redesign by Samanta and Ghosh that used a sophisticated back proliferation neural network (Samanta et al., 2012). Banerjee et al. (2017) state that improved sorting performance was accomplished by introducing a radial basis function prototype developed by Banerjee.

Artificial intelligence (AI) is used by the pest treatment industry for optimal route planning and insect occurrence forecasting. These businesses and farmers can use drones to do remote inspections of their crops, allowing for constant monitoring and the early detection of pests, diseases, soil health issues, and crop degradation. Farmers can take focused action to stop the spread of the illness by collecting data from specific crop areas.

Infectious plant diseases provide serious threats to the world's economy, ecology, consumers, and farmers. Pests and pathogens damage 35% of crops in India, which results in substantial losses for farmers. Due to the toxicity of some chemicals, which can accumulate in the food chain, indiscriminate pesticide usage is also a concern to human health. Monitoring crops for disease, making timely diagnoses, and administering effective treatments are all vital in reducing these negative outcomes. Worldwide, sophisticated computational systems are used to analyse diseases and offer control strategies. Images of infected leaves are analysed to determine what parts of the image are unhealthy and what parts are healthy. Leaves with infections are submitted to research facilities for analysis, where they help identify pests and detect nutrient deficiencies. In Figure, we see a complete framework.

(Boyd et al., 1994) laid the groundwork for later rule-based frameworks. Panigrahi and Francl developed a model for artificial neural networks to combat plant disease (Francl et al., 1997). Other fusion systems were also operational. To diagnose illnesses in phalaenopsis seedlings, Huang proposed a prototype that uses image processing and a neural network model (K. Y. Huang, 2007).

Physical, chemical, and biological measures should all be used as part of an integrated disease control and management model (<https://apps.bea.gov/iTable/iTable.cfm?ReqID=51&step=1#reqid=51&step=1&isuri=1&5114=a&5102=5>, 2018) to keep infections at bay and keep losses to a minimum. Artificial intelligence (AI) approaches are needed for disease control and management since they can

save time and money compared to traditional methods (<http://wssa.net/wp-content/uploads/WSSA-Fact-SheetFinal.pdf>). The expert system's kernel's reasoning can be understood in detail thanks to the Explanation Block (EB) (Ballede et al., 2014). The system makes smart inferences for managing agricultural diseases by using a novel approach of rule promotion based on fuzzy logic. When combined with a text-to-speech (TTS) converter, a text-to-talking user interface can be a powerful tool for real-time interactions on the web (Kolhe et al., 2011). The system that aids in disease detection and treatment recommendation was developed using a rule-based and forward chaining inference engine (Munirah et al., 2013).

V. ARTIFICIAL INTELLIGENCE FOR WATER AND SOIL MANAGEMENT

Irrigation automation is a time-consuming and difficult undertaking in the agricultural industry. Mismanagement of irrigation and soil quality can result in crop loss and contamination, making proper management essential for successful agriculture. A solution to automate irrigation and increase agricultural output is provided by state-of-the-art AI systems that are equipped with previous meteorological data and understanding of crops and soil. Companies like CropIn and Intello Labs are maximising per-acre value and analysing photos using Deep Learning by implementing AI-based technology and sensors to monitor soil health. This AI-driven method not only helps farmers deal with water issues more efficiently, but also helps them save water.

Several studies involving irrigation and soil management are discussed, along with the use of artificial intelligence to these problems. Fuzzy system developers (Sicat et al., 2005) created a method for forecasting crop yields using expert agriculturalist knowledge and land suitability maps. To evaluate the moisture content of the topsoil in rice fields, Arif developed a neural network method (Arif et al., 2013). The radial basis function of the neural network performed better than earlier models when Manek and Singh compared them for rainwater forecasting utilising four separate inputs (Manek et al., 2016).

VI. THE FUTURE OF ARTIFICIAL INTELLIGENCE IN FARMING

1. Using Automation and Robots in Agriculture: The use of RAS (Robotics and Autonomous Systems) has had a profound effect on agriculture, increasing output while decreasing labour costs. In order to boost productivity, researchers are focusing on creating autonomous technologies to replace human labour (Dursun and Ozden, 2011). In agriculture, autonomous robots are used for a variety of duties including weeding, watering, and monitoring, all of which improve precision and plant management. The development of plants is tracked and diseases are identified by automated machinery and biosensors. The use of automated irrigation systems and laser weeding equipment increases productivity even further. The use of RAS has greatly increased agricultural productivity and shows promise for even greater future growth.

- **Irrigation:** Modern automatic irrigation scheduling systems have largely supplanted the older, more labor-intensive methods of manual irrigation based on soil water assessment. These days, automated irrigation systems take into account not only the weather, such as humidity, wind speed, and sun radiations, but also the crop itself, including its growth stage, plant density, soil qualities, and pests. Research conducted

by Kumar et al. (2014) looked into several irrigation techniques with the goal of creating more efficient systems with a smaller environmental impact. Soil pH metres and fertility metres are used to determine how much of key nutrients like potassium, phosphorus, and nitrogen are present in a given soil sample. Automatic plant watering systems using drip irrigation and wireless technologies maximise both soil fertility and water use.

Microcontroller-based "smart irrigation" technologies monitor rainfall, soil temperature, nutrient levels, and sunshine to maximise efficiency and output while decreasing the need for human effort. Through the use of M2M technology, nodes in the agricultural field can easily communicate and share data with servers or cloud platforms (Shekhar et al., 2017). The use of Arduino and Raspberry Pi3 technology in automated irrigation systems is a recent development. These mechanisms constantly check the humidity and temperature, activating the sprinklers as necessary. Because of this automation, less time and fewer people are needed to complete irrigation tasks (Jha et al., 2019). There was a possible 40% increase in output once remote sensors were effectively deployed using Arduino technology (Savitha and UmaMaheshwari, 2018).

Soil moisture detection, temperature measurement, pressure regulation, and molecular sensing are only few of the sensors included in the entire system (Varatharajalu and Ramprabu, 2018) developed to maximise crop yields. Wireless networks like Zigbee and hotspots are used for data transmission by these devices. Overall, these innovations in irrigation technology hope to better manage water, increase crop productivity, and promote sustainable farming methods.

- **Weeding:** A study by the Indian Council of Agricultural Research found that India loses agricultural produce worth over \$11 billion due to weeds every year. This is more than the Centre's budgetary commitment for agriculture for 2017-18. Getting rid of these weeds is crucial since they not only take up valuable space but also stunt the development of desirable crops (Bak and Jakobsen, 2003). A vision-based weed identification technique was proposed in natural lighting (Tang et al., 2000). The genetic algorithm based Hue-Saturation-Intensity (GAHSI) colour space was designed for weed detection in outdoor fields. It takes into account extreme situations such as brightness and shade, and the mosaicking of lighting conditions to determine the propensity of employing GAHSI to recognise the regions or zones in the field based on these two characteristics presented concurrently. When comparing the GAHSI-segmented image to a manually sectioned reference image, we found that the GAHSI performed just as well. Knowing how to tell weed seedlings apart from crop seedlings is essential prior to the creation of an automated weed management system (Chang and Lin, 2018). Carrot seedlings were differentiated from ryegrass using a previously developed approach. This technique was developed by (Aitkenhead et al., 2003) and is based on measuring a few basic morphological features of leaf shape. This technique is used largely to distinguish between plants and weeds by analysing changes in leaf size, and its accuracy ranges from 52% to 75%. Digital imaging was also employed as an alternative method for weeding. A self-organizing neural network was used in this method. Unfortunately, the method did not produce satisfactory results for practical applications. It was discovered that existing

technology based on NN can distinguish different species with a success rate of above 75%. Various physical methods were utilised in the past that involved physical involvement with the weeds, but these have been replaced by modern automated technologies. Both the location and the quantity of weeds play a role in how often they need to be weeded (Nrremark and Griepentrog, 2004). Traditional intra-row weeding was accomplished by tilling the soil and tearing up the root-weed contact, which weakened the weeds. However, tillage can harm the crop-soil interface, thus this approach is not recommended. As a result, techniques like laser treatments (Heisel et al., 2001) and micro spraying were developed; these approaches do not touch the plant, and hence do not break the connection between the roots and the soil.

- 2. AI and UAVs for Crop Management in Precision Agriculture:** Drones, also known as unmanned aerial vehicles (UAVs) or unmanned aerial systems (UASs), are a type of unmanned aircraft used in agriculture (Mogli and Deepak, 2018). They cooperate with the on-board GPS and other sensors to perform their functions. Drones are being used in agriculture for a wide range of tasks, including keeping an eye on crops and irrigation systems, spotting weeds, keeping tabs on livestock and wildlife, and even handling natural disasters (Ahirwar et al., 2019). Agriculture is being profoundly impacted by the use of UAVs for remote sensing picture capture, processing, and analysis (Abdullahi et al., 2015). Drones have been adopted by the agricultural sector as a way to improve upon traditional farming practises (Pederi and Cheporniuk, 2015). According to a recent PwC study, the total market value of drone-powered solutions across all sectors is more than USD 127 billion.

UAVs with multispectral sensors can capture more information than a standard point-and-shoot camera. They let farmers monitor things like soil moisture and plant health that can't be seen with the naked eye. These abilities can be used to assist get over some of the obstacles that have hampered agricultural output. The advancement of unmanned aerial vehicles (UAVs) is coupled with the creation of WSNs. UAVs can make more efficient use of their resources thanks to the information gleaned from WSNs, for as by limiting the application of pesticides to predetermined locations. The control system needs to be as responsive as feasible due to the frequent and unexpected shifts in environmental circumstances. This can be facilitated through integration with WSN (Costa et al., 2012).

Many agricultural tasks, such as soil and field analyses (Primicerio et al., 2012), crop monitoring (Bendig et al., 2012), crop height estimations (Anthony et al., 2014), and pesticide spraying (Faiçal et al., 2017), benefit from the use of unmanned aerial vehicles (UAVs) in precision agriculture. Due to increased population and shifting climatic patterns, the agricultural drone market is predicted to expand by more than 38% in the next years (Puri et al., 2017).

VII. AI-BASED CROP MANAGEMENT IN GENERAL

An interface for global crop management that takes into account all aspects of agriculture is typically provided by the universal crop management system. The initial call to implement AI in agriculture was made by McKinion and Lemmon in their 1985 article "Experts System for Agriculture" (Kinion et al., 1985). Boulanger, in his own thesis

(Boulanger, 1983), suggested using an additional expert system to safeguard the maize harvest. The POMME expert system was proposed by Roach in 1987 (Roach et al., 1987) to aid in the administration of apple orchards. Stone and Toman developed COTFLEX, an additional expert system for crop management (Stone et al., 1989). A new rule-based specialty called COMAX (H. Lemmon, 1990) was developed for managing cotton crops. Remote sensing, hyperspectral imaging, and 3-D laser scanning are indispensable for estimating crop yields across large swaths of farmable land. It has the ability to significantly alter the time and energy spent by farmers on land management. Robinson and Mort (Robinson et al., 1997) suggested a system based on feed-forward neural networks to safeguard citrus fruits from contamination in the field on the Italian island of Sicily. The input and output parameters were binary encoded for use in testing and training the network. In order to create the most accurate prototype possible, the writers used a wide variety of input patterns. The highest-performing prototype developed so far had a 94% accuracy, two output classes, and six input classes. After being trained up to 300,000 times, the unrivalled network's accuracy reached 85.9 percent on average (Li et al., 2002). Soybean crop selection, pest concerns, and fertiliser application were all addressed in Prakash's fuzzy logic-based management plan (Prakash et al., 2013). Farmers must employ a wide range of crop management strategies to overcome water scarcity brought on by poor soil, unfavourable climate, or inadequate irrigation. Guidelines for making decisions must be used to select a system for flexible crop management. The severity, duration, and foreseeability of drought should all be taken into account when weighing the relative merits of different planting strategies (Debaeke et al., 2004). Understanding weather trends can help farmers make decisions that result in high-quality crops (Aubry et al., 1998). When evaluating the operational behaviour of a farm system, PROLOGUE takes into account the capacity, labour availability, and data on authorised and prioritised workers, tractors, and tools, as well as weather information and equipment. Crop output, gross income, and net profit predictions are also included (Lal et al., 1992), both for the entire farm and for specific areas. Crop prediction approach is used to foretell the best crop by detecting a wide range of soil components and climate-related data. Many factors come into play, including soil type, pH, nitrogen, phosphate, potassium, organic carbon, calcium, magnesium, sulphur, manganese, copper, and iron, as well as depth, temperature, rainfall, humidity, and so on (Snehal et al., 2014). Demeter, the rowing machine built for speed, is operated by a computer and is equipped with a global positioning system and two cameras. It can cut crop rows, rotate to cut succeeding rows, move over the field, and detect unexpected barriers, all while planning out the harvesting procedures for the entire field (Pilarski et al., 2002). Artificial intelligence (AI) is used to harvest cucumbers by coordinating the actions of the robot's various hardware and software components. These include the autonomous vehicle, the manipulator, the end-effector, two computer vision systems for detection and 3D imaging of the fruit and the environment, and finally a control scheme that generates collision-free motions for the manipulator during harvesting. Each area can use its own set of meteorological variables and precipitation statistics. Changing the settings of an ANN can improve its ability to predict rice harvests. The number of hidden nodes and the rate of learning needed to optimise a model decreased with the size of the data collection (Ji et al., 2007).

Table 1: AI in Crop Management Summary

Technique	Strength	Limitation	Application
PROLOG	Removes less used farm tools from the farm.	Location-specific.	Lal et al., 1992
CALEX	Can formulate scheduling guidelines for crop management activities.	Takes time.	R. E. Plant, 1989
ROBOTICS-Demeter	Can harvest up to 40 hectares of crop	Expensive: Uses a lot of fuel.	Pilarski et al., 2002
ANN	Predicts crop yeild.	Only captures weather as a factor for crop yeild.	Snehal et al., 2014
ANN	Above 90% success rate in detecting crop nutrition disorder.	A little number of symptoms were considered.	Song et al., 2005
ROBOTICS	Has 80% success rate in harvesting crops	Slow picking speed and accuracy.	Henten et al., 2002
ANN	Can predict the response of crops to soil moisture and salinity.	Considers only soil temperature and texture as factors.	Dai et al., 2011
FUZZY Cognitive Map	Predict cotton yield and improve crop for decision management.	It is relatively slow.	Papageorgiou et al., 2011
ANN	Can accurately predict rice yield.	Time-consuming, limited to a particular climate.	Ji et al., 2007
ANN and Fuzzy Logic	Reduces insects that attack crops.	Shows inability to differentiate between crop and weed.	Yang et al., 2003

VIII. FUTURE OPPORTUNITIES

Irrigation, climate change, groundwater supply, food scarcity, and waste are only some of the major challenges facing the agricultural sector. The future of farming depends on adapting a variety of cognitive solutions. Although studies are being conducted and applications have been developed, the market is still unmet (Shobila & Mood, 2014). In order to effectively collect contextual data, make decisions in real time, and account for changing circumstances, applications need to be robust (Slaughter et al., 2008). The adoption rate of cognitive solutions among farmers can be increased by making them more cost-effective, perhaps through an open-source platform. By forecasting weather, monitoring land quality, groundwater levels, crop cycles, and pest attacks, AI technology can help farmers increase yields and improve seasonal crops. The use of AI-powered sensors has enormous promise for raising output quality. The problems of crop damage and providing accurate information to farmers persist. Protecting crops using AI-enabled picture identification and drone

monitoring is an exciting prospect. The revolutionary effects of AI can help with feeding the world and maintaining healthy farms. The potential benefits of using AI for agricultural digital transformation are substantial. The agricultural process and market conditions will both benefit from the effective application of AI in agriculture.

IX. CONCLUSION

Artificial intelligence's (AI's) promise to revolutionise agriculture and solve the industry's many problems is undeniable. Improvements in agricultural practises, efficiency, and productivity are being pushed by AI-powered technologies. These technologies range from soil monitoring and crop harvesting predictions to pest and disease management, irrigation, and new capabilities like robotics and drones. The ability of AI to assess data, forecast weather, and optimise irrigation and water usage leads to more environmentally friendly and effective farming methods. Early detection is made possible by using AI in pest and disease control, which in turn reduces crop losses and reduces the need for toxic pesticides. In addition, using sensors and drones powered by AI allows for more accurate crop monitoring, which in turn improves both yield and quality. These developments in precision agriculture equip farmers with data-driven insights, allowing them to make decisions in real time and enhancing farming outcomes. The revolutionary effect of AI on agriculture is becoming more and more important as the demand for food rises and environmental issues persist. To realise its full potential, however, the market needs to move beyond the underdeveloped state of AI applications and develop cheaper and more accessible solutions, maybe through open-source platforms. Agriculture can overcome irrigation and climatic difficulties, assure sustainable water management, reduce food waste, and maximise productivity to meet the needs of a growing global population with the use of artificial intelligence (AI) technologies. Better food security and environmental protection can be achieved with the help of AI in agriculture because it will allow for more efficient, resilient, and sustainable farming practises in the future.

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