**Artificial Intelligence in Agriculture**

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**Abstract:**

Artificial Intelligence (AI) has emerged as a transformative technology in various sectors, including agriculture, revolutionizing traditional practices and optimizing crop management AI-driven technologies enable farmers to make data-driven decisions, optimize resource usage, and improve productivity. Smart irrigation systems and AI-based soil health monitoring help conserve water and maintain soil fertility sustainably. AI's early pest detection and disease control measures significantly reduce crop losses. Furthermore, emerging AI capabilities like robotics and drones automate labor-intensive tasks and provide precise field data. As technology continues to evolve, it is imperative to overcome challenges and promote the responsible integration of AI in agriculture to maximize its benefits and create a more resilient and productive agricultural sector. This paper presents an overview of the application of Artificial Intelligence (AI) in various aspects of agriculture, highlighting its potential benefits and challenges, focuses on soil monitoring, crop harvesting monitoring & forecasting, pest management, disease management, crop management, irrigation and soil management as well as emerging AI capabilities in agriculture, including drone, robotics and automation.

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

**1. Introduction:**

During the industrial revolution, machines were introduced to replace human labour in various industries, which significantly increased productivity and efficiency. As technology continued to advance, the 20th century witnessed rapid growth in Information Technology, leading to the development of computers. This technological progress paved the way for the innovation of Artificial Intelligence (AI)-powered machines.

Artificial intelligence mimics human intelligence, enabling machines to replicate human-like thinking and behaviour, including learning and problem-solving. Machine learning, a crucial component of AI, empowers systems to recognize, comprehend, and analyse patterns within data, enhancing their ability to make informed decisions and improve performance. One of the crucial areas of exploration in this cutting-edge technological era of computer science is machine learning. This field is progressing rapidly due to its swift technological advancements and its robust applicability in problems, particularly those that cannot be efficiently resolved by conventional computing structures and even humans (Rich et al.,1991). The future of agriculture depends on innovative ideas and technological advancements to increase yields and optimize resource utilization through unconventional computing tools. Integrating crop models and decision-making tools in agriculture is already enhancing production and resource efficiency. Artificial Intelligence has immense potential to revolutionize agriculture by leveraging advanced technologies, enabling accurate forecasting of agricultural productivity. By harnessing AI's capabilities, farmers can make data-driven decisions, optimize resource allocation, and improve overall agricultural practices, leading to sustainable and productive farming practices (Dutta et al.,2020). To address the existing challenges in agriculture, numerous approaches have been suggested, ranging from databases to decision support systems (Thorpe et al.,1992). Among these solutions, Artificial Intelligence-based systems stand out as highly effective when it comes to robustness and precision. Climatic changes, rising production costs, dwindling water supply for irrigation, and a significant decline in the farm workforce have caused a multitude of challenges to agricultural production systems over the past few decades (Jinha et al.,2021). Furthermore, the disruption of supply systems and food production is endangered due to the COVID-19 pandemic (Outlaw et al.,2020). Such factors pose a threat to the continuity of the environment and the future food supply chain (Andersen et al.,2018). Significant innovations are always a necessity to remain ahead of the ongoing climate change (Hatfield et al.,2014). AI is an advancing technology in the realm of agriculture. AI-powered equipment and machines have elevated today's agricultural system to a new level. This technology has boosted crop production and enhanced real-time monitoring, harvesting, processing, and marketing. The most recent automated systems utilizing agricultural robots and drones have made a significant contribution to the agro-based industry (Liakos et al., 2018). This paper covers the technologies employed for automated irrigation, weeding, and spraying to increase productivity and alleviate the workload on farmers (Wall and King, 2004).

**2. Soil Monitoring :**

Soil plays a crucial role in supporting plant growth, making it essential to monitor soil health at the field scale. In recent times, researchers have made significant advancements in developing tools, technologies, and devices dedicated to soil monitoring. These innovative resources have become invaluable for farmers and growers as they enable the assessment of various soil features, including water holding capacity, moisture levels, chemical composition, and physical properties.

These modern tools also facilitate the monitoring of soil health indicators such as salinity, pH level, soil organic carbon (SOC), electrical conductivity (EC), nitrogen content, potassium levels, and phosphorus levels. By analysing these parameters, farmers can estimate the appropriate number of fertilizers required for optimal plant growth. One noteworthy tool in this field is the Scanner and Lab-in-box introduced by Agro Cares. This advanced equipment serves as a comprehensive soil laboratory, providing valuable information and services that offer insights into the current status of the soil (Vågen el al.,2016). This is the upgraded tool widely adopted by many farmers, eliminating the need for external laboratory sample analysis.

One of the primary challenges in estimating crop water requirements is the consistent monitoring of soil moisture. To address this, employing in situ soil moisture sensors, remote sensing technologies, and various tools can prove to be highly effective strategies for obtaining accurate information about soil moisture levels on many farms. Additionally, numerous operational satellites are dedicated to measuring soil moisture data on a global scale. At the farm level, in situ wireless soil moisture sensors can also be employed to monitor soil moisture efficiently (Ray et al.,2017).

Innovative technologies, including vision-based and wireless sensors, play a crucial role in determining crop factors, such as soil depth, to enhance the efficiency of seeding processes. The field of smart farming has seen significant advancements with the development of various robotic tools aimed at improving crop production. Notable examples include FarmBot and Agribots, which are capable of revolutionizing agriculture. Agribots, a specific type of robot, utilizes the pairing of digital computers with a vehicle vision system to operate effectively in agricultural fields. By leveraging the global positioning system (GPS), Agribots can create location maps and navigate any agricultural land with ease. Additionally, sensors equipped with light-emitting diodes (LEDs) provide essential information about seed flow rates, while remote sensors are also employed for this purpose (Devaux et al.,2014).

#### 3. Crop Harvesting Monitoring and Forecasting:

Crop monitoring throughout the growth period is a fundamental process. Assessing crop yield is not only crucial at the time of harvest, but it also holds importance during the crop's developmental stages and before harvesting. Several factors are necessary for effectively monitoring crop yield, including optimal pollination levels, especially in the face of changing environmental conditions. Additionally, accurate prediction of seed production is essential (Torbick et al.,2017).

Crop prediction is a method that anticipates yields before the actual harvest occurs. Such forecasts are invaluable for farmers as they assist in making informed near-term plans and decisions. Additionally, analysing crop maturity and quality enables the accurate determination of the optimal harvesting time. During the monitoring process, various fruit factors, including color, size, quality, and developmental stages, can also be assessed. Crop disease management strategies and other developmental stages, such as crop yield and quality, can be significantly improved through crop prediction. To achieve this, being aware of the appropriate harvesting schedule becomes essential for optimizing crop outcomes. A novel technology, like the advanced yield monitor, can be integrated with any harvesting machinery. Furthermore, the yield monitor tool can be linked with a smartphone application called FarmRTX, which provides precise harvesting data. Ultimately, this data can be processed on the manufacturer's web-based program ( [**https://www.farmtrx.com/**](https://www.farmtrx.com/) ).

**4. Pest and disease Management with AI**

The most troubling issue in agriculture, causing significant economic losses, is the infestation of infectious pests. Scientists have long worked to combat this problem by developing computer systems that can identify these pests and suggest effective control measures.

Often, the data related to agricultural management is unclear, incomplete, and lacks focus, leading the rule-based expert system to lean towards indecision (Pasqual et al., 1988). To address this uncertainty, several logic-based expert systems were proposed by (Saini et al., 2002) as well as (Siraj et al., 2006).

Ghosh and Samanta utilized an object-oriented approach to organize their rule-based expert system, TEAPEST, for pest management in tea (Ghosh et al., 2003). The system incorporated a sequential consultation and identification process. Later on, Samanta and Ghosh redesigned the system, employing a complex back proliferation neural network (Samanta et al., 2012), which was further enhanced by Banerjee. Banerjee introduced a radial basis function prototype to achieve higher sorting efficiency (Banerjee et al., 2017).

Pest control companies utilize Artificial Intelligence (AI) to optimize pest route planning and predict pest occurrences. Employing drone technology, these companies and farmers can remotely inspect crops, enabling continuous monitoring to detect pests, diseases, soil health issues, or crop degradation. By gathering data from specific crop areas, farmers can take targeted measures to prevent the disease's further spread.

Plant diseases pose significant risks to the global economy, environment, consumers, and farmers. In India, pests and pathogens are responsible for destroying 35% of crops, leading to major losses for farmers. Indiscriminate pesticide use also threatens human health due to the toxic nature of some chemicals, which can become concentrated in the food chain. To mitigate these effects, crop surveillance, disease detection, and appropriate treatment are crucial. Advanced computerized systems are employed worldwide for disease analysis and recommending control methods. Disease detection involves image analysis, where leaf images are partitioned into non-diseased areas, background, and diseased areas. Infected parts of leaves are then sent to labs for further examination, aiding in pest identification and nutrient deficiency sensing. A comprehensive structure is shown in Figure.

 Fig: Disease Detection

In the early years, the establishment of rule-based frameworks was done by (Boyd et al., 1994). To address disease control in various crops, Panigrahi and Francl designed an artificial neural network model (Francl et al., 1997). There were also other fusion systems in place. Huang suggested a prototype using an image processing method and a neural network model to classify diseases in phalaenopsis saplings (K. Y. Huang, 2007).

To effectively control diseases and minimize losses, a farmer should adopt an integrated disease control and management model that includes physical, chemical and biological measures (https://apps.bea.gov/iTable/iTable.cfm?ReqID=51&step=1#reqid=51&step=51&isuri=1&5114=a&5102=5, 2018). To achieve these is time-consuming and not at all that cost-effective (http://wssa.net/wp-content/uploads/WSSA-Fact-SheetFinal.pdf), hence the need for the application of AI approach for disease control and management. Explanation block (EB) gives a clear view of the logic followed by the kernel of the expert system (Balleda et al., 2014). A novel approach of rule promotion based on fuzzy logic is used in the system for drawing intelligent inferences for crop disease management. A text-to-speech (TTS) converter is used for providing the capability of the text-to-talking user interface provide a highly-effective interactive user interface on the web for live interactions (Kolhe et al., 2011). A rule-based and forward chaining inference engine has been used for the development of the system that helps in detecting diseases and provide treatment suggestions in (Munirah et al., 2013).

**5. Irrigation and Soil Management with AI:**

Automating irrigation is a demanding and labour-intensive task in agriculture. Proper management of irrigation and soil quality is crucial for successful cultivation, as mismanagement can lead to crop loss and contamination. Advanced AI systems, equipped with historical weather data and knowledge of crops and soil, offer a solution to mechanize irrigation and boost overall crop yield. By implementing AI-based technologies and sensors to monitor soil health, companies like CropIn and Intello Labs aim to maximize per-acre value and analyse images using Deep Learning. This AI-driven approach not only conserves water but also assists farmers in effectively handling their water-related challenges.

This passage discusses various research studies conducted in the area of irrigation and soil management, utilizing artificial intelligence techniques. (Sicat et al., 2005) developed a fuzzy system that used agriculturalists' information to predict crop yields based on land suitability maps generated by the system. Arif created a neural network system to assess topsoil moisture in paddy fields (Arif et al., 2013). Manek and Singh compared different neural network models for rainwater forecasting using four distinct inputs, finding that the radial basis function of the neural network outperformed previous models (Manek et al., 2016).

**6. Emerging AI Capabilities in Agriculture:**

**6.1 Robotics and Automation in Farming:**
Robotics and Autonomous Systems (RAS) have significantly impacted agriculture, enhancing productivity and efficiency. Researchers emphasize developing autonomous tools to replace human labour, leading to increased efficiency (Dursun and Ozden, 2011). Autonomous robots perform various agricultural tasks, like weeding, irrigation, and monitoring, enhancing precision and managing individual plants effectively. Automated machines and biosensors monitor plant growth and detect diseases. Laser weeding and automated irrigation systems improve efficiency further. RAS has significantly amplified productivity in the agricultural sector, holding the potential for further advancements.

**6.1.1 Irrigation:**
Traditional manual irrigation based on soil water measurement has been replaced by modern automatic irrigation scheduling techniques. Autonomous irrigation machines now consider various atmospheric parameters, such as humidity, wind speed, solar radiations, and crop-specific factors like growth stage, plant density, soil properties, and pests. In (Kumar et al.,2014) study, different irrigation methods were explored to develop systems that reduce resource usage and increase overall efficiency. Fertility meters and pH meters are used to assess soil fertility by detecting the percentage of primary soil ingredients like potassium, phosphorous, and nitrogen. Automatic plant irrigators, employing wireless technology for drip irrigation, ensure optimal soil fertility and water utilization.

Smart irrigation technologies, controlled by microcontrollers, intelligently detect water levels, soil temperature, nutrient content, and weather forecasts, thereby optimizing water usage and increasing productivity without relying heavily on manual labour. Machine-to-Machine (M2M) technology facilitates seamless communication and data sharing between agricultural field nodes and servers or cloud platforms (Shekhar et al., 2017). Recent developments include automated irrigation systems utilizing Arduino and Raspberry Pi3 technology. These systems continuously monitor moisture content and temperature, triggering irrigator pumps as needed. This automation significantly reduces manpower and time required for irrigation processes (Jha et al., 2019). (Savitha and UmaMaheshwari ,2018) successfully implemented remote sensors with Arduino technology, resulting in a potential production increase of up to 40%.

(Varatharajalu and Ramprabu, 2018) designed a comprehensive system featuring different sensors for various purposes, such as soil moisture detection, temperature measurement, pressure regulation, and molecular sensing to optimize crop growth. These sensors transmit data via wireless networks like Zigbee and hotspots. Overall, these advancements in irrigation technologies aim to improve water management, enhance crop yield, and support sustainable agricultural practices.

**6.1.2 Weeding:**According to a study by researchers of the Indian Council for Agricultural Research, India loses agricultural produce worth over $11 billion — more than the Centre's budgetary allocation for agriculture for 2017–18 annually due to weeds*.* Thus, eliminating these weeds from the fields is of paramount importance; otherwise, it will not only occupy the land space but will also adversely impact the growth of other plants (Bak and Jakobsen, 2003).(Tang et al., 2000) proposed a vision-based weed detection technology in natural lighting. It was developed using a genetic algorithm to distinguish regions in Hue-Saturation-Intensity (HSI) color space (GAHSI) for outdoor field weed detection. It considers extreme conditions like brightness and shade, and these lighting conditions were mosaicked to identify the likelihood of using GAHSI to detect the regions or zones in the field based on these two parameters presented simultaneously. The GAHSI performance was evaluated by comparing the GAHSI-segmented image with a corresponding hand-sectioned reference image, and the GAHSI achieved equivalent performance. Before developing an automated weed control system, it is crucial to differentiate between the crop seedlings and the weeds (Chang and Lin, 2018). A method was applied for the recognition of carrot seedlings from ryegrass. (Aitkenhead et al., 2003) implemented this method by measuring the simple morphological characteristics of leaf shape*.* This method's effectiveness ranges from 52% to 75% and is primarily used to differentiate between plants and weeds by analyzing variations in leaf size.Another approach for weeding was implemented using digital imaging. This approach involved a self-organizing neural network. However, this method did not yield the appropriate results as expected for commercial purposes. It was found that an NN-based technology already existed, which allows one to find the differences between species with an accuracy exceeding 75%. In the contemporary world, many automated systems are developed but earlier various physical methods were used that relied on the physical interaction with the weeds. Nørremark and Griepentrog, 2004) suggested that weeding depends on the position and the number of weeds. Classical spring or duck foot tines were used to perform intra-row weeding by breaking the soil and the interface of roots through tillage and thus promoting the wilting of the weeds. But this is not an advisable method as tillage can damage the interface between the crop and the soil. *Therefore, additional non-contact methods like laser treatments (Heisel et al., 2001) and micro spraying, which do not disrupt the contact between the roots and the soil, were developed.*

**6.2 Drones and AI in Precision Agriculture**:
Unmanned aerial vehicles (UAVs) or unmanned aerial systems (UAS), also known as drones, in an agricultural context are unmanned aircraft that can be remotely controlled (Mogli and Deepak, 2018). They operate in conjunction with GPS and other sensors mounted on them. Drones are being utilized in agriculture for various purposes, including crop health monitoring, monitoring irrigation equipment, identifying weeds, monitoring herds and wildlife, and managing disasters (Ahirwar et al., 2019). The implementation of UAVs for image capturing, processing, and analysis through remote sensing is making a substantial impact on agriculture (Abdullahi et al., 2015). The agricultural industry has enthusiastically embraced drone technology, utilizing these advanced tools to transform conventional agricultural methods (Pederi and Cheporniuk, 2015). The overall market value of drone-powered solutions across various industries is estimated to be more than USD 127 billion, as indicated by a recent PwC analysis.

Multispectral sensors equipped in UAVs go beyond a regular point-and-shoot camera for capturing visible images. They allow farmers to gather information that cannot be seen in the visible range, such as soil moisture content and plant health monitoring. These capabilities can help overcome various limitations that hinder agricultural production. The development of UAVs is integrated with Wireless Sensor Networks (WSN). The data obtained from WSN enables UAVs to optimize their usage, for example, limiting the spraying of chemicals to specific designated areas. Given the sudden and continuous changes in environmental conditions, the control system must be able to respond as quickly as possible. Integrating with WSN can facilitate that process (Costa et al., 2012).

In precision agriculture, UAVs find applications in various agriculture operations, including soil and field analysis (Primicerio et al., 2012), crop monitoring (Bendig et al., 2012), crop height estimations (Anthony et al., 2014), and pesticide spraying (Faiçal et al., 2017). The agricultural drone market is expected to grow by over 38% in the coming years, driven by the increasing need for efficient agriculture due to rising population levels and changing climate patterns (Puri et al., 2017).

**7. General Crop Management with AI:**

The universal crop management system often provides an interface for the worldwide management of crops that addresses every aspect of agriculture. McKinion and Lemmon's 1985 publication "Experts System for Agriculture" made the first recommendation for the use of artificial intelligence in crop management (Kinion et al., 1985). In his own thesis, Boulanger proposed an additional expert system for the protection of the maize crop (Boulanger, 1983). In 1987, Roach proposed the POMME expert system, which was designed for managing apple plantations (Roach et al., 1987). For the management of the crop, Stone and Toman created COTFLEX, another expert system (Stone et al., 1989). A new rule-based specialist the Lemmon system, which was also created for cotton crop control, is known as COMAX (H. Lemmon, 1990). To calculate agricultural yields over cultivable land areas, remote sensing, hyperspectral imaging, and 3-D laser scanning techniques are crucial. It has the potential to bring about a radical change in the way farmers manage their lands, both in terms of time and effort. A comprehensive feed-forward neural network-based system proposed by Robinson and Mort was intended to protect citrus fruits from any form of damage in the field on Italy's Sicily island (Robinson et al., 1997). For the purposes of network testing and training, the input and output parameters were encoded in binary form. The authors employed various input patterns to produce a prototype with the highest level of accuracy. The best prototype created thus far had two output classes, six input classes, and a 94% precision. The unsurpassed network that was created included five hidden layers, on average, attained 85.9% accuracy after being trained up to 300000 times (Li et al., 2002). Based on fuzzy logic, Prakash's management plan for the soybean crop offered advice on crop selection, pest problems, and fertiliser application (Prakash et al., 2013). To deal with water deficiency caused by the soil, the weather or insufficient irrigation, farmers must combine a number of crop management techniques. Systems for adaptable crop management based on decision-making guidelines have to be chosen. When comparing cropping options, consideration should be given to the timing, intensity, and predictability of drought (Debaeke et al., 2004). The decision-making process that leads to a high-quality agricultural output can be aided by a proper understanding of weather patterns (Aubry et al., 1998). PROLOG makes use of weather information and equipment for assessing the operational behaviour of a farm system, considering its capacity, labour availability, and data on authorised and prioritised operators, tractors, and tools. For both the entire farm and individual fields, it also provides estimates of crop production, gross income, and net profit (Lal et al., 1992). By detecting numerous soil elements and data connected to the atmosphere, crop prediction methodology is utilised to forecast the most suited crop. Elements such as soil type, PH, nitrogen, phosphate, potassium, organic carbon, calcium, magnesium, sulphur, manganese, copper, and iron, as well as depth, temperature, rainfall, and humidity (Snehal et al., 2014). The speed-rowing machine Demeter is computer-controlled, and it has two cameras, as well as a GPS for navigation. It has the capacity to plan out harvesting operations for an entire field and then carry out those plans by cutting crop rows, rotating to cut subsequent rows, moving around the field and spotting unforeseen obstructions (Pilarski et al., 2002). The individual hardware and software parts of the robot, such as the autonomous vehicle, the manipulator, the end-effector, the 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 are all used to harvest cucumbers using AI (Henten et al., 2002). Field-specific rainfall data and weather variables can be used for each location. Adjusting ANN parameters affects the accuracy of rice yield predictions. Smaller data sets required fewer hidden nodes and lower learning rates in model optimization (Ji et al., 2007).



 TABLE: AI IN CROP MANAGEMENT SUMMARY

**8. Future Opportunities**:

Agriculture faces significant hurdles like irrigation, climate changes, groundwater availability, food scarcity, and wastage. Adopting various cognitive solutions will be crucial for the future of farming. Although research is ongoing and some applications exist, the industry is still underserved (Shobila and Mood, 2014). Robust applications are needed to handle dynamic conditions, enable real-time decision-making, and collect contextual data efficiently (Slaughter et al., 2008). Making cognitive solutions more affordable, possibly through an open-source platform, will broaden their reach among farmers. AI technology can help achieve higher yields and better seasonal crops by predicting weather conditions, monitoring land quality, groundwater levels, crop cycles, and pest attacks. AI-driven sensors hold significant potential in enhancing production. Dealing with crop damage and ensuring proper information for farmers remain challenging tasks. AI-enabled image recognition and drone monitoring show promise in protecting crops. AI's transformative impact can contribute to addressing food challenges and sustainable agriculture. Leveraging AI for digital transformation in agriculture holds great prospects. Proper implementation of AI in agriculture will improve the cultivation process and create a favourable market environment.

**Conclusion:**

In conclusion, the integration of Artificial Intelligence (AI) in agriculture holds tremendous potential to revolutionize the industry and address its various challenges. From soil monitoring and crop harvesting forecasting to pest and disease management, irrigation, and emerging capabilities like robotics and drones, AI-driven technologies are enhancing farming practices, promoting efficiency, and increasing productivity. AI's ability to analyse data, predict weather conditions, and optimize irrigation and water usage ensures more sustainable and resource-efficient agricultural practices. The application of AI in pest and disease management enables early detection, reducing crop losses and minimizing reliance on harmful pesticides. Moreover, the adoption of AI-driven sensors and drones facilitates precise crop monitoring, leading to better yield and quality. These advancements in precision agriculture empower farmers with data-driven insights, enabling real-time decision-making and improving overall farming outcomes. As the demand for food increases and environmental challenges persist, AI's transformative impact in agriculture becomes even more critical. However, to fully unlock its potential, the industry must overcome the current underserved status of AI applications and work towards more affordable and accessible solutions, possibly through open-source platforms. With proper implementation and adoption of AI technologies, agriculture can navigate through irrigation and climate challenges, ensure sustainable water management, reduce food wastage, and optimize production to meet the growing demands of the world's population. AI in agriculture paves the way for a more efficient, resilient, and sustainable farming future, contributing to global food security and environmental conservation.

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**Conflicts of Interest:**

The authors declare no conflict of interest**.**

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