Chapter 2

Book Chapter

The Role of AI and IoT in Seed Harvest and Agriculture Biotechnology

Allwin Ebinesar Jacob Samuel Sehar *[1], Shilpa Sivashankar †[2], Ismail Shareef M ‡[3], Pramod Kumar CV §[4], Ranjitha R ¶[5], Shreya Maga ‖[6], and V Lalith Srivatsa srirangam **[7]

[1]Associate Professor, Dept. of Biotechnology, Acharya Institute of Technology
[2]Associate Professor, Dept. of Biotechnology, Acharya Institute of Technology
[3]Professor, Dept. of Biotechnology, Acharya Institute of Technology
[4]Dept. of Biotechnology, Acharya Institute of Technology
[5]Dept. of Biotechnology, Acharya Institute of Technology
[6]Dept. of Biotechnology, Acharya Institute of Technology
[7]Dept. of Biotechnology, Acharya Institute of Technology

Abstract

The integration of Artificial Intelligence (AI) and the Internet of Things (IoT) is revolutionizing agriculture, particularly in seed harvest and biotechnology. These technologies enhance precision farming by offering data-driven solutions for crop monitoring, disease detection, and resource management. This chapter explores how AI and IoT optimize seed harvest, improve crop yields, and promote sustainable farming. AI analyzes data on soil health, weather, and crops, aiding better decisions in planting, irrigation, and fertilization, while IoT devices provide real-time environmental data. The synergy between AI and IoT

*Email: allwin2979@acharya.ac.in Corresponding Author
†Email: sshilpa@acharya.ac.in
‡Email: ismailshareef@acharya.ac.in
§Email: pramodv21.bebt@acharya.ac.in
¶Email: ranjithar.21.bebt@acharya.ac.in
‖Email: shreyav.21.bebt@acharya.ac.in
**Email: lalithv.21.bebt@acharya.ac.in

improves resource allocation and crop management. Examples from the Netherlands and India demonstrate their success in boosting yields and controlling pests. Despite challenges like high costs and technical expertise, ongoing advancements will support wider adoption. In conclusion, AI and IoT significantly improve agricultural efficiency, productivity, and sustainability, contributing to global food security.

Keywords: Artificial Intelligence (AI). Internet of Things (IoT). Precision Farming. Seed Harvest. Sustainable Agriculture. Crop Monitoring.

1 Precision Farming and Crop Management

Precision farming marks a revolutionary shift in agricultural practices, utilizing state-of-the-art technologies to enhance efficiency, productivity, and sustainability. At its core, precision farming involves the meticulous management of field variability, encompassing factors such as soil conditions, crop health, and environmental variables. Unlike traditional farming methods that apply uniform practices across entire fields, precision farming tailors interventions to the specific needs of different zones within a field (Baylis, 2017). This approach, which leverages technologies such as GPS, remote sensing, artificial intelligence (AI), and the Internet of Things (IoT), is crucial for modern agriculture. It addresses key challenges such as resource wastage, environmental impact, and the need for increased productivity in an era of growing food demands.

1.1 Definition and Importance

Precision farming, by definition, is a technology-driven approach that focuses on managing field variability in crops and soils with a high degree of accuracy. This method integrates various tools and technologies, including GPS systems, remote sensing technologies, and machine learning algorithms, to collect and analyze data. This data-driven approach allows farmers to apply resources such as water, fertilizers, and pesticides with precision, rather than using a one-size-fits-all strategy (Belal et al., 2021). The importance of precision farming is multifaceted. Firstly, it significantly improves resource efficiency. By targeting specific areas that require inputs, precision farming minimizes wastage and reduces the need for over-application. The AI tools and information systems can lead to a reduction in input costs by 10-20%, which is particularly valuable given the rising prices of agricultural inputs. Moreover, precision farming plays a crucial role in promoting environmental sustainability (Strickland, Ess, & Parsons, 1998). Reducing the overuse of fertilizers and pesticides mitigates the risk of nutrient runoff and water pollution, thus contributing to the protection of natural ecosystems. The precise application of resources also helps in conserving water, a critical factor in regions facing water scarcity (Eli-Chukwu, 2019).

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

By tailoring interventions to the specific needs of different field zones, farmers can address issues such as nutrient deficiencies, pest infestations, and water stress more effectively. This targeted approach can lead to improved crop yields and overall productivity. Furthermore, precision farming is grounded in data-driven decision-making. By utilizing advanced technologies to gather and analyze data, farmers can make informed decisions that enhance the accuracy and effectiveness of their practices. This approach supports proactive management of potential issues and facilitates more strategic planning (Gómez-Chabla et al., 2019).

1.2 AI Applications

Artificial Intelligence (AI) has become a cornerstone of precision farming, introducing sophisticated technologies that optimize various aspects of crop management. AI applications in agriculture include machine learning, data analytics, and predictive modeling, all of which contribute to more efficient and effective farming practices. One of the key areas where AI makes a significant impact is in planting schedules (Li & Yost, 2000). MI algorithms analyze extensive datasets from various sources, including historical weather patterns and soil conditions, to predict optimal planting times. AI models can forecast the best planting dates by processing climate data and historical crop yields. This predictive capability ensures that crops are planted at the most favorable times, leading to enhanced growth and yield. In the realm of irrigation and fertilization, AI technologies play a crucial role in optimizing resource use (López et al., 2008). AI systems continuously monitor field conditions and adjust irrigation schedules based on real-time data. For instance, AI-driven irrigation systems analyze soil moisture levels and weather forecasts to quantify the precise amount of water needed. AI-driven irrigation systems can reduce water usage by up to 30%, promoting water conservation and efficient resource management (Montas & Madramootoo, 1992). Similarly, AI models optimize fertilization practices by analyzing nutrient levels in the soil and recommending precise application rates. AI also contributes to pest and disease management. By analyzing data from sensors and historical records, AI systems can detect signs of pest infestations or disease outbreaks before they escalate. This early detection allows for targeted interventions, reducing the need for broad-spectrum pesticides and minimizing environmental impact (Tajik, Ayoubi, & Nourbakhsh, 2012).

1.3 IoT Applications

1. The Internet of Things (IoT) enhances precision farming by providing a network of interconnected devices that collect and transmit real-time data. IoT devices, such as soil moisture sensors and weather stations, play a important role in optimizing crop

Editors: Shilpa Sivashankar, S. Pandikumar, Pallavi M O
DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

management through continuous monitoring and data collection (Levine, Kimes, & Sigillito, 1996).

2. Soil moisture sensors are instrumental in providing real-time data on soil water content. These sensors help farmers avoid over-irrigation and under-irrigation by providing accurate readings of soil moisture levels. This real-time information enables timely adjustments to irrigation schedules, conserving water and ensuring optimal crop growth.

3. Weather stations equipped with IoT technology offer precise and timely weather forecasts, which are essential for planning agricultural activities. Integrating weather data with irrigation systems improved water use efficiency by 25%. Weather stations provide crucial information on temperature, humidity, and precipitation, allowing farmers to make data-driven decisions about irrigation and other field activities (M. Bilgili, 2011).

4. Remote monitoring through IoT devices, including drones, further enhances precision farming. Drones equipped with cameras and sensors capture high-resolution images of crops, facilitating monitoring of plant health, detection of nutrient deficiencies, and identification of pest infestations. By providing a comprehensive view of the field, drones enable more precise and timely interventions (Zhao et al., 2009).

2 Case studies of AI-Driven Precision Farming in John Deere's

Agricultural Practices: Precision farming leverages advanced technologies like machine learning and data analytics (DA) to revolutionize traditional agricultural practices. One prominent example is John Deere's AI-powered equipment, which uses a combination of sensors and GPS technology to optimize planting schedules, irrigation, and fertilization. These machines collect and analyze vast amounts of data from the field, tailoring agricultural processes to the specific needs of each crop section. For planting, AI algorithms analyze soil data, weather forecasts, and historical crop performance to deduce the optimal planting times and patterns. This confirms that seeds are sown at the right depth and spacing to maximize germination rates and yield potential (Elshorbagy & Parasuraman, 2008). During the growing season, sensors continuously monitor soil moisture levels and plant health, allowing the AI system to adjust irrigation schedules in real-time. By delivering the precise amount of water needed, these smart irrigation systems help conserve water and prevent over-irrigation. Fertilization is another area where AI shows significant benefits. John Deere's equipment can assess the nutrient levels in different parts of the field and apply fertilizers accordingly (Chang & Islam, 2000).

Editors: Shilpa Sivashankar, S. Pandikumar, Pallavi M O
DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

This variable rate technology ensures that each field section receives the right amount of nutrients, reducing waste and preventing environmental damage caused by excess fertilizer runoff. The AI system tracks crop growth and health, adjusting fertilization plans as needed to respond to changing conditions and nutrient demands. By applying the right number of resources at the right time and place, farmers can increase crop yields while reducing resource waste. The success of John Deere's AI-powered equipment(figure 1), exemplifies how integrating advanced technologies into agriculture can lead to more efficient and effective farming practices, ultimately ensuring food security and environmental conservation.

Figure 1. John Deere agricultural vehicle using AI and IoT for precision farming

2.1 Crop Management

Crop management is a holistic approach encompassing various activities from sowing to monitoring growth, harvesting, and ultimately storing and distributing the crops(see table 1). These activities aim to enhance the growth and yield of agricultural products. The foundation of effective crop management lies in an extensive understanding of different crop types, their optimal planting times, and the specific soil conditions they thrive. This knowledge is crucial for maximizing crop yield. One advanced approach within crop management is Precision Crop Management (PCM). PCM is designed to tailor crop and soil inputs according to the exact needs of different fields, thereby optimizing profitability and safeguarding the environment (He & Song, 2005). However, the effectiveness of PCM has often been limited by the lack of timely and distributed information on crop and soil conditions. To address this, farmers need to integrate various crop management strategies to manage water deficits, which can result from soil conditions, weather variations, or limited irrigation. Adopting flexible crop management systems based on well-defined decision rules is essential in these scenarios (Papageorgiou, Markinos, & Gemtos, 2011).

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

Furthermore, understanding the timing, intensity, and predictability of drought is critical for selecting the most suitable cropping alternatives. By combining these insights with advanced PCM techniques, farmers can make more informed decisions, ultimately leading to improved crop yields and sustainable agricultural practices. Understanding weather patterns is crucial for high-quality crop yields. Tools like PROLOG use weather data, machinery capacities, labor availability, and information on operators, tractors, and implements to optimize farm operations. This system estimates crop production, gross revenue, and net profit for individual fields and the entire farm, enabling precise decision-making (Dai, Huo, & Wang, 2011).

Crop prediction methodologies now sense various soil and atmospheric parameters, such as soil type, pH, nitrogen, and rainfall, to determine the best crops to plant. Technologies like Demeter, a computer-controlled speed-rowing machine with video cameras and GPS, plan and execute harvesting operations autonomously, increasing efficiency and reducing labor. AI-driven harvesting systems, like those used for cucumbers, integrate autonomous vehicles, manipulators, and computer vision to detect and harvest crops with precision, minimizing damage. Field-specific rainfall data and weather variables fine-tune agricultural practices, with adjusted ANN parameters improving rice yield predictions. These advanced technologies and weather integrations enable farmers to enhance their decision-making, resulting in better crop yields and more sustainable farming practices. For a brief understanding of AI applications in crop management, use of machine learning models for predicting growth patterns, pest detection, yield forecasting, and optimizing irrigation and fertilization strategies, see table 2

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

Table 1. Comparative Analysis of Soil Management Using Different Types of AI

Technique	Strengths	Limitations
MOM	Reduces nitrate release and enhances production.	Measures only nitrogen concentration. Analysis time is longer.
Fuzzy Logic: SRC-DSS	Identifies differences between soil types concerning associated risks.	Requires a large amount of data for analysis.
DSS	Reduces erosion and sediment in soils.	Requires enormous amounts of data for accurate evaluations.
ANN	Predicts enzyme activity, confirms soil properties, and accounts for thermal effects, texture, water content, nutrients, and erosion conditions. It offers low cost and high accuracy.	Limited to quantifying specific enzymes, temperature ranges, and ammonia levels. Cannot be applied in all areas, and predictions may fail in certain weather conditions. Does not improve soil texture. Measures only a few enzymes and focuses more on classification than enhancing soil performance.

Editors: Shilpa Sivashankar, S. Pandikumar, Pallavi M O
DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

Table 2. Summary of AI applications in crop management, detailing the use of machine learning models for predicting growth patterns, pest detection, yield forecasting, and optimizing irrigation and fertilization strategies.

Technique	Strength	Limitation
CALEX	Can articulate norms for carried out the crop management.	Time consuming process
PROLOG	Helps to reduce avoid the unwanted farm tools.	Used only in specific location.
ANN	Predicts crop production rate, moisture, salt concentration, and microbial infection, and detects nutritional disorders with above 90%.	Estimation of crop yield only based on weather conditions of soil and texture of soil. It takes more period of analyse.
ROBOTICS-Demeter	This technology can be used to guess the harvest approximately for 40 hectares	Most expensive process
ROBOTICS	Can able to achieve 80% of effective harvesting rate	Less precession
FUZZY Cognitive Map	Elucidate and improve cotton production and decision management.	Takes more time to analyse the process.
ANN and Fuzzy Logic	Decreases the impact of insects and its effects.	Difficult to observe the variation between crop and weed.

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

2.2 Disease Management

Effective disease management is crucial for optimal agricultural yield, as plant and animal diseases significantly limit productivity. Factors such as genetics, soil type, weather conditions, and temperature all contribute to the incubation and spread of diseases, posing challenges, particularly in large-scale farming. To control diseases and minimize losses, farmers need to adopt an integrated disease management model that combines physical, chemical, and biological measures. However, this approach can be time-consuming and costly. AI offers promising solutions for disease management (Wang et al., 2008). There are various AI tools such as Computer vision system (CVS), genetic algorithm (GA), ANN, Rule-Based Expert Data Base (RBEDB), Fuzzy Logic (FL), Web GIS, Web-Based Intelligent Disease Diagnosis System (WIDDS), TTS converter and Fuzzy Xpert (FXp). See table 3

Table 3. Overview of AI applications in disease management, showing various models used for early detection, diagnosis, and prediction of crop diseases to enhance timely intervention and reduce yield loss.

Method	Asset	Restriction
CVS, GA, ANN	Depicts the results very rapidly with 95% accuracy.	Identification of species based on measurement affect its growth. Additionally, rural farmers cannot access rapidly due to lack internet services.
RBEDB	Delineate with proper result in tested ecology	Errors are very high large scale.
FL Web GIS WIDDS and TTS converter	Capacity to eradicate plant microbial infection problem with less cost.	Inadequacy due to disperse data and finding the location by the mobile tracker. Moreover, it is very difficult to establish the result more than four different seeds.
Expert system using rule-base in disease detection	Fastest process to diagnose the diseases.	Need to wait for long time for continuous monitoring the immunity of pests.
FXp.	More accuracy in the prediction.	Most dependent on internet sources
Web-Based Expert System	High recital.	Wireless network is mandatory.

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

AI applications in this field include expert systems with Explanation Blocks (EB) that clarify the logic used for decision-making, and fuzzy logic systems that draw intelligent inferences for crop disease management. These systems can detect diseases and provide treatment suggestions, leveraging rule-based and forward-chaining inference engines. Advanced AI systems also feature text-to-speech converters for interactive user interfaces, enabling live web interactions that guide farmers in real time. By integrating AI, farmers can more effectively manage diseases, leading to healthier crops and improved yields.

2.3 Weed Management

Weeds significantly reduce farmers' expected profits and yields. For instance, unchecked weed infestations can lead to a 50% of drop in the yields of dried beans and corn crops, and wheat yields can suffer up to a 60% loss due to weed impact. Soybean yields can be reduced by 8%-55%, while sesame crops can experience a 50%-75% yield reduction. These losses often depend on the duration of weed exposure and the spatial distribution of weeds. Weeds also have varied impacts on the ecosystem. They can contribute to flooding during hurricanes, survive rampant fires, and cause health issues such as liver damage and allergic reactions. Weeds compete with crops for water, nutrients, and sunlight, often overpowering them. Despite their detrimental effects, some weeds play essential roles in the ecosystem. AI applications in weed management, as summarized in Table 4, offer innovative solutions to detect, monitor, and control weeds effectively, helping farmers minimize yield losses and maintain healthier crops.AI-powered solutions, such as computer vision and machine learning models, enable precise weed detection and classification through drone or satellite imagery. These technologies can identify weed species, track their growth patterns, and predict their spread, allowing farmers to implement timely interventions. Robotics equipped with AI can automate weed removal, reducing the need for chemical herbicides and promoting sustainable farming practices. Additionally, AI-based decision support systems can provide tailored recommendations for weed management strategies, optimizing resource usage and minimizing environmental impact. By integrating AI with Internet of Things (IoT) sensors, farmers can receive real-time alerts on weed infestations, enabling rapid responses to minimize crop damage. These advancements not only enhance agricultural productivity but also support environmentally friendly practices.

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

Table 4. Summary of AI applications in weed management, describing techniques for identifying weed species, optimizing herbicide use, and implementing precision control strategies to minimize crop competition and resource waste.

Method	Asset	Restriction
ANN, GA	Reduces the number of iterations during optimization.	Need huge data.
Optimization using invasive weed optimization (IVO)	Effective optimization method for weed growth.	It takes more time to analyse new data
Mechanical Control of Weeds.	Easy to eliminates resistant weeds.	Continuous usage of machine affects yield of the product.
UAV, GA	Can swiftly and capably screen weeds.	No limitations on controlling of weeds
Weed management.	High adaptation rate and prediction level.	Requires big data and usage expertise.
Support Vector Machine (SVM)	Rapidly notices stress in the crops that helps to quick specific remedies.	Able to detect less amount of Nitrogen.

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

3 Disease Detection

(AI) is being utilized in innovative ways to manage pests and diseases in agriculture, see figure 2. As farming expands and environmental conditions shift, pests, and diseases are increasingly problematic for crops. AI technology is advancing rapidly and presents new solutions to address this challenge. AI is employed to identify and predict pests and diseases through methods such as image recognition, data analysis, and machine learning, along with the development of intelligent warning systems. Additionally, it focuses on smart decision support systems that assist in managing pests and diseases. This encompasses data-driven decision-making systems, smart farming platforms, and real-time monitoring and response systems (M. Khan, 2002). Automated technologies for detecting plant diseases are vital as they help prevent recurring crop diseases and the associated losses. An AI-based automated disease detection system involves several steps:

1. Placing Sensors: Sensors are deployed in the fields to capture images of plants.
2. Image Processing: These images are processed and segmented for analysis.
3. Machine Learning: The processed images are examined using machine learning algorithms.
4. Disease Prediction: The system forecasts whether a leaf is healthy or diseased.

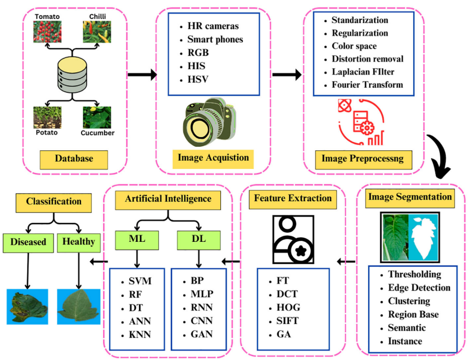

Figure 2. AI-based Automated Disease Detection System in Agriculture. Workflow showing image acquisition, preprocessing, segmentation, feature extraction, and classification using AI models.

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

3.1 Placing Sensors

This step entails strategically positioning various types of sensors throughout the agricultural field. These sensors comprised with cameras, thermal sensors, and multispectral sensors. Their primary role is to capture high-quality images of the plants from multiple angles and under varying lighting conditions. By covering a wide area and continuously monitoring the plants, these sensors can collect detailed visual data on the crops' condition. This information is essential for accurately identifying any signs of disease or stress in the plants. The placement of these sensors is meticulously planned to ensure comprehensive coverage of the field and to obtain images that accurately represent the overall health of the crops (Rao, Wani, & Ladha, 2014).

3.2 Image Processing

Once the sensors capture the images of the plants, these images undergo several stages of processing to prepare them for analysis. Here's a detailed explanation of the process (Datta et al., 2017): Image Acquisition: The first step involves acquiring the raw images from the sensors. These images may contain various visual data and the surrounding environment.

Pre-processing: The raw images are pre-processed to enhance their quality and make them suitable for further analysis. This may involve:

- Noise Reduction: Removing any unwanted noise or distortions from the images.
- Color Correction: Adjust the color balance to accurately reflect the true colors of the plants.
- Contrast Enhancement: Improving the contrast to highlight important features.
- Segmentation: The pre-processed images are then segmented, which means dividing the image into smaller, meaningful sections or regions.
- Thresholding: Converting the image into binary form (black and white) to differentiate between the plant and the background.
- Edge Detection: Identifying the edges of leaves and other plant parts to separate them from the rest of the image.
- Region-Based Segmentation: Dividing the image into regions based on similarities in color, texture, or other features.
- Feature Extraction: After segmentation, specific features are extracted from the sections of the image. These features can include, Measuring the shape and size of leaves or other plant parts. Analysing color patterns that may indicate health or disease. Examine the texture of the leaves to detect any irregularities. The extracted features are then formatted and organized into a dataset. This dataset encompasses all the relevant visual information necessary for accurate disease detection.

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

By processing and segmenting the images in this detailed manner, the system can precisely analyze the visual data, identify any signs of disease, and provide accurate predictions regarding the health of the plants.

3.3 Machine Learning

After processing and segmenting the images, machine learning algorithms are applied to detect diseases. The process begins with training data preparation, where a large dataset of labeled images—classified as either healthy or diseased—is collected, as this labeled data is essential for model training (Mruthul, Halepyati, & Chittapur, 2015). Modern deep learning models, such as Convolutional Neural Networks (CNNs), automatically extract relevant features like patterns, edges, textures, and colors that indicate plant health. CNNs are often preferred due to their efficiency in image-based tasks, though other algorithms like Support Vector Machines (SVM) or Random Forests can also be employed. During training, the model learns to associate specific features with plant health by adjusting its internal parameters to minimize prediction errors (Swanton, Harker, & Anderson, 1993). A portion of the data is reserved for validation to prevent overfitting and fine-tune the model's parameters. After training, the model is tested on a separate dataset to assess its performance. Key metrics such as accuracy, precision, recall, and F1 score are used to evaluate the model's effectiveness, ensuring it can make reliable predictions on new, unseen data (Brazeau, 2018).

3.4 Disease Prediction

The trained machine learning model is then utilized to predict the health status of new, unseen images of plant leaves. Here's how this process works:

- Image Input: The system captures new images of plant leaves using sensors in the field.
- Feature Analysis: The model analyses these new images based on the features it learned during training, processing them to extract relevant visual characteristics.
- Prediction: By comparing the extracted features of the new images to the patterns learned during training, the model predicts whether each leaf is healthy or diseased.

3.5 Output

The system provides the prediction results, indicating which leaves are healthy and which are diseased. This information can assist farmers in taking appropriate actions, such as treating diseased plants or adjusting their management practices. By leveraging machine learning, the system can swiftly and accurately identify plant diseases, enabling farmers to detect and address issues early, reducing damage and improving the quality of seeds.

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

4 Resource Management and Sustainability

Water requirements for irrigation have been rising, and a smart irrigation system can deliver the precise amount of water needed. In response to this demand, Web/Android applications that enable continuous monitoring have been developed and integrated into an Internet of Things (IoT) enabled smart drip irrigation system. This system regulates the drip irrigation system and helps to prevent issues with constant human vigilance and water waste .

Hardware components like a centralized microcontroller unit, several sensors, solenoid valves, Arduino, NodeMCU, and a web application are part of the system design for turning on the drip irrigation system via the Android/web application. Wireless connectivity between the internet layer and the application/UI layer is provided by the NodeMCU, while the web application generates control command signals. By putting in place an IoT-based smart drip irrigation system, software can be utilized for automated drip watering. This system uses data fusion techniques to monitor and control crop-yielding characteristics using software. Data on the state of soil moisture and changes in the environment are gathered using sensors for temperature, humidity, and soil moisture. Pumps for the plantation's water flow are then turned on using the data that has been gathered. Users can remotely monitor and control the irrigation process thanks to the system's connection to an Android and/or web application (Swanton, Harker, & Anderson, 1993).

Using an Internet of Things cloud platform, the controlled data is kept in a web server database. This software-based method offers an inexpensive, low-maintenance, remotely controlled, and energy-efficient option for automatic drip irrigation. By connecting the sensors to the microcontroller and nodeMCU, the sensors in the smart drip irrigation system are controlled. These sensors communicate with the microcontroller and nodeMCU by responding to the moisture content of the soil. The microprocessor sets a threshold value for the moisture state, which determines how much water is required to pass through the solenoid and triggers the pump (Karimi et al., 2006). The computer displays the observed values from the sensors. Depending on the needs of the plant, the pump is automatically turned on or off if the perceived value exceeds the threshold values. The web page receives and stores the water condition data in the cloud. Two metal rods coated in aluminium that are placed far into the field to sense soil moisture are used to build the soil moisture sensor. The controller is connected to the metallic rods by relationships. By utilizing sensor fusion to create a smart drip irrigation system, IoT may be utilized to monitor the health of plants. With web/android applications, this system enables the monitoring and control of various sensor data as well as plant conditions.

Using an Android smartphone, the sensor fusion data is transferred to the IoT cloud platform and saved for analytics. The cloud's recorded data can be used to conduct experiments on soil moisture, temperature, and humidity. Nonetheless, manufacturers are

Editors: Shilpa Sivashankar, S. Pandikumar, Pallavi M O
DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

Table 5. Climate-Related Impacts on Soil and Water Quality and Quantity

Group	Indicator	Measure	Sensitivity to Climate	Link with Climate-Related Changes
Soil Quality	Erosion due to wind	Quantifies soil loss caused by wind	Robust	Increased run-off and precipitation contribute to soil erosion, exacerbating climate change impacts.
	Soil degradation by water	Measured by surface run-off	Moderate	Predictions of climate change remain uncertain due to the complex interplay of management practices.
	Organic content of soil	Composition of C, N, O, and H elements in the soil	Strong	Environmental changes are associated with variations in spring wind speeds.
Water Quality and Quantity	Nitrogen pollution	Measured by nitrogen levels, increased by direct farm contamination	Weak	Nitrogen concentration fluctuates due to run-off, which accelerates soil erosion driven by rainfall variability.
	Phosphorus contamination	Measured by phosphorus content from farm leachates	Weak	Water run-off during precipitation increases phosphorus levels.
	Water supply and use	Availability and usage of water resources	Strong	Climate change is expected to reduce water supply while increasing demand.

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

already providing inexpensive sensors that can be linked to nodes in order to establish systems for monitoring farmland and managing irrigation that are reasonably priced. Given the recent developments in IoT and WSN technologies that can be utilized in the creation of these systems, the state of the art for smart irrigation systems is summarized in this survey. It is decided which parameters—such as soil properties, weather, and water amount and quality—are tracked by irrigation systems. Since agriculture uses a large amount of water, water management is important in areas where there is a shortage of water(see figure 3). In order to guarantee the supply of water for food production and consumption, there is an urgent need for appropriate water management methods due to growing worries about global warming. As a result, studies aimed at cutting down on irrigation water use have gotten more intense recently. Key criteria for monitoring soil, weather, and water quality have been identified by recent advances in IoT irrigation systems for agricultural. To maximize crop irrigation, common nodes in these systems as well as well-liked wireless technologies have been described. Furthermore, the increasing use of IoT systems for irrigation and crop management underscores the possibility of increased productivity (Yang et al., 2002).

A proposed 4-layer architecture for managing crop irrigation underscores the importance of smart irrigation systems that evaluate water quality prior to use, showcasing a future direction in sustainable agricultural practices. In any country, water utilities' main assets and vital infrastructure are their water distribution systems. These systems consist of a number of different parts, such as customers, distribution lines, treatment facilities, reservoirs, and resources. Ensuring the availability, caliber, amount, and dependability of water is essential to managing a sustainable water distribution network. The management and recording of these factors are crucial duties as water becomes a more limited resource. A great deal of work has gone into developing frameworks for monitoring and controlling systems that can automate different phases of the water distribution process. Tracking and analyzing the spatially variable properties and events inside these networks is made possible by technologies like artificial intelligence (AI), the Internet of Things (IoT), and information and communication technology (ICT) (Wheaton & Kulshreshtha, 2017).

In any country, water utilities' main assets and vital infrastructure are their water distribution systems. These systems consist of a number of different parts, such as customers, distribution lines, treatment facilities, reservoirs, and resources. Ensuring the availability, caliber, amount, and dependability of water is essential to managing a sustainable water distribution network (Velayudhan et al., 2022). The management and recording of these factors are crucial duties as water becomes a more limited resource. A great deal of work has gone into developing frameworks for monitoring and controlling systems that can automate different phases of the water distribution process. Tracking and analyzing the spatially variable properties and events inside these networks is made possible by

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

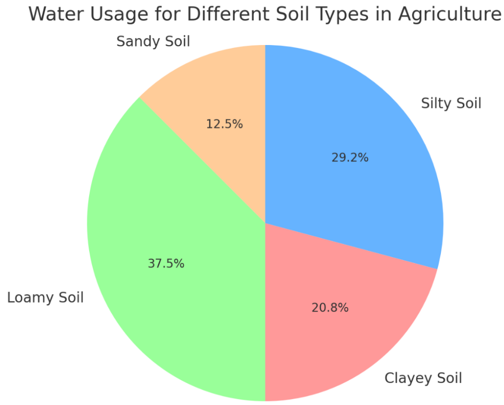

Figure 3. Schematic representation of pie chart on water usage on different soil types in agriculture

technologies like artificial intelligence (AI), the Internet of Things (IoT), and information and communication technology (ICT). It is also important to observe the significance and reach of IoT technology in various phases of water distribution systems. Modern IoT designs for water distribution networks and cutting-edge monitoring and control systems offer vital insights into the state of affairs today and future developments. In order to provide reliable water distribution networks, an IoT Architecture for Intelligent Water Networks (IoTA4IWNet) has been proposed for real-time monitoring and control. This emphasizes how crucial it is to properly design and implement these components (Ghosh & Roy, 2021).

5 Conclusion

AI and IoT significantly enhance farm efficiency by automating processes and providing real-time data, leading to increased productivity and cost savings. These technologies enable precision farming through optimized crop management, improving yields and resource utilization. IoT sensors facilitate continuous monitoring of crops and environmental conditions, allowing timely interventions and better crop health, while AI-driven predictive analytics offer forecasts and insights that aid proactive decision-making and risk management. By promoting optimized resource use and waste reduction, AI and IoT support sustainable farming practices. However, challenges like high costs and data security must be addressed with affordable technology solutions, training, and strong data protection measures. As AI and IoT continue to advance, future innovations, such as integration

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

with blockchain, hold promise for enhanced agricultural outcomes. Their global impact includes improved food security and efficiency, especially in developing regions. The successful implementation of these technologies requires collaboration between tech developers, researchers, and farmers, contributing to modernizing agriculture, addressing food challenges, and supporting sustainable development.

References

Baylis, A. (2017). Advances in precision farming technologies for crop protection. Outlooks on Pest Management, 28(4), 158–161. https://doi.org/10.1564/v28_aug_04

Belal, A. A., EL-Ramady, H., Jalhoum, M., Gad, A., & Mohamed, E. S. (2021). Precision Farming Technologies to Increase Soil and Crop Productivity. Springer Water, 117–154. https://doi.org/10.1007/978-3-030-78574-1_6

Brazeau, M. (2018). Fighting weeds: Can we reduce, or even eliminate, herbicides by utilizing robotics and AI. Genetic Literacy Project, North Wales.

Chang, D. H., & Islam, S. (2000). Estimation of soil physical properties using remote sensing and artificial neural network. Remote Sensing of Environment, 74(3), 534–544. https://doi.org/10.1016/S0034-4257(00)00144-9

Dai, X., Huo, Z., & Wang, H. (2011). Simulation for response of crop yield to soil moisture and salinity with artificial neural network. Field Crops Research, 121(3), 441–449. https://doi.org/10.1016/j.fcr.2011.01.016

Datta, A., Ullah, H., Tursun, N., Pornprom, T., Knezevic, S. Z., & Chauhan, B. S. (2017). Managing weeds using crop competition in soybean [Glycine max (L.) Merr.] Crop Protection, 95, 60–68. https://doi.org/10.1016/j.cropro.2016.09.005

Eli-Chukwu, N. C. (2019). Applications of Artificial Intelligence in Agriculture: A Review. Engineering, Technology and Applied Science Research, 9(4), 4377–4383. https://doi.org/10.48084/etasr.2756

Elshorbagy, A., & Parasuraman, K. (2008). On the relevance of using artificial neural networks for estimating soil moisture content. Journal of Hydrology, 362(1-2), 1–18. https://doi.org/10.1016/j.jhydrol.2008.08.012

Ghosh, A., & Roy, P. (2021). AI Based Automated Model for Plant Disease Detection, a Deep Learning Approach. Communications in Computer and Information Science, 1406 CCIS, 199–213. https://doi.org/10.1007/978-3-030-75529-4_16

Gómez-Chabla, R., Real-Avilés, K., Morán, C., Grijalva, P., & Recalde, T. (2019). IoT Applications in Agriculture: A Systematic Literature Review. Advances in Intelligent Systems and Computing, 901, 68–76. https://doi.org/10.1007/978-3-030-10728-4_8

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

He, Y., & Song, H. (2005). Crop nutrition diagnosis expert system based on artificial neural networks. Nongye Gongcheng Xuebao/Transactions of the Chinese Society of Agricultural Engineering, 21(1), 110–113.

Karimi, Y., Prasher, S. O., Patel, R. M., & Kim, S. H. (2006). Application of support vector machine technology for weed and nitrogen stress detection in corn. Computers and Electronics in Agriculture, 51(1-2), 99–109. https://doi.org/10.1016/j.compag.2005.12.001

Levine, E. R., Kimes, D. S., & Sigillito, V. G. (1996). Classifying soil structure using neural networks. Ecological Modelling, 92(1), 101–108. https://doi.org/10.1016/0304-3800(95)00199-9

Li, M., & Yost, R. S. (2000). Management-oriented modeling: Optimizing nitrogen management with artificial intelligence. Agricultural Systems, 65(1), 1–27. https://doi.org/10.1016/S0308-521X(00)00023-8

López, E. M., García, M., Schuhmacher, M., & Domingo, J. L. (2008). A fuzzy expert system for soil characterization. Environment International, 34(7), 950–958. https://doi.org/10.1016/j.envint.2008.02.005

M. Bilgili. (2011). The use of artificial neural network for forecasting the monthly mean soil temperature in Adana, Turkey. Turkish Journal of Agriculture and Forestry, 35(1), 83–93.

M. Khan, N. H. (2002). Wheat crop yield loss assessment due to weeds. Sarhad Journal of Agriculture (Pakistan), 18(4), 449–453.

Montas, H., & Madramootoo, C. A. (1992). A decision support system for soil conservation planning. Computers and Electronics in Agriculture, 7(3), 187–202. https://doi.org/10.1016/S0168-1699(05)80019-5

Mruthul, T., Halepyati, A. S., & Chittapur, B. M. (2015). Chemical weed management in sesame (Sesamum indicum L.). Karnataka Journal of Agricultural Sciences, 28(2), 151–154.

Papageorgiou, E. I., Markinos, A. T., & Gemtos, T. A. (2011). Fuzzy cognitive map based approach for predicting yield in cotton crop production as a basis for decision support system in precision agriculture application. Applied Soft Computing Journal, 11(4), 3643–3657. https://doi.org/10.1016/j.asoc.2011.01.036

Rao, A. N., Wani, S. P., & Ladha, J. K. (2014). Weed management research in India - an analysis of past and outlook for future. DWR Publication No. 18. In: Souvenir (1989-2014) Directorate of Weed Research, 1–26. http://oar.icrisat.org/8592/

Strickland, R. M., Ess, D. R., & Parsons, S. D. (1998). Precision farming and precision pest management: The power of new crop production technologies. Journal of Nematology, 30(4), 431–435.

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1

Swanton, C. J., Harker, K. N., & Anderson, R. L. (1993). Crop Losses Due to Weeds in Canada. Weed Technology, 7(2), 537–542. https://doi.org/10.1017/s0890037x00028049

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. https://doi.org/10.1089/ees.2011.0313

Velayudhan, N. K., Pradeep, P., Rao, S. N., Devidas, A. R., & Ramesh, M. V. (2022). IoT-Enabled Water Distribution Systems - A Comparative Technological Review. IEEE Access, 10, 101042–101070. https://doi.org/10.1109/ACCESS.2022.3208142

Wang, X., Zhang, M., Zhu, J., & Geng, S. (2008). Spectral prediction of Phytophthora infestans infection on tomatoes using artificial neural network (ANN). International Journal of Remote Sensing, 29(6), 1693–1706. https://doi.org/10.1080/01431160701281007

Wheaton, E., & Kulshreshtha, S. (2017). Environmental sustainability of agriculture stressed by changing extremes of drought and excess moisture: A conceptual review. Sustainability (Switzerland), 9(6). https://doi.org/10.3390/su9060970

Yang, C. C., Prasher, S. O., Landry, J. A., & Ramaswamy, H. S. (2002). Development of neural networks for weed recognition in corn fields. Transactions of the American Society of Agricultural Engineers, 45(3), 859–864. https://doi.org/10.13031/2013.8854

Zhao, Z., Chow, T. L., Rees, H. W., Yang, Q., Xing, Z., & Meng, F. R. (2009). Predict soil texture distributions using an artificial neural network model. Computers and Electronics in Agriculture, 65(1), 36–48. https://doi.org/10.1016/j.compag.2008.07.008

DOI:10.48001/978-81-966500-0-1-2 | ISBN: 978-81-966500-0-1