AI-Driven Techniques for Real-Time Crop Monitoring in Smart Agriculture

1st Ms. Shruthi M R
PG Student, Department of CSE
Rajeev Institute of Technology
(VTU)
Hassan, India
Shruthimr93@gmail.com

2nd Mr. Anil Kumar K N
Assistant Professor,
Department of CSE
Rajeev Institute of Technology
(VTU)
Hassan, India
akanilgowda@rithassan.ac.in

Abstract*—The application of Artificial Intelligence (AI) with IoT-based sensors for real-time crop monitoring using center pivot sprinkler systems to achieve smart agriculture. The proposed system integrates deep learning algorithms, computer vision techniques, and center pivot irrigation to manage key agricultural parameters, including irrigation levels, water consumption, soil conditions, wind speed, humidity, and weather forecasts. It also provides plant health analysis, disease detection, and fertilizer recommendations to enhance crop productivity. Data from cameras and environmental sensors is processed through AI models to generate actionable insights, supporting precision farming and resource optimization. Although initial implementation costs may be high, the long-term benefits—such as improved crop planning, reduced manual labor, higher yields, minimized losses, and enhanced sustainability—make this approach cost-effective and essential for modern agriculture. This AI-driven framework addresses current challenges, ensuring efficient resource use and sustainable food production.

Keywords*—Artificial Intelligence, Smart Agriculture, Precision Farming, Computer Vision, IoT Sensors, Crop Monitoring, Sustainable Agriculture.

I. INTRODUCTION

The global agricultural sector is undergoing a transformative shift with the integration of advanced technologies such as artificial intelligence (AI), the Internet of Things (IoT), and computer vision. These innovations are driving the emergence of smart agriculture, a modern approach aimed at optimizing agricultural productivity, resource management, and sustainability. As the global population continues to rise, traditional farming practices are proving insufficient to meet food demand, conserve natural resources, and adapt to changing climate conditions. While AI has been applied in existing smart irrigation models, most current systems focus on fixed-rule irrigation scheduling or rely on limited environmental parameters. In contrast, this study introduces a **novel AI-driven, multi-modal irrigation framework** that integrates deep learning–based crop health assessment, adaptive water distribution algorithms, and sensor fusion from soil, climate, and visual data sources. Unlike conventional systems, our approach dynamically adjusts irrigation strategies in real time by combining computer vision–driven plant stress detection with predictive weather and soil moisture analytics.

The system employs IoT-based sensors, drones, and satellite imagery to collect high-resolution data on soil health, moisture levels, weather patterns, pest activity, and crop growth stages. Machine learning and deep learning algorithms then process this diverse dataset to generate precise, context-aware irrigation recommendations. The proposed method advances beyond existing solutions by:

1. **Integrating multi-source environmental and visual data for holistic decision-making**
2. **Utilizing adaptive AI models that learn from seasonal and crop-specific patterns**
3. **Providing scalable, modular architecture suitable for diverse crop types and geographies**

This work demonstrates how AI can move beyond traditional fixed irrigation schedules, enabling a more autonomous, resource-efficient, and sustainable farming ecosystem. The long-term benefits—improved crop yields, reduced manual labor, optimized water usage, and environmental sustainability—highlight the transformative potential of the proposed approach.

II. LITERATURE SURVEY

In recent years, numerous studies have explored the integration of AI and sensors in agriculture to improve productivity and sustainability. Researchers have demonstrated that the use of sensors in agriculture helps to identify plant disease detection in the early initial phase using an image classification technique. Similarly, IoT-based solutions have been proposed for real-time monitoring of soil moisture, and weather forecast helps to automate the irrigation systems. Several works have focused on precision farming, utilizing AI algorithms to optimize resource allocation such as fertilizers, water, and pesticides. Studies in [1] and [2] highlight the use of AI, including sensors for crop yield prediction and weather forecasting, emphasizing how predictive analytics can help farmers in planning and reducing crop loss. Despite these advances, challenges remain in scalability, data integration, and the high initial cost of deployment for long-term farming. This paper builds upon these foundations by proposing an integrated system that combines deep learning, computer vision, and sensor-based monitoring into a cohesive AI-driven framework with sensors for smart agriculture.

III. Proposed System

The proposed system introduces an AI-integrated **center pivot sprinkler irrigation system** equipped with a comprehensive array of **IoT sensors**, image-processing units, and automated control mechanisms to enable real-time crop monitoring and precision resource management throughout the entire crop lifecycle—from germination to harvest.

VOLUME: 09 ISSUE: 08 | AUG - 2025 SJIF RATING: 8.586 ISSN: 2582-3930

A. Centre Pivot Sprinkler System

The Centre pivot sprinkler mechanism is the base for the method, and all other sensors are fitted on the central pivot sprinkler. This mechanism is retrofitted with advanced sensors, which monitor various environmental and crop-specific parameters directly from the farm field. Unlike traditional irrigation methods, the centre pivot system in this architecture is enhanced with intelligent control logic that allows it to **sprinkle water only where necessary**. This ensures that water is not wasted in non-cultivated areas such as:

- Regions with houses or man-made structures,
- Fields intersected by electrical lines,
- Unused or barren land.

This **targeted irrigation strategy** significantly reduces water consumption and promotes sustainable farming practices.

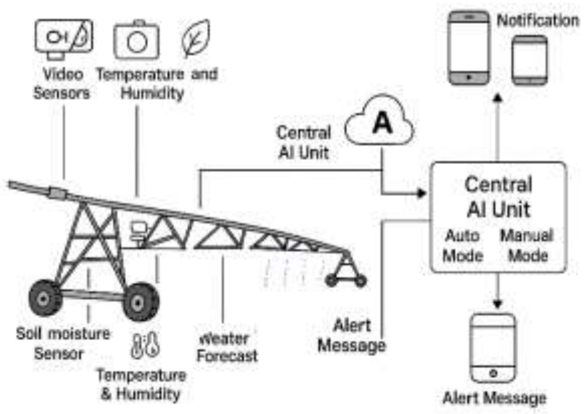

Fig. 1. Diagram of a center pivot irrigation system illustrating the pivot point, pipeline, sprinkler nozzles, and travel direction.

1. Irrigation Requirement Formula

$$I = \begin{cases} 0, & \text{if } P > 0 \\ \max(WR - S, 0), & \text{otherwise} \end{cases}$$

Where:

- I = Irrigation amount (mm or litres/m²)
- P= Precipitation forecast (mm)
- WR = Water requirement of the crop (mm)
- S = Current soil moisture content (mm)

Explanation:

- If rainfall is forecasted (P>0P > 0P>0), the system **skips irrigation** entirely to prevent overwatering.
- If no rainfall is expected (P=0P = 0P=0), the system calculates the **difference between the water requirement and current soil moisture**, and irrigates only if the soil moisture is insufficient.
- The use of the max () function ensures **no negative irrigation value** is generated.

2. Water Requirement Formula

$$WR = ET_c - P$$

Where:

- WR= Water requirement of the crop (mm)
- ETc = Crop evapotranspiration (mm)
- P= Precipitation forecast (mm)

Explanation:

- ETc represents the total water loss due to **evaporation from soil and transpiration from plants**.
- P is the expected rainfall, which directly reduces the water requirement.
- This ensures irrigation is only based on **net water need** after accounting for natural rainfall.

Putting It All Together

Step-by-step Evaluation:

1. Check Rain Forecast:

   If P > 0,

   I = 0

   Irrigation is skipped.

2. If No Rain Forecasted:

   - Calculate crop water requirement:

   W R = E Tc − P

   - Compare with current soil moisture:

   I = max (W R − S, 0)

Irrigation happens **only if** soil moisture is **less than** the water requirement.

B. Sensor-Driven Monitoring and Analysis

The center pivot sprinkler unit is equipped with a combination of Capacitive Soil Moisture Sensors (e.g., SKU:SEN0193, operating voltage 3.3–5V, accuracy ±3%), DHT22 Temperature and Humidity Sensors (operating range –40°C to +80°C, humidity accuracy ±2–5%), and an Optical NPK Nutrient Detection Module (measuring Nitrogen, Phosphorus, and Potassium levels in mg/kg with ±2% accuracy). These sensors collect high-resolution, real-time data from the field, enabling the system to:

- Determine the exact volumetric water content in the soil (0–100% range)
- Calculate the precise irrigation volume required for optimal crop growth
- Monitor plant growth patterns and nutrient requirements at various stages of development

The system is integrated with **live weather forecasting services** [8] via an API, enabling predictive irrigation control. If rainfall exceeding a predefined threshold (e.g., 5 mm in the next 24 hours) is forecasted, the sprinkler unit automatically suspends irrigation to prevent overwatering, thus improving water use efficiency and reducing operational costs.

C. Image and Video Analysis

In addition to physical sensors, the pivot system features **high-resolution cameras** and **video capture units** mounted on the sprinkler structure, that collect data used for:

- Monitoring plant growth and development,
- Detecting plant diseases through deep learning models (e.g., CNNs),
- Identifying pest infestations and areas requiring intervention.

This visual analysis is processed daily using AI algorithms to provide farmers with diagnostic reports, fertilizer recommendations, and early warning alerts. This can be scheduled on an hourly/daily/weekly/monthly basis to monitor the crop health.

D. Decision Support and Alerts

All data collected from sensors and image processing modules is transmitted to a central processing unit or cloud-based analytics platform. Using machine learning algorithms and decision tree models, the system generates actionable insights. Farmers receive timely notifications and recommendations through network-connected devices like mobile, tablet, and desktop dashboards, and email notifications to the registered email and connected mobile; these may include:

- Irrigation schedules based on soil and weather data,
- Fertilizer application advice,
- Disease or pest treatment suggestions.

E. Benefits

This smart irrigation and monitoring framework allows farmers to:

- Optimize water usage, reducing waste,
- Increase crop yields through data-driven interventions,
- Minimize manual effort with automated alerts and recommendations,
- Track crop health and needs on a day-to-day basis.

IV. Comparison Between the Existing System and the Proposed Method

1. Water Usage Efficiency

Existing System:

- Uses traditional sprinklers that operate at a constant flow rate.
- Sprays water uniformly across the field.
- Leads to significant water wastage due to over-irrigation and runoff in non-cultivated areas like paths, edges, or rocky patches.
- Cannot detect if it's going to rain and may still irrigate unnecessarily.

Proposed System:

- Center pivot sprinkler equipped with soil moisture sensors that determine the actual water requirement of each section of the field.
- Uses AI-driven decision-making to precisely control water flow and sprinkling zones.
- Automatically skips irrigation in uncultivated regions (e.g., areas with houses, electrical poles, or drylands).
- Integrates weather forecasting—suspends watering if rainfall is expected, leading to zero overflow and optimal water conservation.

2. Sensor and Data-Driven Operation

Existing System:

- Insensitive; no real-time feedback from the soil or plants.
- Operates in manual or timer-based mode, requiring human intervention.
- Cannot detect environmental changes, plant stress, or nutrient levels.

Proposed System:

- Center pivot sprinkler equipped with IoT-based sensors for:
  - Soil moisture
  - Temperature and humidity
  - Nutrient levels
- Continuously collects real-time environmental data.
- Enables automated control and dynamic adjustment of water, fertilizers, and pest control actions using live analytics.

3. Crop Monitoring and Management

Existing System:

- **No built-in crop monitoring** capabilities.
- Formerly dependent on manual observation daily, which is time-consuming and requires manual efforts
- We could not detect soil moisture and pests in the early stage.

Proposed System:

- Uses cameras and drones for image and video capturing.
- Applies deep learning models (e.g., CNNs) to:
  - Detect plant diseases at early stages,
  - Monitor growth rates and plant health,
  - Assess field productivity visually.
- Farmers receive automated alerts and suggestions on:
  - Pest control,

- Fertilizer application,
- Crop health status.

4. Automation and Labour Requirements

Existing System:

- Requires **manual operation** for starting/stopping irrigation, checking soil, and identifying issues.
- High dependency on human labour and regular maintenance.
- Not scalable for large farms due to limited automation.

Proposed System:

- Offers fully **automated operation**:
  - Real-time sensor feedback loop.
  - Auto-adjustment of sprinkler heads.
  - AI-guided recommendations for next steps.
- Low maintenance due to smart diagnostics.
- Highly scalable for small to large farms, reducing labour costs significantly.

5. Resource Optimization and Sustainability

Existing System:

- Inefficient resource usage (water, fertilizers).
- No sustainability metrics or tracking.
- Often results in soil erosion, nutrient leaching, and low yield over time.

Proposed System:

- Promotes precision farming.
- Ensures minimal water and chemical usage.
- Supports sustainable agriculture by:
  - Reducing environmental impact,
  - Increasing yield per unit resource,
  - Encouraging responsible farming practices.

🔴 ***Existing Irrigation System (Traditional Sprinklers):***

- Delivers water at a constant, unregulated rate**.**
- Causes **overwatering**, especially on non-cultivated or unused areas.
- Results in **300 liters/m²** by day 30.

🟢 ***Proposed System (Centre Pivot + AI + Sensors):***

- Uses sensors to check the moisture in the soil and check weather data to dynamically adjust **s**prinkler watering.
- Avoids watering in the unnecessary regions like houses, electric lines, or fallow land.
- Considers rain forecasts to reduce the waste of water. The Sprinkler will check the weather forecast on an hourly basis. This can be customizable
- Cumulative usage is significantly lower **(**around 180 litres/m² by day 30), achieving ~40% water savings**.**

V. Conclusion

Artificial intelligence holds significant promise for transforming traditional agricultural practices into intelligent, efficient, and sustainable smart systems. The proposed framework demonstrates how a combination of deep learning, IoT, and computer vision can provide farmers with real-time insights for better decision-making. The system helps improve farming by solving problems like managing water, detecting diseases, and predicting the weather, which can help make farming more efficient.

Future work includes enhancing the scalability of the model, integrating satellite data, and reducing the cost of deployment to ensure broader accessibility for farmers worldwide.

References:

[1] Fuentes-Peñailillo, F.; Gutter, K.; Vega, R.; Silva, G. C. Transformative Technologies in Digital Agriculture: Leveraging Internet of Things, Remote Sensing, and Artificial Intelligence for Smart Crop Management. *J. Sens. Actuator Netw.* **2024**, *13* (4), 39.

[2] Pal, A.; Dubey, S. K.; Goel, S.; Kalita, P. K. Portable Sensors in Precision Agriculture: Assessing Advances and Challenges in Soil Nutrient Determination. *TrAC, Trends Anal. Chem.* **2024**, *180*, 117981.

[3] Talaviya, T., Shah, D., Patel, N., et al., 2020. Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. Artificial Intelligence in Agriculture. 4, 58–73.

[4] Pérez-Blanco, C.D., Hrast-Essenfelder, A., Perry, C., 2020. Irrigation technology and water conservation: A review of the theory and evidence. Review of Environmental Economics and Policy. 14(2), 216–239.

[5] Wang, X., Zhang, J., Shahid, S., et al., 2014. Adaptation to climate change impacts on water demand. Mitigation and Adaptation Strategies for Global Change. 21(1), 81–99.

[6] Blessy, J.A., Kumar, A. (editors), 2021. Smart irrigation system techniques using artificial intelligence and IoT. 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV); 2021 Feb 04–06; Tirunelveli, India. USA: IEEE. p. 1355–1359.

[7] Anil Chougule, M., Mashalkar, A.S., 2022. A comprehensive review of agricultural irrigation using artificial intelligence for crop production. Computational Intelligence in Manufacturing. 187–200.

[8] Guravaiah, K., Raju, S.S. (editors), 2020. e-Agriculture: Irrigation system based on weather forecasting. 2020 IEEE 15th International Conference on Industrial and Information Systems (ICIIS); 2020 Nov 26–28; RUPNAGAR, India. p. 617–622.

[9] Saigal, A.; Aremu, B.; Perumal, A. Plants Health Monitoring and Prediction for Precision Horticulture. World J. Adv. Res. Rev. **2023**,

[10] T. A. Shaikh, T. Rasool, and F. R. Lone, "Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming," Computers and Electronics in Agriculture, vol. 198, p. 107119, 2022.

[11] U. Shandilya and V. Khanduja, ''Intelligent farming system with weather forecast support and crop prediction,'' in Proc. 5th Int. Conf.

Comput., Commun. Secur. (ICCCS), Patna, India, Oct. 2020, doi: 10.1109/icccs49678.2020.9277437.

[12] P. Peddi, A. Dasgupta, and V. H. Gaidhane, ‘‘Smart irrigation systems: Soil monitoring and disease detection for precision agriculture,’’ in Proc. IEEE Int. IoT, Electron. Mechatronics Conf. (IEMTRONICS), Toronto, ON, Canada, Jun. 2022, doi: 10.1109/IEMTRONICS55184.2022.9795747.

[13] B. Swaminathan, S. Palani, S. Vairavasundaram, K. Kotecha, and V. Kumar, ‘‘IoT-driven artificial intelligence technique for fertilizer recommendation model,’’ IEEE Consum. Electron. Mag., vol. 12, no. 2, pp. 109–117, Mar. 2023, doi: 10.1109/MCE.2022.3151325.

[14] S. Stevanoska, D. Davcev, E. M. Jovanovska, and K. Mitreski, ‘‘IoT-based system for real-time monitoring and insect detection in vineyards,’’ in Proc. 18th ACM Symp. Mobility Manage. Wireless Access, Nov. 2020, pp. 133–136, doi: 10.1145/3416012.3424634.

[15] R. Gill, A. Tripathi, and P. Chawla, ‘‘Designing a IoT based prototype for crop monitoring and smart irrigation,’’ in Proc. 2nd Int. Conf. Technological Advancements Comput. Sci. (ICTACS), Tashkent, Uzbekistan, Oct. 2022, doi: 10.1109/ictacs56270.2022.9987789.