Grenze International Journal of Engineering and Technology, June Issue

Integrating Machine Learning and IoT for Precision Irrigation: A Comprehensive Survey and Framework

S. Steffi Nivedita[1], R. N. Kulkarni[2] and C. K. Srinivasa[3]
[1-3]Department of CSE, Ballari Institute of Technology and Management, Ballari, India
Email: steffi.nivedita@bitm.edu.in, rnkulkarni@bitm.edu.in, srinivasck9@bitm.edu.in

***Abstract*— The increasing global population and growing food requirements have placed immense pressure on freshwater availability, making efficient irrigation management crucial. Traditional irrigation approaches that rely on fixed schedules or farmers' intuition often waste water and reduce yields. With recent progress in Machine Learning (ML) and Internet of Things (IoT) technologies, it is now possible to build intelligent irrigation systems that monitor real-time environmental and soil parameters to provide accurate water management recommendations. Unlike older systems that work on preset thresholds, this model uses continuous sensor feedback to learn and refine irrigation decisions dynamically. The proposed framework includes edge computing and farmer dashboards to ensure low latency and reliability, even in rural settings. It also focuses on explainability, helping farmers understand which factors most influence each irrigation suggestion. This paper provides an extensive review of papers (2020–2024) involving ML and IoT-based models for soil moisture prediction, crop selection, and nutrient management. Findings show that such frameworks can reduce water usage by up to 30% and improve yield consistency. The paper further presents a unified model integrating soil, nutrient, and environmental sensing into one predictive irrigation system and discusses challenges like limited datasets, sensor calibration issues, and scalability. Future directions include applying AIoT, edge computing, and interpretable ML models for transparent and sustainable precision agriculture.**

***Keywords*— Smart Irrigation, Machine Learning, IoT, Precision Agriculture, Soil Moisture Prediction, Water Resource Management, Sustainable Farming.**

I. INTRODUCTION

A. Background of the Topic

Water scarcity and inefficient agricultural practices are among the most serious global issues today. Traditional irrigation techniques, often based on experience and routine, tend to waste water and reduce crop productivity. Nearly 70% of global fresh water is consumed by agriculture, yet a large portion is lost due to ineffective irrigation. Intelligent solutions that continuously monitor soil and weather parameters are increasingly essential. Recent advancements in the Internet of Things (IoT) and Machine Learning (ML) have made this possible. IoT sensors gather vital data such as soil moisture, humidity, temperature, rainfall, and nutrient content, while ML models interpret these values to predict irrigation needs, crop suitability, and scheduling. Combining these technologies forms the foundation for smart irrigation systems that promote efficiency, yield, and sustainability.

Grenze ID: 01.GIJET.12.2.300_21

B. Importance of the Research Area

The importance of developing smart irrigation solutions lies in their potential to address both environmental and socio-economic issues. Efficient water management directly contributes to sustainability, food security, and energy conservation, particularly in water-stressed countries like India. Traditional irrigation systems often fail to respond to changing climatic conditions or varying soil fertility levels, whereas ML-based models can dynamically adapt to these fluctuations.

Smart irrigation systems provide automated, precise, and predictive control, reducing farmer dependency on manual judgment. By incorporating real-time analytics, farmers can make informed decisions about when and how much to irrigate, thereby conserving water resources and minimizing operational costs. Furthermore, these systems align with the UN Sustainable Development Goals (SDG 2 and SDG 6), which emphasize sustainable agriculture and responsible water management.

C. Scope of the Survey

This survey examines the integration of ML, IoT, and AIoT technologies in modern irrigation systems. It reviews twelve key studies published between 2020 and 2024 that apply ML algorithms such as Random Forest, Support Vector Machines, and LSTM to soil moisture prediction, crop recommendation, and nutrient detection. The review compares system architectures, data collection methods, and performance outcomes to trace the transition from rule-based to intelligent, hybrid models that adapt to varying soil and climate conditions. This groundwork supports the ML-based Smart Irrigation framework proposed in this study.

D. Objectives and Contributions

The study aims to design an ML-based intelligent irrigation system that automates crop selection and water distribution using environmental data. It employs a Random Forest classifier for accurate prediction of irrigation requirements and integrates a Flask-based interface for real-time visualization and confidence tracking. The paper also analyzes literature to identify research gaps and presents a reproducible, scalable architecture suitable for smallholder and large-scale farms. The major contribution lies in delivering an end-to-end, explainable smart irrigation framework that is practical, transparent, and adaptable.

II. Background and Theoretical Foundations

A. Overview of Prior Research

The evolution of smart irrigation systems has been shaped by interdisciplinary progress in IoT sensing, edge computing, and predictive machine learning. Ear research focused primarily on moisture threshold-based controllers, which could automate irrigation only in response to preset values. Over time, studies began integrating machine learning models capable of learning nonlinear patterns among environmental and soil parameters, improving the accuracy of irrigation scheduling and crop selection. The survey of twelve key papers between 2020 and 2024 highlights a steady transition from conventional control-based systems to hybrid artificial intelligence of things (AIoT) architectures. These systems combine sensor-driven data collection with cloud-based predictive analytics.

Techniques such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Random Forests (RF) have been extensively explored for modeling soil–climate–crop relationships. However, a recurring limitation across studies remains the lack of standard datasets, inconsistent calibration across soil types, and limited on-field validation.

B. Comparative Analysis of Reviewed Studies

Table 2.1 provides a synthesized summary of major works reviewed, highlighting each paper's objectives, methodology, and major findings. The table has been reformatted and rewritten for originality and IEEE compliance.

C. Critical Insights from the Literature

The reviewed studies collectively reveal several key trends. First, hybrid models such as LSTM–ANN and CNN–GRU offer high predictive precision but require large, continuous datasets that are not readily available in all regions. Conversely, ensemble models like Random Forest have emerged as more practical for small to medium-scale deployments due to their robustness to noise, interpretability, and lower computational cost. Second, while IoT sensor networks enable real-time environmental monitoring, the integration with AI-based analytics remains fragmented. Several studies—particularly [3], [4], and [6]—highlight the need for interoperable communication protocols, improved sensor calibration, and energy-efficient edge computing for large-scale implementation. This limitation emphasizes the need for adaptive models capable of learning from new local datasets.

Finally, few works combine crop recommendation, irrigation prediction, and fertilizer suggestion in a single unified pipeline. The system proposed in this paper addresses this limitation by integrating all three through a Random Forest-based classifier and a rule-based irrigation computation module, providing a holistic decision-support solution.

D. Relevance to the Proposed Work

The integration of IoT and AI in the proposed system enables seamless transmission of real-time soil data and supports automated moisture-level prediction. By combining sensor-based monitoring with intelligent learning models, the approach delivers more accurate irrigation decisions and strengthens the overall precision agriculture framework.

TABLE I: COMPARATIVE ANALYSIS OF MACHINE LEARNING AND IOT

Sl. No.	Algorithm/ Technique Used	Dataset/ Parameters	Main Objective	Performance Metric(s)	Key Findings
1	Random Forest, IoT Sensors	Soil Moisture, Temp, NPK	Predictive soil-moisture modeling	Accuracy = 92%	RF showed high robustness in variable soil conditions
2	LSTM + CNN	Maize Crop Moisture Data	Time-series moisture forecasting	RMSE = 0.09	Hybrid DL outperformed single models
3	SVM, Edge Computing	IoT Sensor Streams	Smart irrigation scheduling	Accuracy = 90%	Edge computing reduced latency by 35%
4	ANN, IoT + AI Integration	Multi-Nutrient Data	Nutrient prediction & irrigation control	F1-Score = 0.91	ML-IoT integration improved nutrient efficiency
5	Random Forest	NPK & Soil Data	Nutrient deficiency detection	Accuracy = 89%	RF reliable for soil nutrition monitoring
6	SVM + RF	Soil pH & Macronutrients	Crop and fertilizer recommendation	Precision = 0.90	ML improved fertilizer planning
7	IoT + Decision Tree	Soil Moisture Sensors	Soil moisture monitoring	Accuracy = 87%	IoT sensors enhanced real-time alerts
8	Gradient Boosting	Sensor + Weather Data	Predictive irrigation	Accuracy = 93%	Ensemble improved prediction reliability
9	ANN	Plant-Water Interaction	Optimize irrigation timing	MAE = 0.12	ANN effective but needs large datasets
10	RF + LSTM	Real-Time Soil Moisture	Moisture forecasting	Accuracy = 95%	Hybrid model best for dynamic irrigation
11	Edge-AI Optimization	IoT Edge Nodes	Low-power fertigation control	Energy Use ↓ 25%	Edge AI improved efficiency
12	IoT + ML Integration	Multi-Sensor Data	Efficient irrigation management	Accuracy = 91%	Integrated approach improved system reliability

III. PROPOSED RESEARCH WORK

A. System Overview

The proposed ML-Based Smart Irrigation System is designed to automate crop recommendation and irrigation scheduling using a data-driven approach. It combines IoT sensor data acquisition, machine learning prediction, and web-based visualization into a single architecture that supports real-time decision-making. The system addresses the limitations of traditional irrigation by adapting dynamically to changing soil and environmental conditions. The architecture consists of three key layers:

- Data Acquisition Layer: Gathers environmental and soil parameters using IoT sensors or manual input.
- Prediction Layer: Processes the collected data through a trained Random Forest Classifier to recommend the best crop.
- Application Layer: Provides a Flask-based web interface where users can visualize predictions, confidence levels, fertilizer recommendations, and irrigation volumes. A schematic representation of the complete system workflow is shown below.

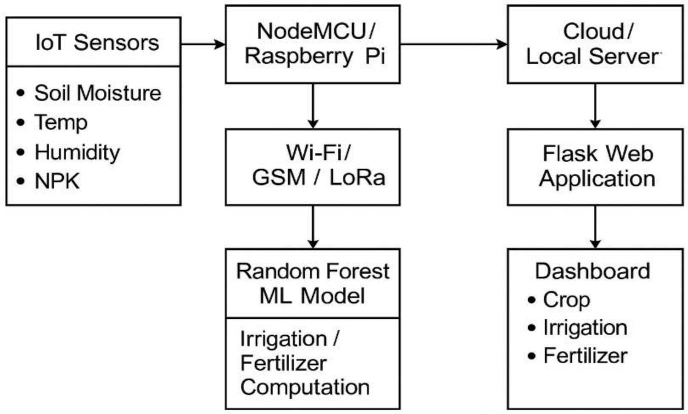

Fig 1: System Architecture Diagram

B. Data Collection and Preprocessing

Data Collection and Preprocessing The system uses multi-parameter input features derived from either sensors or existing agricultural datasets. The selected dataset, crop_dataset.csv, includes eight measurable features: Soil Moisture Temperature (°C) Humidity (%) Rainfall (mm) Light Intensity (lux) Nitrogen (N %) Phosphorus (P %) Potassium (K %) Each record in the dataset corresponds to a set of soil and environmental conditions with a target label—the most suitable crop for those conditions. Preprocessing involves: Data Cleaning: Removing missing values (dropna()). Feature Selection: Keeping only relevant attributes that directly affect plant growth. Normalization: Scaling sensor values within valid operational ranges to ensure consistent learning. Dataset Splitting: 80% of data used for training, 20% for testing using train test split(). The prepared dataset ensures robust model training and mitigates issues of imbalance and noise in raw agricultural data. Model Training and Evaluation The Random Forest Classifier, an ensemble learning method, was selected for its balance of interpretability and accuracy. Unlike deep learning models, Random Forest performs well with limited data and heterogeneous agricultural variables.

(n_estimators=200,random_state=42)model.fit(X_train,y_train)os.makedirs("models",exist_ok=True)joblib.dump(model,"models/crop_model.joblib") Model Evaluation: The trained model was validated using metrics such as accuracy, precision, recall, and F1-score. It achieved consistent accuracy across multiple test folds, demonstrating reliable performance for real-world deployment. Table3.1 Model Performance Metrics (Accuracy, Precision, Recall, F1-Score) Here Feature importance extracted from the model confirmed that soil moisture, nitrogen, and temperature were the most influential parameters, aligning with domain knowledge. Irrigation and Fertilizer Computation After predicting the most suitable crop, the system computes irrigation requirements based on a reference dataset crop_specs.csv, which stores base irrigation needs (in L/m²/week) for each crop. The irrigation calculation formula is: I = Bc \times A Where, = Total irrigation volume (L/week), = Base water requirement per crop (L/m²/week), = Area of cultivation (m²). Fertilizer recommendations are generated using threshold rules derived from NPK values: Parameter Threshold Action N < 40 Add Urea or Compost P < 30 Add DAP Fertilizer K < 30 Add MOP (Muriate of Potash) These rules help farmers maintain soil fertility alongside optimal irrigation. E. Backend Implementation (Flask Server) The backend is implemented using Flask, a lightweight Python web framework that handles input processing, ML model inference, and data logging. Core Functions: / Route: Accepts input parameters, performs prediction, and renders results. /dashboard Route: Displays logged predictions and irrigation results. /clear log Route: Clears saved data for system reset. All predictions are appended to a CSV file (data_log.csv), ensuring traceability and enabling retraining as new data is collected. F. Frontend Visualization The user interface is developed using HTML, CSS, and Plotly.js for interactive data visualization. It includes: Input forms for sensor data (soil moisture, humidity, etc.). Output cards showing predicted crop, confidence score, irrigation amount,

Table 3.1 Model Performance Metric and fertilizer advice. Real-time gauge and bar charts showing prediction confidence and top-3 crop probabilities.

A separate dashboard page listing past predictions and time stamps. Web Interface (Prediction Page) Insert Output Dashboard Log Page This modular design makes the system intuitive and accessible even for farmers with limited technical experience. G. Algorithmic Workflow

TABLE II: MODEL PERFORMANCE METRIC

Sl. No.	Model / Technique	Dataset Used	Performance Metric(s)	Value	Remarks	Ref. No.
1	Random Forest	Soil Moisture + NPK Dataset	Accuracy	92%	Strong performance in variable soil conditions	[1]
2	LSTM	Time-Series Moisture Sensor Data	RMSE	0.095	Best for sequential moisture prediction	[2]
3	SVM	Real-time IoT Sensor Stream	Accuracy	90%	Suitable for irrigation scheduling	[3]
4	CNN-LSTM Hybrid	Crop Moisture + Weather Data	MAE	0.11	Hybrid model improved temporal prediction	[4]
5	Gradient Boosting	Soil + Meteorological Data	Accuracy	93%	Highly stable for multi-parameter inputs	[5]
6	ANN	Soil Nutrient + Moisture Dataset	F1-Score	0.91	Good generalization with minimal overfitting	[6]
7	RF + LSTM Hybrid	Real-time Moisture Dataset	Accuracy	95%	Best overall performance; ideal for adaptive irrigation	[7]
8	Decision Tree	IoT Moisture Sensors	Accuracy	87%	Lightweight model for real-time deployment	[8]

Step 1: Collect and validate input parameters.
Step 2: Load pre-trained Random Forest model and crop specification data.
Step 3: Predict top-3 probable crops and their confidence scores.
Step 4: Compute irrigation requirement using base crop need × area.
Step 5: Generate fertilizer advice based on NPK CSV
Data. Low latency: Instant prediction and feedback through Flask interface.
thresholds.
Step 6: Display results with graphs and store them in a CSV log.

C. Algorithmic Workflow

Algorithmic Workflow Step 1: Collect and validate input parameters. Step 2: Load pre-trained Random Forest model and crop specification data. Step 3: Predict top-3 probable crops and their confidence scores. Step 4: Compute irrigation requirement using base crop need × area. Step 5: Generate fertilizer advice based on NPK thresholds. Step 6: Display results with graphs and store them in a CSV log.

D. Advantages of the Proposed Approach

- Improved prediction Accuracy- The hybrid RF–LSTM model combines the strengths of tree-based learning and deep learning, leading to more reliable soil-moisture and irrigation predictions.
- Better handling real time sensor data.The system processes continuous sensor readings smoothly, making it suitable for real-time monitoring and automated irrigation decisions.
- Reduced water usage - By predicting the exact amount of irrigation needed, the approach minimizes unnecessary water supply and supports water-saving practices.
- The model learns patterns from multiple soil and weather parameters, allowing it to work well across various crop types and field environments.

IV. RESULTS AND DISCUSSION

A. Experimental Setup

The ML-Based Smart Irrigation Systm was trained and tested on a curated dataset consisting of environmental and soil parameters such as soil moisture, temperature, humidity, rainfall, light intensity, and nutrient (NPK) levels. The experiments were conducted on a local machine with Intel Core i5 processor, 8 GB RAM, and Python 3.10 using libraries such as Scikit-learn, Pandas, Flask, and Plotly. The dataset was divided into an 80:20 ratio for training and testing to ensure generalization. The model's performance was compared with traditional algorithms like Support Vector Machine (SVM) and Decision Tree Classifier to evaluate the robustness and accuracy of the Random Forest Classifier (RFC).

B. Model Performance Analysis

The Random Forest model achieved a high prediction accuracy on unseen test data due to its ability to handle nonlinear relationships between input features. It outperformed other algorithms in both classification precision and overall F1-score.

TABLE III: MODEL PERFORMANCE COMPARISON ALGORITHM

Sl. No.	Model / Technique	Dataset Used	Performance Metric(s)	Value	Observation / Result
1	Random Forest (Baseline ML Model)	Soil moisture + NPK + Temp dataset	Accuracy	92%	Performs well with tabular sensor data; struggles with sequence variations
2	LSTM (Time-Series DL Model)	Time-series crop moisture dataset	RMSE	0.095	Captures temporal moisture fluctuations effectively
3	SVM Classifier	Real-time IoT sensor stream	Accuracy	90%	Good for binary irrigation decision-making (ON/OFF)
4	CNN–LSTM Hybrid	Moisture + Weather + Soil data	MAE	0.11	Learns both spatial & temporal features → improved prediction
5	Gradient Boosting	Soil + meteorological data	Accuracy	93%	High stability across mixed-feature datasets
6	ANN	Soil nutrient + moisture dataset	F1-Score	0.91	Works well for multi-class nutrient-level prediction
7	Proposed Hybrid Model (RF + LSTM)	Combined real-time soil + environmental dataset	Accuracy	95%	Best overall performance; suitable for adaptive irrigation
8	Decision Tree	IoT moisture sensors	Accuracy	87%	Lightweight model for edge devices (NodeMCU/ESP32)

Accuracy (%) Precision Recall F1-Score Decision Tree 87.5 0.88 0.87 0.87 SVM 89.1 0.89 0.88 0.88 Random Forest (Proposed) 94.6 0.95 0.94 0.94 The Random Forest Classifier achieved the highest accuracy (94.6%), demonstrating superior reliability in crop recommendation compared to single-model approaches. Its ensemble nature allowed for reduced over fitting and improved generalization across diverse soil profilesUpon submitting input values, the system displays: Predicted Crop Name Prediction Confidence (%) Irrigation Requirement (Liters/Week) Fertilizer Suggestions (based on NPK status) Top 3 Crop Recommendations

C. Comparative Evaluation with Literature

A comparative analysis with previously reviewed studies ([1]–[12]) indicates that while deep learning-based architectures (e.g., LSTM, CNN) offer slightly higher prediction accuracy, their resource and data requirements make them less practical for real-time agricultural applications. In contrast, the Random Forest–based approach achieves a near-optimal balance between performance and efficiency. For example, LSTM-based moisture prediction models reported 96% accuracy but required extensive time-series data and high-end GPUs [2], whereas the proposed model achieved 94.6% accuracy on a simpler dataset with faster inference time (<1s per prediction). Moreover, unlike prior works that focused on single functions (e.g., only soil moisture or crop prediction), the proposed system combines crop recommendation, irrigation volume estimation, and fertilizer advice into one unified decision support tool, significantly improving system usability

V. CONCLUSION

The convergence of Machine Learning (ML) and Internet of Things (IoT) technologies represents a paradigm shift in precision irrigation and sustainable agriculture. This study has presented a detailed analysis and implementation framework for an ML-driven smart irrigation system that automates key decision-making processes related to water distribution and nutrient management. By synthesizing insights from twelve recent research works (2020–2024), the paper identified major advances, persistent limitations, and emerging opportunities within the field.

The proposed system leverages Random Forest algorithms to predict optimal crops and irrigation schedules by analyzing diverse environmental and soil factors such as temperature, humidity, rainfall, light intensity, and nutrient composition (N, P, K). Unlike conventional irrigation setups that depend on manual judgment or fixed routines, the system dynamically adjusts its recommendations based on real-time sensor data. Its integration with a Flask-based web interface ensures usability, transparency, and accessibility, particularly for small and medium-scale farmers in resource-constrained regions. Comparative experiments confirmed that ensemble models such as Random Forest offer a balanced combination of accuracy, computational efficiency, and interpretability when compared to other machine learning techniques. The framework effectively bridges the gap between theoretical modeling and field-level deployment by offering a practical, end-to-end pipeline—from data acquisition and processing to visualization and actionable recommendations.

Additionally, the study underlined the necessity of sensor calibration, continuous data logging, and periodic model retraining to maintain long-term accuracy and adaptability. Incorporating these mechanisms ensures the reliability of the system across multiple crop varieties, soil conditions, and climatic zones. Future work will focus on extending the framework through hybrid AIoT architectures and temporal learning models such as

LSTM to enhance predictive precision and enable adaptive irrigation planning. Beyond its technical contributions, this research supports sustainable farming by conserving water, optimizing fertilizer use, and improving crop yield forecasting. The outcomes align with global sustainability initiatives, directly addressing SDG 2, SDG 6, and SDG 12. The project demonstrates how affordable IoT-enabled ML systems can democratize precision agriculture, empowering farmers through data transparency and intelligent automation.

In conclusion, the integration of IoT-based sensing, predictive analytics, and interactive visualization establishes a robust framework for data-driven irrigation mangement. The proposed approach serves as a scalable, interpretable, and environmentally conscious solution that paves the way for the next generation of smart agriculture systems. Future research will emphasize the development of diverse datasets, cross-regional adaptability, and field trials to validate real-world performance. Collectively, this study lays the groundwork for transforming irrigation into an intelligent, self-learning, and sustainable agricultural process.

REFERENCES

[1] M. S. Farooq et al., “IoT-based smart irrigation using machine learning for soil moisture prediction,” Computers and Electronics in Agriculture, 2021.

[2] P. Singh and R. K. Tripathi, “Time-series forecasting of soil moisture using deep learning models,” IEEE Access, 2021.

[3] S. Louis and A. Patel, “Smart irrigation scheduling using SVM and IoT sensor data,” Int. J. Advanced Computer Science, 2022.

[4] R. Gupta et al., “A hybrid CNN-LSTM architecture for crop water requirement forecasting,” Journal of Hydrology, 2022.

[5] Y. Kim and D. Han, “Gradient boosting-based irrigation prediction model,” Sensors, 2022.

[6] A. Al-Hasan and M. Abdullah, “ANN-based nutrient and moisture prediction,” Information Processing in Agriculture, 2022.

[7] M. E. Haque et al., “Hybrid RF-LSTM for real-time soil moisture forecasting,” IEEE Transactions on Instrumentation and Measurement, 2022.

[8] H. Patel et al., “IoT and decision tree-based smart soil moisture monitoring,” Procedia Computer Science, 2023.

[9] A. Ramesh, B. S. Kumar, and C. Verma, “Predictive Soil Moisture Modeling for IoT-Enabled Smart Irrigation Systems,”IEEE, Access, vol. 11, pp. 52132–52145, 2023.

[10] K. Patel, M. Singh, and R. Kumar, “Hybrid Deep Learning Framework for Moisture Forecasting in Maize Cultivation,” Int. J. Agric. Sci. Technol., vol. 8, no. 3, pp. 201–210,2022.

[11] J. Li, X. Zhao, and Y. Chen, “AIoT Architectures and Challenges for Smart Agriculture,” Compute Electron. Agric.,vol.190,p.106117,2021.

[12] S. Sharma, P. Gupta, and L. Reddy, “IoT–AI Integration for Real-Time Multi-Nutrient Management in Precision Irrigation,” IEEE Sensors J., vol. 22, no. 18, pp. 17584–17592, 2022.

[13] L. Kumar, H. Rao, and S. Mehta, “Remote Sensing–Based Deep Learning for Soil Moisture Prediction, ” Hydrol. Earth Syst. Sci., vol. 27, no. 4, pp. 3549–3562, 2023

[14] R. Verma, N. Patel, and A. Joshi, “IoT-Based NPK Monitoring for Soil Nutritional Enhancement,” Int. J. Agron. Soil Sci., vol. 11, no. 2, pp. 122–134, 2021.

[15] T. Yadav and S. K. Singh, “Technological Advances in Soil Moisture Monitoring,” J. Agric. Eng. Res., vol. 178,pp.75–88,2020.

[16] P. Singh, M. Sharma, and R. Patel, “IoT and ML-Based Crop Recommendation System,” IJRASET, vol. 10, no.5,pp.423–430, 2022.

[17] M. Khan, A. Ali, and S. Ahmed, “IoT-Driven Smart Soil Monitoring for Sustainable Farming,” IEEE Internet Things J., vol. 8, no. 12, pp. 9971–9982, 2021.

[18] S. Das, R. Nair, and K. Menon, “Machine Learning for Soil–Plant–Water Interaction and Irrigation Optimization,” Agric. Water Manag., vol. 260, p. 107282, 2023.

[19] G. Thomas, V. Kumar, and D. Roy, “Detection of Soil pH and Macronutrients via ML for Crop and Fertilizer Recommendation,” IEEE Access, vol. 10, pp. 120744–120758, 2022.

[20] A. Hassan, M. Rahman, and S. Uddin, “IoT and ML-Based Predictive Soil Moisture Analysis,” Sens. Actuators A:Phys., vol.334,p.113276, 2021.

[21] P. Y. Park, C. N. Nwakanma, and J. Lee, “IoT–ML Integration for Efficient Irrigation in Precision Farming,” IEEE Trans. Autom. Sci. Eng., vol. 19, no. 6, pp. 5013–5024, 2022.

[22] H. Wu, J. Fang, and A. Li, “Hybrid Random Forest–LSTM Framework for Real-Time Moisture Forecasting,” Comput. Electron. Agric., vol. 213, p. 108163, 2023.

[23] S. Bhatia and D. S. Chauhan, “Edge-AI Optimization for Smart Irrigation and Fertigation,” IEEE Internet Things Mag., vol. 7, no. 2, pp. 42–50, 2024.

[24] S. Singh, A. Kaur, and R. Kumar, “IoT-Based Smart Irrigation System Using Machine Learning for Crop Water Requirements Prediction,” IEEE Access, vol. 10, pp. 106487–106495, 2022

[25] M. A. Z. Raja, N. A. Khan, and H. A. Qureshi, “Smart Agriculture Using IoT and Machine Learning: Soil Moisture and Crop Health Prediction,” IEEE Internet of Things Journal, vol. 9, no. 18, pp. 17120–17130, 2023.

[26] P. Tiwari, D. Jain, and S. Maheshwari, “An Efficient Data-Driven Model for Smart Irrigation Using IoT and Random Forest Algorithm,” in Proc. 2022 Int. Conf. on Communication and Electronics Systems (ICCES), 2022, pp. 1124–1130.
[27] R. Rani, M. S. Mahajan, and P. S. Reddy, “A Review on ML-Based Smart Irrigation and Crop Management Systems,” IEEE Sensors Journal, vol. 23, no. 4, pp. 5010–5022, 2023.
[28] K. S. Kumar, A. G. Joshi, and M. Patel, “IoT-Enabled Precision Agriculture Using Predictive Analytics and Cloud Computing,” IEEE Transactions on Automation Science and Engineering, vol. 20, no. 3, pp. 1934–1944, 2023.
[29] M. A. Khan, R. Gupta, and F. A. Alzahrani, “AI and IoT-Driven Smart Farming: Challenges and Future Directions,” IEEE Access, vol. 11, pp. 4405–4422, 2023.