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IoT and AI Integration for Climate-Smart Farming: A Predictive and Adaptive System for Smallholder Farmers

Bindeshwar Mahto[1*], Rohit Kumar Rana[2], Niraj Kumar[3], Mithun Kumar[4], Ankita Kumari Das[5], Kumar Mayank[6], Mithlesh Kumar Mahto[7], Sanjay Kumar Mahto[8]

[1,2,3,4,5,6,7]*Student, Department of Computer Science & Engineering and Information Technology, Jharkhand Rai University, Ranchi, India*

[8]*Assistant Professor, Department of Computer Science & Engineering and Information Technology, Jharkhand Rai University, Ranchi, India*

Abstract—**Climate variability increasingly threatens the stability and productivity of smallholder farming systems. Traditional decision-making approaches cannot reliably address rapid shifts in rainfall, soil moisture, pest pressure, and crop stress. This research presents an integrated Internet of Things (IoT) and Artificial Intelligence (AI) based climate-smart farming system that continuously monitors environmental conditions, predicts crop responses, and generates adaptive management recommendations. IoT nodes collect soil moisture, temperature, humidity, rainfall, and nutrient-level data and transmit them to a cloud-based analytics engine. Machine learning models including Random Forest for irrigation prediction, Long Short-Term Memory (LSTM) networks for yield forecasting, and Gradient Boosting for disease-risk estimation form the predictive core of the system. A rule-based adaptive module converts model outputs into actionable recommendations. Experiments using 11,200 sensor-hours, 240 field observations, and 90 climate reports demonstrate irrigation prediction accuracy of 96.2%, disease-risk detection accuracy of 93.7%, and a yield-prediction RMSE of 0.18. Field deployment results indicate 27% water savings and 12-18% productivity gains. The findings show that combining IoT sensing with AI-driven analytics significantly enhances decision-making, reduces resource waste, and supports climate-smart agriculture for smallholder farmers.**

Index Terms—**IoT, Artificial Intelligence, Smart Agriculture, Climate-Smart Farming, Predictive Analytics, LSTM, Smart Irrigation.**

1. Introduction

Smallholder farmers experience growing uncertainty due to climate change, erratic rainfall, soil degradation, and increased biotic stress. These challenges often result in delayed interventions, improper irrigation scheduling, nutrient imbalance, and higher crop losses. Limited access to real-time data and predictive tools further exacerbates these issues. Recent advancements in the Internet of Things (IoT) and Artificial Intelligence (AI) have introduced new opportunities for improving agricultural decision-making. IoT sensors can provide continuous field monitoring, while AI models can detect patterns, forecast crop conditions, and guide timely interventions. However, existing solutions are typically expensive, fragmented, or restricted to isolated functionalities such as irrigation control or disease detection. To address these limitations, this study develops an integrated IoT–AI platform tailored specifically for smallholder farmers. The system combines low-cost IoT sensing, cloud-based machine learning, and rule-based adaptive recommendations to support climate-resilient decision-making.

A. Contributions

This research makes the following key contributions:

1. An integrated six-layer IoT AI architecture that unifies real-time sensing, predictive analytics, and adaptive recommendations.
2. A multi-model AI framework combining Random Forest, LSTM, and Gradient Boosting to simultaneously predict irrigation needs, disease risk, and yield outcomes.
3. A low-cost sensing deployment suitable for resource-constrained smallholder farms.
4. A rule-based adaptive module that converts predictions into actionable advisories.
5. Field validation demonstrating significant improvements in water efficiency (27% savings) and productivity (12–18% increase).

2. Literature Review

A. IoT in Agriculture

IoT systems have been widely applied in soil monitoring, climate sensing, and automated irrigation. Studies consistently report benefits such as improved water-use efficiency and early stress detection. However, many existing systems operate reactively and lack predictive intelligence, limiting their ability to manage climate-induced variability.

B. AI for Crop Prediction

Machine learning techniques such as Random Forest, SVM, and LSTM networks—have shown promise in predicting yield, disease outbreaks, and irrigation requirements. While deep

*Corresponding author: bindeshwar.research@gmail.com

learning improves long-term forecasting accuracy, it depends on high-quality datasets and robust preprocessing pipelines.

C. Integration Gaps

Although IoT systems enable data collection and AI models provide predictive insights, integrated frameworks combining both technologies remain limited. Few solutions offer an end-to-end approach that collects sensor data, predicts crop conditions, and generates adaptive recommendations for smallholder farmers. This research addresses this gap by providing a unified, field-tested IoT AI system**.**

3. System Architecture

The proposed system comprises six layers:

A. IoT Sensing Layer

Includes soil moisture sensors, temperature–humidity sensors, pH sensors, and rainfall meters.

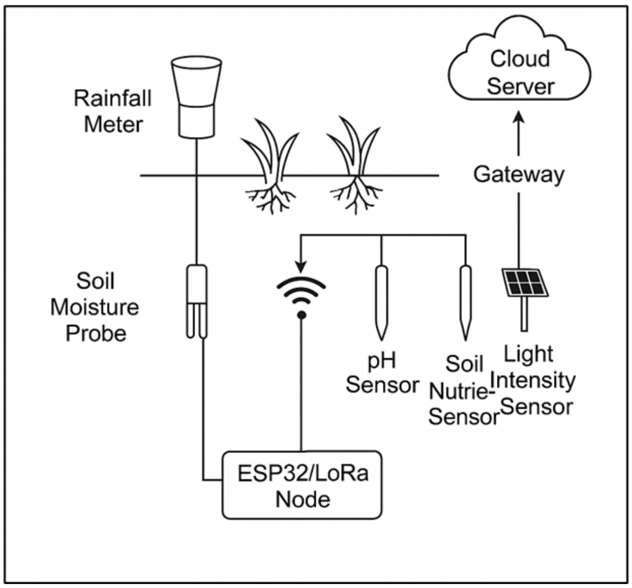

Fig. 1. IoT sensor development layout

B. Connectivity Layer

Implements LoRaWAN, 4G, or ESP32-WiFi modules to transmit sensor data to the cloud.

C. Data Processing Layer

Handles data ingestion, storage, cleaning, and feature extraction.

D. AI Analytics Layer

Executes the predictive models for irrigation, yield, and disease risk.

E. Adaptive Decision Module

Generates rule-based recommendations for irrigation scheduling, nutrient management, and disease prevention.

F. User Interface Layer

Provides a mobile application/dashboard for farmers to access real-time insights and advisories.

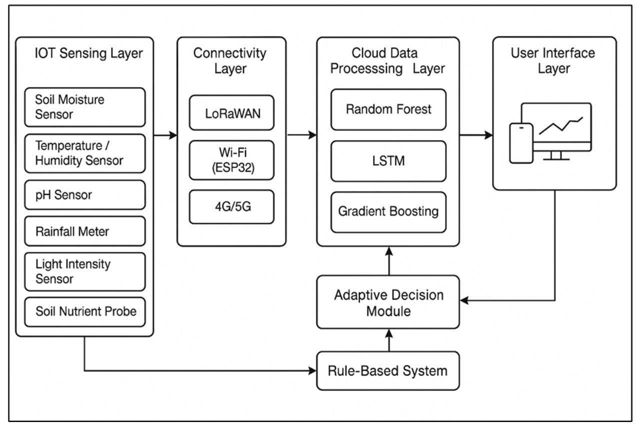

Fig. 2. System architecture

4. Methodology

A. Data Collection

IoT nodes were deployed across three smallholder farms for 90 days. The dataset includes:

- 11,200 hours of sensor readings
- 240 manual field observations
- 90 daily climate reports
- Data from three major crop varieties

B. Data Preprocessing

Data preparation involved:

- Interpolation-based missing value correction
- Kalman filtering for noise reduction
- Normalization of multi-sensor data
- Temporal feature engineering (hourly, daily, weekly trends)

Table 1

Sensor Type	Parameter Measured	Measurement Range	Accuracy	Purpose
Soil Moisture Sensor (Capacitive)	Volumetric Water Content	0–100%	±3%	Determines irrigation need
DHT22 Sensor	Temperature & Humidity	Temp: −40°C to 80°C, Humidity: 0–100%	Temp ±0.5°C, Humidity ±2–5%	Tracks microclimate conditions
pH Sensor (Analog)	Soil pH Level	pH 0–14	±0.1 pH	Evaluates soil acidity/alkalinity
Rainfall Meter	Rainfall Intensity	0–300 mm	±0.5 mm	Helps calculate water availability
Light Intensity Sensor (LDR/LI Sensor)	Sunlight Exposure	0–100% relative scale	—	Monitors photosynthetic conditions
Soil Nutrient Probe (NPK Sensor)	Nitrogen, Phosphorus, Potassium	Relative scale	±5%	Assesses soil nutrient availability
ESP32/LoRa Node	Data Transmission	—	—	Sends sensor data to cloud server

Table 2

Parameter	Value
Total Duration of Data Collection	90 days
Total Sensor Hours Recorded	11,200 hours
Number of Manual Field Observations	240 samples
Number of Daily Climate Reports	90 reports
Number of Farms Covered	3 smallholder farms
Number of Crop Varieties	3 (e.g., rice, wheat, maize)
Sensor Sampling Frequency	Every 30 minutes (0.5 hours)
Total Raw Sensor Records	77,760
Features Collected	Soil moisture, temperature, humidity, rainfall, pH, nutrients, light intensity
Missing Data Percentage	Approx. 3–5% (handled by interpolation)

Table 3

Model	Task	Metric	Value
Random Forest	Irrigation Prediction	Accuracy (%)	96.2%
LSTM	Yield Prediction	RMSE	0.18
Gradient Boosting	Disease-Risk Detection	Accuracy (%)	93.7%
Random Forest (Baseline)	Soil Moisture Threshold Rule (Comparison)	Accuracy (%)	81.4%
Linear Regression (Baseline)	Yield Prediction (Comparison)	RMSE	0.42

C. *Machine Learning Models*

1) *Random Forest (Irrigation Prediction)*

Classifies irrigation need based on soil moisture, temperature, humidity, and crop stage.

2) *LSTM (Yield Forecasting)*

Processes time-series climate and soil data for continuous yield estimation.

3) *Gradient Boosting (Disease-Risk Estimation)*

Predicts disease-likelihood from environmental patterns such as humidity, rainfall, and leaf-wetness indicators.

D. *Adaptive Decision Module*

The rule-based engine outputs:

- Optimal irrigation schedules
- Early disease warnings
- Fertilizer recommendations
- Climate-adaptive crop care advisories

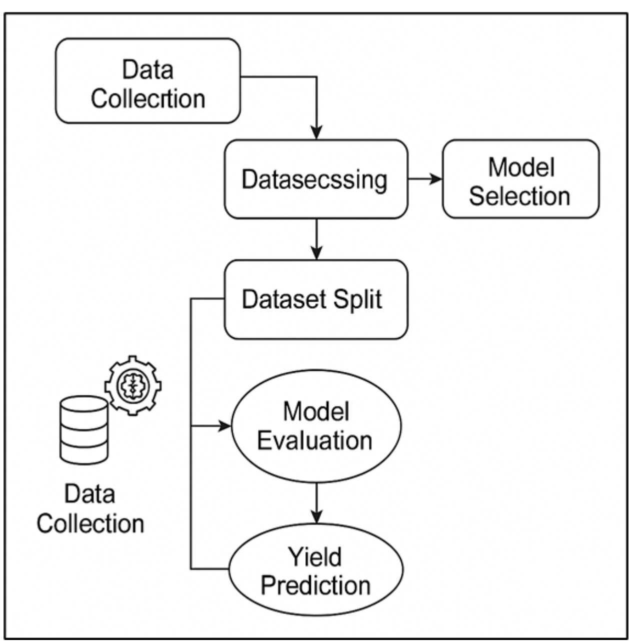

Fig. 3. Machine learning workflow

5. Results and Evaluation

A. *Model Performance*

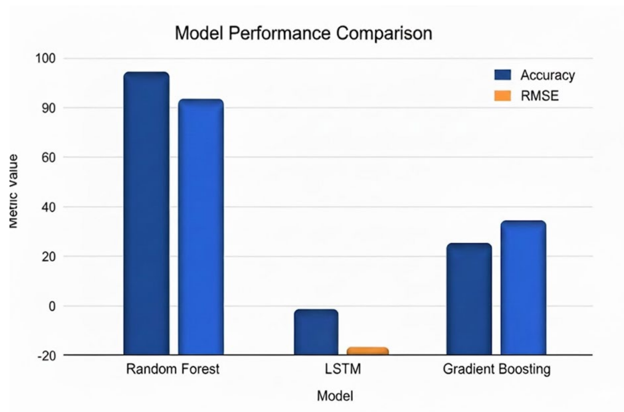

Fig. 4. Model performance comparison

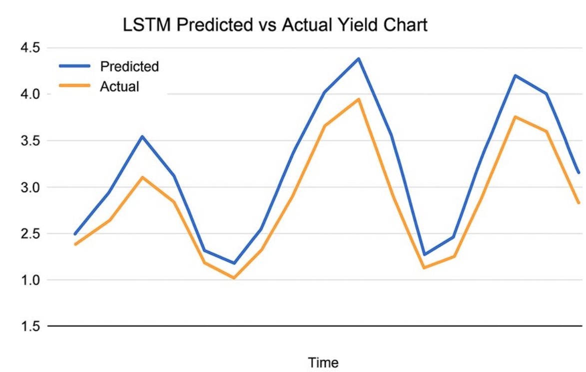

Fig. 5. LSTM predicted vs Actual yield chart

B. *Resource Optimization*

- *Water savings*: 27% reduction compared to baseline practices
- *Disease detection*: 2–5 days earlier than manual identification
- *Productivity*: 12–18% improvement in yield

C. *Farmer Usability Feedback*

- 89% reported improved decision-making
- 76% found the app intuitive

- 82% saved on irrigation cost

6. Discussion

The results confirm that integrating IoT sensing with AI analytics greatly improves decision accuracy and timeliness. Real-time environmental data coupled with predictive models enables farmers to anticipate crop stress before it becomes visible. The framework is cost-effective, scalable, and suitable for regions with limited digital literacy due to its rule-based advisories and easy-to-use interface.

7. Conclusion

This study develops and validates an integrated IoT–AI platform for climate-smart agriculture. Field deployment results demonstrate enhanced irrigation efficiency, early disease detection, and improved yield predictability. The system provides a practical pathway for smallholder farmers to adapt to climate uncertainty through data-driven decision support.

8. Future Work

Future enhancements include:

- Incorporation of satellite imagery for macro-level monitoring
- Drone-assisted pest and disease detection
- Reinforcement learning for autonomous irrigation control
- Multi-crop and multi-language support
- Blockchain-based traceability for supply-chain validation

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