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ORIGINAL CONTRIBUTION

AI-Powered Climate-Aware Crop Recommendation System using IoT and Machine Learning

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ABSTRACT

Increasing climatic unpredictability has made traditional, experience-based crop selection increasingly unreliable for Indian farmers. This paper proposes an AI-Powered Climate-Aware Crop Recommendation System that combines IoT-based environmental sensing with Machine Learning to deliver real-time, data-driven crop recommendations. The proposed architecture spans an ESP32 microcontroller with DHT22 and soil sensors, a Node.js/PostgreSQL backend, a Random Forest Classifier trained on agricultural crop-recommendation data, and a Next.js dashboard that presents recommendations to the farmer. For this symposium demonstration phase, given hardware and time constraints, the crop-recommendation inference was simulated using Google's Gemini API with manually entered field parameter values in place of live sensor feeds, in order to validate the end-to-end recommendation logic and dashboard pipeline ahead of full hardware and model deployment. Sample simulation results demonstrate the system correctly identifying high-confidence crop matches from a given set of atmospheric and soil-nutrient parameters, indicating strong potential for real-world precision-agriculture deployment.

KEYWORDS: IoT, Machine Learning, Random Forest, Crop Recommendation, Precision Agriculture, Generative AI, Gemini API, ESP32

1. INTRODUCTION

Agriculture remains the backbone of the Indian economy, employing a large share of the rural population and contributing significantly to national GDP. However, increasing climatic unpredictability — irregular monsoons, sudden droughts, untimely floods, and extreme weather events — has made traditional, history-based crop selection increasingly unreliable. Farmers largely continue to rely on seasonal experience and word-of-mouth advice passed down over generations, which is no longer sufficient to cope with the pace of environmental change.

This project proposes an AI-Powered Climate-Aware Crop Recommendation System that combines IoT-based environmental sensing with Machine Learning to deliver real-time, data-driven crop recommendations. By continuously

monitoring soil and atmospheric parameters directly from the field and applying a trained predictive model, the system converts raw sensor readings into a clear, actionable recommendation — helping farmers make informed planting decisions without needing any technical expertise themselves.

2. PROBLEM STATEMENT

Farmers today lack access to real-time, localized environmental data and intelligent decision-support tools. Crop selection is still largely based on seasonal experience rather than current soil and atmospheric conditions, which frequently leads to poor yield, wasted inputs, and avoidable economic loss. This gap is especially severe in rural and resource-constrained regions where access to agronomists or advisory services is limited.

The key challenges this project addresses are: (i) irregular and unpredictable rainfall causing either water stress or waterlogging, (ii) fluctuating soil moisture directly affecting seed germination and yield, (iii) little to no access to real-time environmental monitoring in most small and marginal farms, (iv) recurring economic losses due to uninformed planting decisions, and (v) the absence of an integrated, low-cost, intelligent system built specifically for agricultural decision support.

3. PROPOSED SYSTEM

We propose a three-tier IoT–Cloud–ML system that spans embedded hardware, backend infrastructure, and a machine learning inference layer. At the sensing layer, an ESP32 microcontroller is interfaced with a DHT22 sensor (temperature & humidity) and a capacitive soil moisture sensor to continuously capture field conditions. These readings are transmitted over Wi-Fi via REST APIs at defined intervals, ensuring the system always reflects near real-time conditions rather than stale historical averages.

At the storage and processing layer, a Node.js/Express backend receives incoming sensor data and persists it in a PostgreSQL database, enabling both live queries and historical trend analysis. A Random Forest Classifier, trained offline on a public agricultural crop-recommendation dataset, is deployed as a REST API microservice to generate a crop prediction along with a confidence score.

Finally, at the presentation layer, a Next.js web dashboard renders the live sensor readings, the recommended crop, its confidence score, and historical trends in a simple, farmer-friendly interface, prioritising clarity over technical detail.

3.1 Simulation Using Generative AI (Gemini API)

Given the limited time available ahead of the symposium, full hardware deployment and offline model training were kept as the next implementation phase. For the purpose of this symposium demonstration, the crop-recommendation inference was simulated using Google's Gemini API through contextual, structured prompting, with field parameter values entered manually in place of live ESP32/DHT22 sensor feeds. This allowed the complete recommendation pipeline — from parameter input to a ranked, confidence-scored crop

recommendation with an agronomic rationale — to be validated end-to-end on the existing dashboard, ahead of the planned Random Forest model deployment on real sensor data.

4. SYSTEM ARCHITECTURE

The figure below illustrates the end-to-end data flow of the proposed system, from sensor-level data acquisition to the final recommendation shown to the farmer.

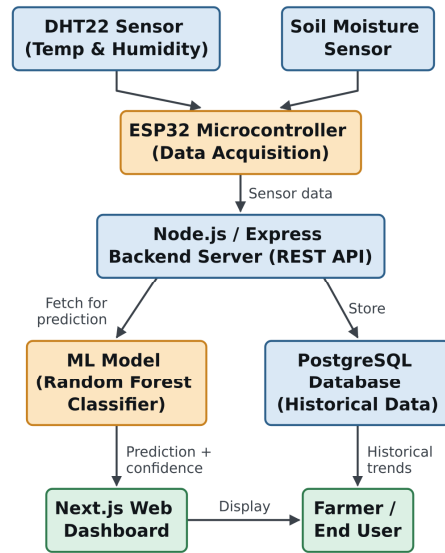


Figure 1: Block diagram of the proposed IoT–Cloud–ML architecture.

The DHT22 and soil sensors feed raw readings to the ESP32, which pushes them to the backend server over REST APIs. The backend persists readings in PostgreSQL for historical logging and feeds the latest reading to the prediction layer, which returns a predicted crop with a confidence score for the Next.js dashboard to render alongside live values and past trends.

5. SIMULATION RESULTS: EXAMPLE INPUT & OUTPUT

A sample interaction with the simulated system is shown below to illustrate how field parameters translate into a crop recommendation.

5.1 Input Parameters

INPUT PARAMETERS

IoT Field Sensor Feeds

MANUAL TEST BED

01. ATMOSPHERE & HYDROL

Micro-Climates & Soil Moisture

Temperature (°C) 28 °C

Humidity (%) 89 %

Soil Moisture (%) 62 %

Soil pH 7.3

Acidic (<6.0) Neutral (6.0-7.5) Alkaline (>7.5)

Figure 2a: Manually entered atmospheric and soil-moisture parameters.

02. NPK SOIL STOICHIOMETRY

Nutrient Concentrations (mg/kg)

Nitrogen (N) 5 mg/kg

Phosphorus (P) 45 mg/kg

Potassium (K) 140 mg/kg

STATE / REGION West Bengal

SEASON Kharif

ANALYZE FIELD SENSOR DATA

Figure 2b: Manually entered soil NPK and regional/seasonal parameters.

Parameter	Value
Temperature	28 °C
Humidity	89 %
Soil Moisture	62 %
Soil pH	7.3 (Neutral)
Nitrogen (N)	5 mg/kg
Phosphorus (P)	45 mg/kg
Potassium (K)	140 mg/kg
Region / Season	West Bengal / Kharif

5.2 Recommendation Output

TOP 3 RECOMMENDED CROPS

CONFIDENCE LEVEL: HIGH

RANK #1 96%

Rice (Paddy)

OPTIMAL MATCH

RANK #2 89%

Jute

HIGH MATCH

RANK #3 82%

Sugarcane

HIGH MATCH

AGRONOMIC RATIONALE

Why This Crop?

High soil moisture (62%) and relative humidity (75%) paired with warm temperatures (28°C) provide ideal semi-aquatic growth conditions for paddy.

PARAMETRIC MONITORS

Parameter Watch

All parameters are in optimal range.

Figure 3: Top-3 recommended crops with confidence scores and agronomic rationale.

Given warm, humid conditions with high soil moisture and NPK levels within a favourable range, the system ranked Rice (Paddy) as the optimal match at 96% confidence, followed by Jute (89%) and Sugarcane (82%), with the accompanying rationale correctly identifying the semi-aquatic growth conditions favouring paddy.

5.3 Soil Nutrient Analysis

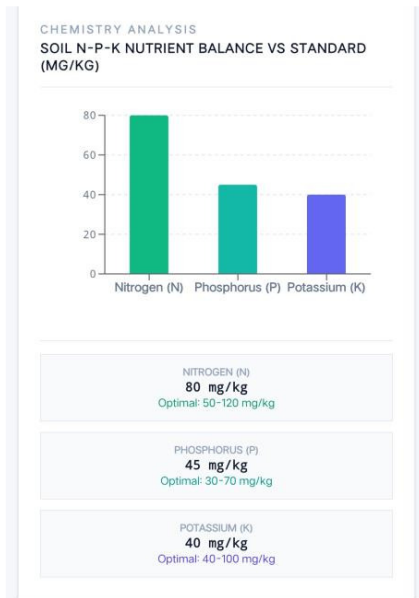


Figure 4: Soil N-P-K nutrient balance compared against optimal reference ranges.

6. IMPLEMENTATION SNAPSHOTS

A few representative code snippets from the system's backend and ML layer illustrate the core data and prediction flow.

6.1 POST Request — Adding Sensor Data to the Database

```
app.post('/api/sensor-data', async (req, res) => {
  const { temperature, humidity, soilMoisture,
    n, p, k } = req.body;
  const result = await db.query(
    `INSERT INTO sensor_readings
    (temperature, humidity, soil_moisture,
    n, p, k, recorded_at)
    VALUES ($1,$2,$3,$4,$5,$6,NOW())
    RETURNING *`,
    [temperature, humidity, soilMoisture, n, p, k]
  );
  res.status(201).json(result.rows[0]);
});
```

6.2 ML Model — Training the Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split

X = data[['temperature', 'humidity', 'soil_moisture',
  'N', 'P', 'K', 'ph']]
y = data['label'] # crop name
X_train, X_test, y_train, y_test = train_test_split(
  X, y, test_size=0.2)
model = RandomForestClassifier(n_estimators=100,
  random_state=42)

model.fit(X_train, y_train)
joblib.dump(model, 'crop_model.pkl')
```

6.3 Prediction Endpoint

```
@app.route('/predict', methods=['POST'])
def predict():
  data = request.get_json()
  features = [[data['temperature'],
    data['humidity'],
    data['soil_moisture'], data['N'],
    data['P'], data['K'], data['ph']]]
  prediction = model.predict(features)[0]
  confidence = max(
    model.predict_proba(features)[0]) * 100
  return jsonify({'crop': prediction,
    'confidence': round(confidence,1)})
```

7. ADVANTAGES OVER TRADITIONAL METHODS

Unlike conventional crop selection, which relies on seasonal memory and generalised regional advice, this system grounds every recommendation in the farmer's own field data captured at that moment. Recommendations adapt automatically as weather and soil conditions shift through the season; the inclusion of NPK sensing means nutrient deficiencies are accounted for, not just moisture and temperature; historical data logging allows trend analysis across a full growing season; and the entire stack is built on affordable, open-source hardware and software, keeping the solution realistic to deploy for small and marginal farmers.

8. CONCLUSION

The proposed system demonstrates a practical convergence of embedded systems, cloud infrastructure, and machine learning to address a real agricultural problem. The symposium demonstration, validated through Gemini API-based simulation of the recommendation logic, confirms the viability of the end-to-end pipeline ahead of full hardware and Random Forest model deployment. By replacing static, history-based crop selection with continuous, sensor-driven recommendations that account for both weather and soil nutrient status, the project offers a low-cost, deployable proof-of-concept with clear real-world relevance and strong potential for extension towards genuine precision farming for resource-constrained farmers.

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