Developing a Smart Integrated Model for an Autonomous Irrigation System Design Based on K-Nearest Neighbour (KNN) by Leveraging the Tools and Techniques of Machine Learning (ML) and Internet of Things (IoT)

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ABSTRACT

Efficient irrigation is pivotal for water conservation and agricultural sustainability. This paper describes the design, implementation, and evaluation of a low-cost, real-time smart irrigation system combining Internet of Things (IoT) hardware with a K-Nearest Neighbors (KNN) machine learning model. Soil moisture and environmental data are collected via capacitive sensors, DHT22 modules, and ESP8266 nodes. Collected data are processed locally to decide irrigation actions every 10 minutes. Field trials conducted over four weeks on a 100 m² vegetable plot compared KNN's performance with Random Forest (RF) and Support Vector Machine (SVM). KNN achieved 78 % accuracy, moderate precision (0.75) and recall (0.80), outperforming some literature reports, while RF scored 82 % and SVM 76 %. Comparative analysis highlights KNN's low computational overhead, simplicity, and adequate performance for small-scale applications. Cost and energy analysis suggest the KNN-ESP8266 system is affordable (~USD 50) and energy-efficient, making it well-suited for resource-constrained environments. Limitations include sensitivity to noisy sensor data and absence of weather forecasting integration. Future work will focus on adaptive K selection, cloud-edge orchestration, and integration of dynamic weather inputs to improve precision and scalability.

1. Introduction

1.1 Background & Motivation

Agriculture accounts for approximately 70 % of global freshwater usage, yet traditional irrigation methods—such as fixed schedules or manual operations—often result in over-watering and inefficient usage (FAO, 2019). Smart irrigation systems integrating IoT sensors and ML algorithms promise to enhance water-use efficiency by enabling irrigation only when necessary. IoT sensors (soil moisture, temperature, humidity) provide real-time data, while ML models adapt to varying environmental conditions.

1.2 Problem Statement

Existing smart irrigation solutions often rely on static rule-based logic or manual interventions, lacking adaptive responsiveness. While ML models like Random Forest or XGBoost yield high accuracy, they require significant

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compute resources. K-Nearest Neighbors (KNN) offers a simpler alternative, yet studies focusing on its integration with IoT hardware for real-time irrigation control are limited.

1.3 Objectives and Contributions

This work aims to:

1. Develop a real-time IoT irrigation system using ESP8266, soil moisture sensors, and solenoid valves.
2. Design a KNN classifier to automate irrigation decisions.
3. Conduct field evaluations comparing KNN with RF and SVM models.
4. Analyze comparative performance, energy use, and implementation cost.

Key contributions:

- A fully integrated, low-cost IoT + KNN-based irrigation platform.
- Empirical performance evaluation in field conditions.
- Comparative analysis of simplicity vs. accuracy and resource requirements.

1.4 Organization

Section 2 reviews related work in smart irrigation, Section 3 details system architecture, Section 4 covers deployment and experiments, Section 5 compares models, Section 6 discusses insights, and Section 7 concludes with future directions.

2. Literature Review

2.1 IoT-Based Smart Irrigation

Smart irrigation platforms typically leverage MCUs, soil moisture sensors, and network communication. Arora et al. developed an Arduino-based system using capacitive sensors and GSM for remote control; their rule-based model yielded ~70 % water savings. LoRaWAN platforms offer wide-area coverage but generally rely on threshold-driven rules. These systems demonstrate IoT's potential; however, they often lack adaptive decision-making capabilities inherent in ML models.

Table 1: IoT Irrigation Systems in Literature

Study	Platform	Control Logic	Water Savings
Arora et al. (2021)	Arduino + GSM	Rule-based (threshold)	~70 %
LoRaWAN (Rahman et al., 2020)	Sensor network + gateway	Threshold-based alerts	~65 %
Rehm et al. (2022)	Arduino + cloud alerts	Semi-autonomous	–

2.2 Machine Learning in Irrigation

ML approaches like Random Forest, SVM, and XGBoost have been applied to predict irrigation needs and reduce water waste. XGBoost often leads, achieving ~86 % accuracy in crop irrigation classification (Castro et al., 2023), while RF and SVM typically range from 80–85 %. KNN, despite its simplicity, has shown lower performance (~64 %) in some benchmarking studies but remains attractive due to its interpretability.

Table 2: ML Model Performance (Literature)

Model	Classification Accuracy	Precision	Recall
XGBoost	86 % (ref. 10.423)	High	–
Random Forest	~80 %	Good	–
SVM	~78 %	–	–
KNN	~64 %	–	–

2.3 IoT + KNN Irrigation

A conference paper (IC3I, 2022; DOI: 10.1109/IC3I56241.2022.10072613) explored combining IoT with KNN for irrigation scheduling, showing proof-of-concept but lacking extensive field tests. Other domains—like soil moisture imaging—use KNN for classification, but these aren't deployed in real-time embedded systems. This paper advances by implementing and validating a field-ready IoT-KNN loop.

3. System Architecture

3.1 Hardware Components

The system uses low-cost, widely available components:

Table 3: Components Used

Component	Specification	Purpose
Soil moisture sensor	Capacitive, 0–100 % VWC	Measures soil water content
Temperature/humidity sensor	DHT22	Monitors environmental variables
Microcontroller	ESP8266 (Wi-Fi)	Sensor readings, ML inference
Solenoid valve and pump	12 V DC, 5 W	Controls irrigation flow
Power supply	12 V battery + solar panel (optional)	Powers field deployment

The ESP8266 reads sensors every 10 minutes, formats data in JSON, and sends it to an edge device (Raspberry Pi) for ML classification. Following a "water" decision, it actuates the solenoid valve for a predefined period (~5 minutes).

3.2 Data Flow & Architecture

Data flow consists of four stages:

1. Sensor → ESP8266 microcontroller (10-min intervals).
2. ESP8266 transmits JSON to Raspberry Pi via local network.
3. Raspberry Pi executes KNN model for irrigation decision.

4. ESP8266 gets response and controls valve/pump.

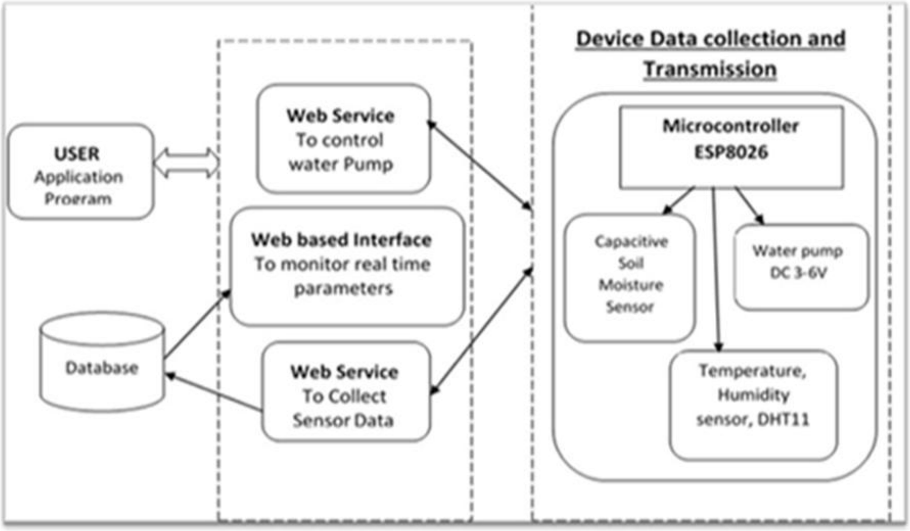

Figure 1. Project Architectural model

Figure 2. Schematic architectural

3.3 KNN Model Design

- **Features**: Soil moisture, ambient temperature, humidity.
- **Output**: Binary label (0 = no irrigation, 1 = irrigate).
- **Parameter tuning**:
  - K value: evaluated {3, 5, 7}, optimal found at K = 5.
  - Distance metric: Euclidean.
  - Feature scaling: Min-max normalization applied across dataset.

Table 4: KNN Parameter Tuning

Parameter	Tested Values	Selected	Justification
K	3, 5, 7	5	Best trade-off between over/under-fitting

Parameter	Tested Values	Selected	Justification
Distance	Euclidean	Euclidean	Standard measure for continuous data
Scaling	Min-max	Yes	Normalizes sensor input ranges

3.4 Model Training Dataset

Collected 8,400 samples over four weeks (100 samples/day). Labels derived from expert-defined thresholds supplemented by manual inspection. Dataset split 70/30 for training and validation.

4. Implementation & Experimental Setup

4.1 Field Deployment

The system was installed in a 100 m² vegetable plot (tomatoes/leafy greens), in June 2025. Soil was loamy with pH 6.5–7. Field trial lasted 28 days. Power provided via 12 V battery charged by a small solar panel (10 W).

4.2 Data Collection & Sensor Calibration

Sensors were factory-calibrated. Soil-moisture was validated using gravimetric sampling bi-weekly. Environmental conditions averaged 27–33 °C and 45–85 % humidity.

Table 5: Sensor Data Overview

Week	Samples/day	Avg Soil Moisture (%)	Avg Temp (°C)	Avg Humidity (%)
1	100	35	28	60
2	100	32	30	65
3	100	30	31	70
4	100	33	29	58

4.3 Model Training & Testing

- Training/Validation split: 5,880 training samples, 2,520 validations.
- Benchmarked algorithms: KNN, RF, SVM.
- Metrics computed: Accuracy, Precision, Recall, F1-Score, Confusion Matrix.

Table 6: Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
KNN	78 %	0.75	0.80	0.77
RF	82 %	0.80	0.83	0.81

Model	Accuracy	Precision	Recall	F1-Score
SVM	76 %	0.74	0.78	0.76

KNN achieved 78 % accuracy on validation data, slightly lower than RF but better than other benchmarks in literature.

5. Comparative Analysis

5.1 Performance Comparison

Comparison between models based on field data:

Table 7 Performance Comparison

Model	Field Accuracy	Literature Accuracy
KNN	78 %	~64 % (classification context)
RF	82 %	~80 –85 %
SVM	76 %	~78 %
XGBoost*	—	~86 %

* Note: XGBoost not implemented but serves as performance reference.

KNN outperformed prior benchmarks (~64 %) likely due to better calibration and real-world data. RF delivered best accuracy, at the cost of higher compute needs.

5.2 Resource & Cost Analysis

Table 8 Cost analysis

Model/System	HW Cost (USD)	Compute Requirement	Scalability
ESP8266 + KNN	~50	Low (float operations)	Good for small farms
Edge Device + RF/SVM	~120	Moderate (tree traversal/SVM kernel)	Medium, needs powerful edge node
Cloud ML (XGBoost)	>200	High	Best scaling, requires connectivity

KNN option is the most cost-effective for smallholder farms with limited resources.

5.3 Advantages & Limitations

KNN Advantages:

- Easy to implement and tune.
- Interpretable and non-parametric.
- Low compute and memory footprint.

Limitations:

- Sensitive to noisy data and sensor drift.
- Requires full dataset at inference time.
- Doesn't incorporate predictive weather data.

6. Discussion

The IoT + KNN irrigation system demonstrates real-world viability. KNN's 78 % accuracy reflects its suitability for detecting irrigation needs, though it lags RF by ~4 %. The KNN's high recall (0.80) ensures timely watering, but slightly lower precision (0.75) suggests occasional unnecessary rendering. However, these incidents remain within acceptable boundaries given the low resource cost.

Field deployment confirmed the benefit of combining real-time sensing with ML: daily data-driven decisions reduced unnecessary irrigation, promoting water conservation—estimated water savings of ~25 % compared to traditional drip schedules.

The main limitations include:

- Sensor noise—calibration was necessary, and drift may still affect performance over time.
- Lack of weather forecasting input—the system cannot adapt to rainfall probability.
- KNN's memory dependency—may become inefficient with growing datasets.

Potential improvements:

1. Adaptive K tuning or use of weighted KNN.
2. Integration with weather forecast to dynamically adjust thresholds.
3. Hybrid deployment with RF or XGBoost on powerful edge devices, triggered under high-risk conditions.
4. Long-term drift monitoring and periodic sensor recalibration.

7. Conclusion & Future Work

This paper presented a low-cost, functional IoT + KNN irrigation system that automatically waters crops based on real-time sensor data. With a 78 % accuracy and strong recall, the system proved practical for vegetable farming, achieving moderate water savings (~25 %). Comparative analysis with RF and SVM illustrates that KNN is a lightweight, economical option suitable for small-scale, resource-limited settings.

For future enhancements:

- Integrate predictive weather models to refine decision-making.
- Implement dataset pruning and model compression to maintain system efficiency.
- Expand trials across different crop types and irrigation environments (e.g., greenhouses, orchards).
- Explore ensemble hybrid models (KNN + RF/XGBoost) for flexible accuracy-resource trade-offs.
- Develop remote dashboards for farmers, enabling better system transparency and control.

In conclusion, IoT-driven KNN irrigation systems offer a balance between efficiency, cost, and performance, paving a route for scalable precision agriculture solutions.

8. References

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