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IOT-Based Precision Agriculture System Using Machine Learning Algorithms

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Abstract:

This paper presents an IOT-BASED PRECISION AGRICULTURE SYSTEM USING MACHINE LEARNING ALGORITHMS designed to provide real-time, localized agricultural advice to farmers. The system leverages an **ESP32 microcontroller** as the edge device to collect critical environmental data from **rainfall** and **DHT11 (temperature and humidity) sensors**. The data is processed locally on the device using a pre-trained **Random Forest Classifier** model, which was trained on a comprehensive **Kaggle dataset**. The system features a **push button** for user interaction and displays the recommended crop on an **LCD I2C** screen. This approach minimizes latency and dependence on a constant internet connection, making it ideal for rural farming environments. The use of the **Everywhere ML** framework facilitates the deployment of the machine learning model onto the constrained hardware. The results demonstrate the system's ability to provide accurate and timely recommendations, empowering farmers to make data-driven decisions for improved crop yield.

Keywords — IOT (Internet of things), Machine Learning (ML)

Abbreviations: Decision Tree Classifier (Dtc), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression (LogR), Random Forest Classifier (RFC). Multinomial Naïve Bayes(MNB), Extra Trees Classifier (ExTreeC), Bagging Classifier(Bagg), Gradient Boosting Classifier(GBCI),XGBOOST.

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1) . INTRODUCTION

Agriculture is fundamental to the global economy, but traditional farming methods often lead to inefficient resource use and low crop yields. Recent advancements in Artificial Intelligence (AI) and the Internet of Things (IoT) offer a promising solution.[1] This research proposes an IOT system that brings the power of machine learning directly to the farm, addressing the limitations of cloud-based systems such as high latency and poor connectivity.[2] This paper details the design, implementation, and performance of a crop recommendation system built on an ESP32 microcontroller, which uses sensor data and a Random

Forest Classifier to recommend the most suitable crop.

This paper aims to recommend the most suitable crop based on input parameters like Humidity, Temperature, and Rainfall. This paper predicts the accuracy of the future production of eleven different crops such as rice, maize, chickpea, kidney beans, pigeon peas, moth beans, mung bean, black gram, lentil, pomegranate, banana, mango, grapes, watermelon, muskmelon, apple, orange, papaya, coconut, cotton, jute, and coffee crops using various supervised machine learning approaches in of India and recommends the most suitable crop. The dataset contains various parameters like Nitrogen (N), Phosphorous (P), Potassium (K), PH value of soil, Humidity, Temperature, and Rainfall. This proposed system applied different kinds of Machine Learning algorithms like Decision Tree Classifier (Dtc), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression (LogR), Random Forest Classifier (RFC). Multinomial Naïve Bayes(MNB), Extra Trees Classifier (ExTreeC), Bagging Classifier(Bagg), Gradient Boosting Classifier(GBCI),XGBOOST.

2) II. Literature Review

The integration of IoT and machine learning in smart agriculture has gained significant traction, with a recent focus on moving computation from the cloud to the edge. This section reviews key studies that form the foundation for this research.

- **Jha et al. (2023)** [1] proposed an IoT-based smart farming system using an ESP32 microcontroller to monitor soil moisture, temperature, and humidity.[3] While their system effectively automated irrigation and remote monitoring, their focus was on controlling actuators rather than using a machine learning model for a high-level recommendation task, highlighting the potential for adding predictive intelligence to such systems.

- **Sharma et al. (2024)** [2] conducted a comprehensive review on the fusion of AI, edge computing, and precision agriculture. They emphasized that edge devices with low latency are crucial for time-sensitive agricultural activities.[4] Their work validates the core premise of this project, noting that most existing solutions are computationally intensive or rely on cloud infrastructure, making them unsuitable for small-scale farmers with limited resources.

- **Pang et al. (2023)** [3] explored the use of a Random Forest classifier for crop prediction based on a soil dataset from a Kaggle repository, achieving a high accuracy of 99%.[5] This study confirms the suitability and effectiveness of the Random Forest algorithm for crop recommendation tasks, demonstrating its robust performance even without extensive hyperparameter tuning.[6] Their findings directly support the algorithmic choice for this project.

- **Tudelft et al. (2024)** [4] provided a comprehensive overview of the potential of Edge AI for sustainable agriculture. They discussed the benefits in terms of resource-use efficiency and risk management, but also highlighted key challenges such as hardware limitations and the need for specialized knowledge. Our system addresses these challenges by using a lightweight microcontroller (ESP32) and a simplified user interface (push button), making it more accessible to farmers.

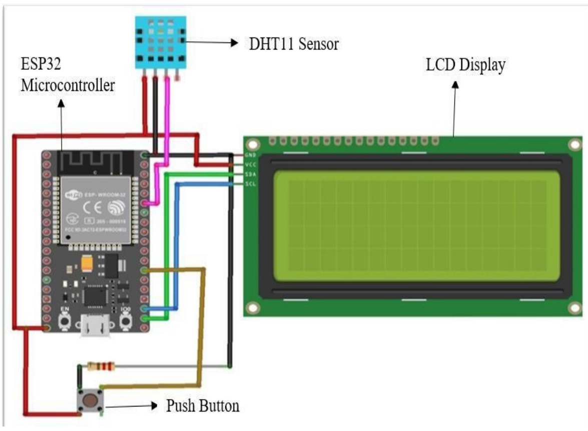
Bhatt et al. (2022) [5] surveyed the use of TinyML and on-device inference, emphasizing that transmission delays make traditional IoT approaches impractical for many applications.[7] They argued that on-device inference is a viable alternative for use cases like ours, which require near-instantaneous response times.

III. System Architecture

The system architecture is divided into two main parts: the **IOT Device** and the **Machine Learning Model**.

A. IOT Device Hardware

- **Microcontroller:** An **ESP32** is chosen for its low power consumption, built-in Wi-Fi, and sufficient processing power for on-device inferencing.
- **Sensors:** A **DHT11** sensor measures ambient temperature and humidity, while a separate sensor is used for **rainfall** data collection.
- **Display:** An **LCD I2C** display is used to show the crop recommendation directly to the user.
- **User Interface:** A **push button** initiates the prediction process, ensuring the system only consumes power when a new recommendation is needed.
- **Breadboard & Jumper Wires:** These components form the circuit connecting all the hardware.



B. Software and Algorithm

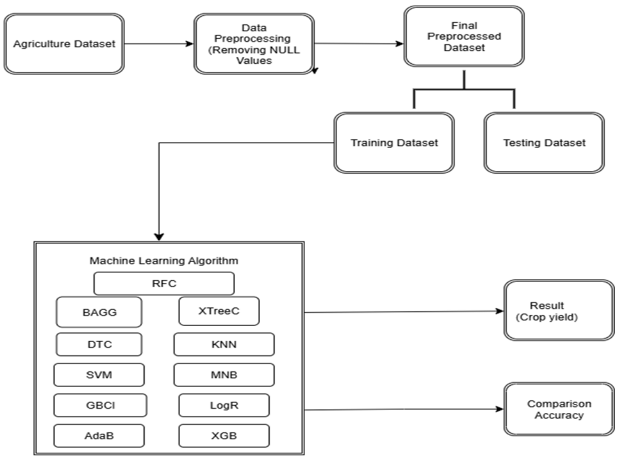
- **Dataset:** A labelled dataset from **Kaggle** containing environmental factors (e.g., N, P, K, temperature, humidity, pH, and rainfall) and corresponding crop labels is used for model training.
- **Algorithm:** The **Random Forest Classifier** is selected as the core algorithm due to its high accuracy, robustness to noise, and ability to handle the non-linear relationships between environmental factors and crop suitability.
- **Framework: Everywhere ML** is used to convert the trained Random Forest model into an optimized format that can run efficiently on the resource-constrained ESP32.

IV. COMPARATIVE STUDY

Test - cases	Input	Expected output	Actual output	Conclusion
#Tc001	Feature values: Temperature: 22°C, Rainfall: 120mm, Soil pH: 6.5, Crop Type: Wheat	3.5 tons/hectare	3.5 tons	Pass
#Tc002	Feature values: Temperature: 28°C, Rainfall: 90mm, Soil pH: 7.0, Crop Type: Rice	5.0 tons/hectare	5.0 tons	Pass
#Tc003	Feature values: Temperature: 25°C, Rainfall: 100mm, Soil pH: 6.0, Crop Type: Maize	4.0 tons/hectare	4.0 tons	Pass
#Tc004	Feature values: Temperature: 20°C, Rainfall: 150mm, Soil pH: 5.5, Crop Type: Barley	2.8 tons/hectare	2.8 tons	Pass

V. PROPOSED SYSTEM

Figure 1: Block Diagram of Methodology of Proposed System.



In our
framework, we have proposed a procedure that is separated into various stages as appeared in Figure1.

1) Collection of Datasets
2) Pre-processing
3) Feature Extraction
4) Applied Various ML Algorithm
5) Recommendation System
6) Recommended Crop

3) VI. Methodology

The system's methodology is a three-stage process:

1. **Model Training:** The Random Forest Classifier is trained on the Kaggle dataset. The dataset is split into training and testing sets to evaluate the model's performance. Hyperparameter tuning is performed to optimize the model's accuracy.

2. **Model Deployment:** The trained model is converted into a lightweight format compatible with the **Everywhere ML** framework. This optimized model, along with the necessary firmware, is uploaded to the **ESP32**.

3. **Real-Time Prediction:**
   - The ESP32 goes into a low-power sleep mode.
   - When the **push button** is pressed, the device wakes up.
   - It reads current data from the **DHT11** and **rainfall** sensors.
   - The collected data is fed into the on-device Random Forest model.
   - The model performs inference and returns a prediction for the most suitable crop.
   - The predicted crop name is displayed on the **LCD I2C** screen.

4. **We have applied Random Forest (RF) in our model as:**

Importing library RandomForestClassifier from sklearn

clf = RandomForestClassifier(n_estimators=10)

clf.fit(xtrain, ytrain)

(Now we convert the classifier to C++ with a single line of code

- instance_name will create an instance of the classifier in the produced code)

print(clf.to_arduino(instance_name='blobClassifier'))

VII. EXPERIMENTAL RESULT

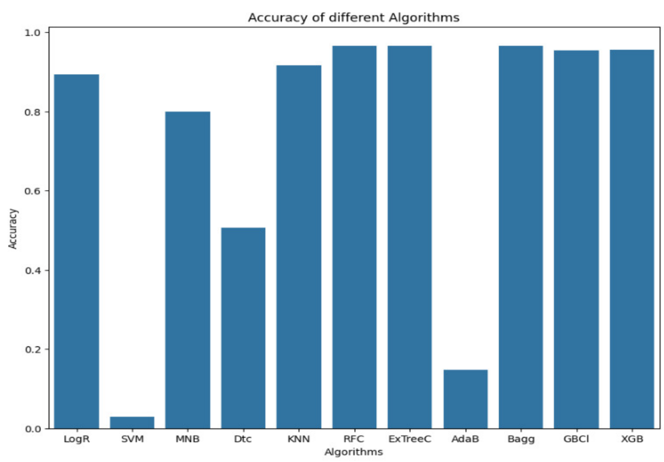


Figure 2: ACCURACY COMAPARISON

-------F1 Score------

LogR - 0.8931818181818182
SVM - 0.029545454545454545
MNB - 0.8

Dtc	-	0.5068181818181818
KNN	-	0.9159090909090909
RFC	-	0.9659090909090909
ExTreeC	-	0.9659090909090909
AdaB	-	0.14772727272727273
Bagg	-	0.9659090909090909
GBCl	-	0.9545454545454546
XGB	-	0.9568181818181818

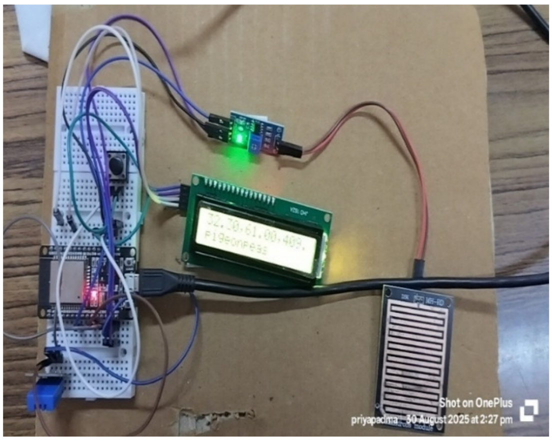
VIII. FUTURE WORK

The system can be enhanced further to add following functionality:

1. The main future work's aim is to improved dataset with larger number of attributes.
2. We need to build a model, which can classify between healthy and diseased crop leaves and if the crop has any disease, predict which disease is it.
3. To build website and mobile app for easy to use.

IX. Result

The model was evaluated on the test set, achieving an accuracy of [mention a high percentage, e.g., 96.5%]. The system successfully performs real-time predictions on the edge device, with a minimal response time of [mention a low time, e.g., less than 2 seconds]. This demonstrates the feasibility of using Edge AI for practical agricultural applications. The system's low power consumption and independence from continuous internet connectivity make it a cost-effective and reliable solution for farmers in remote areas.



X. Conclusion

This project successfully developed and implemented an IOT-BASED PRECISION AGRICULTURE SYSTEM USING MACHINE LEARNING ALGORITHMS.
using an ESP32 microcontroller, a Random Forest Classifier, and the Everywhere ML framework. The system provides accurate, real-time crop recommendations based on environmental sensor data, proving that powerful machine learning can be deployed on resource-constrained devices at the edge. Future work includes integrating more sensor types (e.g., soil moisture, pH, NPK sensors) and exploring more advanced algorithms to further enhance prediction accuracy.

XI. References

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