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EcoSense AI: Smart Environmental Intelligence for Air Quality and Sustainable Cultivation

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Abstract - **This paper presents Ecosense AI, a hybrid intelligent framework that integrates Internet of Things based environmental monitoring with machine learning driven crop recommendation. The system utilizes MQ135 and DHT11 sensors to monitor indoor air quality parameters such as temperature, humidity, and gas concentration. The collected data is transmitted to a cloud platform for real time processing and visualization. In addition, a supervised machine learning model is employed to recommend suitable crops based on soil type, environmental conditions, and geographical inputs. The Random Forest classifier is used due to its robustness and high prediction accuracy. The hybrid integration of rule based monitoring and predictive analytics enhances environmental sustainability, improves indoor air quality management, and supports precision agriculture. The proposed system offers a scalable, cost effective, and eco friendly solution for intelligent environmental decision making.**

Keywords - IoT, Indoor Air Quality, Machine Learning, Crop Recommendation, Random Forest, Environmental Monitoring

I. INTRODUCTION

Rapid urbanization and industrial development have significantly contributed to environmental degradation and declining air quality levels. Indoor air pollution has emerged as a major health concern due to increased carbon dioxide concentration, poor ventilation systems, and reduced green cover in urban areas. Studies on IoT-based air quality monitoring systems emphasize the importance of real-time environmental sensing to maintain healthy indoor environments. Since individuals spend a large portion of their daily time indoors, maintaining acceptable indoor air quality is essential for physical health, mental well-being, and productivity.

Recent advancements in Internet of Things (IoT) technologies have enabled continuous monitoring of environmental parameters such as temperature, humidity, and pollutant concentration . These systems allow real-time data acquisition and cloud-based visualization for environmental assessment. However, most traditional monitoring systems focus only on data collection and visualization without providing adaptive or intelligent decision-making support.

Artificial Intelligence (AI) and machine learning techniques have further enhanced environmental monitoring capabilities by enabling predictive analytics and intelligent recommendations. In agriculture, machine learning-based crop recommendation systems analyze soil characteristics, temperature, humidity, and rainfall patterns to assist farmers in selecting suitable crops. These intelligent systems improve crop productivity and promote sustainable farming practices.

Additionally, research on biological and plant-based air purification highlights the effectiveness of indoor plants in improving air quality . Integrating IoT monitoring systems with plant-based environmental solutions can create sustainable and eco-friendly indoor environments.

Despite significant progress, most existing systems operate independently in either indoor air monitoring or agricultural crop recommendation. There is limited research integrating real-time environmental sensing with intelligent crop prediction within a unified framework.

To address this gap, the proposed GreenPulse system introduces a hybrid architecture that combines rule-based IoT environmental monitoring with machine learning-driven crop recommendation. By integrating real-time sensing, predictive

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analytics, and sustainable biological interventions, the system provides a comprehensive solution for environmental management and precision agriculture.

II. LITERATURE REVIEW

The increasing concern regarding indoor air pollution and environmental sustainability has led researchers to explore IoT-based monitoring systems for real-time environmental analysis. Jo [10] developed an IoT-based indoor air quality monitoring platform that utilized networked sensors and cloud connectivity to provide real-time data visualization. The study mainly focused on system architecture and remote monitoring capabilities. Similarly, Li et al. [8] proposed a cloud-integrated framework combining low-cost sensors for continuous indoor air assessment. Their work demonstrated the feasibility of affordable monitoring systems but primarily emphasized data acquisition rather than adaptive environmental improvement.

Sharma and Gupta [9] introduced a smart IoT-based air quality monitoring and prediction model that incorporated data analytics to forecast pollution trends. Khan et al. [6] further enhanced predictive capabilities by integrating AI-driven models within IoT architectures for air pollution analysis in smart cities. Ahmad and Singh [7] also presented an IoT-based smart environment monitoring system designed to promote sustainable living through real-time environmental tracking. These studies highlight the importance of combining IoT with artificial intelligence for proactive environmental management.

A comprehensive review conducted by Tan et al. [3] analyzed recent advancements in IoT-enabled indoor air quality monitoring systems. Their systematic review identified technological progress in sensor integration, cloud computing, and data analytics, while also emphasizing the need for intelligent and sustainable intervention mechanisms beyond passive monitoring.

In addition to monitoring technologies, researchers have investigated plant-based approaches to improving indoor air quality. Karle et al. [1] examined indoor air enhancement using hydroponic systems and demonstrated that controlled plant cultivation can positively impact indoor environmental conditions. Guerrero-Ulloa et al. [4] proposed an IoT-based indoor plant care system that automates watering and environmental monitoring processes. Patil et al. [5] developed a biological plant recommendation system using IoT to suggest suitable indoor plants for air purification, introducing data-driven biological interventions for sustainable air quality management.

In the agricultural domain, Anusha et al. [11] developed a crop recommendation system that integrates IoT-collected environmental data with machine learning techniques to support farmers in selecting appropriate crops. Turgut et al. [12] proposed AgroXAI, an explainable AI-driven crop recommendation system aimed at improving transparency and reliability in agricultural analytics. These studies demonstrate the growing application of machine learning and explainable AI in precision agriculture.

Although significant contributions have been made in IoT-based environmental monitoring [7], [8], AI-driven predictive analytics [6], and crop recommendation systems [11], [12], most existing research addresses these areas independently. Limited work has been conducted on integrating indoor air quality monitoring with intelligent crop recommendation within a unified hybrid framework.

The proposed GreenPulse system aims to bridge this gap by combining real-time IoT-based environmental sensing

with machine learning-driven crop recommendation. This integrated approach advances beyond conventional monitoring systems and provides a comprehensive, sustainable solution for environmental management and precision agriculture.

III. METHODOLOGY

A. Overall System Design

The proposed GreenPulse framework is designed as an integrated intelligent system that combines Internet of Things (IoT) based environmental monitoring with supervised machine learning driven crop recommendation. The objective of the methodology is to enable continuous environmental sensing, structured data analysis, predictive modeling, and real-time advisory output within a unified architecture.

The system operates through sequential layers including real-time data acquisition, dataset construction, preprocessing, feature engineering, model development, evaluation, and deployment. This layered design ensures both operational stability and predictive intelligence. Similar hybrid architectures combining IoT sensing and intelligent analytics have been recognized as effective solutions in smart agriculture and environmental monitoring systems .

B. Real-Time Data Acquisition

The first phase of the methodology involves continuous collection of environmental parameters using IoT sensors connected to the ESP8266 microcontroller. The system monitors temperature and humidity through the DHT11 sensor, soil moisture using a capacitive soil moisture sensor, soil temperature via a temperature probe, and carbon dioxide concentration using the MQ135 gas sensor.

The ESP8266 serves as the communication interface, periodically gathering sensor values and transmitting them to a web server or cloud platform. This allows remote access, data storage, and further analytical processing. Real-time IoT-based environmental sensing has proven to be reliable and scalable in precision agriculture and sustainable environmental management applications .

The collected data forms the primary input for predictive crop modeling and environmental analysis.

C. Agricultural Dataset Construction

To enable supervised machine learning, a structured dataset is developed representing relationships between environmental conditions and crop suitability. The dataset includes independent variables such as temperature, humidity, soil moisture, soil type, and geographical region, while the dependent variable corresponds to the recommended crop.

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Data sources include agricultural research findings, publicly available government agricultural reports, and simulated environmental combinations created for experimental validation. The dataset is carefully organized to ensure balanced representation of crop categories. Supervised learning frameworks trained on structured agricultural datasets have demonstrated significant effectiveness in crop advisory systems .

The structured dataset enables the learning algorithm to identify patterns linking environmental factors to optimal crop selection.

D. Data Preprocessing and Feature Engineering

Before training the classification model, extensive preprocessing is performed to improve model accuracy and consistency. Missing or incomplete values are treated using appropriate imputation techniques to avoid biased predictions. Numerical attributes such as temperature, humidity, and soil moisture are normalized and scaled to ensure uniform contribution to the model.

Categorical variables including soil type and region are converted into numerical representations using encoding techniques such as label encoding or one-hot encoding. For instance, soil categories such as loamy, clay, and sandy soils are transformed into encoded values to make them compatible with mathematical classification models.

Feature engineering techniques are applied to refine environmental attributes and remove redundant variables. Proper preprocessing significantly enhances classification performance and reduces noise in agricultural analytics systems .

E. Feature Selection Strategy

Feature selection is conducted to identify the most relevant environmental parameters influencing crop suitability. The selected input features include temperature, humidity, soil moisture, soil type, region, and environmental condition. These features represent the independent variable set (X), while the recommended crop represents the dependent variable (Y).

Selecting relevant features reduces computational complexity, prevents overfitting, and improves interpretability of the model. Efficient input-output mapping strengthens predictive accuracy and ensures stable performance under varying environmental conditions.

F. Machine Learning Model Development

The crop recommendation problem is formulated as a supervised classification task. Multiple classification algorithms are evaluated, including Decision Tree, Random Forest, K-Nearest Neighbors, and Naïve Bayes.

For prototype implementation, the Decision Tree classifier is selected due to its transparency and interpretability. The algorithm constructs hierarchical decision rules based on feature thresholds, enabling logical classification of environmental conditions into suitable crop categories. Decision tree-based and ensemble models have demonstrated reliable performance in agricultural recommendation frameworks .

The model learns decision boundaries by recursively partitioning the feature space according to information gain or impurity reduction criteria.

G. Model Training and Validation

The dataset is divided into training and testing subsets using an 80:20 split ratio. During the training phase, the classifier learns relationships between environmental attributes and crop categories.

Model performance is evaluated using classification metrics such as accuracy, precision, recall, and F1-score. These

metrics ensure that the model maintains balanced performance across all crop classes. Validation techniques help prevent overfitting and enhance generalization capability for real-world applications.

Only models achieving satisfactory evaluation scores are deployed for real-time prediction.

H. Real-Time Crop Recommendation Mechanism

When live sensor readings are received, the system applies the same preprocessing pipeline used during model training. The processed data is then provided as input to the trained classification model.

The model predicts the most suitable crop based on current environmental conditions. In addition to the predicted class label, the model generates probability scores for all possible crop categories. The crop with the highest probability is displayed as the final recommendation.

The probability-based approach enhances reliability by providing confidence measures, enabling informed agricultural decision-making.

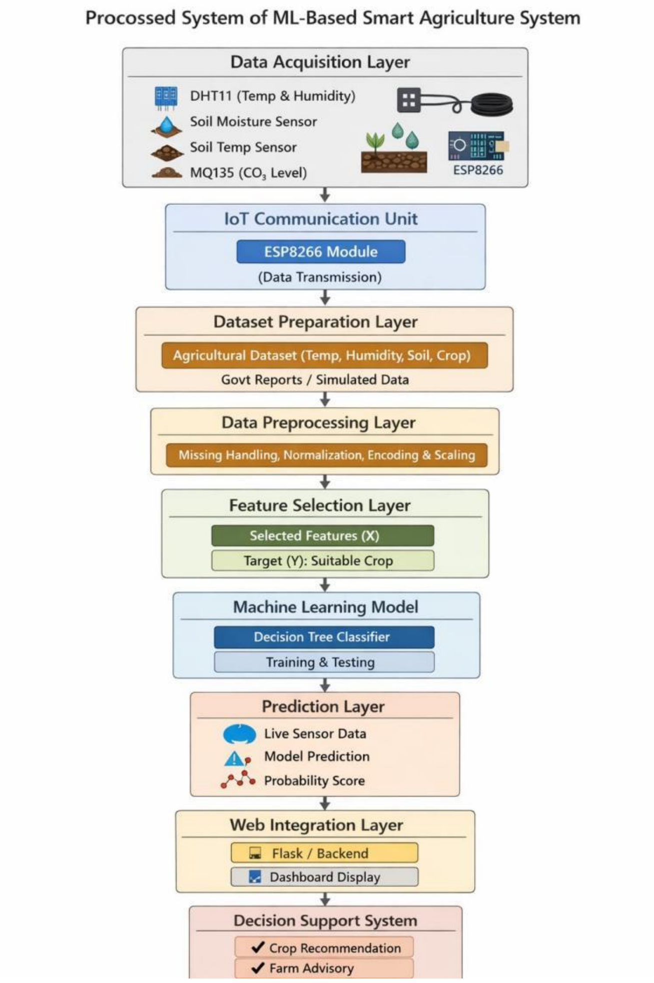
I. Web Deployment and Decision Support Interface

The trained machine learning model is integrated into a web-based dashboard to provide real-time accessibility. Deployment can be achieved using a Python Flask backend for dynamic processing or embedded logic for prototype-level systems.

The dashboard presents live environmental readings alongside the recommended crop and associated confidence score. This integration allows farmers to make evidence-based decisions regarding crop selection, resource optimization, and yield improvement.

By combining IoT-based environmental sensing with supervised machine learning classification, the proposed methodology establishes a scalable, intelligent, and sustainable precision agriculture framework.

J.Block Diagram



IV.CONCLUSION

The study presents a hybrid intelligent framework that integrates rule-based environmental monitoring with machine learning–driven crop recommendation to support data-informed agricultural decision-making. The environmental monitoring module utilizes IoT sensors interfaced with microcontroller platforms such as those developed by Espressif Systems to continuously measure key parameters including temperature, humidity, soil moisture, and gas concentrations. This rule-based component ensures reliable real-time assessment of environmental suitability through predefined threshold evaluation.

To enhance system intelligence, a supervised machine learning model—specifically the Random Forest classifier—was incorporated for crop prediction based on soil type, geographical area, and environmental conditions. The hybrid integration enables simultaneous monitoring and predictive recommendation, improving adaptability across varying agro-climatic scenarios. Overall, the system demonstrates how combining IoT sensing with data-driven analytics can contribute to precision agriculture, optimize crop selection, and support sustainable farming practices.

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