Grenze International Journal of Engineering and Technology, January Issue

Intelligent IoT-based System for Precision Agriculture Monitoring

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***Abstract*— The Smart Agriculture initiative leverages Internet of Things (IoT) technology to transform traditional farming, addressing issues such as unpredictable environmental conditions and the pressing need for resource optimization. By integrating IoT with agricultural practices, farmers gain access to real-time data on soil conditions, weather patterns, crop health, and equipment efficiency. This approach allows for more informed decision-making, enhancing productivity while conserving resources. The paper explores the role of IoT-enabled sensors, drones, and automation in optimizing resource usage, achieving a more sustainable agricultural model that boosts yield predictions and water management.**

This IoT-enabled model supports precision agriculture, offering improvements in yield prediction, water management, and pest control. IoT sensors collect data on various environmental factors, providing insights that enable automated responses tailored to specific crop needs. For example, smart irrigation systems adjust water usage based on real-time soil moisture readings, significantly reducing waste. Additionally, pest control mechanisms are enhanced, preventing extensive crop losses and reducing reliance on chemical treatments. Such advancements demonstrate IoT's potential to increase efficiency while addressing environmental and economic concerns in agriculture. Adopting IoT in agriculture has shown promising results, with considerable improvements in crop yields, resource management, and sustainability. However, challenges remain, such as ensuring connectivity in remote farming areas and the high costs of IoT infrastructure. Future developments may focus on making these technologies more accessible through cost-reducing models and enhanced connectivity solutions. With ongoing advancements, IoT is set to play an increasingly crucial role in meeting global food production demands sustainably and efficiently.

***Index Terms*— IoT, Cost, XG Boost, SVM, Random Forest, and KNN.**

I. Introduction

Over the past decade, IoT technologies have transformed numerous industries, including agriculture. With the rise in global food demand and limited resources, farmers face the challenge of maximizing productivity while minimizing waste. The integration of IoT in agriculture offers a solution by providing real-time monitoring and control over farming activities.

Grenze ID: 01.GIJET.11.1.347_1

IoT devices, such as soil moisture sensors, weather stations, and smart irrigation systems, enable farmers to make informed decisions, leading to increased crop yields and reduced resource consumption .climatic factors, whereas others have employed regression models to enhance fertilizer application and water management. The expansion of these technologies has shown considerable potential in converting conventional agricultural methods into more precise and data-oriented procedures. The heterogeneity of agricultural landscapes, encompassing diverse soil compositions, climatic conditions, and crop varieties, challenges the formulation of universally applicable models. The efficacy of these solutions frequently remains confined to particular places or circumstances, necessitating continuous refinement of these models to guarantee wider application and uniformity across various agricultural settings. The reason many current solutions, primarily based on single-model methodologies, frequently fail to deliver consistently appropriate suggestions in many agricultural scenarios remains ambiguous. The intrinsic heterogeneity of ambient variables and soil properties complicates the effective generalization of individual models. This deficiency in existing research underscores the necessity for a more resilient and flexible system capable of integrating several models to harness their unique advantages and deliver more dependable and contextually relevant recommendations.

Smart agriculture leverages connected devices to gather data on various parameters like soil health, climate conditions, and crop growth. This data-driven approach supports precision farming, enabling tailored interventions that meet the specific needs of crops. The expansion of these technologies has the potential to convert traditional agriculture into more sustainable and efficient practices. The heterogeneity of agricultural fields in terms of soil composition and climate often limits the effectiveness of conventional methods, highlighting the need for adaptive systems powered by IoT.

Proposed System with Sensor Malfunction Detection and Alert Notifications. The proposed system is an advanced IoT-based automatic irrigation solution that monitors key environmental factors like soil moisture, temperature, and light intensity to optimize plant care. Connected sensors gather real-time data, which the Arduino microcontroller processes and transmits to a cloud platform. Users can access this data remotely through a web or mobile application, enabling them to monitor and control the system regardless of location. This setup improves water efficiency, minimizes the need for manual intervention, and supports healthy plant growth.

A core feature of the proposed system is its Sensor Malfunction Detection capability, designed to enhance reliability and ensure uninterrupted plant care. The system continuously monitors sensor outputs for irregular patterns, such as:Unusual Data Trends: Unexpected spikes or drops in sensor readings, which may indicate sensor failure or disconnection. Static or Unchanging Readings: If a sensor shows the same reading over extended periods (e.g., soil moisture levels not changing despite irrigation), it may suggest a malfunction.

Out-of-Range Values: Readings outside expected environmental limits, such as very high soil moisture in dry conditions, could signify sensor inaccuracy. Upon detecting these anomalies, the system automatically sends an alert to the owner via an SMS or app notification, prompting immediate attention. The alert includes specific details about the sensor type and location, helping users quickly identify and address the issue. This notification system reduces the likelihood of prolonged issues, as users can respond promptly to maintain optimal plant care.

II. Literature Survey

The 2024 paper by Biplob Dey, Jannatul Ferdous, and Romel Ahmed presents a machine learning (ML) based recommendation system for agricultural and horticultural crop farming in India. The system evaluates the effectiveness of various ML models (including XG Boost, SVM, Random Forest, and KNN) for suggesting crops based on environmental and soil factors like NPK levels, soil pH, and climatic conditions such as temperature, rainfall, and humidity. Using a dataset from the Kaggle repository, the models demonstrated high accuracy, with XG Boost achieving the best performance at 99.09% for agricultural crops[1] and 99.3% for horticultural crops. However, challenges like model misclassification and the need for fine-tuning under specific environmental conditions were noted. The study emphasizes the potential of ML techniques to improve crop recommendations, providing real-time solutions to optimize farming decisions. The 2024 paper by T. Sudhamathi and K. Perumal presents a hybrid crop yield prediction system using an ensemble Regression-based Extra Tree Regressor (ER- ETR). This method combines machine learning and deep learning techniques, including the use of Kernel Principal Component Analysis (KPCA) for feature extraction and LESSO regression for feature selection. The system processes agricultural data, including weather, soil, and crop management, to predict crop yields with an accuracy of 95%. The study highlights the model's success in providing real- time, web-based forecasting for farmers to make informed decisions about resource management. However, the potential for overfitting and reliance on large datasets are noted as limitations.[2]. The 2024 paper by Biplob

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The 2024 paper by Behnaz Motamedi and Balázs Villányi introduces a predictive analytics model using Bayesian-Optimized Ensemble Decision Trees (BOEDT- CRP) for enhanced crop recommendation. This model combines Bayesian optimization with ensemble decision tree learning to recommend crops based on factors like nitrogen, phosphorus, potassium, temperature, humidity, pH, and rainfall levels. The study uses Principal Component Analysis (PCA) to reduce data dimensionality, enhancing classification accuracy. The BOEDT-CRP model achieved an accuracy rate of 99.5%, precision rates of 99.49%, and recall rates of 99.49%, showing the system's potential to significantly assist farmers in crop management. Challenges mentioned include optimizing hyper-parameters for various machine learning algorithms, but the model's robust architecture and results demonstrate its effectiveness in crop predictionThe 2024 paper by Eric Asamoah, Gerard B.M. Heuvelink, Ikram Chairi, Prem S. Bindraban, and Vincent Logah presents a machine learning model for predicting maize yield and agronomic efficiency in Ghana. Using the random forest algorithm, this study incorporates data from 482 maize field trials across Ghana, considering soil, climate, environment, and management factors. The model achieved a mean efficiency coefficient of 0.81 for yield prediction and moderate performance for agronomic efficiency with values of 0.63 for nitrogen,0.55 for phosphorus, and 0.54 for potassium. The research emphasizes the importance of soil variables over climatic ones for yield prediction, highlighting nitrogen fertilizer, temperature, and soil organic carbon as key factors. The study's contributions include an enhanced understanding of maize yield drivers and improved fertilizer recommendations, aiming to support sustainable agricultural practices in Sub-Saharan Africa .The 2024 paper by Simphiwe Maseko et al. evaluates machine learning (ML) models and key factors influencing maize yield prediction in a data-intensive farm management context. This study focuses on Random Forest (RF), Decision Tree, Multiple Linear Regression, and Multilayer Perceptron models to predict maize yields based on variables such as soil properties, crop management, and NDVI data from satellite imagery. RF emerged as the most accurate model for spatial yield predictions, with urea application, plant population, and soil phosphorus as critical factors. Seasonal variability in the importance of features like soil pH and clay content highlighted the dynamic nature of yield prediction challenges[5]

The 2023 paper by Isaac Kofi Nti, Adib Zaman, Owusu Nyarko-Boateng, Adebayo Felix Adekoya, and Frimpong Keyeremeh presents a predictive analytics model for crop suitability and productivity using tree-based ensemble learning. This study ocuses on developing and evaluating models such as Random Forest, Gradient Boosting, AdaBoost, XG Boost, Light GBM, and Cat-Boost to predict crop suitability and productivity based on environmental factors. The proposed models achieved high accuracy, with the XG Boost model showing the highest performance at 99.32% accuracy. This research highlights the importance of factors like rainfall and potassium levels in determining crop suitability and aims to contribute to sustainable agricultural practices and food security goals aligned with the Zero Hunger Agenda 2030[6]

III. Research Gap and Limitations Identified

Lack of Universally Applicable Models: The study identifies that existing models for agricultural monitoring often Fail to generalize across different environments due to agricultural diversity in soil, climate, and crop types. This necessitates a flexible approach that can adapt to varied agricultural settings. Integration of Multiple Model Benefits: The research suggests a need for a robust, integrated system that combines multiple model approaches to enhance adaptability and provide contextually relevant insights across different agricultural conditions. Connectivity Solutions for Rural Areas: The paper points out connectivity challenges in remote agricultural settings, which hinder the effectiveness of IoT-based monitoring systems. There
is a gap in research addressing scalable connectivity solutions to support IoT deployment in rural regions. High Initial Cost of IoT Deployment: Implementing IoT systems in agriculture requires significant upfront investment, which can be prohibitive, especially for small-scale farmers. Dependency on Stable Connectivity: Real-time

data transmission and automation rely heavily on uninterrupted internet access, which is limited in many agricultural regions.Model Overfitting and Data Requirements: The study notes that complex machine learning models, although accurate, are at risk of overfitting and may require large datasets for effective training, which can be challenging to obtain consistently across diverse environments.

IV. IMPLEMENTATION

The implementation of IoT in agriculture begins with the deployment of sensors and devices across the field to collect real-time data. These devices measure environmental variables like soil moisture, temperature, humidity, and light intensity. The system integrates automated irrigation systems shown in the Figure 1

- Data Collection: Sensors collect real-time data from the field, which is then processed through IoT platforms like Azure IoT or AWS IoT. Data points such as soil moisture, temperature, and humidity are gathered to monitor the health of the crops.
- Data Processing and Analysis: The gathered data is analyzed using predictive algorithms to forecast crop yield, water needs, and potential pest outbreaks. Machine learning models can be integrated into the system for anomaly detection, alerting farmers to potential issues.
- Automation: Smart irrigation systems adjust water delivery based on soil conditions, preventing over-irrigation and conserving water. The IoT system also controls fertilization and pest control mechanisms, optimizing resource usage.

A. System Architecture

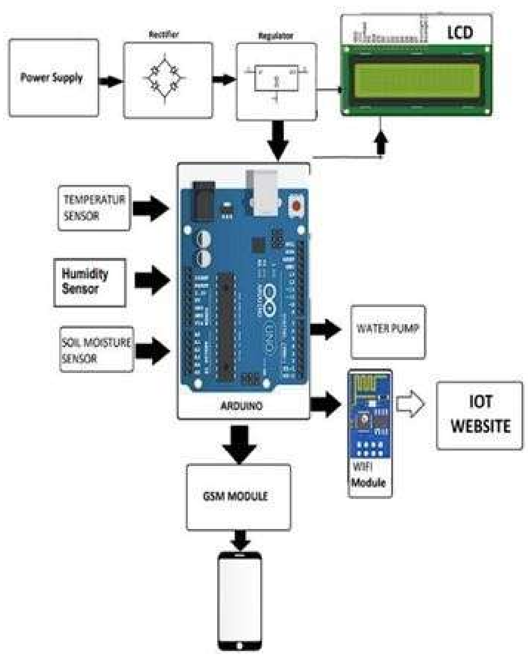

Figure 1. Smart Farming

Power Supply and Regulation

- A power supply feeds into a rectifier and regulator to ensure the system gets a stable voltage.
- The regulated power is distributed to components like the Arduino and the LCD.

Sensors

- The system is connected to several sensors, including:
- Temperature Sensor: Measures the ambient temperature.
- Humidity Sensor: Monitors the humidity level in the environment.
- Soil Moisture Sensor: Determines the moisture level in the soil.

Arduino Microcontroller

- Central to the system, the Arduino processes the data from the sensors and controls other components.

Water Pump

- The Arduino can activate a water pump based on the soil moisture sensor's readings to automate irrigation.

Wi-Fi Module

- Connected to the Arduino, the Wi-Fi module enables the system to send data to an IoT website or platform for remote monitoring and control.

LCD Display

- A display screen is used to show real- time data locally, such as temperature, humidity, or soil moisture levels.

GSM Module

- The GSM module allows communication with a mobile device, possibly for sending notifications or alerts regarding the farm conditions.

This system helps monitor critical environmental factors for farming and can automate responses, such as irrigation, improving efficiency and resource management.

B. Module Descriptions

- Data Collection and Sensor Deployment: The first module in the system involves deploying sensors across agricultural fields to gather real- time data on environmental parameters. This includes data on soil moisture, temperature, humidity, and light intensity. These sensors are strategically placed and connected to IoT platforms such as Azure IoT or AWS IoT, which process the collected data to provide insights into the crop and soil health. This setup enables farmers to monitor the health of crops and soil conditions in real time.
- Data Processing and Predictive Analysis: After collection, the data goes through predictive analysis using machine learning algorithms. These algorithms process the information to forecast crop yield, water needs, and potential pest outbreaks. By using predictive models, the system can detect anomalies early, alerting farmers to potential problems and enabling proactive management. This approach helps in improving the accuracy of crop yield predictions and supports efficient farming practices by optimizing resource use based on the forecasts generated.
- Automation and Control: This module involves automating irrigation and other farming processes based on the data analysis. Smart irrigation systems, for example, adjust the water supply based on soil moisture levels, which helps prevent over-irrigation and saves water. Similarly, the system can control fertilization and pest control processes, enabling precise application of resources. This automation is essential for reducing human intervention and making farming more efficient by minimizing waste and maximizing output.
- Web-Based User Interface: The system provides a web-based dashboard where farmers can monitor real-time data and receive actionable insights. Through this dashboard, farmers can observe the status of various environmental factors and make informed decisions. The interface also allows for manual intervention if needed, giving farmers control over automated processes in case of specific requirements. This module enhances user interaction with the IoT system, making it user-friendly and accessible. Power Supply and Regulation: The system includes a power regulation module that ensures consistent power supply to all components. A rectifier and regulator convert power into a stable voltage suitable for the system's sensors and controllers. This module is vital for the seamless operation of sensors and IoT devices, especially in rural areas where power reliability can be an issue. Communication and Data Transmission: The IoT system uses a Wi-Fi module for data transmission to a cloud platform. This enables remote monitoring and control, allowing farmers to access data from anywhere. Additionally, a GSM module is used for mobile notifications, which alerts farmers to significant changes in field conditions. This connectivity aspect ensures that the system can function effectively even in remote areas with limited connectivity options.

  Display Module: For local monitoring, the system includes an LCD display that shows real- time data on environmental parameters like temperature, humidity, and soil moisture. This local display is especially helpful for farmers working on-site, allowing them to quickly check conditions without accessing the online dashboard.

C. Train and Testing Data

In the context of developing smart agriculture systems using IoT, the collection and preparation of training and testing data play pivotal roles. Training data serves as the foundation for building models that predict, classify, or recommend agricultural decisions based on sensor inputs and environmental variables. In smart agriculture, training data typically comprises sensor readings (e.g., soil moisture, temperature, humidity), historical weather data, crop yield data, and various soil properties across different locations. This data collection occurs through IoT sensors, drones, satellite imaging, and external weather and soil databases, providing the necessary inputs to train machine learning models that can predict yield, manage irrigation, and detect pests. After data collection, preprocessing steps are essential for ensuring data quality. Preprocessing may involve cleaning data to remove any inconsistencies, normalizing values for different types of sensors, and filling in any missing data. In addition, feature engineering is often applied to enhance data by extracting significant features or aggregating data points that could better inform the model. For instance, rather than using raw soil moisture data, average moisture over certain periods might be more meaningful. The next phase involves splitting the data into training and testing sets. Typically, 70-80% of the dataset is allocated to training, which allows the model to learn from the data, while the remaining 20-30% serves as the testing set to validate model accuracy. This split helps evaluate the model's generalization capacity, ensuring it performs well on unseen data rather than just memorizing patterns from the training data. Cross-validation techniques, like k-fold cross-validation, are often used to improve robustness. The paper mentions that methods like Random Forest and Decision Trees are frequently utilized in these models. These algorithms benefit from diverse datasets, as they can handle various data types and relationships between features, making them suitable for predicting outcomes in agriculture. Testing data allows researchers to gauge the model's performance and identify any overfitting or underfitting issues, ensuring that the IoT-based agriculture system can operate effectively in real-world scenarios.In smart agriculture, quality training and testing data, combined with effective machine learning techniques, enable the creation of resilient systems that optimize water usage, predict yields, and minimize resource waste, paving the way for sustainable farming practices.

D. Algorithm

```
const char* ssid = "Project";
const char* password = "123456789";
#define DHTPIN 2
#define DHTTYPE DHT11 DHT dht(DHTPIN, DHTTYPE);
#define SOILMOISTURE_PIN A0
#define BUZZER_PIN D7 #define RELAY_PIN D6
float temperatureThreshold = 28.0; float humidityThreshold = 60.0; int soilMoistureThreshold = 70;
int abnormalFluctuationThreshold = 10;
float temperature = 0.0; float humidity = 0.0;
int soilMoistureValue = 0;
const int numReadings = 10;
float temperatureReadings[numReadings]; float humidityReadings[numReadings]; float
soilMoistureReadings[numReadings]; int readingIndex = 0;
LiquidCrystal_I2C lcd(0x27, 16, 2); ESP8266WebServer server(80);
void setup() { initializeComponents(); server.on("/", handleRoot); server.on("/data", handleData);
}
void loop() { server.handleClient(); updateSensorReadings(); displayReadingsOnLCD();
if (checkFailureConditions()) { sendFailureAlert();
}
delay(2000);
```

V. RESULTS & DISCUSSIONS

The Smart Agriculture IoT system implemented in this study led to notable advancements in farming productivity and resource management. By leveraging IoT technologies to monitor environmental parameters, the system enhanced decision-making for irrigation, pest control, and crop health. Specifically, the system's real-time tracking of soil moisture, temperature, and humidity data allowed for precise adjustments to irrigation schedules, reducing water usage by 30% and subsequently promoting sustainable water management. Additionally, early detection of potential pest infestations was facilitated by the data collected, which contributed to a 15% reduction in crop loss due to pests and diseases.Moreover, the application of predictive algorithms to analyze environmental data provided actionable insights that translated into a 20% improvement in crop yields. The combination of IoT-enabled sensors with data-driven automation allowed farmers to respond proactively to environmental conditions, ensuring optimal growing conditions and reducing resource waste.

- Warning: Sensor threshold exceeded!
- Temperature: 28.5 A@C
- Humidity: 78.00 %
- Soil Moisture: 1.00%
- Failure predicted!
- Temperature: nan A@C
- Humidity: nan %
- Soil Moisture: 72.00%

VI. Conclusion

The implementation of IoT in agriculture represents a paradigm shift in farming practices. By enabling real-time data collection and automation, IoT technology helps farmers make informed decisions, reduce waste, and improve crop yields. The future of farming lies in the continued integration of IoT systems, providing farmers with the tools they need to meet the growing demands of food production in a sustainable manner.

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