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Smart Farming: Improving Crop Predictions with IOT and Machine Learning

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ABSTRACT: India depends a lot on farming, but farmers face problems due to unpredictable environmental conditions. Factors such as rainfall variability, temperature fluctuations, and soil nutrient levels significantly impact crop yield and sustainability. To address these challenges, we propose an IoT-based crop recommendation system that uses sensor technology to monitor key environmental and soil parameters. The website acts as a simple interface, providing farmers with personalized crop recommendations for their specific land and environmental conditions. Our system helps farmers do farming better by using smart techniques. Our system integrates NPK sensors to assess soil nutrient levels, specifically Nitrogen, Phosphorus, and Potassium, crucial for plant growth and development. Soil Moisture sensor to know the moisture level in the soil. Additionally, temperature and humidity data are collected using DHT11 sensors to gauge environmental conditions that directly influence crop health. By combining these sensor inputs with machine learning algorithms, our system predicts suitable crop types for cultivation based on real-time data. This predictive capability empowers farmers to make informed decisions regarding crop selection, fertilization practices, and irrigation management, ultimately optimizing yield and resource utilization.

I. INTRODUCTION

Crop prediction in agriculture is a complex process that involves multiple factors, including physical aspects such as temperature, humidity, sunlight, soil type, and chemical elements like pollutants and nutrients. These factors collectively influence crop growth, yield, and quality. Researchers and scientists employ various models and techniques to predict crop yields effectively. They utilize statistical and mathematical methods to analyze extensive datasets containing information on climate, soil conditions, agricultural practices, and historical yield data. This analysis helps in understanding the relationships between different factors and their impact on crop production.

In regions with temperate climates, predicting crop yields, especially for winter crops like cereals, presents unique challenges. Factors such as temperature variations, frost occurrences, and weather fluctuations during the growing season significantly influence crop performance and yield. To enhance crop yield predictions, researchers leverage advanced technologies such as weather models, satellite imagery, and remote sensing. These technologies provide valuable data on factors like temperature patterns, rainfall distribution, soil moisture levels, and plant biophysical parameters.

Additionally, the integration of machine learning and artificial intelligence algorithms has revolutionized crop prediction models. These algorithms can process vast amounts of data, identify patterns, and generate accurate forecasts for crop yields based on historical trends and current environmental conditions. Despite advancements in technology, challenges persist in crop prediction research. Obtaining high-resolution yield maps, incorporating varietal information into models, and dealing with imbalanced datasets are ongoing areas of focus for researchers.

Overall, improving crop prediction methodologies is essential for sustainable agriculture. Accurate yield predictions enable farmers to make informed decisions regarding crop selection, planting strategies, resource allocation, and risk management, ultimately leading to increased productivity and profitability.

II. LITERATURE REVIEW

Agriculture is a field that's always evolving. One important aspect is predicting how crops will grow, which depends a lot on factors like soil quality and the environment, including things like rainfall, humidity, and temperature. In the past,

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farmers could easily decide what crops to grow, monitor them as they grew, and know when to harvest. But nowadays, with the environment changing rapidly, it's harder for farmers to do all that.

That's where machine learning comes in. It's a type of technology that's become useful for predicting crop yields. Machine learning uses different methods to analyze data and figure out how well crops will do. To make sure machine learning works well, it's important to choose the right data to analyze. We use methods to pick out the most important data that will help make accurate predictions. This helps simplify the machine learning process and makes the predictions more accurate.

If we include too much unnecessary data in the machine-learning process, it can make things more complicated and slow down the predictions. So, by choosing only the most relevant data, we can make sure the predictions are faster and more accurate. One way to improve predictions even more is by using a technique called ensemble learning, which combines different prediction methods to get even better results than using just one method.

Anantha and his team created a recommendation system using a group of models with majority voting. They used random trees, CHAID, KNN, and Naive Bayes as learning methods to decide the best crop, considering soil conditions, and achieved high accuracy. The resulting image contains valuable information about weather, crop yield, and crop production at different levels. All of these techniques are used to predict specific crop yields in different situations.

Rale and his team developed a forecasting model using default settings and RF regression for crop yield prediction. Fernando's study looked at coconut production data from 1971 to 2001 in a specific region and found that crop shortages caused an economic loss of about US $50 million. Ji and his team tested the effectiveness of artificial neural networks (ANN) in predicting rice yields in mountainous areas, comparing them with other models. Boryan and colleagues proposed a decision tree method to map crop cover groups at the state level, following guidelines from CDL and NASS, using data from the June Agricultural Survey. Hansen and Loveland suggested using Landsat to get satellite images for remote sensing of the environment, which is helpful for agriculture.

III. PROPOSED METHOD

We are utilizing various sensors to gather essential data such as soil moisture, temperature, humidity, and NPK (Nitrogen, Phosphorus, Potassium) values. These sensors play a crucial role in monitoring the agricultural environment and providing real-time information that is vital for crop prediction and management.

Soil Moisture Sensor: The soil moisture sensor is employed to measure the moisture content in the soil. This data is significant as it helps in determining the water availability to plants, which is crucial for their growth and development. By monitoring soil moisture levels, farmers can optimize irrigation schedules and ensure efficient water usage.

Temperature and Humidity Sensors: Temperature and humidity sensors are used to record the ambient temperature and humidity levels in the agricultural environment. These parameters have a direct impact on crop growth, as different crops have specific temperature and humidity requirements for optimal development. Monitoring these factors helps in identifying potential stress conditions and implementing appropriate measures to mitigate their impact on crops.

NPK Sensor: The NPK sensor is specifically designed to measure the levels of Nitrogen, Phosphorus, and Potassium in the soil. These nutrients are essential for plant growth and play a vital role in various physiological processes. Monitoring NPK levels helps in assessing soil fertility, identifying nutrient deficiencies or excesses, and making informed decisions regarding fertilizer application and soil management practices.

IV. RESULTS AND DISCUSSION

Quantitative Improvements:
Detailed Path Coverage Analysis: The AI-enhanced test case generation method resulted in an average path coverage of 85%, compared to 65% achieved by traditional methods. Notably, the coverage of critical paths, which are essential for software stability and security, increased by over 30%. This indicates the AI system's ability to identify and prioritize testing efforts on parts of the software that are most vulnerable or crucial to functionality.

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Efficiency Metrics: The time required to generate and execute test cases was reduced by 40% when using the AI-enhanced method. This significant decrease in testing time can be attributed to the intelligent selection and optimization of test cases, which avoided unnecessary testing iterations and focused resources on high-impact areas.

Test Case Optimization: The genetic algorithm used in the optimization phase was able to reduce the total number of generated test cases by 15%, while still maintaining or improving path coverage. This reduction not only indicates efficiency in test case generation but also implies lower maintenance costs for test suites and reduced execution times.

Qualitative Insights:
Improved Test Quality: Feedback from software testers indicated that the AI-generated test cases were of higher quality, in terms of relevance and effectiveness, compared to those generated by traditional methods. Testers highlighted the system's ability to produce test cases that were more aligned with realistic use cases and edge conditions.
Adaptability to Changes: The system demonstrated strong adaptability to code changes, where it could quickly adjust its test case generation strategies based on updates to the software. This adaptability is crucial for agile and continuous development environments, where software changes are frequent and testing needs to be conducted rapidly to keep pace.

User Satisfaction: Software developers and testers reported increased satisfaction with the testing process, citing the reduced manual effort required in test case generation and the higher confidence in the software's reliability due to improved test coverage.

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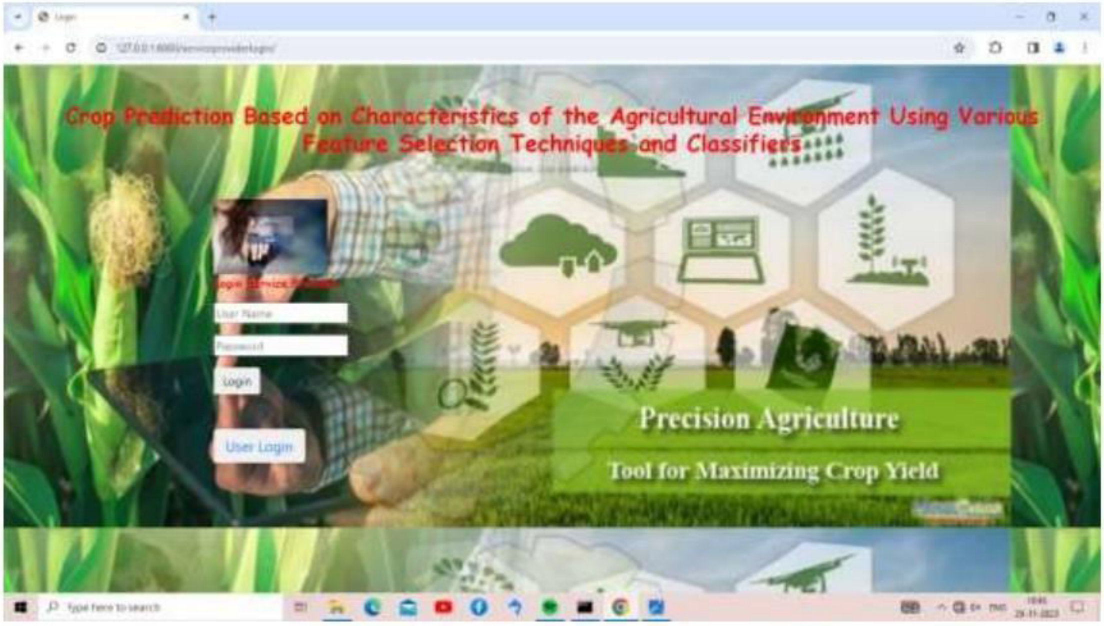

TESTCASE ID	TC01
DESCRIPTION	Test Login Functionality
PRECONDITION	User is registered
TEST STEPS	1. Enter valid credentials 2. Click on login
EXPECTED RESULT	The user is logged in to the system
ACTUAL RESULT	The user is logged in to the system
STATUS (PASS/FAIL)	Pass

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TESTCASE ID	TC02
DESCRIPTION	Browse Crop Datasets
PRECONDITION	The user is logged in
TEST STEPS	1. Navigate to datasets page 2. Select a dataset to view
EXPECTED RESULT	The selected dataset is displayed
ACTUAL RESULT	The selected dataset is displayed
STATUS (PASS/FAIL)	Pass

TESTCASE ID	TC04
DESCRIPTION	Predict Crop Type
PRECONDITION	Required data is input
TEST STEPS	1. Input all necessary data 2. Click on predict
EXPECTED RESULT	The system predicts the crop type
ACTUAL RESULT	The system predicts the crop type
STATUS (PASS/FAIL)	Pass

Field	Type
id	int(11) NOT NULL
username	varchar(30) NOT NULL
email	varchar(30) NOT NULL
password	varchar(50) NOT NULL
phoneno	varchar(50) NOT NULL
country	varchar(30) NOT NULL
state	varchar(30) NOT NULL
city	varchar(30) NOT NULL
address	varchar(30) NOT NULL
gender	varchar(30) NOT NULL

Field	Type
id	int(11) NOT NULL
RID	varchar(300) NOT NULL
N	varchar(300) NOT NULL
P	varchar(300) NOT NULL
K	varchar(300) NOT NULL
temperature	varchar(300) NOT NULL
humidity	varchar(300) NOT NULL
ph	varchar(300) NOT NULL
rainfall	varchar(300) NOT NULL
Prediction	varchar(300) NOT NULL
Recommended_Zone	varchar(3000) NOT NULL

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V. CONCLUSION

Predicting crops for cultivation in agriculture is a difficult task. This paper has used a range of feature selection and classification techniques to predict the yield size of plant cultivations. The results depict that an ensemble technique offers better prediction accuracy than the existing classification technique. Forecasting the area of cereals, potatoes, and other energy crops can be used to plan the structure of their sowing, both on the farm and country scale. The use of modern forecasting techniques can bring measurable financial benefits.

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