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AGRISMART: Revolutionizing with AI-Driven Smart Systems

Angelin Rosy M¹, Chandru Aadithya V²

¹Assistant Professor, ²MCA, Department of Master of Computer Applications, Er.Perumal Manimekalai College of Engineering, Hosur,

Abstract: This project focuses on developing an intelligent farming system powered by Artificial Intelligence (AI) and Machine Learning (ML), without relying on physical sensors. Instead, it leverages existing agricultural data sources—including weather patterns, crop varieties, soil characteristics, and fertilizer application—to forecast crop yields, suggest the most appropriate crops, and enhance decision-making in agriculture. The primary objective is to boost farm productivity, minimize resource wastage, and promote a more data-driven approach to farming.

Keywords: Smart Farming , Artificial Intelligence, Machine Learning , PrecisionAgriculture , Crop Yield Prediction .

I. INTRODUCTION

Agriculture is a vital component of both food supply and economic development. Despite its importance, conventional farming methods often struggle with issues such as limited productivity, shifting climate conditions, and insufficient advisory support. This project introduces an intelligent approach that utilizes Artificial Intelligence (AI) and Machine Learning (ML) to process historical and current agricultural data sourced from publicly available databases. Without the need for physical sensors or plant disease detection, the system offers farmers valuable insights through smart algorithms, including crop selection guidance, yield estimation, and fertilizer management strategies.

II. PROPOSED WORK

The developed system leverages Artificial Intelligence (AI) and Machine Learning (ML) to support intelligent farming decisions without depending on physical sensors. It processes agricultural information, including cropping trends, climate predictions, soil composition, and fertilizer application records. Using this data, the system identifies the best-suited crops, estimates potential yields, and advises on optimal fertilizer use. By utilizing machine learning models trained on both past and present data, the platform empowers farmers to make informed, data-driven decisions.

III. MODULES

A. Data Collection:

The effectiveness of any machine learning model is highly influenced by the quality of the data used for training. In this project, datasets are carefully compiled from reliable open-source platforms and agricultural research institutions. The data includes comprehensive records of soil and climate attributes from different regions across India, aligned with appropriate crop types. Each entry consists of seven key features: Nitrogen (N), Phosphorus (P), Potassium (K), Temperature, Humidity, Soil pH, and Rainfall. These factors are selected based on established agricultural research that highlights their importance in assessing crop suitability. Since the system operates without real-time sensor data, it depends on rich historical and pre-processed datasets that closely represent actual farming scenarios. This approach makes the solution scalable and cost-effective, eliminating the need for expensive IoT devices. Additionally, the dataset encompasses various seasons, soil categories, and climatic conditions, ensuring the model is robust and adaptable to diverse agricultural environments.

B. Preprocessing

Raw datasets often come with challenges such as incomplete entries, anomalies, or inaccurate information. The data preprocessing stage is essential to refine this raw input into a structured format suitable for training machine learning models. In the AgriSmart system, each data record undergoes careful inspection, with missing values addressed through imputation methods like using the mean or median, depending on context. Outliers are detected using statistical analysis and visualization tools, and are either corrected or excluded based on their potential impact on model performance.



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Since Random Forest algorithms are robust to unscaled features, normalization or standardization is not applied, preserving the data's original distribution for better feature interpretability. Encoding techniques like label or one-hot encoding are not required here, as the target variable (crop name) is already properly categorized. The dataset is divided into training and testing subsets in an 80:20 ratio to evaluate the model's ability to generalize. To enhance reliability, cross-validation is also implemented. All preprocessing operations are executed through automated Python scripts, ensuring consistency and reproducibility throughout the workflow.

C. Model Training:

Model training forms the central technical process of this system. Following the data preprocessing stage, a Random Forest Classifier is employed due to its ensemble-based approach, which combines multiple decision trees to enhance prediction accuracy and model reliability. Each decision tree is built using randomly selected subsets of both data samples and features, a method that helps mitigate overfitting and ensures greater model robustness. During training, key hyperparameters—such as the number of estimators, maximum tree depth, and minimum samples required to split a node—are optimized through grid search or manual adjustment. The model is trained on the prepared training set and then tested on the reserved test set, with performance evaluated using metrics like accuracy, precision, recall, and F1-score. Due to its strong performance and ease of interpretation, Random Forest is well-suited for predictive tasks in agriculture. Once the model reaches a desirable performance threshold (typically exceeding 98% accuracy), it is saved using serialization tools such as joblib or pickle for integration into a Flask-based web application.

D. Prediction Module :

The prediction module is built to deliver instant results based on user-provided data. Instead of retraining the model with every request, it utilizes the pre-trained and stored model to generate outputs efficiently. When a user submits the input form via the interface, the data is collected and transmitted to the backend, where it is processed for prediction. The system ensures that inputs are accurately converted into the required format—numerical (float) values arranged in the correct sequence—and reshaped into a NumPy array before being passed to the model's .predict() function. The predicted crop name is then sent back to the frontend and displayed within a styled message box for user clarity. Designed for speed and efficiency, the module delivers quick responses, even on systems with limited computational power. Robust error-handling mechanisms are also in place to detect and report invalid inputs—such as non-numeric entries—providing clear feedback to users for a smooth experience.

E. Recommendation Module:

While the vaticination module answers" what crop is suitable?", the recommendation module addresses" why this crop?". It enhances the stoner experience by furnishing logic behind the prognosticated crop. For illustration, if the prognosticated crop is" Rice", the system may mention that the high nitrogen and downfall situations are ideal for rice civilization. This helps make stoner trust and improves translucency. also, the module can offer tips similar as recommended sowing ages or water conditions for the prognosticated crop. Though presently limited to static textbook suggestions, unborn performances can enhance this module by integrating agrarian APIs or exploration- grounded databases for dynamic content generation. This module acts as a digital counsel, helping druggies understand how their soil and environmental conditions align with specific crops.

F. User Interface:

AgriSmart's user interface serves as a crucial bridge between the intelligent model and the end-user, ensuring ease of access and interaction. Developed using standard HTML and CSS, the interface features a clean, professional layout with visually appealing design elements. On the left side, users find a well-organized input form labeled for the seven essential parameters, while the right side presents the prediction result in a bold, centered format with clear visual distinction. The UI maintains a consistent color scheme and structured spacing to enhance readability across all screen types. Built-in input validation ensures users provide complete and correct data, reducing errors. Additional functionalities such as a reset button, input tips, and descriptive result boxes enhance the overall user experience. The interface is completely adaptable, seamlessly resizing to fit different devices—from large desktop monitors to small smartphone screens.

IV. RESULT

AgriSmart is revolutionizing farming by integrating advanced artificial intelligence technologies into agricultural practices. By utilizing smart automation and insightful data analysis, AgriSmart improves crop monitoring, maximizes the efficient use of resources, and increases overall farm output.



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This forward-thinking solution enables farmers to make more informed choices, minimize waste, and achieve higher yields in an eco-friendly way, ushering in a new phase of precision agriculture driven by advanced AI tools.

V. CONCLUSION

The AI and ML-powered Smart Farming System provides an effective solution to assist farmers without the need for costly sensors. Leveraging data analysis, it delivers precise advice on crops, forecasts yields, and recommends fertilizers. This method lowers expenses, enhances efficiency, and introduces advanced technology to conventional farming, promoting sustainable agriculture while using minimal resources.

VI. ACKNOWLEDGMENT

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