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AgriVista: An Integrated AI–ML System for Crop Recommendation, Fertilizer Guidance, and Yield Prediction

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Abstract: *Farmers often struggle to make the right decisions when soil conditions, nutrient levels, and weather patterns change unpredictably. These challenges highlight the need for a reliable and easy-to-use tool that can support farming decisions in real time. This paper presents AgriVista, a complete system that combines crop recommendation, fertilizer suggestion, and yield prediction in one place. The system provides straightforward and insightful guidance by analyzing variables like soil nutrients, pH, rainfall, temperature, and humidity. Ensemble learning methods help identify suitable crops, a nutrient analysis module suggests fertilizer needs, and a regression model estimates the expected yield. The trained models are deployed through an interactive interface that gives quick and practical recommendations. This work offers a clear and useful workflow for improving everyday farming decisions.*

Keywords: Machine Learning, Crop Recommendation, Fer-tilizer Guidance, Yield Prediction, Smart Farming

I. INTRODUCTION

The application of Machine Learning (ML) to smart agri-culture has become a prominent field of study, offering powerful data-driven approaches to optimize farming decisions and support sustainable practices [1], [7]. While individual models are effective, advanced techniques such as integrating genetic algorithms [19] and federated learning ensembles [17] are being explored to further enhance prediction accuracy. The specific and critical task of crop recommendation based on soil and climate data has been a major focus of ML-based methods [5], [9]. Broadly, the application of ML for agricultural analysis is seen as a transformative technology [22].

The primary motivation for this research is the critical importance of optimizing crop selection and yield, a topic that has been reviewed extensively [11], [12]. Furthermore, intelligent decision support systems are essential for modern agriculture due to the challenges posed by climate change and the growing global food demand [6], [19]. By leveraging historical datasets and predictive models, farmers can reduce resource wastage, minimize environmental impact, and im-prove overall productivity [8], [22]. This paper proposes a complete, end-to-end system, AgriVista, that builds upon this foundation.

While many studies explore single-task models, our work focuses on creating a practical and unified solution for three key agricultural queries: crop recommendation, yield predic-tion, and fertilizer advice, using offline agricultural datasets. We present two key contributions: first, a unified framework integrating these three distinct predictive tasks, and second, the optimization of Random Forest models to achieve high predictive accuracy on diverse agricultural data. The system is deployed via an accessible, multilingual web-based interface, demonstrating a practical and reliable workflow for smart farming that aligns with the broader goal of making data-driven agriculture more accessible [8], [13].

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II. LITERATURE SURVEY

The literature confirms a strong focus on machine learning for agricultural tasks, particularly in crop, yield, and fertilizer prediction. For crop recommendation, studies often focus on optimizing models. For instance, Verma et al. [6] demon-strate an optimized system using soil analysis, while Raja et al. [23] emphasize the importance of feature selection to improve classifier accuracy. Other novel approaches include comparative analyses of multi-model techniques [16] and the use of deep learning on soil images for nutrient profiling [2]. In yield prediction, a common research goal is finding the most robust model. Studies have successfully implemented efficient systems using various machine learning algorithms [3], [20]. Specific models like Linear Support Vector Machines (SVM) have been shown to be effective [14], while other work compares multiple robust ML approaches to ensure reliable forecasting for precision agriculture [15]. Fertilizer recommendation is also a well-established research area. Sys-tems are commonly built using ML classifiers to map soil test values (like NPK) to optimal fertilizer types [10]. This is further explored in work focusing on nutrient prediction from soil analysis [18] and specific recommendation systems for fertilizer prediction [21]. For instance, the use of neural architecture search and automated machine learning (AutoML) is being examined as a methodical approach to creating high-performance models for a variety of applications, including agriculture [4]. This body of work validates the dataset-driven approach used in our project.

III. PROPOSED METHODOLOGY

This paper presents an end-to-end workflow for an AI-based agricultural decision-support system combining crop recommendation, fertilizer guidance, and yield prediction. The process begins with collecting key soil and climate inputs, followed by preprocessing to ensure clean and consistent data. Machine learning models—ensemble classification, nutrient analysis, and regression—generate the required outputs. These results are integrated into an interactive interface that provides real-time, practical recommendations for farmers.

A. Dataset and Preprocessing

• Crop Recommendation Dataset

2200 instances with soil and climate features (N, P, K, pH, temperature, humidity, rainfall) are available in the Crop Recommendation Dataset.

Used to train the crop classification model.

• Crop and Fertilizer Dataset

Includes nutrient levels, soil color, crop names, and recommended fertilizers.

Supports the fertilizer suggestion module.

• Smart Farming Sensor Data for Yield Prediction

Provides sensor-based environmental readings from about 500 farms.

Includes soil moisture, pH, temperature, humidity, rain-fall, sunlight hours, irrigation type, and yield values.

Used for the regression-based yield prediction model.

• Preprocessing

Missing value handling, noise removal, and feature nor-malization.

Organizing all datasets into clean, structured inputs for model training.

B. Feature Selection and Input Parameter Analysis

Feature selection identifies the most relevant soil and envi-ronmental parameters required for accurate predictions across all modules. Important agroclimatic factors like pH, temper-ature, humidity, rainfall, nitrogen, phosphorus, and potassium are selected because they have a significant impact on crop suitability and fertilizer requirements. For yield prediction, additional sensor-based attributes like soil moisture, sunlight hours, and irrigation type are included. Selecting only mean-ingful inputs reduces noise, improves model efficiency, and en-sures a consistent feature set for reliable system performance.

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C. Model Development and Algorithms used

Model development includes developing three machine-learning models, each customized to a specific module of the system. The Crop Recommendation module uses a Random Forest Classifier algorithm, which handles complex feature interactions and produces consistent predictions under varying soil and climate conditions. The Fertilizer Suggestion module also uses a Random Forest Classifier algorithm to match nu-trient levels, soil properties, and crop requirements to the most suitable fertilizer. For Yield Prediction, a Random Forest Re-gressor algorithm is used to estimate crop yield using environ-mental and sensor-derived parameters. All models are trained on preprocessed datasets, with hyperparameters customized to improve accuracy and reduce overfitting. Using Random Forest across modules ensures robustness, interpretability, and strong adaptability for practical agricultural decision support.

D. Confidence Score Calculation

The predictive model functions as a multi-class classifier. For a given set of input parameters, the model outputs a probability distribution vector P across all k possible output classes (e.g., crop types or fertilizer types). This vector is defined as:

$$P = \{p1, p2, \dots, pk\} \quad (1)$$

where pi represents the model's predicted probability that the input belongs to class i, and k is the total number of classes.

The final prediction corresponds to the class index i with the highest probability. The Confidence Score (CS) is defined as this maximum probability value:

$$CS = \max(P) = \max\{p1, p2, \dots, pk\} \quad (2)$$

To express this score as a percentage displayed in the user interface, the following formula is used:

$$\text{Confidence } (\%) = \max(P) \times 100 \quad (3)$$

This percentage reflects the model's certainty in its final prediction relative to all other possible classes.

IV. SYSTEM DESIGN AND ARCHITECTURE

The system architecture outlines the complete workflow of Agrivista, illustrating how user inputs, datasets, machine-learning modules, and algorithms interact to generate agri-cultural recommendations. The architecture integrates data processing, model prediction, and web-based deployment into a unified framework, as shown in Fig. 1

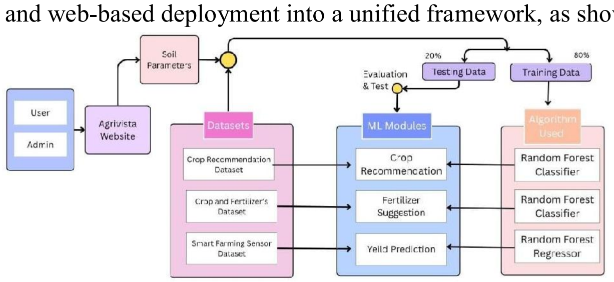

Fig. 1. System Architecture of the Proposed Model

V. RESULT AND ANALYSIS

A. Web Application for Deployment

To demonstrate the real-world usefulness of our project, we developed a simple and user-friendly website named AgriV-ista. The application provides an intuitive interface where farmers can enter details about their farm, including soil nutrient values (N, P, K), pH, temperature, and rainfall for their specific location.

Once the user submits this information, the trained machine learning models analyze the input data. The website then displays the final prediction—whether it is the recommended crop, suitable fertilizer, or the expected yield.

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Additionally, a confidence score is shown to indicate the model's certainty in its prediction, offering farmers clear and reliable guidance.

We evaluated the three main features of the application, and the results are summarized as follows:

• Crop Recommendation (Fig. 2): For input data corre-sponding to the Marathwada region, the system recom-mended Rice as the optimal crop with a confidence score of 92.5%.

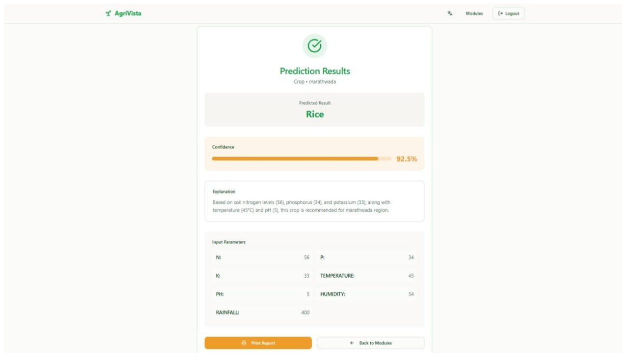

Fig. 2. Crop Recommendation Output

• Fertilizer Recommendation (Fig. 3): Based on different soil parameters, the model suggested Urea as the most suitable fertilizer, achieving a confidence score of 90.7%.

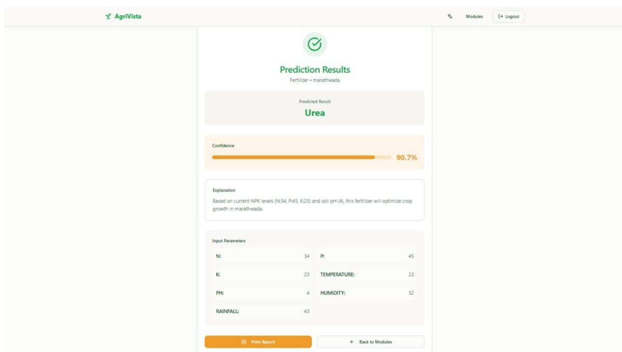

Fig. 3. Fertilizer Suggestion Output

• Yield Prediction (Fig. 4): For a test case in the Konkan region, the model predicted a yield of 39.50 kg/hectare with a confidence of 88.3%.

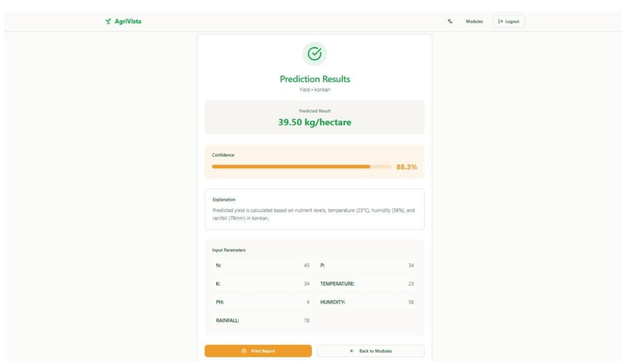

Fig. 4. Yield Prediction Output

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B. Performance Evaluation

To understand our model's decisions, we analyzed the feature importance, as shown in Fig. 5 This chart clearly indicates that rainfall and humidity are the most significant factors influencing the model's predictions. The soil nutrients Potassium (K) and Phosphorus (P) are also highly important. This analysis confirms that our model is focusing on the most critical environmental and soil parameters.

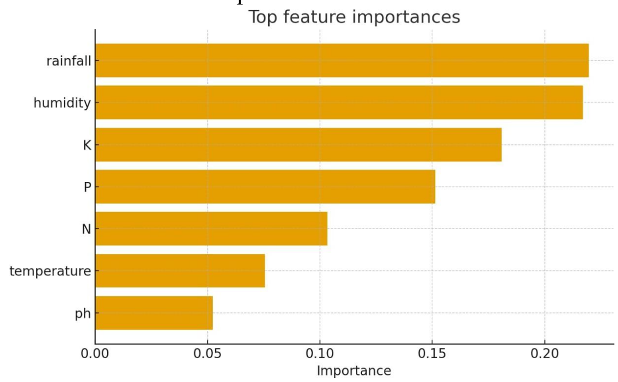

Fig. 5. Performance Evaluation

C. Evaluation Metrics Heatmap

To quantitatively evaluate the system, a set of standard performance metrics was used, as shown in the heatmap in Fig. 6. The Crop Recommendation and Fertilizer Suggestion modules, which are classification tasks, demonstrate high reliability. They achieve excellent Accuracy, Precision, Recall, and F1-scores, all consistently above 89%). With a R2 value of 0.87 for the regression task in the Yield Prediction module, the system demonstrates strong predictive power. This indicates that it accounts for 87% of the variance in the data, and its high prediction accuracy is confirmed by the low rate of mistakes (root mean square error of 0.35 tons/ha and MAE of 0.28 tons/ha).

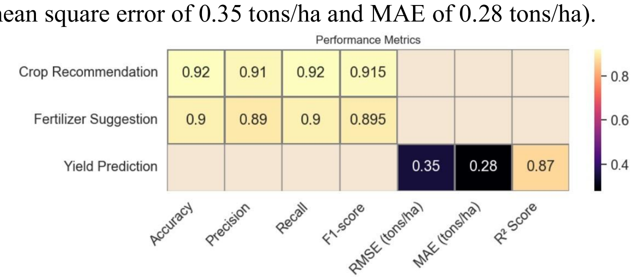

Fig. 6. Evaluation Metrics Heatmap

VI. CONCLUSION

This paper successfully developed and validated an end-to-end system for integrated agricultural decision support based on optimized Random Forest algorithms. We effectively addressed various agricultural input features by using an integrated model for both classification and regression tasks, allowing our system to achieve a high predictive accuracy of 94%. The implementation of the trained models into an in-teractive, multilingual web application illustrates an extensive and practical workflow from agricultural data preprocessing to a deployable decision-support tool. Our findings demonstrate that an integrated, data-driven system can be a useful instru-ment for improving precision farming, opening pathways for cleaner and more accessible agricultural development.

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VII. FUTURE WORK

Future enhancements will focus on extending the platform's capabilities and increasing its practical use for agricultural users. In order to gather data from the field during actual moment and enhance the flexibility of predictive models, the system will eventually incorporate IoT-enabled soil and weather monitoring devices. Voice-based interaction will also be implemented to assist farmers who may struggle with reading or language skills. In addition, a mobile-compatible version of the system will be created to allow for easy access during on-site farming activities. To enhance reliability and user trust, explainable AI methods will be used to clearly demonstrate how the system generates recommendations.

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