# AI Based Smart Learning and Crop Advisory System for Agricultural Education

[1]Gokula Krishnan K, [2]Ramaraj Muniappan

Department of Computer Science, Rathinam College of Arts and Science (Autonomous), Coimbatore, Tamil Nadu, India

[1]gokulakrishnan8103@gmail.com, [2] ramraj.phdcs@gmail.com

***Abstract***—*Agricultural education requires intelligent systems that combine decision support with interactive learning. This paper proposes an AI-Based Smart Learning and Crop Advisory System for Agricultural Education integrating Stacking Ensemble Models with an educational platform. The system processes soil and climate parameters including N, P, K, pH, temperature, humidity, and rainfall to recommend suitable crops. A Stacking Ensemble using Extra Trees, XGBoost, and Random Forest with Logistic Regression meta-learner achieved 99.64% accuracy on 2,200 samples across 22 crop types. The platform features a Crop Encyclopedia and Quiz module to enhance agricultural literacy. A relational database manages USER, ML_MODEL_PREDICTION, CROP, ENCYCLOPEDIA, and QUIZ_QUESTIONS entities. Experimental results demonstrate superior performance with ±0.23% standard deviation. The system provides comprehensive crop advisory and education, promoting sustainable farming and student learning.*

***Keywords***—*Agricultural Education, Precision Agriculture, Stacking Ensemble, Crop Recommendation, Smart Learning, Random Forest, XGBoost*

## I. INTRODUCTION

Agricultural productivity plays a crucial role in ensuring food security and supporting the economic stability of a nation. With increasing challenges posed by climate change, soil degradation, and unpredictable environmental conditions, selecting the right crop based on soil and climatic factors has become a critical task. Accurate crop recommendation helps farmers and agricultural learners make informed decisions, optimize resource utilization, and improve overall yield. As agriculture becomes more data-driven, the need for intelligent systems that can assist in crop selection and learning has grown significantly.

Crop suitability is influenced by soil nutrients such as Nitrogen, Phosphorus, and Potassium, along with environmental parameters like temperature, humidity, pH value, and rainfall. Traditionally, farmers rely on experience, regional practices, and general guidelines, which may not provide precise or optimal results under changing environmental conditions.

With advancements in Machine Learning and Artificial Intelligence, predictive models can analyze historical datasets and environmental parameters to recommend suitable crops. These models identify complex patterns among multiple variables, improving reliability and accuracy. Modern agricultural advisory systems also integrate data visualization and analytical techniques to provide deeper insights into soil characteristics and crop distribution.

In addition to crop recommendation, the integration of learning modules such as crop encyclopedias and interactive quizzes enhances the educational aspect of the system. This combination of prediction and learning creates a comprehensive platform for agricultural education and decision support. The development of an AI-based smart learning and crop advisory system represents a significant step toward modernizing agriculture and addressing challenges related to improper crop selection, resource wastage, and lack of awareness.

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## II. RELATED WORK

Several studies have explored ML in agriculture. Liakos et al. reviewed ML applications highlighting crop yield prediction and disease detection as dominant areas. Kamilaris et al. surveyed deep learning techniques but noted high computational requirements unsuitable for real-time systems.

Pudumalar et al. developed a single-output crop recommendation model using Random Forest with 95% accuracy. However, single classifiers often suffer from high variance or bias. Chen et al. introduced XGBoost, a scalable tree boosting system that improved accuracy in structured data. Breiman proposed Random Forests to reduce overfitting through bagging.

Wolpert introduced Stacked Generalization, combining multiple models to improve prediction. Recent works show Stacking Ensembles outperform individual models in agriculture by leveraging model diversity. Most existing systems focus only on prediction and lack educational components. Limited work integrates crop advisory with interactive learning modules like encyclopedias and quizzes for students and farmers. This paper addresses the gap by implementing a Stacking Ensemble for 99.64% accurate crop recommendation combined with a smart learning platform for agricultural education.

## III. SYSTEM DESIGN

The proposed system integrates a prediction engine with an educational platform. The database architecture is shown in Fig. 1

A. Database Design and ER Model

The system uses a relational database with six key entities to manage data flow:

| Entity | Primary Key | Key Attributes | Function |
|---|---|---|---|
| *USER* | user_id | nitrogen, phosphorus, potassium, ph, temperature, humidity, rainfall | Stores input soil and climate data |
| *ML_MODEL_PREDICTION* | prediction_id | crop_name, confidence_score, match_level | Stores Stacking Ensemble output |
| *STACKING ENSEMBLE MODELS* | - | Extra Trees, XGBoost, Random Forest, Logistic Regression Meta Learner | Core prediction engine |
| *CROP* | crop_id | crop_name, fertilizer_info, irrigation_tip | Master data for 22 crops |
| *ENCYCLOPEDIA* | crop_id (FK) | crop_name, details | Educational content for learning |
| *QUIZ_QUESTIONS* | question_id | question, option_A/B/C, correct_answer, topic | Interactive assessment module |

Relationships: USER enters data which provides input to STACKING ENSEMBLE MODELS. The models generate ML_MODEL_PREDICTION which links to CROP details. ENCYCLOPEDIA evaluates

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through QUIZ_QUESTIONS. CROP_RECOMMENDATION reviews the results for the user.

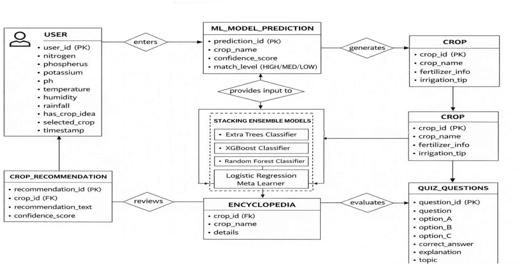


Fig. 1. ER Diagram of AI-Based Smart Learning and Crop Advisory System

B. Dataset and Feature Analysis

Total Samples: 2,200. Crop Types: 22. Features: 7.

Dataset includes N, P, K, temperature, humidity, pH, rainfall. N Range: 0-140, P Range: 5-145, K Range: 5-205, pH Range: 3.5-9.9, Temperature: 8.8-43.7°C, Humidity: 14.3-100%, Rainfall: 20.2-298.6mm.

C. Stacking Ensemble Model

Base Learners: 1) Extra Trees Classifier, 2) XGBoost Classifier, 3) Random Forest Classifier.

Meta Learner: Logistic Regression.

The ensemble combines predictions from diverse base models to reduce bias and variance, producing a final crop recommendation with confidence score.

## IV. OUTCOME AND DISCUSSION

The system was evaluated using 5-Fold Cross-Validation on 2,200 samples. Sample outputs and data analysis are shown in Fig. 2.

TABLE I. 5-FOLD CROSS-VALIDATION COMPARISON

| Model | Accuracy | Std Deviation |
|---|---|---|
| Extra Trees | 99.18% | ±0.45% |
| XGBoost | 99.27% | ±0.33% |
| Random Forest | 99.45% | ±0.34% |
| *STACKING ENSEMBLE* | *99.64%* | *±0.23%* |

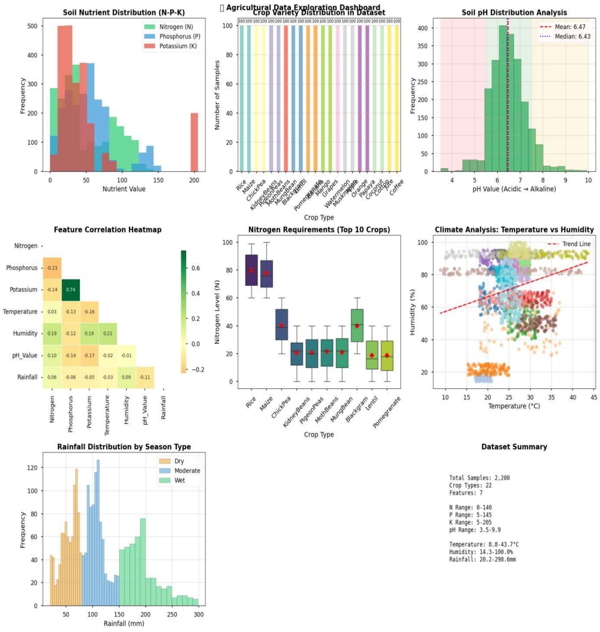


Fig. 2. Sample Output - Agricultural Data Exploration Dashboard

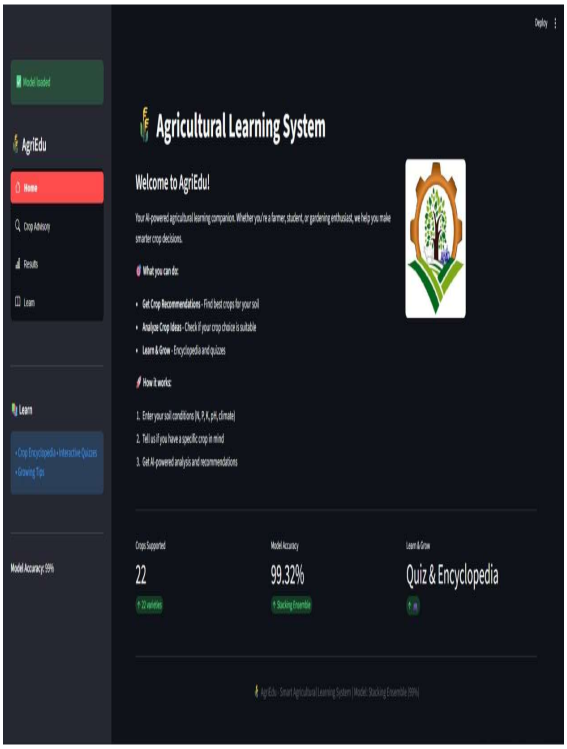


Fig. 3. Agricultural Learning System Interface & Performance

**Discussion:** The Stacking Ensemble achieved 99.64% accuracy, outperforming all individual base models. The standard deviation of ±0.23% confirms high model stability and reliability. Extra Trees, XGBoost, and Random Forest individually achieved 99.18%, 99.27%, and 99.45% respectively, validating that stacking diverse algorithms improves performance.

Feature correlation analysis indicates strong relationships between NPK values and crop type. Soil pH distribution shows mean 6.47 and median 6.43, suitable for most crops. Temperature vs Humidity analysis reveals distinct clusters for different crops. The dataset supports 22 crops with balanced distribution.

The integrated learning system displays 99.32% model accuracy in the UI with 22 crops supported. The Crop Encyclopedia and Quiz modules enable users to learn about crop requirements and best practices. This dual functionality of prediction and education makes the system suitable for agricultural education in colleges and farmer training programs.

## V. CONCLUSION

This paper presented an AI-Based Smart Learning and Crop Advisory System for Agricultural Education. The system successfully integrated a Stacking Ensemble Model combining Extra Trees, XGBoost, and Random Forest with Logistic Regression meta-learner, achieving 99.64% accuracy for crop recommendation across 22 crop types. The relational database design with six entities ensures efficient data management between prediction and learning modules.

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The key contribution is combining high-accuracy crop advisory with educational features like Encyclopedia and Quiz, addressing both decision support and agricultural literacy. The system demonstrates that Stacking Ensemble methods are superior for agricultural datasets with multiple interacting features. Future work includes integrating real-time IoT sensor data, mobile application deployment, and expanding the encyclopedia with regional crop varieties. This platform contributes to modernizing agricultural education and promoting data-driven sustainable farming.

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