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AgriSmart: An Explainable Multi-Criteria Crop Recommendation System using Simulated Real-Time Data

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Abstract*:* Crop selection in Indian agriculture is largely governed by traditional knowledge and guesswork, leading to yield mismatches, nutrient imbalance, and financial risk. This paper presents AgriSmart, a cloud-enabled, explainable, multi-criteria crop recommendation system that integrates a Random Forest classifier, the TOPSIS multi-criteria decision-making method, and SHAP (SHapley Additive exPlanations) to recommend and rank suitable crops based on soil nutrient levels (N, P, K), pH, and climatic parameters (temperature, humidity, rainfall). Unlike single-output, black-box crop advisory tools, AgriSmart ranks the top six candidate crops on a 0–100% suitability score, explains the contribution of each input feature to the recommendation, and generates a downloadable soil health report with fertilizer and remediation guidance. The system is implemented as a responsive React.js web application that communicates with a cloud-hosted machine learning backend, requiring no local server infrastructure. Experimental evaluation shows that the integrated pipeline produces consistent, transparent, and actionable recommendations within a few seconds, indicating strong potential as a decision-support tool for farmers, agricultural officers, and researchers.

Keywords*:* Crop Recommendation, Random Forest, TOPSIS, Explainable AI, SHAP, Precision Agriculture, Multi-Criteria Decision Making, Soil Health

I. INTRODUCTION

Agriculture underpins the livelihood of more than half of India's population, yet crop selection - one of the most consequential decisions a farmer makes each season - is still frequently guided by tradition, peer suggestion, or guesswork rather than scientific evidence [1], [2]. The suitability of a crop depends on a dynamic combination of soil nutrient levels, soil pH, rainfall, temperature, humidity, and market conditions, and a mismatch between these factors and the chosen crop leads to poor yields, nutrient depletion, and financial loss. Existing digital advisory tools typically evaluate only a single dimension - soil or weather - in isolation, rank a single "best" crop without alternatives, and rarely explain the reasoning behind a recommendation [3].

This paper presents AgriSmart, a web-based decision-support system that addresses these gaps by combining supervised machine learning, multi-criteria ranking, and explainable AI in a single pipeline. The system predicts candidate crops using a Random Forest classifier trained on soil and climate features, ranks the candidates using the TOPSIS multi-criteria decision-making technique across suitability, yield, and economic criteria, and explains each recommendation using SHAP values. AgriSmart further generates a soil health report identifying nutrient deficiencies and recommending corrective fertilizers, and presents all outputs through an interactive React.js interface with Recharts-based visualizations.

The remainder of this paper is organized as follows. Section II reviews related work in ML-based crop prediction, multi-criteria agricultural decision-making, and explainable AI. Section III describes the proposed system architecture and methodology. Section IV discusses implementation details. Section V presents results and discussion. Section VI outlines applications, and Section VII concludes the paper with directions for future work.

II. LITERATURE SURVEY

A. Machine Learning-Based Crop Prediction

Sontakke and Pimprikar [1] compared SVM, Random Forest, KNN, and Decision Tree classifiers for crop prediction and found that ensemble methods such as Random Forest generalize better on nonlinear soil-climate data, motivating its use as AgriSmart's core predictor. Reddy et al. [2] showed that region-specific training data improves prediction accuracy, reinforcing the value of localized soil and weather inputs. Van Klompenburg et al. [8] conducted a systematic review of ML-based crop yield prediction and reported that ensemble and deep-learning models consistently outperform simple regressors, but noted a persistent lack of interpretability across the surveyed literature. More recently, Elbasi et al. [9] and Musanase et al. [10] applied ensemble classifiers and hybrid crop-and-fertilizer recommendation pipelines respectively, while Senapaty et al. [11] proposed an IoT-enabled soil-nutrient-driven recommendation model for precision agriculture. Across this body of work, a common limitation persists: most systems output only a single top prediction, without a ranking mechanism or economic context.

B. Multi-Criteria Crop Recommendation

Doshi et al.'s AgroConsultant [3] aggregated soil and weather data through a web interface but lacked multi-criteria ranking, profitability

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analysis, and explainability. Several recent studies have explored multi-criteria decision-making (MCDM) methods for crop selection specifically. A TOPSIS-based framework evaluated field crops against yield, price, and cost criteria to identify the most suitable option under given agro-economic conditions [12]. Similarly, a CRITIC-TOPSIS hybrid model was used to prioritize crops for family-farming production units under variable climatic and resource constraints [13], and a CRITIC-driven TOPSIS-WASPAS framework was proposed for sustainability-oriented crop selection [14]. These studies confirm that TOPSIS is well suited to agricultural decision-making because it can simultaneously weigh conflicting, differently-scaled criteria such as soil compatibility, yield, and market value - the same rationale underlying AgriSmart's ranking module.

C. Explainable AI in Agriculture

Lundberg and Lee [15] introduced SHAP as a unified, game-theoretic framework for attributing a model's output to individual input features, which has since become a standard tool for interpreting black-box classifiers. Akkem et al. [4] argued specifically that the absence of explainability in crop-recommendation tools reduces farmer trust and adoption, and demonstrated that SHAP-based feature attribution improves confidence in ML-driven agricultural advice. Shastri et al. [16] similarly combined supervised learning with explainable AI to justify crop recommendations to end users, reporting improved interpretability without sacrificing predictive accuracy. AgriSmart adopts this same philosophy, using SHAP to expose the contribution of each soil and weather parameter to every recommended crop.

D. Weather Variability and Soil Health Reporting

Pradhan and Patel [5] demonstrated that real-time weather parameters significantly affect the reliability of agricultural prediction models, supporting AgriSmart's use of simulated real-time weather inputs when live feeds are unavailable. Menon and George [6] emphasized the value of detailed soil health reporting - including NPK deficiency analysis - for sustainable agriculture, which directly informs AgriSmart's soil health report module. Collectively, the reviewed literature confirms that while ML-based prediction, MCDM ranking, and explainability have each been studied independently, few systems integrate all three with real-time adaptability and farmer-facing visualization, which is precisely the gap AgriSmart addresses.

III. PROPOSED SYSTEM AND METHODOLOGY

A. System Architecture

AgriSmart follows a three-tier architecture. The Presentation Tier is a React.js client that collects soil parameters (N, P, K, pH) and climatic inputs (temperature, humidity, rainfall) and renders ranked recommendations, SHAP explanations, and soil reports. The Logic Tier is a cloud-hosted AI service running the Random Forest classifier, TOPSIS ranking module, and SHAP explainer. The Data Tier supplies the trained soil dataset and simulated or live weather data in CSV/JSON form. This separation of concerns allows the client to run on any device without a local backend server, while the ML logic can be retrained or scaled independently. Fig. 1 illustrates this three-tier architecture.

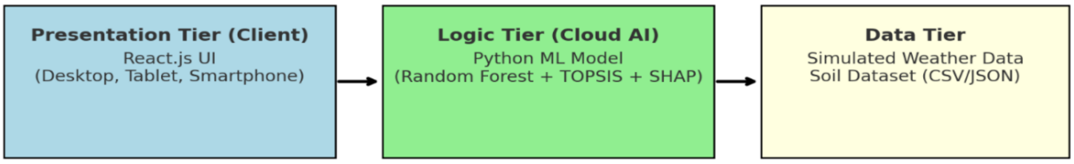

Fig. 1. Three-tier system architecture of AgriSmart (Presentation, Logic, and Data tiers).

B. Machine Learning Pipeline

The dataset comprising N, P, K, pH, temperature, humidity, rainfall, and crop labels is cleaned, normalized, and split into training and test sets. A Random Forest classifier is trained on this data because ensemble tree-based models handle nonlinear feature interactions and noisy agricultural data more robustly than single decision trees or linear models [1]. Model performance is evaluated using accuracy, precision, recall, and the confusion matrix before the trained model is deployed to the cloud for real-time inference. The complete pipeline, from dataset collection to real-time TOPSIS- and SHAP-based prediction, is summarized in Fig. 2.

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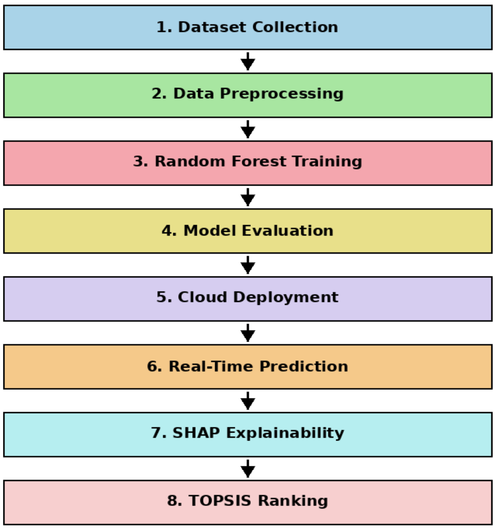

Fig. 2. Machine learning workflow from dataset collection to real-time TOPSIS/SHAP-based prediction.

C. TOPSIS Multi-Criteria Ranking

Given the set of candidate crops output by the Random Forest model, TOPSIS ranks them using multiple weighted criteria - soil suitability, weather compatibility, yield potential, market value, and risk. The procedure is as follows:

- Construct a decision matrix with crops as rows and criteria as columns.
- Normalize the matrix so criteria measured in different units become comparable.
- Apply criterion weights reflecting relative importance (e.g., soil and weather match weighted higher than water requirement).
- Determine the ideal-best and ideal-worst values for each criterion.
- Compute each crop's Euclidean distance to the ideal-best and ideal-worst solutions.
- Compute the relative closeness score: Score = $D^- / (D^+ + D^-)$, where D^+ and D^- are the distances to the ideal-best and ideal-worst solutions respectively.

Crops are ranked in descending order of this score, and the top six are presented to the user with a suitability percentage.

D. Explainability with SHAP

For each recommended crop, SHAP values quantify how much each input feature (e.g., nitrogen level, rainfall) pushed the model's prediction toward or away from that crop, relative to a baseline. AgriSmart visualizes these contributions as feature-importance charts, allowing a non-technical user to see, for example, that a recommendation for rice was driven primarily by high rainfall and favorable pH rather than an opaque model score.

E. Dataset and Experimental Setup

The Random Forest classifier is trained on a crop-recommendation dataset comprising seven input features - Nitrogen (N), Phosphorus (P), Potassium (K), pH, temperature, humidity, and rainfall - and a categorical crop label, compiled from agricultural research repositories and government open-data platforms and combined with simulated weather values to model seasonal variability where live meteorological feeds are unavailable. The dataset was split into training and test subsets in a [80:20] ratio, and the Random Forest was configured with [n_estimators = 100, max_depth = None, random_state = 42] (values to be confirmed against the final training configuration); TOPSIS criterion weights were assigned by domain judgement, weighting soil match and weather match more heavily than water requirement, consistent with the procedure in Section III-C.

IV. IMPLEMENTATION

A. Frontend Implementation

The user interface is implemented entirely in React.js as a set of modular, reusable components: a soil and weather input module for collecting N, P, K, pH, temperature, humidity, and rainfall values; a weather simulation module that generates realistic temperature, humidity, and rainfall values when live data is unavailable; a recommendation display module that renders the TOPSIS-ranked crop cards; a SHAP explanation module that visualizes feature-level contributions; a soil health report module; and crop-detail panels showing cultivation practices, fertilizer schedules, cost/profit breakdowns, and market-price trends. Recharts is used throughout for bar, pie, radar, and line visualizations, and the layout is fully responsive across desktop, tablet, and smartphone form factors, with a card-based design and colour-coded panels intended to keep the interface usable for non-technical, low-digital-literacy users.

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B. Machine Learning Model Implementation

The prediction backend is implemented in Python using scikit-learn. A Random Forest classifier, chosen for its robustness to nonlinear soil-climate interactions, is trained on the cleaned N, P, K, pH, temperature, humidity, and rainfall dataset. The candidate crops produced by the classifier are passed to the TOPSIS module, which scores each candidate against soil compatibility, weather suitability, yield potential, economic value, and water requirement, and to a SHAP explainer that attributes the classifier's output to individual input features. The end-to-end training workflow comprises six steps: dataset collection, data cleaning and preprocessing, Random Forest training, accuracy validation on a held-out test set using precision, recall, and the confusion matrix, SHAP value generation, and export of the trained model for cloud deployment.

C. Cloud Deployment and System Integration

The trained model, TOPSIS module, and SHAP explainer are deployed behind a single cloud-hosted REST API endpoint that accepts soil and weather parameters and returns the ranked crops, TOPSIS scores, and SHAP contribution values as JSON. Integration follows a simple request-response flow: the React client collects user input and submits it via a fetch() call, the cloud service performs Random Forest inference, TOPSIS ranking, and SHAP explanation generation, and the response is rendered in the UI as ranked cards, explanation charts, and a downloadable PDF soil health report. Because all computation is offloaded to the cloud, the client itself requires no local server, dependencies, or installation, allowing AgriSmart to run on any device with a modern browser, including low-connectivity rural settings.

V. RESULTS AND DISCUSSION

AgriSmart was evaluated using a range of soil samples and simulated weather inputs entered through the React interface. The Random Forest model produced consistent predictions across input combinations, and the TOPSIS module generated a ranked list of the top six crops with suitability scores; for example, a representative test case (N=60 kg/ha, P=50 kg/ha, K=50 kg/ha, pH=6.8, temperature=26°C, humidity=70%, rainfall=850 mm) yielded Coffee, Jute, and Rice as the top three crops with suitability scores of 29.75%, 25.71%, and 22.75%, respectively, along with estimated profit-per-acre figures. The SHAP explanation module clearly attributed these outcomes to specific nutrient and climate factors, and the soil health report correctly flagged nitrogen and potassium as low relative to the ideal range and suggested corrective fertilizer dosages. The end-to-end recommendation process, including ranking and explanation generation, completed within a few seconds, and the interface remained responsive on both desktop and mobile form factors. Representative snapshots of the system are shown in Fig. 3 (input interface), Fig. 4 (ranked crop recommendations), Fig. 5 (soil health report), Fig. 6 (detailed crop information page), and Fig. 7 (plant disease detection module). For this test case, the auto-generated soil health report (Fig. 5) computed an overall soil health score of 70/100 ("Good"), correctly flagged nitrogen and potassium as low relative to the ideal range, and recommended urea (50–100 kg/acre) and MOP (40–60 kg/acre) as corrective fertilizers, illustrating the actionable, farmer-facing nature of the report.

These results indicate that combining a Random Forest predictor with TOPSIS ranking and SHAP explainability yields a system that is both accurate and transparent - addressing the single-output, black-box limitations identified in prior work [1]-[3]. A current limitation is that weather inputs are simulated rather than sourced from live sensors or APIs; integrating real-time or IoT-based weather and soil-sensor feeds, as explored in [10], [11], is a natural next step to further improve localization accuracy.

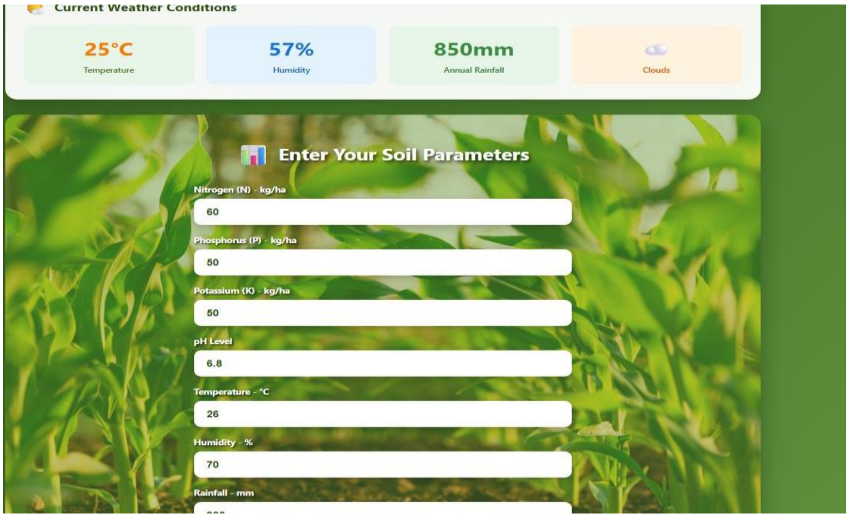

Fig. 3. AgriSmart main interface for soil parameter and weather input.

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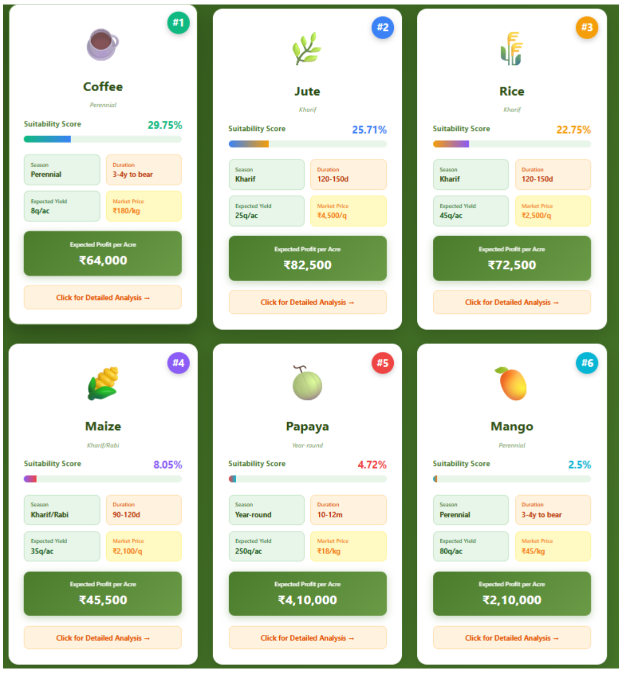

Fig. 4. Top six ranked crop recommendations with TOPSIS suitability scores.

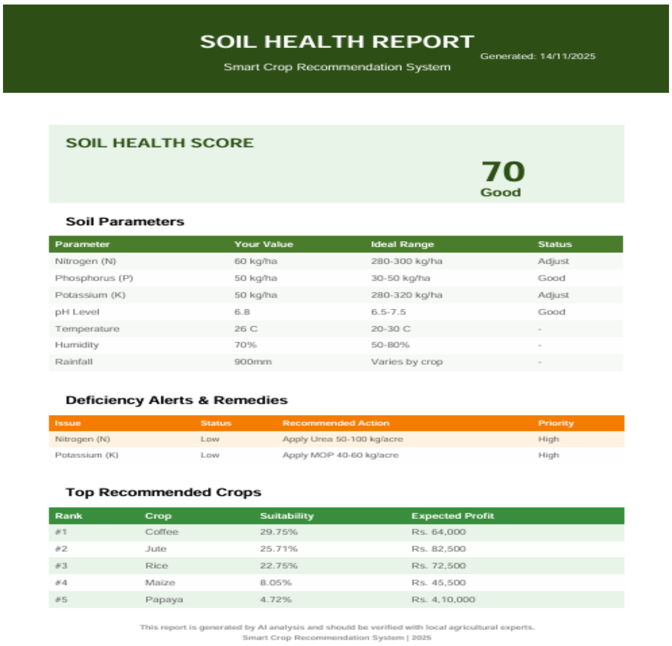

Fig. 5. Auto-generated soil health report with deficiency alerts and remedies.

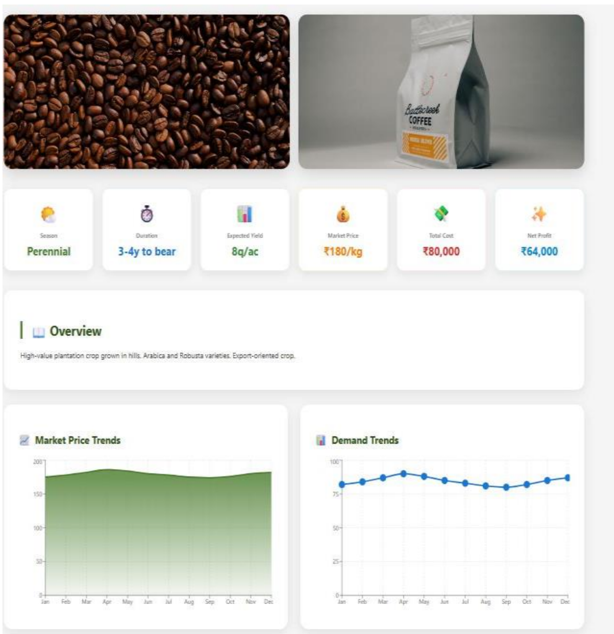

Fig. 6. Detailed crop information page with cost, profit, and market trend charts.

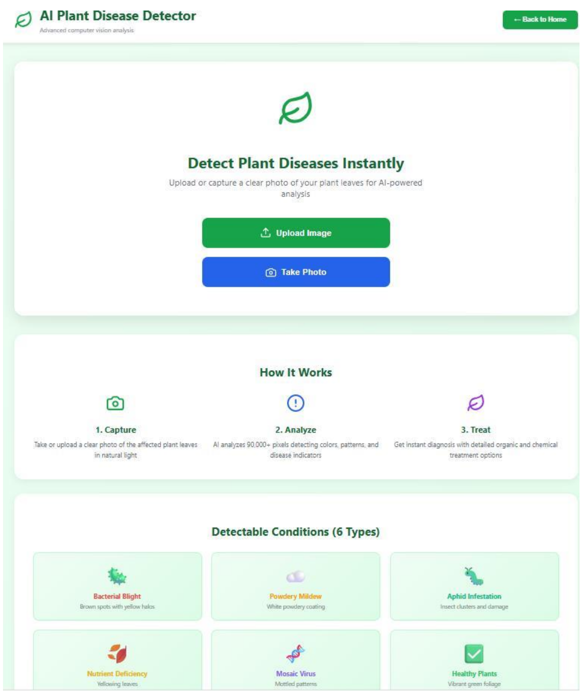

Fig. 7. AI-based plant disease detection module.

VI. APPLICATIONS

- Crop recommendation support for individual farmers to improve yield and reduce input waste.
- Scientific advisory support for agricultural extension officers in rural regions.
- Soil health assessment and fertilizer planning at the farm or field level.
- A teaching tool for agriculture and data-science students to study applied ML and XAI.
- A recommendation module embeddable within larger precision-agriculture or smart-farming platforms.

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VII. CONCLUSION AND FUTURE SCOPE

This paper presented AgriSmart, a cloud-enabled, explainable, multi-criteria crop recommendation system that unifies Random Forest-based prediction, TOPSIS multi-criteria ranking, and SHAP explainability within a responsive React.js interface. Unlike prior single-output or black-box advisory tools, AgriSmart provides a ranked list of suitable crops with transparent, feature-level explanations and an actionable soil health report. Evaluation across representative soil and weather inputs shows that the system delivers fast, consistent, and interpretable recommendations. Future work includes integrating live weather APIs and IoT-based soil sensors, expanding the crop and regional dataset, adding satellite-based climate forecasting, and developing a dedicated mobile application to widen accessibility for rural farmers.

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