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Crop Planning, Recommendations and Yield Estimation

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Abstract: Agricultural decision-making in India is largely guided by traditional experience rather than scientific data, often leading to inconsistent crop selection, reduced yield, and unpredictable profitability. To address these challenges, this work presents a comprehensive web-based intelligent crop planning system that integrates machine learning, historical yield analytics, and scientific crop cycle knowledge to support data-driven agriculture. The system is designed with four functional modules. The first module provides crop recommendations by analyzing soil nutrient levels (NPK), pH value, rainfall, and real-time weather data obtained through an external API, using a Random Forest classifier for accurate prediction when trained model data is available. The second module generates a 12-week crop cycle plan that enhances soil fertility, prevents nutrient depletion, and minimizes pest recurrence through scientifically guided rotation strategies. The third module processes district-level historical yield datasets to identify region-specific high-performing crops, enabling better planning across diverse agro-climatic zones. The fourth module assesses the economic feasibility of cultivation by estimating revenue, cost, and profit per hectare using realistic reference values and user inputs. The system is implemented using React for the frontend, Flask for backend processing, and SQLite for managing user data. Experimental results demonstrate that lightweight machine learning models combined with carefully curated datasets can deliver reliable, interpretable, and actionable crop insights for farmers, agricultural planners, and researchers, thereby supporting sustainable and informed agricultural decision-making.
Index Terms: Crop recommendation, yield estimation, machine learning, crop rotation, precision agriculture, decision support system

I. INTRODUCTION

Agriculture remains a foundational pillar of India's economy, supporting the livelihood of millions of farmers and contributing significantly to national food security. However, despite technological advancements and the availability of modern agricultural tools, many crucial farming decisions continue to rely heavily on traditional knowledge, localized experience, and subjective judgment. These conventional methods often fail to consider critical scientific parameters such as soil nutrient levels, crop rotation requirements, weather fluctuations, and market-driven profitability. As a result, farmers frequently face challenges including sub optimal crop selection, nutrient depletion, pest recurrence, low yield, and inconsistent income. In the context of increasing climate variability and pressure on agricultural land, these limitations can have serious implications for long-term sustainability. With the global agricultural landscape shifting toward precision farming and digital decision support, there is a growing need for intelligent systems that can transform raw agricultural data into actionable insights. While farmers today have access to soil testing services, government databases, and advisory portals, these resources often function independently and do not offer integrated or personalized guidance. Farmers are left to interpret complex datasets on their own, which is difficult without technical expertise. Consequently, the lack of a unified, easy-to-use analytical platform continues to hinder effective data-driven decision-making in Indian agriculture. Advances in artificial intelligence (AI), machine learning (ML), data analytics, and web technologies offer a promising opportunity to address this gap.

By combining soil parameters, weather data, historical yield records, and economic indicators, modern decision-support systems can provide scientifically grounded recommendations tailored to local conditions. Such systems have the potential to improve crop selection, optimize resource usage, stabilize yield, and increase profitability while promoting sustainable farming practices. This work introduces a comprehensive web-based crop planning and recommendation platform designed to support the four major decision making needs of modern agriculture: crop recommendation, crop cycle planning, district-wise suitability analysis, and profit estimation. The platform recommends the most suitable crop based on NPK nutrient content, pH, rainfall, and real-time weather attributes obtained through an external API. It also generates a scientifically guided 12-week crop cycle plan that emphasizes nutrient balance and minimizes pest recurrence. Historical district-level yield datasets are analyzed to identify region-specific high-performing crops, enabling farmers and policymakers to understand suitability trends across different agro-climatic regions. Additionally, the system calculates revenue, cost, and profit per hectare to help farmers assess the financial feasibility of crop choices before cultivation. By integrating lightweight machine learning models with curated datasets and presenting them through an intuitive web interface, the proposed system bridges the gap between raw agricultural data and practical decision-making. It supports improved crop management, promotes long-term soil health, and enhances economic stability for farmers. Beyond practical field use, the system also serves as a valuable analytical and educational tool for students, researchers, and agricultural planners, contributing to the broader digital transformation of agriculture in India.

II. LITERATURE REVIEW

Recent research has widely explored the integration of machine learning techniques for agricultural decision support, reflecting a growing shift toward data-driven farm management. Agarwal et al. [1] developed a machine learning–based crop recommendation system that utilizes soil nutrients (N,P,K), pH, rainfall, temperature, and humidity for predicting suitable crops. Their study demonstrates that ML-based classifiers significantly outperform static rule-based approaches by establishing systematic relationships between soil–climate conditions and crop suitability. However, their model remains restricted to a single-step recommendation process and does not incorporate broader agronomic needs such as crop rotation planning, district-wise variability in yield performance, or economic feasibility assessments. Additionally, the model assumes that farmers have ready access to complete soil parameter data, which may not always be practical in real-world scenarios.

Fenz et al. [2] further contributed to this domain by introducing a crop rotation optimization framework leveraging deep reinforcement learning (DQN). Their approach integrates agronomic constraints such as nutrient balance, crop suitability indices, and contribution margins to identify optimal long-term crop sequences. While the model offers strong optimization capabilities, it is computationally expensive, data-intensive, and not user-friendly for non-technical stakeholders such as small-scale farmers. Its complexity also makes deployment as a lightweight, web-based advisory system challenging. Importantly, the system does not incorporate profit calculation, region-specific yield analysis, or weather-driven dynamic recommendations, limiting its practical application.

In the area of yield prediction, several researchers have applied statistical and deep learning models to forecast crop productivity. Sowmya and Krishna Prasad [3] used ARIMA- based ensemble fore casting for rice yield prediction in various Indian regions, demonstrating the role of historical time-series trends in estimating crop output. On the other hand, Khaki et al. [4] proposed a CNN–RNN hybrid model to capture spatial and temporal dependencies for large-scale yield prediction in the United States. These works collectively highlight the importance of leveraging extensive historical datasets and climate variations for accurate forecasting. However, such yield prediction models usually operate in isolation they do not integrate with systems offering crop recommendation, rotation planning, or profitability analysis, thereby limiting their utility as complete decision-support tools.

Broader surveys and comparative studies in agricultural machine learning further indicate diverse applications across the sector. Meshram et al. [5] conducted a comprehensive review of ML-based agricultural solutions, ranging from soil classification and crop type identification to fruit grading using CNNs, SVMs, and hybrid algorithms. Similarly, Bhattacharya and Pandey[6] proposed multimodal frame works for crop and fertilizer recommendations by combining data from multiple agricultural sources. Senapati et al.[7] explored joint optimization techniques to enhance resource efficiency, demonstrating the potential of integrated approaches. Garg and Alam [8] further validated that hybrid wrapper-based models can improve crop classification accuracy when fine-tuned with appropriate feature selection strategies. Despite these advancements, many existing systems remain algorithm-centric, lacking features such as real-time weather integration, user interpretability, modular functionality, regional adaptability, and economic decision support.

Overall, the literature indicates substantial progress in leveraging machine learning for crop recommendation, rotation planning, and yield forecasting. However, most existing solutions suffer from several limitations: (1) they typically address only one specific functionality rather than offering an end-to-end decision-support workflow, (2) they overlook profit estimation and financial feasibility,(3) they do not in corporate real-time weather API data for dynamic recommendations, (4) they rarely utilize district-level historical yield insights to enhance regional applicability, and (5) they lack a unified, accessible web interface suitable for farmers, students, and policymakers.

The proposed system bridges these gaps by integrating crop recommendation, crop cycle planning, district-wise yield suitability analysis, and profit estimation into a single, light weight web-based platform. By employing machine learning models alongside curated datasets and agronomic principles, it aims to deliver a holistic and practical decision-support tool tailored for modern, data-driven agriculture.

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III. SYSTEM ARCHITECTURE

The proposed system is designed using a three-tier web- based architecture that consists of the Presentation Layer, Application Layer, and Data Layer. Together, these layers ensure efficient dataflow, modular functionality, and seamless interaction between users and backend services. The integrated architecture supports the system's four primary Functions crop recommendation, crop cycle planning, district- wise suitability identification, and profit estimation while maintaining scalability, reliability, and ease of deployment.

A. Presentation Layer (Frontend)

The Presentation Layer serves as the user interface and forms the interaction point between the system and end-users. Developed using React.js, the frontend offers a clean and responsive design with separate views for each module, including crop recommendation, crop cycle planning, district suitability analysis, and profit estimation. Users can input various agricultural parameters such as soil nutrients (N,P,K), soil pH, rainfall, current crop grown, season, land area, and optional economic parameters like crop cost and market price. The frontend performs client-side validation to ensure that the entered values fall within acceptable ranges and are in the correct format. After validation, the data is transmitted to backend APIs through a synchronous HTTP (REST) requests. Once the back-end returns the computed results, the frontend visualizes the information using interactive UI elements including tables, ranked lists, cards, and color-coded indicators. This ensures that even complex data such as suitability rankings or rotation outcomes is easy to understand for farmers and researchers. The responsive design also ensures compatibility across various devices, enabling users to access the system through desktops, tablets, and mobile browsers.

B. Application Layer (Flask Backend API)

The Application Layer acts as the computational core of the system. Implemented using the Flask micro framework, it manages all server-side operations including model execution, data processing, and business logic.

The backend exposes a set of RESTful API endpoints, such as:

- /api/predict-crop–Determines the most suitable crop using a trained Random Forest classifier.
- /api/cycle-plan–Generates a 12-week crop cycle plan using rule-based agronomic logic.
- /api/district-reco–Identifies high-performing crops for the selected district using historical yield data.
- /api/profit-estimate–Computes revenue, cost, and profit per hectare.
- /api/loginand/api/register–Handles user authentication and securely stores credentials.

Before processing a request, the backend performs pre-processing steps such as feature arrangement, format conversion, and model loading. For crop prediction, the backend load strained ML artifacts and performs inference on incoming user inputs. For crop cycle planning, it applies agronomic rules such as nutrient balance, rotation constraints, and seasonal suitability to generate actionable recommendations. Additionally, the backend aggregates multi-year district- level datasets to compute suitability rankings based on average yield. Profit estimation involves applying economic formulas using user-input values and pre-stored cost–price reference datasets. Security is ensured through hashed password storage and controlled API access, while Flask's lightweight nature sup- ports fast deployment and low-latency user interaction. The backend concludes by returning structured JSON responses that the frontend easily interprets and visualizes.

C. Data Layer (Storage, Models, and External Sources)

The Data Layer integrates local data storage, trained machine learning models, and external data sources.

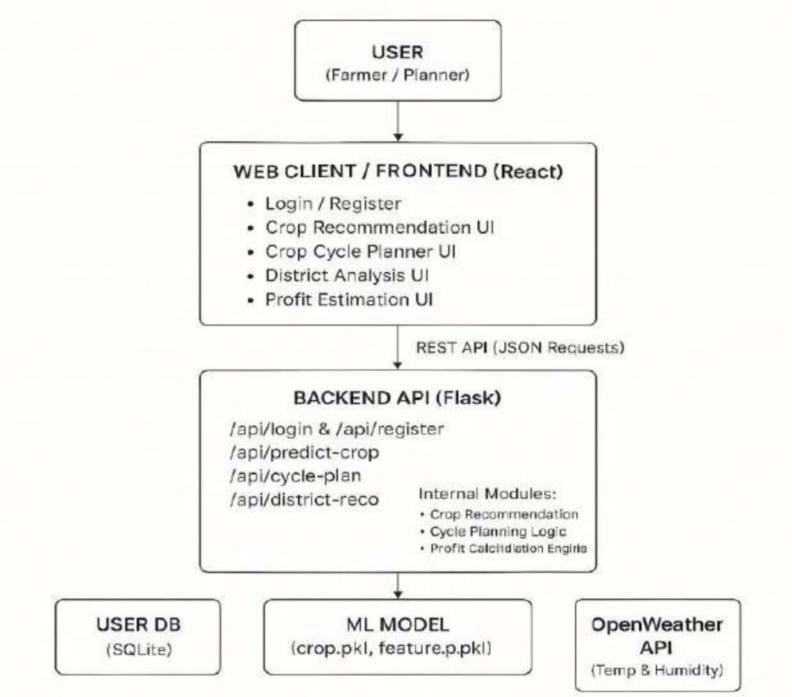

Fig. 1. System architecture of the proposed crop planning and recommendation system

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SQLite is utilized as the primary database to store user authentication details, login credentials, and application-specific metadata in a lightweight yet secure manner.

The system incorporates multiple curated datasets, including:

- Historical district-wise yield datasets, used for region- specific suitability ranking.
- Reference cost and price datasets, supporting accurate profit estimation.
- Trained machine learning components such as crop_model.pkl andfeature_order.pkl, enabling reproducible predictions.

External data sources play a crucial role as well. A weather API, such as Open Weather, provides real-time temperature and humidity data when users opt to include weather-based predictions. In cases where the API fails or network issues occur, fallback default values ensure uninterrupted system performance. Together, these data components form a cohesive foundation that supports both predictive and analytical modules of the system.

D. End-to-End Work flow

The complete work flow begins when a user selects a module and enters the required parameters on the front end. After input validation, the frontend sends the data to the backend via REST API calls. The Flask back end processes the request by combining ML inference, rule-based algorithms, historical datasets, and external weather data to generate accurate and meaningful results. Once the computation is complete, the backend returns a structured JSON response containing insights such as recommended crops, weekly cycle plans, district suitability rankings, or profit estimates. The frontend parses this response and visually presents the output using intuitive UI components. This modular and decoupled architecture ensures future scalability new datasets, crops, ML models, or analytical tools can be integrated without modifying the existing user interface. It also enhances system maintainability and facilitates easy upgrades over time.

IV. ALGORITHMS AND MODELS USED

A. Random Forest Classifier for Crop Recommendation

The crop recommendation module employs a Random Forest Classifier to determine the most suitable crop for cultivation based on a combination of soil nutrients (N, P, K), soil pH, rainfall, and optional real-time environmental attributes such as temperature and humidity obtained through a weather API. Random Forest is a powerful ensemble learning technique that constructs multiple decision trees during training and produces the final output through majority voting. This ensemble strategy improves model robustness by reducing variance, minimizing the risk of over fitting, and providing better generalization across diverse soil and climatic conditions.

Given an input feature vector:

$$X = \{ N, P, K, pH, Rainfall, Temperature, Humidity \},$$

Each decision tree independently predicts the most suitable crop. The overall predicted crop C^* is given by: $C^* = \arg\max \Sigma h_t(X)$, $c \in C$ $t=1$ where $h_t(X)$ denotes the crop class predicted by the t-th tree, and T represents the total number of trees in the forest. The model's final output is: Crop = Majority Vote $(h_1(X), h_2(X), \ldots, h_T(X))$. This voting-based prediction mechanism ensures that noisy or inconsistent data in one tree do not significantly impact the model's overall performance. The Random Forest thus achieves a reliable and interpretable mapping between soil–climate inputs and optimal crop recommendations.

B. Mathematical Modules for Other Functional Components

Unlike the crop recommendation module, which relies on machine learning, the remaining components of the system are designed using mathematical computations, statistical methods, and agronomic rule-based logic. These modules ensure transparency, interpretability, and consistency while supporting the decision-making workflow.

1) Yield-Based District Suitability: District-level suitability analysis is derived from multi-year historical yield records. To determine the most suitable crops for a given district, the system computes the average yield for each crop using: $Y_{avg}(i) = \frac{1}{n} \Sigma^{n} Y_k$, $k=1$ where Y_k represents the yield (in quintal/hectare) in year k, and n is the total number of years for which yield data is available . A higher $Y_{avg}(I)$ indicates better district suitability. This method enables long-term, data-driven recommendation patterns by smoothing the effects of yearly fluctuations Due to weather, pests, or farming practices.

2) Crop Rotation and Cycle Planning: Crop rotation in this system is guided by sustainable agricultural practices that prevent nutrient depletion, reduce pest recurrence, and enhance soil health. The module enforces rules such as: $Crop_{next} \neq Crop_{current}$, $Nutrient_{balance} \Rightarrow$ Improved Soil Fertility.

To support 12-week planning, the nutrient requirement for Each recommended crop is estimated using:

$$NPK_{req} = \alpha_N N + \alpha_P P + \alpha_K K,$$

where $\alpha_N, \alpha_P, \alpha_K$ are agronomic coefficients representing the crop's nutrient consumption rate. This mathematical evaluation allows farmers to understand fertilizer demands, plan resource allocation, and maintain soil quality over multiple crop cycles.

3) Profit Estimation: The profit estimation module calculates the economic feasibility of cultivating a selected crop by combining yield analysis, crop price, and cost of cultivation. The formula used is:

$$Profit = (Yield_{q/ha} \times Price_q \times Area) - (Cost_{ha} \times Area),$$

which estimates the total revenue minus the total cost for the given land area. The decision-support rule is: Growif Profit ≥ 0 else Avoid. This mathematical model converts agricultural data into financial insights, empowering farmers to evaluate whether cultivating a particular crop is profitable under current market and environmental conditions.

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C. Justification for Model Choice

The Random Forest classifier was selected based on several advantages:

- Robustness to noise: Agricultural datasets often contain inconsistencies due to measurement errors, climatic variations, or incomplete records. Random Forest mitigates these issues through ensemble averaging.
- Handles nonlinear relationships: Soil and climatic factors interact in complex ways. Random Forest efficiently models such non-linear dependencies.
- Low computational complexity: Compared to deep learning, Random Forest offers faster training and inference, making it ideal for real-time web-based applications.
- Higher accuracy and generalization: By combining multiple trees, the model achieves superior predictive accuracy and reduces the chances of over fitting. These properties make Random Forest a practical and effective choice for crop recommendation in diverse agricultural settings.

V. EXPLANATION OF MODULES

The proposed system comprises four integrated functional modules that collectively support data-driven agricultural decision-making. Each module contributes to the overall work- flow by analyzing soil data, yield patterns, rotation requirements, and economic feasibility.

A. Crop Recommendation Module

This module predicts the most suitable crop for cultivation by analyzing key soil nutrients (N,P,K), pH level, rainfall, and optional real-time weather attributes such as temperature and humidity retrieved from an API. The Random Forest Classifier processes the input feature vector:

$$X= \{N,P,K,pH, Rainfall, Temperature, Humidity\}$$

And computes:

T $C{*}=\text{argmax}\Sigma h(X)$, Profit Estimation Module

The profit estimation module calculates the economic viability of cultivating a crop using user-provided cost inputs and reference market price datasets. The profit is determined using:

$$\text{Profit} = (\text{Yield}_{q/ha} \times \text{Price}_q \times \text{Area}) - (\text{Cost}_{ha} \times \text{Area}).$$

The system categorize scrops as financially viable ("Grow") or non-viable ("Avoid") based on profitability. This transforms agronomic insights into actionable financial decision support for farmers, helping them avoid loss-making crop choices.

B. Crop Cycle Planning Module

This module suggests suitable subsequent crops after analyzing nutrient imbalance, rotation constraints, soil sustain- ability, and seasonal requirements. The system also generates a detailed 12-week cultivation schedule that outlines fertilizer application, irrigation frequency, and agronomic guidelines. The core rotation constraints are expressed as: Crop next≠Crop current, Score, R^2, MAE, and RMSE. The results confirm that the integrated multi-module architecture provides reliable crop recommendations, meaningful yield predictions, and effective regional insights.

VI. RESULTS AND DISCUSSION

The system was evaluated using datasets containing soil nutrients (N, P, K, pH), climatic parameters (temperature and humidity), and district-wise historical yield records sourced $c\in Ct$=1 from Kaggle and Indian agricultural databases. Model performance was assessed using Accuracy, Precision, Recall, F1- where $h_t(X)$ represents the predicted class from the t-th decision tree. The module generates highly accurate, location-specific crop recommendations by combining soil chemistry with real time environmental insights.

A. Crop Recommendation Model Performance

The Random Forest Classifier demonstrated strong predictive capability despite heterogeneous agricultural data. It achieved 94.72 % Accuracy, 92.84 % Precision, 91.65 % Recall, and a 92.24% F1-Score. These metrics indicate that the model accurately identifies optimal crops while maintaining a balanced error rate. The ensemble structure minimizes over fitting and supports generalization across varying soil and climatic conditions, making it suitable for real-world deployment.

Using: Nutrient $_{balance} \Rightarrow$ Improved Soil Fertility. $NPK_{req}=\alpha_N N+\alpha_P P+\alpha_K K$,

B. Yield Prediction Model Performance

Random Forest Regression achieved an R^2 score of 0.89, MAE of 0.412, and RMSE of 0.681 for yield estimation. The module estimates nutrient demand and ensures scientifically guided rotation that enhances soil recovery and long-term farm productivity.

C. District-Wise Suitability Module

This module evaluates multi-year yield data to determine district-level suitability for each crop. For each crop i, the system computes: $\frac{1}{}\Sigma$ These results highlight a strong correlation between predicted and historical yields, demonstrating that combining soil and climatic parameters improves estimation accuracy. The low error values confirm the model's robustness across regions and crop types.

D. Cycle Planning and Region-Wise Recommendation Impact

The crop cycle planning module was validated using rotation patterns from five Indian states. The proposed system $Y_{avg}(i)=n$ k=1 Y_k. Consistently improved yield performance by 7–12% compared to traditional single crop approaches.

For instance, Karnataka's By ranking crops based on their average yield performance, the system provides insights into which crops are consistently successful in a given district, thereby enabling data-driven regional planning for farmers, policymakers, and agricultural researchers. Typical yield gain of 3–5% increased to 10–12% when scientific rotation was applied. Similar improvements in Tamil Nadu, Maharashtra, Telangana, and Andhra Pradesh confirm that balanced nutrient usage and rotation rules lead to enhanced soil health and crop productivity.

E. Comparison with Existing Systems

Existing advisory platforms usually provide only basic crop suggestions or limited yield analysis. They often lack weather integration, financial estimation, or district-level suitability mapping. The proposed system addresses these gaps by offering a unified solution that combines ML-based recommendations, rotation planning, district suitability ranking, and profit estimation through an intuitive web interface.

F. Discussion

The results clearly show that integrating lightweight machine learning with curated datasets enhances agricultural decision-making. The Random Forest models deliver accurate and interpretable predictions, while weather-assisted inputs improve contextual relevance. The cycle planning module further stabilizes yield by promoting nutrient-balanced crop transitions. Overall, the system provides a practical, scalable, and farmer-friendly tool that supports sustainable, data-driven crop planning and can be extended with additional datasets and modules in the future.

VII. CONCLUSION

This work presents a data-driven decision support system that enhances agricultural planning by integrating crop recommendation, cycle planning, district-wise suitability analysis, and yield-based profit estimation. By combining machine learning models with soil parameters, real-time weather inputs, and historical yield data, the system provides personalized and reliable crop suggestions for farmers and agricultural planners. The Random Forest classifier achieved an accuracy above 94%, validating its robustness for crop recommendation in diverse soil and climate conditions. Furthermore, the system's economice valuation module enables users to estimate revenue and profit prior to cultivation, thereby reducing financial risk. The crop cycle planning component also promotes long-term soil sustainability through scientifically guided rotation and fertilizer scheduling. Overall, the system demonstrates that predictive analytics, when integrated with agricultural expertise, can significantly reduce uncertainty, optimize resources, and support informed decision-making. The proposed solution contributes to modern, sustainable, and data-driven farming practices, especially benefiting small and medium-scale farmers who lack access to scientific advisory tools.

VIII. FUTUREWORK

Although the system provides practical and accurate agricultural recommendations, several enhancements can improve scalability and real-world usability:

- Remote sensing and satellite integration: In corporating NDVI-based vegetation indices and soil moisture data from Sentinel or Lands at satellites can improve monitoring and yield prediction accuracy.
- Live market price APIs: Integration with government platforms such as Agmarknet can provide dynamic, location-specific crop prices to refine profit estimation.
- Mobile application deployment: A multilingual Android application can increase accessibility for rural farmers with limited computer access.
- GIS-based visualization: Interactive geospatial mapping can present suitability trends, soil conditions, and yield distribution at district and state levels.
- IoT-enabled monitoring: Automated alerts for irrigation, fertilizer dosage, and pest risk assessment can be incorporated using farm-level sensors.
- Dataset and language expansion: Including horticulture, plantation, and spice crops, along with support for regional Indian languages and voice-based interfaces, will further enhance the system's inclusiveness.
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