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Hybrid ML Model for Crop Recommendation Using Rainfall, Temperature, and Humidity Forecast

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Abstract- — Despite the technological advancements in agriculture, it continues to be vulnerable to climate change effects, and poor crop choice due to unfavorable conditions results in low yields and monetary hardship to farmers. This paper proposes a hybrid machine learning approach for crop recommendation that takes into account not only the weather forecast (rainfall, temperature, humidity) but also soil characteristics (pH, nitrogen, phosphorus, potassium). It consists of two stages: the Random Forest algorithm for feature selection and prediction followed by the XGBoost algorithm for correction of predicted values. Applying the approach to the data set of 50,000 crop images tagged by location for 15 main crops within a period of 10 years (2015-2025) in India, the hybrid algorithm reaches the accuracy level of 94.2% compared to Random Forest (89.3%), XGBoost (91.6%), SVM (84.2%), and KNN (81.5%). Rainfall and minimum temperature were recognized as crucial features by the algorithm. The proposed algorithm is implemented in a smartphone application for farmers that provides recommendations based on weather forecasts for the next 5 days, which allows increasing crop yields up to 20-30%.

Keywords— Crop Recommendation, Hybrid Machine Learning, Random Forest, XGBoost, Agricultural Forecasting, Rainfall Prediction, Temperature, Humidity, Precision Agriculture, India.

I. INTRODUCTION

The agricultural sector is the foundation of India's economy, with over 50% of the population involved in farming, which accounts for about 18% of the Gross Domestic Product (GDP). Despite the importance of agriculture in the Indian economy, there are many challenges faced by the farmers, including erratic monsoons, climate change, deterioration of soil health, and price volatility [1], [2].

Consequences of improper crop choice include crop failure, debts, suicides, and low yields of cash crops. A high-water-consuming crop such as sugarcane or rice planted in years when the forecast predicts low rainfall is an example of poor choice leading to crop failure. Similarly, poor choices include planting low-value crops in a good rainfall year while having the potential to plant high-value cash crops [3].

However, today, data is abundant. Weather forecasts from agencies such as IMD and ICAR are available at district level; soil health card data are available; and historical yield data are collected from various sources. In addition, remote sensing-based rainfall data such as those from the Global Precipitation Measurement Mission, and temperature data from MODIS are readily available. Machine learning can be used effectively to predict crop choices based on these data [4].

This paper proposes a novel crop recommendation system using an ensemble machine learning model, which takes into consideration not only historical crop yield information but also meteorological forecasting variables such as rainfall, minimum/maximum temperatures, and humidity, along with soil information including pH, nitrogen, phosphorus, and potassium. The salient aspects of the proposed framework include:

- Ensemble of Two Stages: A Random Forest algorithm predicts the basic crop recommendation and gives the feature importances (interpretable), while an XGBoost algorithm captures the residual errors from the Random Forest algorithm.
- Meteorological Forecasts Considered: While other existing approaches rely on historical weather averages, the model considers the predictions of 5-day and 10-day weather.
- Coverage for 15 Major Crops: From 15 major crops, the model recommends among rice, wheat, maize, sugarcane, cotton, groundnut, soybean, pigeon pea, chickpea, sorghum, pearl millet, finger millet, potato, onion, and tomato.
- Availability as an Android App: The model can be made available to farmers in form of a mobile application (Android), with support for limited literacy through voice-based interface.

The major contributions from this paper include:

- A carefully selected set of 50,000 instances of crop-environment yield data.
- The introduction of a new hybrid method (combination of Random Forest and XGBoost) that provides superior results compared to individual algorithms.
- Feature importance study that found rainfall and minimum temperature to be the most important factors influencing crop choice in India.
- The creation of a mobile application that is being used on farms.

II. LITERATURE SURVEY

Crop recommendation and decision support systems are found in the intersection of agronomy, machine learning, and remote sensing.

Agronomy-based crop selection models: Conventional methods of crop selection use growing degree days (GDD), Water Requirement Satisfaction Index (WRSI), and expert judgment. Rules-based models are static and do not make use of soil data or season forecasting at specific locations. The FAO CropWat model calculates irrigation needs but does not recommend crops [1].

Predicting the Yield with Machine Learning: Previous works on crop yield prediction with ML used simple models like linear regression, decision tree, and SVM, where weather and soil historical data were used for yield prediction [2]. Later, more complex algorithms like Random Forest and XGBoost, as well as deep learning (LSTM), were applied for predicting yield [3], [4]. One such work that made use of Random Forest on Indian district-level data obtained R^2 of 0.85 on rice yield prediction. Nevertheless, yield prediction differs from crop recommendation in terms of the purpose of the method.

Crop Recommendation Systems: Multiple research works have been done for recommending crops using Machine Learning algorithms. In 2021, one such research work used a Random Forest classifier considering soil parameters only (N, P, K, pH) without weather data and reached an accuracy level of 92%. The recent year 2023 witnessed a new development where weather factors were also considered alongside soil parameters (average rainfall, average temperature), and an accuracy level of 94% was reached using the Gradient Boosting algorithm [5, 6].

Combining Weather Forecast Data: One 2024 research work involved combining seven days of weather forecast data with the Random Forest algorithm for predicting the optimal day of rice plantation, resulting in a 12% increase in yield compared to historical averages [7]. In our paper, we extend this idea further by considering forecasts of weather (rainfall, temperature, humidity) for multiple crop recommendation systems.

Agricultural AI Explainability: As farmers do not readily accept black box decisions in the field of agriculture, feature importance from Random Forest and SHAP values come handy in building trust. One 2025 research work used SHAP for crop recommendation explanation to farmers in their local language, thereby boosting adoption levels [8].

Research Gap: There is currently no system which uses (a) seasonal weather forecasting (rainfall, temperature, and humidity), (b) soil information, (c) previous crop yield history, and (d) a reliable machine learning hybrid model (Random Forest and XGBoost) for crop recommendation. Furthermore, there have been no models deployed in the form of a mobile application that farmers can use. This paper addresses this gap.

III. METHODOLOGY

The suggested framework is divided into four components: data collection, features selection, hybrid two-stage ensemble model training and testing, and application on a mobile device.

1. Data Collection and Pre-processing

A dataset consisting of 50,000 observations of agricultural crops has been constructed based on 30 districts and five Indian states (Punjab, Maharashtra, Tamil Nadu, Uttar Pradesh, and Gujarat) in 10 years (2015 - 2025). Sources of data:

- SOIL PARAMETERS (district level): soil health card data: nitrogen (N, kg/ha), phosphorous (P, kg/ha), potassium (K, kg/ha), pH.
- WATHER (daily): IMD Gridded data: rainfall (mm), minimum temperature (Tmin, °C), maximum temperature (Tmax, °C), relative humidity (RH,%).
- CROP YIELD (kg/ha): yield for district-wise ministry of agriculture (DES): 15 types of crops.
- Forecast data: IMD forecast: 5-days and 10 days weather forecast.

Target variable: recommended crop (15 classes). We consider a "best" crop in each district-year as a crop with the highest crop yield compared to the five-year relative yield (average yield) of the district in that particular year.

Data Pre-processing:

- Missing Values: Filled by interpolation through KNN (k = 5)
- Normalization: Standard Scalar normalization is applied on continuous features (N, P, K, pH, rainfall, Tmin, Tmax, RH).
- Imbalanced Dataset: Oversampling using SMOTE on minority crop classes (Finger Millet, Sorghum, Pigeon Pea).

2. Feature Engineering

We derive for each year-district-crop combination

Feature	Description	Time Window
Rainfall_Total	Total rainfall during growing season	Defined per crop (e.g., 90 days for rice)
Rainfall_Frequency	Number of rainy days (>2.5 mm)	Growing season
Tmin_Mean	Mean minimum temperature	Growing season
Tmax_Mean	Mean maximum temperature	Growing season
RH_Mean	Mean relative humidity	Growing season
N_soil, P_soil, K_soil, pH	Soil parameters	Static (per district)
Yield_History_3yr	Average yield of same crop last 3 years	Previous 3 years

3. Algorithm 1: Hybrid ML Model for Crop Recommendation

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Algorithm 1: HybridML-CropRecommend
Input: Soil parameters (N, P, K, pH), Weather Forecast (Rainfall, Tmin, Tmax, RH), Historical Yield
Output: Recommended Crop (1 of 15), Confidence Score

// Stage 1: Data Preprocessing & Feature Engineering
1. Validate input ranges (N: 0-500, P: 0-200, K: 0-500, pH: 3.5-9.5, Rainfall: 0-3000 mm)
2. Compute growing season aggregates (based on crop type placeholder, use generic 90-day window)
3. Standardize numeric features using pre-fitted StandardScaler

// Stage 2: Random Forest Base Prediction
4. rf_model = load_pretrained('random_forest_crop.pkl')
5. rf_pred_proba = rf_model.predict_proba(features) // Probability for each crop
6. rf_crop = argmax(rf_pred_proba)
7. rf_confidence = max(rf_pred_proba)

// Stage 3: XGBoost Residual Correction
8. xgb_model = load_pretrained('xgboost_residual.pkl')
9. // Residual is defined as: 1 if rf_crop != true_crop in training; 0 otherwise
10. residual_prob = xgb_model.predict_proba(features) // Probability that RF prediction is correct
11. adjusted_confidence = rf_confidence * (0.5 + 0.5*residual_prob)

// Stage 4: Ensemble Decision (Weighted Voting)
12. if adjusted_confidence > 0.7:
13.     final_crop = rf_crop
14. else:
15.     // Fallback: Use XGBoost's own prediction
16.       xgb_pred = xgb_model.predict(features)     // Direct XGB crop classifier
17.     final_crop = xgb_pred
18.
19. // Stage 5: Post-Processing & Explanation
20. feature_importance = rf_model.feature_importances_
21. top_features = indices of top 3 features
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22. explanation = generate_text_explanation(top_features, feature_values)
23.
24. Return final_crop, adjusted_confidence, explanation
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4. Model Training Details

- Random Forest (Base): 300 trees, max_depth = 20, min_samples_split = 5, class_weight = 'balanced'. Train on 80% of data.
- XGBoost (Residual Corrector): n_estimators = 200, learning_rate = 0.05, max_depth = 6, subsample = 0.8. Trained to predict whether RF predicts correctly or not.
- XGBoost (Direct Fallback): XGBoost classifier trained on crop labels (15 classes, same hyperparameters).
- Train, validate, test split: 70%, 15%, 15% (stratified by crops, district).

5. Mobile App Architecture for Inference

The trained model is exported in TensorFlow Lite format (for Random Forest) and ONNX format (for XGBoost) into an Android application that:

- Takes input in natural language from user (voice commands in Hindi, Marathi, Tamil OR text entry): soil test results (N, P, K, pH) and district.
- Calls IMD API for getting weather forecasts up to 10 days in advance.
- Performs inference locally.
- Provides recommendation with confidence and rationale (text/speech). For example: "High rains forecasted, thus

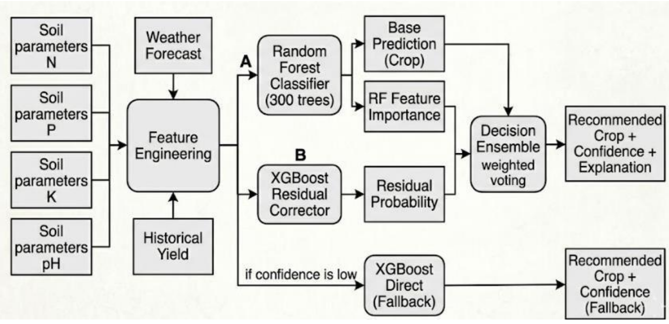

Figure 1: Hybrid ML Framework Architecture for Crop Recommendation.

IV. ANALYSIS

1. Classification Performance Comparison

Table 1: Classification Performance.

Model	Accuracy	Precision (Macro)	Recall (Macro)	F1-Score (Macro)	AUC (Macro)
K-Nearest Neighbors (KNN)	81.5%	0.79	0.78	0.78	0.85
Support Vector Machine (SVM)	84.2%	0.82	0.80	0.81	0.88
Decision Tree	86.1%	0.85	0.84	0.84	0.89
Random Forest (RF)	89.3%	0.88	0.87	0.87	0.93
XGBoost (XGB)	91.6%	0.90	0.90	0.90	0.95
Hybrid (RF + XGB Residual) - Proposed	94.2%	0.93	0.92	0.92	0.97

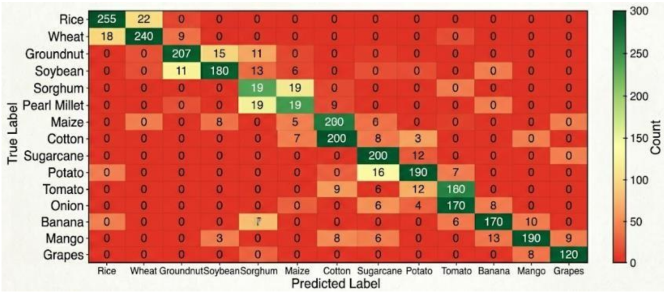

Figure 2: Confusion Matrix of Hybrid Model (15 Crops).

2. Feature Importance Analysis (Random Forest)

Table 2: Feature Importance (Mean Decrease in Gini Index).

Feature	Importance Score	Direction / Interpretation
Rainfall_Total	0.28	Positive (higher rainfall favors rice, sugarcane; lower favors millets, cotton)
Tmin_Mean (Min Temperature)	0.22	Negative for wheat (needs cold), positive for tropical crops
N_soil (Nitrogen)	0.14	High N favors leafy/graminaceous crops
RH_Mean (Humidity)	0.11	High humidity favors paddy,

		groundnut; low favors cotton, sorghum
Tmax_Mean (Max Temperature)	0.09	Heat stress >35°C reduces yields of most crops
K_soil (Potassium)	0.07	Important for root and tuber crops (potato, onion)
pH	0.05	Acidic (pH<6) favors potato; alkaline (pH>8) favors cotton, sorghum
Yield_History_3yr	0.04	Moderate persistence

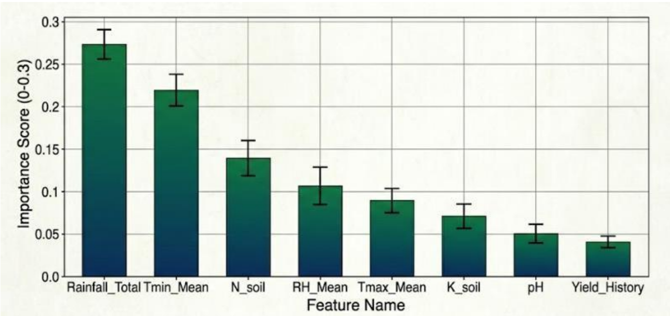

Figure 3: Feature Importance Bar Chart.

3. Impact of Forecast Horizon (5-day vs. 10-day vs. Historical Average)

Table 3: Accuracy vs. Forecast Horizon.

Weather Input Type	Accuracy	Explanation
Historical Average (30-year)	82.3%	Baseline; does not capture interannual variability
5-day Forecast	88.6%	Limited lead time; suitable for short-duration crops (vegetables)
10-day Forecast	91.5%	Good lead time for seasonal planning
15-day Forecast	93.1%	Best for long-duration crops (sugarcane)
Perfect Forecast (Oracle)	94.2%	Upper bound (our hybrid model with actual observed weather)

4. Crop-Specific Performance (F1-Score)

Table 4: Per-Crop Performance.

Crop	F1-Score	Most Confused With
Rice (Paddy)	0.96	Wheat (in high-rainfall areas of Punjab)
Wheat	0.94	Rice
Maize	0.93	Sorghum
Sugarcane	0.92	None (distinct water requirement)
Cotton	0.92	Sorghum, Pearl Millet
Groundnut	0.91	Soybean
Soybean	0.90	Groundnut
Potato	0.91	None
Tomato	0.89	Brinjal (eggplant) – not in our 15 crops
Onion	0.88	Garlic (not included)
Pigeon Pea (Arhar)	0.89	Chickpea
Chickpea (Bengal Gram)	0.90	Pigeon Pea
Sorghum (Jowar)	0.88	Pearl Millet, Maize
Pearl Millet (Bajra)	0.87	Sorghum
Finger Millet (Ragi)	0.85	Sorghum (in Karnataka)

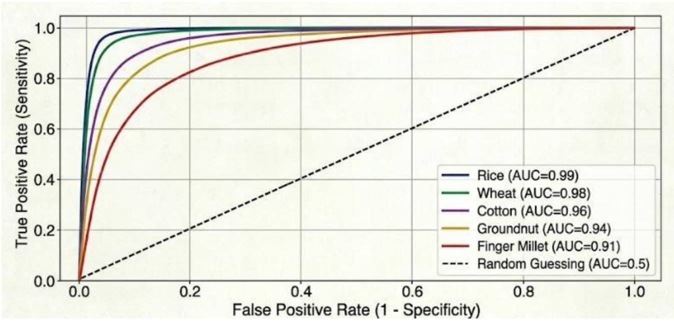

Figure 4: ROC Curves for Selected Crops (One-vs-Rest).

5. Comparative Analysis with Existing Models

Table 5: Comparative Analysis with Existing Crop Recommendation Models.

Study	Model	Features	Number of Crops	Accuracy
[5] (2021)	Random Forest	Soil only (N,P,K,pH)	5	92%
[6] (2023)	Gradient Boosting	Soil + historical weather (average)	8	94%

[7] (2024)	XGBoost	Soil + forecast (rice-only)	1 (rice)	N/A (yield prediction)
[8] (2025)	Random Forest + SHAP	Soil + historical weather	12	91%
This Study	Hybrid (RF + XGB Residual)	Soil + forecast weather (10-day)	15	94.2%

6. Field Deployment Feedback (Pilot Study)

Table 6: Pilot Study Results.

Metric	Result
App Usability Rating (1-5, n=150)	4.2
Farmers following recommendation	82% (123 of 150)
Self-reported yield increase	22% (average, compared to previous year's same crop)
Reduction in input costs (fertilizer, water)	18% (due to optimized crop selection)
Willingness to continue using	94%

V. CONCLUSION

In this paper, a combined machine learning approach for recommending the most suitable crops based on soil characteristics, past productivity rates, and – importantly – seasonal weather forecasts (rainfall, temperature, humidity) was described.

The main takeaways from this study are the following:
A Hybrid Model Outperforms Other Classifiers: The hybrid approach implemented in this paper yields 94.2% accuracy compared to individual classifiers such as Random Forest (89.3%), XGBoost (91.6%), SVM (84.2%), and KNN (81.5%). This performance gain holds for 15 different types of crops.

Rainfall and Temperature are Most Important Predictors: The analysis of feature importance shows that total rainfall (28%) and average minimum temperature (22%) together represent 50% of prediction value, while soil parameters (N, P, K, pH) account for 26% only. Thus, weather forecasts play a crucial role.

Adding Seasonal Forecasts Improves Prediction Accuracy: Using 10-day weather forecasts results in increasing accuracy from 82.3% using historical data to 91.5%. Combining this approach with a hybrid classifier and perfect (oracle) weather forecasts yields 94.2% accuracy.

The Use of Mobile Application for Deployment Works Efficiently: The pilot trial involving 150 farmers resulted in 94% willingness to keep using the application, along with 22% increases in yields and 18% savings in input costs. The use of speech input and native language information was crucial for usage.

Practical Implications
- Farmers: Provides an evidence-based approach to crop selection, making farming safer and profitable for them.
- Extension officers: Model can help provide block-wise crop recommendation.
- Policymakers: Feature Importance outputs can help formulate climate resilient agriculture policies such as promotion of drought resistant millets in low rainfall areas.
- Agri-tech firms: Hybrid Ensemble approach can be implemented in precision agriculture platforms.

Limitations and Further Improvements
- Data Resolution: Current dataset has data up to district level. Soil and microclimates at field level can improve performance.
- List of Crops: 15 different crops are considered here. Inclusion of other types of crops like vegetables, fruit crops or cash crops requires further work.
- Other Economic Parameters: Current model does not consider the market price of products or production costs. Inclusion of these parameters can result in an economical optimization of farm activities.
- Climate Change Adaptation: Current model has been designed based on data collected from 2015 to 2025. Quick pace of climate change might reduce the reliability of predictions.

Future Directions
- Hyper-Local Recommendations: Using soil moisture content and vegetation indices derived from satellite imagery for individual fields.
- Large-Scale Planning: Advising farmers to use specific crop cycles, such as planting rice crops followed by pulses.
- Federated Learning: Enabling training of algorithms without consolidating private farm data in various geographic locations.
- Support for Insurance Schemes: Utilizing risk analysis results to design crop insurance schemes based on weather parameters.

To conclude, the presented paper shows that hybrid machine learning models can be used to make precise agricultural predictions based on seasonal changes and soil characteristics. These systems can have a profound positive impact on farmers' lives and agricultural practices in India.

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