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Crop Recommendation Using Machine Learning

Yadwinder Singh[1], Dr. Amrit Kaur[2]

[1]Department of Computer Science and Engineering, Punjabi University, Patiala, Punjab, India
Email: *yadwinderbains62[at]gmail.com*

[2]Department of Computer Science and Engineering, Punjabi University, Patiala, Punjab, India

Abstract: ***The use of intelligent systems in agriculture has grown quite a bit lately, especially since farmers are dealing with more and more pressure from climate variability, less land availability, and higher productivity expectations all at once. One of the developments that looks particularly promising is the crop recommendation system, it uses machine learning to help farmers figure out what to cultivate, based on their soil nutrient makeup and the surrounding climatic situation. In this area, many methods have been explored for this reason, such as Random Forest, Support Vector Machine, Decision Tree, k-Nearest Neighbor, Artificial Neural Networks, XGBoost, LightGBM , and each tends to show different levels of performance. Still, a lot of existing systems don't fully meet the needs that matter. In the literature you often see things like imbalanced datasets, incomplete preprocessing steps, features that are basically redundant, and weak generalization when the model is moved to new regions. To address these kinds of shortcomings, this study presents a hybrid framework that merges three complementary approaches: Synthetic Minority Oversampling Technique (SMOTE) to handle class imbalance, Random Forest for feature selection (or relevant attribute picking), and XGBoost for the real crop classification activity. A review of 27 studies was conducted to see what performs well, what fails, and where the research gaps actually sit. The input set for the proposed system consists of Nitrogen (N), Phosphorus (P), Potassium (K), soil pH, temperature, humidity, and rainfall. The overall aim is to create a crop recommendation framework that is not only accurate, but also usable in practice and scalable enough to support precision agriculture in the real world.***

Keywords: Crop Recommendation, Precision Agriculture, Machine Learning, kNN, Decision Tree, Random Forest, Agricultural Decision Support System.

1. Introduction

Agriculture is sort of the backbone of many economies, and it stays critically important for keeping food security steady all over the world. At the same time, the whole sector is under more and more pressure. Population growth, odd weather shifts, and the gradual depletion of fertile land are all working together to make it harder to keep crop output stable. In this setting, picking the right crop for a specific season isn't only "important"- it is essential. Get that choice wrong, and the results can be messy: weak yields, squandered inputs, and money losses for the farmer.

For generations, producers have relied on experience and what they can directly see to decide. They would look at what did well in prior years, how the soil seemed, or what local elders would usually recommend. This kind of know-how is useful, but it doesn't really keep up with the complicated side of modern farming problems. Climate changes, soil degradation, and also market conditions that shift all the time call for a more systematic method. And that's exactly where Artificial Intelligence (AI) and Machine Learning (ML) use in [1], [2].

ML-based systems can pick up on patterns across huge data sets- patterns that human observation might simply fail to notice. When they analyze soil nutrient measurements, weather records, and different environmental signals all together, they can generate crop suggestions that match the actual conditions. Research has already looked at many algorithm families for this job, such as Support Vector Machine (SVM), Artificial Neural Network (ANN), Decision Tree (DT), K-Nearest Neighbor (KNN), Logistic Regression (LR), Random Forest (RF), XGBoost, LightGBM, CatBoost, plus various ensemble techniques [3]– [8].

Among those options, ensemble and boosting approaches tend to stand out the most, in practice. For example, Kulkarni et al. [3] combined Random Forest, Naïve Bayes, and Linear SVM through majority voting, and reported 99.91% accuracy. Apat et al. [10] worked with CatBoost using SMOTE based balancing, and ended up with 99.5129% accuracy. In a similar direction Senapaty et al. [21] showed that SGDC can hit perfect accuracy values on SMOTE balanced data. Overall these outcomes suggest that stronger ensemble methods could really matter.

The research line has also started to blend with Internet of Things (IoT) devices, smartphone apps, and cloud services, which helps with real time data gathering and context-aware recommendations [6], [22], [23]. Deep learning setups, especially CNNs and LSTMs, have been tried for farming scenarios, but the same issue appears again, their complexity makes them hard to roll out in practice [9], [23].

Even with that, there are still a number of unresolved matters. A lot of systems are trained on datasets from particular regions, so they do not generalize that well to other places [7], [13], [18]. Class imbalance is often overlooked, and feature selection is frequently carried out without serious checking, so redundant attributes slip in and may lower dependable model behavior [10], [21]. Also, the transparency of a model, which is quite important for farmers and agronomists, is seldom treated in a proper way [17], [22].

One recurring conclusion in the reviewed work is that nitrogen (N), phosphorus (P), potassium (K), soil pH, temperature, humidity, and rainfall are usually the most influential drivers for crop choice [5], [6], [10], [18], [24]. However, only a small number of papers try to connect preprocessing, feature selection, and ensemble classification in one connected workflow.

Because of these gaps, this study puts forward a Hybrid SMOTE–Random Forest–XGBoost framework. The idea is to reduce class imbalance via SMOTE, then pinpoint the most informative signals through Random Forest, andTry doing robust classification by using XGBoost, in a way that's still solid across different conditions. The idea is to build a crop recommendation system that's accurate yet interpretable, and also generalize enough so it can actually be used in various agricultural settings not just one.

2. Literature Review

I reviewed twenty-six studies on ML crop recommendation systems, kind of to see how researchers actually approached the whole problem, which methods looked strongest, and where the weak points are. The summaries below aim to capture the main takeaways from each paper, even if some reports were a bit inconsistent.

Rajak et al. [1] looked into SVM, ANN, Random Tree, and Naïve Bayes classifiers for crop prediction on a site by site basis, and they used an ensemble voting tactic to make the output feel more steady. The paper did give a reasonable argument for ensemble approaches in precision agriculture, but it didn't really spell out numerical accuracy values, so it's hard to judge the magnitude.

joshi et al. [2] built a system dubbed AgroConsultant , where a rainfall predictor was paired with a crop suitability predictor. They applied DT, KNN, RF, and Neural Networks across the modules. In that setup the rainfall part reached 71% accuracy and the crop prediction part reached 91%, which suggests modular design, can pay off.

Kulkarni et al. [3] created an ensemble arrangement too, combining Random Forest, Naïve Bayes, and Linear SVM through majority voting. They reported 99.91% accuracy on a dataset that used soil type, rainfall, and surface temperature, so it supports the idea that ensemble methods can indeed drive classification quality extremely high.

Bondre and Mahagaonkar [4] tried to tackle crop yield prediction and fertilizer recommendation at the same time, by using RF and SVM. Their contribution is also about linking two related tasks, but they didn't provide clear accuracy numbers for verification or comparison.

Pande et al. [5] tested five algorithms- RF, ANN, KNN, SVM, and Multivariate Linear Regression- for mobile based crop recommendation, using GPS, soil, and climate signals. Random Forest came out best at 95%, then KNN at 90%, which gives a pretty direct sense of relative performance.

Gosai et al. [6] developed an IoT -enhanced recommendation system, and it brought in NPK nutrients, soil pH, humidity, temperature, plus rainfall. They tested a bunch of algorithms, DT, Naïve Bayes, SVM, LR, RF, and XGBoost, and it turned out XGBoost was the best, even if the paper never really gave exact numbers.

Ali et al. [7] instead emphasized climate- based crop suggestions for farmers in Pakistan, mainly through Linear and Polynomial Regression. They reported an average accuracy near 90%, which kind of implies regression approaches remain handy when climate signals are the dominant ingredients, rather than other missing factors.

Parameswari et al. [8] went with rule-learning approaches- PART, JRip, and Decision Table- and they observed PART edges ahead, giving 98.33% accuracy with quicker model construction. so, it feels attractive whenever interpretability is the main goal, or when people need the logic readable.

Motwani et al. [9] did a comparison between CNN and Random Forest for a crop recommendation setup driven by soil analysis. CNN beat RF by a wide margin, reaching 95.21% compared to 75%, so the results underline the benefit of deep learning when the input encoding is richer.

Apat et al. [10] used SMOTE to rebalance the training data, then assessed several ML classifiers on a conventional NPK -rainfall-humidity-pH dataset. CatBoost showed up on top, with 99.5129% accuracy, 0.9918 precision, and 0.8870 Kappa, which basically confirms that boosting plus thoughtful preprocessing can be a strong combo

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Upadhyay and Vikas [11] relied on Random Forest applied to structured soil–climate variables, and they reached 99% accuracy. This further reinforces RF, as a sensible default for crop categorization problems, when you want something dependable without too much tuning.

Deo et al. [12] evaluated LR, DT, SVM, plus Gaussian Naïve Bayes. They achieved 96.08% accuracy and 93% precision, but recall stayed much lower, about 45% , suggesting minority classes might not be captured well, or at least not consistently enough.

Charishma et al. [13] built a hybrid model focused on southern India, mixing seasonal signals, meteorological and agronomic factors. The work sort of pointed out that region-specific elements matter a lot, but the final accuracy figure was not really given.
Ramachandra et al. [14] ran a comparison of SVM, RF and Gaussian Naïve Bayes using NPK plus climate related features. It made the case that this set of predictors works well, but they did not disclose any concrete accuracy numbers.

Kumar et al. [15] tested five classifiers—RF, NB, KNN, DT, and LR—with an emphasis on supporting soil health via better crop selection. However, the numerical accuracy was not clearly stated.

Pravallika et al. [16] applied supervised learning techniques such as DT, RF, NB, and SVM to crop selection, showing a clear practical benefit, even though specific performance metrics were not provided.

Lokhande and Dixit [17] developed a web- based recommendation setup that, also, could identify nutrient deficiencies. Random Forest reached 99.09% accuracy which made it the top performer among RF, SVM, and LR, and it seems naturally suited for online use.

Nimmadala et al. [18] suggested a hybrid ML framework that combined geospatial precipitation data with NPK and climate variables, and they also took "market awareness" into account. Even so, accuracy values were not clearly reported.

Padmavathi et al. [19] compared six boosting and ensemble strategies. RF and CatBoost both reported 0.9977 accuracy, and CatBoost also delivered a perfect AUC of 1.0000, suggesting that newer ensemble methods are pushing classification performance higher.

Iniyan et al. [20] merged crop and fertilizer recommendation into a single workflow using LR, RF, and KNN together with outlier detection. The combined pipeline looked useful in practice, but the detailed accuracy metrics were not included. Senapaty et al. [21] did this broad side by side comparison of thirteen ML classifiers, with SMOTE balancing and without. For SGDC it ended up at a perfect score of 1.00 for all metrics once SMOTE was used. So yeah data balancing, it can seriously boost the results, apparently.

Priyanka et al. [22] built an IoT smart agriculture setup where DHT11 sensors feed real-time temperature plus humidity readings. They said performance was better than earlier benchmarks, but the exact numbers are basically not given.

Koli et al. [23] also moved IoT into deep learning, they compared a Sequential model with LSTM while trying different activation functions. The paper suggested that deep learning can be paired with sensor data pretty well, but the accuracy values, they were not laid out in a clear way.

Kaura and Sidhu [24] tested LR, DT, RF, and LightGBM on a standard NPK climate dataset. RF and LightGBM were both at 0.99 accuracy which beats DT at 0.98 and LR at 0.95. This result kind of strengthens the idea that tree- based ensemble models have a practical edge, right.

Kavya and Pampapathi [25] put together a Flask based web application using RF, LR, and XGBoost. RF and XGBoost were around 99% accuracy while LR stayed closer to 95%. It indicates that systems meant for deployment can still reach very high performance, even in the real world.

Allam et al. [26] talked about why geographic location plus seasonal factors should be integrated into crop recommendation. They tried KNN, SVM, and also deep learning frameworks, although the accuracy figures were not reported clearly, or at least not in a straightforward manner.

Table 2.1: Summary of Reviewed Studies

Ref.	Main Algorithm (s)	Input Features	Reported Result
[1]	SVM, ANN, Ensemble	Soil parameters	NR
[2]	DT, KNN, RF, NN	Soil, rainfall, location, temp	91% crop; 71% rainfall
[3]	RF, NB, Linear SVM	Soil, rainfall, temperature	99.91%
[4]	RF, SVM	Soil nutrients, fertilizer data	NR
[5]	RF, ANN, KNN, SVM, MLR	GPS, soil, rainfall, temp, season	RF 95%; KNN 90%
[6]	DT, NB, SVM, LR, RF, XGBoost	NPK, pH, humidity, temp, rainfall	XGBoost best; NR
[7]	Linear & Poly Regression	Temperature, season	90%
[8]	PART, JRip, Decision Table	Soil, weather, pH, rainfall	PART 98.33%
[9]	CNN, RF	Soil, region, yield, price	CNN 95.21%; RF 75%
[10]	CatBoost + ML models	NPK, temp, humidity, pH, rainfall	CatBoost 99.5129%
[11]	RF	Soil quality, climate	99%
[12]	LR, DT, SVM, GNB	Temp, rainfall, pH, humidity	96.08%
[13]	Hybrid classifier	Season, temp, soil, fertilizers	NR
[14]	SVM, RF, Gaussian NB	NPK, rainfall, temp, pH	NR
[15]	RF, NB, KNN, DT, LR	Rainfall, temp, pH, NPK	NR
[16]	DT, RF, NB, SVM	Soil and climate	NR
[17]	RF, SVM, LR	Temp, rainfall, pH, humidity	RF 99.09%
[18]	Hybrid ML	NPK, temp, pH, precipitation	NR
[19]	RF, GB, XGB, AdaBoost, LGB, CB	NPK, temp, humidity, pH, rainfall	RF/CB 0.9977
[20]	LR, RF, KNN	Soil, climate, crop history	NR
[21]	13 classifiers + SMOTE	Historical crop data	SGDC 1.00
[22]	IoT + ML	Sensors, NPK, pH, rainfall	NR
[23]	Sequential DL, LSTM	Temp, humidity, soil moisture	NR
[24]	LR, DT, RF, LightGBM	NPK, humidity, temp, pH, rainfall	RF/LGB 0.99
[25]	LR, RF, XGBoost	Soil and climate attributes	RF/XGB 99%
[26]	KNN, SVM, TensorFlow, Keras	Season, soil, location	NR

NR = Not Reported

3. Objectives

The objectives are as follows;

1) To study and analyze existing Machine Learning based approaches for crop recommendation system.
2) To extract key parameters influencing crop recommendation systems.
3) To preprocess the dataset.
4) To evaluate the proposed approach.

4. Background Techniques

This part sort of sketches the principal machine learning methods that people use in crop recommendation studies. In general these methods learn from older soil and climate records, then they try to reuse those patterns, to guess which crop seems the better match for a set of conditions.

4.1 Logistic Regression (LR)

Logistic Regression is one of the more straightforward classification tools you can pick. Even if the name sounds like something to do with regression, it is in practice used for classification problems. The idea is that it estimates the chance, that a particular sample ends up in a certain category, and it does that using a sigmoid function. So in crop recommendation terms, it's like estimating how plausible it is that a certain mix of soil factors and weather inputs lines up with a specific crop type.

The probability comes out as:
P(Y=1) = 1 / (1 + e^(-z))
where P(Y=1) denotes the probability of the crop class, and z is the weighted linear mash-up of the input features. One notable strong point is that it usually runs quickly, and the model is easy to interpret. But it can be weaker when the connection between inputs and the crop labels is highly nonlinear, so it may underperform

4.2 Decision Tree (DT)

A Decision Tree handles classification by turning it into a sequence of simple yes / no questions. Each split is chosen based on which feature separates the classes the most, often assessed via information gain, or using Gini impurity. What you get is basically a tree form, and if you trace the path from the root, down through the branches to a leaf, you end up with the predicted class, or at least the category it assigns.

Decision Trees are kind of popular in agricultural research, because they are highly interpretable, so a farmer can actually follow the decision logic and kinda see why a specific crop was suggested. But yeah they can be overfit pretty easily, especially when the dataset is noisy, or when there are a lot of features floating around.

4.3 Random Forest (RF)

Random Forest helps with that overfitting issue, by basically mixing many trees together. Each tree gets trained on a random slice of the data, and also a random slice of the features. Then the end result comes from a majority vote across all those trees:

$$\hat{y} = \text{mode}(T_1, T_2, ..., T_n)$$

This whole setup is usually more resilient than relying on just one Decision Tree. Random Forest can also rank predictors by their importance, which is a big deal for spotting which soil and climate variables are the real drivers in crop selection. Honestly, it shows up a lot in the crop recommendation literature for a reason, it manages to balance accuracy, robustness and interpretability in a way that only a few other approaches match.

4.4 LightGBM

LightGBM is a gradient boosting method, made by Microsoft, and it is tuned for speed and efficiency. Instead of growing decision trees in a more "layer by layer" fashion like many older boosting routines, LightGBM adds them leaf by leaf, so it spends computation exactly where it can cut the error the most. Because of that it tends to run much faster than alternatives such as XGBoost, particularly when you have big datasets, while still keeping accuracy at a very high level.

For crop recommendation problems, LightGBM has been competitive with Random Forest, especially when the dataset is large or when training time is kind of a strict constraint. Plus, its lower memory use and quicker convergence make it a practical candidate for deployment in settings where resources are limited, not just in theory but in real situations too.

5. Methodology

The methodology built for this study follows a kinda structured pipeline that goes from data collection through preprocessing, feature analysis, and finally model training and evaluation. Each part was set up to handle a particular weakness that shows up in the previous literature, pretty consistently.

The dataset used in this work was taken from a publicly accessible GitHub repository (https://github.com/gabbygab1233/CropRecommender/blob/main/Crop_recommendation.csv). This dataset is basically a combined set of Indian agricultural observations, it brings together rainfall, climate, and soil fertilizer details. It has 2,200 records and 8 features, so it works as a fairly broad reference point for crop classification style tasks.

Table 5.1 talks about the features in the dataset. The input variables include the three major macronutrients in soil (Nitrogen, Phosphorus, and Potassium), plus four environmental parameters: rainfall amount, relative humidity, soil pH, and temperature. As summarized across the reviewed literature, those seven variables (yes seven, not more) tend to act as the most influential indicators for crop suitability.

Table 5.1: Dataset Feature Description

Attribute	Description
Nitrogen (N)	Proportion of nitrogen content present in the soil
Phosphorus (P)	Proportion of phosphorus content present in the soil
Potassium (K)	Proportion of potassium content present in the soil
Rainfall	Amount of rainfall received (mm)
Humidity	Relative humidity (%)
pH Level	Soil acidity or alkalinity value
Temperature	Temperature (°C)

After the data was collected it was sent through preprocessing, so it would be clean enough for model training. Raw agricultural data from different sourcing locations is rarely perfect, it might include missing values, outliers, or class distributions that are skewed, which can mess things up.

The proposed framework then applies SMOTE to sort of resolve any class imbalance in the dataset. When some crops show up far more frequently than others in the training data, the classifiers can start to be biased toward the majority class, and that happens even when everything looks "fine" at first. SMOTE generates synthetic examples for the underrepresented classes by interpolating between existing minority samples, effectively balancing things out without throwing away any of the majority class data.

After that, Random Forest gets used for the feature importance analysis. By checking how much each feature

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contributes to reducing classification error across all the trees in the ensemble, Random Forest delivers an importance ranking. This ranking then can be used to cut out low-value features, lower dimensionality, and generally help the final classifier concentrate on the more informative inputs.

The selected features are then fed into XGBoost for classification. XGBoost is a gradient-boosted decision tree approach that builds models step-by-step, with each new tree trying to correct the mistakes made by the previous one. It's commonly valued for its strong predictive accuracy, regularization strength, and computational efficiency. Overall, the combined SMOTE-RF-XGBoost pipeline is aimed at being more stable and generalizable than any single piece used by itself.

6. Results

It tells how well the proposed framework works, four machine learning classifiers were tested: Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), and LightGBM. The assessment was based on standard classification metrics- Accuracy, Precision, Recall, and F1-Score- these collectively offer a pretty rounded view of how each model performs

6.1 Evaluation Metrics

Precision:
Precision basically tells us what share of the crops the model claimed to be a certain type were in fact that type. It kinda penalizes the false positives:
Precision = TP / (TP + FP)

Recall:
Recall however, looks at how many of the real instances of a crop were actually caught correctly. It penalizes false negatives:
Recall = TP / (TP + FN)

F1-Score:
The F1-Score mashes both precision and recall into one value, using their harmonic mean. This tends to be handy when the dataset shows some imbalance between the classes:
F1-Score = 2 × (Precision × Recall) / (Precision + Recall)
When you use all three metrics alongside overall accuracy, you can make sure that no single model is kind of treated unfairly because of how the data is spread across crop categories.

6.2 Comparison of Classifiers

Table 6.1 gives the accuracy numbers from each classifier tried on the dataset. The overall outcome is pretty consistent: tree- based ensemble approaches beat the simpler ones like Logistic Regression by a lot.

Table 6.1: Classifier Accuracy Comparison

Algorithm / Classifier	Accuracy (%)
Decision Tree	0.98
Random Forest	0.99
Logistic Regression	0.92
LightGBM	0.98

Random Forest got the top accuracy at 99%, closely followed by Decision Tree at 98%. Light gbm produced solid results around 98%, while Logistic Regression fell to 92% , and that matches what the literature often reports- linear models tend to struggle with the tangled, non- linear ties between soil nutrients, local climate, and crop fit.

Overall, these findings back the main motivation here. Random Forest does not only work very well as a classifier, but it also yields the feature importance ordering that we then use in the proposed preprocessing pipeline.

Conclusion:

Table 7.2: Accuracy of Algorithms

Algorithm / Classifier	Accuracy (%)
Decision Tree	0.98
Random Forest	0.99
Logistic Regression	0.92
LightGBM	0.98

As by using these algorithm as in the table 7.2 campared the accuracy of the algorithms after evalution got that by comaprison that the Random Forest is more compatable than other algorithms the accuracy level of Random Forest is high that is 0.99% that is more accurate for getting results.

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