2025 International Conference on Intelligent Computing
July 26-29, Ningbo, China
https://www.ic-icc.cn/2025/index.php

Research on Personalized Recommendation System for Crop Cultivation

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Abstract. This paper introduces a personalized crop recommendation system using ensemble learning and collaborative filtering algorithm to tackle traditional cultivation's reliance on experience and low economic returns. A soft voting ensemble model combining KNN, SVM, and RF boosts recommendation accuracy to 99.13%, and alleviates the cold start issue. An Intelligent Integrated Scoring Mechanism merges collaborative filtering scores with market price scores in a 1:1 ratio, producing a ranked crop list and an Intelligent Integrated Recommendation Score, further increasing accuracy to 99.27% and achieving Pareto optimality between yield and economic benefits. Experiments show the system improves the F1 score by 7.2% and 2.1% over KNN and SVM baselines, respectively, and raises the NDCG metric by 16% compared to collaborative filtering algorithm, enhancing recommendation quality and farmers' economic outcomes.

Keywords: Crop Cultivation Recommendation, Soft Voting Ensemble Model, Intelligent Integrated Scoring Mechanism, Cold Start, Pareto Optimal Cultivation

1 Introduction

Currently, planting decisions largely rely on the experience and judgment of farmers, which tend to be highly subjective, with insufficient scientific and intelligent support [1]making it difficult to meet the demands of modern agriculture, especially in terms of economic benefits. The rapid development of machine learning and recommendation algorithms [2] has provided new technical paths for building data-driven crop-cultivation decision-making systems. In particular, crop cultivation recommendation systems [3], by integrating multi-dimensional data such as soil and market information, offer reliable technical support for planting decisions, improving crop yields and economic benefits.

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2 Related Work

In recent years, crop cultivation recommendation methods have gradually become a research hotspot in agriculture. In 2020, Jaiswal et al. [4] proposed a hybrid recommendation system combining KNN and collaborative filtering algorithm. It predicts planting interests by analyzing farmers' data and recommends crop plans. Experiments showed that KNN outperformed SVM with 78% accuracy, offering effective planting support. However, the system didn't address the cold start issue for new users and relied solely on personal data, neglecting economic benefit considerations.

In 2021, Hui et al. [5] developed a collaborative filtering model integrating user features, using geographic location and primary crops to create initial profiles. They merged user feature and rating matrix similarities into a weighted overall similarity, employing the Top-N method for personalized crop recommendations. The model boosted accuracy by 2-7%, recall by 2-9%, and achieved a 71% F1 score over traditional methods, effectively tackling the cold start problem and improving recommendation quality. However, it relied solely on user data, neglecting external factors like soil and climate, limiting its comprehensiveness and practicality.

In 2022, Gopi et al. [6] proposed a new crop cultivation recommendation and yield prediction technique based on multimodal machine learning. This technique used a KELM-based balanced optimizer for crop cultivation recommendations and RF for precise crop yield prediction. Experimental results showed that the MMML-CRYP method significantly outperforms comparison methods, achieving a maximum accuracy of 97.91%. However, the recommendation logic of this model relies solely on soil and climate features. It lacks consideration for farmers' differentiated economic benefit needs, leading to recommendation results that may not meet farmers' demands for profits in practical applications.

In 2023, Aryaman et al. [7] introduced a crop-cultivation decision support method using key features to aid farmers in making informed planting choices. They combined four classifiers—Extra Tree, RF, Naïve Bayes, and QDA—in pairs, evaluating the accuracy, F1 scores, and other metrics to build a voting ensemble framework with RF and QDA for decision-making. However, the study prioritized algorithm optimization over farmers' profitability preferences, lacking personalized recommendations to address diverse farmer needs.

Current research in crop cultivation recommendations still faces limitations such as insufficient personalization, the cold start problem, and inadequate consideration of economic benefits. To address these limitations, this paper designed a personalized crop recommendation system integrating ensemble learning and collaborative filtering algorithms. The main contributions include:

- Constructing a soft voting ensemble model based on KNN, SVM, and RF: Fully leveraging the sensitivity of KNN to local structures, the excellent generalization ability of SVM, and the robustness of RF. Using the soft voting mechanism combines the advantages of these models, improving crop recommendation accuracy.

- Integrating the soft voting ensemble model's recommendations with a user-based collaborative filtering algorithm to achieve personalized crop cultivation recommendations.
- Designing the Intelligent Integrated Scoring Mechanism that combines the crop cultivation recommendation score generated by the collaborative filtering algorithm with the market price score in a 1:1 ratio, providing a weighted fusion to generate a crop cultivation recommendation list and an Intelligent Integrated Recommendation Score, supporting decision-making for maximizing farmers' economic benefits.

3 Algorithm Design and **Experiment**

3.1 **Model** Architecture

This paper designed and implemented a personalized crop cultivation recommendation system, as shown in **Fig. 1**. A soft voting ensemble model based on KNN, SVM, and RF was constructed. Through the soft voting mechanism, the advantages of the three classifiers were combined, significantly improving the overall crop recommendation performance. The recommendation prediction probabilities generated by the soft voting ensemble model were converted into classification scores and integrated with the user-based collaborative filtering algorithm, effectively alleviating the cold-start problem for new users. Additionally, this paper incorporated crop market prices into the recommendation system and designed an Intelligent Integrated Scoring Mechanism that merges collaborative filtering scores with market price scores in a 1:1 ratio, producing a ranked crop list and an Intelligent Integrated Recommendation Score. This strategy ensures that while crop cultivation recommendation yields are safeguarded, the economic benefits for farmers are also improved.

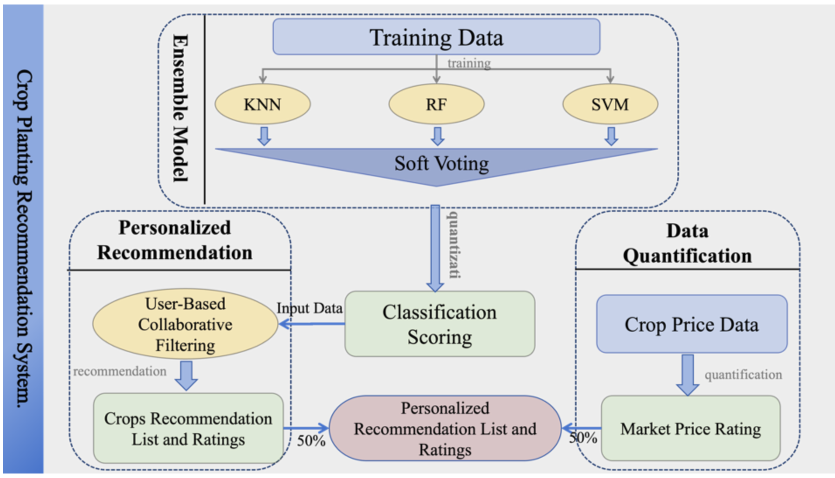

Fig. 1. Framework of Personalized Crop Cultivation Recommendation System

3.2 Feature Selection

The crop cultivation recommendation system uses feature selection to ensure accurate and applicable recommendations. Key features must represent the ecological and production conditions for crop growth, providing reliable data. This study identified seven core features based on essential growth factors: nitrogen, phosphorus, potassium, soil pH, temperature, humidity, and precipitation. These features capture the crop's ecological environment across soil and climate dimensions. By analyzing these multi-dimensional features, the system offers scientific and practical planting recommendations, aiding farmers in precise decision-making.

3.3 Dataset Selection

In this study, the publicly available dataset from the Kaggle [8] platform was used, which includes 2,200 data samples. Each data entry consists of variables related to soil features as well as the type of crop best suited for planting. The dataset comprises 22 distinct crop types, including cotton, coffee, and others. For the experimental process, 70% of the dataset was designated as the training set, while the remaining 30% was used for testing purposes. To prevent the impact of differences in data ranges among different features on model performance, the dataset was normalized using equation (1) before model training. A portion of the normalized data is presented in Table 1.

$$X_{nor} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

where X_{nor} represents the normalized data, and X_{min} and X_{max} denote the minimum and maximum values of the soil features, respectively.

Table 1. Normalized Dataset Example

N	P	K	PH	Temperature	Humidity	Rainfall	Crop Type
-0.462	-0.241	-0.537	-0.227	0.496	0.505	-1.191	Mung Bean
-0.678	0.830	-0.598	-1.126	-1.271	-2.169	0.0364	Kidney Beans
1.612	-0.761	-0.435	0.599	0.413	-0.312	1.629	Coffee
-0.381	-0.088	-0.496	0.082	0.788	0.770	-0.847	Mung Bean
-1.351	0.707	-0.618	-0.576	0.545	-0.871	0.802	Pigeon Peas

3.4 Feature Correlation Analysis

Pearson Correlation Coefficient.
The Pearson correlation coefficient measures the strength and direction of the linear relationship between two features, ranging from [−1, 1]. A value closer to 1 indicates a stronger linear correlation, while the sign denotes the relationship's direction.

$$\rho(X, Y) = \frac{cov(X,Y)}{\sigma_X \cdot \sigma_Y} \tag{2}$$

where *Cov (X, Y)* represents the covariance between features *X* and *Y* in soil characteristics, and σ_i denotes the standard deviation of the feature data.

This paper used equation (2) to calculate the correlation coefficients of soil features for each crop. The results showed that all correlation coefficients are below 0.2, indicating no significant correlation between these features. Thus, they are suitable as input variables for crop planting recommendations. **Fig. 2** illustrates the distribution of soil feature correlation coefficients for typical crops such as rice, watermelon, and cotton.

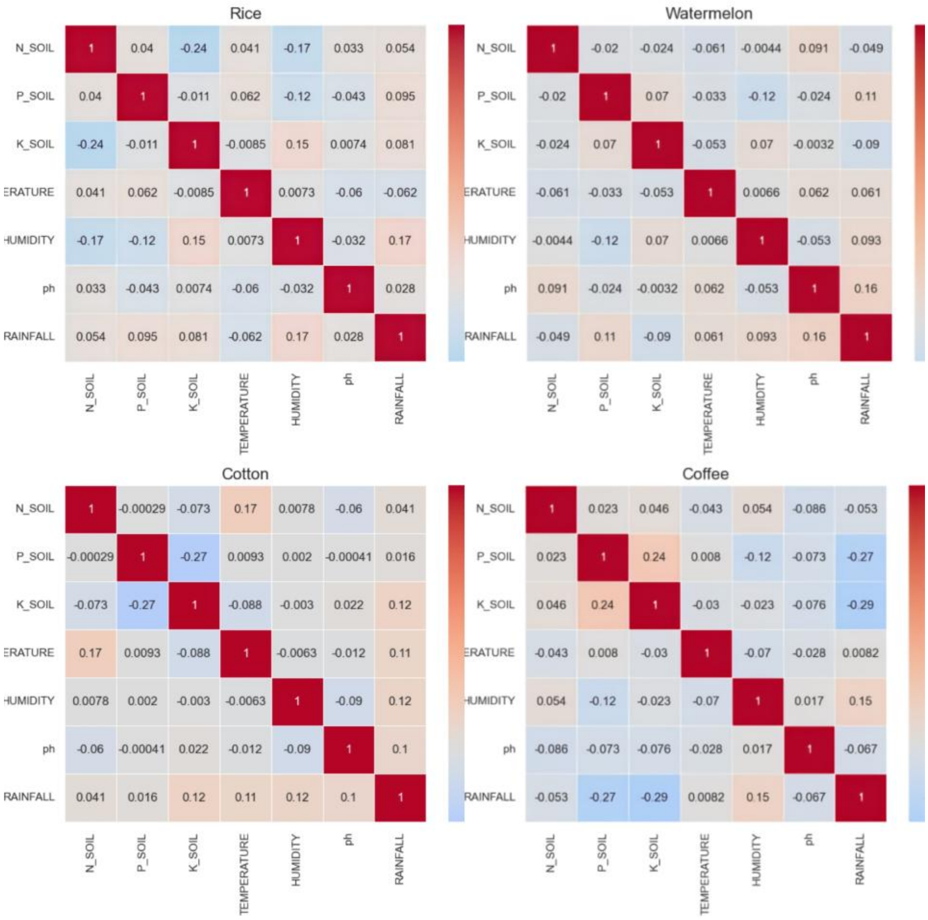

Fig. 2. Soil Feature Correlation Distribution

Variance Inflation Factor (VIF)

VIF assesses multicollinearity among soil features, occurring when they are highly linearly correlated, potentially destabilizing model parameter estimation and reducing recommendation accuracy. It quantifies a feature's linear dependence on others, with higher values indicating stronger correlations and potential multicollinearity.

$$VIF(X_j) = \frac{1}{1 - R_j^2} \tag{3}$$

where $VIF(X_j)$represents the variance inflation factor for soil feature X_j, and R_j^2 is the coefficient of determination obtained by regressing $X_j$against the other soil features.

According to formula (3), this paper calculated the VIF values for the seven soil features. As shown in Table 2, the VIF values for each soil feature are relatively small, indicating no significant linear correlation among the features. This result showed that the selected soil features are suitable as conditions for crop planting recommendations.

Table 2. VIF of Soil Features

Feature	N	P	K	PH	Temperature	Humidity	Rainfall
VIF	1.09	2.63	2.79	1.05	1.11	1.36	1.03

3.5 Ensemble Model Design

RF Classification Model.

RF [9] uses multiple independent decision trees, employing bootstrap sampling to create new training subsets and randomly selecting features for node splitting. For each new soil sample, each tree predicts the best crop category, with the final recommendation determined by majority voting. RF Algorithm steps: (1) Split the dataset into training set S and test set T, and set the number of trees t. (2) Perform bootstrap sampling N times from S with replacement to generate subset S(i). Randomly select soil features as root node samples to train a decision tree. (3) Repeat step (2) t times to build a random forest of t trees. (4) For each soil sample in T, RF using equation (4) calculates the predicted recommendation probability for each crop category.

$$P\big((C_i|x)\big) = \frac{n}{T} \tag{4}$$

where T represents the total number of decision trees; C_i represents the i-th crop category in the dataset.; n_i represents the number of times C_i appears in the classification results output by all decision trees.

SVM Classification Model

The core idea of SVM [10] is to find an optimal hyperplane separating crop categories, influenced by key soil data points called support vectors. For non-linear data, the kernel trick maps it to a higher-dimensional space. SVM-based Crop Recommendation steps: (1) Transform soil features using the Radial Basis Function kernel shown in equation (5). (2) Reformulate the optimization into a convex quadratic problem with Lagrange multipliers. (3) Solve the dual problem via Sequential Minimal Optimization to identify support vectors. (4) Build a decision function using support vectors and Lagrange multipliers to compute crop recommendation probabilities.

$$K(x, y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right) \quad (5)$$

where x represents the soil feature vector, y denotes the crop category label, and σ is the standard deviation of soil features.

KNN Classification Model

The core idea of KNN [11] is to measure the distance between an unclassified soil sample and labeled crop samples, identify the K nearest neighbors, and use majority voting for crop recommendation. KNN Algorithm Steps: (1) Create a training dataset containing soil features and corresponding crop labels. (2) Choose an appropriate K value, representing the number of nearest neighbors considered. (3) Calculate the Euclidean distance between the new soil sample and all samples in the training set using equation (6), where x and y represent two soil samples in the dataset. (4) Identify the K nearest neighbors, analyze the crop category distribution, and compute the recommendation probability for each crop category.

$$L(x, y) = \left(\sum_{i=1}^{n} \|x_i - y_i\|^2\right)^{1/2} \quad (6)$$

Ensemble Classification Model

In this study, grid search was employed to optimize the parameters of the three base learners mentioned earlier. The optimal parameters obtained for each model are presented in Table 3.

Table 3. Optimal Parameters of KNN, RF, and SVM

Model	KNN	RF	SVM
Parameter	k=3	ples_leaf=3 ax_features='sqrt' min_samples_split=2 min_samK=2	probability=True c=10 kernel='rbf' degree=3

From Table 4, it can be observed that compared to using default parameters, the crop recommendation accuracy of KNN improved from 97.12% to 97.27%; RF improved from 99.09% to 99.24%; and SVM improved from 98.18% to 98.24%. RF performed the best in overall recommendation accuracy.

Table 4. Optimized KNN, RF, and SVM Model Comparison

Algorithm / Parameter	KNN	RF	SVM
Default Parameter	97.12%	99.09%	98.18%
Optimal Parameter	97.27%	99.24%	98.24%

However, Significant accuracy differences were observed among RF, SVM, and KNN for specific crops. ROC curve in **Fig. 3**. further analyzed their performance. For Watermelon, all classifiers performed similarly. SVM excelled in Banana classification, RF in Orange, and KNN in Lentil. Combining KNN, RF, and SVM into an ensemble model could improve crop recommendation accuracy.

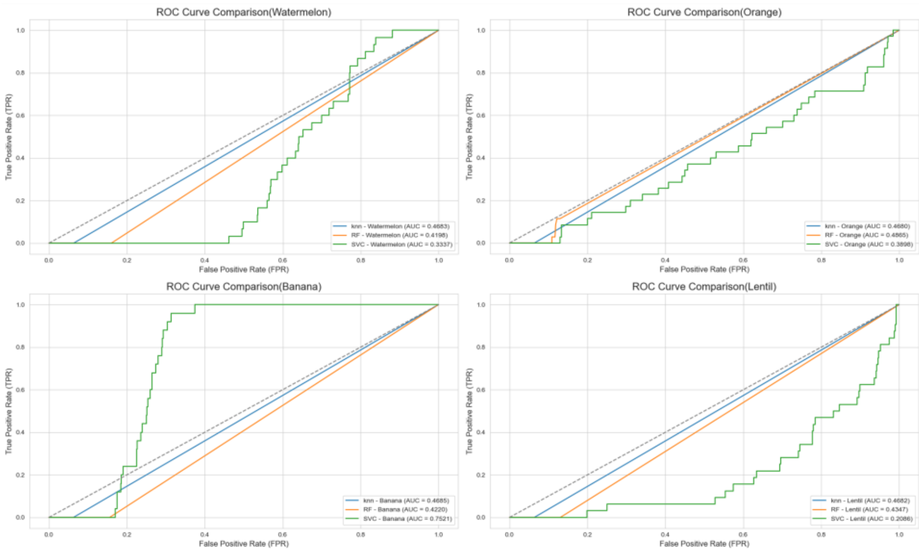

Fig. 3. ROC Curve Comparison for Different Crop Classifications

Ensemble algorithms [12] combine multiple weak learners to create a strong learner, enhancing prediction performance and reducing bias and variance. Voting, a type of ensemble method, generates multiple training subsets via bootstrap sampling. Different base learners are trained on these subsets, and their predictions are integrated through averaging or voting. Due to the independence of base learners, voting supports parallel computing, boosting efficiency. Voting methods include hard and soft voting, as illustrated in **Fig. 4**. For example, if KNN predicts Crop A while SVM and RF predict Crop B, Hard Voting: The crop with the most votes (Crop B) is recommended. Soft Voting: Prediction probabilities are weighted, and the crop with the highest probability (Crop A) is recommended. Due to its flexibility, this study adopts a soft voting ensemble model, integrating KNN, RF, and SVM.

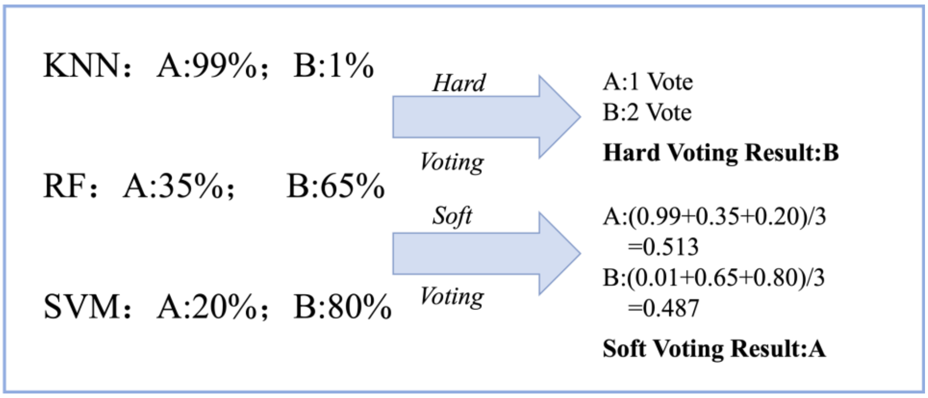

Fig. 4. Soft Voting vs Hard Voting Mechanisms

Experimental Results

Experimental results showed that the KNN model performs weakly across various metrics, especially with complex non-linear data, leading to lower recommendation accuracy. As shown in **Fig. 5**, its accuracy, recall, and F1 scores are 93.42%, 92.39%, and 91.8%, respectively, with a precision of 92.37%. While acceptable, KNN is weaker than other models, indicating limited applicability in complex data environments. The SVM model performs better with 97.62% accuracy, 97.06% recall, 96.89% F1 score, and 96.32% precision. Though superior to KNN, its precision is still lower than RF. The RF model excels with 99.11% accuracy, 99.02% recall, 98.99% F1 score, and 99.14% precision, demonstrating strong performance and stability as the best-performing model. The Soft Voting ensemble model performs the best in all metrics, with a recommendation accuracy of 99.13%, recall of 99.09%, F1 score of 99.03%, and crop recommendation precision of 99.19%. This model slightly outperforms all other single models in recommendation precision, recall, F1 score, and accuracy, validating the effectiveness of ensemble learning methods in enhancing classification accuracy and model robustness. Therefore, the Soft Voting ensemble model was ultimately selected for score transformation to obtain more precise soil sample scores.

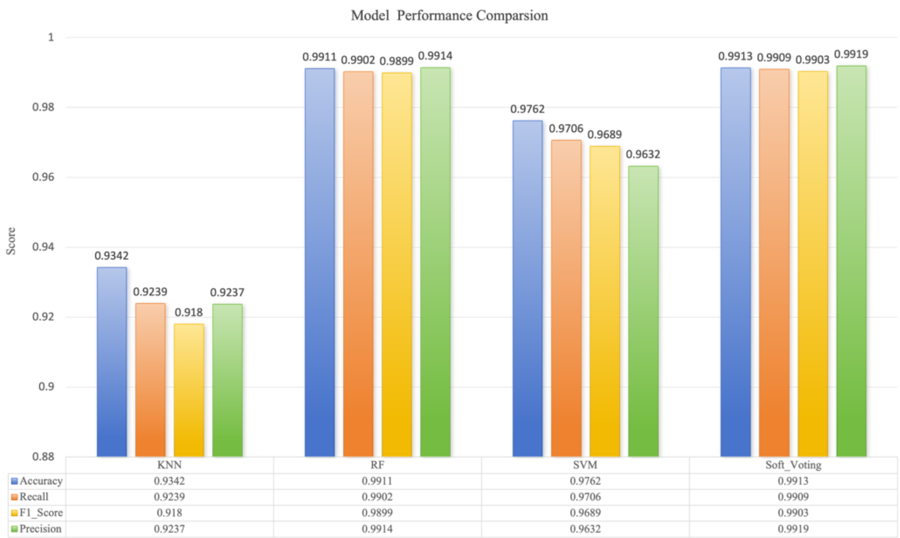

Fig. 5. Soft Voting Ensemble vs Individual Model Performance

3.6 Soil Sample Scoring

Since nitrogen, phosphorus, and potassium levels in soil can be effectively adjusted through fertilization measures, and the rainfall required for crop growth can be supplemented through irrigation, while other features such as soil temperature, pH, and humidity are more difficult to adjust—especially soil humidity, which is closely related to local climate conditions and is hard to manipulate—this study adopted interval overlap as an evaluation metric to quantify the degree of matching between soil characteristics and crop growth conditions. A matching scoring system was designed: 0 points represent a complete mismatch, and 4 points represent a complete match. Based on the crop recommendation results from the ensemble model, the planting recommendation probability for each crop on different soil samples can be derived. Scoring rules were established based on these probabilities, as shown in Table 5.

Table 5. Soil Scoring Rule Table

Recommendation Probability	0	0-0.25	0.25-0.5	0.5-0.75	0.75-1
User-Score	0	1	2	3	4

According to the scoring rules, all soil samples were quantified, and the soil sample scoring data was obtained. A portion of the scores is shown in Table 6.

Table 6. Partial Soil Sample Scoring Table

N	P	K	PH	Temperature	Humidity	Rainfall	Soil Sample Scoring
76	60	39	6.76	20.04	80.34	208.58	Rice：4 Mize:1
35	58	20	5.76	29.39	63.48	90.05	Chick Pea：3 Pigeon Peas：2
13	7	43	7.01	18.20	91.12	109.66	Pomegranate：4 Lentil：2

3.7 Intelligent Integrated Scoring Mechanism

Planting Recommendation Scoring

In collaborative filtering algorithms, new soil samples without crop planting records introduce a cold-start problem, making it difficult to generate effective recommendations. This study used the ensemble model to generate new soil sample scores as a solution for new user data. During the experiment, soil samples in the test set were treated as new users, representing newly encountered soil conditions. When new soil feature data is input, the ensemble model can generate corresponding soil sample scores based on the features. These scores were added to the user-crop rating matrix as initial data for new users, avoiding the limitations of relying entirely on historical rating data. This effectively alleviates the cold-start problem and provides reliable crop planting recommendations for new soil samples. Some experimental results are shown in Table 7.

Table 7. Partial User-Crop Planting Score Overview

Crop / User	Apple	Banana	Papaya	Watermelon	Jute	Kidney Beans	Lentil
User1	0	3	0	0	0	1	0
User2	0	0	3	2	0	0	1
User3	0	2	2	0	1	1	0
User4	2	0	1	0	0	0	3
User5	1	0	1	0	2	1	0

This study treated each soil sample as a user, with the soil feature data from the training set acting as existing users. The ensemble model generated corresponding soil sample scores, representing user preferences and forming a user-crop rating matrix. Using this matrix, the system applied a user-based collaborative filtering algorithm to provide crop planting recommendations. The soil data from the test set served as the target users, i.e., the soils that require crop recommendations. These soils may be newly cultivated land or existing land that needs planting strategy adjustments.

Using Equation (7), the system calculated the similarity between the target user and other users to evaluate the resemblance of their soil features. The higher the similarity, the more similar the characteristics of the two soils. The system identified the 100 users most similar to the target user and designated them as the neighbor set. These neighboring users represent soil samples whose characteristics are most similar to the target soil, and their planting experiences provide valuable references for recommending crops to the target soil.

$$\cos_{\mathrm{sim}(A,B)} = \frac{A \cdot B}{\|A\|\|B\|} \tag{7}$$

where A·B is the inner product of user A and user B, and ‖A‖ is the norm of user A.

Using equation (8), the soil user ratings for each crop in the neighbor set were weighted by similarity and summed to generate the target user’s planting recommendation scores for each crop. If a neighbor has not rated a specific crop, that rating is ignored. The system ranked all crops according to the predicted scores, generating the target user’s crop recommendation list along with corresponding planting recommendation scores. The higher the score, the greater the planting potential of that crop for the target soil, enabling personalized crop planting recommendations tailored to different soil characteristics.

$$r_{UI} = \frac{\sum_{u\in N(U)} S(U,u)\cdot r_{uI}}{\sum_{u\in N(U)} S(U,u)} \tag{8}$$

In this context, r_{UI} is the planting recommendation score for crop *I* corresponding to the new soil *U*; *N(U)* is the set of similar soil samples to the target soil *U*; *S(U, u)* is the similarity between the target soil *U*, and the similar soil sample u; r_{uI} is the rating given by the similar soil sample u for crop *I*.

Market Price Scoring.

To assess the market value and economic benefits of crops, this study collected market price data for relevant crops over the past two years from the NCDEX website. Considering the impact of market price fluctuations on scoring, the average market price of different crops was converted into a 1-5 scoring system to intuitively reflect crop price levels. A score of 1-2 indicates that the crop's market price has been relatively low over the past two years, while a score of 3-4 suggests a moderate price range and a score of 5 signifies a high market price over the same period. A partial list of crop price scores is shown in Table 8. To ensure fairness and consistency in the data, the price data was standardized using equation (1), eliminating differences between different crops.

Table 8. Market Price Scoring Table

Crop	Rice	Maize	Apple	Coffee	Watermelon	Cotton	Jute	Mango
Price Rating	2	1	4	3	5	5	3	1

Intelligent Integrated Recommendation Scoring

The user-based collaborative filtering algorithm captures soil characteristic similarities to recommend crops suitable for cultivation, generating a planting recommendation score that ensures high crop yields for farmers. Introducing a market price score reflects the economic benefits of crops, helping farmers select more profitable crops. To balance yield and economic value, this study introduced the Intelligent Integrated Recommendation Score. This score combined the planting recommendation score with the market price score to provide “personalized and profit-driven” crop recommendations.

To further optimize the recommendation effect, this study compared the impact of different weight distributions (90:10, 80:20, 70:30, 60:40, and 50:50) on the system’s performance. The evaluation metrics included precision, F1 score, recall, and NDCG. Through testing, integrating the planting recommendation score and market price score in a 1:1 ratio yielded optimal results.

The experimental results showed that recommendation accuracy reached 99.27% with all weight distributions, improving by 0.14% compared to the soft voting ensemble model. This demonstrates the system’s ability to recommend suitable crops based on soil characteristics. As the price weight increased, recall improved, indicating better alignment with farmers’ needs. The F1 score increased by 10%, highlighting overall model performance improvement. The NDCG value rose by 16%, suggesting better recommendation quality, ensuring high yields, and maximizing economic benefits. These results, shown in **Fig. 6**, validate the effectiveness of the Intelligent Integrated Recommendation Score in balancing yield and profitability.

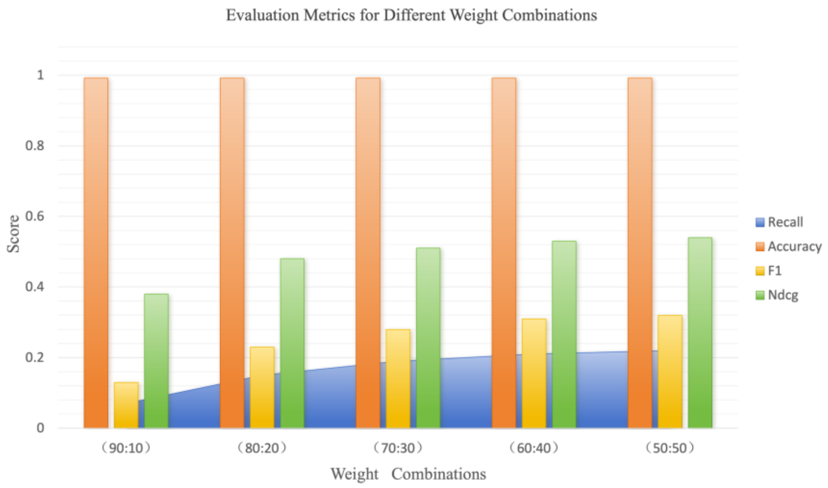

Fig. 6. Performance Comparison of System under Varying Weights

4 Conclusion and Outlook

This study combined KNN, SVM, and RF via a soft voting strategy to build an ensemble model, achieving 99.13% accuracy. By converting the model's recommendations into soil scores and integrating them with collaborative filtering algorithm, the cold start problem for new users was effectively addressed, enhancing system practicality. Pareto frontier analysis determined a 1:1 ratio for collaborative filtering and market price scores, boosting crop recommendation accuracy to 99.27%. Experiments showed the system's F1 score improved by 7.2% and 2.1% over baseline KNN and SVM models, respectively, while NDCG increased by 16% compared to traditional collaborative filtering algorithm. This system ensures crop yield and maximizes farmers' economic benefits.

Despite some notable achievements, certain limitations remain. The dataset used constrains the model's performance, and further validation is needed to assess its generalization ability. The price scoring method only considers annual averages, failing to fully account for seasonal fluctuations that affect recommendation results. Additionally, the linear weighting strategy may lead to suboptimal solutions when there is a significant disparity between yield and economic benefits. Future research will focus on three key areas: expanding the dataset to enhance the model's applicability, introducing a dynamic weight allocation mechanism to better adapt to seasonal and market fluctuations, and incorporating additional factors influencing crop cultivation to develop a multi-objective optimization recommendation system.

Acknowledgment. This research was supported by the National Natural Science Foundation of China (No.62306212) and Tianjin University of Technology 2024 Innovation and Entrepreneurship Training Program for College Students (No. 202410060007, No.202410060107).

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