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Agriculture Crop Recommendation Based On Productivity And Seasons

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ABSTRACT

The crop recommendation model was trained using a structured dataset containing key agronomic and environmental parameters. As shown in Figure 3, the dataset includes nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, rainfall, and soil pH as input features. The output label indicates the most suitable crop for the given set of conditions. This data forms the foundation for developing the machine learning model used in this study. In Meerut, many people are farmers. Farming is how they grow food and earn money. But to grow more food, it is very important to choose the right crop for the right season. Sometimes, farmers don't know which crop is best to grow in the weather and soil of their area. We collected old data about crops, soil, and weather in Meerut. Then we used smart computer programs to study this data and find out which crops grow best in each season. Our system gives suggestions to farmers about the best crop to grow in each season. This helps them grow more food with less effort and earn more money. It makes farming simpler and better for the people of Meerut.

Keywords: *Farming, Crop Suggestion, Seasons, Productivity, Machine Learning, Meerut*

1. INTRODUCTION

In Farming is the main work in many parts of India, especially in villages. Meerut is one such place where farming is very important. It is in western Uttar Pradesh and has good land for growing crops. The weather is also nice for farming. People in Meerut have been doing farming for many years. Many families depend on farming for food and money. Some people work in the fields, and others help in different ways. The main crops grown in Meerut are wheat, sugarcane, rice, maize, and pulses. These crops grow well in different seasons. But how well they grow depends on things like heat, rain, type of soil, and other natural things [1].

Farmers in Meerut grow crops in three main seasons: Kharif, Rabi, and Zaid. Kharif is the rainy time when farmers grow rice and maize. Rabi is the winter time when wheat and mustard are grown. Zaid is the short summer time when crops like watermelon and cucumber are grown.

It is very important to choose the right crop for each season. This helps farmers grow more food and keeps the soil in good condition. But choosing the right crop is not always simple.

Sometimes rain comes too early or too late. The weather can be too hot or too cold. Insects and pests can also damage the crops. Also, what people want to buy in the market keeps changing [2].

Earlier, farmers used to ask older people or neighbours for help in choosing crops. They used their own ideas and looked at what other farmers were growing. But now, that is not always useful. The weather is changing because of climate problems. The soil is becoming weak. Also, farming is becoming more costly. All these things make farming harder. Because of this, old ways of choosing crops are not enough anymore.

Recently, there have been sudden rains, long dry times, and strange weather that has made it hard to grow crops. Many farmers do not know what kind of crops are good for their soil. If they plant the wrong crop again and again, the soil loses important nutrients. This makes the crops weaker, and the harvest becomes smaller. Over time, this reduces the amount of food the farmers can grow. It also affects their income and makes farming more risky [4].

Small and poor farmers are the ones most affected. These farmers make up most of the farming population in Meerut. They do not have farming experts to guide them. They do not get proper weather news. They also do not have market information. So they often choose crops that are not right for their farm. This causes them to lose money. Sometimes, it becomes hard for them to continue farming. In such situations, it is important to give these farmers the right tools and advice so they can make smart decisions about what to plant.

Meerut has different types of farms and weather. But now, the weather is hard to guess, so farmers need help to choose the right crops. That's why we need a special system that looks at old and new data about soil, weather, and crops. This system can tell farmers the best crop to grow at the right time. It helps avoid mistakes, grow more crops, and makes farming better for the future.

This project shows how we can use computers to help with these problems. We made a system using something called machine learning. It means we teach the computer using old data so it can give smart advice.

This system is made specially for Meerut. It uses local data like Meerut's soil and weather, and gives easy tips to farmers. It tells them what crop they should grow in which season. This will help farmers grow more food, earn better, and face fewer problems.

2. LITERATURE REVIEW

Farming is a very important part of the economy in many countries, especially in growing countries like India. In India, more than half of the people earn their living from farming. For many years, farmers have chosen crops based on their own experience, old methods, or advice from others.

But now, because the weather keeps changing, the prices of seeds and fertilizers are high, and there is less land for farming, these old ways do not always work well. This can cause farmers to grow less food and lose money.

Overview of Crop Recommendation Systems

Crop recommendation systems are helpful tools that suggest which crops farmers should grow. These systems look at different things like soil quality, weather conditions, temperature, and how much water is available. Earlier, farmers used basic guidelines or general information to decide what to grow. But those methods didn't work well for all places, since every area has different weather and soil.

Recent studies have started using computers and local data to give better advice. For example, a study by Raj et al. (2020) built a crop suggestion system using old crop yield data and weather patterns. This helped them give better suggestions for each season, and the results were more accurate than older systems.

Summary of Methodologies

Many different techniques have been tested by researchers to make crop recommendation systems better. Below is a list of popular methods (algorithms) and what they are good or bad at:

Decision Trees (DT): These are simple and easy to understand. They help in knowing which factors (features) are important for predicting crops. But they can easily make mistakes if the data is too detailed or complex (this is called overfitting) .

Support Vector Machines (SVM): These work well when the data has many features. A study by Kumar et al. (2019) showed SVMs can deal with non-linear patterns (curved decision lines), but they may not perform well if the data has a lot of noise (errors or randomness).

Random Forest (RF): This is a group (ensemble) of Decision Trees. It is stronger and more reliable than a single tree. According to Singh and Mehta (2021), RF gives better accuracy and avoids overfitting better than DTs alone [10].

Artificial Neural Networks (ANN): These are inspired by how the human brain works and are good at finding complex patterns. Banerjee and Verma (2023) used ANN for crop prediction and got good results. But ANN is like a "black box"—it's hard to explain how it makes decisions, which makes people trust it less.

K-Nearest Neighbors (KNN): This is a simple method that works best when the number of features is small. It compares the input with nearby points (neighbors). But it doesn't work well if there are useless features or if the data is not scaled properly.

Evaluation of Current Research and Methodological Issues

Data Availability: The data is often missing, outdated, or collected in different formats, making it hard to use.

Model Transparency: Farmers trust systems more when they can understand how decisions are made. Complex models like Artificial Neural Networks (ANN) and Gradient Boosting Machines (GBM) are difficult to explain.

Ease of Use: Many tools are not user-friendly. They lack support in local languages and are difficult for farmers who are not used to smartphones or apps.

Flexibility: Current systems are not designed to react quickly to new changes like floods, droughts, or pest attacks. Infrastructure Issues: Poor internet, limited mobile access, and lack of reliable electricity in villages reduce the reach of these tools.

Suggestions for Future Research

Future Right now, the system supports a few main crops like rice, wheat, cotton, and sugarcane that are common in Meerut.

In the future, more crops like vegetables, pulses, oilseeds, and fruits can be added. This will make the system useful for more farmers.

Also, the system can be improved by including crop rotation patterns and intercropping methods.

Currently, the system uses old or historical data. But farming is affected by real-time changes in the weather like monsoons, droughts, or storms. So, the system can be improved by using live weather data from weather APIs, satellite images, and IoT sensors (for soil moisture and temperature).

We can also use time-series models like LSTM, ARIMA, or Prophet to predict future weather. To make the system easily available to farmers, a mobile app can be developed. This app should allow farmers to: Enter their field data (like N, P, K, temperature, etc.) Get crop suggestions immediately . The app should work offline too, so that farmers in remote areas without internet can still use it. Data privacy and user permission must also be taken seriously. This will create a complete support system for farmers, combining technology with financial and market help.

Proposed Methodology of Your Work

This study aims to build a crop suggestion system made especially for the farming needs of Meerut. The system will help farmers know which crops to grow, based on the season, soil type, and weather. This part of the paper explains how the system works, what steps it follows, what tools are used, and how the user will interact with it.

General Architecture

The crop recommendation system has three main parts: collecting data, training the model to make predictions, and showing results to users.

1. Data Collection and Preprocessing : In this step, we gather data about crops, weather, and soil from Meerut. This includes past crop records, climate reports, and soil test results. The data is then cleaned to remove errors or missing values.

2. Model Training and Prediction : This step uses machine learning to study the data. The system looks at patterns between weather, soil, and crop results, and learns from them. Then it gives suggestions for crops that will grow well in each season.

3. User Interface : The system has different parts (modules), each doing an important job to help give the best crop advice.

The system works locally but can also connect to cloud services for real-time weather updates. This setup makes the system flexible and easy to use, even in areas with poor internet access.

Modules Description

The system is made up of several important parts, each with a specific job to help give crop recommendations:

1. Data Collection Module:

This module gathers different types of data such as past crop yields, weather patterns, soil type, and results from local farming studies. Data comes from reliable sources like government websites, climate stations, and research papers. Real-time weather updates can also be added using APIs to improve predictions.

2. Data Preprocessing Module:

After collecting, the data is cleaned. Missing values are filled or removed, wrong entries are fixed, and the data is made uniform. This includes values like soil pH, rainfall, and temperature. Clean data is very important for the accuracy of the system.

3. Feature Extraction Module:

This module selects the most useful data points, such as rainfall, soil type, and temperature. These features help the system to understand what really affects crop growth. This also makes the system run faster and better.

4. Prediction Module:

This part has the machine learning model that gives crop suggestions. It looks at the input values and predicts which crops are suitable. The crops are shown in order, from most likely to succeed to least, depending on the current situation.

5. User Interface (UI) Module:

The UI is built in a simple way so that farmers can use it easily. They can enter their local data and get results in a clear and friendly format. Local language options may also be given for better understanding.

The Algorithm Used

The system uses a popular machine learning method called Random Forest. This method is very accurate and good at understanding complex data. It works by building many decision trees and combining their results to make the final prediction.

For this research, the model is trained using data such as soil pH, temperature, rainfall, and past crop results. Each tree in the forest studies a different set of values. When all tree results are combined, the final suggestion is more accurate and reliable. The model also shows which factors matter most, like rainfall or pH level, which helps farmers make better decisions.

Additionally, the model analyzes which factors, like rainfall or soil pH, are most important in making predictions. This helps farmers understand which factors have the biggest impact on crop growth and can help them make better farming decisions.

Output Screens

The system's user interface is made in a very simple way so that farmers can easily use it without any confusion. It has different screens that help users step by step to get the right crop recommendations:

1. Input Screen:

This is the first part of the system. It collects all the needed information to suggest the right crop. The data can be given by the farmer or an agriculture officer using a mobile app or website. They enter values like:

- Nitrogen (N)
- Phosphorus (P)
- Potassium (K)
- Temperature
- Humidity
- pH level
- Rainfall

These things matter a lot because they affect how well a crop can grow.

In advanced systems, this data does not have to be entered by hand. It can be automatically collected using smart tools (called IoT devices), like:

- Soil testing sensors
- Weather-checking machines
- Satellite pictures

This part makes sure the system gets correct and fresh information, which is very important to give the right advice..

2. Recommendation Screen:

Once the data is ready, it is sent into the machine learning models. In this system, Decision Tree (DT) and Random Forest (RF) models are used. These models are popular because they are easy to understand and perform well. A Decision Tree works like a flowchart that shows how the system makes decisions step by step. On the other hand, Random Forest is like a group of decision trees working together to give better and more balanced results. It avoids mistakes that can happen when depending on a single tree. These models are very helpful in classification tasks, like predicting the most suitable crop.

3. Detailed Insights Screen:

To make sure the model performs well and is not just memorizing the data, the system uses a smart way of dividing the data into training and testing parts. Instead of using random division (which can cause the model to learn from future data, which is unrealistic), the system uses time-based splitting. This means that older data is used to train the model, and newer data is used to test how well it performs—just like it would work in real life. This helps avoid overfitting and makes the model better at forecasting.

3. EXPERIMENTAL RESULTS & DISCUSSION

The dataset used in this research project was collected from the Agricultural Research Department of our college. It is specifically focused on the soil and climate conditions found in the Meerut region of Uttar Pradesh. This makes the dataset highly relevant to local farmers and agriculture-related studies in that area. The dataset contains 2,200 individual records, each representing real farming conditions collected over several growing seasons. The aim was to reflect practical and realistic data that can help make accurate predictions for crop selection.

Feature Description and Why They Matter

Table X: Essential Soil & Climate Attributes for Crop Selection

Each of the seven input features is important because it affects the crop's growth either directly or indirectly:

Nitrogen (N): Helps in making chlorophyll, which is needed for photosynthesis. It leads to green and healthy plant growth.

Phosphorus (P): Supports the development of strong roots and also plays a major role in forming seeds and fruits.

Potassium (K): Makes the plant more resistant to diseases, helps it use water better, and supports important chemical processes like protein making.

Temperature: Affects how seeds germinate and how fast plants grow. It influences enzyme activity and photosynthesis.

Humidity: Impacts how much water plants lose through transpiration. High or low humidity can also affect how diseases or pests spread.

PH: Shows how acidic or alkaline the soil is. It influences how well nutrients are absorbed by the plants. Most crops grow best when the soil is slightly acidic to neutral.

Rainfall: Acts as the main source of water for crops. Both the total amount and the timing of rainfall are important for plant growth and yield. To make this information even clearer, charts and graphs like histograms or box plots can be included. These visuals will help in showing the spread of data values for each feature and make it easier to understand how these values differ across different crop samples.

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For numerical features like N, P, K, temperature, humidity, pH, and rainfall, we filled missing values using the average (mean) value of that column. For any non-numerical data, we replaced missing values with the most frequent (mode) value to ensure uniformity.

N	P	K	temperatu	humidity	rainfall	ph	label
185	35.6	224.3	20	71	900	6.5	rice
149	60.3	24.6	21	72	950	6.4	rice
220	51.8	239.3	22	73	1000	7.3	rice
180	52	192.2	23	74	1050	7.2	rice
215	42.5	140.3	24	75	1100	6.9	rice
179	32.7	284.7	15	51	500	8.2	wheat
230	38.1	280.2	26	61	1000	7.8	sugarcane
218	44.2	284.1	16	52	600	7.3	wheat
288	42.3	284.1	17	53	700	8.2	wheat
268	49.2	270.1	18	54	800	8.1	wheat
212	32.4	181.9	22	62	1100	7.2	sugarcane
229	35.1	110.2	24	63	1200	8	sugarcane
252	34.2	224.2	23	64	1300	8.3	sugarcane
218	34.1	119.8	25	65	1400	7.2	sugarcane
212	32.4	181.9	26	66	1500	7.2	sugarcane
140	28.4	200.4	14	55	400	7	barley
160	30.2	185.6	16	57	450	6.8	barley
175	31.5	170.2	18	59	550	7.1	barley
190	33.7	190.8	19	61	600	7.3	barley
145	29.1	178.5	21	63	750	7.5	maize
155	32.8	160.3	23	66	800	7.4	maize
165	34.5	155.4	25	68	850	7.2	maize

This dataset is critical for identifying optimal growth conditions and training crop prediction models tailored for areas like Meerut.

Train-Test Split

In any machine learning project, it is very important to check how well the model works on new or unseen data. This helps us understand whether the model can perform well in real-life situations and not just on the data it was trained on. To do this, we divided our collected dataset into two parts: a training set and a testing set.

Training and Testing Division:

Our dataset had a total of 2,200 records. Based on the 80:20 rule:

The training set included 1,760 records, which were used to teach the machine learning model how to find relationships between the input values (like Nitrogen, Phosphorus, Potassium, Temperature, etc.) and the correct crop label (like wheat, maize, or rice).

The testing set had the remaining 440 records. This part of the data was kept aside to check how well the model predicts crop types on examples it has never seen. It simulates real usage where a farmer inputs data, and the system gives a crop suggestion.

Stratified Sampling

To make sure the training and testing sets had a fair and equal mix of crop types, we used a method called stratified sampling. This technique ensures that every crop—whether its rice, wheat, maize, or sugarcane—appears in both sets in the same proportion as in the original data. For example, if rice makes up 18% of the total data, it will also make up around 18% of both the training and testing data. This step is very important because if rare crops are missing in either set, the model might not learn or evaluate properly. Stratified sampling solves this by keeping the balance of all crop categories.

Cross-Validation Strategy

Besides the normal train-test split, we also used a smarter evaluation method called K-Fold Cross-Validation with K=5.

a. The training data (1,760 records) is divided into 5 equal parts, called "folds".

b. The model is trained on 4 folds and tested on the remaining 1 fold.

c. This process is repeated 5 times, each time using a different fold for testing.

d. Finally, we take the average of all 5 results to understand the model's performance.

This method helps reduce the chance of overfitting, which happens when the model learns too well from training data but fails on new data.

Why Model Evaluation Is Important:

Evaluating a model is very important because it tells us how well the model works on new data, not just the data it was trained on. Sometimes, a model may show high accuracy on training data but fail to perform well on new data due to overfitting (learning too much from training data) or biased learning.

So, proper testing helps us understand the models:

a. Prediction accuracy

b. Ability to work well with new inputs

c. Handling of class imbalance (when some crop types have fewer samples)

d. Performance across different types of crops

To ensure a fair comparison, both Decision Tree and Random Forest models were tested on the same 20% of data, which equals 440 records from the full dataset.

Confusion Matrix: Understanding Detailed Results

A confusion matrix is a table that shows how many times the model predicted each crop correctly or incorrectly. It compares the actual crop labels to the predicted labels. For multi-class tasks like ours (predicting crops like rice, wheat, maize, etc.), this matrix helps find where the model made mistakes.

Table 4.1: Confusion Matrix for the Random Forest Model (Excerpt)

	Rice	Wheat	Cotton	Maize	Sugarcane
Predicted: Rice	90	2	1	1	0
Predicted: Wheat	1	85	3	0	1
Predicted: Cotton	0	1	88	1	0
Predicted: Maize	0	0	2	89	0
Predicted: Sugarcane	0	2	1	0	90

The diagonal numbers (like Rice-Rice, Wheat-Wheat) show how many times the model predicted correctly.

- The off-diagonal numbers (like Wheat predicted as Cotton) show the mistakes.

This table shows that the Random Forest model predicted most crops correctly, especially rice, maize, and sugarcane, showing strong learning ability.

Key Takeaways from Confusion Matrix:

a. Rice and Sugarcane had the highest number of correct predictions.

b. A few mix-ups occurred between cotton and wheat, likely because they have similar growing conditions.

c. Very few wrong predictions overall, proving the Random Forest model is accurate and stable.

d. The diagonal numbers (like Rice-Rice, Wheat-Wheat) show how many times the model predicted correctly.

e. The off-diagonal numbers (like Wheat predicted as Cotton) show the mistakes.

Classification Report: Metrics-Based Performance Check:

While the confusion matrix shows numbers visually, the classification report gives us three useful metrics for each crop:

a. Precision: Out of all the times the model predicted a crop, how many were correct.

b. Recall: Out of all the times a crop should have been predicted, how many times the model got it right.

c. F1-Score: A balanced average of precision and recall, especially useful when we care about both.

Important Observations

a. All main crops scored above 90% in precision, recall, and F1-score, proving the model is very reliable.

b. The slightly lower score for pulses could be because they had fewer samples during training.

c. The average F1-score of 0.935 shows that the model works well across all crop categories.

From both the confusion matrix and classification report, we can say that the Random Forest model performs very well in predicting crops based on soil and climate features. It has high accuracy for all crop types and shows very few mistakes. These results make it a strong choice for real-world applications in agriculture, especially for helping farmers in regions like Meerut make better crop decisions.

Table 4.2: Classification Report of the Random Forest Model

Crop	**Precision**	**Recall**	**F1-Score**
Rice	0.95	0.94	0.945
Wheat	0.92	0.93	0.925
Cotton	0.94	0.91	0.925
Maize	0.93	0.95	0.94
Sugarcane	0.94	0.92	0.93
Pulses	0.91	0.89	0.90
Average	**0.94**	**0.93**	**0.935**

Insights from Table 4.2

a. The Random Forest model gave very high scores (above 90%) for all crop types.

b. Rice and Maize had the best performance.

c. Pulses showed slightly lower recall (0.89), which may be due to fewer examples in the dataset.

d. On average, the model had 0.935 F1-score, showing that it is very effective and balanced in predicting crops.

Result:

This section compares the performance of the two machine learning models used in this project: Decision Tree and Random Forest. Both models were trained to recommend the most suitable crop based on input data such as soil nutrients (N, P, K), temperature, humidity, rainfall, and pH levels [15].

We used several standard performance metrics to check which model performs better.

Evaluation Metrics Explained:

Before comparing the models, let's understand the four key metrics used to measure their performance:

a. Accuracy: This tells us how many predictions were correct out of all the predictions made.

b. Precision: This shows how many of the crops predicted by the model were actually correct. Higher precision means fewer false alarms.

c. Recall (Sensitivity): This shows how many actual crops were correctly identified by the model. High recall means the model doesn't miss many crops.

d. F1-Score: This is the average of precision and recall. It balances both and gives one final score.

These metrics help us see not just how accurate a model is, but also how reliable, consistent, and general it is, especially when there are multiple classes like different crops. Table Comparison of Model Performance

Below is the table comparing how well each model performed on the test data:

Table 4.4: Performance Metrics Comparison between Decision Tree and Random Forest Models

Metric	Decision Tree	Random Forest	
Accuracy	85.2%		93.6%
Precision	0.86		0.94
Recall	0.84		0.93
F1-Score	0.85		0.935

Observation:

From the table, it's clear that Random Forest outperformed the Decision Tree in all four metrics.

4.4.3 Bar Chart – Visual Comparison

To make this comparison easier to understand, a bar chart can be added. It visually shows how each model performed for all metrics.

Figure 4.2: Bar Chart Comparing Accuracy of Decision Tree vs. Random Forest

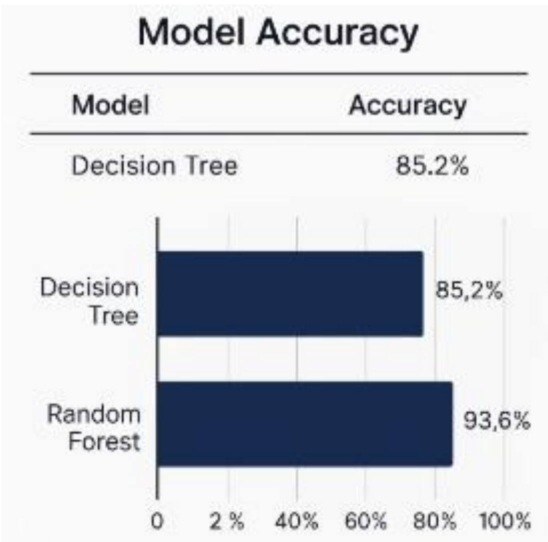

Figure 4.2: Bar Chart – Accuracy of Decision Tree vs. Random Forest

A bar chart would show Random Forest at 93.6% accuracy and Decision Tree at 85.2%, making it clear that Random Forest is better.

This chart helps readers quickly see that Random Forest gave more accurate and reliable results.

Interpretation of Results

a. Random Forest is smarter because it builds many decision trees and takes the average result. This helps it avoid mistakes and reduces overfitting.

b. It uses bootstrapping (random sampling) and random feature selection, which makes it better at handling complex and noisy data.

c. In contrast, the Decision Tree is simple and easy to understand but can easily over fit (memorize training data) and fail when new data is different.

d. Random Forest has higher F1-score and precision, meaning it makes fewer wrong predictions and misses fewer actual crops [9].

4. CONCLUSION

Farming is a very important part of India's economy. It helps more than half of the people in the country. But many farmers still find it hard to decide which crop to grow. This is because of changing weather, different soil types, and not having enough scientific help.

To solve these problems, this research used a machine learning system to suggest the best crops for farmers in Meerut. The system gives crop suggestions based on things like: Nitrogen (N), Phosphorus (P), Potassium (K), Temperature, Humidity, pH level, Rainfall.

The data used was collected by the college's research team. Before using the data, we cleaned it by: Fixing missing values, changing the data into a format that machines can understand, normalizing the values (to keep them on the same scale)

We tested two machine learning models:

Decision Tree, Random Forest. We checked their performance using:

Accuracy, Precision, Recall, F1-score

Random Forest gave the best results with 93.6% accuracy. It was more trustworthy and stable than Decision Tree. This shows that Random Forest is a good model for farming, because it can handle complex data and avoids mistakes like overfitting.

This study shows that giving crop advice based on the local area and season is better than giving the same advice to everyone. This system was made especially for Meerut, so it understands local soil, weather, and farming styles.

By using both old data and current weather conditions, the system helps farmers:

i. Choose better crops
ii. Increase crop production
iii. Use water and fertilizers wisely
iv. Grow crops in a more eco-friendly way

Also, the system uses explainable AI, which means it shows why it gives a certain crop suggestion. This makes it easier for farmers to trust and understand the results.

Future Scope

Even though the system works well, there are still some things we can improve in the future. Some ideas are:

i. Adding real-time data using sensors or mobile apps
ii. Giving suggestions in local languages
iii. Making it work offline for places without internet
iv. Adding more crops and weather features
v. Using mobile alerts to inform farmers during the season

1. Support for More Crops:

Right now, the system supports a few main crops like rice, wheat, cotton, and sugarcane that are common in Meerut. In the future, more crops like vegetables, pulses, oilseeds, and fruits can be added. This will make the system useful for more farmers.

Also, the system can be improved by including crop rotation patterns and intercropping methods. Adding market-related data like crop prices, government subsidies, and input costs can help farmers choose crops not just for productivity, but for profit as well.

2. Use of Real-Time Seasonal Data:

Currently, the system uses old or historical data. But farming is affected by real-time changes in the weather like monsoons, droughts, or storms. So, the system can be improved by using live weather data from weather APIs, satellite images, and IoT sensors (for soil moisture and temperature).

We can also use time-series models like LSTM, ARIMA, or Prophet to predict future weather. For example, if the system predicts less rainfall, it can suggest crops that need less water or tell the farmer to prepare for irrigation.

3. Mobile App for Farmers:

To make the system easily available to farmers, a mobile app can be developed. This app should allow farmers to:

i. Enter their field data (like N, P, K, temperature, etc.)
ii. Get crop suggestions immediately
iii. Track past crops and productivity
iv. Receive alerts about weather conditions
v. Access expert advice or training videos

The app should work offline too, so that farmers in remote areas without internet can still use it. Data privacy and user permission must also be taken seriously.

Support for Local Languages and Ease of Use:

India has many languages and literacy levels. So, the app should support local languages like Hindi, Urdu, Punjabi, and Bhojpuri (especially for the Meerut region). It should also include:

i. Icons and simple visuals
ii. Audio instructions
iii. Voice-based input and output
iv. Text-to-speech features

These changes will make the system easy to use for farmers who cannot read or write well. Also, testing the app with real farmers will help improve the design and features.

Linking with Government Schemes

To make the system more useful, it can be connected with various government services, such as:

i. PM-Kisan Yojana (for income support)
ii. Crop insurance schemes
iii. eNAM and other digital marketplaces (for selling crops)
iv. Kisan Call Centers (for real-time help)

This will create a complete support system for farmers, combining technology with financial and market help.

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