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Climate-Smart Crop Recommendation System Using Random Forest Algorithm

Dr. S. Mohana[1], S. Menaka[2], N.Sanjai[3]
[1] *Assistant Professor Department of Computer Science , Sri Ramakrishna College of Arts & Science*
[2,3]*PG Student, Department of Computer Science , Sri Ramakrishna College of Arts & Science*

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Corresponding Author:
N.Sanjai

Abstract:
Climate change has significantly impacted agricultural production since it has altered soil conditions, temperature ranges, and rainfall patterns. In order to help farmers choose the best crops for shifting climate circumstances, this project suggests a Climate-Smart Crop Recommendation System that makes use of artificial intelligence and data analytics. Temperature, precipitation, humidity, soil nutrients (N, P, and K), pH, and other environmental factors are among the historical and current data that the system analyzes. The Random Forest machine learning technique is used to analyze patterns and forecast suitable crops. Model performance and prediction reliability are enhanced by feature engineering and methodical data pretreatment. With an overall accuracy of 90% on the test dataset, the Random Forest model showed excellent generalization and predictive power. Through encouraging effective resource use and lowering the chance of crop failure, the suggested strategy promotes sustainable agriculture. The technology improves food security, resilience, and agricultural output in climate-sensitive areas by offering smart, data-driven crop recommendations.

Keywords: Crop recommendation systems, artificial intelligence, machine learning, data analytics, climate-smart agriculture, and sustainable farming

1. INTRODUCTION

One of the most significant issues facing agriculture globally now is climate change. Crop productivity and food security are directly impacted by rising temperatures, erratic rainfall patterns, protracted droughts, and frequent extreme weather events. Farmers find it more challenging to choose the right crops and schedule their cultivation cycles as a result of these changes. Through changes in moisture content and nutrient availability, climate variability also affects soil fertility. Crop failures, lower yields, and financial losses stem from conventional farming methods' inability to adjust to quickly changing environmental conditions. These difficulties show how urgently adaptive and sustainable farming methods are needed. To ensure long-term stability and resilience, agricultural decision-making must take climate awareness into account. In order to reduce negative effects and promote sustainable development, modern technology is essential.

Climate-smart farming has become a viable solution in this situation. It seeks to boost agricultural output while lessening its negative effects on the environment and preparing for climate change. It assists farmers in making well-informed choices about crop selection and resource management by examining soil and climate variables.

Soil degradation and resource waste are decreased when water, fertilisers, and other inputs are used efficiently. Additionally, climate-smart techniques can reduce greenhouse gas emissions and increase resilience against erratic weather patterns. Better crop planning and risk management are made possible by real-time monitoring and forecasting made possible by technology integration. Sustainability and productivity are further improved by data-driven insights. Therefore, climate-smart farming ensures sustainable agricultural expansion for the future by successfully bridging the gap between environmental protection and the needs for food security.

2. LITERATURE REVIEW

Global agricultural production and food security are now seriously threatened by climate change. Climate-smart agriculture was developed by the Food and Agriculture Organization (FAO) to increase resilience, boost productivity, and lessen environmental effects in the face of changing climate conditions [1]. Schmidhuber and Tubiello [2] further underlined that rising temperatures, unpredictable rainfall patterns and extreme climate events directly affect crop growth and long-term food availability, emphasising the necessity for adaptive and data-driven agriculture solutions.

Data analytics and artificial intelligence techniques have been widely used to promote smart farming operations due to the growing availability of agricultural and environmental data. In their assessment of the use of big data analytics and machine learning in agriculture, Kamilaris et al. [3] found that AI-based systems make it possible to handle large-scale crop, soil, and climatic datasets effectively to aid in decision-making. Their research showed that data-driven strategies can spot intricate relationships between environmental variables and agricultural results that are challenging to model with conventional techniques.

Crop recommendation and yield prediction using machine learning algorithms have been the subject of numerous studies. By evaluating meteorological and soil characteristics, Ramesh and Vardhan [4] introduced machine learning-based methods for crop selection and yield prediction. They demonstrated that predictive models can greatly assist farmers in choosing appropriate crops for specific environmental situations. In a similar vein, Mythili and Mohamed Shanavas [5] looked at data mining methods for predicting crop yield and stressed the significance of feature selection, data preprocessing, and appropriate model training to increase forecast accuracy and dependability.

The wider application of AI in smart agriculture has also been emphasised by recent studies. In their discussion of a variety of AI applications, including crop monitoring, decision support systems, and precision agriculture, Singh et al. [6] made the point that intelligent systems can optimise resource use and lessen environmental effect. They did, however, also point up issues with data quality, model resilience, and the practical use of intelligent agricultural systems.

The majority of current systems primarily concentrate on yield prediction or crop classification without completely integrating climate-smart aims and sustainability considerations, despite research showing the efficacy of machine learning and data analytics for agricultural decision support. Furthermore, integrating thorough climate, soil, and geographic variables with methodical feature engineering for trustworthy crop recommendation has received little attention. These constraints drive the creation of a climate-smart crop recommendation system that combines data analytics and artificial intelligence to give farmers accurate, dependable, and long-lasting decision help in the face of shifting climate circumstances.

3. PROPOSED SYSTEM ARCHITECTURE

3.1 System Overview

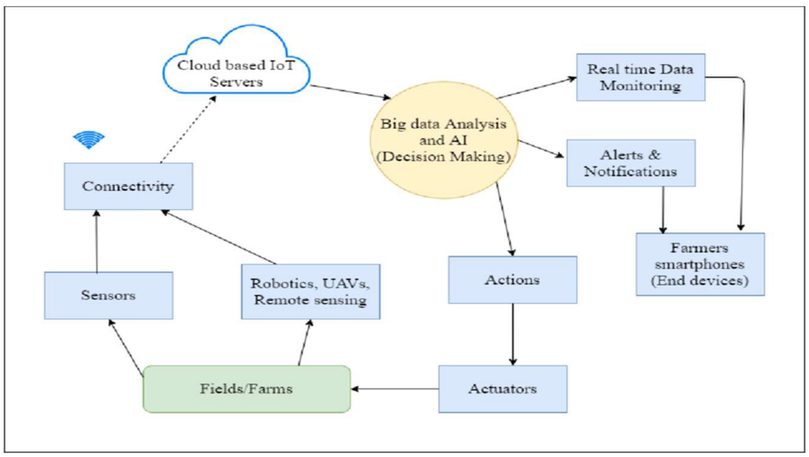


Figure 1: Overall Architecture of the Climate-Smart Crop Recommendation System

The general architecture of the suggested climate-smart crop recommendation system is shown in this picture. It shows how crop datasets, soil characteristics, and climate data are integrated. Before the Random Forest model processes the input, preprocessing and feature engineering are applied. Based on environmental factors, the system then recommends appropriate crops.

To suggest appropriate crops, the suggested method combines crop databases, soil factors, and climatic data. Temperature, precipitation, and humidity are examples of climate data. pH, moisture, and nutrient levels make up soil data. Preprocessing uses normalisation and cleaning to guarantee data quality. An AI-based model receives the processed data. The model forecasts the best crops by analysing patterns. Farmers are given crop recommendations by the recommendation module. This method facilitates decision-making in the face of shifting climate conditions. It improves sustainability and productivity. Automation guarantees quick and precise suggestions. The architecture is scalable and modular.

4. DATASET DESCRIPTION

4.1 Climate Dataset

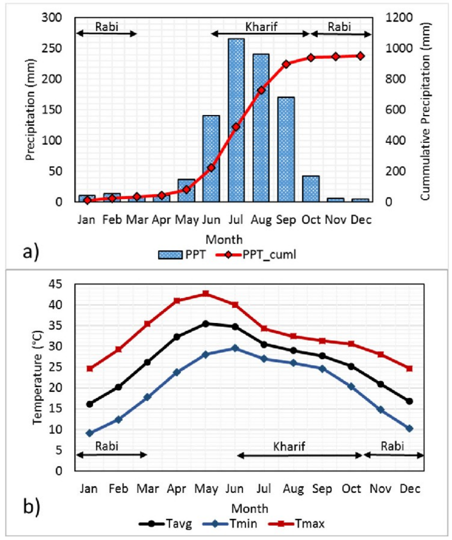


Figure 2: Sample Distribution of Climate Parameters

The distribution of important climate variables utilised in the study, including temperature, rainfall, and humidity, is displayed in this image. Seasonal and regional differences that have a big impact on crop development and suitability are highlighted in the visualisation. These characteristics of the climate are crucial inputs for the prediction model.

The climate dataset includes variables including humidity, rainfall, and temperature. These characteristics show how the environment influences crop growth. Information is gathered from trustworthy meteorological sources. Included are regional and seasonal variations. Preprocessing takes care of missing values. Crop suitability is heavily influenced by climate data. It records the fluctuations in the climate over time. Prediction performance is enhanced with accurate climatic data. Consistency is ensured by feature scaling. The AI model uses this dataset as a crucial input.

4.2 Soil Dataset

Features including pH, nitrogen, phosphorus, potassium, and moisture are included in the soil dataset. Crop output is directly impacted by soil fertility. Various types of soil are represented in the dataset. Fair feature contribution is ensured by data normalisation. Crop selection is aided by the evaluation of soil quality. It is possible to detect poor soil conditions early on. Climate data is complemented by this dataset. The accuracy of recommendations is increased by combined analysis. Monitoring soil health promotes sustainable agriculture. Long-term productivity is improved by it.

4.3 Crop Dataset

The crop dataset includes details about different crops and what they need to grow. An appropriate climate and soil conditions are linked to each crop. Included are attributes linked to yield. Multi-crop recommendations are supported by the dataset. Crop types are represented by class labels. Model performance is enhanced with balanced data. Recommendation flexibility is improved by crop diversification. Comparative analysis is made possible by this dataset. It facilitates wise decision-making. Agricultural planning is enhanced by crop mapping.

2,200 records covering 22 distinct crop varieties were gathered from publicly accessible agricultural sources to create the combined dataset. Soil nutrients (N, P, and K), temperature, humidity, rainfall, and pH data are all included in each record. To ensure accurate performance evaluation and generalisation capabilities, the dataset was split into 80% training data and 20% testing data for model evaluation.

5. METHODOLOGY

5.1 Data Collection and Understanding

- Data on agriculture, soil, and climate are gathered from reputable public sources.
- The dataset includes information on crop type, temperature, rainfall, and soil nutrients.
- To comprehend data distribution and feature importance, preliminary analysis is carried out.
- Duplicate entries and inconsistent records are found.
- Improved model design and data quality are supported by this stage.

5.2 Data Pre-processing and Cleansing

- Using appropriate methods, missing and inconsistent values are eliminated or imputed.
- Using the proper encoding, categorical attributes are transformed into numerical form.
- To preserve a consistent scale, numerical features are normalised.
- To reduce their impact on forecasts, outliers are examined.
- These actions increase learning effectiveness and data dependability.

5.3 Feature Engineering and Selection

- Existing qualities are converted into new, significant features.
- To find pertinent variables, correlation and importance analysis are used.
- To cut down on noise, redundant and irrelevant elements are eliminated.
- Feature selection helps to lower computational complexity.
- Both prediction accuracy and model generalisation are enhanced by this procedure.

5.4 Model Development and Training

For crop recommendation, the Random Forest method was chosen as the main machine learning model. In order to increase prediction accuracy and decrease overfitting, Random Forest is an ensemble learning technique that builds several decision trees during training and mixes their outputs using majority voting. Random Forest works well with agricultural datasets that comprise a variety of soil and climate characteristics because of its resilience to noise, robustness, and capacity to handle high-dimensional data.

Nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, soil pH, and rainfall were among the important input features used to train the model. Crop yield and growth are greatly influenced by these characteristics. To guarantee that each variable contributed equally, the dataset was preprocessed using feature scaling and normalization before to training.

To objectively assess model performance, the dataset was split between training and testing subsets using a suitable split ratio. The decision trees were constructed using the training data, and the generalization ability was evaluated using the testing data. To get the best results, hyperparameters like the number of trees, maximum depth, and minimum samples per split were adjusted. After training, the final model was incorporated into the crop recommendation system to provide predictions in real time.

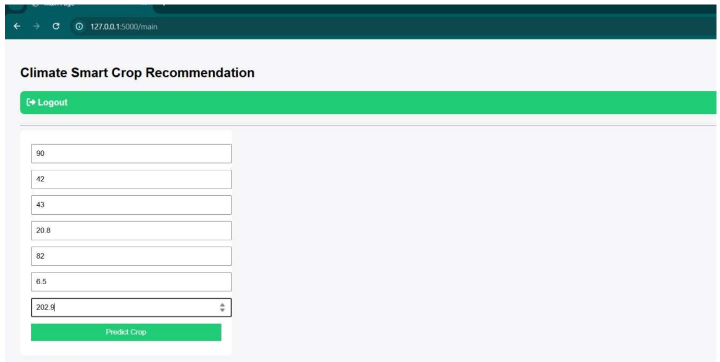
5.5 Hyperparameter Optimisation

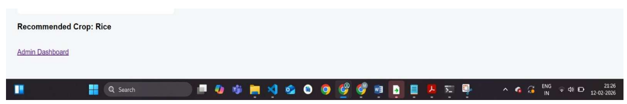
- Cross-validated search methods are used to adjust model parameters.
- During training, several combinations of parameters are assessed.
- Convergence and prediction accuracy are enhanced via optimisation.
- Underfitting and overfitting issues are lessened by this process.
- For every model, the optimal configuration is chosen.

6. EXPERIMENTAL RESULTS

6.1 Results Analysis

In order to offer real-time crop suggestions, the trained Random Forest model was successfully incorporated into a web application created with Flask. Nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, and rainfall are among the soil and climate characteristics that users enter. The method forecasts the best crop for the specified environmental circumstances based on these characteristics. The system interface and the final crop forecast output show how the suggested system is really put into practice. Using common classification measures, the Random Forest model's performance was assessed. On the test dataset, the model's overall accuracy of 90% demonstrated its strong predictive abilities. To evaluate the classification performance across several crop classes, F1-score, recall, accuracy, and precision were calculated. The findings show that the model accurately depicts the interplay among crop appropriateness, climate, and soil nutrients. When compared to single decision tree models, Random Forest's ensemble nature helped to improve generalization and decrease overfitting. The majority of crop types were accurately categorized with few misclassification mistakes, according to the confusion matrix study. The effectiveness of the suggested climate-smart crop recommendation system in assisting with data-driven agricultural decision-making is confirmed by these results.





6.2 Confusion Matrix and Feature Importance Analysis

A confusion matrix was created to examine class-wise prediction accuracy in order to assess classification performance even more. The matrix shows that there were very few misclassification errors and that most crop classifications were correctly identified. Strong generalization ability over a range of soil and climate variables is demonstrated by the Random Forest model.

To find the most important factors influencing crop recommendation, feature importance analysis was also carried out. According to the findings, soil pH, rainfall, and nitrogen (N) are some of the most important variables influencing precise crop forecast. Nonlinear interactions between crop suitability and environmental factors are well captured by Random Forest's ensemble learning structure.

The suggested climate-smart crop recommendation system is more dependable and easier to understand thanks to these visual evaluations.

7. DISCUSSION

7.1 Discussion of Findings

The experimental results indicate that integrating climate and soil parameters significantly improves the accuracy of crop recommendations. The Random Forest algorithm demonstrated strong predictive performance due to its ensemble learning structure, which reduces overfitting and captures complex nonlinear relationships between environmental variables and crop suitability. The achieved accuracy of 90% confirms the effectiveness of combining soil nutrients (N, P, K), temperature, humidity, rainfall, and pH for reliable crop prediction.

Systematic preprocessing, feature engineering, and hyperparameter optimization are responsible for the model's resilience. Random Forest efficiently handles climate variability and high-dimensional agriculture datasets. Additionally, the confusion matrix analysis demonstrates robust generalization performance with low misclassification across crop categories.

Practically speaking, the approach helps farmers choose crops based on science and lessens reliance on manual decision-making. The approach lowers economic risks related to climate fluctuation and encourages sustainable farming practices by matching crop selections with climatic appropriateness.

7.2 Limitations of the Proposed System

Although the suggested Climate-Smart Crop Recommendation System performs well in terms of prediction, there are certain drawbacks:
The accuracy and comprehensiveness of historical soil and climate datasets are crucial to the model. Prediction reliability may be immediately impacted by any errors, missing numbers, or skewed data. The model's performance may suffer when applied to areas with radically differing environmental circumstances because it was trained on pre-collected datasets.

Satellite imaging and real-time data from IoT sensors are not incorporated into the present system. As a result, the recommendations might not immediately account for abrupt environmental changes like unexpected rainfall, drought, or temperature surges.

Despite its excellent accuracy, the Random Forest method is a black-box model that makes it challenging to interpret complex decision limits. Although feature importance is known, there is still little information accessible regarding the specific logic underlying each prediction

A small number of crop types and geographical areas are covered by the dataset utilized in this study. Therefore, without additional training utilizing region-specific datasets, the system might not be able to properly generalize to other agroclimatic zones.

Conditions not included in the training data may be introduced by extreme climate events brought on by rapid climate change. Unseen environmental trends may cause forecast accuracy to decline in such situations.

At the moment, the system simply considers climate conditions and soil nutrients. Not mentioned are other significant agricultural elements that could affect final crop suitability decisions, such as insect outbreaks, market demand, irrigation availability, and farming techniques.

8. CONCLUSION

An artificial intelligence and data analytics-based Climate-Smart Crop Recommendation System was introduced in this study. The suggested system offers precise and trustworthy crop predictions based on environmental circumstances by combining soil, climate, and crop datasets. With an overall accuracy of 90%, the Random Forest model proved to be robust and highly predictive in agricultural decision-making tasks.

By maximizing the use of resources, decreasing the likelihood of crop failure, and promoting climate-adaptive farming practices, the system improves sustainable agriculture. The suggested strategy enhances agricultural production, environmental sustainability, and long-term food security through clever automation and data-driven insights. The outcomes validate AI-based models' ability to develop intelligent and climate-resilient farming systems.

9. FUTURE WORK

Figure 3: Future Enhancement Framework of the Proposed System

The suggested system's possible future improvements are depicted in this picture, which includes the incorporation of real-time IoT sensors, satellite data, mobile application support, pest and disease prediction, and sophisticated deep learning models. The goal of these enhancements is to make the system more accurate, scalable, and useful for farmers.

In the future, real-time IoT data integration might be incorporated into the projects. The strength of the model will grow as the databases grow. One can explore advanced deep learning models. The web and mobile applications can facilitate access. Relevance: Regional customisation can be used to increase the relevance. Diseases and pests can be predicted. Weather forecasts can enhance the accuracy. Multilingual assistance can be displayed to farmers. Continuous learning models can evolve over time. The future will bring improvements that will enhance climate-smart agriculture.

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