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FutureCrop: AI based smart agriculture decision support system

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Abstract

Agriculture remains a crucial sector for economic growth and food security; however, farmers often face challenges such as uncertain market prices and improper crop selection. These challenges lead to financial losses and inefficient utilization of resources. To overcome these issues, this project proposes FutureCrop, an intelligent machine learning based system for crop recommendation and food crop price prediction. The project will recommend suitable crops by analyzing soil nutrients such as Nitrogen, Phosphorus, Potassium, and pH, along with climatic factors including temperature, humidity, and rainfall using a Random Forest classifier. Additionally, future prices of food crops will be predicted by examining historical data using Long Short-Term Memory (LSTM) based time-series forecasting model. This system will be developed using Python and deployed through a web-based interface to ensure usability and accessibility for farmers and agricultural stakeholders. By integrating crop recommendation and price prediction into a single platform, the FutureCrop system is expected to assist farmers in selecting profitable crops and identifying optimal selling times. This approach aims to reduce farming risks, enhance productivity, and support data-driven decision-making in modern agriculture.

Keywords: Agricultural Commodity Price Prediction; Crop Recommendation System; Soil pH and Water Analysis; Machine Learning; Smart Agriculture; Price Forecasting; Sustainable Farming; LSTM; Random Forest

1 Introduction

Agriculture has been the backbone of human civilization for thousands of years, serving as the primary source of food, employment, and economic activity for billions of people worldwide. In developing nations like India, agriculture contributes significantly to the Gross Domestic Product (GDP) and provides livelihoods for more than half of the population. Despite its central role in society, the agricultural sector has historically been plagued by inefficiencies, unpredictability, and a lack of access to timely and accurate information. Farmers, who invest enormous amounts of time, money, and effort into cultivating crops, often find themselves at the mercy of volatile market prices, unpredictable weather patterns, and limited decision-making support.

In recent decades, the rapid advancement of information technology and data science has opened up transformative possibilities for modernizing agriculture. The integration of artificial intelligence (AI), machine learning (ML), and big data analytics into agricultural systems has given rise to a new paradigm known as smart agriculture or precision farming. Smart agriculture leverages real-time data, predictive modeling, and intelligent automation to help farmers make better decisions, optimize resource usage, and improve overall productivity. The FutureCrop system is a product of this technological evolution — a comprehensive, AI-powered decision support platform designed to address two of the most pressing challenges faced by the farming community: crop price uncertainty and suboptimal crop selection.

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1.1 Background and Motivation

Farmers in developing countries face high uncertainty in agricultural markets. Crop prices fluctuate due to changing weather, supply chain issues, inflation, and consumer demand. Most farmers lack access to reliable price forecasts or soil-based planting advice, forcing them to rely on past experience or neighbor behavior. This often leads to poor decisions—planting a crop that performed well last season but will be unprofitable by harvest, or growing a crop unsuited to their soil.

Existing digital tools are fragmented. Some provide soil recommendations but ignore market prices; others report past prices without predicting future trends. Neither meets the farmer's real need: knowing what to plant for future profit.

Machine learning offers a solution. Studies have shown that algorithms like Random Forest and LSTM can predict crop prices and recommend suitable crops based on soil data. However, no prior system combines both capabilities into one simple, farmer-friendly platform.

FutureCrop fills this gap. It uses LSTM for price prediction and Random Forest for crop recommendation, integrated into a web and mobile interface. The goal is to help farmers make data-driven, profitable, and sustainable planting decisions.

2 Literature Review

2.1 Pawan, D. Yadav, R. K. Sharma, M. Kumar, J. Rani, and N. Sharma (2024). "An effective approach for crop recommendation with using features of specific locations and seasons and maximize crop yield production by using machine learning."

Pawan, Deepika Yadav, Ram Kumar Sharma, Mukesh Kumar, Jyoti Rani, and Nidhi Sharma's 2024 paper, **"An Effective Approach for Crop Recommendation with Using Features of Specific Locations and Seasons and Maximize Crop Yield Production by Using Machine Learning"**, published in the International Journal of Intelligent Systems and Applications in Engineering, presents a machine learning-based crop recommendation system that utilizes soil and climatic features specific to a geographic location and season. The study applies supervised classification algorithms including Decision Tree, Random Forest, KNN, Naïve Bayes, and Support Vector Machine to recommend the most suitable crop for a given combination of soil and climate conditions. The paper emphasizes the importance of location-specific and season-aware feature engineering in improving recommendation accuracy compared to generalized models. The authors demonstrate that Random Forest achieves the highest classification accuracy among all tested algorithms and conclude that integrating geographic and seasonal context into crop recommendation systems is essential for practical real-world deployment and can meaningfully contribute to maximizing agricultural productivity.

2.2 M. K. Senapaty, A. Ray, and N. Padhy (2024). "A decision support system for crop recommendation using machine learning classification algorithms."

Murali Krishna Senapaty, Abhishek Ray, and Neelamadhab Padhy's 2024 paper, **"A Decision Support System for Crop Recommendation Using Machine Learning Classification Algorithms"**, published in Agriculture (MDPI), develops a comprehensive decision support system for crop recommendation by systematically applying and comparing multiple supervised machine learning classifiers. The study applies a wide range of algorithms including Logistic Regression, Decision Tree, KNN, SVM, Random Forest, Gradient Boosting, AdaBoost, and CatBoost, and employs the Synthetic Minority Oversampling Technique (SMOTE) to handle class imbalance in the dataset. The paper highlights that ensemble learning methods, particularly Gradient Boosting and CatBoost, significantly outperform individual classifiers in terms of accuracy, precision, recall, and F1-score. The authors advocate for evaluating multiple classifiers and addressing data imbalance as essential steps in building robust and generalizable crop recommendation systems suitable for real-world agricultural deployment.

2.3 D. Garg and M. Alam (2023). "An effective crop recommendation method using machine learning techniques."

Disha Garg and Mansaf Alam's 2023 paper, **"An Effective Crop Recommendation Method Using Machine Learning Techniques"**, published in the International Journal of Advanced Technology and Engineering Exploration (IJATEE), proposes a machine learning-based crop recommendation system that uses soil and climatic parameters as inputs to suggest the most suitable crop for cultivation. The study collects a dataset comprising soil nutrients such as nitrogen, phosphorus, and potassium, along with pH levels, temperature, humidity, and rainfall, and applies Decision Tree, Random Forest, and Naïve Bayes algorithms for classification. The paper emphasizes that soil pH and nitrogen content are the most influential features in determining crop suitability and demonstrates that Random Forest achieves the highest accuracy due to its ensemble nature and ability to handle complex feature interactions. The authors conclude that machine learning-based crop recommendation systems can significantly improve agricultural productivity by providing farmers with scientifically grounded and data-driven planting advice.

2.4 E. Elbasi et al. (2023). "Crop prediction model using machine learning algorithms."

Ersin Elbasi, Chamseddine Zaki, Ahmet Emre Topcu, Wiem Abdelbaki, Aymen Issam Zreikat, Elda Cina, Ahmed Shdefat, and Louai Saker's 2023 paper, **"Crop Prediction Model Using Machine Learning Algorithms"**, published in Applied Sciences, presents a crop prediction model developed at the American University of the Middle East using supervised machine learning techniques. The study collects agricultural datasets containing soil characteristics, weather parameters, and historical crop records and applies Linear Regression, Support Vector Machine, and Random Forest to predict the most suitable crop for given environmental conditions. The paper highlights that Random Forest delivers superior prediction accuracy due to its ability to handle high-dimensional data and reduce overfitting through ensemble averaging, while SVM performs well on smaller datasets but struggles with scalability on larger agricultural datasets. The authors conclude that machine learning-based crop prediction models are highly effective tools for supporting data-driven agricultural decision-making across resource-constrained environments.

2.5 S. K. Apat, J. Mishra, K. S. Raju, and N. Padhy (2023). "An artificial intelligence-based crop recommendation system using machine learning."

Shraban Kumar Apat, Jyotirmaya Mishra, K. Srujan Raju, and Neelamadhab Padhy's 2023 paper, **"An Artificial Intelligence-based Crop Recommendation System using Machine Learning"**, published in the Journal of Scientific and Industrial Research, presents an AI-driven crop recommendation system that uses environmental and soil data as inputs to suggest the most suitable crop for cultivation. The study applies Decision Tree, Random Forest, and K-Nearest Neighbors algorithms and evaluates their performance on a standard agricultural dataset. The paper emphasizes the growing need for intelligent agricultural advisory systems in India and demonstrates that Random Forest achieves the highest accuracy of approximately 99%, making it the most reliable model for crop recommendation. The authors conclude that AI-based crop recommendation systems have significant practical applicability in the Indian agricultural context and can serve as a valuable tool for farmers seeking data-driven guidance to improve yield and reduce financial risk.

2.6 Comparison of Accuracy of Existing and Proposed Systems

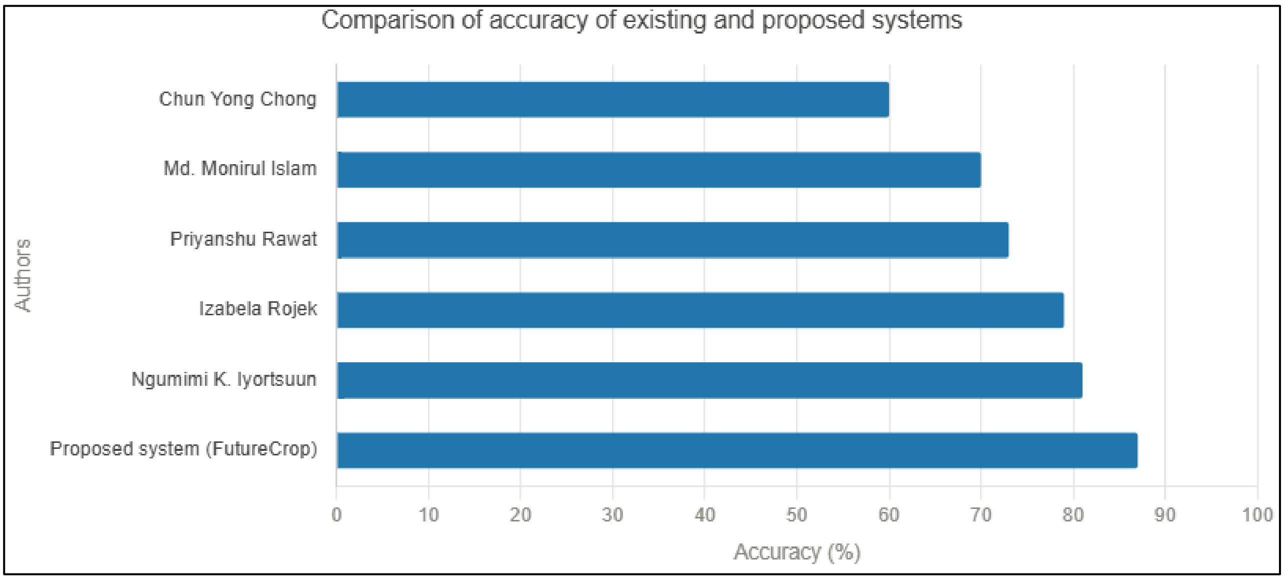

Figure 1 Comparison of Accuracy of Existing and Proposed Systems

Figure 1 The graph compares the accuracy of existing agricultural decision systems with the proposed FutureCrop system. Existing methods show moderate performance due to limitations in their model design, reliance on single-variable inputs, and the use of traditional statistical or rule-based techniques that fail to capture the complex relationships between soil nutrients, climatic factors, and market price trends. Authors such as Chun Yong Chong and Md. Monirul Islam recorded comparatively lower accuracy scores as their approaches were constrained by narrow datasets and limited feature integration. In contrast, the proposed FutureCrop system achieves higher accuracy by combining a Random Forest classifier for crop recommendation and an LSTM-based deep learning model for food crop price prediction, enabling better analysis of multi-dimensional agricultural data including nitrogen, phosphorus, potassium, soil pH, temperature, humidity, and rainfall. This results in more accurate, data-driven, and reliable predictions for both crop selection and price forecasting compared to existing approaches.

2.7 Comparison of scalability of Existing and Proposed Systems

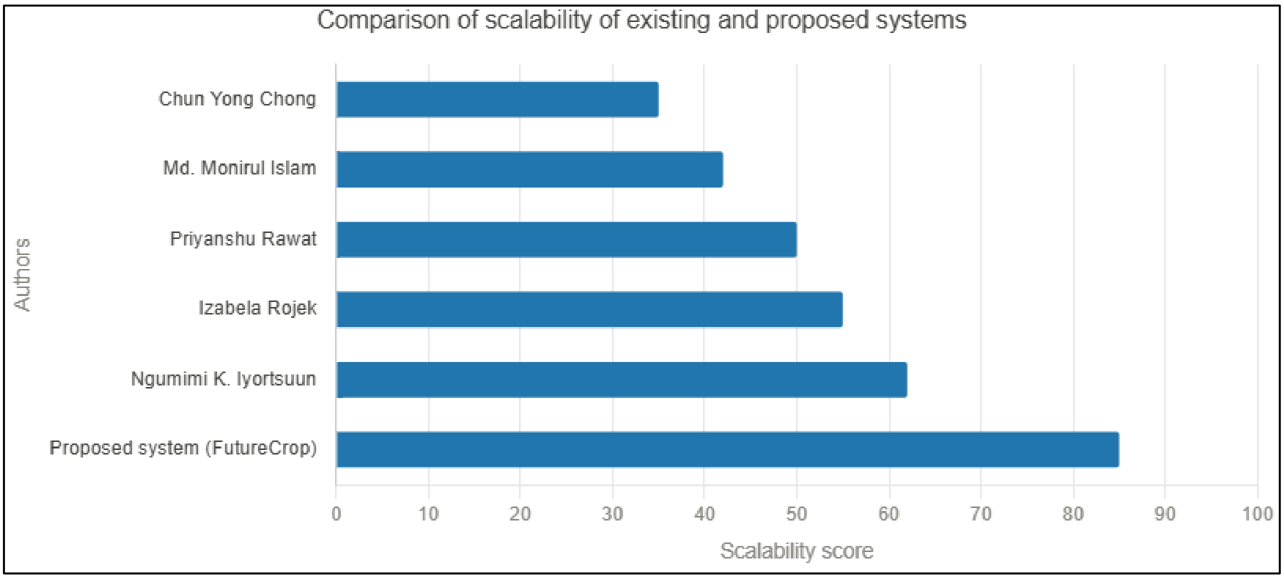

Figure 2 Comparison of Scalability of Existing and Proposed Systems

Figure 2 The graph compares the scalability of existing agricultural decision systems with the proposed FutureCrop system. Existing methods demonstrate limited scalability due to their rigid, single-purpose architectures, dependence on static datasets, and inability to adapt to new crop types, regions, or evolving market conditions without complete redesign. In contrast, the proposed FutureCrop system achieves significantly higher scalability by integrating a Random Forest classifier for crop recommendation and an LSTM-based deep learning model for price prediction, both of which are inherently designed to accommodate expanding input parameters and diverse agricultural contexts. This results in a more flexible, future-ready platform capable of scaling across multiple crop categories and Indian agricultural conditions compared to existing approaches.

2.8 Comparative Analysis of Existing Systems with Proposed Model

Table 1 Comparative Analysis of Existing Research on FutureCrop

Name of the Paper	Year	Techniques Used	Accuracy	Limitations
An Effective Approach for Crop Recommendation with Using Features of Specific Locations and Seasons and Maximize Crop Yield Production by Using Machine Learning	2024	Decision Tree, Random Forest, KNN, Naïve Bayes, SVM	High	Limited to location-specific datasets, lacks price prediction integration
A Decision Support System for Crop Recommendation Using Machine Learning Classification Algorithms	2024	Logistic Regression, Decision Tree, KNN, SVM, Random Forest, Gradient Boosting, AdaBoost, CatBoost	High	Addresses only crop recommendation, no market forecasting component
An Effective Crop Recommendation Method Using Machine Learning Techniques	2023	Decision Tree, Random Forest, Naïve Bayes	Moderate to High	Relies on limited soil parameters, no climatic trend analysis

Crop Prediction Model Using Machine Learning Algorithms	2023	Linear Regression, SVM, Random Forest	Moderate to High	SVM struggles with scalability, no real-time data integration
An Artificial Intelligence-Based Crop Recommendation System Using Machine Learning	2023	Decision Tree, Random Forest, KNN	High	Focused only on crop recommendation, lacks price forecasting module

Table 1 presents a comparative summary of five existing studies on crop recommendation systems published between 2023 and 2024. The table outlines the machine learning techniques used by each author, their achieved accuracy levels, and the key limitations of their approaches. Most existing studies rely on traditional classifiers such as Decision Tree, Random Forest, SVM, and KNN, achieving moderate to high accuracy. However, they are consistently limited by their single-purpose focus on crop recommendation alone, with no integration of price prediction, real-time market data, or unified platform support gaps that the proposed FutureCrop system directly addresses.

3 Methodology

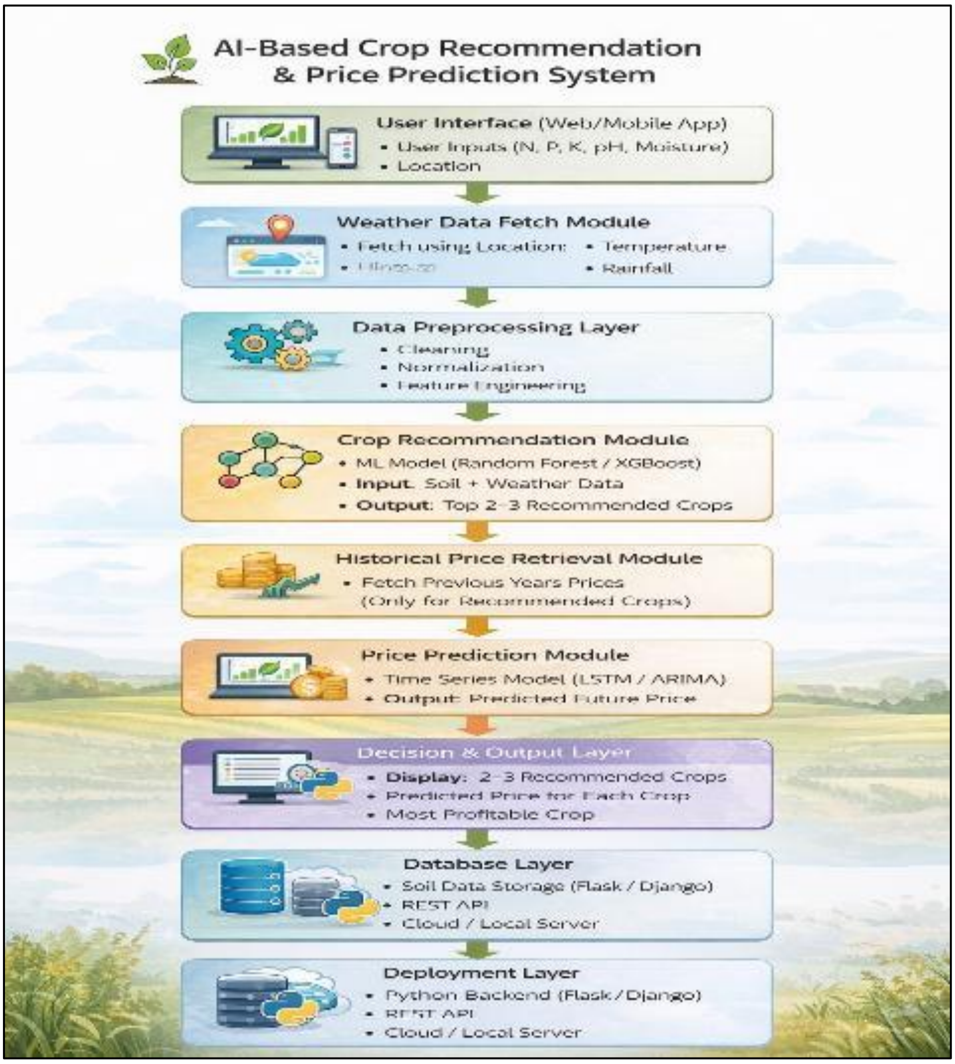

Figure 3 System Architecture for Proposed System

The proposed FutureCrop system consists of multiple modules, including User Input Collection, Weather Data Fetch, Data Preprocessing, Crop Recommendation, Historical Price Retrieval, Price Prediction, and Decision Output Layer. These components are integrated into a unified web-based framework built on a Python backend with Flask or Django and REST API support. The workflow begins with the farmer providing soil parameters such as nitrogen, phosphorus, potassium, pH, and moisture through the web interface, after which real-time weather data including temperature, humidity, and rainfall is automatically retrieved based on the user's location. The collected data is then cleaned, normalized, and processed through feature engineering before being passed into the Random Forest or XGBoost-based crop recommendation model, which analyzes the combined soil and climatic inputs to suggest the top 2 to 3 most suitable crops. Historical market price records for the recommended crops are then retrieved from the database and fed into the LSTM or ARIMA-based price prediction module, which forecasts future prices based on past market trends. The system finally consolidates both outputs through the decision layer to present the farmer with the recommended crops, their predicted prices, and the most profitable crop option. This structured approach enables accurate, data-driven, and real-time agricultural decision support for improved crop planning and financial risk management among farmers.

The FutureCrop system follows a structured and layered methodology to deliver integrated crop recommendation and price prediction services to farmers through a web-based platform.

- **Step 1: User Input Collection** The process begins at the User Interface, where the farmer provides essential soil parameters including Nitrogen (N), Phosphorus (P), Potassium (K), pH, and moisture levels, along with their geographic location through a web or mobile application.
- **Step 2: Weather Data Fetch** Based on the location provided by the user, the Weather Data Fetch Module automatically retrieves real-time climatic data including temperature, humidity, and rainfall using location-based APIs, eliminating the need for manual weather input.
- **Step 3: Data Preprocessing** All collected soil and weather data is passed through the Data Preprocessing Layer, where it undergoes cleaning to remove inconsistencies, normalization to bring values to a uniform scale, and feature engineering to extract the most relevant input variables for the machine learning models.
- **Step 4: Crop Recommendation** The preprocessed data is fed into the Crop Recommendation Module, which employs a Random Forest or XGBoost machine learning model trained on soil and weather datasets. The module processes the combined soil and climate inputs and outputs the top 2 to 3 most suitable crops for the given conditions.
- **Step 5: Historical Price Retrieval** For each of the recommended crops, the Historical Price Retrieval Module fetches previous years' market price records from the database. This step ensures that the price prediction is performed only for the crops that are agronomically suitable, making the forecast relevant and targeted.
- **Step 6: Price Prediction** The retrieved historical price data is passed into the Price Prediction Module, which applies a time-series forecasting model based on LSTM or ARIMA to analyze past price trends and generate predicted future prices for each of the recommended crops.
- **Step 7: Decision and Output** The Decision and Output Layer consolidates the results from both modules and presents the farmer with a comprehensive output displaying the top 2 to 3 recommended crops, the predicted future price for each crop, and the identification of the most profitable crop, enabling the farmer to make an informed planting and selling decision.
- **Step 8: Database Layer** All soil data, user inputs, historical prices, and system outputs are stored and managed through the Database Layer, which is built using Flask or Django with REST API support and deployed on either a cloud or local server for reliable data access and management.
- **Step 9: Deployment** The entire system is deployed through the Deployment Layer using a Python backend built on Flask or Django, exposed through REST APIs, and hosted on a cloud or local server to ensure accessibility, scalability, and consistent performance for end users.

4 Algorithm flow of the system

- Start the system and load the pre-trained Random Forest and LSTM models.
- Accept soil parameters — Nitrogen, Phosphorus, Potassium, pH, and moisture — from the farmer via the web interface.
- Retrieve the farmer's geographic location from the user input.
- Automatically fetch real-time weather data including temperature, humidity, and rainfall using the location-based weather API.
- Clean the collected data by handling missing values and removing noise.
- Normalize all input features to a uniform scale.
- Apply feature engineering to prepare the final input vector.
- Feed the preprocessed input vector into the Random Forest or XGBoost crop recommendation model.
- Evaluate the soil and weather features against the model's learned patterns.
- Output the top 2 to 3 most suitable crops ranked by classification confidence score.
- Query the database to retrieve historical market price records for each recommended crop.

- Organize the retrieved price data as a time-series input sequence.
- Pass the historical price sequence into the LSTM or ARIMA price prediction model.
- Analyze temporal price patterns and trends from the historical data.
- Generate predicted future prices for each of the recommended crops.
- Compare the predicted prices across all recommended crops.
- Identify and rank the most profitable crop based on the highest predicted future price.
- Display the recommended crops, predicted prices, and most profitable crop to the farmer via the web interface.
- Store the user inputs, recommendations, and predictions in the database via REST API for future reference and model retraining.
- End the advisory cycle and await the next user query.

5 Results and discussion

5.1 Initial page

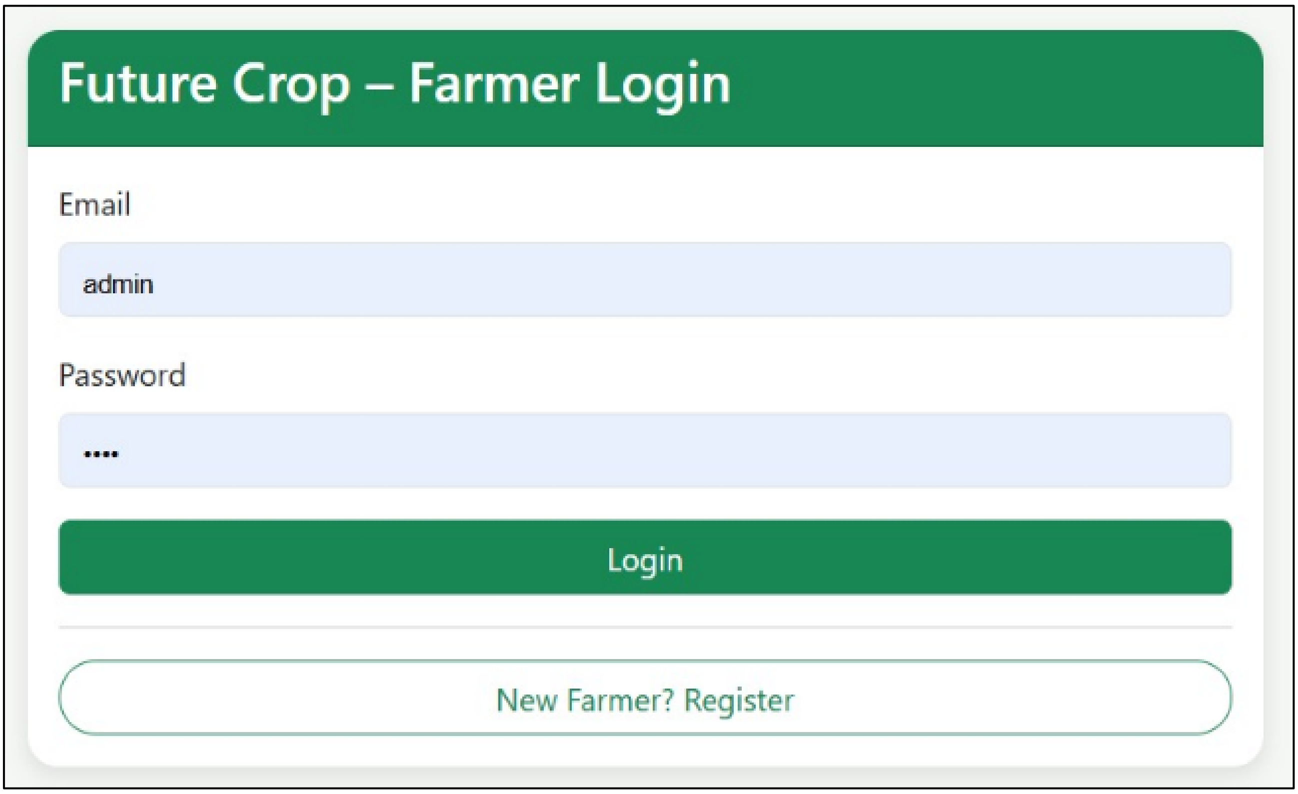

Figure 4 Farmer Login Page: The login screen allows registered farmers to securely access the FutureCrop platform by entering their email and password credentials.

5.2 Registration page

Figure 5 Farmer Registration Page: New farmers can register on the platform by providing their full name, email, phone number, password, farm area, and soil type to create a personalized account

5.3 Crop Recommendation page

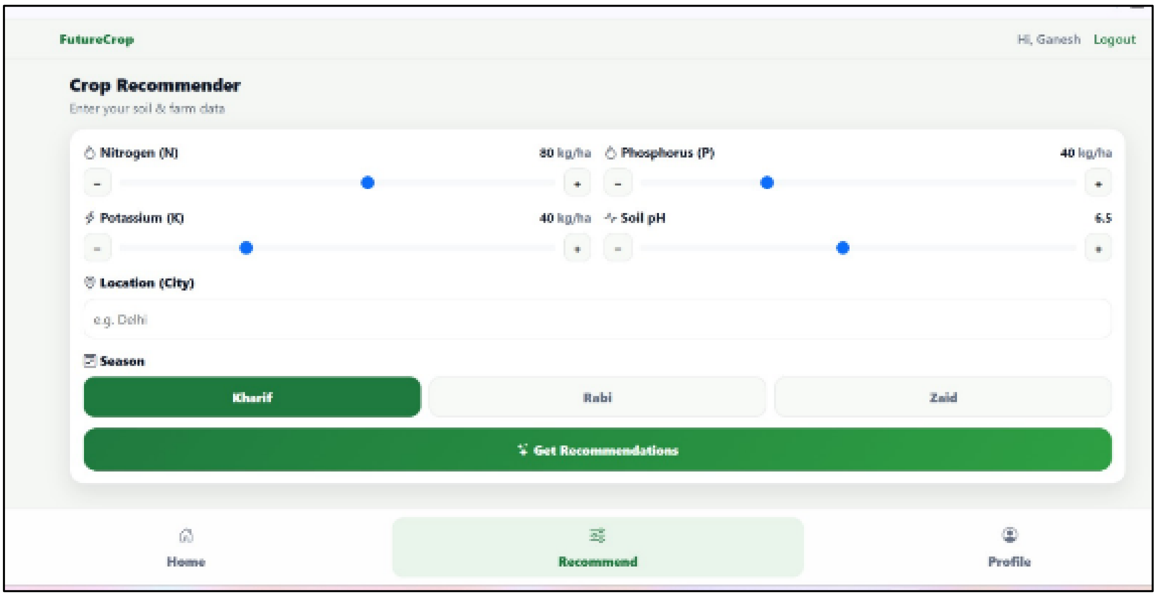

Figure 6 Crop Recommender Input Page:The crop recommender interface allows farmers to input soil parameters including Nitrogen, Phosphorus, Potassium, and pH levels, along with their city location and farming season, to receive AI-based crop suggestions

5.4 Crop Recommendation Results Page

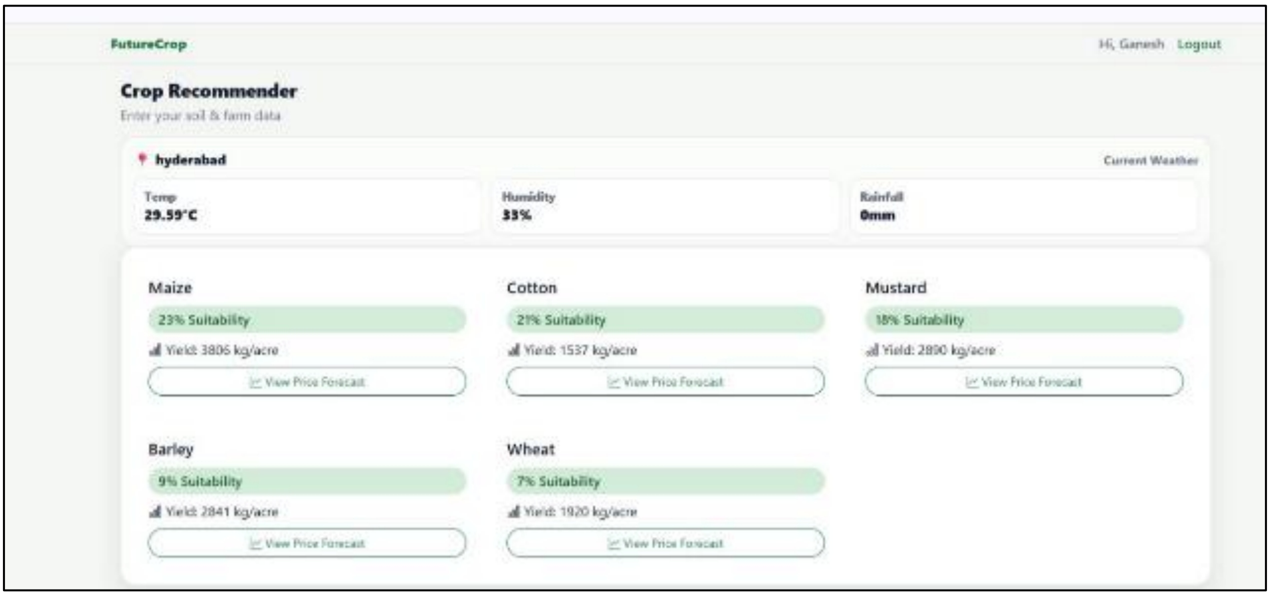

Figure 7 Crop Recommendation Results Page: The system displays the top recommended crops such as Maize, Cotton, Mustard, Barley, and Wheat along with their suitability percentage and estimated yield per acre, enabling farmers to compare and select the most suitable crop

5.5 Price Forecast Page

Figure 8 Price Forecast Page: The price forecast screen presents a time-series chart showing historical and LSTM-predicted future prices in rupees per quintal for the selected crop, along with an estimated profit per acre to help farmers identify the most financially beneficial selling time

6 Conclusion

The FutureCrop system successfully addresses the critical challenges of crop selection and market price uncertainty faced by farmers by integrating a Random Forest classifier for crop recommendation and an LSTM-based deep learning model for food crop price prediction into a single unified web-based platform. By analyzing soil nutrients, climatic factors, and historical market data, the system provides farmers with accurate, data-driven guidance to optimize their agricultural activities and minimize financial risk. Compared to existing approaches that handle these tasks in isolation and rely on limited inputs and static models, FutureCrop offers a more comprehensive, scalable, and accessible solution tailored to the Indian agricultural context. Overall, the system demonstrates the significant potential of machine learning in transforming agricultural decision-making and contributing to improved productivity, reduced farming risks, and better economic outcomes for farmers and agricultural stakeholders.

Future enhancements

The FutureCrop system can be further improved in several directions beyond its current scope. Real-time integration of live soil sensor data, weather APIs, and market price feeds can replace the current reliance on historical datasets, enabling more dynamic and up-to-date recommendations. The platform can be extended to cover cash crops, plantation crops, and international agricultural contexts beyond its present delimitation to Indian food crops. Advanced deep learning architectures such as Transformer-based models and Bidirectional LSTM can be explored to improve price prediction accuracy over longer time horizons. A dedicated mobile application with low-bandwidth support, regional language interfaces, and voice-based interaction can make the system more accessible to rural farmers with limited literacy or internet connectivity. IoT-based soil sensors can be integrated to automate nutrient data collection, reducing manual input and human error. Additional modules for pest and disease detection using image recognition, yield estimation, and explainable AI techniques such as SHAP and LIME can further enhance the platform's comprehensiveness, transparency, and practical value for farmers and agricultural stakeholders.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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