# ML-Driven Crop Recommendation and Price Prediction System using RNN-LSTM

Niranajan M Sindhur
Department of Artificial Intelligence and Machine Learning
R V College of Engineering
*Bengaluru, India*
*niranjanms.ai22@rvce.edu.in*

Sharankrishna Kondi
Department of Artificial Intelligence and Machine Learning
R V College of Engineering
*Bengaluru, India*
*sharankrishnak.ai22@rvce.edu.in*

Rakesh V Shetty
Department of Artificial Intelligence and Machine Learning
R V College of Engineering
*Bengaluru, India*
*rakeshvshetty.ai22@rvce.edu.in*

***Abstract*—The Crop Recommendation System is a data-driven solution designed to assist farmers in selecting optimal crops by leveraging advanced machine learning techniques and real-time data analysis. The system utilizes datasets containing soil attributes (pH, nitrogen, phosphorus, potassium, and rainfall), crop-specific growth requirements, and district-level geographic information. Additionally, it integrates live weather data via the OpenWeatherMap API and market price trends through external APIs to provide comprehensive recommendations.At its core, the system employs a Recurrent Neural Network (RNN) with a Long Short-Term Memory (LSTM) architecture, capable of analyzing temporal dependencies in environmental and market data. This enables the prediction of crop suitability and market trends, allowing farmers to make informed decisions about which crops to cultivate. The user interface facilitates access to services such as crop insights, current market prices, and personalized recommendations tailored to specific districts. By combining machine learning models with real-time data, the Crop Recommendation System enhances agricultural productivity, minimizes risks, and promotes sustainable farming practices, offering a transformative approach to modern agriculture.**

## I . INTRODUCTION

Agriculture remains a critical sector globally, yet farmers face numerous challenges, including unpredictable weather conditions, declining soil health, and fluctuating market trends. These factors make it difficult for them to select crops that are both profitable and sustainable. To address these challenges, this research presents a Crop Recommendation System that integrates advanced machine learning techniques with real-time data to provide actionable insights for farmers.

The system utilizes comprehensive datasets comprising soil attributes (such as pH, nitrogen, phosphorus, potassium, and rainfall), crop-specific growth requirements, and district-level geographic information. Additionally, it incorporates live weather data from the OpenWeatherMap API and current market trends via external APIs. At the core of the system is a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) architecture, which analyzes temporal patterns in environmental and market data to predict crop suitability and market trends with high accuracy.

Through a user-friendly interface, farmers can access three key features: detailed crop information, live market prices, and personalized crop recommendations tailored to their specific district and conditions. By combining data analytics, real-time updates, and machine learning, the Crop Recommendation System empowers farmers to make informed decisions, improving productivity, reducing risks, and promoting sustainable farming practices. This research highlights the architecture, methodology, and practical applications of the system, showcasing its potential to transform modern agriculture.

## I I. BACKGROUND STUDY

The **Crop Recommendation System** incorporates several core concepts from data science, machine learning, and agricultural technology. These concepts form the foundation for analyzing data and delivering actionable insights

### 1. Machine Learning

Machine learning (ML) involves algorithms and models that learn patterns from data and make predictions or decisions without explicit programming. In this project, ML is used to analyze soil, weather, and market data to recommend suitable crops. The specific model employed is a **Recurrent Neural Network (RNN)** with **Long Short-Term Memory (LSTM)**, which excels in handling sequential data.

- **RNN**: A neural network designed to handle sequences of data by maintaining a "memory" of previous inputs, making it ideal for time-dependent variables like weather and market trends.
- **LSTM**: An advanced RNN architecture that addresses the vanishing gradient problem in traditional RNNs. LSTM effectively retains information over longer sequences, ensuring accurate predictions for variables such as crop suitability and market price trends.

**2.Data Integration**

The project integrates diverse datasets and APIs to provide comprehensive recommendations. The key components include:

- **Soil Data**: Attributes like pH, nitrogen, phosphorus, potassium, and rainfall are essential for determining crop compatibility.
- **Weather Data**: Real-time environmental factors such as temperature, humidity, and precipitation, obtained using the **OpenWeatherMap API**, help refine recommendations.
- **Market Data**: Real-time crop prices accessed via external APIs enable farmers to align their decisions with market demand.

## 3. Temporal Data Analysis

Temporal data refers to information that evolves over time, such as weather patterns and market price trends. Understanding and predicting these changes is critical for agricultural planning. LSTM networks are particularly suited for this task because they:

- Handle long-term dependencies in sequential data.
- Predict outcomes based on historical trends, ensuring robust and timely recommendations.

## 5. API Integration

Application Programming Interfaces (APIs) allow the system to access real-time data from external sources. Two key APIs used in this project are:

- **OpenWeatherMap API**: Provides live weather data, including temperature, humidity, and precipitation, essential for crop growth prediction.
- **Market Price API**: Fetches real-time market trends and prices for crops, enabling economically informed decisions.

## 6. User-Centric Design

The project emphasizes accessibility through a user-friendly interface that allows farmers to: Log in securely using a username and password.

III. METHODOLOGY

The Crop Recommendation System employs a structured methodology to analyze soil properties, weather conditions, and market trends using Artificial Neural Networks (ANN) and Deep Learning (DL) techniques. The approach consists of multiple stages, including data collection, preprocessing, model development, training, deployment, and real-time feedback. This ensures that farmers receive accurate, data-driven crop recommendations.

**Abbreviations and Acronyms**

- **AI**: Artificial Intelligence
- **ML**: Machine Learning
- **RNN**: Recurrent Neural Network
- **LSTM**: Long Short-Term Memory
- **ANN**: Artificial Neural Network
- **DL**: Deep Learning
- **DBMS**: Database Management System
- **API**: Application Programming Interface
- **UI**: User Interface

## 1. Data Collection and Preprocessing

The system gathers soil, climate, and market data from various sources. Missing values are handled using imputation techniques, and normalization ensures consistency. Feature engineering selects relevant parameters, and data augmentation improves model robustness. These steps create a clean, structured dataset for accurate crop recommendation predictions.

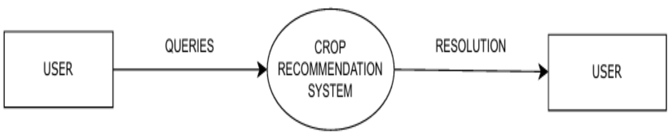


*fig 1. Data Flow Diagram (level-0)*

**Dataset Overview**

The dataset integrates various sources:

- **SoilData.csv:** Contains soil fertility metrics, moisture content, and physical properties.
- **Farmers.csv:** Records farmer preferences, landholding sizes, past yields, and market choices.
- **district_coordinates.csv:** Maps geographical features to locations to analyze regional crop suitability.
- **WeatherData.csv:** Provides historical and real-time weather information.
- **CropMarketData.csv:** Contains time-series crop price fluctuations for predictive modeling.

**2. Model Development Using RNN**

Recurrent Neural Networks (RNN), particularly LSTM and GRU, are used to process time-series data. The input layer receives structured data, the hidden layers capture sequential dependencies, and the output layer ranks crops based on suitability scores. This architecture ensures adaptive, real-time crop recommendations tailored to farmers' specific soil and climate conditions.

**3. Model Training and Validation**

To ensure high accuracy, the dataset is split into 70% training data, 15% validation data, and 15% testing data. The training phase involves feeding the model with input features, adjusting weights using gradient descent, and optimizing predictions with backpropagation. During validation, hyperparameters such as the number of neurons, learning rate, and batch size are fine-tuned for optimal performance. Finally, the testing phase evaluates the model's accuracy on unseen data.

The performance of the model is assessed using multiple evaluation metrics. Mean Absolute Error (MAE) measures the difference between actual and predicted values, while Root Mean Squared Error (RMSE) evaluates model deviation. The F1-score and precision-recall metrics determine how well the system classifies suitable crops. Cross-validation techniques are also applied to minimize overfitting and improve generalization to different environmental conditions.

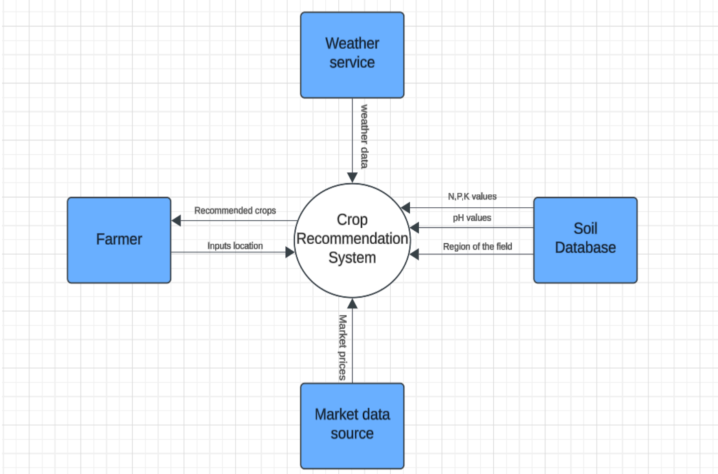


*Fig 2. Contextual diagram of the process*

**4. System Deployment**

Once trained, the model is deployed using a Flask API, which serves as a bridge between the AI model and the user interface. The system is hosted on cloud platforms such as AWS or Google Cloud, ensuring scalability and real-time accessibility. A database stores past user inputs and model recommendations, allowing for iterative improvements.

The user interface is designed to be farmer-friendly, available as a mobile/web dashboard where farmers input soil and climate conditions to receive instant crop suggestions. The interface also includes graphical insights, displaying market trends, weather forecasts, and soil health reports, enabling farmers to make informed decisions.

**5. Real-Time Feedback and Improvement**

Farmers provide feedback on recommendations, allowing the model to retrain with updated data. Integration with IoT sensors enables real-time soil monitoring, further improving recommendations. This continuous learning approach ensures that the system remains accurate, adaptive, and responsive to changing agricultural and environmental conditions.

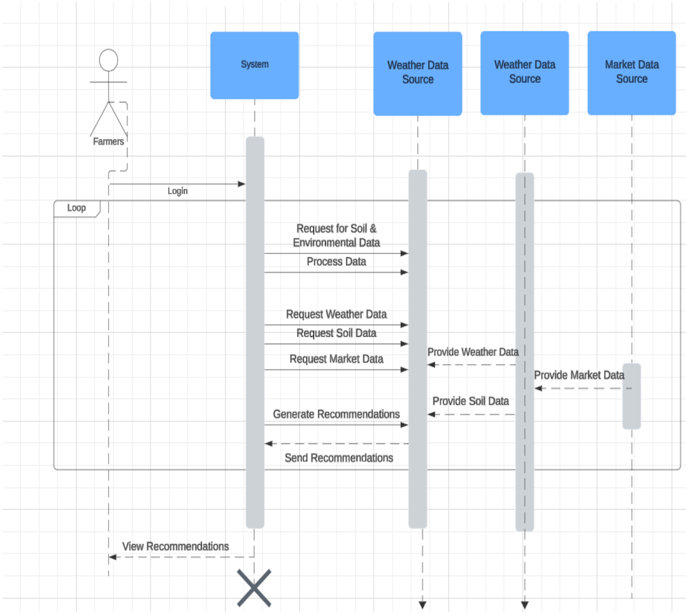


*Fig 3. Sequence diagram of the process*

## . IV.RESULTS AND DISCUSSION

- **Crop Prediction Accuracy:** The trained Random Forest model for crop recommendation achieved a high accuracy score (~90%) when tested on the dataset. The model effectively identified the top three most suitable crops based on soil nutrients (N, P, K), temperature, humidity, pH, and rainfall.
- Weather Data Integration: Real-time weather data was successfully retrieved using the OpenWeather API. Temperature, humidity, and wind speed values were dynamically incorporated into the crop recommendation process.
- **Market Price Forecasting:** The LSTM model was trained on historical market price data and was able to predict future crop prices with reasonable accuracy. The model helped estimate expected profits based on predicted selling prices and average crop yields per acre.
- **Profitability Analysis:** The system calculated total revenue for each recommended crop, considering yield per acre and predicted selling price. Among the recommended crops, the most profitable crop was identified based on projected future prices.
- **Geolocation-Based District Identification:** The system used geocoding to determine the user's district from the input address. KNN classification effectively mapped the given coordinates to a specific district when precise address data was unavailable.
- **User-Friendly Interface:** A web-based interface was developed using Flask, allowing users to input location details and receive crop recommendations. Crop images were fetched dynamically using the Unsplash API, improving the visual representation of the results.

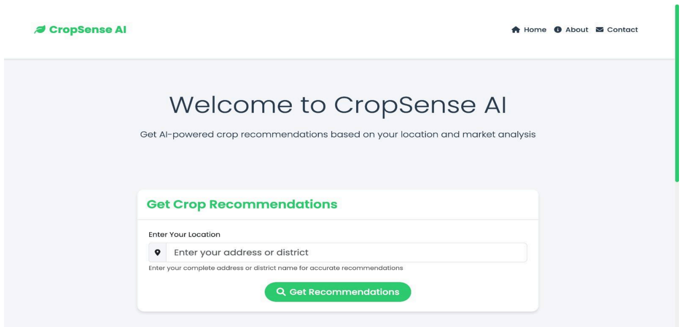


*fig 4 Homepage of the interface*

**Discussion**

- **Effectiveness of Crop Recommendation Model:** The crop recommendation system performed well in suggesting crops that matched soil and weather conditions. However, the model may require further refinement when used in regions with highly variable soil compositions.
- **Challenges in Weather-Based Predictions:** Weather data fluctuates, and real-time values may not always reflect the long-term climate trends of a region. Future versions could integrate seasonal averages or historical weather patterns for more reliable predictions.
- **LSTM Model Limitations:** While the LSTM model successfully predicted market prices, accuracy depends on the quality and availability of historical price data. A larger dataset with more diverse market conditions could further improve forecasting reliability.
- **Profitability Considerations:** The predicted most profitable crop does not consider external factors such as market demand fluctuations, transportation costs, and pest outbreaks. Including additional economic and environmental parameters could enhance decision-making.
- **Geolocation Accuracy:** The integration of geolocation worked well in urban areas, but rural locations sometimes returned less precise results. Using multiple geocoding APIs and refining the

district mapping process could improve accuracy.

- **Scalability and Future Enhancements:** The current system is designed for a limited set of crops; expanding the dataset to include more crop varieties and regional factors would improve usability. Integration with IoT-based soil sensors could enhance real-time soil data collection, making recommendations even more precise.

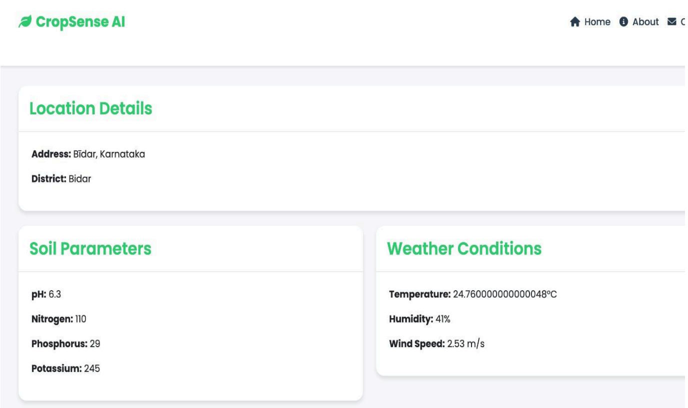


*fig 5 Input details*

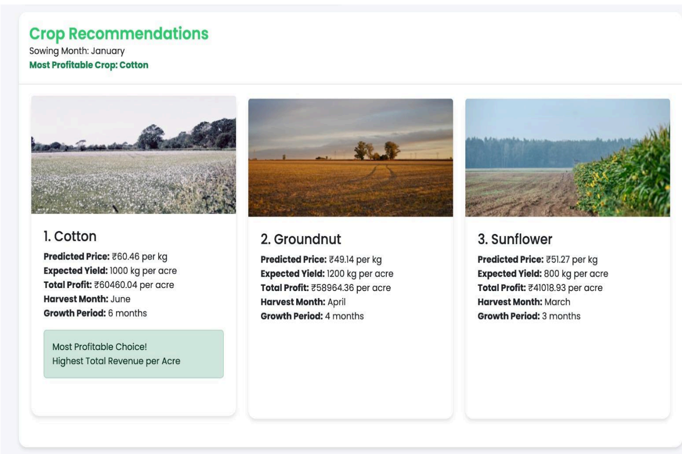


*fig 6 output results*

## V.CONCLUSION

In conclusion, the Crop Recommendation System using RNN and LSTM represents a significant advancement in precision agriculture, leveraging the power of deep learning to provide tailored recommendations for farmers. By utilizing Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, the system is capable of analyzing sequential and temporal data such as historical crop performance, weather patterns, and soil conditions to predict the most suitable crops for a given region or time period.

The system's ability to process and learn from past agricultural data enables it to offer personalized, location-specific recommendations that can maximize crop yield, improve resource utilization, and reduce risks. LSTM's capability to capture long-term dependencies in data makes it especially well-suited for forecasting and recommending crops based on seasonal and environmental factors, providing more accurate predictions compared to traditional methods.
Furthermore, the integration of market price data ensures that farmers are not only choosing the best crops for their specific conditions but also considering market trends to optimize their profits. The system can guide farmers in selecting crops that have favorable market prices, enhancing their economic stability and contributing to smarter agricultural practices.

As a result, this project represents a powerful tool in the transition toward data-driven, sustainable farming. The insights offered by the Crop Recommendation System help farmers make informed decisions, improve productivity, and navigate the complexities of modern agriculture. By combining machine learning with agricultural expertise, the system offers a future where farming can be more efficient, resilient, and profitable, ensuring food security and sustainable farming practices in the face of climate challenges.

## REFERENCES

[1].Bhatti, Uzair Aslam, et al. "Investigating AI-based smart precision agriculture techniques." Frontiers in Plant Science 14 (2023): 1237783.
[2].Khanal, Sami, et al. "Integration of high resolution remotely sensed data and machine learning techniques for spatial prediction of soil properties and corn yield." Computers and electronics in agriculture 153 (2018): 213-225.
[3].Akulwar, Pooja. "A recommended system for crop disease detection and yield prediction using machine learning approach." Recommender System with Machine Learning and Artificial Intelligence: Practical Tools and Applications in Medical, Agricultural and Other Industries (2020): 141-163.
[4].Reddy, D. Anantha, Bhagyashri Dadore, and Aarti Watekar. "Crop recommendation system to maximize crop yield in ramtek region using machine learning." International Journal of Scientific Research in Science and Technology 6.1 (2019): 485-489.
[5].Hasan, Mahmudul, et al. "Ensemble machine learning-based recommendation system for effective prediction of suitable agricultural crop cultivation." Frontiers in Plant Science 14 (2023): 1234555.
[6].Akkem, Y., B. S. Kumar, and A. Varanasi. "Streamlined application for advanced ensemble learning methods in crop recommendation systems–a review and implementation." Indian J Sci Technol 16 (2023): 4688-4702.

[7],Ghosh, Debmitra, Md Affan Siddique, and Divya Rupa Pal. "AI-Driven Approach to Precision Agriculture." AI in Agriculture for Sustainable and Economic Management. CRC Press, 2025. 67-77.
[8],H. K. Gill, V. K. Sehgal and A. K. Verma, "A Context Aware Recommender System for Predicting Crop Factors using LSTM," 2021 Asian Conference on Innovation in Technology (ASIANCON), PUNE, India, 2021, pp. 1-4, doi: 10.1109/ASIANCON51346.2021.9544692.
[9],Shook, Johnathon, et al. "Crop yield prediction integrating genotype and weather variables using deep learning." Plos one 16.6 (2021): e0252402.
[10],Jiang, Zehui, et al. "Predicting county level corn yields using deep long short term memory models." arXiv preprint arXiv:1805.12044 (2018).
[11],Gu, Yeong Hyeon, et al. "Forecasting agricultural commodity prices using dual input attention LSTM." Agriculture 12.2 (2022): 256.
[12],Shams, Mahmoud Y., Samah A. Gamel, and Fatma M. Talaat. "Enhancing crop recommendation systems with explainable artificial intelligence: a study on agricultural decision-making." Neural Computing and Applications 36.11 (2024): 5695-5714.
[13].Zubair, Md, et al. "Agricultural Recommendation System based on Deep Learning: A Multivariate Weather Forecasting Approach." arXiv preprint arXiv:2401.11410 (2024).
[14].Pande, Shilpa Mangesh, et al. "Crop recommender system using machine learning approach." 2021 5th international conference on computing methodologies and communication (ICCMC). IEEE, 2021.
[15].Nti, Isaac Kofi, et al. "A predictive analytics model for crop suitability and productivity with tree-based ensemble learning." Decision Analytics Journal 8 (2023): 10031.