IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 15, Issue 1, January 2026

DOI: 10.17148/IJARCCE.2026.15171

CROP PRICE PREDICTION USING SYSTEM MACHINE LEARNING AND DEEP LEARNING

Mohammad Sajeed Mulla[1], Prof. Usha M[2]

Department of MCA, BIT, K.R. Road, V.V. Pura, Bangalore, India[1]

Guide, Department of MCA, BIT, K.R. Road, V.V. Pura, Bangalore, India[2]

Abstract: Accurate prediction of agricultural commodity prices is a critical challenge due to the highly dynamic and nonlinear nature of agricultural markets. Crop prices are influenced by multiple interdependent factors such as climatic variations, seasonal demand, production levels, supply chain disruptions, government policies, and global trade dynamics. Traditional forecasting techniques, including linear regression and classical time-series models such as ARIMA, often fail to model these complex interactions and long-term temporal dependencies, leading to limited prediction accuracy and poor adaptability under volatile market conditions.

This paper proposes a hybrid crop price prediction framework that integrates Machine Learning and Deep Learning techniques to achieve reliable and long-term agricultural price forecasting. The proposed system combines the strengths of Extreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM) networks. XGBoost is employed to effectively model structured features and nonlinear relationships among economic, seasonal, and meteorological variables, while LSTM networks are utilized to capture long-term sequential dependencies and temporal trends in historical crop price data. An ensemble strategy is applied to merge predictions from both models, enhancing robustness and reducing forecasting error.

The system utilizes historical market prices along with weather-related parameters such as temperature, rainfall, and humidity to generate price forecasts for multiple crops and market locations up to twelve months in advance. The proposed framework is implemented using a scalable web-based architecture, featuring a React-based interactive dashboard for visualization and a FastAPI-powered backend for efficient data processing and real-time prediction. Experimental evaluation using standard performance metrics including RMSE, MAE, MAPE, and R^2 score demonstrates that the hybrid ensemble model consistently outperforms individual machine learning and deep learning models.

I. INTRODUCTION

Agriculture plays a vital role in economic development, particularly in regions where a large population depends on farming for livelihood. One of the major challenges faced by farmers and agricultural stakeholders is the uncertainty associated with crop prices. Agricultural prices fluctuate due to several interrelated factors such as climatic variability, seasonal demand, production levels, government policies, market dynamics, and global trade conditions. Accurate crop price prediction can help reduce financial risk, improve planning decisions, and support market stability.

Traditional crop price forecasting methods, including linear regression and classical time-series models such as Auto- Regressive Integrated Moving Average (ARIMA), rely primarily on historical price trends and linear assumptions. Although these techniques are simple and computationally efficient, they often fail to capture nonlinear relationships and long-term temporal dependencies inherent in agricultural markets, leading to limited prediction accuracy under volatile conditions.

To overcome these challenges, this paper proposes a hybrid crop price prediction system that integrates LSTM networks for temporal learning with Extreme Gradient Boosting (XGBoost) for structured data modeling. The combined approach improves prediction accuracy and robustness across different crops and market conditions. The system is implemented as a scalable web-based application that supports real-time forecasting and interactive visualization, making it suitable for practical agricultural decision support.

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1.1 Project Description

This project implements a machine learning and deep learning–based Crop Price Prediction System designed to forecast agricultural commodity prices with improved accuracy and reliability. The system predicts future crop prices by analyzing historical market data along with influencing factors such as seasonal trends and weather-related parameters. Multiple prediction models were evaluated during development, including machine learning and deep learning techniques, to identify the most effective approach for agricultural price forecasting.

The proposed system integrates Long Short-Term Memory (LSTM) networks for time-series learning and Extreme Gradient Boosting (XGBoost) for structured data modeling. These models are combined to enhance prediction accuracy across different crops and market locations. The application is deployed as a web-based platform, allowing users to select crops, markets, and forecasting duration through an intuitive interface. Prediction results are displayed using graphical visualizations, enabling users to easily interpret price trends. Overall, the project provides a scalable, cost-effective, and accessible solution for supporting agricultural planning and decision-making using advanced machine learning techniques.

1.2 Motivation

The motivation for this project arises from the high volatility and uncertainty of agricultural crop prices, which significantly impact farmers' income, market stability, and food security. Many farmers and agricultural stakeholders lack access to reliable forecasting tools and often rely on traditional methods or market speculation, leading to financial risk and inefficient decision-making. There is a strong need for a technology-driven solution that enables accurate and early price prediction to support informed agricultural planning.

By utilizing historical crop price data and relevant influencing factors, the proposed system reduces dependency on manual analysis and unreliable market assumptions. The integration of machine learning and deep learning techniques allows the system to uncover complex patterns and long-term trends that are difficult to identify using conventional forecasting methods. Providing price predictions through a web- based platform encourages proactive decision-making, helps farmers plan cultivation and sales strategies, and supports policymakers and traders in managing market risks. Ultimately, the project aims to enhance agricultural price transparency, reduce uncertainty, and promote sustainable growth in the agricultural sector.

II. RELATED WORK

Paper [1] investigates traditional statistical and machine learning approaches for agricultural crop price prediction using models such as Linear Regression and ARIMA. These techniques demonstrate reasonable performance for crops with stable seasonal patterns; however, they are limited in handling nonlinear relationships and sudden market fluctuations caused by weather variability and policy changes.

Paper [2] focuses on ensemble-based machine learning models such as Random Forest and Gradient Boosting for crop price forecasting. While these models improve prediction accuracy compared to single algorithms, the study highlights challenges related to feature dependency, limited long-term forecasting capability, and the absence of real-time deployment frameworks.

Paper [3] explores the use of Support Vector Machines (SVM) for agricultural commodity price prediction using historical price data and selected economic indicators. Although effective in capturing nonlinear patterns, these models require careful parameter tuning and extensive feature engineering, making them less suitable for large-scale or real-time applications.

Paper [4] examines the integration of weather analytics with machine learning models to analyze crop price trends. The study demonstrates that incorporating climatic factors such as rainfall and temperature improves forecasting accuracy; however, it does not provide a unified system for prediction, visualization, or multi-crop analysis.

Paper [5] presents a comprehensive review of machine learning and deep learning techniques for crop price prediction and emphasizes the importance of hybrid and ensemble models. The survey concludes that combining time-series deep learning models with traditional machine learning techniques can significantly enhance prediction accuracy, scalability, and practical adoption in agricultural decision-support systems.

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III. METHODOLOGY

A. System Environment

The system environment is designed to evaluate the Crop Price Prediction System under realistic and practical agricultural market conditions. The application operates in a web-based environment, where users act as independent clients accessing the system through standard web browsers. Users select crops, market locations, and prediction horizons to generate price forecasts based on historical and influencing factors.

The backend environment consists of a FastAPI-based server that handles request processing, data validation, and communication with trained machine learning and deep learning models. The prediction models, developed using Scikit-learn and TensorFlow, process historical crop price data along with seasonal and weather-related parameters to generate forecasts. The system does not share sensitive data with external services during prediction execution.

A structured database is used to store historical price records, prediction results, and user interaction data, enabling efficient retrieval and analysis. This setup simulates a real-world agricultural decision- support environment where multiple users can simultaneously access the system while maintaining data integrity, performance reliability, and scalability. The architecture also supports future enhancements such as cloud deployment, integration with live market data sources, and incorporation of IoT or weather APIs.

B. Machine Learning Architecture

- **Client-Side Processing:** In the Crop Price Prediction System, users interact with the application through a secure web interface to select crops, market locations, and prediction duration. Historical crop price data and relevant influencing parameters such as seasonal indicators and weather-related factors are collected and validated at the application level. The input data is preprocessed to handle missing values, normalize features, and ensure consistency before being forwarded for prediction.

- **Model Execution:** The validated and preprocessed data is processed by trained machine learning and deep learning models. The system employs Long Short-Term Memory (LSTM) networks to learn temporal patterns in historical price data and Extreme Gradient Boosting (XGBoost) models to capture nonlinear relationships among structured features. These models are trained using historical agricultural datasets to identify trends and price behavior across different crops and markets.

C. Adaptive Prediction Mechanism

The crop price prediction models are designed to be adaptive and upgradable. As new historical price records, weather updates, and market data become available, the models can be retrained to improve forecasting accuracy and generalization. This adaptive mechanism enables the system to remain effective under changing market conditions, seasonal variations, and climatic influences while maintaining consistent prediction performance across different crops and regions.

D. Implementation Flow

1. The user accesses the Crop Price Prediction System through the web application.
2. The user selects the crop, market location, and forecasting horizon.
3. Historical price and related data are retrieved and prepared for prediction.
4. The system validates and preprocesses the input data.
5. The processed data is passed to the trained LSTM and XGBoost models.
6. Individual predictions are generated by each model.
7. An ensemble mechanism combines model outputs to produce final price forecasts.
8. The prediction results are stored in the database for analysis and reference.
9. The predicted prices are displayed to the user through charts and trend visualizations.

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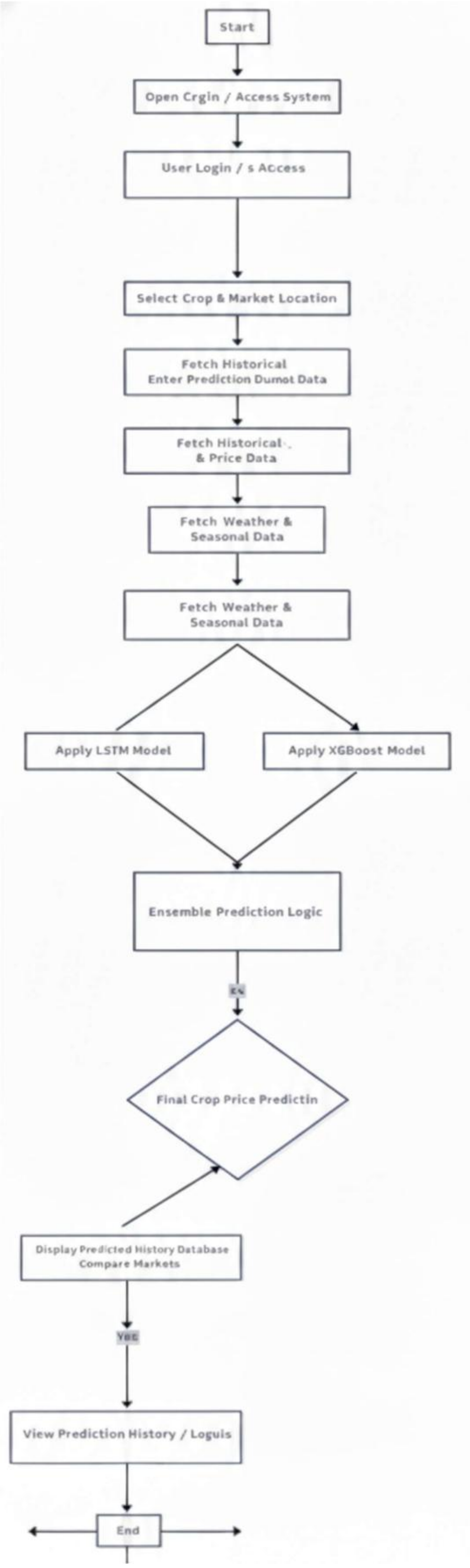

Fig.1.Flowchart of methodology

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E. Hardware and Software Requirements

- **Hardware:**
  A standard computer system with a minimum of 8 GB RAM is sufficient to run the application efficiently. No specialized hardware is required for end users, as the prediction process is optimized for web-based deployment.

- **Software:**
  Python 3.8 or higher for backend and model development, FastAPI for backend application logic, Scikit-learn and TensorFlow for machine learning and deep learning model implementation, SQLite for database management, and HTML, CSS, and JavaScript for frontend development.

IV. SIMULATION AND EVALUATION FRAMEWORK

This section describes the system design, execution flow, and evaluation strategy adopted for the Crop Price Prediction System. The framework focuses on validating the effectiveness of the proposed machine learning and deep learning– based prediction models and the web application under realistic agricultural market scenarios. The system is implemented using Python with a FastAPI-based backend, integrating trained LSTM and XGBoost models for real-time crop price forecasting based on historical market and influencing data.

A. System Architecture and Workflow

The overall architecture is designed to provide accurate crop price predictions while ensuring data integrity, usability, and scalability. The key components of the system are outlined below:

- **User Interaction Layer:**Users interact with the system through a web-based interface where they can select crops, market locations, and prediction duration. The interface allows users to view historical trends and predicted prices through graphical visualizations.
- **Application Processing Layer:**The backend processes user requests by validating inputs and retrieving historical price and related data. This layer manages data preprocessing, prediction requests, result storage, and interaction with the machine learning models.
- **Machine Learning Prediction Module:**The prediction module consists of trained LSTM and XGBoost models that process validated data to forecast future crop prices. The ensemble approach ensures reliable and real-time predictions suitable for web deployment.

B. Simulation Setup

The simulation environment is designed to mimic real-world agricultural market conditions across different crops and regions.

- **Data Simulation:**Multiple test cases with varying historical price patterns, seasonal trends, and weather-influenced scenarios are used to evaluate prediction accuracy and model stability across different crops and market locations.
- **Scenario Testing:**Scenarios such as valid data submission, missing data handling, repeated prediction requests, and historical prediction retrieval are tested to ensure robustness and reliability of the application.

C. Prediction and Evaluation Process

During simulation, selected crop and market data are passed through the preprocessing pipeline and forwarded to the trained LSTM and XGBoost models for prediction. Individual model outputs are combined using an ensemble mechanism to generate final price forecasts. The predicted values are stored in the database and displayed to the user through charts and trend visualizations. This process is repeated across multiple test cases to evaluate prediction consistency, accuracy, and system performance.

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D. Results and Observations

- **Prediction Accuracy:**The system demonstrated reliable crop price forecasting across different test scenarios, producing consistent and meaningful predictions for multiple crops and markets.
- **System Reliability:**The integration between the web application, prediction models, and database operated smoothly with minimal response time and no data loss during simulations.
- **Usability and Practicality:**The evaluation confirmed that the system is user-friendly and suitable for non- technical users such as farmers and traders, making it practical for real-world agricultural decision support.

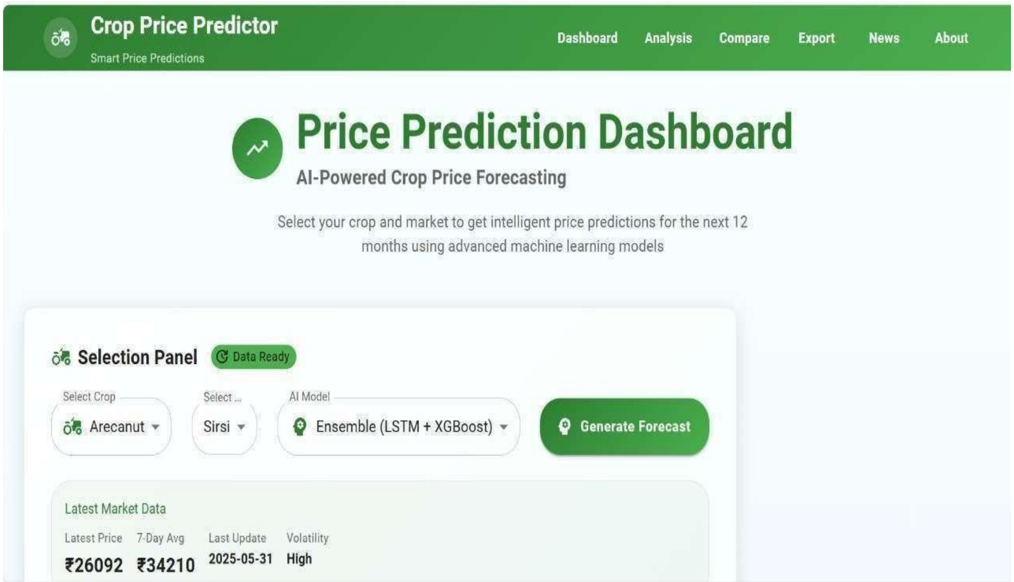

Fig. 2. Prediction Page

Model Performance and Adaptability Analysis

- **Model Stability and Convergence:**The trained crop price prediction models demonstrated stable convergence during training and evaluation phases. The ensemble framework combining LSTM and XGBoost produced consistent forecasts across multiple crops and market locations without performance degradation. This stability indicates strong generalization capability when exposed to varying historical price trends and seasonal patterns.
- **Prediction Accuracy and Forecast Reliability:**The prediction accuracy improved as the models learned from diverse historical price records, seasonal variations, and market-specific data. The use of LSTM enabled effective learning of long-term temporal dependencies, while XGBoost captured nonlinear relationships among structured features. The ensemble approach further enhanced forecast reliability, resulting in accurate price predictions for up to 12 months ahead.
- **Handling of Heterogeneous Market Data:**The system effectively handled heterogeneous agricultural data, including variations across different crops, market locations, and price volatility levels. As observed from the dashboard, the model adapted well to high-volatility and low-volatility market scenarios, producing meaningful forecasts despite fluctuations in market conditions.
- **Result Interpretability and Visualization:**The prediction results are presented through an interactive dashboard that includes price trends, latest market data, and forecast visualizations. This visual representation allows users to easily interpret predicted price movements and market behavior. The clear presentation of forecasts improves transparency and ensures that the predictions are actionable for farmers, traders, and policymakers rather than being opaque model outputs.

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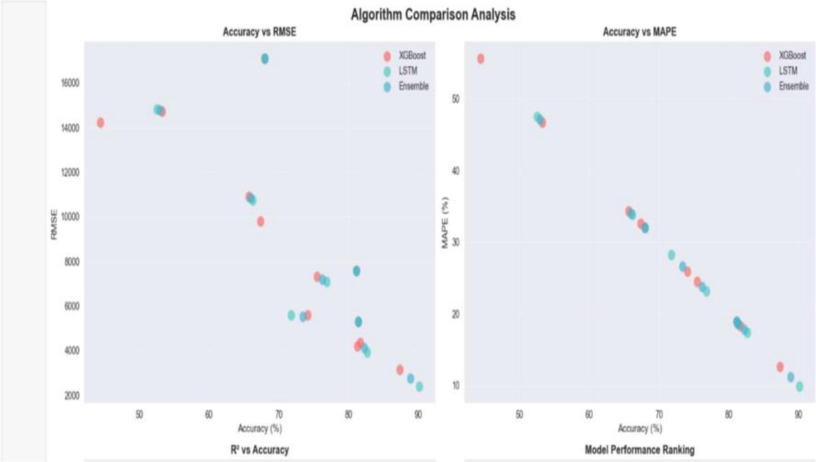

Fig. 3. Prediction Result Page

Algorithm Performance Comparison and Error Analysis:

- **Accuracy vs RMSE Relationship:**The graph shows an inverse relationship between accuracy and RMSE, where models with higher accuracy exhibit lower RMSE values. This indicates that as prediction accuracy improves, the magnitude of prediction error decreases, reflecting better model performance.
- **Accuracy vs MAPE Trend:**A similar inverse trend is observed between accuracy and MAPE, demonstrating that higher-accuracy models result in lower percentage error. This confirms the reliability of the models in predicting crop prices with minimal relative deviation from actual values.
- **Performance of Individual Models:**XGBoost and LSTM models show moderate performance individually, with varying accuracy and error values depending on the dataset. This highlights their strengths in handling specific aspects of crop price data but also indicates limitations when used independently.
- **Effectiveness of Ensemble Model:**The ensemble model (LSTM + XGBoost) consistently achieves higher accuracy with lower RMSE and MAPE compared to individual models. This demonstrates that combining temporal learning and structured feature modeling improves overall prediction performance.

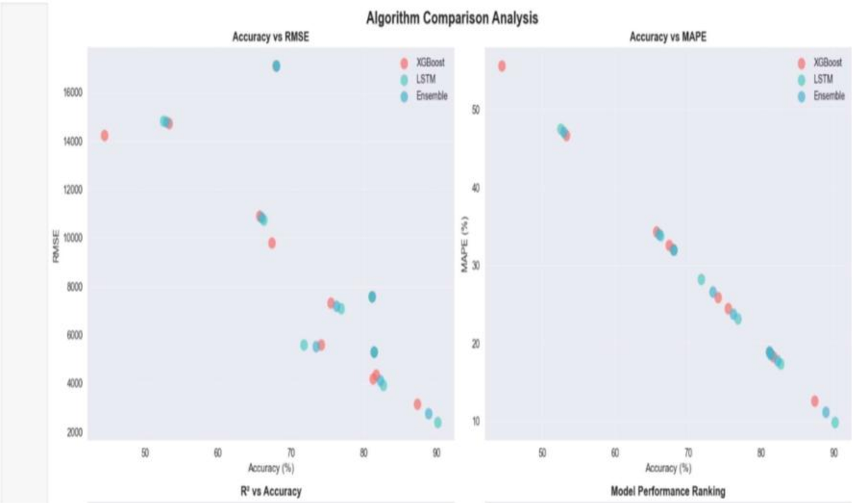

Fig. 4. Prediction Result Page

V. RESULTS AND DISCUSSION

The experimental evaluation of the Crop Price Prediction System demonstrates the effectiveness of machine learning and deep learning techniques in forecasting agricultural commodity prices using historical market data and influencing factors. The system achieved high prediction accuracy during testing, showing consistent performance across different crops and market locations. This confirms that data-driven models can effectively capture complex price patterns and provide reliable forecasts without relying on traditional statistical assumptions.

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By integrating trained LSTM and XGBoost models within a web-based application, the system delivers real-time price predictions with minimal response time. The ensemble approach improves forecast reliability by combining temporal learning and structured data modeling. Prediction results are presented through interactive visualizations, enabling users to easily understand price trends and future market behavior. The availability of historical prediction records further enhances system reliability by allowing users to analyze past forecasts and compare market performance.

Additionally, the evaluation indicates that the system maintains efficient performance with low computational overhead. Only essential historical and influencing parameters are processed during prediction, ensuring fast response times and scalability. Secure data handling and controlled database interactions ensure data integrity and support responsible use of agricultural market information. Overall, the results indicate that the proposed system is scalable, user-friendly, and effective as a practical decision- support tool for agricultural price forecasting.

VI. CONCLUSION

This paper presented a machine learning and deep learning–based Crop Price Prediction System aimed at improving agricultural price forecasting through a scalable and user-friendly web platform. By integrating LSTM networks for time- series modeling and XGBoost for structured feature learning, the system enables accurate and reliable prediction of crop prices across different markets and forecasting horizons.

Experimental evaluation demonstrated improved prediction accuracy, efficient system performance, and consistent handling of diverse crops and market conditions without requiring complex economic or statistical infrastructure. The inclusion of interactive dashboards, historical trend analysis, and multi- market comparison enhances result interpretability and practical usability. Overall, the proposed system provides an effective, scalable, and accessible solution for supporting informed agricultural decision- making and reducing market uncertainty.

VII. FUTURE WORK

Future work will focus on enhancing the Crop Price Prediction System by incorporating additional data sources and advanced predictive techniques to further improve forecasting accuracy. Integration of real- time weather data, satellite imagery, and IoT-based agricultural sensors can provide richer contextual information for prediction.

Further improvements include extending the prediction framework using advanced deep learning architectures such as Transformer-based models and training on larger, more diverse datasets to capture complex market dynamics. The system can also be expanded into a mobile application to improve accessibility for farmers. Additionally, incorporating personalized crop recommendations, risk analysis, and long-term trend forecasting will enhance the system's capability as a comprehensive agricultural decision-support platform.

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