FARMSTOCK: AI-DRIVEN AGRICULTURAL ADVISORY PLATFORM FOR CROP PRICE FORECASTING AND MARKET INTELLIGENCE

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Abstract**—**Agricultural decision-making in India is often affected by the lack of timely market intelligence, limited forecasting tools, and delayed identification of crop diseases, leading to significant financial losses for farmers. This paper presents FarmStock, an AI-powered agricultural intelligence platform that integrates machine learning, real-time data processing, and intelligent advisory systems to support informed decision-making. The system employs supervised machine learning models trained on historical market data to predict crop prices and generate multi-day forecasts, while an AI-driven module provides crop disease risk analysis based on seasonal and environmental factors. Additionally, a WebSocket-based real-time alert system delivers instant updates on market changes and agricultural events. The key contribution of this work is the integration of price prediction, forecasting, crop health advisory, and real-time alerting into a unified bilingual system (English and Tamil), enabling farmers to optimize selling strategies, reduce crop losses, and improve overall economic outcomes.

Keywords: Crop Price Prediction, Machine Learning, Price Forecasting, Crop Health Monitoring, Smart Agriculture, Bilingual Interface, Voice Assistant.

I. INTRODUCTION

Agriculture remains one of the most critical sectors in India, supporting the livelihood of a large portion of the population. Despite its importance, many farmers continue to face significant economic losses due to unpredictable crop prices, delayed disease identification, and lack of access to timely market intelligence. Traditional decision-making in farming often depends on local traders, historical assumptions, and fragmented government reports, which do not provide accurate or personalized recommendations for farmers at the right time. As a result, farmers frequently sell produce at unfavorable prices and fail to detect crop diseases during the early stages, leading to reduced income and lower productivity.

Recent advances in Artificial Intelligence (AI), Machine Learning (ML), and real-time data processing have created opportunities to improve agricultural decision support systems. Machine learning models can analyze historical market trends to estimate future crop prices, while intelligent advisory systems can assess environmental conditions and provide preventive crop health recommendations. However, many existing agricultural platforms focus only on a single aspect such as market price reporting or weather forecasting, without integrating multiple decision-support services into one unified platform.

To address these limitations, this paper presents FarmStock, an AI-powered agricultural intelligence platform designed to assist farmers in making informed decisions regarding crop selling time, disease prevention, and market monitoring. The system combines machine learning-based crop price prediction, multi-day forecasting, AI-assisted crop health analysis, and WebSocket-based real-time alert delivery within a bilingual web application. The platform trains a predictive model that analyzes historical agricultural market data to generate actionable insights.

A key challenge in agricultural intelligence systems is the integration of heterogeneous data sources such as historical price records, seasonal patterns, weather indicators, and market-specific characteristics into a unified predictive framework. FarmStock addresses this by constructing a multi-feature input representation that captures temporal trends, crop-specific properties, and external influencing factors such as festival demand and harvest cycles. This enables the system to generate more context-aware predictions compared to traditional approaches that rely solely on past price averages or simple statistical methods.

The main contribution of this work is the design and implementation of an integrated agricultural support system that combines predictive analytics and intelligent advisory services in a single platform. By delivering timely recommendations in both English and Tamil, the proposed system improves accessibility while helping farmers reduce uncertainty, minimize crop loss, and maximize potential profit.

II LITERATURE REVIEW

Recent advancements in agricultural technology have led to the development of integrated platforms that support farm stock management, digital trading, and intelligent decision-making. Existing solutions can be categorized into digital marketplace platforms, inventory management systems, mobile-based applications, AI-driven prediction systems, and hybrid integrated frameworks. While these systems address specific agricultural challenges, there is still a gap in providing a unified, scalable, and user-friendly solution that combines all functionalities effectively.

Digital Marketplace

Digital marketplace platforms are widely implemented to connect farmers directly with consumers, retailers, and wholesalers. These systems typically consist of modules such as user registration, product listing, order processing, and payment integration.
The user management module handles authentication, profile creation, and role-based access (farmer, buyer, admin). The product listing module enables farmers to upload crop details such as type, quantity, pricing, quality grade, and images. The order management module manages order placement, tracking, and history, while the payment module integrates secure online transactions.

Additionally, some systems include review and rating modules to build trust and search/filter modules for better product discovery.However, these platforms lack real-time inventory synchronization, price prediction, and decision-support tools, which limits their effectiveness in dynamic agricultural markets.

Farm Inventory and Stock Management

Farm inventory systems are designed to manage agricultural stock efficiently by monitoring storage levels and product movement. These implementations include modules such as stock entry, stock update, warehouse management, and reporting dashboards.The stock management module updates crop quantities automatically after sales or storage. The warehouse module categorizes products based on storage conditions such as temperature and humidity. The alert module notifies farmers about low stock levels or spoilage risks. The reporting module generates insights such as demand trends, wastage analysis, and stock turnover rates.

Despite these features, these systems are often not integrated with live market platforms, making it difficult for farmers to align stock with demand, leading to overstocking or wastage.

Mobile and Web-Based Agricultural Applications

With the increasing use of smartphones, many agricultural systems are implemented as mobile or web applications to improve accessibility for farmers. These applications include modules such as dashboards, notifications, and real-time updates.The mobile interface module provides a user-friendly dashboard for managing stock and sales. The notification module sends alerts for new orders, stock updates, and price changes. The cloud synchronization module ensures data consistency across multiple devices. The offline support module (in some systems) allows limited functionality without internet access.

However, many applications suffer from poor UI/UX design, limited scalability, security concerns, and lack of integration with AI-based analytics, reducing their overall effectiveness.

IoT-Based Smart Agriculture Monitoring System

IoT-based smart agriculture systems have been widely developed to monitor environmental and field conditions using interconnected sensors and communication technologies. These systems collect real-time data on parameters such as soil moisture, temperature, humidity, and crop conditions through wireless sensor networks integrated with cloud platforms. In some implementations, IoT devices are also connected to automated irrigation systems, enabling efficient water management and optimized resource utilization.

These systems significantly improve farm-level decision-making by providing continuous and accurate environmental insights, reducing the need for manual monitoring. They also support precision agriculture practices by enabling timely interventions and improving crop productivity.

However, most IoT-based systems are highly dependent on hardware infrastructure and focus primarily on environmental monitoring. They lack integration with economic factors such as market demand, pricing strategies, and inventory management, limiting their ability to support comprehensive farm and business decision-making within a unified platform.

Integrated Farm Management

Hybrid agricultural platforms combine multiple functionalities such as marketplace operations, inventory tracking, mobile access, and AI-based analytics into a single system.The integrated dashboard module provides a centralized interface for monitoring stock, sales, and predictions. The communication module enables direct interaction between farmers and buyers. The analytics module offers insights into demand trends and pricing strategies. The security module ensures safe data handling and transaction processing.

Despite their comprehensive nature, these systems are often complex, resource-intensive, and require technical expertise, making them less suitable for small and medium-scale farmers.

Limitations of Existing Systems

Despite the availability of various agricultural management solutions, several limitations persist. Digital marketplace platforms focus primarily on buying and selling without integrating stock management and predictive analysis. Inventory systems lack real-time synchronization with market demand, leading to inefficient stock utilization and wastage.

Mobile and web-based applications improve accessibility but often lack advanced analytics, security robustness, and seamless backend integration. AI-based systems depend heavily on high-quality datasets, and their performance is affected by data inconsistency, limited datasets, and computational complexity.

Hybrid systems, although comprehensive, are often difficult to use, require high infrastructure costs, and may not be scalable for rural environments. Additionally, many existing systems lack user-friendly interfaces, multi-language support, and cost-effective deployment models.

Therefore, there is a need for a FarmStock system that integrates marketplace functionality, inventory management, mobile accessibility, and AI-based prediction into a simple, scalable, cost-efficient, and user-centric platform.

Table 1 — Comparative Analysis of Existing Agricultural Systems

Technique Used	**Advantages**	**Research Gap**
Digital Marketplace	Enable direct farmer-to-consumer interaction, reduce intermediaries, improve market reach	Lack integration with inventory systems, no real-time stock updates, no predictive pricing
Inventory Management	Provide accurate stock tracking, reduce wastage, support monitoring	Operate independently, no linkage with market demand or pricing systems
Web Applications	Improve accessibility, enable remote monitoring and notifications	Limited intelligent features, poor usability in rural contexts, weak backend integration
Supply Chain	Optimize logistics and distribution efficiency	Limited transparency, weak farmer-consumer interaction, no predictive analytics
Hybrid Integrated	Combine multiple functionalities into a unified platform	High complexity, scalability challenges, difficult for non-technical users

III SYSTEM ARCHITECTURE

The proposed system, FarmStock is designed as an integrated agricultural intelligence platform that enables farmers to make informed decisions regarding crop pricing, selling strategies, and crop health management. The system combines machine learning-based prediction, time-series forecasting, intelligent advisory mechanisms, and real-time communication within a unified framework. The primary objective of the system is to reduce uncertainty in agricultural decision-making by transforming historical data into actionable insights. Unlike existing solutions that address isolated problems, the proposed system integrates multiple analytical components to provide a comprehensive decision-support environment.

3.1 Data Acquisition

The system begins with the acquisition of historical agricultural market data, which forms the foundation for all predictive and analytical processes within the FarmStock platform. The collected data includes crop prices, timestamps, and market-specific attributes obtained from agricultural databases and pre-existing datasets. These datasets capture critical aspects such as temporal variations, seasonal trends, and regional price differences, all of which play a significant role in determining crop price behavior. Since agricultural markets are highly dynamic and influenced by multiple external factors such as climate conditions, demand fluctuations, and supply chain disruptions, it is essential to gather sufficiently large and diverse datasets to ensure that the model can generalize effectively across different scenarios.

However, real-world agricultural datasets are often unstructured and contain several inconsistencies, including missing values, duplicate entries, irregular updates, and noise introduced through manual data collection and reporting errors.

Additionally, variations across different markets and regions can lead to heterogeneity in the data, making it challenging to directly use for machine learning purposes. To address these challenges, an initial validation and filtering process is performed to ensure data reliability and consistency before further processing. This includes verifying data completeness, removing invalid records, and standardizing formats.Such preprocessing at the acquisition stage is critical,as the overall accuracy and robustness of the predictive models are directly dependent on the quality and integrity of the input data.

3.2 Data Preprocessing

In this stage, the raw agricultural dataset is transformed into a structured and consistent format suitable for machine learning models. Since real-world agricultural data often contains missing values, inconsistencies, and noise due to irregular data collection processes, preprocessing becomes a critical step to ensure data quality. Missing values are handled using interpolation techniques, which estimate unknown values based on neighboring data points, thereby preserving the continuity of time-series information. Additionally, noisy data and outliers caused by sudden market disruptions or recording errors are identified and removed to prevent distortion in model training. Without these corrections, the model may learn incorrect patterns, leading to unreliable predictions.

Furthermore, agricultural price data typically varies significantly across regions and time periods, resulting in large differences in value ranges. To address this, normalization is applied to scale all features into a consistent range using:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

This ensures that no single feature disproportionately influences the model due to its magnitude, thereby improving convergence and stability during training. In addition, to reduce short-term fluctuations and irregular spikes in price data, a moving average technique is applied:

$$MA_t = \frac{1}{n}\sum_{i=0}^{n-1} y_{t-i}$$

This smoothing process helps highlight long-term trends while suppressing noise caused by temporary disturbances such as weather changes, sudden demand shifts, or local market anomalies. As a result, the model can focus on meaningful patterns, leading to more stable and accurate predictions.

3.3 Feature Engineering

Feature engineering is a crucial step in enhancing the predictive performance of the FarmStock system, as it transforms raw and preprocessed data into meaningful inputs that can effectively capture underlying patterns in agricultural markets. In this stage, temporal features such as day, month, and seasonal indices are extracted from timestamp data to model periodic trends in crop pricing.

These features are particularly important because agricultural prices are highly influenced by seasonal factors such as sowing periods, harvesting cycles, and market demand fluctuations during festivals or climatic changes. By incorporating these temporal attributes, the system is able to better understand cyclical behaviors and improve the accuracy of predictions over time.

To further strengthen the model’s ability to identify significant relationships between variables, statistical techniques such as correlation analysis are applied. The correlation coefficient is computed as:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sigma_x \sigma_y}$$

This measure quantifies the strength and direction of the relationship between input features and crop prices, enabling the identification of highly influential variables. Features with strong correlations are prioritized, while redundant or weakly correlated features are eliminated to reduce noise and computational complexity. This selective approach not only improves model efficiency but also helps prevent overfitting by ensuring that the model focuses on the most relevant information. As a result, the system achieves better generalization and more reliable predictions when applied to unseen data.

3.4 Machine Learning Model for Price Prediction

The core component of the FarmStock system is a supervised machine learning model designed to predict crop prices based on the engineered features derived from historical and contextual data. The prediction task is formulated as a regression problem, where the objective is to learn a functional relationship between multiple input variables such as temporal features, seasonal indicators, and past price trends and the target output, which is the crop price. By modeling this relationship, the system is able to capture both linear and non-linear dependencies present in agricultural data. Multiple models, including ensemble techniques such as Random Forest, Gradient Boosting, and XGBoost, are trained and evaluated to identify the most suitable approach for accurate prediction. These models are particularly effective in handling complex data patterns, noise, and feature interactions that are common in agricultural price datasets.

To ensure that the model produces reliable and accurate predictions, performance evaluation is carried out using standard regression error metrics. The Mean Squared Error (MSE) is defined as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

This metric penalizes larger errors more heavily, thereby encouraging the model to minimize significant deviations between predicted and actual values. In addition, Root Mean Squared Error (RMSE) is used:

$$RMSE = \sqrt{MSE}$$

RMSE provides an interpretable measure of prediction error in the same unit as the target variable (price), making it easier to assess model performance in practical scenarios. Together, these metrics enable a comprehensive evaluation of model accuracy, stability, and robustness, ensuring that the selected model delivers consistent and dependable predictions for real-world agricultural decision-making.

3.5 Time-Series Forecasting

Agricultural price data is inherently time-dependent, where current market prices are strongly influenced by historical trends, seasonal patterns, and previous fluctuations. To effectively capture these temporal dependencies, the FarmStock system incorporates time-series forecasting techniques that model the relationship between past observations and future values. This approach allows the system to learn sequential patterns in crop prices, such as recurring seasonal increases during harvest periods or price drops due to surplus supply. By considering both historical price data and contextual features, the forecasting model is able to generate more realistic and trend-aware predictions compared to static regression methods that ignore time-based dependencies.

For multi-day forecasting, the system employs a recursive prediction strategy, where the predicted value at a given time step is used as an input for subsequent predictions:

$$\hat{y}_{t+1} = f(y_t, y_{t-1}, \ldots, X_{t+1})$$

This iterative approach enables the generation of future price sequences over multiple time horizons, allowing farmers to analyze trends and make informed decisions regarding the optimal timing for selling their produce. By continuously updating predictions based on previous outputs, the system adapts to evolving market conditions and captures dynamic changes in price behavior. Without incorporating time-series modeling, the system would fail to account for temporal dependencies, resulting in less accurate and less reliable predictions for real-world agricultural scenarios.

3.6 Crop Health Advisory

The proposed FarmStock system incorporates a Crop Health Advisory module to provide intelligent, real-time insights into potential crop diseases and environmental risks. Unlike traditional advisory systems that rely on static rules or generic seasonal guidelines, this module utilizes contextual data and artificial intelligence to generate dynamic and location-specific recommendations.

The module takes multiple input parameters such as crop type, geographic location, seasonal period, temperature, and rainfall conditions, which are critical factors influencing crop health. These inputs are processed through an AI-driven backend that analyzes environmental conditions and generates tailored advisory outputs, enabling the system to move beyond static recommendations and deliver adaptive, situation-aware guidance.

The advisory output is structured to provide actionable insights, including disease risk levels, identification of possible crop diseases, preventive measures, and weather-based recommendations. By continuously incorporating environmental data, the system dynamically adjusts its recommendations based on changing conditions, allowing farmers to take timely preventive actions. This early warning capability is particularly important in agriculture, where delays in identifying crop diseases can lead to significant yield losses.

Furthermore, the module integrates bilingual support, delivering recommendations in both English and Tamil to ensure accessibility for a wider range of users. By combining predictive intelligence with practical advisory outputs, the Crop Health module enhances decision-making and contributes to reducing crop loss while improving overall agricultural productivity.

3.7 Real-Time Alert System

To ensure timely and continuous delivery of critical information, the FarmStock system incorporates a WebSocket-based real-time communication mechanism. Unlike traditional request-response architectures, where the client must repeatedly send requests to receive updates, the WebSocket protocol establishes a persistent bi-directional connection between the client and server. This allows the server to push updates instantly whenever new data becomes available, such as changes in crop prices, forecast outputs, or advisory recommendations. By eliminating the need for repeated polling, this approach significantly reduces latency and network overhead, ensuring faster and more efficient data transmission.

The real-time alert system plays a crucial role in enabling proactive decision-making for farmers by delivering instant notifications regarding market fluctuations and crop health advisories. In highly dynamic agricultural markets, even small delays in accessing updated price information can lead to financial losses or missed selling opportunities. By providing immediate alerts, the system ensures that farmers can respond quickly to favorable market conditions or potential risks.

Additionally, the integration of this module with other components, such as prediction and advisory systems, ensures that all updates are synchronized and consistently delivered to the user interface. This enhances the overall responsiveness and reliability of the platform, making it more effective for real-world agricultural applications.

3.8 Voice Assistant

To improve accessibility and usability for farmers, especially those who may have limited literacy or are not comfortable using text-based interfaces, the proposed system incorporates a voice assistant module. This module enables users to interact with the system through speech input and receive responses in audio format, thereby reducing dependency on manual typing and navigation. The voice assistant is integrated with speech recognition and text-to-speech technologies, allowing it to convert spoken queries into textual input, process them through the backend system, and deliver results as voice responses.

The primary motivation behind incorporating a voice interface is to address the usability gap present in existing digital agricultural platforms, where most systems assume that users are comfortable with reading, typing, and navigating complex interfaces. In rural agricultural settings, this assumption is often unrealistic.

By enabling voice-based interaction, the system allows farmers to easily request information such as crop price predictions, forecast trends, and advisory recommendations using natural language queries. This significantly reduces the learning curve and improves system adoption.

From an implementation perspective, the voice assistant operates by capturing user input through a microphone interface, converting it into text using speech recognition algorithms, and forwarding the processed query to the backend API. The backend then performs prediction or advisory processing, and the response is converted back into speech using text-to-speech synthesis. This bidirectional conversion ensures seamless interaction between the user and the system.

3.9 Bilingual Support System

In addition to voice interaction, the system incorporates a bilingual support mechanism to ensure accessibility for users from diverse linguistic backgrounds. The interface supports both English and Tamil languages, allowing users to interact with the system in their preferred language. This is particularly important in agricultural applications, where language barriers can significantly limit the adoption of digital tools.

The bilingual functionality is implemented at both the frontend and backend levels. At the frontend, the user interface dynamically switches between languages based on user selection, ensuring that all textual elements, labels, and outputs are presented in the chosen language. At the backend, translation mechanisms are integrated to process user queries and generate responses accordingly. This ensures that both input interpretation and output generation are consistent with the selected language.

The inclusion of bilingual support enhances user engagement by making the system more intuitive and culturally adaptable. Farmers can better understand predictions, forecasts, and advisory messages when presented in their native language, reducing misinterpretation and improving decision-making accuracy.

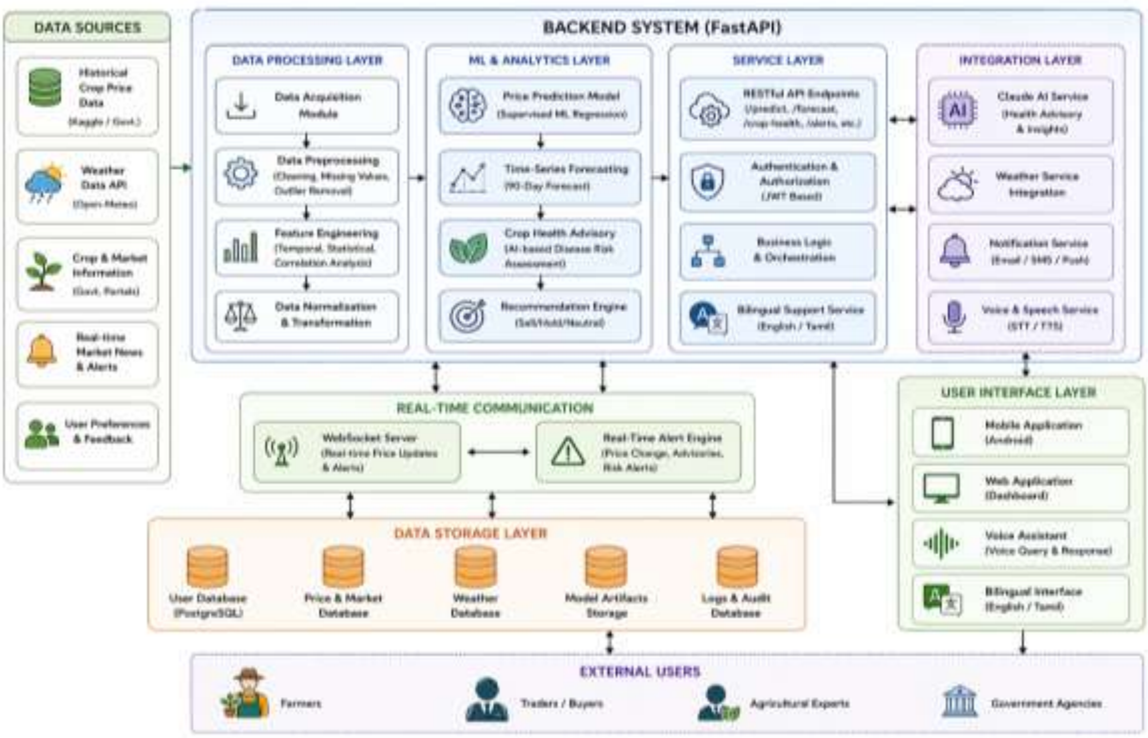

Fig. 1. System Architecture

IV IMPLEMENTATION AND EXPERIMENTAL SETUP

The implementation of the proposed FarmStock system translates the conceptual agricultural decision-support framework into a fully functional and scalable processing pipeline. The system is designed to handle real-world agricultural data, perform predictive analytics, generate multi-day forecasts, and deliver actionable insights through an interactive and user-friendly interface. The complete workflow integrates multiple components including data acquisition, preprocessing, machine learning model training, forecasting, advisory generation, and real-time alert mechanisms. Each of these components operates in a coordinated manner to ensure accurate prediction, efficient computation, and seamless user interaction.

From a system perspective, the implementation follows a modular architecture in which each functional unit is independently designed yet interconnected through backend APIs and real-time communication protocols. The backend system processes data and executes predictive models, while the frontend interface presents results in an accessible format using dashboards, charts, and voice-assisted navigation. This layered design not only improves maintainability but also enables scalability and future enhancements. The overall system architecture is illustrated in Figure .2.

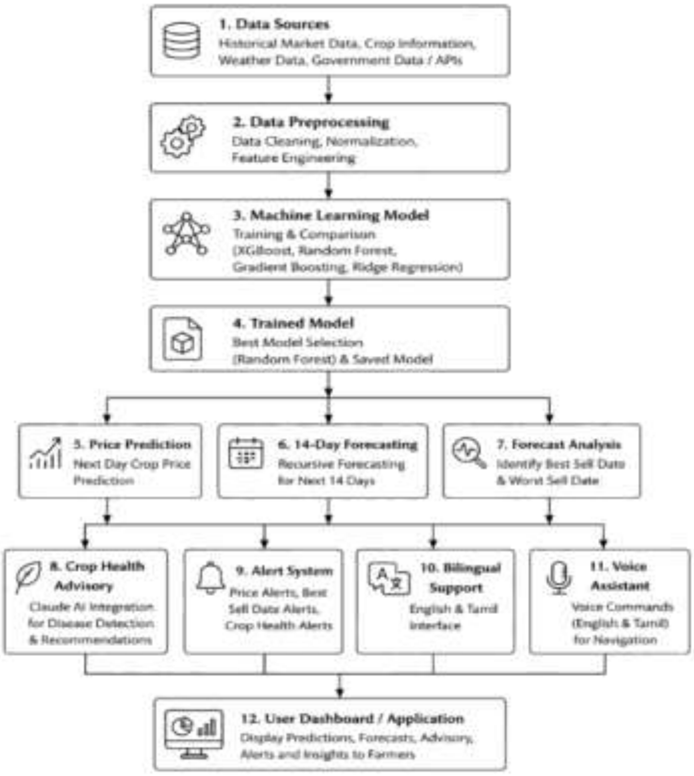

Fig. 2. System Flow of Farmstock

4.1 Data Acquisition and Preprocessing

The implementation begins with the acquisition of historical agricultural market data obtained from structured datasets containing crop prices, timestamps, and market-specific attributes. These datasets form the foundation for all predictive tasks within the system. However, real-world agricultural data is often incomplete and inconsistent due to irregular updates and manual data collection processes. To address these issues, the system incorporates a preprocessing pipeline that performs data cleaning, missing value handling, and noise reduction before model training.

Missing values are handled using interpolation techniques, ensuring continuity in time-series data, while irrelevant or redundant attributes are removed to improve model efficiency. Additionally, the date attribute is transformed into meaningful temporal features such as day, month, and seasonal indicators, allowing the model to capture cyclical price variations. The dataset is further normalized to ensure uniform scaling of features, preventing bias during model training. After preprocessing, the dataset is split into training and testing sets, enabling accurate evaluation of model performance.

4.2 Machine Learning Model Training and Comparison

To identify the most effective prediction model, multiple regression-based machine learning algorithms are implemented, including XGBoost, Random Forest, Gradient Boosting, and Ridge Regression. These models are selected due to their complementary strengths in handling structured agricultural data, where price patterns are influenced by non-linear relationships, seasonal trends, and market fluctuations. Each model is trained using the same preprocessed dataset and identical train-test split to ensure a fair and unbiased comparison. Hyperparameters such as the number of trees, learning rate, and depth are tuned to balance model complexity and generalization, preventing both underfitting and overfitting during training. This comparative approach allows the system to evaluate how different learning strategies perform under the same data conditions.

The prediction task is formulated as a regression problem, where the model learns a mapping function between input features and crop price:

$$y = f(X)$$

where Xrepresents features such as historical prices and temporal attributes, and $y$represents the predicted crop price. Model performance is evaluated using metrics such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), which quantify prediction error, along with R² score to measure the proportion of variance explained by the model. Lower error values and higher R² scores indicate better predictive performance and generalization capability.

Through experimental comparison, Random Forest is selected as the most suitable model due to its ensemble-based structure, which aggregates multiple decision trees to reduce variance and improve stability. It demonstrates consistent performance across different crops and seasonal variations, making it more robust than boosting and linear models for this application. This selection ensures that the final system achieves both high accuracy and reliability in real-world agricultural scenarios.

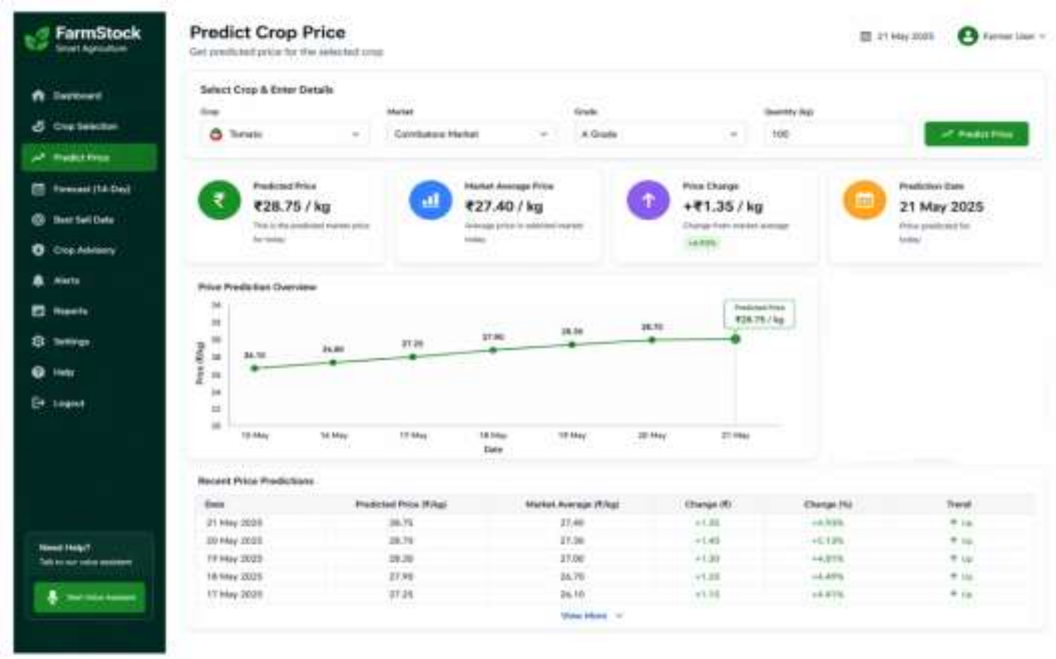

Fig. 3. Price Prediction

4.3 Saved Model for Efficient Prediction

To improve runtime efficiency and ensure low-latency response, the trained machine learning models are serialized and stored after the training phase using model persistence techniques. Instead of retraining the model for every incoming prediction request, the system directly loads the pre-trained Random Forest model into memory, significantly reducing computational overhead and response time.

This approach is particularly important in real-time agricultural applications, where farmers require instant predictions without delay. By eliminating redundant training operations, the system optimizes resource utilization, reduces CPU load, and enables faster inference even under multiple concurrent user requests. Additionally, the use of a pre-trained model ensures consistency in predictions, as all users interact with the same validated model rather than dynamically changing training outputs.

Furthermore, the system incorporates a periodic offline retraining mechanism to maintain prediction accuracy as new market data becomes available. This retraining process is executed independently of the live system, ensuring that model updates do not interrupt user interactions or system availability.

Once retraining is completed, the updated model is seamlessly deployed, replacing the existing model without affecting ongoing operations. This strategy ensures adaptability to evolving market trends while maintaining system stability. The combination of model persistence, efficient loading, and scheduled retraining enhances scalability, reliability, and overall system performance, making the FarmStock platform suitable for real-world deployment.

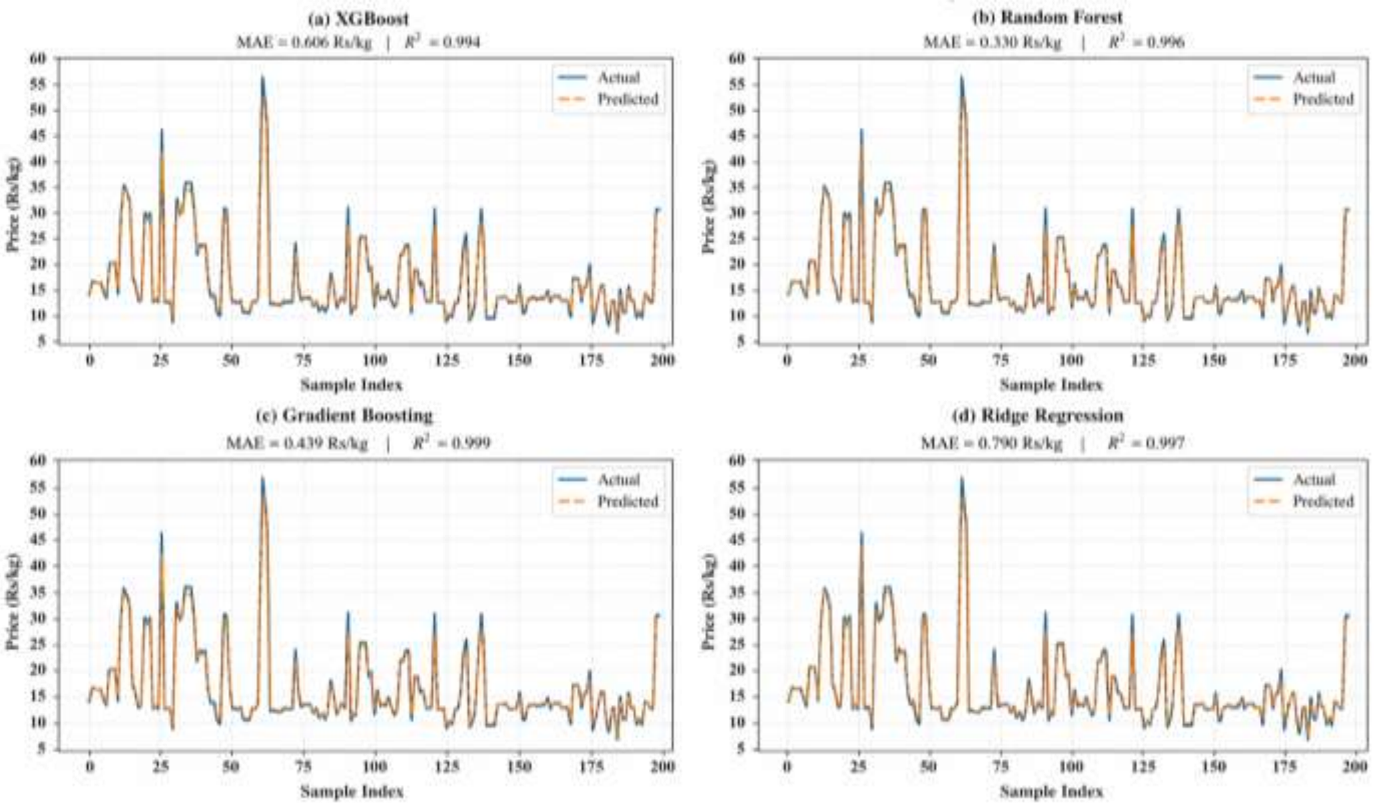

Fig. 4. Model Comparison

4.4 Fourteen-Day Price Forecasting

The system extends single-day predictions into a multi-day forecasting framework using a recursive prediction strategy, enabling the generation of a 14-day price outlook. Initially, the trained model predicts the crop price for the next day based on recent historical observations and engineered temporal features. The recursive forecasting process is mathematically represented as:

$$\hat{y}_{t+1} = f(y_t, y_{t-1}, \dots, X_{t+1})$$

where $y_t, y_{t-1}, \ldots$represent past observed prices and X_{t+1}denotes the corresponding feature set for the next time step. The predicted value $\hat{y}_{t+1}$is appended to the dataset and subsequently used as input for predicting future values. This iterative process continues until predictions for all 14 days are generated, allowing the model to capture temporal dependencies and sequential price patterns inherent in agricultural markets.

To ensure stability and reliability over multiple forecasting steps, the system leverages the robustness of ensemble-based models, which help reduce variance and improve generalization. Although recursive forecasting may introduce cumulative error due to the reuse of predicted values, the system mitigates this effect through smoothed input features and consistent model behavior. The forecasting performance can be evaluated using metrics such as:

which quantifies the deviation between predicted and actual values over the forecast horizon. The generated forecast is visualized through interactive charts, enabling farmers to easily interpret price trends, identify peaks and troughs, and determine optimal selling periods. This transforms the forecasting module from a predictive component into a practical decision-support tool for real-world agricultural applications.

4.5 Best Sell Date and Worst Sell Date Identification

To provide actionable decision support, the system analyzes the predicted 14-day price sequence to identify the most favorable and unfavorable selling dates. Given the forecasted price series $\{\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_{14}\}$, the system determines both the optimal selling day and the corresponding price values using mathematical optimization.

The best and worst selling dates are computed as:

$$t_{best} = \arg \max_{t \in \{1,2,\ldots,14\}} \hat{y}_t, t_{worst} = \arg \min_{t \in \{1,2,\ldots,14\}} \hat{y}_t$$

In addition to identifying the time indices, the corresponding maximum and minimum predicted prices are obtained as:

$$Price_{max} = \max_t \hat{y}_t, Price_{min} = \min_t \hat{y}_t$$

where $\hat{y}_t$represents the predicted crop price on day t. This formulation ensures that both the optimal decision point and its expected economic value are explicitly determined. The use of $\arg\max$and $\arg\min$transforms the forecasting output into a quantitative optimization problem, eliminating ambiguity in interpreting prediction graphs.

By leveraging future price predictions rather than relying solely on current market conditions, the system enables farmers to make informed and profit-oriented decisions. This automated analysis removes the need for manual inspection of forecast trends and provides clear recommendations for maximizing revenue while avoiding unfavorable selling periods.

Additionally, the computational simplicity of this approach allows it to be efficiently integrated into real-time systems, ensuring fast and reliable decision support. Overall, this module enhances the practical utility of the FarmStock platform by converting predictive insights into direct, actionable strategies for agricultural stakeholders.

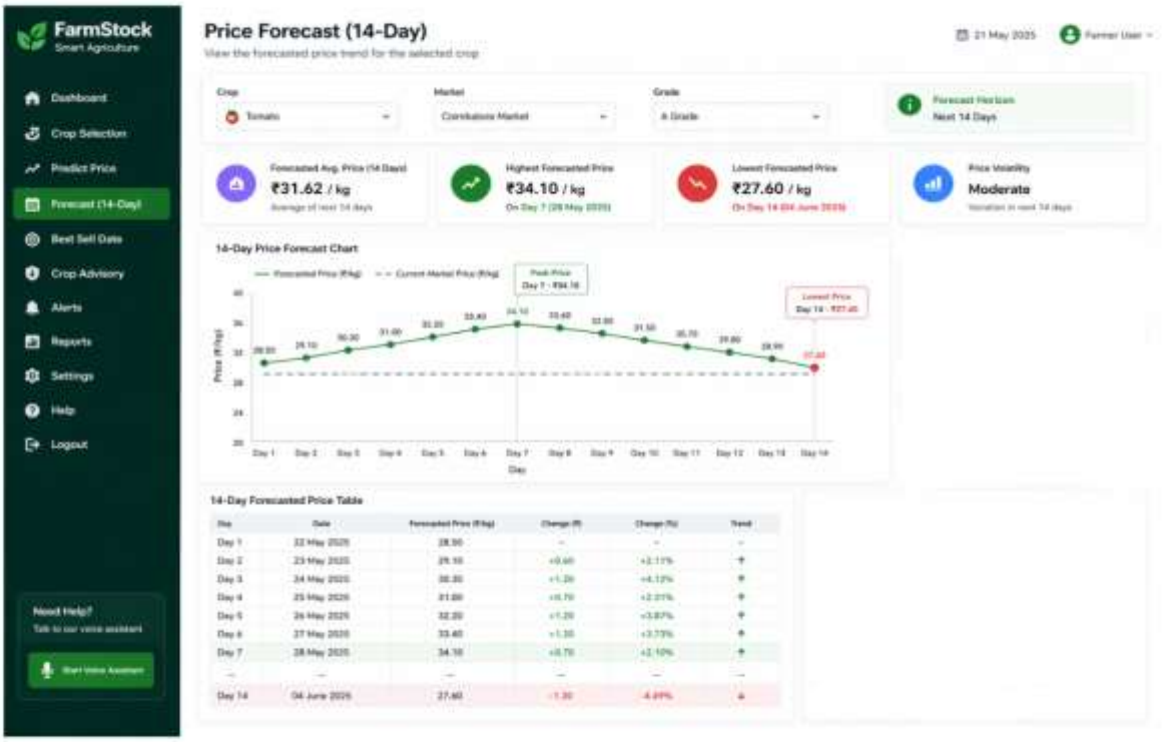

Fig. 5. Price Forecast

4.6 Crop Health Advisory Using AI Integration

The crop health advisory module enhances the FarmStock system by providing intelligent, context-aware insights into potential crop diseases and environmental risks using AI-based analysis. When a farmer selects a crop, the system processes multiple input parameters, including crop type, geographic location, seasonal period, temperature, and rainfall conditions. These inputs collectively form a feature vector that represents the environmental and agronomic context of the crop. Based on this information, the system generates advisory outputs such as potential diseases, symptoms to monitor, and recommended preventive measures. This dynamic approach replaces traditional static advisory systems by adapting recommendations to real-time conditions, thereby improving relevance and accuracy.

The advisory mechanism can be interpreted using a probabilistic framework, where the likelihood of a disease given observed conditions is estimated as:

$$P(\text{disease} \mid X) = \frac{P(X \mid \text{disease}) \cdot P(\text{disease})}{P(X)}$$

where Xrepresents the observed environmental and crop-specific features. This formulation allows the system to prioritize risks based on probability rather than fixed rules. By identifying potential threats at an early stage, the system enables farmers to take preventive actions such as applying appropriate treatments or adjusting cultivation practices, thereby reducing crop loss and improving productivity. The integration of this advisory module with price prediction and forecasting ensures that farmers receive comprehensive decision support, combining both economic and crop health perspectives within a unified platform.

4.7 Alert Notification System

The alert notification system in FarmStock is designed to provide real-time, event-driven updates by continuously monitoring prediction outputs, forecasting trends, and advisory signals. The system evaluates changes in predicted price sequences and identifies significant events such as sudden price spikes, sharp declines, or the proximity of optimal selling dates. These events are detected using predefined threshold conditions and trend analysis, ensuring that only meaningful changes trigger notifications.

Once a condition is satisfied, alerts are generated and pushed instantly to the user interface, eliminating delays associated with manual monitoring. This real-time mechanism ensures that farmers remain continuously informed about critical market dynamics without actively tracking the system.In addition to price-based alerts, the system integrates crop health advisory outputs to generate risk-based notifications related to potential diseases or environmental threats.

This dual-alert mechanism ensures that both economic and agronomic risks are communicated effectively. By delivering timely notifications, the system enables proactive decision-making, allowing farmers to take immediate action such as selling at peak prices or applying preventive measures against crop diseases. The integration of alert logic with predictive and advisory modules enhances system responsiveness and reduces the likelihood of missed opportunities, making it a critical component for real-world agricultural applications.

4.8 Bilingual Support Implementation

To address accessibility challenges in diverse agricultural communities, the FarmStock system incorporates a bilingual support mechanism that enables interaction in both English and Tamil. The system is designed to dynamically adapt the user interface based on the selected language, ensuring that all textual components, including navigation elements, prediction outputs, alerts, and advisory messages, are displayed in a familiar and understandable format. This dynamic language switching is implemented at the frontend level, allowing seamless transitions without affecting system performance or workflow continuity.

At the backend level, the system ensures consistency in input interpretation and output generation across both languages by integrating translation mechanisms within the processing pipeline. This allows user queries and system responses to remain contextually accurate regardless of the selected language. The inclusion of bilingual support significantly reduces language barriers, which are a major limitation in the adoption of digital agricultural systems in rural environments. By improving comprehension and usability, this feature enhances user engagement and ensures that critical information is effectively communicated, ultimately contributing to better decision-making and increased system adoption.

4.9 Voice Assistant Navigation

The voice assistant module enhances user interaction by enabling farmers to access system functionalities through spoken commands, reducing reliance on manual input and complex navigation. The system captures audio input through a microphone interface and processes it using speech recognition algorithms to convert speech into text.

This textual input is then mapped to predefined commands and forwarded to the backend system, where the appropriate prediction, forecasting, or advisory function is executed. The response generated by the system can also be converted into audio output using text-to-speech synthesis, enabling a complete bidirectional voice interaction.

The integration of bilingual voice support allows users to interact with the system in either English or Tamil, further improving accessibility for users with limited literacy or technical expertise. This feature is particularly beneficial in real-world agricultural environments, where farmers may need to access information while working in the field.

By enabling hands-free operation and natural language interaction, the voice assistant reduces the learning curve associated with digital platforms and increases system usability. The combination of speech recognition, command mapping, and response generation ensures seamless interaction, making the system more inclusive and practical for a wide range of users.

4.10 Experimental Evaluation

The performance of the FarmStock system is evaluated using standard regression metrics to measure prediction accuracy and model reliability. The primary evaluation metric
used is Mean Absolute Error (MAE), which quantifies the average deviation between predicted and actual crop prices:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

In addition to MAE, metrics such as Root Mean Squared Error (RMSE) and R² score are used to provide a comprehensive assessment of model performance. RMSE penalizes larger errors more heavily, while R² measures the proportion of variance explained by the model, offering insight into its predictive capability. These metrics collectively ensure that both accuracy and stability are evaluated across different models.

Experimental results indicate that the Random Forest model achieves the best balance between accuracy and generalization, outperforming other models in terms of error minimization and consistency across different crops and time periods. The system is tested using multiple datasets and real-world scenarios to validate its robustness and applicability.

The results demonstrate that the integration of prediction, forecasting, advisory, and alert modules produces a cohesive system capable of delivering accurate and actionable insights. This confirms the effectiveness of the FarmStock platform as a reliable agricultural decision-support system suitable for real-world deployment.

Table 2 — Performance Comparison of Machine Learning Models

Model	**Description**	**R² Score**	**Accuracy (%)**	**Best Model Status**	**Advantages**
XGBoost	Ensemble boosting model that builds trees sequentially, optimizing errors with regularization	0.9940	99.40	—	Handles complex non-linear data, built-in regularization, high performance
Random Forest	Ensemble of multiple decision trees using bagging and random feature selection for stability	0.9964	99.64	Best (Overall)	Robust to noise, reduces overfitting, stable predictions
Gradient Boosting	Sequential model where each tree corrects previous errors to improve accuracy	0.9990	99.90	Best (RMSE & R²)	High precision, captures subtle patterns
Ridge Regression	Linear regression model with L2 regularization to reduce overfitting	0.9967	99.67	Baseline Model	Simple, interpretable, useful for linear relationships

V EXPECTED RESULTS AND DISCUSSION

Prediction Accuracy and Model Performance

The expected results of the FarmStock system indicate a high level of prediction accuracy achieved through the implementation of ensemble-based machine learning models. Among the evaluated models, Random Forest is anticipated to outperform other approaches such as XGBoost, Gradient Boosting, and Ridge Regression due to its ability to capture non-linear relationships and reduce overfitting through ensemble learning. The evaluation metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R² score, are expected to demonstrate minimal deviation between predicted and actual crop prices, with MAE values remaining within a low error range and R² scores approaching values close to 1.0. These results indicate that the model can effectively learn underlying price patterns from historical data.

The graphical analysis of actual versus predicted values further supports the model's effectiveness, showing strong alignment between real and predicted price trends with minimal divergence. Additionally, feature importance analysis highlights that rolling averages and lag-based features significantly influence prediction outcomes, validating the effectiveness of the feature engineering process. This confirms that the system is not only accurate but also interpretable, allowing stakeholders to understand the factors influencing predictions. Overall, the expected performance demonstrates that the system can reliably predict crop prices under varying market conditions, providing a strong foundation for decision-making.

Forecasting Effectiveness and Decision Support

The multi-day forecasting capability of the FarmStock system is expected to provide valuable insights into short-term market trends, enabling farmers to make informed selling decisions. By generating a sequence of predicted prices over a 14-day or 30-day horizon using recursive prediction, the system captures temporal dependencies and seasonal fluctuations in agricultural markets. The forecast graph is expected to show stable trend patterns with identifiable peaks and troughs, which can be directly used to determine optimal selling periods.

One of the key expected outcomes is the accurate identification of best sell and worst sell dates based on predicted price variations. This functionality transforms raw predictions into actionable recommendations, eliminating the need for manual interpretation. Even in scenarios where price changes are subtle, the system is expected to detect small fluctuations that can significantly impact profit margins over large quantities of produce. Additionally, the forecasting module helps farmers anticipate unfavorable market conditions, allowing them to delay selling or explore alternative strategies. By integrating forecasting with prediction models, the system moves beyond static analysis and provides dynamic decision support, which is critical in highly volatile agricultural markets.

System Usability and Real-World Impact

Beyond predictive accuracy, the FarmStock system is expected to demonstrate significant improvements in usability and accessibility, particularly for farmers in rural and semi-urban regions. The integration of bilingual support in English and Tamil ensures that users can interact with the system in their preferred language, reducing dependency on technical knowledge and minimizing the risk of misinterpretation. Furthermore, the voice assistant module is expected to enhance user interaction by enabling hands-free navigation and query processing, making the system more accessible to users with limited literacy or familiarity with digital interfaces.

The real-time alert system is another critical component that contributes to the system’s practical impact. By providing instant notifications related to price changes, forecast updates, and crop health advisories, the system ensures that farmers can respond promptly to dynamic market conditions. Additionally, the crop health advisory module is expected to assist in early detection of potential diseases and risks, enabling preventive measures that can reduce crop loss. Collectively, these features contribute to a user-centric design that bridges the gap between advanced analytics and real-world usability. The expected outcome is a system that not only improves decision-making accuracy but also enhances adoption and practical utility in real agricultural environments.

VI CONCLUSION

The FarmStock system presents a comprehensive agricultural decision-support platform that integrates machine learning-based price prediction, time-series forecasting, crop health advisory, and real-time alert mechanisms into a unified framework. By leveraging historical market data and advanced regression models, the system is able to generate accurate crop price predictions and short-term forecasts, enabling farmers to identify optimal selling periods and make informed decisions. The use of ensemble models, particularly Random Forest, ensures robustness and reliability in handling non-linear and dynamic agricultural data.

In addition to predictive capabilities, the system emphasizes usability through features such as bilingual support and voice-assisted interaction, making it accessible to farmers with varying levels of technical expertise. The integration of advisory and alert modules further enhances its practical value by providing timely insights and risk mitigation strategies. Overall, FarmStock successfully bridges the gap between advanced analytics and real-world agricultural needs, offering a scalable and user-centric solution that improves productivity, reduces uncertainty, and supports data-driven farming practices.

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