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IndiGenius Mart: AI-Based Crop Price Forecasting for Indigenous Farmers Using Time-Series and Ensemble Learning

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Abstract

Indigenous farmers often face challenges in determining fair prices for agricultural commodities due to limited access to timely and reliable market information, weakening their bargaining power and income stability. In this study, we aimed to: (1) identify challenges facing indigenous farmers when determining accurate prices for agricultural commodities, (2) determine how the features of IndiGenius Mart address these issues, and (3) evaluate the acceptability of the proposed system based on the ISO/IEC 25010 software quality model in terms of functional suitability, performance efficiency, usability, reliability, and portability. We conducted a questionnaire survey among 50 indigenous farmers using purposive sampling. Results indicated a strong consensus (weighted mean = 4.47) that inadequate price information leads to unfair pricing, financial losses, and inefficient selling schedules. To address these concerns, we developed the IndiGenius Mart, an AI-based, offline-capable mobile application for crop price forecasting that integrates time-series analysis and ensemble machine learning models. The model achieved a high coefficient of determination ($R^2 = 0.982$) and demonstrated consistent prediction accuracy on unseen data (96–98%). Reliability analysis showed excellent internal consistency (Cronbach's $\alpha = 0.93–0.96$; overall $\alpha = 0.95$). System evaluation yielded acceptable ratings across all ISO/IEC 25010 criteria, with a weighted overall mean of 3.90 (SD = 0.29), interpreted as Acceptable. We conclude that accessible and localized AI-driven crop price forecasting tools enhance price transparency and improve decision-making among indigenous farmers, consistent with prior data-driven agriculture studies. Future research should focus on expanding localized datasets and evaluating long-term real-world deployment across diverse regions.

Keywords: Indigenous farmers, crop price forecasting, ensemble learning, time-series analysis, machine learning, agricultural markets, ISO/IEC 25010, decision support system

INTRODUCTION

Agricultural commodity pricing plays a critical role in sustaining farmers' livelihoods and maintaining stability in food supply systems. Accurate and timely price information enables farmers to make informed decisions regarding production planning, harvesting schedules, storage strategies, and market participation. Farmers are essential contributors to food security, economic development, and cultural preservation, particularly among indigenous communities that rely heavily on agriculture as their primary source of income (Ibáñez et al., 2023). However, many small-scale and indigenous farmers in developing regions continue to face difficulties in accessing reliable market information and forecasting tools. Limited digital infrastructure, geographic isolation, and information asymmetry within agricultural supply chains often place farmers at a disadvantage during price negotiations. Consequently, farmers frequently accept buyer-determined prices that may not reflect actual market values, resulting in reduced income and increased economic vulnerability.

Recent advancements in artificial intelligence (AI) and machine learning have demonstrated significant potential in addressing challenges related to agricultural market forecasting. Machine learning techniques, particularly time-series analysis and ensemble learning models, have been widely applied to predict commodity prices by analyzing historical market patterns and price trends. Ensemble learning methods combine multiple predictive models to improve forecasting accuracy and robustness (Huang & Wang, 2023). Several studies have reported the effectiveness of machine learning models such as Random Forest, Gradient Boosting, and Extreme Gradient Boosting (XGBoost) in capturing complex nonlinear relationships in price prediction tasks (Tripathi et al., 2018; Zhao, 2024). Additionally, research highlights the importance of data preprocessing, feature engineering, and model selection in improving predictive performance for commodity price forecasting (Karaca & Dökmen, 2024). In agricultural contexts, machine learning models have also been successfully applied to forecast crop yields, detect plant diseases, and analyze soil conditions, demonstrating the transformative role of AI in modern agriculture (Bhardwaj & Tiwari, 2022; Tran et al., 2023).

Despite these advancements, existing agricultural price prediction systems are often designed for general market environments and rarely address the specific needs of indigenous farmers who operate in geographically isolated areas with limited access to digital technologies. Indigenous agricultural markets are particularly vulnerable to price volatility due to weak market linkages, limited access to price forecasting tools, and insufficient digital infrastructure (Ma et al., 2019). Furthermore, many forecasting platforms require continuous internet connectivity and lack localization features such as language accessibility, which restricts their usability among marginalized farming communities.

To address these limitations, this study proposes IndiGenius Mart, an AI-driven decision-support system designed to forecast retail prices of selected crops for indigenous agricultural markets. The application integrates time-series forecasting with ensemble machine learning techniques, including Random Forest, Gradient Boosting, AdaBoost, and Extreme Gradient Boosting (XGBoost), to analyze historical market data and generate accurate price predictions. Market dynamics are further examined using ALP phases (Normal, Stress, Alert, and Crisis), which represent varying levels of food security conditions and market disruptions influencing commodity price volatility.

The developed forecasting model has been implemented using a mobile phone application that will work without online access. This will allow farmers in rural areas, without stable internet connections, to still have access to price forecasts for agricultural goods. Filipino language support has also been added to the system to further improve accessibility and inclusivity. Interactions with the platform through a familiar language interface allow for greater participation of the user community with the latest in technology. The combination of an indigenous community-based digital platform with machine learning prediction methods is being used in this study to (1) identify issues facing indigenous farmers when determining accurate prices for food commodities, (2) identify how the features of IndiGenius Mart will help with these issues, and (3) evaluate the extent of acceptability of the proposed system per the ISO/IEC 25010 quality model for software according to functional suitability, performance efficiency, usability, reliability and portability. Ultimately, the objective of the study is to enhance price transparency, facilitate data-driven decision-making, and enhance the economic resilience of low-income agricultural markets.

While this system will mainly focus on Indigenous agricultural communities, it will also help other groups involved in agriculture as well. Examples of those would be small farmer producers, farmers market traders, farmer coops, and farmers and other agricultural participants in the local markets. Providing farmers with information about market prices and trends increases transparency in price negotiations, as well as reduces the imbalance of information when negotiating prices, allowing farmers to negotiate better prices and make more accurate marketing decisions. As a result, farmers will have increased stability in their incomes and less economic vulnerability.

Additionally, the system will support more efficient use of resources (input) and more effective planning of agricultural production, helping to reduce losses within the agriculture sector and improving the availability of products in relation to the demand for those same products. The study illustrates clearly how this will contribute to the reduction of poverty, food security, the sustainable economy, and the sustainable use of resources rather than acknowledging that aligning with any of those four broad objectives is sufficient.

LITERATURE REVIEW

Agricultural commodity price forecasting has become a critical component in supporting data-driven decision-making among farmers, traders, and policymakers, particularly in the context of volatile market conditions and increasing data availability. The existing body of literature demonstrates a clear methodological evolution from traditional statistical techniques toward more advanced machine learning approaches. Earlier studies predominantly employed regression and time series models, which were effective in identifying linear trends but were inherently limited in capturing the nonlinear and dynamic behavior of real-world agricultural markets (Tripathi et al., 2018; Zhao, 2024). As a result, contemporary research has increasingly adopted machine learning techniques capable of modeling complex, high-dimensional relationships within diverse datasets.

Recent advancements highlight the effectiveness of models such as support vector machines, random forests, gradient boosting, and artificial neural networks in improving predictive accuracy and generalization performance. Moreover, ensemble learning techniques have further enhanced robustness by integrating multiple models, thereby reducing prediction errors and improving stability across varying market conditions (Huang & Wang, 2023; Karaca & Dökmen, 2024). These developments underscore a broader shift toward data-driven and computation-intensive forecasting paradigms.

The applicability of these approaches extends beyond agriculture into commercial and financial domains, where machine learning has been successfully utilized to predict product prices, consumer demand, and stock market trends (Bhatnagar et al., 2024; Shanti et al., 2021; Izzah et al., 2017; Liu et al., 2024). Notably, these studies also emphasize the integration of predictive models into user-facing platforms, particularly mobile applications, to enhance accessibility and real-time usability. This trend signals an emerging convergence between predictive analytics and user-centered system design.

Within the agricultural domain, machine learning has demonstrated strong potential not only in price forecasting but also in related applications such as crop yield prediction, disease detection, and supply chain optimization (Bhardwaj & Tiwari, 2022). Hybrid modeling approaches, which combine multiple algorithms, have been shown to outperform single-model techniques in capturing complex market dynamics (Hwase & Fofanah, 2021; Selvaraj et al., 2024). Additionally, efforts toward interpretable forecasting models have sought to enhance transparency and support decision-making among farmers, particularly in small-scale and marginal contexts (Ma et al., 2019).

Furthermore, recent studies emphasize the integration of heterogeneous datasets, including weather conditions, production levels, transportation costs, and macroeconomic indicators to improve predictive performance (Tran et al., 2023). While these multi-source datasets significantly enhance model accuracy, they also introduce challenges related to data availability, processing complexity, and system scalability, particularly in resource-constrained environments.

Dataset Comparison of Prior Studies. To provide a structured comparison of existing approaches, Table 1 summarizes the datasets utilized in prior agricultural price forecasting studies.

The comparison reveals a clear progression from simple, structured datasets toward increasingly complex and heterogeneous data sources. While this evolution has substantially improved predictive performance, it has also resulted in systems that are highly dependent on computational resources, stable connectivity, and continuous data streams. Consequently, the practical deployment of such systems remains limited in real-world agricultural settings, particularly in developing regions.

Table 1
Summary of Datasets Used in Prior Agricultural Price Forecasting Studies

Author(s)	Domain	Dataset Type	Key Variables	Data Characteristics	Limitation
Tripathi et al. (2018); Zhao (2024)	Agriculture	Historical time-series	Commodity prices	Structured, numerical	Limited nonlinear modeling
Huang & Wang (2023); Karaca & Dökmen (2024)	Agriculture / ML	Multi-source	Price, weather, economic data	Large, high-dimensional	High computational cost
Bhatnagar et al. (2024); Shanti et al. (2021)	Commercial	Product pricing	Demand, features, pricing	E-commerce datasets	Limited agricultural relevance
Huwse & Fofanah (2021); Selvaraj et al. (2024)	Agriculture	Hybrid datasets	Market, seasonal, production	Integrated datasets	System complexity
Tran et al. (2023)	Agriculture	Multi-factor	Weather, transport, production	Dynamic, heterogeneous	Data inconsistency
Ma et al. (2019)	Agriculture	Interpretable datasets	Market indicators	Explainable models	Limited scalability
Ibáñez et al. (2023); Paleo & Castiñeiras (2023)	Socio-technical	Contextual	Socio-economic factors	Real-world context	Infrastructure constraints

Despite significant advancements in predictive modeling, the literature exposes persistent gaps in the design and implementation of agricultural price forecasting systems. A key limitation lies in the disconnect between technical model performance and practical usability. Existing studies largely prioritize accuracy metrics, such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2), while giving comparatively less attention to usability, interpretability, and accessibility. As a result, many proposed systems remain confined to experimental or theoretical contexts, with limited real-world adoption among non-technical users.

Moreover, the reliance on complex, multi-source datasets and computation-intensive models restricts the applicability of these systems in low-resource environments. Most existing solutions are designed for contexts with stable internet connectivity and advanced technological infrastructure, thereby excluding indigenous and marginalized farming communities who operate under significantly different conditions. Issues such as language barriers, limited digital literacy, and lack of localized system design further exacerbate this gap. Additionally, although some studies have explored mobile-based implementations, the development of fully integrated, field-deployable decision support systems remains limited. In particular, there is a lack of solutions that combine predictive accuracy with real-time usability, offline or low-connectivity functionality, and user-centered interface design.

In response to these limitations, the present study proposes a mobile-based, community-oriented agricultural price forecasting system that integrates machine learning models with a user-centered design framework. Unlike prior approaches that emphasize predictive performance in isolation, this study adopts a holistic perspective that balances accuracy with accessibility, interpretability, and practical usability. The system is specifically designed to operate in low-connectivity environments, incorporating localized language support and simplified data structures to ensure inclusivity and ease of use.

By bridging the gap between advanced machine learning techniques and real-world agricultural applications, this study contributes to the development of more sustainable and inclusive decision-support systems. It advances the field not only by improving predictive capability but also by addressing the critical socio-technical factors that influence system adoption and effectiveness in marginalized farming communities.

Conceptual Framework. In order to help customers make informed decisions about the food supply chain, Indienius Mart combines Ensemble Learning Methods (ELM) to create a sample product catalogue that can forecast the price of food commodities, conduct price trend analysis, and provide users with the opportunity for action. The architecture of this ELM system consists of predictive machine learning algorithms that use historical pricing data as an input to detect trends in pricing behavior based on dynamic market factors. In addition to this, high-level architecture is illustrated in the input-process-output model as represented by Figure 1.

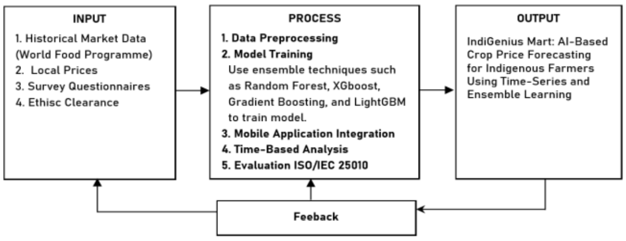

Figure 1
Relationship of Variables for the Development of IndiGENIUS Mart

METHODS

This study employed a quantitative research approach to develop and evaluate IndiGenius Mart, an AI-driven mobile application designed to forecast retail prices of selected agricultural commodities. The methodology integrates data collection, machine learning-based forecasting, and system evaluation to assess the effectiveness of the proposed decision-support system. The research process includes dataset preparation, model training using ensemble learning algorithms, and system evaluation using the ISO/IEC 25010 software quality framework.

Research Design. This study employed an experimental research design to develop and evaluate an artificial intelligence-based price forecasting system for selected agricultural commodities. The research focused on the development of IndiGenius Mart, a decision-support system designed to forecast retail prices of selected crops for indigenous farmers using machine learning techniques trained on historical market data. The study integrates predictive analytics, mobile application development, and system evaluation to ensure both the accuracy of the forecasting models and the usability of the developed platform.

The system development process followed an Agile-based development approach, which allows iterative refinement of the forecasting models and application features through continuous testing and improvement. This approach enabled the integration of predictive modeling, system design, and user feedback during the development process. The methodological workflow consisted of several stages including data collection, data preprocessing, machine learning model training, forecasting model evaluation, mobile application development, and system evaluation.

Data Sources and Data Preparation. This study accesses historical agricultural price data obtained from the WFP from May 2020 through September 2025 in a single market (in Zambales) with approximately one month of time between observation periods for each agricultural commodity. Key variables in the datasets are listed below: (market name), Date (MMMM YYYY), Commodity Price, ALPS Phase Classification - Normal, Stress, Alert. Commodities can be classified into four major groups: The commodities are categorized into four major groups: Fruits (Banana-Lakatan, Banana-Latundan, Calamansi, Coconut, Mangoes-Carabao, and Papaya), Grains (Rice), Poultry (Eggs), and Vegetables (Beans-String, Eggplants, Ginger, Onions-Red, Onions-White, Squash, and Tomatoes).

There are 910 observations in the dataset. This includes price data for 14 different commodities over a period of 65 months. The WFP datasets are collected through standardized monitoring systems, so they can provide consistent and reliable information.

To incorporate contextual market information, the study utilized ALP phase indicators, which classify market conditions into four categories: Normal, Stress, Alert, and Crisis. These indicators represent different levels of food security conditions and market disruptions that may influence commodity price volatility. Incorporating these contextual variables allows the forecasting models to better capture fluctuations caused by market instability and supply disruptions.

Prior to model development, the collected datasets underwent several data preprocessing procedures to ensure data quality and compatibility with machine learning algorithms. Multiple preprocessing steps helped to assure data quality and make it usable for time-series forecasting by transforming the originally collected data set (910 observations). After all relevant observations were collected 0 records were deleted from the final data set as all of the selected commodities had complete entries through the chosen time frame. Any minor amounts of missing values that were found in the time series were handled via the use of linear interpolation, which allowed for the use of the values immediately before or after an observation to find an estimated value of price for the missing data point to maintain the continuity of time and to not disrupt the sequential patterns of data.

Standardized numerical variables (such as commodity price) have been normalized (min-max scaled) to fall within a 0-1 range to facilitate convergence of the model and enable comparability between commodities due to different price ranges. Categorical variables (commodity type and market Id) have been converted from their categorical form into a label-encoded numerical form for machine learning applications. Through these preprocessing procedures, this dataset was preserved with completeness, consistency and appropriate structure for both time series analysis and machine learning modeling while also keeping the integrity of its temporal dependencies intact.

Feature Engineering for Time-Series Modeling. The ability to predict future outcomes was improved by transforming historical price data into a series of time-dependent features through systematic feature engineering. Multiple statistical features and lag-based features were generated in order to capture both short-term and long-term temporal dependencies in commodity prices.

Included in the data were these model input variables: Price Features Price - 1 (Price value per absolute position, Lag Time & Value) Price - 3 (Price three periods back) Price - 6 (Price six periods back) Price - 12 (Price twelve periods back capturing annual seasonality). By including all these lag statistics enables models to use temporal autocorrelated patterns based on history within an agricultural price. Statistical Features, Moving Relative to Time Frame, were also created by using a series of stat stats as defined throughout this submission's methodology.

3-period moving average 6-period moving average 3-period rolling standard deviation 6-period rolling standard deviation These variables represent the most recent short-term price trends and market volatility. ALPS Phase Encoding the ALPS phase classification (Normal, Stress, Alert, or Crisis) has been added as a categorical variable encoded with labels as follows: Normal = 0 Stress = 1 Alert = 2 Crisis = 3.

Market condition signals associated with food insecurity; commodity price instability will be taken into account through this encoding of market conditions. Creating New Time Features Seasonality effects will be captured in the models using these time variables: Month (1-12) Year index (normalized) These features allow the models to have well-structured inputs capturing historical dependencies, seasonal behaviour, and market conditions, which results in improved forecasting performance.

Machine Learning Models. This study used ensemble-based machine learning methods plus time series analyses to create price forecasts for agricultural commodities by capitalizing on both the nonlinear relationships

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between the price data as well as the temporal patterns (time) seen in a series of past prices. Time series analyses were employed since commodity prices are sequential or time-based, meaning something that happens today affects what will happen tomorrow based on past trends in relation to the present and also consistent cycles due to seasonality in addition to the cyclical market behavior. Combining these two techniques/models together allows the modelling to be able to learn both the short-term and long-term dynamics of an agricultural commodity's price.

An ensemble of four models has been created, including those using additional predictive algorithms like Gradient Boosting, AdaBoost and Extreme Gradient Boosting (XGBoost). These techniques have been used because they do improve the final predictive accuracy of all prediction methods compared to just having one. Furthermore, historical commodity pricing data were used to train the four different models to assist in discovering periodic cycles and patterns within market dynamics.

Table 2
Model Hyperparameters

Model	Key Parameters
Random Forest	n_estimators=100, max_depth=None
Gradient Boosting	learning_rate=0.1, n_estimators=100
AdaBoost	n_estimators=50, learning_rate=1.0
XGBoost	max_depth=6, learning_rate=0.1, n_estimators=100

The models were set up using predefined (standard) hyperparams, which allow reliable baseline performance and consistency across models. Table 2 includes all hyperparam combinations (Default Hyperparam Configurations Used) used in this research. The models were evaluated using time-series cross-validation ensuring temporal dependencies are preserved to avoid data leakage. The predictive performance of each model was evaluated by calculating their mean absolute errors (MAE), root mean square error (RMSE), and coefficient of determination (R2) to assess both model accuracy and credibility in making predictions.

Model Evaluation Metrics. Three basic regression metrics, known as mean absolute error (MAE), root mean squared error (RMSE) and coefficient of determination (R^2), were used to evaluate the performance of forecasting models. These three-regression metrics provide a complete assessment of the performance of forecasting models by combining both prediction quality and reliability of the model itself.

The Mean Absolute Error (MAE) measures the average magnitude of prediction errors between predicted and actual values, providing an indication of overall prediction accuracy. It is computed as:

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

where:

- yi = actual value
- ŷi = predicted value
- n = total number of observations

The Root Mean Squared Error (RMSE) evaluates the magnitude of prediction errors while assigning greater weight to larger deviations. It is computed as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i}$$

The coefficient of determination (R^2) measures how well the model explains the variance observed in the dataset. It is computed as:

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

where:

- ȳ = mean of the actual values

The Mean Absolute Percentage Error (MAPE) measures the average percentage difference between predicted and actual values, making it useful for interpreting model performance in relative terms. It is computed as:

$$\mathrm{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\%$$

Lower MAE, RMSE, and MAPE values indicate better model performance, while R^2 values closer to 1 indicate stronger explanatory power. To improve interpretability for end-users, particularly farmers and agricultural stakeholders, model performance was also expressed as accuracy (%), derived from MAPE as:

Accuracy (%) = (1−MAPE) × 100

Another way to evaluate a model's accuracy is to calculate its reliability using confidence intervals and scores. A confidence interval provides an estimate of the expected variability of predicted prices based on how variable all predictions generated from an ensemble of individual models (like decision trees and boosting iterated) are from each other. When an individual instance is passed, an ensemble model generates multiple predictions (or outputs) including a minimum and maximum predicted value.

To quantify the reliability of the prediction, a confidence score was computed as a custom metric based on the relative width of the confidence interval. The confidence score is defined as:

Confidence Score (%) = (1−Upper Bound−Lower Bound/Predicted Value) × 100

where:

- Upper Bound = maximum predicted value
- Lower Bound = minimum predicted value
- Predicted Value = final forecasted price

Predictions with smaller confidence ranges will have a more stable and consistent output as indicated through a higher confidence score. The confidence value is reported as a percentage with higher percentages indicating more reliable outputs. The confidence value is derived from a model and therefore should not be interpreted as a formal statistical confidence (standard errors & confidence intervals); it should only be used for interpretability purposes in communicating prediction reliability to end users.

System Development. The forecasting framework was implemented through IndiGenius Mart, an AI-driven mobile decision-support system designed to provide agricultural price forecasts for indigenous farmers. The system integrates machine learning prediction modules with a mobile application interface that allows users to access price forecasts and view market trend information.

The mobile application was designed to function offline, enabling farmers in remote areas to access price predictions even without continuous internet connectivity. The application stores forecasting outputs locally and presents prediction results through an intuitive user interface. To improve accessibility for local users, the application also incorporates Filipino language support, allowing farmers to interact with the platform using familiar language settings.

Survey of Indigenous Farmers. Fifty indigenous farmers served as respondents in this study and were selected using purposive sampling. This sampling technique ensured that all participants had firsthand experience in pricing agricultural commodities. The criteria for selecting respondents included the following: (1) they are currently active indigenous farmers, (2) they are engaged in producing and selling agricultural commodities, and (3) they are members of or affiliated with a local farming association. Individuals who were not involved in farming or had no experience in commodity pricing were excluded from the study.

All participants provided informed consent prior to data collection, indicating their understanding of the nature and purpose of the study as well as the voluntary nature of their participation. The research adhered to ethical standards approved by the Polytechnic University of the Philippines. The rights, privacy, and welfare of the respondents were protected throughout the duration of the study through proper ethical clearance procedures.

To understand the challenges experienced by indigenous farmers in determining agricultural commodity prices, a questionnaire survey was conducted among members of indigenous farming communities. The survey aimed to collect information regarding farmers' experiences with price information availability and their decision-making processes in agricultural marketing.

A structured questionnaire using a 5-point Likert scale was developed to enable respondents to indicate their level of agreement with statements related to challenges in determining agricultural commodity prices. These challenges were categorized into: (1) difficulty in obtaining accurate price information, (2) market uncertainty, and (3) challenges in making pricing decisions among indigenous farmers.

The research instrument was validated through an expert review process conducted by the President of the Samahang Katutubo Cadmang Farmers Association in Cadmang, Cabangan, Zambales. The expert possesses extensive knowledge of traditional agricultural practices and commodity pricing within indigenous communities. The review confirmed that the questionnaire items were relevant, clear, and appropriately contextualized for the intended respondents. The expert's direct involvement with the local farming community further strengthened the cultural and practical validity of the instrument.

In addition to expert validation, the reliability of the instrument was assessed using Cronbach's Alpha to determine the internal consistency of the questionnaire. This statistical measure was used to evaluate whether the items within each category consistently measure the intended constructs. The inclusion of Cronbach's Alpha provided quantitative support to the instrument's reliability, complementing the qualitative validation performed by the expert.
To further evaluate the developed system, the study utilized the ISO/IEC 25010 software quality framework, which is an internationally recognized standard for assessing software quality. The same fifty indigenous farmers who participated in the needs assessment were also involved in evaluating the system. The evaluation focused on five key quality characteristics: functional suitability, performance efficiency, usability, reliability, and portability.

A weighted mean was used to determine the level of acceptability of the system based on the responses of the participants. The collected data from both the needs assessment and system evaluation were analyzed to identify the primary challenges faced by indigenous farmers in pricing agricultural commodities and to assess how effectively the developed forecasting system addressed these challenges and supported their decision-making processes.

System Evaluation. The developed system was evaluated using the ISO/IEC 25010 software quality framework, which provides a standardized model for assessing software quality. The evaluation focused on key quality characteristics, namely functional suitability, performance efficiency, usability, reliability, and portability. The use of the ISO/IEC 25010 framework ensures that the evaluation follows internationally accepted standards for software quality assessment.

The five selected quality attributes were considered relevant to the users' experience, particularly in the context of Android-based application performance. Other ISO/IEC 25010 characteristics, namely security, maintainability, and compatibility, were excluded as they were beyond the scope of the study. Security was not evaluated because the system primarily functions as a decision-support tool and does not process sensitive personal data nor require continuous internet connectivity, thereby minimizing exposure to common security risks. Maintainability was also excluded since it pertains to the responsibilities of developers during system modification and debugging, which are not directly observable or accessible by end users. Similarly, compatibility was not included because the system was designed and tested within a specific Android environment, without consideration for cross-platform deployment such as iOS or web-based systems.

The respondents were asked to use the developed system and complete a structured evaluation questionnaire to assess the application based on the identified quality characteristics. This procedure ensures that the evaluation reflects actual user interaction and experience with the system.

Table 3
Scale of Acceptability Levels in System Evaluation

Scale Value	Mean Range	Interpretation for Level of Acceptability (System Evaluation)
5	4.21 - 5.00	Highly Acceptable
4	3.41 - 4.20	Acceptable
3	2.61 - 3.40	Moderately Acceptable
2	1.81 - 2.60	Slightly Acceptable
1	1.00 - 1.80	Not Acceptable

Statistical Treatment. To analyze the responses of the participants, the Weighted Mean and Standard Deviation were used. The weighted mean was utilized to determine the average level of acceptability for each criterion, while the standard deviation was used to measure the variability or dispersion of the responses. The standard deviation is computed using the following formula:

- where σ represents the standard deviation, x_i refers to each individual response, $\bar{x}$ is the mean of the responses, and n is the total number of responses.

A low standard deviation indicates that the responses are closely clustered around the mean, implying consistency among respondents, while a high standard deviation indicates greater variability in responses.

Reliability of the Evaluation Instrument. To ensure the consistency and reliability of the evaluation instrument, Cronbach's Alpha was used to measure the internal consistency of the items under each quality characteristic. This statistical measure determines how closely related a set of items are as a group, thereby strengthens the validity of evaluation results.

Cronbach's Alpha is computed using the following formula:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_t^2}\right)$$

where:

- α = Cronbach's Alpha (reliability coefficient)
- k = Number of items in the instrument
- σ^2_i = Variance of item i,
- σ^2_t = Variance of the total scores (sum of all items)

where:

- α (alpha) represents the reliability coefficient
- k is the number of items,
- σ^2_i (sigma squared sub i) is the variance of each item, and
- σ^2_t (sigma squared sub t) is the variance of the total scores (sum of all item scores).

The following scale was used to interpret the Cronbach's Alpha values (Table 4):

Table 4
Scale for Interpreting Cronbach's Alpha Values

Cronbach's Alpha Value	Interpretation
≥ 0.90	Excellent
0.80 - 0.89	Good
0.70 - 0.79	Acceptable

By focusing on user-centered quality attributes, the evaluation highlights how effectively and efficiently users can interact with the system.

This approach ensures that the assessment reflects real user experiences while acknowledging that other technical aspects of system quality may be addressed in future improvements and system iterations.

RESULTS AND DISCUSSION

This section presents the findings of the study alongside their corresponding interpretations, integrating both results and discussion to provide a comprehensive analysis of the effectiveness of the IndiGenius Mart system.

Descriptive Analysis of Challenges Faced by Indigenous Farmers. Table 5 presents descriptive statistics on the difficulties indigenous farmers face in accurately assessing food commodity prices, based on the sources of available price information. The findings reveal a consistently high level of consensus across all four indicators, with an overall mean of 4.47, which is interpreted as Strongly Agree. This suggests that the respondents commonly encounter challenges related to insufficient and unreliable price information.

Table 5
Challenges Faced by Indigenous Farmers

No.	Statement	Mean	Descriptive Interpretation
1	I find it difficult to sell my products at a fair price because I have limited price information.	4.48	Strongly Agree
2	I sometimes sell my products at a loss because the price information I receive is incorrect or outdated.	4.40	Strongly Agree
3	I find it hard to plan when to harvest or sell my products because I lack reliable price information.	4.46	Strongly Agree
4	I feel pressured to accept the buyer's offered price because I do not know the correct market price.	4.52	Strongly Agree
Overall Weighted Mean		4.47	Strongly Agree

Among the indicators, the statement "I feel pressured to accept the buyer's offered price because I do not know the correct market price" received the highest average score (4.52), indicating that insufficient access to reliable price information puts indigenous farmers at a disadvantage in price discussions. This underscores the existence and presence of information asymmetry between farmers and buyers.

The other items also produced high average values, demonstrating that a lack of price information impacts farmers' capability to sell at equitable prices, causes financial setbacks, and limits their planning choices concerning harvesting and selling. The comparatively low standard deviation values suggest that the responses were similar among the participants. The results indicate that limited access to dependable price information poses a major problem for indigenous farmers, influencing their income, decision-making processes, and negotiating strength. These findings clearly align with research objective 1 and offer evidence for the necessity of enhanced price information or resources designed specifically for indigenous farming communities.

Model Performance on Training Data. Table 6 presents the results obtained from the evaluated models. The performance of the ensemble learning models was evaluated using three regression metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). These metrics were used to measure the accuracy of the forecasting models in predicting retail prices of selected crops based on historical market data.

Table 6
Model Performance on Training Data

Model	MAE	RMSE	R^2
Random Forest	2.6	3.4	0.975
Gradient Boosting	2.3	3.1	0.978
AdaBoost	2.8	3.6	0.971
XGBoost	2.1	2.8	0.982

The prediction results show that XGBoost has better predictive performance than Random Forests, Gradient Boosting, and AdaBoost with an R^2 of 0.982; this is a much greater level of predictive accuracy than what was previously reported by Tripathi et al (2018), who produced strong but less extreme predictive ability using ensemble methods for agricultural price prediction. Huang and Wang (2023) also reported moderate levels of prediction accuracy for traditional machine learning models due to their limited ability to represent features adequately.

There are many reasons that can explain the outperformance of XGBoost compared to other algorithms. One reason is that XGBoost uses gradient boosting with regularization. Regularization reduces overfitting, and gradient boosting captures non-linear relationships between price inputs. The other main reason for XGBoost's superior performance is the model's inherent ability to account for interaction between features. As a result, XGBoost can make better use of additional inputs (e.g., lagged prices, rolling averages) that are engineered from the original dataset. Lastly, because XGBoost optimizes the residual error at each iteration of the optimization process, XGBoost is better able to learn the underlying temporal patterns of commodity prices than bagging-based methods (e.g., Random Forest) do.

The findings contribute to a large body of academic research that supports the use of boosting algorithms for accurate time-series forecasting of complex patterns and rapidly changing data. Moreover, based on the findings, it appears that ensemble boosting approaches may have significant advantages over other types of algorithms for predicting agricultural prices due to their significant robustness and flexibility.

In terms of practicality, an R^2 of 0.982 represents a very high degree of variation in prices being explained by the system, therefore providing significant support for farmers in making decisions. The agricultural forecasting systems currently available to farmers are less accessible than IndiGenius Mart and, therefore, would not be appropriate for use within indigenous communities because they require an ongoing internet connection and do not provide localized forecasts. The apparent benefits of this product demonstrate an increase in predictive accuracy, usability, and availability within resource-constrained contexts.

All of the models produced good results on their training datasets, with XGBoost having the best performance in predicting values (i.e., R^2 = 0.982). It's worth mentioning that verifying how well models perform during training does not necessarily mean those models will work equally well with unseen data due to potential overfitting; this will be discussed more below.

To address this limitation, the models were further evaluated using unseen data through time-series validation and real-world comparison of predicted and actual prices, as shown in Table 5.

Predicted Prices per Commodity Category (January 2026). Table 7 presents the predicted prices generated by the system for selected commodities for January 2026. The model estimated prices of ₱111.09 per kilogram for Lakatan bananas, ₱50.21 per kilogram for rice, ₱8.86 per piece for eggs, and ₱137.93 per kilogram for eggplants. These predictions are derived from historical price data and time-series trend analysis, enabling the system to forecast future prices based on established patterns and seasonal behavior.

Table 7
Price Prediction Result

Category	Commodity	Predicted Price	Actual Market Price	Unit	Confidence Interval	Confidence Score
Fruits	Bananas (Lakatan)	₱ 111.09	₱ 100.00-₱130.00	Kg	₱ 106.36-₱115.81	96.0 %
Grains	Rice	₱ 50.12	₱ 40.00-₱55.00	Kg	₱ 49.30-₱ 51.18	98.0 %
Poultry	Eggs	₱ 8.86	₱ 7.00-₱11.00	Pc	₱ 8.52-₱ 9.19	96.0 %
Vegetables	Eggplants	₱ 137.93	₱ 130.00-₱180.00	Kg	₱ 133.39-₱180.00	97.0 %

To account for uncertainty, each prediction is accompanied by a confidence interval, representing the range within which the actual market price is expected to fall. For instance, Lakatan bananas have an estimated range of ₱106.36–₱115.81, while rice falls within ₱49.30–₱51.18. These intervals indicate that although the system provides a point estimate, actual prices may vary within defined bounds due to market fluctuations. Narrow intervals reflect higher certainty, whereas wider intervals indicate greater variability. The confidence intervals were computed based on prediction errors during model validation, thereby capturing real-world uncertainty.

In addition, the system provides confidence scores ranging from 96% to 98%, indicating high prediction stability and reliability across multiple models runs. Higher confidence scores suggest that the model consistently captures underlying price trends. While this metric reflects model-based reliability rather than formal statistical confidence, it serves as a practical indicator of prediction dependability for end users.

Validation against actual market price ranges sourced from the World Food Programme (WFP) for Zambales shows that all predicted values fall within observed price bounds. This confirms the model's ability to generalize effectively to unseen data. Since actual prices are represented as ranges, this approach provides a realistic validation framework, where predictions are considered accurate when they lie within observed market limits. The variability within these ranges reflects natural fluctuations influenced by supply-demand dynamics and local market conditions. Overall, the results demonstrate that the system produces accurate, reliable, and contextually valid forecasts across multiple commodity categories. Although the use of range-based validation introduces minor limitations in computing exact point-based errors, the combined evidence from model performance and real-world validation strongly supports the robustness of the forecasting approach. This demonstrates that the system is a reliable decision-support tool capable of improving price awareness, reducing information asymmetry, and enhancing strategic decision-making among indigenous farmers.

Time Series Analysis of Predicted Prices for Selected Fruits, Grains, Poultry, and Vegetables of Ensemble Learning. This section details the findings from monthly time-series price predictions for selected commodities using ensemble learning techniques, specifically XGBoost. The examination focused on four key commodities across major agricultural sectors: Lakatan bananas (fruit), rice (regular, milled grain), eggs (poultry), and eggplants (vegetable).

The forecasting models were based exclusively on historical price data, converted into lagged features because the dataset lacks additional explanatory variables such as weather patterns. The analysis of price trends was informed by market dynamics and food security indicators present in the dataset, such as the ALPS Phase.

Time Series Analysis of Predicted Prices for Fruits- Bananas (Lakatan). Figure 2 shows that the anticipated prices of Lakatan bananas tend to remain stable in the initial months, with only slight variations, primarily classified as Normal (Stable) and occasional Stress (Concerns). A significant decline is observed around the midpoint, succeeded by a gradual rebound and a steep upward movement in the final months, signaling a shift to an Alert (Rising) price condition. This indicates mounting market pressure and a likely increase in retail prices.

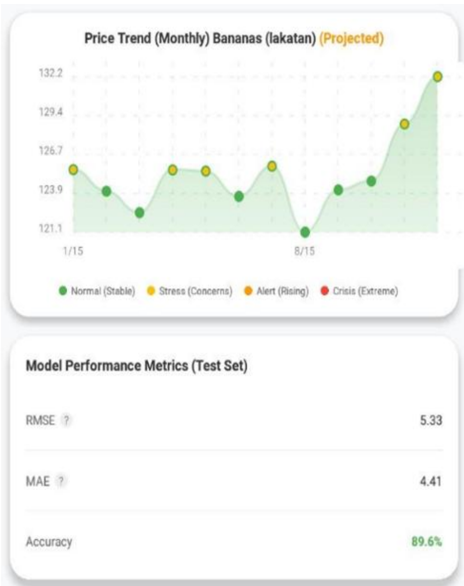

Figure 2
Bananas (Lakatan) Time-Based Analysis

Time Series Analysis of Predicted Prices for Grains- Rice. Figure 3 shows that anticipated rice prices initially decrease slightly, remaining mostly within the Normal (Stable) range in the early months. In the middle period, prices rise significantly and peak, classified as Stress (Concerns), indicating temporary market strain. This is followed by a subsequent decrease, bringing prices back to a more stable level. Overall, the trend demonstrates moderate fluctuations without entering Alert (Rising) or Crisis (Extreme) levels.

Figure 3
Rice Time-Based Analysis

Time Series Analysis of Predicted Prices for Poultry- Eggs. Figure 4 illustrates that egg prices exhibit short-term fluctuations over the projected months, beginning with an initial decrease, followed by a gradual rise in the later stages. Most price changes remain within the Normal (Stable) range, with several cases classified as Stress (Concerns), indicating slight but manageable price pressure. The upward trend toward the end of the timeframe suggests a possible increase in demand or supply constraints, although prices do not reach Alert (Rising) or Crisis (Extreme) levels.

Figure 4
Eggs Time-Based Analysis

Time Series Analysis of Predicted Prices for Vegetables- Eggplants. Figure 5 illustrates a significant drop in eggplant prices during the initial period, which is followed by a phase of relative stability at lower price points. In the middle and latter months, prices exhibit a consistent upward trend, with several instances classified as Stress (Concerns) and Alert (Rising) conditions, ultimately reaching a Crisis (Extreme) level by the end of the projection period. This trend reflects increasing price volatility and possible supply-side challenges in the later months.

Figure 5
Eggplants Time-Based Analysis

Time-Series Forecasting Performance. Table 8 reveals that all of the commodities that have been selected can be effectively predicted by the forecasting model. The forecasting model achieved a low level of forecasting error (RMSE = 5.33, MAE = 4.41) for Lakatan banana and has an accuracy level of 89.6% based on the trends it was able to track accurately.

The model for rice produced 92.6% accuracy which indicates it does a good job tracking price changes even though some fluctuations do occur within the time series, however, aren't significant. Egg prices also show a high level of accuracy (93.2%) compared to other products; thus, the model has great potential for tracking short-term pricing changes. The eggplant model produced the lowest RMSE (2.19) and MAE (1.67) values of any product with an accuracy of only 88.4%. This means that while predictions tend to produce more consistent prices within eggplants, they are affected significantly by the fluctuations that exist throughout the price trends of all other vegetables in the sample.

In general, the results show that this model can successfully forecast commodity price movements with adequate accuracy, allowing it to be used for monitoring prices and making forecasts, along with making decisions about the agricultural sector.

Table 8
Per-Commodity Time-Series Forecasting Performance

Commodity	RMSE	MAE	MAPE	Accuracy (%)
Bananas (Lakatan)	5.33	4.41	0.104	89.6%
Rice	5.49	4.30	0.074	92.6%
Eggs	5.78	4.33	0.068	93.2%
Eggplants	2.19	1.67	0.116	88.4%

System Evaluation. Table 9 presents the system evaluation results of *IndiGenius Mart* based on the ISO/IEC 25010 framework. The overall weighted mean of 3.90 (SD = 0.29), interpreted as *Acceptable*, indicates that the system meets the required standards in terms of functionality, performance efficiency, usability, reliability, and portability. The standard deviation values across all criteria range from 0.17 to 0.36, indicating low to moderate variability and suggesting a generally consistent level of agreement among respondents regarding the system's performance.

Table 9
Respondent's Overall Evaluation Level of Acceptability

Characteristics	Mean	Standard Deviation (SD)	Interpretation
Functional Suitability	3.89	0.31	Acceptable
Performance Efficiency	3.84	0.36	Acceptable
Usability	3.97	0.17	Acceptable
Reliability	3.90	0.31	Acceptable
Portability	3.89	0.32	Acceptable
Weighted Overall Mean	3.90	0.29	Acceptable

Among the evaluated characteristics, Usability obtained the highest mean score of 3.97 (SD = 0.17), indicating that respondents found the application intuitive, easy to navigate, and accessible. The relatively low standard deviation reflects a strong level of consensus among users, highlighting usability as the most influential factor in the overall system evaluation. This finding emphasizes the importance of user-centered design, particularly for indigenous farmers who may have limited familiarity with digital technologies.

Reliability recorded a mean score of 3.90 (SD = 0.31), while Functional Suitability achieved 3.89 (SD = 0.31). These results indicate that the system consistently performs its intended functions and maintains stable operation during use. The moderate variability suggests that while most users had positive experiences, there were slight differences in perception, which is expected in real-world usage conditions.

In terms of Portability, the system obtained a mean score of 3.89 (SD = 0.32), indicating that the application performs effectively across different mobile environments. The observed variability may reflect differences in device specifications, operating systems, or network conditions, which can influence user experience.

Meanwhile, Performance Efficiency obtained the lowest mean score of 3.84 (SD = 0.36) among all characteristics, although still within the "Acceptable" range. The higher standard deviation indicates greater variation in user responses, suggesting that some users experienced differences in system responsiveness or resource utilization. This highlights performance efficiency as a potential area for further optimization.

Overall, the combined analysis of mean scores and standard deviation values indicates that Usability is the primary driver of the system's overall evaluation, followed by Reliability and Functional Suitability, while Performance Efficiency shows the least consistency among users. These findings suggest that for systems designed to support indigenous farmers, ease of use, accessibility, and dependable functionality are more critical to user acceptance than purely technical performance aspects.

Summary of Reliability Analysis (Cronbach's Alpha). Table 10 results reveal that all evaluated categories obtained weighted mean values ranging from 3.84 to 3.97, which are interpreted as acceptable. This indicates that respondents generally perceive the system as functional, efficient, usable, reliable, and portable.

Table 10
Reliability Analysis of the Instrument Using Cronbach's Alpha

Variables / Category	No. of Items	Cronbach's Alpha	Interpretation
Functional Suitability	4	0.96	Excellent
Performance Efficiency	4	0.94	Excellent
Usability	4	0.95	Excellent
Reliability	4	0.93	Excellent
Portability	4	0.94	Excellent
Overall	20	0.95	Excellent

Furthermore, the reliability analysis using Cronbach's Alpha showed values ranging from 0.93 to 0.96, indicating excellent internal consistency across all categories. This confirms that the survey instrument is highly reliable and that the responses are consistent. The alignment between the high weighted mean scores and excellent reliability coefficients suggests that the system performs well and that the evaluation results are dependable and valid.

Conclusion. This study developed IndiGenius Mart, an artificial intelligence-based decision-support system designed to forecast retail prices of selected agricultural commodities using ensemble machine learning techniques. The forecasting framework integrates time-series analysis with multiple ensemble algorithms, including Random Forest, Gradient Boosting, AdaBoost, and Extreme Gradient Boosting (XGBoost), to analyze historical commodity price datasets and generate predictive price insights.

The survey conducted among indigenous farmers revealed that the lack of reliable price information remains a significant challenge, with an overall weighted mean of 4.47, interpreted as Strongly Agree. This finding highlights the presence of information asymmetry that affects farmers' pricing decisions, income stability, and bargaining power, thereby establishing the need for a data-driven forecasting solution.

The experimental results showed that XGBoost achieved the highest predictive performance, with an R^2 value of 0.982, MAE of 2.1, and RMSE of 2.8, outperforming the other evaluated ensemble models. These results confirm the effectiveness of boosting-based ensemble learning techniques for modeling complex agricultural price patterns. It is important to note that this R^2 value was obtained from the training dataset; however, further validation using unseen data, including comparisons with actual market price ranges in Zambales, demonstrated that predicted prices consistently fell within observed bounds, supported by high confidence scores, indicating reliable real-world performance.

The developed system directly addresses this issue by providing an accessible mobile forecasting platform capable of delivering price predictions even in offline environments. The integration of offline functionality, dataset updating mechanisms, and Filipino language support enhances the system's accessibility and usability for indigenous farming communities. Evaluation based on the ISO/IEC 25010 framework confirms that the application meets acceptable standards in terms of functional suitability, performance efficiency, usability, reliability, and portability.

Collectively, the results indicate that integrating ensemble machine learning with mobile decision-support systems improves price transparency and enables more informed, data-driven decision-making among farmers. Beyond the immediate results, this study establishes that accessible and localized AI-driven forecasting systems can effectively reduce information asymmetry, strengthen the bargaining capacity of marginalized farmers, and support more equitable participation in agricultural markets. Furthermore, the successful implementation of an offline-capable system provides a scalable model for deploying intelligent decision-support technologies in resource-constrained and low-connectivity environments, contributing to inclusive and sustainable agricultural development.

Limitations of the Study. Despite the promising results, several limitations must be acknowledged regarding the data sources and feature design used in this study.

The ALPS Phase Indicators are often helpful in recording overall macroeconomic conditions; however, they are usually assigned at either a national or regional level. Therefore, they may not capture the localized conditions of indigenous farmers that are affected by localized small and/or informal trading systems. This may introduce a bias into the model, because localized price fluctuations due to supply and demand at a community level are not explicitly recorded.

The second consideration is that the use of World Food Programme price data may not accurately reflect prices in all of the informal markets where many indigenous farmers sell their products. Prices in informal markets may vary widely based on how prices are negotiated, how much transportation is available, and other social factors that are not included in formal databases. Therefore, while the model may provide predictions that reflect the overall trends of formal markets, those predictions are less likely to represent the prices farmers encounter in localized situations.

In addition, since the data only contains one location (Zambales) and a small sample size (N=910), it limits the ability to produce a generalizable model to use in all locations due to differing market structures, climate conditions, and economic conditions across other locations.

Ultimately, this model can only partially explain price variability due to the lack of any external factors. These include climate conditions, fuel prices, and disruptions in the supply chain. Therefore, future research must utilize multiple resources to increase the model's robustness and contextual accuracy.

These limitations suggest that while the model performs well within the study context, caution must be exercised when applying it to different regions or market environments.

Recommendations

1. ***Incorporation of Exogenous Variables.*** Given that the current model does not account for external factors such as climate conditions, fuel prices, transportation costs, and supply chain disruptions, future studies should incorporate a wider range of exogenous variables. This will improve the model's ability to capture real-world price variability and enhance its contextual sensitivity, particularly in localized agricultural settings.

2. ***Expansion of Dataset Scope and Geographic Coverage.*** Considering that the dataset is

limited to a single location, Zambales, and a relatively small sample size, future research should include a broader range of geographic areas and longer timeframes. Expanding the dataset will improve the generalizability and adaptability of the forecasting models across diverse market structures, climate conditions, and economic environments.

3. ***Integration of Hybrid Forecasting Models.*** To further enhance predictive performance, future studies should explore hybrid modeling approaches that combine statistical methods (e.g., ARIMA) with advanced machine learning and deep learning techniques (e.g., LSTM or GRU). Such integration may improve the model's ability to capture both linear and complex temporal patterns in agricultural price data.

4. ***Incorporation of Localized and Informal Market Data.*** Given that World Food Programme (WFP) data may not fully reflect price dynamics in informal or community-based markets, future research should incorporate localized data sources, including community-level price monitoring and farmer-reported pricing. This will reduce bias and improve the accuracy of predictions in real-world indigenous farming contexts.

5. ***Enhanced Data Updating Mechanisms.*** To address the limitations of static datasets, future system enhancements should implement periodic online synchronization features. This will enable dynamic updates of market data while maintaining offline functionality, ensuring that users receive more timely and relevant price information.

6. ***Longitudinal Pilot Deployment and Impact Assessment.*** Future studies should conduct long-term pilot implementations of the system in actual farming communities to assess its sustained impact on farmers' income, pricing decisions, and market participation. This will provide stronger empirical evidence of the system's real-world effectiveness and usability over time.

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