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Research Article

Prototype of AI-Integrated Chatbot for Shallot Price Forecasting and Advisory Support to Assist Farmer Decision Making

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Abstract

Forecasting agricultural commodity prices is a fundamental tool for sustainable development in the agricultural economy and broader economic stability. With rapid and simple access to information on future prices, farmers can plan their planting schedules to optimize profits. This study presents a prototype AI chatbot that integrates price forecasting and advisory functions to assist farmers in decision-making and interact as an extension agent. Price forecasting employed Random Forest regression, achieving MAPE of 8.34% (training), 13.98% (validation), and 15.62% (testing). The chatbot was developed to access price forecasting information for the next four months. This system also integrates an LLM-AI model for consultations on planting schedules and other topics using a trusted knowledge base. During the testing phase, the chatbot successfully made predictions, provided recommendations, and interacted as an extension agent. Although demonstrating promising results, this study is limited to shallot price forecasting in Yogyakarta, highlighting the need for broader commodity and regional coverage in future studies. Unlike previous studies that focused only on forecasting or advisory, this study integrates predictive analytics with conversational AI in a farmer-friendly chatbot.

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1. Introduction

Agriculture is the backbone of the Indonesian economy, providing 28.17% of the total labor (Pusat Data dan Sistem Informasi Pertanian, 2024). In 2022, the agriculture sector contributed to the national gross domestic income (GDI) of 19.59 trillion rupiah, which is approximately 13.2% of the total national GDI (Pusat Data dan Sistem Informasi Pertanian, 2023). However, this sector is also a major contributor to inflation, especially due to the volatility of strategic food prices, such as rice, shallots,

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and chili (Lestari et al., 2024). Fluctuating prices of agricultural commodities are considered a national issue that requires serious attention (Salsabila & Silvia, 2024).

The uncertainty of agricultural commodity prices impacts both producers and consumers. For consumers, especially low-income ones, they cannot purchase food when the price is spiking, and for the producer, the received income potentially is lower than the break-even point (BEP) when the price drops, weakening the farmer's economy (Matondang et al., 2024). This increases the risk of malnutrition and food insecurity (Chaudhry et al., 2021).

Price forecasting of agricultural commodities has the potential to be a sophisticated tool for supporting a sustainable agricultural economy and stabilizing national prices. The information obtained by predicting future prices can guide farmers to make informed decisions regarding which crops are profitable (Manogna et al., 2025). Farmers are guided to choose when to plant and sell commodities, allowing them to optimize their profits. Price forecasting is essential for farmers and consumers and offers future agricultural commodity price insights that can aid the government in formulating policies to ensure stable prices. Therefore, an agricultural commodity price forecasting model was developed.

Recent studies have employed several methods to develop a model to forecast agricultural commodity prices, such as the traditional regression method ARIMA (autoregressive integrated moving average) for forecasting sunflower seed prices in India (KumarMahto et al., 2019), seasonal ARIMA (SARIMA) to predict the price movement of fruits and vegetables (Dharavath & Khosla, 2019), support vector regression for hog prices (Liu et al., 2019), artificial neural networks (Nhita et al., 2019; Paul et al., 2022), long short-term memory for several agricultural commodities (Murugesan et al., 2022), and the ensemble method random forest (Ibrahim, 2025; Mohanty et al., 2023). Among them, random forest was selected over other methods because of its ability to handle nonlinear relationships, robustness to outliers, and computational efficiency, making it suitable for real-time chatbot integration.

For the price forecasting model to be used by farmers, a channel must be provided, usually with the help of agricultural extension services. One option is to build an application that can handle user interaction, manage data, and conduct price forecasting. However, this option has a disadvantage, especially since users must first become accustomed to and able to use it. It would take a longer time to introduce it, and users may not adopt it and revert to old practices. Furthermore, the introduction of new technologies usually meets with resistance from the targeted users.

Another option is to use a chatbot that works within messaging applications, such as WhatsApp and Telegram. Both applications are familiar in Indonesia and have features that provide chatbots to engage with users, mimicking human interaction. The advantage of familiarity with messaging tools can bypass user resistance and facilitate faster dissemination. By deploying the chatbot in these applications, most farmers are already accustomed to the familiar platform and do not perceive it as a difficult technology to use, which is a critical factor for the system to be adopted by users in the long term (Masi et al., 2023). Moreover, with the rise of artificial intelligence (AI) conversational agents that use large language models (LLMs), chatbots can interact with users in a manner that resembles talking to a trusted expert. Therefore, the development of an AI-integrated chatbot is proposed as an advisory agent that can guide farmers' decision-making.

The development of chatbots as agricultural advisory services has recently received attention, especially in developing nations. This is due to the limitations in scaling and real-time information processing inherent in agricultural extension services. Current research on chatbot topics has reported that chatbots have successfully helped farmers by increasing yield, improving pest management, and reducing water use (Bambhaniya & Makwana, 2025; N. Singh et al., 2024). Singh et al., 2024). (Bambhaniya & Makwana, 2025; N. Singh et al., 2024). For example, prior studies have proposed Telegram-based monitoring systems, expert systems for crop disease diagnosis, and Internet of Things-enabled smart farming platforms. Several agricultural information systems and chatbot-based applications have been developed in Indonesia, focusing on farm monitoring, pest and disease diagnosis, smart irrigation, and general extension services (Barus & Barus, 2023; Ramadhan, 2024; Rasendriya et al., 2025; Wijaya et al., 2024; Yusuf et al., 2025). However, these systems primarily provide reactive or descriptive advisory functions and do not integrate forward-looking commodity price forecasting into the consultation processes. However, these systems primarily provide reactive or descriptive advisory functions and do not integrate forward-looking commodity price forecasting into the consultation processes. This study aims to address this gap by developing a prototype that integrates random forest price forecasting into an LLM-powered chatbot, enabling farmers to receive both predictive insights and advisory support on a familiar platform (Telegram). To the best of our knowledge, only a few studies have combined price forecasting with a conversational AI advisory system. This study aims to address this gap by developing a prototype that integrates Random Forest price forecasting into an LLM-powered chatbot, enabling farmers to receive both predictive insights and advisory support on a familiar platform (Telegram).

This prototype research specifically focuses on shallot price forecasting in the Yogyakarta region and the development of an integrated system that combines predictive analytics with conversational AI LLMs on a platform familiar to farmers. The current prototype does not incorporate detailed agro-climatic variables or planting calendars. This limitation serves to provide a tested and measurable proof of concept (PoC) for the integration of price forecasting and consultation features within the chatbot system and is explicitly acknowledged to avoid generalization. Focusing on a single commodity and region allows for effective validation of the forecasting model and the functional workflow of the chatbot. Future development will integrate seasonal planting constraints, weather information, and commodity-specific agronomic requirements to further reduce the risk of inappropriate recommendations for crop management.

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2. Material and Methods

2.1 Chatbot Structure and Development

The chatbot, named "Eneng Tani," was developed in a Telegram messaging bot application for its simplicity and wide use. The chatbot functionality was built separately on a local server and connected using the API key provided by Telegram. The system was designed with scalability in mind and used an asynchronous feature to handle multiple concurrent users. When a user accesses the chatbot for the first time, it asks for the user's nickname and address regency area (Kabupaten) and stores this information in the database. If the user accesses the chatbot for the second time, it will remember them based on their Telegram username.

To simulate the experience of consulting with an agricultural extension service, three main features were provided: (1) forecasting the price, (2) recommending profitable crops, and (3) general consultation. During the conversation, the chatbot guided the interaction with inline messages.

The price forecasting feature was implemented using a developed machine learning model and historical data of commodity monthly prices at different regencies based on user information. The chatbot asks for the planting date and then generates a monthly price prediction within 1–4 months. A four-month forecasting horizon is considered the time of harvest (2–3 months) plus its shelf life (Direktorat Sayur dan Tanaman Obat, 2017). This information provides farmers with alternatives to wait until the selling price is favorable.

The crop recommendation function takes the planting month as a user input and generates a list of recommended crops. The recommendation is based on whether the selling price is higher than the BEP. Government official data on BEP were employed as a reference (Direktorat Sayur dan Tanaman Obat, 2017). If no crop is profitable in that planting season, the chatbot informs the user that there is no recommended crop and suggests postponing the planting season.

General consultation employs AI LLMs that are available online, such as Gemini, through its API. It serves as a helpful extension agent. Overall, the system is designed to handle multimodal interactions, including text-based queries for price predictions and conversational interfaces for agricultural advice. Figure 1 shows the workflow of the proposed chatbot.

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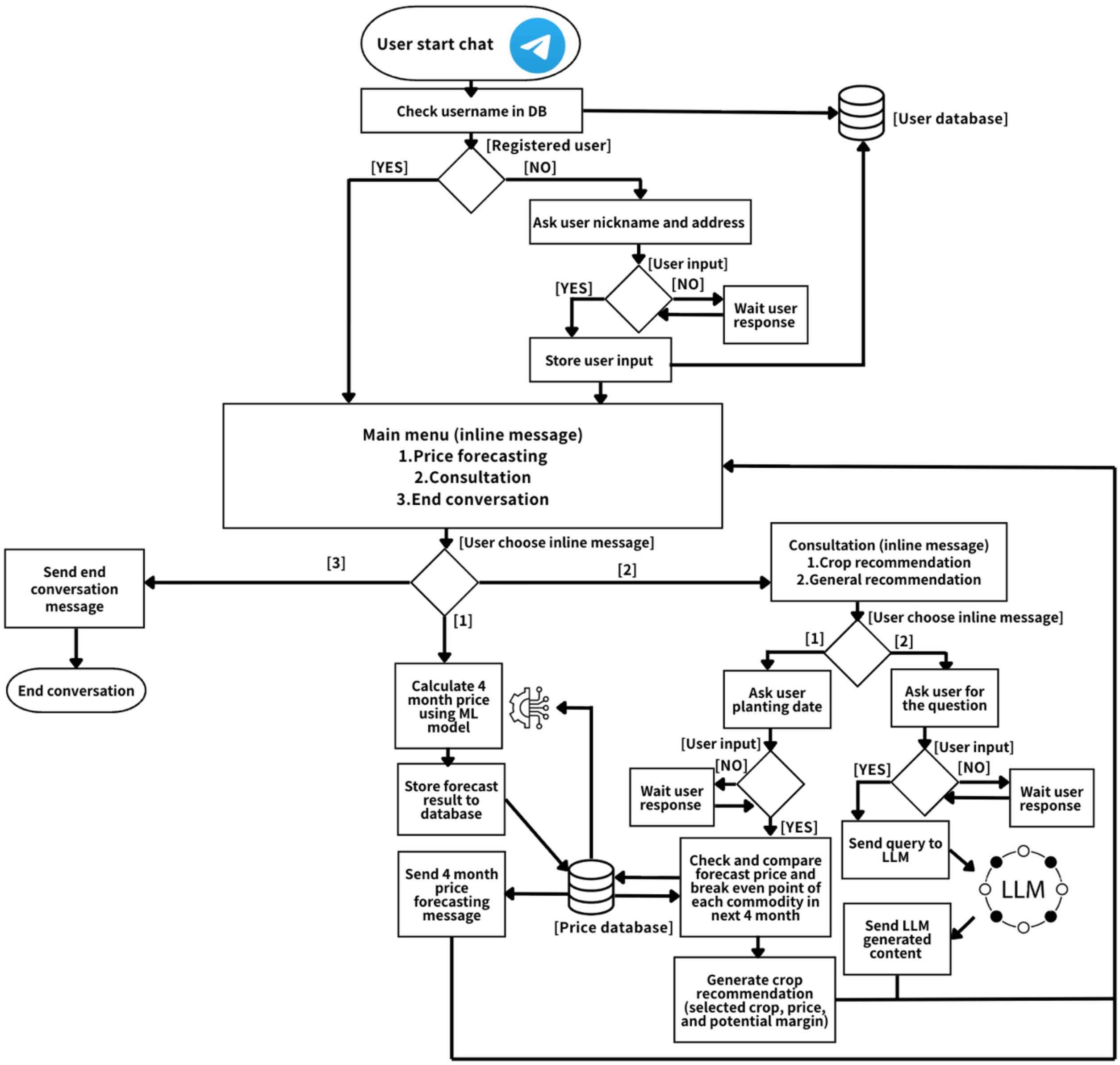

Figure 1. Chatbot workflow based on user experience.

2.2 Price Data Preprocessing

Commodity price data were acquired from the Pusat Informasi Harga Pangan Strategis PIHPS (translation: Strategic Food Price Information Center) official website. The website provides monthly data for each Indonesian regency. For the prototype, we used shallot price data from Yogyakarta City, ranging from the oldest to the latest sets of data (August 2018 to August 2025). There are several types of selling prices on the website; in this case, the "Produsen" data source was chosen.

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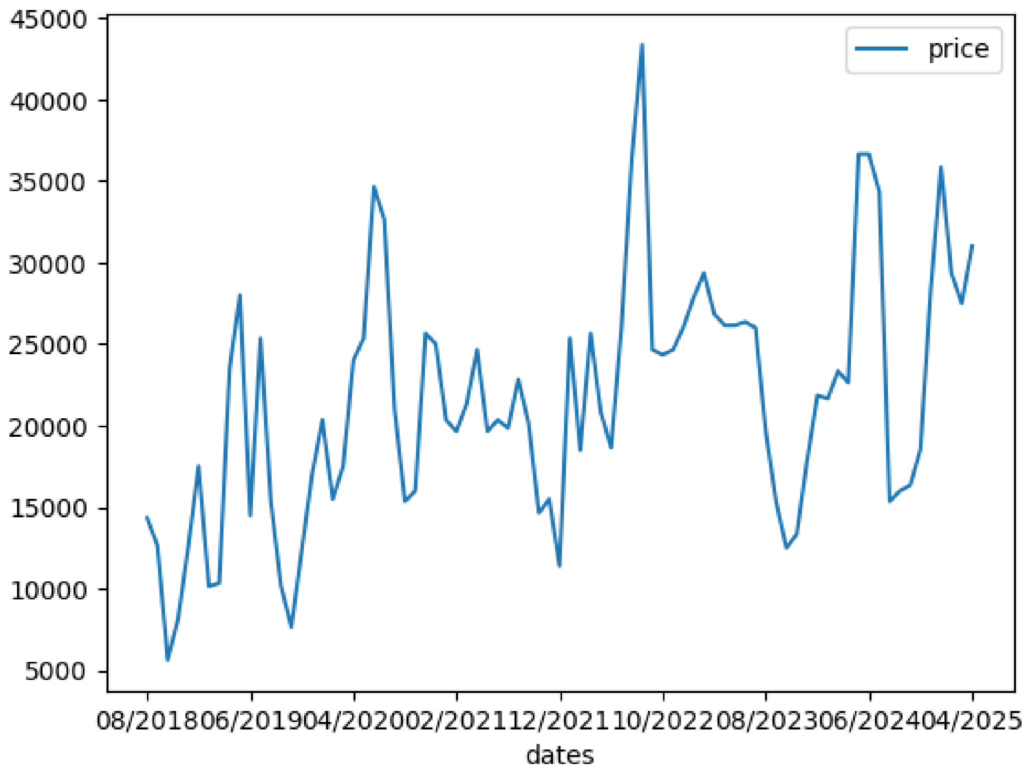

Figure 2. Yogyakarta's shallot price movement from August 2018 to August 2025.

2.3 Machine Learning Model Development

The price forecasting model was developed using random forest regression, an ensemble learning algorithm that combines multiple decision trees to achieve robust prediction accuracy. Random forest was selected because of its effectiveness in handling complex temporal patterns and its proven performance in agricultural price forecasting applications (Zelingher, 2024).

For training purposes, the original time-series price data were used until April 2025 and then split into an 80/20 ratio: 80% for training (August 2018 to February 2024) and 20% for validation (Mar 2024 to April 2025). The remaining data from May to August 2025 are used as test data in the testing phase to represent price forecasting in a real-world setting.

A lag feature was introduced in the training phase to enrich the training data and allow the model to recognize the correlation of past values. In this setting, the model was trained to predict the price

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using the training window configuration of the previous seven months and one year prior, to predict up to a 4-month forecasting horizon. The model can make more informed predictions by considering the behavior of the target variable in the past and capturing short-term and seasonal price dependencies. The lag feature was generated using the sliding window method. Table 1 illustrates the sliding window method and how it enriches the training data.

Table 1. Lag features 7 months and 1 year were formed using the sliding window method. The arrows indicate the sliding movement of data lag n.

Date	Price	Lag (monthly)							
		Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag12
		(last mo. price)	prev. 2 mo. price	prev. 3 mo. price	prev. 4 mo. price	prev. 5 mo. price	prev. 6 mo. price	prev. 7 mo. price	last yr. price
Aug-18	14350								
Sep-18	12650	14350							
Oct-18	5650	12650	14350						
.									
.									
.									
Jan-24	21850	17850	13350	12500	15350	19650	26000	26350	27850
Feb-24	21650	21850	17850	13350	12500	15350	19650	26000	29350

The hyperparameter "number of estimators " applied in the training model was n=50. This was considered the optimum number of trees without impeding the calculation speed (Kaewchada et al., 2023).

Validation data were used to assess the capability of the trained model. The model was evaluated using the mean absolute percentage error (MAPE) in the training and validation phases, as follows:

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

Where n = total numbers of data points, y_i = Actual value of the target variable for data points i, $\hat{y}_i$ = Predicted value of the target variable for data points i, $\bar{y}$ = Mean (average) of the actual values. Low MAPE values indicate better accuracy and precision of the model in predicting the price.

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2.4 Testing Phase

The testing phase evaluated both the performance of the price forecasting model and the chatbot functionality in delivering advice. During model performance testing, the error between the predicted and actual prices from May to August 2025 was evaluated using MAPE, as shown in Equation (1). Chatbot functionality was assessed based on its ability to deliver three main features: price forecasting, crop recommendation, and general consultation. The chatbot must properly direct the conversation and generate a response, as shown in Figure 1. To evaluate the user experience, the response time for each message was recorded and analyzed.

3. Results and Discussion

3.1 Model Fitting and Training Performance

Using MAPE as the performance metric, the random forest regression model demonstrated significant performance during the training phase, achieving an MAPE of 8.28% by training it with historical price data for more than five years. A previous study also reported similar results; Kaewchada et al. (2023) achieved a 9% MAPE using a random forest to forecast pumpkin prices in Thailand. Based on this result, the model is considered capable of handling agricultural commodity price volatility and seasonal variations. Figure 3 presents the fitted model after training, and the 4-month interval markers are included for visualization purposes to align the model output with the forecasting horizon used in the chatbot system.

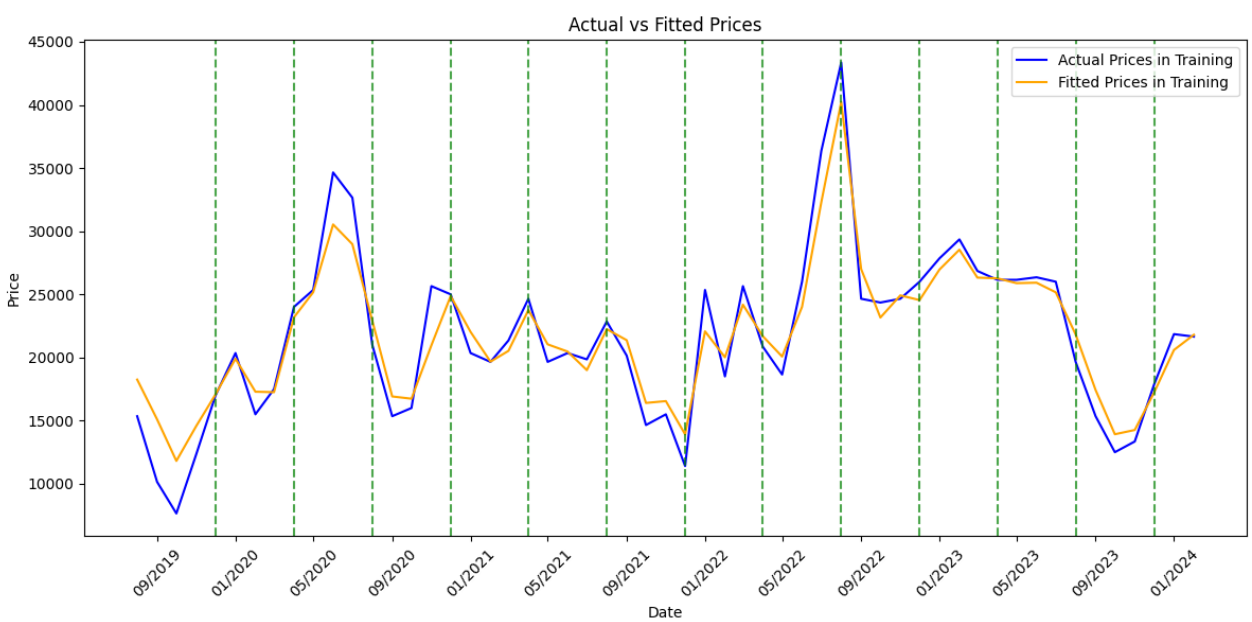

Figure 3. Model fitting in the training data: actual (blue) and fitted or predicted (orange) data prices, with 4-month interval markers to illustrate the forecasting horizon (green).

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3.2 Model Evaluation in Validation Phase

The model achieved sufficient accuracy in the validation phase, with a MAPE score of 13.98 %. In this step, the trained fitted model predicts the price based on the validation dataset from Mar 2024 to April 2025. The validation phase evaluates the performance of the fitted model using a new set of supervised data. Figure 4 shows how the model can predict prices up to 13 months.

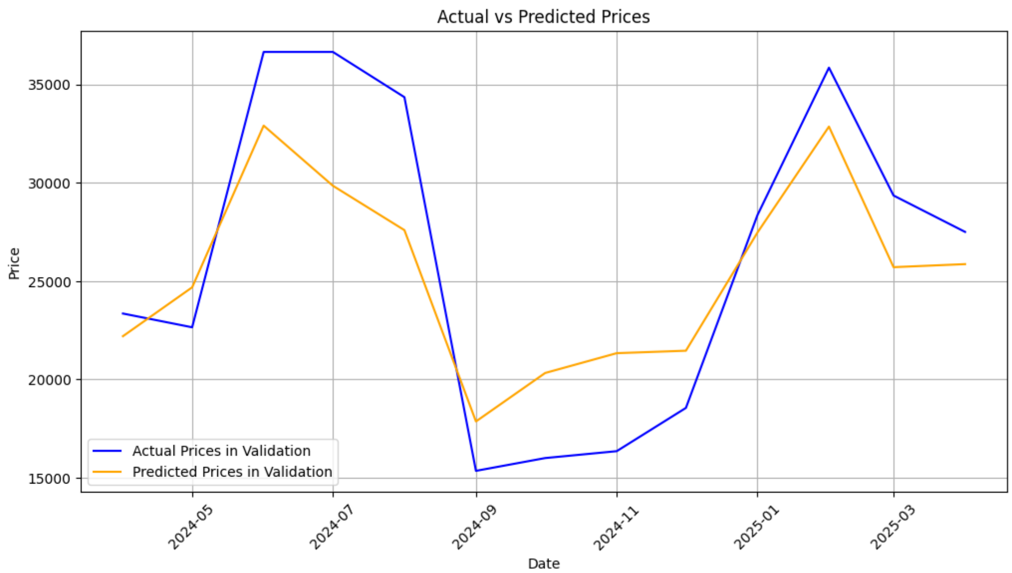

Figure 4. Model performance of forecasting prices in the validation phase: actual (blue) and predicted (orange) data prices.

Using visual evaluation, the predicted price can catch up with the price trend but falls short in capturing outliers and extreme volatility.

As shown in Figure 4, the error between the actual and predicted price is between 1,500–6,700 Rp/kg, with an average error of 3, 414 Rp/kg. Considering this error gap, the price predicted in the testing phase, which was generated by the chatbot, is presented as a predicted price with a range of average errors to anticipate severe price fluctuations.

From an economic perspective, a maximum prediction error of IDR 6,700/kg can be significant for smallholder farmers, particularly when operating near the break-even point. However, forecasting output is intended to support strategic decision making rather than provide exact price guarantees. By presenting forecast trends and estimated error ranges, the system enables farmers to assess the relative market conditions and manage price-related risks more effectively.

3.3 Chatbot Functionality Test and Forecasting Model Performance in Testing

The chatbot system successfully demonstrated its three main functionalities during the testing phase. When a user contacted the chatbot for the first time, the chatbot asked for the name and

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city/regency in which the user lived, as shown in Figure 5. When contacted for the second time, the chatbot no longer requested this information.

3.4 Biodegradability of the Freshness Indicator Labels

The results of the DMRT test (Table 1) indicated a significant difference between the freshness indicator labels and SPI concentrations.

Figure 5. Name and address the inquiry process.

The chatbot is triggered by any user message. After the chatbot flow is started, three choices are immediately presented: (1) forecasting the next four-month prices, (2) crop recommendation, and (3) ending the conversation.

The first feature is to generate the predicted price using the forecasting model. To generate the predicted price, the chatbot takes the current month as the starting date. However, for testing purposes, the latest dataset of prices (April 2025) was set as the starting month, and the chatbot was expected to generate the price from May to Aug 2025 to simulate the next four-month forecast. Figure 6 displays the generated response of the chatbot when conducting forecasting.

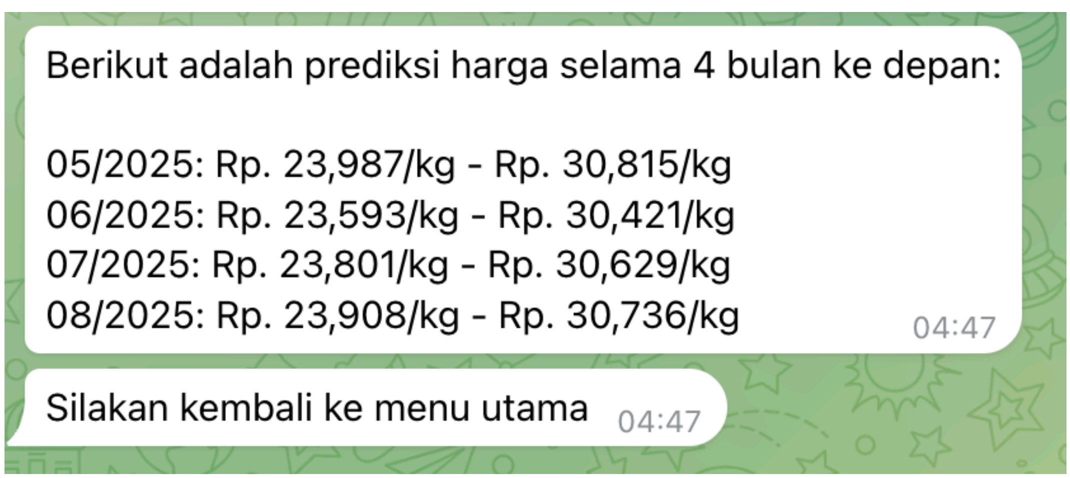

Figure 6. Generated response for price forecasting.

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The generated forecasting price accuracy was evaluated using the MAPE against the actual price from May to August 2025. Table 2 shows the price comparison between the actual and predicted data with their MAPE scores.

Table 2. Evaluation of model testing in the phase.

Date (mm/yyyy)	Actual Price (Rp/kg)	Predicted Price (Rp/kg)
05/2025	34,000	27,401
06/2025	27,650	27,007
07/2025	34,000	27,217
08/2025	30,350	27,322
MAPE Score		**15.82%**

During the testing phase, the model achieved an acceptable MAPE score of 15.82%. Based on Table 2. both of predicted price in May and Jul are outside the compensation range while Jun and Aug 2025 price are still in range. The model predicts the price in the stable period but does not account for the severity of volatility. The model struggled with extreme volatility, particularly in May and July, which may be attributed to sudden policy interventions and seasonal demand shocks. Incorporating exogenous variables, such as rainfall or holiday events, could improve accuracy.

The second feature provides crop recommendations based on selling price, with the commodity BEP as a reference. The user is asked when they begin to plant crops. Figure 7 shows the crop recommendations generated by the chatbot.

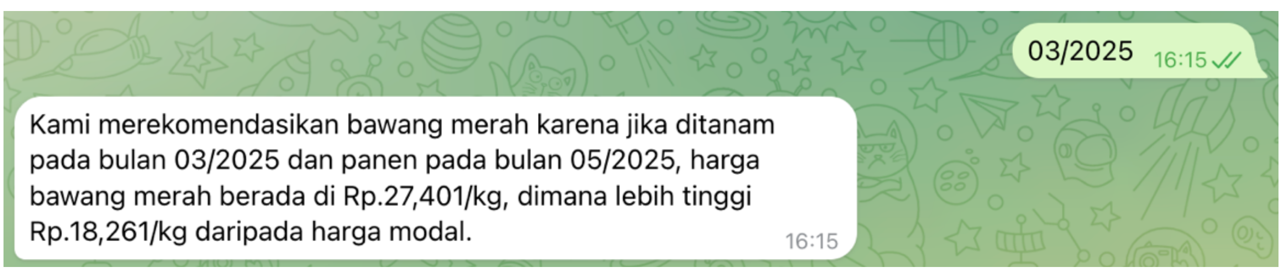

Figure 7. Generated responses for crop recommendations.

The third feature provides general consultation by asking the user about the problem or question they want to ask an extension agent. The message from the user is processed with the LLM model, and the chatbot replies to the user with content generated by AI. Figure 8 shows the generated message in the general consultation process.

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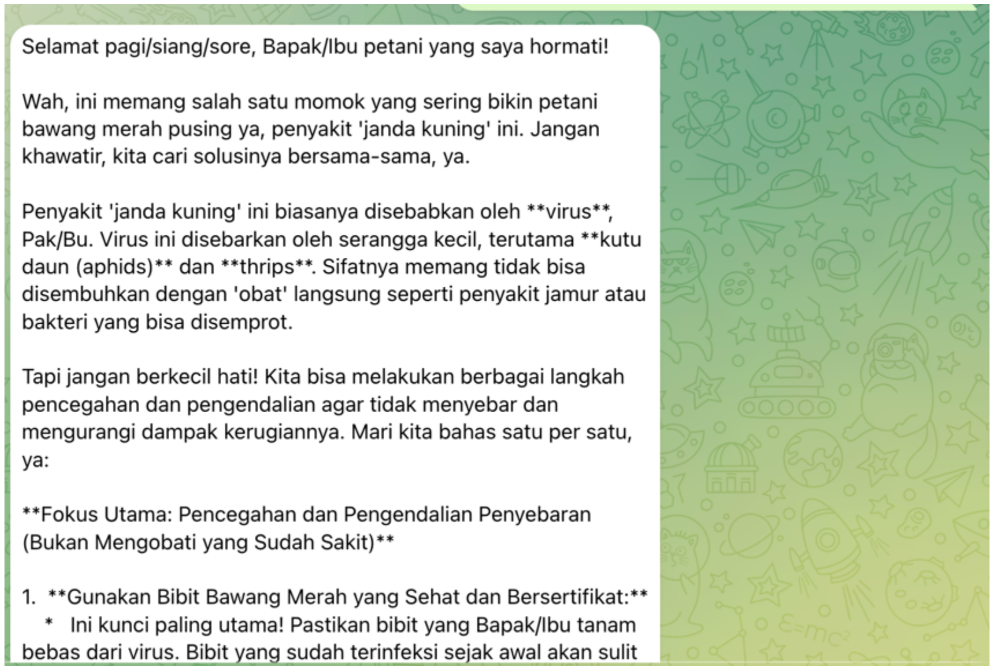

Figure 8. Responses generated for general consultation using AI LLM.

User experience was evaluated using the response time of each feature, as shown in Table 3. Overall, the system provides a smooth experience, except for the LLM, which replies after more than 10 s because it depends on the length of the generated response. Although the functionality was verified, future studies should conduct usability testing with farmers to evaluate adoption, satisfaction, and practical impact.

Table 3. Response time of each feature.

Feature	Response time (ms)
Forecast price	523.51
Crop recommendation	37.94
General consultation (504 words)	14,182.33

A waiting time of 14 s can significantly decrease the user experience and hinder the long-term adoption of chatbot systems by farmers. In the context of digital agricultural extension services, where farmers require fast and real-time answers, high latency can trigger frustration and cause users to revert to conventional methods. Future research should prioritize the optimization of the speed of AI LLM's to overcome this obstacle. Optimizing speed in the consultation feature is crucial for maintaining interaction momentum and ensuring the system's sustained utility

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4. Conclusion

This study proposed and validated a novel integration of random forest price forecasting with an AI-powered chatbot, enabling predictive and advisory support for farmers, achieving a training mean absolute percentage error (MAPE) of 8.34% and a validation MAPE of 13.98%. The model demonstrated its ability to capture price trends; however, it had limitations in addressing extreme volatility.

The integrated chatbot system facilitated user interaction by offering three key functionalities: price forecasting, crop recommendations, and general consultation. During the testing phase, the chatbot achieved a MAPE of 15.82% for price predictions, indicating acceptable accuracy and emphasizing the need for improved handling of price fluctuations in future research.

Overall, the results suggest that this approach can significantly aid farmers by providing timely and relevant market information to improve their decision-making. Future work should extend the model's responsiveness to price volatility, such as hybrid deep learning methods, expand its capabilities to further support farmers in diverse contexts, such as by incorporating weather compatibility with commodities, improving response time, integrating additional socioeconomic variables, and conducting large-scale field trials with farmers.

5. AI Writing Statement

The author used the Generative AI tool (Gemini 3 series) solely for language editing and grammar checking in the Introduction, Material and Methods section. All analyses, data interpretations, and conclusions are the result of the author’s own thinking.

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