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Chicken Egg Price Forecasting in East Java Using LSTM and GRU

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ABSTRACT

Chicken egg prices in East Java Province fluctuate considerably due to external factors, including day-old chick prices, livestock feed prices, and egg supply, making accurate price forecasting essential for supporting decision-making. This study compares the performance of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models for forecasting chicken egg prices and implements the best-performing model in a web-based forecasting system. Historical data from 2020 to 2025 were collected from SIMPONI-Ternak and Statistics Indonesia and processed through data transformation, cleaning, missing value handling, normalization, dataset splitting, and hyperparameter optimization using Bayesian Optimization. Both recursive and non-recursive forecasting approaches were evaluated using Mean Absolute Error, Root Mean Square Error, and Mean Absolute Percentage Error. The results indicate that the recursive approach consistently outperformed the non-recursive approach for both models. The Recursive LSTM achieved the best performance with a Mean Absolute Error of 224.80, a Root Mean Square Error of 363.04, and a Mean Absolute Percentage Error of 0.84%, outperforming the Recursive GRU model. Validation using actual price data for January 2026 confirmed that the Recursive LSTM produced the most accurate and stable forecasts. The selected model was successfully implemented in a Flask-based web application to provide practical and accessible chicken egg price forecasting.

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INTRODUCTION

Chicken eggs are one of the primary sources of animal protein and play an important role in supporting food security in Indonesia. However, chicken egg prices frequently experience significant fluctuations, making it difficult for small-scale farmers, who constitute the majority of producers, to plan production strategies effectively (Marzuqi et al., 2024). According to Ilham and Saptana (2023), fluctuations in chicken egg prices are influenced by several structural factors, including changes in Day-Old Chick (DOC) prices, livestock feed prices, and egg supply.

Marzuqi et al. (2024) reported that price fluctuations at the producer level in East Java reached 1.27092, considerably higher than those at the consumer level (0.5154), indicating that price instability has a greater impact on producers than consumers. Therefore, an accurate forecasting system is required to anticipate future price movements and support more effective production and marketing decisions. To address this challenge, machine learning has emerged as a promising forecasting approach because it can learn complex patterns from historical data and adapt to changing market conditions. Among machine learning techniques, deep learning has demonstrated superior capability in modeling temporal dependencies and nonlinear relationships compared with conventional forecasting methods (Lim & Zohren, 2020).

Among deep learning approaches, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) have been widely adopted for time series forecasting due to their ability to capture temporal dependencies in sequential data. Hidayat and Wibisonya (2024) employed LSTM to forecast rice prices in Indonesia and reported satisfactory prediction accuracy. Dhuhita et al. (2023) utilized LSTM with Grid Search hyperparameter optimization for gold price forecasting and achieved low prediction error. Meanwhile, Ananda (2023) applied GRU to forecast food commodity prices using multivariate data with external variables and obtained promising forecasting performance. More recently, Diyasa et al. (2025) integrated GRU with Bayesian Optimization for stock price forecasting, demonstrating that this optimization technique can improve deep learning performance by identifying more suitable hyperparameter configurations.

Although previous studies have demonstrated the effectiveness of LSTM and GRU for time series forecasting, several research gaps remain. Most studies focus on a single forecasting model or compare different models without systematically evaluating both recursive and non-recursive multi-step forecasting strategies. In addition, hyperparameter optimization is commonly performed using manual trial-and-error or Grid Search, whereas the application of Bayesian Optimization in agricultural commodity price forecasting remains limited. Furthermore, existing studies primarily emphasize prediction performance without implementing the best-performing model into a practical web-based forecasting system that can be directly utilized by stakeholders.

Based on these research gaps, this study compares the forecasting performance of LSTM and GRU using recursive and non-recursive forecasting approaches to predict chicken egg prices in East Java Province. Bayesian Optimization is employed to determine the optimal hyperparameter configuration for each model in order to improve forecasting accuracy. Model performance is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Finally, the best-performing model is deployed in a Flask-based web application to provide an accessible forecasting tool that supports decision-making in the poultry sector.

RESEARCH METHOD

This study compares the forecasting performance of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models using recursive and non-recursive multi-step forecasting approaches for predicting chicken egg prices in East Java Province. The research methodology consists of data collection, data preprocessing, data splitting, forecasting scheme, model development, hyperparameter optimization, model evaluation, result visualization, and model deployment. The overall research workflow is presented in Figure 1.

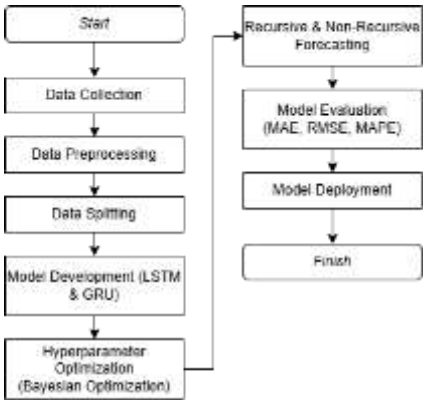


Figure 1. Research Workflow

Figure 1 presents the overall workflow of the proposed forecasting framework. The process begins with data collection, followed by data preprocessing and dataset splitting. The preprocessed data are then used to develop LSTM and GRU models using recursive and non-recursive forecasting approaches. Hyperparameter optimization is performed to obtain the optimal model configuration, after which the models are evaluated using forecasting performance metrics. Finally, the best-performing model is deployed as a web-based forecasting application.

1. Data Collection

   This study uses a multivariate time series dataset consisting of historical chicken egg prices, Day-Old Chick (DOC) prices, livestock feed prices, and egg supply in East Java Province. Historical data covering the period from January 2020 to December 2025 were collected from the SIMPONI-Ternak information system and

Badan Pusat Statistik (BPS). In addition, actual data from January 2026 were used to evaluate the forecasting performance of the proposed models. Chicken egg price was defined as the target variable, while DOC price, livestock feed price, and egg supply were used as input features.

2. Data Preprocessing
   The collected datasets were merged based on the observation date to produce a unified dataset. Data preprocessing consisted of data transformation, data cleaning, missing value handling, and data normalization. Missing values were handled using linear interpolation followed by forward filling and backward filling to maintain data continuity. Subsequently, all variables were normalized using Min-Max Scaling to transform the data into a range between 0 and 1, thereby improving the convergence of the deep learning models during training.
3. Data Splitting
   The normalized dataset was divided into training, validation, and testing sets to ensure an objective evaluation of model performance and reduce the risk of overfitting. For the LSTM model, the dataset was split into 70% training, 10% validation, and 20% testing. Meanwhile, the GRU model used a data split of 60% training, 20% validation, and 20% testing.
4. Forecasting Scheme
   This study employs two multi-step forecasting strategies, namely recursive and non-recursive forecasting, to predict chicken egg prices for the next 30 days. Both strategies use multivariate input sequences consisting of four variables: chicken egg price, DOC price, livestock feed price, and egg supply. The forecasting process for each strategy is illustrated in Figure 2.

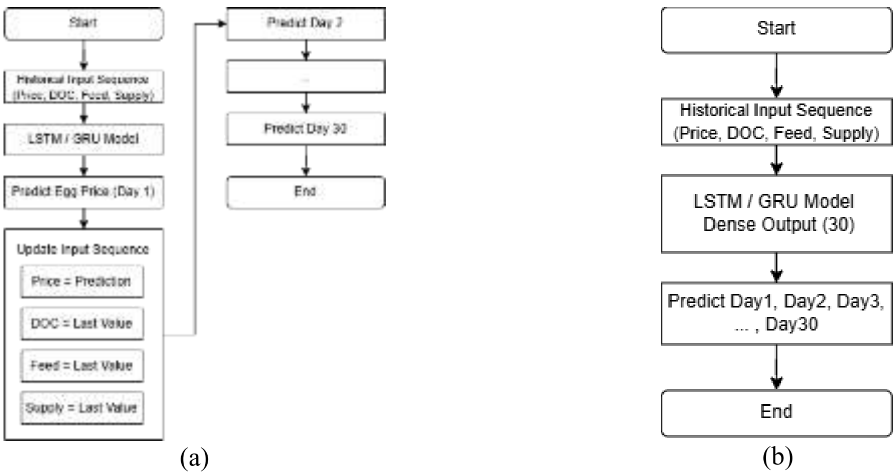


Figure 2. Multi-step Forecasting Strategies Using (a) Recursive and (b) Non-Recursive Approaches

In the recursive forecasting strategy, the model is trained using a single-step forecasting approach, where each input sequence predicts the chicken egg price for the next day. During forecasting, the last historical input sequence is first provided to the trained model to generate the prediction for the first forecasting day. The predicted egg price is then inserted into the input sequence by replacing the oldest target value, while the values of the exogenous variables (DOC price, livestock feed price, and egg supply) are retained from the last observed time step because their future values are unavailable. The updated sequence is subsequently used to predict the following day. This iterative process continues until forecasts for the next 30 days are obtained.
In the non-recursive forecasting strategy, the model is trained using a multi-output architecture in which each historical input sequence is directly mapped to the chicken egg prices for the next 30 days. During forecasting, the last historical input sequence is provided only once to the trained model, and all 30 future egg prices are generated simultaneously through the output layer. Unlike the recursive approach, the predicted values are not fed back into the input sequence. The exogenous variables (DOC price, livestock feed price, and egg supply) are only included in the historical input sequence and are not updated during the forecasting process.

5. Model Development and Hyperparameter Optimization
   Two deep learning models, namely Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), were developed using the same input variables to ensure a fair comparison. To improve forecasting performance, the hyperparameters of both models were optimized using Bayesian Optimization implemented through Keras Tuner. The optimization process was performed iteratively to identify the optimal configuration based on the lowest validation error. The optimized hyperparameters included the number of recurrent layers, hidden units, dropout rate, optimizer, learning rate, batch size, and timestamp. Early stopping with a maximum

of 100 epochs was applied to prevent overfitting by terminating the training process when no further improvement was observed on the validation data. The hyperparameter search space was adopted from previous studies, which demonstrated that suitable hyperparameter configurations vary depending on the characteristics of the dataset (Af'idah & Susanto, 2025; Diyasa et al., 2025; Wahyuddin et al., 2025). The corresponding hyperparameter search space is presented in Table 1.

Table 1. Hyperparameter Search Space

Hyperparameter	LSTM Search Range	GRU Search Range
Number of LSTM/GRU layers	1-3	1-3
Number of units layers	100-500	50-400
Dropout rate layers	0-0.5	0-0.5
Batch Size	1-64	1-64
Optimizer	Adam, RMSprop	Adam, RMSprop
Learning Rate	0.01, 0.00001	0.01, 0.005
Timestamps	5-30	10-50
Epoch	100 (Early Stopping)	100 (Early Stopping)

6. Model Evaluation
   The forecasting performance of the developed models was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics were calculated using the testing dataset to compare the performance of LSTM and GRU under recursive and non-recursive forecasting approaches. Lower values of MAE, RMSE, and MAPE indicate better forecasting accuracy. The best-performing model was subsequently deployed as a Flask-based web application to provide an accessible forecasting tool for predicting chicken egg prices in East Java Province.

RESULTS AND DISCUSSION

This section presents the experimental results obtained from the proposed forecasting framework for predicting chicken egg prices in East Java Province. The discussion begins with the results of data preprocessing to ensure data quality before model development. Subsequently, the results of hyperparameter optimization and forecasting performance are presented and analyzed by comparing the recursive and non-recursive forecasting approaches. Finally, the best-performing model is implemented in a Flask-based web application to demonstrate its practical applicability.

1. Data Preprocessing
   This section presents the results of the data preprocessing stage, which was conducted to prepare the collected datasets before model development. The preprocessing process included data transformation, data cleaning, outlier detection, missing value handling, and data normalization. The final preprocessed dataset used for model training is presented in Table 2.

Table 2. Sample of the Preprocessed Dataset

Date	Chicken Egg Price	DOC Price	Livestock Feed Price	Egg Supply
2020-01-01	0.472753	0.514346	0.04614	0.488837
2020-01-02	0.425923	0.514346	0.04614	0.474538
2021-01-03	0.397979	0.514346	0.04614	0.492234
2023-01-04	0.424808	0.514346	0.04614	0.511940
2024-01-05	0.431916	0.514346	0.04614	0.472379

As shown in Table 2, all variables were successfully transformed into a consistent numerical format and aligned to a daily time interval. The annual egg supply data obtained from Badan Pusat Statistik (BPS) were transformed into daily observations to match the frequency of the historical price data. Outlier detection was then performed to identify abnormal observations, and the detected outliers were removed from the dataset. The resulting missing values, together with the original missing values, were subsequently handled using linear interpolation, followed by forward and backward filling to maintain data continuity. Finally, all variables were normalized using *Min-Max Scaling*, producing a complete and standardized dataset that was ready for model development.

2. Hyperparameter Optimization
   This section presents the results of hyperparameter optimization for the Recursive LSTM, Non-Recursive LSTM, Recursive GRU, and Non-Recursive GRU models. *Bayesian Optimization* was employed to identify the optimal hyperparameter configuration for each forecasting model by minimizing the validation error during the tuning process. The optimal hyperparameter configurations obtained for each model are presented in Table

Table 3. Hyperparameter

No	Hyperparameter	LSTM (Recursive)	LSTM (Non-Recursive)	GRU (Recursive)	GRU (Non-Recursive)
1	Number of LSTM/GRU Layers	1.75	2.18	2.36	1.99
2	Number of Units	480.29	118.58	263.54	113.69
3	Dropout	0.37	0.30	0.40	0.01
4	Optimizer	(0.06) Adam	(0.97) RMSprop	(0.31) Adam	(0.68) RMSprop
5	Learning Rate	0.0060	0.0017	0.0024	0.0015
6	Batch Size	10.83	5.10	20.37	28.49
7	Time Steps	8.90	28.72	49.78	20.87

Table 3 shows that each forecasting model produced a different optimal hyperparameter configuration. These differences indicate that the optimal model settings depend not only on the deep learning architecture but also on the forecasting strategy employed. The selected configurations were subsequently used to train the final forecasting models.

Table 4. Best MAPE Values Obtained from Hyperparameter Optimization

No	Forecasting Approach	LSTM MAPE	GRU MAPE
1	Recursive	0.65%	0.65%
2	Non-Recursive	2.13%	3.09%

The forecasting performance achieved by the optimal hyperparameter configurations is presented in Table 4. Among the four forecasting models, the Recursive LSTM and Recursive GRU models achieved the lowest MAPE, indicating that the selected hyperparameter combination provided the highest forecasting accuracy during the hyperparameter optimization process. Therefore, the optimal hyperparameter configurations obtained from this stage were used in the subsequent model evaluation on the testing dataset.

3. Forecasting Performance Evaluation

This section presents the forecasting performance of the four developed models, namely Recursive LSTM, Non-Recursive LSTM, Recursive GRU, and Non-Recursive GRU. The models were evaluated using the testing dataset based on Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The evaluation results are summarized in Table 5.

Table 5. Forecasting Performance of Recursive and Non-Recursive LSTM and GRU Models

No	Model	MAE	RMSE	MAPE
1	Recursive LSTM	224.80	363.04	0.84%
2	Non-Recursive LSTM	714.96	825.33	2.72%
3	Recursive GRU	246.57	385.80	0.92%
4	Non-Recursive GRU	492.04	580.66	1.85%

As shown in Table 5, the Recursive LSTM model achieved the lowest MAE, RMSE, and MAPE values, indicating the highest forecasting accuracy among the evaluated models. In contrast, the non-recursive models produced relatively higher prediction errors, suggesting that the recursive forecasting strategy was more effective for multi-step chicken egg price forecasting. Furthermore, the superior performance of the LSTM model indicates that its memory cell architecture is better suited to capture long-term temporal dependencies and nonlinear patterns in the historical chicken egg price data.

4. Thirty-Day Forecasting Results

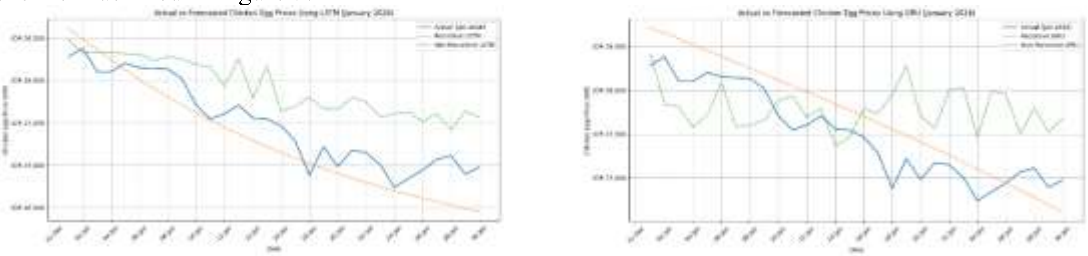
This section presents the 30-day forecasting results for January 2026 generated by the Recursive LSTM, Non-Recursive LSTM, Recursive GRU, and Non-Recursive GRU models. The forecasting models were trained using historical data from 2020 to 2025. Since the actual chicken egg prices for January 2026 were available from SIMPONI Ternak, the predicted values could be directly compared with the observed data to evaluate the forecasting performance. A sample of the forecasting results is presented in Table 6.

Table 6. Sample of 30-Day Chicken Egg Price Forecasting Results

Date	Actual Price	30 Day Forecasting Results			
		LSTM (Recursive)	LSTM (Non-Recursive)	GRU (Recursive)	GRU (Non-Recursive)
2026-01-01	28285	28617	28483	28706	28411
2026-01-02	28380	28484	28319	28654	27838

2026-01-03	28104	28363	28335	28585	27816
...	...	...	...	...	...
2026-01-30	26977	26454	27567	26609	27686

Based on Table 6, each forecasting model generated different prediction values throughout the forecasting period. To provide a clearer comparison between the predicted and actual chicken egg prices, the forecasting results are illustrated in Figure 3.



(a) (b)

Figure 3. Comparison of Actual and Forecasted Chicken Egg Prices Using Recursive and Non-Recursive (a) LSTM and (b) GRU Models

Figure 3 illustrates the comparison between the actual and forecasted chicken egg prices generated by the Recursive and Non-Recursive LSTM and GRU models during the 30-day forecasting period. Overall, the recursive forecasting approach produces prediction curves that more closely follow the actual price movements than the non-recursive approach. For the LSTM model, the recursive forecasts capture the overall price trend more accurately, whereas the non-recursive forecasts exhibit larger deviations from the actual values at several time steps. A similar pattern is observed for the GRU model, where the recursive approach generates forecasts that are generally closer to the actual prices than the non-recursive approach. These findings indicate that the recursive forecasting strategy is more effective in capturing temporal dependencies and daily price fluctuations.

To quantitatively assess the forecasting performance, the prediction errors of the four models were evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The evaluation results are presented in Table 7.

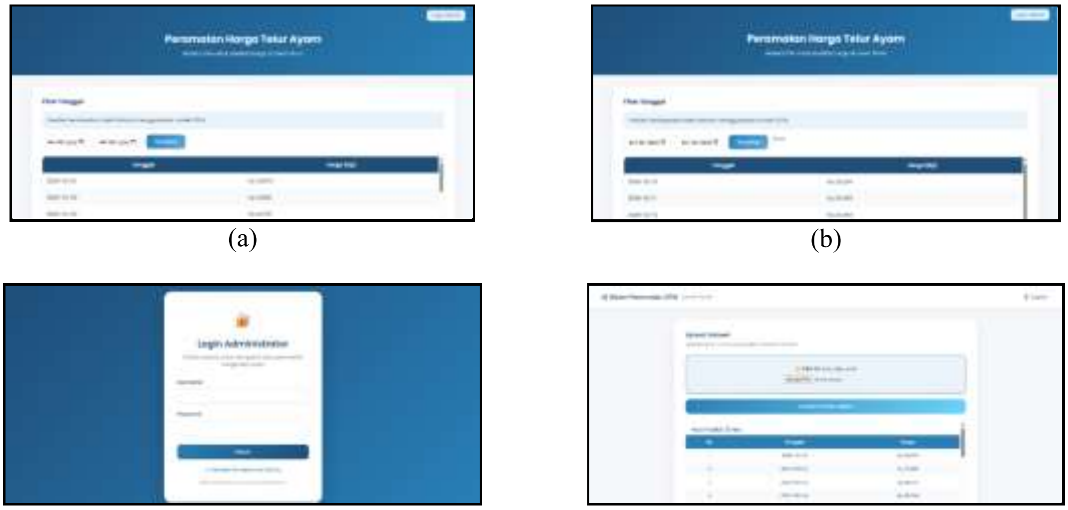
Table 7. Forecasting Performance of Recursive and Non-Recursive LSTM and GRU Models for the 30-Day Forecasting Period

No	Model	MAE	RMSE	MAPE
1	Recursive LSTM	254.74	290.65	0.93%
2	Non-Recursive LSTM	436.65	499.13	1.60%
3	Recursive GRU	286.49	318.13	1.04%
4	Non-Recursive GRU	524.16	614.46	1.92%

As presented in Table 7, the Recursive LSTM model achieved the lowest MAE, RMSE, and MAPE values among the evaluated models, indicating the highest forecasting accuracy during the 30-day forecasting period. The recursive forecasting approach consistently outperformed the non-recursive approach for both LSTM and GRU models. Therefore, the Recursive LSTM model was selected for implementation in the proposed web-based forecasting system due to its superior predictive performance and its ability to better capture the temporal dynamics of chicken egg prices.

5. Web-Based Forecasting System Implementation

The best-performing model, namely Recursive LSTM, was implemented into a web-based forecasting system using the Flask framework. The implementation was conducted to enable the trained model to process new input data and generate chicken egg price forecasts for the next 30 days. The trained model was stored in the *.h5* format, while the normalization parameters were stored in the *.pkl* format and loaded into the system to maintain consistency between the training and prediction processes. The developed system performs several processes, including dataset uploading, automatic preprocessing, data normalization, forecasting using the LSTM model, denormalization of prediction results, and visualization of forecasting outputs. The generated predictions are displayed in the form of tables and graphs to help users observe future chicken egg price trends.



(a) (b) (c) (d)

Figure 4. Web-Based Chicken Egg Price Forecasting System Interface (a) User Page, (b) Forecasting Date Selection, (c) Admin Login, and (d) Dataset Upload Dashboard

Figure 4 presents the interface of the developed forecasting system. The system provides a forecasting page that displays the 30-day predicted chicken egg prices along with graphical visualization. In addition, an admin page is provided to upload updated datasets and manage the forecasting process. The implementation demonstrates that the proposed forecasting model can be integrated into a practical web-based application to support decision-making in chicken egg price management. Black Box Testing was conducted to verify the functionality of the developed system. The test results showed that all major features operated as expected.

CONCLUSION

This study developed a chicken egg price forecasting framework in East Java Province using Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models with recursive and non-recursive forecasting approaches. The experimental results demonstrated that the recursive forecasting strategy generally achieved better performance than the non-recursive approach. Among the evaluated models, the Recursive LSTM model obtained the best forecasting performance with the lowest error values based on MAE, RMSE, and MAPE, indicating its capability to capture temporal dependencies and nonlinear patterns in chicken egg price fluctuations.

The optimized Recursive LSTM model was subsequently implemented into a Flask-based web application to provide a practical forecasting tool for predicting chicken egg prices. The developed system enables users to generate 30-day forecasts and visualize future price trends, while also supporting dataset updates through the admin interface.

For future research, the forecasting performance can be further improved by incorporating additional external variables that may influence chicken egg prices, such as weather conditions, market demand, and macroeconomic factors. Furthermore, alternative approaches for handling outliers should be investigated instead of directly replacing detected outliers with missing values followed by interpolation, as these values may represent actual market conditions and preserve important characteristics of the data.

REFERENCES

Af'idah, D. I., & Susanto, A. (2025). HYPERPARAMETER TUNING SEQ2SEQ GATED RECURRENT UNIT UNTUK PENERJEMAHAN BAHASA DAERAH KE NASIONAL. *Jurnal Informatika Teknologi Dan Sains (Jinteks)*, *6*(4), 1238–1248. https://doi.org/10.51401/jinteks.v6i4.5645

Ananda, M. I. (2023). The Multivariate Forecasting of Chicken and Beef Prices Involving Weather, Economic, and Health Factors Using the Gated Recurrent Unit Method. *Jurnal Ilmu Komputer Dan Agri-Informatika*, *10*(1), 111–120. https://doi.org/10.29244/jika.10.1.111-120

Dhuhita, W. M. P., Farid, M. F. A., Yaqin, A., Haryoko, H., & Huda, A. A. (2023). Gold Price Prediction Based On Yahoo Finance Data Using Lstm Algorithm. *2023 International Conference on Informatics, Multimedia, Cyber and Informations System (ICIMCIS)*, 420–425. https://doi.org/10.1109/ICIMCIS60089.2023.10349035

Ilham, N., & Saptana, N. (2023). Fluktuasi Harga Telur Ayam Ras dan Faktor Penyebabnya. *Analisis Kebijakan Pertanian*, *17*(1), 27–38. https://doi.org/10.21082/akp.v17n1.2019.27-38

Lim, B., & Zohren, S. (2020). *Time Series Forecasting With Deep Learning: A Survey*. https://doi.org/10.48550/ARXIV.2004.13408

Marzuqi, M. A., Hidayat, S. I., & Setiawan, R. F. (2024). Analisis Volatilitas Harga Komoditas Telur Ayam Ras di Provinsi Jawa Timur. *JURNAL AGRICA*, *17*(2), 152–161. https://doi.org/10.31289/agrica.v17i2.11865

Mas Diyasa, I. G. S., Akmal, M. F., & Junaidi, A. (2025). Penerapan Gated Recurrent Unit dengan Bayesian Optimization dalam Prediksi Harga Saham Sektor FMCG. *Journal of Information Engineering and Educational Technology*, *9*(1), 36–41. https://doi.org/10.26740/jieet.v9n1.p36-41

Rahmat Hidayat & Irawan Wibisonya. (2024). Rice Price Prediction with Long Short-Term Memory (LSTM) Neural Network. *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, *8*(5), 658–664. https://doi.org/10.29207/resti.v8i5.6041

Wahyuddin, E. P., Caraka, R. E., Kurniawan, R., Caesarendra, W., Gio, P. U., & Pardamean, B. (2025). Improved LSTM hyperparameters alongside sentiment walk-forward validation for time series prediction. *Journal of Open Innovation: Technology, Market, and Complexity*, *11*(1), 100458. https://doi.org/10.1016/j.joitmc.2024.100458