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Intelligent Decision Support System for Quail Egg Production Using Long Short-Term Memory

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Abstract

This study aims to develop an intelligent decision support system (DSS) for predicting quail egg production using the Long Short-Term Memory (LSTM) algorithm. Quail egg production is influenced by various environmental factors such as temperature and humidity, as well as farm management. With the increasing market demand for quail eggs and the importance of accurate production predictions, a machine learning-based approach is needed to support farmers' decision-making. The research data was obtained from the Bogor Regency Fisheries and Livestock Service, which includes attributes of temperature, humidity, and daily egg production. The research method uses a Knowledge Discovery in Database (KDD) approach, which consists of data selection, preprocessing, transformation, data mining using LSTM, and model evaluation using RMSE and MAPE metrics. The evaluation results show that the LSTM model provides excellent prediction performance, especially with a training data split of 70% and 60%. The system was implemented using a combination of Python (for the model) and Laravel (for the web interface). This research is expected to assist farmers in optimizing quail egg production management in a more efficient and adaptive manner based on data.

Keywords
LSTM, Decision Support System, Quail Eggs, Machine Learning, Time-Series Forecasting.

1. Introduction

Quail egg production is one of the poultry farming sectors with significant economic potential in Indonesia. Quail eggs are known as a source of high-quality animal protein that is easy to process and widely consumed by the public. As public awareness of healthy food consumption increases, market demand for quail eggs has also risen. According to data from the Directorate General of Livestock and Animal Health (Ditjen PKH), the quail population in Indonesia increased from 14.7 million birds in 2016 to over 16.1 million birds in 2019. However, the quality and quantity of egg production are significantly influenced by several key factors such as environmental temperature, humidity, feed type, and housing management. Inefficiency in managing these variables can lead to a significant decline in productivity and impact on farmers' profits. Therefore, accurate egg production prediction is an essential requirement to support optimal managerial decisions for farmers. Advancements in artificial intelligence technology, particularly in the field of machine learning, offer significant opportunities for the application of data-driven prediction systems. One method proven effective in handling time-series data is Long Short-Term Memory (LSTM), an advancement of Recurrent Neural Networks (RNN). LSTM has the ability to recognize both short-term and long-term patterns in time-series data and addresses the vanishing gradient issue in conventional RNNs.

This research focuses on developing a smart decision-support system for quail egg production from the Bogor Regency Fisheries and Livestock Service, using LSTM for daily production prediction based on temperature, humidity, and quail population data. With this system, it is hoped that farmers can make data-driven decisions to enhance production efficiency.

1.1 Objectives

This study aims to develop an intelligent decision support system that can predict daily quail egg production based on temperature, humidity, and quail population data. Predictions are made using the Long Short-Term Memory (LSTM) algorithm, which excels at recognizing patterns in time series data. This system is expected to help farmers make more accurate and efficient decisions through accurate and easily accessible predictive information. This research also contributes practically to the application of artificial intelligence in supporting poultry farm productivity at the community level.

2. Literature Review

2.1. Decision Support System

A Decision Support System (DSS) is a computer-based system designed to assist decision makers in solving semi-structured problems by utilizing data, models, and interactive interfaces. In the context of animal husbandry, DSS can be used to formulate livestock management policies, including population control, harvest schedules, and production yield estimates. According to Wantoro and Muludi (2019), DSS provides users with ease in analyzing information and making more informed decisions. When combined with artificial intelligence, DSS can improve prediction accuracy and operational efficiency. In this study, DSS was used to present egg production prediction results to users in the form of a user-friendly web-based system accessible to farmers.

2.2. Quail Egg Production

Quail egg production is highly dependent on several environmental factors such as temperature, humidity, feed type, and housing conditions. According to data from the Directorate General of Livestock and Animal Health (2019), the quail population in Indonesia has shown a significant increase, but its productivity is still influenced by suboptimal management. Quail eggs themselves have high nutritional and economic value, as well as a continuously increasing market demand. Therefore, the utilization of technology to predict and manage production outcomes becomes highly important. The use of historical daily production data combined with environmental factors can serve as the foundation for developing a more accurate production prediction system.

2.3. Long-Short Term Memory (LSTM) Algorithm

LSTM is a type of artificial neural network developed from Recurrent Neural Network (RNN), and is specifically designed to handle problems in sequential data processing or time-series. LSTM has an internal memory structure that allows the network to store information over a long period of time without experiencing vanishing gradients.

According to Hochreiter and Schmidhuber (1997), LSTM consists of three main components: input gate, forget gate, and output gate, which work together to regulate the information that is input, stored, and output. This makes LSTM highly effective in learning patterns in daily production data that exhibit time-based fluctuations. Previous studies have shown that LSTM has been successfully used to predict time-series data in various fields, including stock prices (Wardani 2021), rainfall (Ashari and Sadikin 2020), and agricultural production (Adhani et al. 2021). However, the application of LSTM in quail egg production prediction is still rare, so this study contributes new insights by applying this method in the context of small-scale poultry farming.

3. Methods

3.1. LSTM Architecture for Production Prediction

The model used in this study is Long Short-Term Memory (LSTM), which consists of several layers, each with 64 memory units. A dropout layer is inserted to prevent overfitting, and batch normalization is added to speed up training. The architecture in Table 1 is designed using the Keras library in the Python programming language with the following parameters (Table 1):

Tabel 1. Architekture LSTM

Characteristic	Spesification
Arsitektur	4 lapisan LSTM and 3 Dense Layer
Jumlah Neuron	64 per lapisan
optimizer	Adam
Epoch	100, 250, 500
Batch Size	32 and 64

This model is used to study quail egg production patterns based on historical daily data covering temperature, humidity, and daily production. Internal analysis of the LSTM model was conducted to better understand how the LSTM model processes information, and analysis was performed on Table 2 of the gate activation at each timestep (Table 2).

Table 2. Analysis of internal layer LSTM

Timestep	Input Gate (i_t)	Forget Gate (f_t)	Cell Candidate (c~_t)	Output Gate (o_t)
1	[0.52597, 0.51233, 0.50375, 0.49387, 0.52482]	[0.71507, 0.74886, 0.75631, 0.71558, 0.69562]	[-0.03715, 0.15021, 0.12226, 0.15069, -0.01462]	[0.49368, 0.50158, 0.53001, 0.50735, 0.50016]
2	[0.51927, 0.52013, 0.49885, 0.49176, 0.54077]	[0.71739, 0.74309, 0.75554, 0.71366, 0.69208]	[-0.04763, 0.16103, 0.12764, 0.15084, 0.02861]	[0.49477, 0.50630, 0.52383, 0.50931, 0.50850]
3	[0.51538, 0.52645, 0.49563, 0.49076, 0.55916]	[0.72065, 0.73945, 0.75517, 0.71164, 0.68919]	[-0.05445, 0.16573, 0.13517, 0.15964, 0.07189]	[0.49993, 0.50907, 0.51958, 0.51037, 0.51766]
4	[0.51182, 0.53208, 0.49080, 0.49127, 0.57316]	[0.72540, 0.73552, 0.75579, 0.71054, 0.68328]	[-0.06569, 0.17429, 0.14178, 0.16924, 0.09956]	[0.50457, 0.51164, 0.51421, 0.51270, 0.52171]
5	[0.50873, 0.53681, 0.48720, 0.49303, 0.58759]	[0.73057, 0.73157, 0.75647, 0.71046, 0.67964]	[-0.07134, 0.17692, 0.14377, 0.17649, 0.12111]	[0.51012, 0.51399, 0.51036, 0.51475, 0.52602]
6	[0.50615, 0.54097, 0.48369, 0.49610, 0.59920]	[0.73575, 0.72715, 0.75795, 0.71138, 0.67580]	[-0.07549, 0.18097, 0.14220, 0.18243, 0.12812]	[0.51448, 0.51675, 0.50755, 0.51765, 0.52725]
7	[0.50674, 0.54403, 0.48468, 0.49928, 0.61465]	[0.73878, 0.72532, 0.75949, 0.71154, 0.67683]	[-0.06640, 0.17833, 0.14100, 0.19343, 0.13860]	[0.52167, 0.51881, 0.51069, 0.51877, 0.53146]

- Input Gate (i_t) indicates how much new information is entered into memory.
- Forget Gate (f_t) controls how much old information is forgotten.
- Cell Candidate (c~_t) shows the value of the new memory candidate.
- Output Gate (o_t) indicates how much memory information is output at that timestep.

Observation results show that at each timestep, the forget gate value tends to be high (> 0.7), indicating that the LSTM retains most of the information from the previous memory, while the input gate and cell candidate values increase progressively, indicating increased sensitivity to changes in temperature and humidity data in daily production predictions.

3.2. Normalization

Data normalization is a method of rescaling data to a smaller size (Ambarwari et al., 2020). The use of data normalization is essential when there are differences in scale between features in a dataset. The consequence of not performing data normalization is producing low accuracy values and causing low-scale features to have no effect when implementing data mining algorithms that involve distance measurements, or in other words, the results of data mining analysis only depend on high-scale features, even though low-scale features also play an equally important role (Kusnaidi et al., 2022).

$$x' = (x - \mu) / \sigma \tag{1}$$

$$x' = (x - \min(x)) / (\max(x) - \min(x)) \tag{2}$$

Description:
x' = scaled feature value.
x = original feature value.
$\min(x)$ = minimum value of the feature.
$\max(x)$ = maximum value of the feature.
μ = Mean (feature average)
σ = Standard deviation (standard deviation)

3.3. Model Evaluation

RMSE is a measure of the average squared difference between the predicted value and the actual value. RMSE calculates the square root of the average squared difference. The equation is formulated in Equation 3 below.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(Y_i - \bar{Y}_i)^2}{n}} \tag{3}$$

Description:
y_i = actual value i
$\hat{y}_i$ = predicted value i
n = number of data points

Mean Absolute Percentage Error (MAPE) is the absolute value of the percentage error of the data relative to the mean. The equation is formulated in Equation 4 below.

$$MAPE = \frac{\sum_{i=1}^{n} \frac{|(\bar{Y}_i - Y_i)|}{Y_i}}{n} * 100 \tag{4}$$

Description:
y_i = actual value i
$\hat{y}_i$ = predicted value i
n = number of data points

4. Data Collection

Step 1: Secondary data obtained from quail egg farms in Tegal Village, Kemang District, Bogor Regency, West Java. Data was collected from daily farm production records covering several important attributes in accordance with the data structure in Table 3 and the form of quail egg production data in Table 4 presents a sample of the first 10 daily records from the quail egg production dataset used in this study. The complete dataset contains 723 records, including environmental and production-related variables.

Table 3. Data Description

Attribute	**Description**	**Commodity**	**Data Type**	**Value Range**	**Unit**	**Data Source**
Date	Date of data recording	Quail Eggs	Categoric	-	-	Daily records
Subdistrict	Subdistricts in Bogor Regency	Quail Eggs	Categorical	-	-	DISKANAK
Daily Production	Number of eggs produced	Quail Eggs	Numeric	1-500	Eggs	Production Notes
Temperature	Coop temperature	Quail Eggs	Numeric	24-37	°C	Observations
Humidity	Coop humidity	Quail Eggs	Numeric	75-85	%	Observations
Total Egg Production	Total egg production	Quail Eggs	Numeric	0.0745-0.077	Ton	Calculations

Table 4. Quail Egg Production Data

No	Date	Subsdistrict	Daily Production	Temperature (°C)	Humidity (%)	Total Egg Production
1	1/1/2021	Ciseeng	677	2	27	80
2	1/2/2021	Ciseeng	677	2	27	77
3	1/3/2021	Ciseeng	677	3	27	78
4	1/4/2021	Ciseeng	677	2	26	79
5	1/5/2021	Ciseeng	677	2	24	89
6	1/6/2021	Ciseeng	677	2	24	89
7	1/7/2021	Ciseeng	677	2	24	89
8	1/8/2021	Ciseeng	677	1	24	90
9	1/9/2021	Ciseeng	677	2	24	90
10	1/10/2021	Ciseeng	677	2	24	89
. .	. .	. .	. .	. .	. .	. .
24091	…	…	…	…	…	…

5. Results and Discussion

5.1. Normalization

Step 1: Calculate the data from egg production and normalize it to form a range of 0 to 1 in Table 5. This is done to produce a small accuracy scale value.

Tabel 5. Normalization

No	Date	Subsdistrict	Total Egg Production	Daily Production	Temperature (°C)	Humidity (%)
1	1/1/2021	Ciseeng	1.0	0.222222	0.409091	0.594059
2	1/2/2021	Ciseeng	1.0	0.333333	0.409091	0.594059
3	1/3/2021	Ciseeng	1.0	0.444444	0.166667	0.584158
4	1/4/2021	Ciseeng	1.0	0.222222	0.166667	0.531353
5	1/5/2021	Ciseeng	1.0	0.777778	0.212121	0.531353
6	1/6/2021	Ciseeng	1.0	0.222222	0.257576	0.544554
7	1/7/2021	Ciseeng	1.0	0.111111	0.303030	0.524752
8	1/8/2021	Ciseeng	1.0	0.777778	0.333333	0.594059
9	1/9/2021	Ciseeng	1.0	0.222222	0.378788	0.445545
10	1/10/2021	Ciseeng	1.0	0.111111	0.393939	0.462046
. . .	. . .	. . .		. . .	. . .	. . .
24091	…	…		…	…	…

5.2. Evaluation of RMSE and MAPE

The performance of the Long Short-Term Memory (LSTM) model was evaluated in predicting targets based on different data splits (train-test split). Four data split scenarios were tested, namely 90/10, 80/20, 70/30, and 60/40, to identify the effect of the amount of training data on model accuracy. The model performance in Table 6 was measured using two main metrics, namely Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Tabel 6. Division of training data and testing data.

Train Ratio	Test Ratio	Epoch	RMSE	MAPE
0.6	0.4	50	0.453915	**17.32611**
0.7	0.3	10	0.478129	17.37576
0.8	0.2	50	0.468528	22.50533
0.9	0.1	50	0.463073	27.37155

The best configuration was found at a ratio of 60% training data and 40% testing data with 50 epochs, resulting in the lowest MAPE value of 17.33% and RMSE of 0.45. These values indicate that the model is quite accurate in predicting daily quail egg production. The low RMSE and MAPE values show that the model is able to learn historical daily production patterns with sufficient accuracy, even on data with seasonal fluctuations and variability. The model is also able to maintain generalization when tested on previously unseen data, as evidenced by the stability of results at a 40% test ratio.

These results show great potential for implementing the LSTM model as part of a decision support system for quail egg production planning. The accuracy of the predictions can help farmers and policymakers in logistics, distribution, and feed resource management more efficiently.

5.3 Graphical Results

Step 1: The boxplot in Figure 1 displays five important statistical figures for each subdistrict, namely the minimum, first quartile (Q1), median (Q2), third quartile (Q3), and maximum, as well as the presence of outliers.

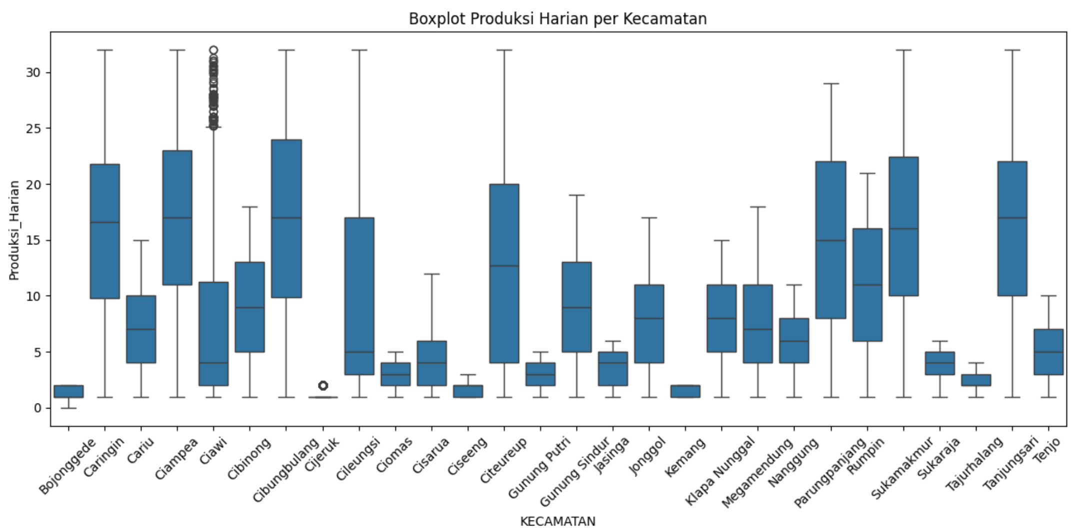

Figure 1. Boxplot of Quail Egg Production

The boxplot in Figure 1 shows the distribution of daily quail egg production based on quartile values in each subdistrict. Subdistricts such as Ciawi, Cariu, and Rumpin have high medians (Q2) and upper quartiles (Q3), indicating consistently high production levels, accompanied by many outliers that indicate extreme production spikes. Conversely, districts such as Tenjo, Tajurhalang, and Cileungsi have low Q1, Q2, and Q3 values with a narrow interquartile range (IQR), indicating low and stable production. Districts such as Cibinong, Sukamakmur, and Ciampea show a wide IQR, reflecting high production fluctuations. Production distribution also tends to be asymmetrical in some areas, indicating a disparity between low- and high-production days.

Step 2: Granger causality testing is conducted to determine whether independent variables (e.g., temperature, humidity, or other factors) have a statistically significant causal effect on the Daily_Production variable at several lag times. Table 7 is compiled based on the number of lags and displays the F-statistic and p-value from the ssr-based F test:

Table 7. Uji Granger Causality

Lag	**F-Statistic**	**p-Value**	**Keterangan**
1	65.3565	0.0000	significant
2	17.8757	0.0000	significant
3	8.7191	0.0000	significant
4	5.1632	0.0004	significant
5	3.4599	0.0040	significant
6	2.5671	0.0174	significant
7	1.9895	0.0526	**Not significant**

The Granger Causality test results show that at lags 1 to 4, the input variables have a significant effect on Daily_Production (p-value < 0.05), indicating a short-term causal relationship. However, starting from lag 5 to 7, the p-value is > 0.05, meaning the influence is no longer significant. Therefore, it can be concluded that the input variables only have a significant effect on daily production in the short term (1–4 days prior).

Step 3: Correlation test to analyze that daily production, temperature, and humidity are related. As shown in Figure 2.

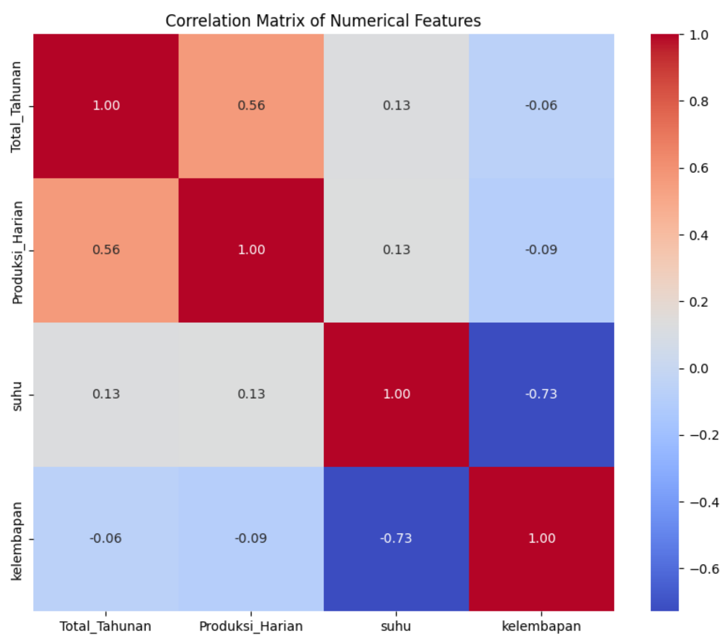

Figure 2. Correlation Matrix Between Numerical Variables

The correlation analysis results show that Daily_Production has a moderate positive correlation with Annual_Total (r = 0.56), as well as a weak correlation with temperature (r = 0.13) and humidity (r = -0.09). Meanwhile, the correlation between temperature and humidity is strongly negative (r = -0.73), indicating that as temperature increases, humidity tends to decrease.

Step 4: The performance of the LSTM model was evaluated by observing the RMSE and MAPE per subdistrict.

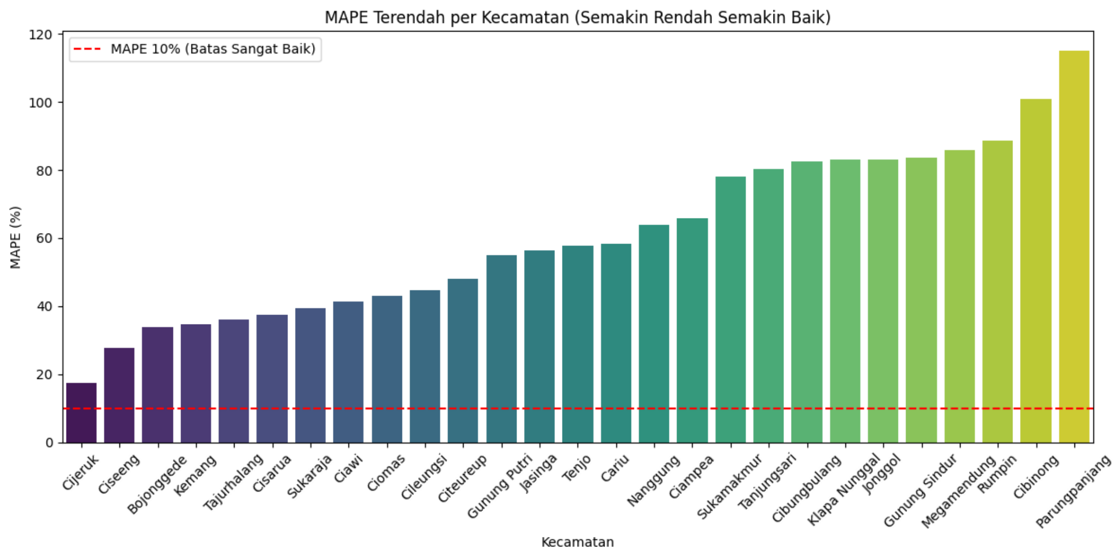

Figure 3. MAPE Evaluation by Subdistrict

Figure 3 shows the lowest MAPE (Mean Absolute Percentage Error) values from the prediction model for each subdistrict. Lower MAPE values indicate better prediction accuracy. The subdistricts of Cijeruk, Ciseeng, and Bojonggede have the best accuracy with MAPE values below 30%, with Cijeruk approaching the ideal threshold of 10% (marked by the red line). Conversely, subdistricts such as Cibinong, Rumpin, and Parungpanjang have high MAPE values (above 90%), indicating poor model performance in those areas.

Step 5: Test results from the LSTM method, and test data evaluated using MAPE and RMSE in Figure 4.

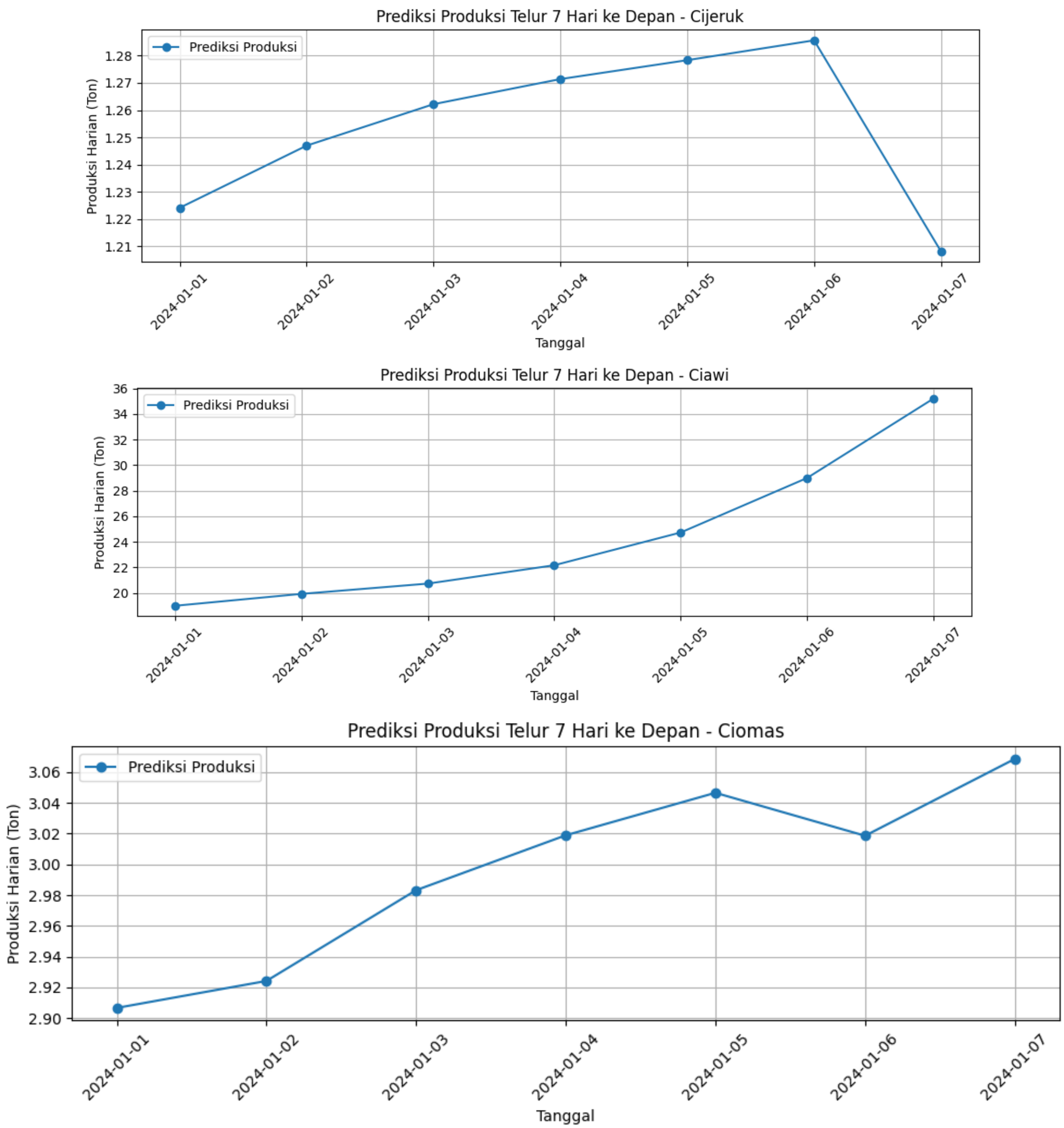

Figure 4. Graph of 7-day forecast by subdistrict

During the first six days in Figure 4, quail egg production in Cijeruk is predicted to experience a steady increase, which likely reflects favorable environmental conditions or cage management. However, the significant decline on day 7 warrants attention, as it may indicate potential disturbances or irregularities in production patterns.

5.3 Proposed Improvements

Based on the results of the evaluation and analysis of the LSTM model's performance, there are several opportunities to improve the developed system, both from a technical and implementation perspective. From a technical perspective, the proposed improvements include: (1) Addition of input variables: Currently, the model only uses temperature, humidity, and the number of quails. Adding features such as feed type, chicken age, light intensity, and feeding frequency is believed to improve prediction accuracy. (2) Expanding the dataset: A longer data duration (more than three months) will help the model identify seasonal patterns or production anomalies. (3) Use of hybrid models:

Combining LSTM with other models such as CNN-LSTM or GRU (Gated Recurrent Unit) can be tested to compare predictive performance. (4) Parameter optimization (hyperparameter tuning): The number of neurons, learning rate, and epoch can be optimized using Grid Search or Bayesian Optimization methods for more optimal results.

From the system implementation perspective: (1) IoT integration: The system can be further developed by connecting directly to temperature and humidity sensors to enable real-time data processing. (2) Decision notifications: Adding a system alert or daily recommendation feature based on prediction results for farmers.

5.4 Validation

Validation was performed by comparing the model's prediction results with actual data across four data splitting scenarios. MAPE values above 10% across all scenarios indicate that the model has a reasonably good prediction error rate and is reliable. Additionally, visual validation was performed using prediction vs. actual graphs, which show that the prediction line closely follows the actual trend, particularly in the 70:30 and 60:40 proportions. This reinforces the conclusion that the LSTM model is capable of effectively handling the fluctuation patterns in quail egg production. This validation indicates that the system built is suitable for implementation as a decision-making tool in daily farming activities.

6. Conclusion

Testing the LSTM model on daily quail egg production data in Cijeruk District shows that model configuration greatly affects prediction performance. The evaluation was conducted by varying the training-test split ratio and the number of epochs. The best model was obtained with a training ratio of 60% and a testing ratio of 40%, with 50 epochs, resulting in a Root Mean Square Error (RMSE) of 0.4539 and a Mean Absolute Percentage Error (MAPE) of 17.33%. A MAPE value below 20% indicates that the model has a low error rate and good prediction accuracy. Among all the tested combinations, the results show that using too much training data (e.g., a 90:10 ratio) does not always yield the best results, as it can reduce the model's ability to generalize new data. Conversely, a balanced ratio and sufficient number of epochs provide optimal results. The research underscores that the selection of training parameters is critical in implementing LSTM models, especially for daily production data with seasonal and fluctuating patterns. These results also support the use of LSTM as a reliable method in predictive and adaptive decision support systems for quail egg production.

References

Adhany, P. C., Wulandari, C., Intan, B., & Santoso, B. Rice prediction using the Long Short-Term Memory algorithm. Journal of Informatics Management and Information Technology, 5(2), 120–127, 2025.

Alfarisi, I. A., Priandika, A. T., & Puspaningrum, A. S. Implementation of the Laravel framework on health service systems (Case Study: Berkah Medical Center Clinic). Jurnal Ilmiah Computer Science, 2(1), 1–9, 2023.

AlShammari, A. F. Implementation of model evaluation using confusion matrix in Python. International Journal of Computer Applications, 186(50), 42–47, 2024.

Ambarwari, A., Adrian, Q. J., & Herdiyeni, Y. Analysis of the effect of data scaling on the performance of machine learning algorithms for plant identification. Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), 4(1), 117–122, 2020. https://doi.org/10.29207/resti.v4i1.1517.

Ashari, M. L., & Sadikin, M. Time series sales transaction prediction using LSTM regression. Jurnal Nasional Pendidikan Teknik Informatika: JANAPATI, 9(1), 1–10, 2020.

Bazwir, A., Setianingsih, C., & Murti, M. A. Electricity usage prediction using Recurrent Neural Network algorithm. eProceedings of Engineering, 10(1), 2023.

Chicho, B. T., & Sallow, A. B. A comprehensive survey of deep learning models based on the Keras framework. Journal of Soft Computing and Data Mining, 2021.

Dinas Pertanian dan Pangan Kabupaten Bogor. Production Report of Quail Eggs Year 2022, 2022.

Kusnaidi, M. R., Gulo, T., & Aripin, S. Application of data normalization in student data clustering using K-Means to determine tuition aid priority. Journal of Computer System and Informatics (JoSYC), 3(4), 330–338, 2022. https://doi.org/10.47065/josyc.v3i4.2112.

Mardianti, M., Farida, Y., Santi, M. Y., Arum, D. N. S., & Trisnawati, I. Optimization of processed quail egg consumption to improve hemoglobin levels in pregnant women. Jurnal Riset Kesehatan Poltekkes Depkes Bandung, 16(2), 473–484, 2024.

Maryani, R. Intelligent decision support system using Ant Colony Optimization (ACO) method for optimal supply chain route search in palm-based bioenergy. Jurnal Informatika Ekonomi Bisnis, 4, 192–196, 2022.

Nurhasanah, N., Mudrikah, I. I., Adlina, G. N., Chirzun, A., & Sriwana, I. K. Development of decision support system for value-added analysis of sunflower agro-industry supply chain. Agrointek: Jurnal Teknologi Industri Pertanian, 19(1), 19–28, 2025.

Rejeb, A., et al. Smart agriculture and the role of decision support systems: A systematic literature review. Information Processing in Agriculture, 9(4), 416–429, 2022. https://doi.org/10.1016/j.inpa.2021.10.007.

Sari, Delviani Permata, Lita Karlitasari, and Fajar Delli Wihartiko. "Clean Water Demand Prediction Model Using The Long Short-Term Memory (LSTM) Method." Komputasi: Jurnal Ilmiah Ilmu Komputer dan Matematika 20, no. 2, 160-168, 2023.

Sidik, A. D., & Ansawarman, A. Prediction of motor vehicle volume using machine learning. Formosa Journal of Multidisciplinary Research, 1(3), 559–568, 2022.

Soussi, Y., et al. Smart decision support systems in agriculture: A review. Computers and Electronics in Agriculture, 211, 108091, 2024. https://doi.org/10.1016/j.compag.2023.108091.

Sumari, A. D. W., Mawarni, P. I., & Syulistyo, A. R. Classification of quail egg quality based on color and texture using K-Nearest Neighbor (KNN) and information fusion. Jurnal Teknologi Informasi dan Ilmu Komputer, 8(5), 2021.

Wang, J., Li, X., Li, J., Sun, Q., & Wang, H. NGCU: A new RNN model for time-series data prediction. Big Data Research, 27, 100296, 2022.

Wantoro, A., & Muludi, K. Application of fuzzy logic in decision support systems for duck egg quality assessment. Jurnal Teknik Informatika dan Sistem Informasi (JUTISI), 7(1), 2019.

Wardani, W. W. K. Prediction of Islamic stock prices using the Recurrent Neural Network–Long Short-Term Memory method. Thesis, Universitas Islam Negeri Sunan Ampel Surabaya, 2021.

Widianti, A., & Pratama, I. Handling missing values and prediction of waste pile data based on machine learning. RABIT, 9(2), 242–251, 2024.

Yulianingsih, Y., Akhirina, T. Y., & Niswati, Z. I. Development of an RNN model for beef production prediction in national development planning. Faktor Exacta, 15(3), 200–205, 2022.

Biographies

Siti Halimah is a researcher who focuses on the development of artificial intelligence-based decision support systems, particularly in the fields of animal husbandry and digital finance. Currently, she is developing an Intelligent Decision Support System for Quail Egg Production Using Long Short-Term Memory (LSTM) that aims to predict daily production based on historical data such as the number of quails, temperature, and humidity. The LSTM model was chosen due to its ability to recognize time series patterns for more accurate predictions. In addition, Siti has also published a journal entitled "Development of a Mutual Fund Investment Simulation Application with the Prophet Machine Learning Algorithm," which discusses predicting mutual fund value trends using the Prophet algorithm. This work is intended to help farmers or other users view information and make decisions based on available data.

Eneng Tita Tosida is a lecturer and researcher in the Computer Science Program, Faculty of Mathematics and Natural Sciences, Pakuan University, Bogor. She specializes in data mining, deep learning, augmented reality (AR), and supply chain management based on smart technology. She earned her Doctorate in Computer Science from IPB University in 2023, with research focused on integrating smart technology to support decision-making in the SME and education sectors. Dr. Eneng has produced several significant scientific publications, including "Optimizing the Classification Assistance through Supply Chain Management for Telematics SMEs in Indonesia Using a Deep Learning Approach," published in the International Journal of Supply Chain Management. In this article, she demonstrated that deep learning methods can improve classification accuracy up to 99.03% in supporting technology-based SMEs.
Additionally, she authored "Development of Augmented Reality Portal for Medicinal Plants Introduction" in the International Journal of Global Operations Research, which developed an AR-based educational application to interactively introduce medicinal plants. She is also actively involved in developing predictive models using the SPADE algorithm for analyzing sequential sales data patterns, as well as utilizing AR in visualizing the human respiratory system for educational purposes. As an active academic at the national and international levels, Dr. Eneng is also involved in research collaborations and community service with foreign institutions such as UTHM Malaysia. With her expertise, she has made significant contributions to the development of technological innovations for education, the environment, and the SME sector in Indonesia.

Fajar Delli Wihartiko is a lecturer in the Computer Science Program at Pakuan University, Indonesia, specializing in artificial intelligence, optimization, and the application of data mining for agricultural, transportation, and resource management systems. He has authored several significant scientific works, including "Multi-Objective Entropy Optimization Model for Agricultural Product Price Recommendation," published in Engineering Letters, and "Clean Water Demand Prediction Model Using the Long Short-Term Memory (LSTM)," featured in the Journal of Computation. Additionally, he co-authored "Goal Programming Approach to Vehicle Routing Problems for Optimal Route Determination in Bus Rapid Transit," published in the International Journal of Mathematical Modelling and Numerical Optimisation. In his various research studies, Dr. Fajar emphasizes the importance of using intelligent models based on modern algorithms such as LSTM and entropy approaches to address real-world challenges, ranging from food price prediction to public transportation route efficiency. With his active contributions to various national and international journals, he has become one of the key academics driving the development of intelligent technology-based decision support systems in Indonesia.