



Palm Oil Production Prediction Using a Multi-Architecture Deep Learning Approach Based on Long Short-Term Memory and Gated Recurrent Unit

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Abstract

Palm oil production in Riau Province fluctuates due to seasonal factors and complex temporal patterns, making accurate forecasting with conventional statistical methods challenging. This study aims to compare the performance of six deep learning architectures Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), Stacked LSTM, Gated Recurrent Unit (GRU), Bidirectional GRU (Bi-GRU), and Stacked GRU in predicting monthly palm oil production and identifying the most effective model. Two datasets obtained from PT Perkebunan Nusantara (PTPN) and Badan Pusat Statistik (BPS), covering the period from 2014 to 2023, were employed in this study. All models were evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The experimental results demonstrate that the GRU model consistently outperformed the other architectures, achieving the highest prediction accuracy of 95.84% and the lowest MAPE of 4.16% on the BPS dataset, while also producing the best overall performance on the PTPN dataset. These findings indicate that the research objective was successfully achieved and demonstrate that GRU provides a reliable, computationally efficient approach for forecasting palm oil production with limited time-series data. The proposed comparative evaluation provides practical insights for selecting appropriate deep learning architectures to support production planning and decision-making in the plantation sector.

Keywords: Deep Learning, Multi-Architecture, Palm Oil, Production, Prediction.

1. INTRODUCTION

Indonesia is an agrarian country with the plantation sector as one of the main pillars of the national economy [1][2]. Palm oil is a strategic commodity due to its contribution to the Gross Domestic Product (GDP), employment, and export earnings [3][4]. Based on data from the Badan Pusat Statistik (BPS), Indonesia's palm oil production in 2023 will reach around 47 million tons, making Indonesia the world's largest palm oil producer [5]. This confirms the importance of palm oil for the national economy and Indonesia's position in the global market. Riau Province is the largest palm oil producer in Indonesia, contributing around 9.22 million tons or 19.6% of total national production [6]. The magnitude of this contribution means that fluctuations in palm oil production in Riau have a direct impact on the stability of domestic supply, the price of crude palm oil (CPO), and the national export policy [7][8]. Therefore, palm oil production forecasts in this province are very important for the government and industry players in managing supply and distribution chains. Accurate forecasting is essential not only for production planning but also for inventory management, export policy formulation, investment planning, and maintaining the stability of the national palm oil supply chain. Inaccurate forecasts may lead to production inefficiencies, financial losses, and suboptimal policy decisions [9].

However, palm oil production in Riau Province fluctuates from year to year. This variability is influenced by factors such as rainfall, temperature, soil conditions, plant age, planting area, maintenance practices, and plantation management [10]. These factors cause production data to exhibit seasonal characteristics, long-term trends, and complex nonlinear relationships, making it difficult to predict accurately

with conventional methods [11]. Badan Pusat Statistik (BPS) provides official and consistent historical data on palm oil production, but this data is generally aggregated and does not include additional explanatory variables. The main challenge is how to leverage this limited time-series data to generate accurate predictions. Palm oil production predictions are urgently needed by the industry for factory capacity planning and supply management, as well as by the government to support export policies, price stabilization, and food security planning [12].

Conventional statistical methods, such as linear regression and Autoregressive Integrated Moving Average (ARIMA), are often unable to capture non-linear, seasonal, and long-term dependency patterns in palm oil production data [13][14]. Palm oil production time series data has a lag effect characteristic, whereby production in a given period is influenced by production in the previous period [12][15]. This condition requires the use of a more adaptive modeling approach that is capable of learning data patterns in depth.

Advances in deep learning have enabled more effective modeling of complex time-series data than conventional statistical methods. Among various deep learning techniques, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) have become two of the most widely adopted recurrent neural network architectures for forecasting tasks because they are specifically designed to capture long-term temporal dependencies while overcoming the vanishing gradient problem commonly encountered in standard RNNs [16][17]. LSTM employs memory cells and gating mechanisms that enable the model to retain important information over long sequences, making it suitable for data characterized by seasonal fluctuations and nonlinear relationships[18]. Meanwhile, GRU utilizes a simpler gating structure with fewer trainable parameters, resulting in lower computational complexity and faster training while maintaining competitive predictive performance [19]. Previous studies have demonstrated the effectiveness of LSTM and GRU in various forecasting applications, including agricultural production, commodity prices, and other nonlinear time-series problems [20], [21]. In addition to the basic architecture, the development of models such as Bidirectional LSTM (Bi-LSTM), Stacked LSTM, Bidirectional GRU (Bi-GRU), and Stacked GRU enables deeper and more comprehensive modeling of complex production patterns [22][20]. Therefore, these architectures were selected for this study to evaluate their ability to model monthly palm oil production data and to identify the most suitable architecture for limited agricultural time-series datasets.

Several previous studies have successfully applied machine learning and deep learning methods, including Support Vector Regression (SVR), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), for forecasting agricultural commodities. In Indonesia, LSTM has been reported to outperform Artificial Neural Networks (ANN) in modeling crude palm oil production [21], while studies on crude palm oil price forecasting have shown that GRU is effective in capturing complex temporal patterns with relatively low computational complexity [23]. These findings demonstrate the potential of deep learning architectures for modeling nonlinear agricultural time-series data. However, previous studies on palm oil forecasting have predominantly focused on either production prediction using a single deep learning architecture or crude palm oil price forecasting. In addition, comprehensive comparisons of advanced variants, such as Bidirectional LSTM (Bi-LSTM), Stacked LSTM, Bidirectional GRU (Bi-GRU), and Stacked GRU, remain limited, particularly for monthly palm oil production using official datasets from Riau Province. Therefore, there remains a lack of empirical evidence on the most suitable deep learning architecture for forecasting palm oil production from limited agricultural time-series data. To address this gap, this study systematically compares six LSTM- and GRU-based architectures using two official monthly production datasets obtained from PT Perkebunan Nusantara (PTPN) and Badan Pusat Statistik (BPS). Unlike many previous studies, all models are evaluated using identical preprocessing procedures, hyperparameter settings, and evaluation metrics to ensure an objective comparison. This comparative evaluation provides empirical evidence on the relative performance of advanced LSTM- and GRU-based architectures under identical experimental settings, thereby providing practical guidance for selecting appropriate deep learning models for palm oil production forecasting with limited time-series data.

2. MATERIAL AND METHOD

This study adopts a quantitative approach using time-series forecasting techniques. The sequence of research stages is illustrated in Figure 1, which presents a structured workflow of the study. The diagram outlines the process systematically, beginning with data collection and preprocessing, then the modeling phase, and concluding with model performance evaluation.

2.1. Planning Stage

The research begins by identifying the issue of fluctuating palm oil production and establishing the objective of comparing LSTM- and GRU-based models. Subsequently, a literature review is conducted to determine the most suitable modeling techniques and evaluation methods to apply.

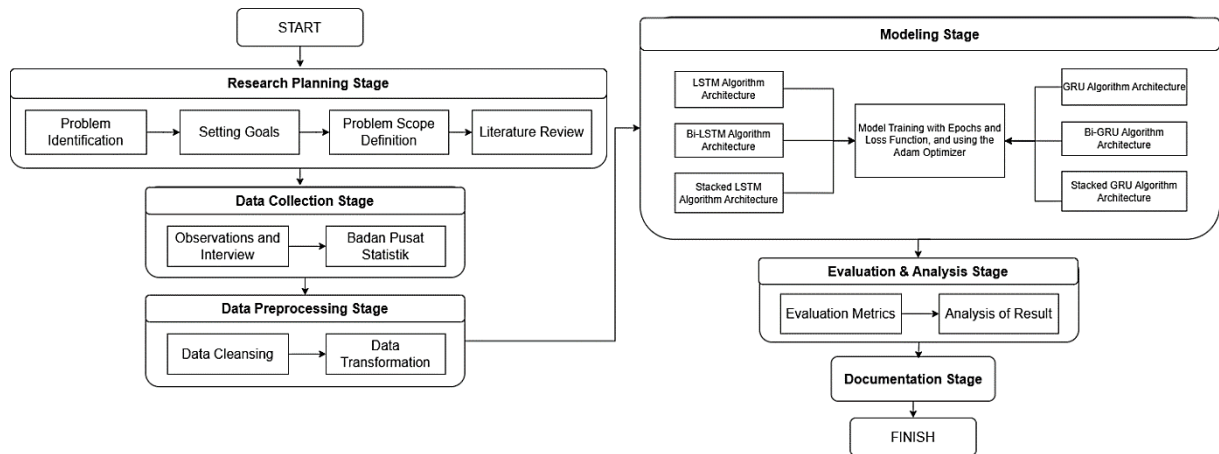


Figure 1. Research Methodology

2.2. Data Collection Stage

The data collection stage involved compiling historical monthly palm oil production data from two sources. The first dataset was obtained from PT Perkebunan Nusantara (PTPN) with a total of 120 records for the period January 2014 to December 2023, and the second dataset was obtained from the Badan Pusat Statistik (BPS) with the same range, namely the period January 2014 to December 2023, covering 120 records of monthly palm oil production. All data were collected in a monthly time series to support modeling and forecasting of palm oil production.

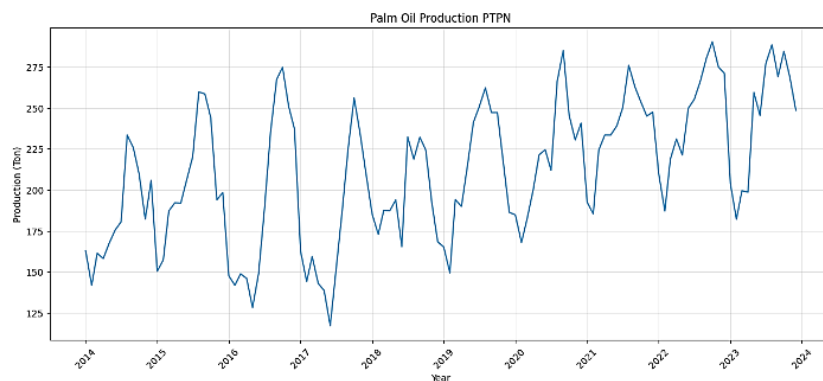


Figure 1. Visualization of the Entire PTPN Dataset

Figure 2 shows a visualization of the entire PTPN dataset, which shows monthly palm oil production from 2014 to 2023, which fluctuates from month to month, reflecting the influence of seasonal factors, weather conditions, and plantation management practices.

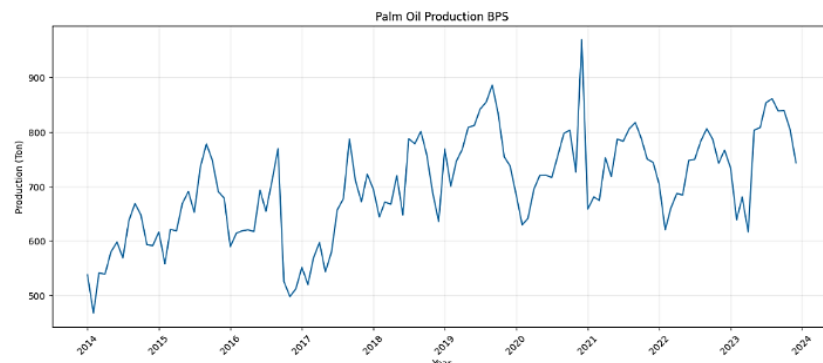


Figure 2. Visualization of the Entire BPS Dataset

Figure 3 also displays a visualization of the entire dataset from BPS. This data illustrates monthly palm oil production from 2014 to 2023, with fluctuations occurring between months due to seasonal influences, weather conditions, and plantation management.

2.3. Data Preprocessing Stage

Data preprocessing is conducted to ensure the dataset quality prior to modeling. This process includes checking for missing values, identifying and removing duplicate entries, and organizing the data to maintain a proper chronological time series structure. Subsequently, the data is normalized using the Min-Max Scaler within the range of [0, 1] to enhance model learning stability. Finally, the dataset is partitioned using a time-based splitting approach into training, validation, and testing sets to preserve temporal dependencies and avoid information leakage.

2.4. Deep Learning Models

This study applies deep learning, a subfield of machine learning that leverages multi-layer neural network architectures to capture complex data representations and generate accurate predictions [23][24]. In particular, a Recurrent Neural Network (RNN) framework is adopted as the primary approach due to its capability to process sequential data, such as time series, through feedback connections [23]. However, standard RNNs have limitations in learning long-term dependencies because of the vanishing gradient problem [25]. To overcome this limitation, advanced architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are applied, as they use gating mechanisms to preserve key temporal information and facilitate better modeling of complex patterns [26].

LSTM employs three primary gates, namely input, forget, and output gates, to capture long-term dependencies and serves as the baseline model in this study [19]. Its extended variants include Bidirectional LSTM (Bi-LSTM), which processes sequences in both forward and backward directions to capture richer temporal context [27][28], and Stacked LSTM, which consists of multiple layers to improve the model's ability to learn complex and nonlinear relationships [29][30]. Similarly, GRU is a more streamlined version of LSTM with fewer parameters, using update and reset gates to control information flow while maintaining computational efficiency [31]. Its variants include Bidirectional GRU (Bi-GRU), which enhances contextual understanding through bidirectional processing [32][33], and Stacked GRU, which increases model depth to better capture intricate temporal features [34][35].

These LSTM- and GRU-based architectures are implemented to capture both short- and long-term dependencies in monthly palm oil production data, which exhibit nonlinear patterns, seasonal variations, and long-term trends. The comparative analysis of these models is conducted to determine the most effective architecture for achieving accurate predictions.

2.5. Optimizer

The optimizer plays a crucial role in controlling the weight update process in deep learning models, enabling the minimization of prediction errors during training [36]. In this study, the Adaptive Moment Estimation (Adam) optimizer is used for its ability to adaptively adjust the learning rate throughout the training process. The application of Adam facilitates faster, more stable convergence when training LSTM- and GRU-based models on highly volatile monthly palm oil production data, thereby improving error reduction and overall model performance.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) \cdot g_t \quad (1)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) \cdot g_t^2 \quad (2)$$

2.6. Hyperparameter

Hyperparameter selection is a critical stage in the modeling process, as it significantly influences the performance and stability of the prediction model [37]. These hyperparameters govern key aspects of the neural network's learning process, including the number of neuron units, layers, batch size, epochs, and activation functions. In this study, all models are configured with 120 units, 150 epochs, a batch size of 16, and the ReLU activation function. These settings are applied consistently across all architectures to ensure a fair and unbiased comparison. Specifically, the standard LSTM and GRU models use a single layer, whereas their Bidirectional and Stacked variants use two layers, allowing the models to better capture temporal patterns while maintaining training stability.

2.7. Model Evaluation

The performance evaluation of the models in this study assessed the ability of LSTM, Bi-LSTM, Stacked LSTM, GRU, Bi-GRU, and Stacked GRU architectures to predict monthly palm oil production. The evaluation process used test data that were not used in the training stage, so the evaluation results reflected the model's generalization to new data. Model performance was measured using four evaluation metrics, namely Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These four metrics were used to provide a comprehensive overview of the

prediction error rate, expressed as squared error, mean absolute error, and relative error as a percentage. The model with the lowest error is declared the best for predicting palm oil production.

3. RESULT AND DISCUSSION

This study evaluates the performance of six deep learning architectures, namely LSTM, Bi-LSTM, Stacked LSTM, GRU, Bi-GRU, and Stacked GRU, in forecasting monthly palm oil production using two datasets (BPS and PTPN). Model evaluation is carried out using MSE, RMSE, MAE, and MAPE as performance metrics. Table 1 summarizes the comparative results of all evaluated models.

Table 1. Model Evaluation Result

Dataset	Architecture	Accuracy	MSE	RMSE	MAE	MAPE
BPS	LSTM	92.00%	5305.00	72.84	65.33	8.00%
	Bi-LSTM	91.83 %	5623.83	74.99	66.83	8.17 %
	Stacked LSTM	90.47 %	8006.67	89.48	79.33	9.53 %
	GRU	95.84 %	1810.67	42.55	33.67	4.16 %
	Bi-GRU	91.84 %	5558.33	74.55	67.00	8.16 %
	Stacked GRU	92.54 %	5022.50	70.87	60.83	7.46 %
PTPN	LSTM	89.85 %	1099.17	33.15	28.17	10.15 %
	Bi-LSTM	90.13 %	1003.00	31.67	26.67	9.87 %
	Stacked LSTM	89.61 %	1093.33	33.07	28.00	10.39 %
	GRU	92.57 %	596.67	24.43	20.33	7.43 %
	Bi-GRU	89.56 %	1060.50	32.57	27.83	10.44 %
	Stacked GRU	90.97 %	840.17	28.99	24.83	9.03 %

Table 1 shows that the GRU model consistently achieved the best performance across both datasets, obtaining the highest accuracy and the lowest MSE, RMSE, MAE, and MAPE values among all evaluated architectures. On the BPS dataset, GRU achieved an accuracy of 95.84% with a MAPE of 4.16%, while on the PTPN dataset, it achieved an accuracy of 92.57% with a MAPE of 7.43%. In general, all models performed better on the BPS dataset than on the PTPN dataset, indicating that the BPS data exhibit more learnable temporal patterns. Furthermore, the Bidirectional and Stacked variants did not consistently outperform the baseline LSTM and GRU models, suggesting that the additional architectural complexity did not provide significant advantages for the relatively limited monthly palm oil production datasets used in this study. These findings are further supported by the accuracy comparison in Figure 3, which consistently shows the GRU model's superior performance. To further demonstrate the GRU model's performance, Figures 4 and 5 compare predicted values with actual observations for both datasets.

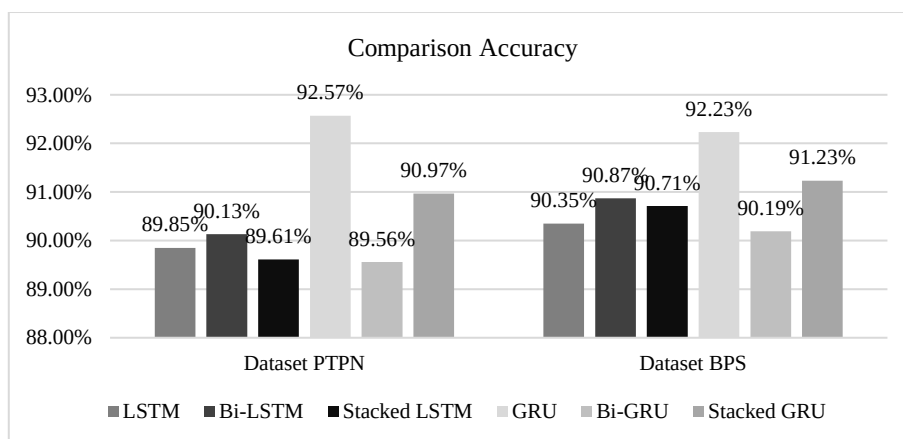


Figure 3. Comparison Accuracy

The prediction results shown in Figures 4 and 5 further confirm the superior performance of the GRU model, as the predicted values closely follow the actual production trends in both the BPS and PTPN datasets. This performance can be attributed to the simpler gating mechanism of GRU, which requires fewer trainable parameters than LSTM while remaining effective in capturing long-term temporal dependencies. Given that the datasets consist of only 120 monthly observations, the lower model complexity of GRU may reduce the risk of overfitting and enable more efficient learning of temporal patterns. In contrast, the Bidirectional and Stacked architectures introduce additional network complexity that generally requires larger datasets to fully exploit their representational capacity, which may explain why these variants did not consistently outperform the baseline models in this study. These findings are consistent with previous studies by Ulama et al. [21] and

Tardini and Suharjito [23], which reported that LSTM- and GRU-based models are effective for palm oil forecasting, with GRU offering competitive predictive performance while maintaining lower computational complexity. From a practical perspective, these results suggest that the GRU model is a suitable approach for forecasting monthly palm oil production using limited agricultural time-series data and can support production planning, inventory management, and decision-making in the plantation sector.

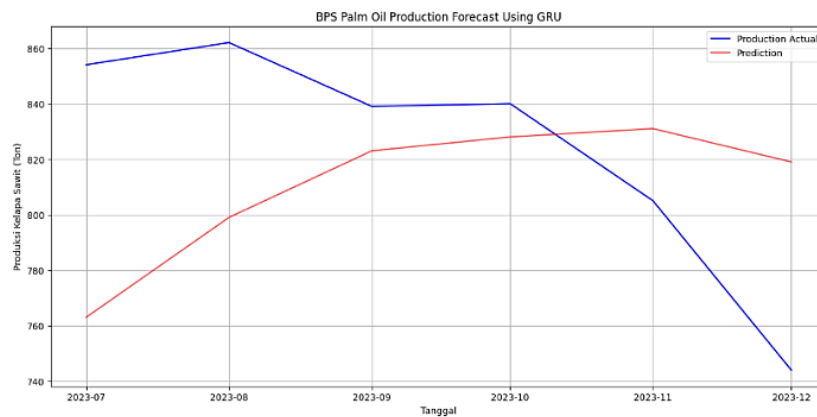


Figure 4. GRU Model Prediction on BPS Dataset Test Data

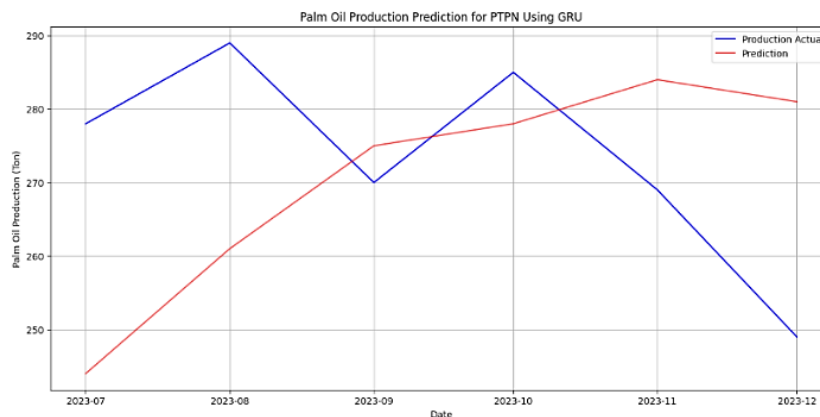


Figure 5. GRU Model Prediction on PTPN Dataset Test Data

4. CONCLUSION

This study aimed to compare the performance of six LSTM- and GRU-based deep learning architectures in forecasting monthly palm oil production in Riau Province using limited time-series data from the BPS and PTPN datasets. The experimental results demonstrate that the GRU model consistently outperformed the other architectures by achieving the highest prediction accuracy and the lowest forecasting errors across both datasets. These findings indicate that GRU is highly effective in capturing temporal dependencies and seasonal patterns while maintaining efficient learning on limited datasets. Unlike many previous studies that evaluated only a single architecture or dataset, this study provides a comprehensive comparison of six deep learning architectures under identical preprocessing procedures, hyperparameter settings, and evaluation metrics, thereby contributing empirical evidence for selecting an appropriate forecasting model for palm oil production. The findings offer practical insights for supporting production planning, supply chain management, and decision-making in the agricultural sector. Future research may investigate the integration of additional explanatory variables, larger datasets, or hybrid deep learning models to further improve forecasting accuracy and model generalization..

REFERENCES

- [1] D. Khatiwada, C. Palmén, and S. Silveira, "Evaluating the palm oil demand in Indonesia: production trends, yields, and emerging issues," *Biofuels*, vol. 12, no. 2, pp. 135–147, 2021, doi: 10.1080/17597269.2018.1461520.
- [2] B. M. Pratama, M. I. Ali, M. H. Wati, R. Rhonsina, and S. Wulandari, "Kontribusi Subsektor Perkebunan Dalam Mendukung Pertumbuhan Ekonomi Masyarakat di Sumatera Utara," *El-Mal J. Kaji. Ekon. Bisnis Islam*, vol. 4, no. 6, pp. 1637–1645, 2023, doi: 10.47467/elmal.v4i6.3079.
- [3] T. Santika *et al.*, "Impact of palm oil sustainability certification on village well-being and poverty in

- Indonesia,” *Nat. Sustain.*, vol. 4, no. 2, pp. 109–119, 2021, doi: 10.1038/s41893-020-00630-1.
- [4] N. Rani, “Dampak Kelapa Sawit Dalam Pembangunan Berkelanjutan : Analisis Kebijakan Publik Di Indonesia,” *J. Governansi*, vol. 11, no. 1, pp. 73–82, 2025, doi: 10.30997/jgs.v11i1.16314.
 - [5] BPS, “Statistik Tanaman Indonesia 2022,” Badan Pusat Statistika. Accessed: May 05, 2025. [Online]. Available: <https://www.bps.go.id/id/publication/2023/11/30/160f211bfc4f91e1b77974e1/statistik-kelapa-sawit-indonesia-2022.html>
 - [6] B. P. S. P. Riau, “Statistik Kelapa Sawit Provinsi Riau 2023,” 14000.25002. [Online]. Available: <https://riau.bps.go.id/id/publication/2025/01/31/f8df1fdb5cc3a3dea7970b86/statistik-kelapa-sawit-provinsi-riau-2023.html>
 - [7] R. D. Maulidah, Zevira Saffa Komara, and Dewi Rohma Wati, “Peramalan jumlah produksi kelapa sawit di Provinsi Riau Periode Tahun 2023 - 2025,” *Agrivet J. Ilmu-Ilmu Pertan. dan Peternak. (Journal Agric. Sci. Veteriner)*, vol. 13, no. 1, pp. 22–32, 2025, doi: 10.31949/agrivet.v13i1.12242.
 - [8] F. Djam'an, A. K. Fil'ardy, N. D. S. Saudi, R. Fitrianti, S. Djaya, and N. Uditia, *Analysis of the Development of Production and Exports of Crude Palm Oil (CPO) in West Sumatra Province*, no. Icame 2023. Atlantis Press International BV, 2024. doi: 10.2991/978-94-6463-400-6_45.
 - [9] A. F. Ramsey and M. K. Adjemian, “Forecast combination in agricultural economics: Past, present, and the future,” *Appl. Econ. Perspect. Policy*, vol. 46, no. 4, pp. 1450–1478, 2024, doi: 10.1002/aep.13445.
 - [10] P. Hashemvand Khiabani and W. Takeuchi, “Assessment of oil palm yield and biophysical suitability in Indonesia and Malaysia,” *Int. J. Remote Sens.*, vol. 41, no. 22, pp. 8520–8546, 2020, doi: 10.1080/01431161.2020.1782503.
 - [11] N. Khan *et al.*, “Prediction of Oil Palm Yield Using Machine Learning in the Perspective of Fluctuating Weather and Soil Moisture Conditions: Evaluation of a Generic Workflow,” *Plants*, vol. 11, no. 13, 2022, doi: 10.3390/plants11131697.
 - [12] F. Husaini, I. Permana, M. Afdal, and F. N. Salisah, “Penerapan Algoritma Long Short-Term Memory untuk Prediksi Produksi Kelapa Sawit,” *MALCOM Indones. J. Mach. Learn. Comput. Sci.*, vol. 4, no. 2, pp. 366–374, Feb. 2024, doi: 10.57152/malcom.v4i2.1187.
 - [13] M. A. KAMARUDDIN, “Prediction of Oil Palm Yield Using Machine Learning: Comparison of Linear and Non-Linear Algorithms With Multivariate Time Series Data,” *J. Oil Palm Res.*, 2025, doi: 10.21894/jopr.2025.0044.
 - [14] W. A. Pratiwi, I. M. Sumertajaya, and K. A. Notodiputro, “Comparison of ARIMA , LSTM , and Ensemble Averaging Models for Short-Term and Long- Term Forecasting of Non-Stationary Time Series Data,” vol. 8, no. 3, pp. 231–241, 2025, doi: <http://dx.doi.org/10.12962%2Fj27213862.v8i3.22643>.
 - [15] E. M. Putri, V. C. Hardita, and C. Elmayantie, “Application of Time Series for Palm Oil Production Prediction at PT. Dwie Warna Karya,” *J. Sains Komput. dan Teknol. Inf.*, vol. 7, no. 2, pp. 9–14, 2025, doi: 10.33084/jsakti.v7i2.9446.
 - [16] A. Ahmadi, A. Daccache, M. Sadegh, and R. L. Snyder, “Statistical and deep learning models for reference evapotranspiration time series forecasting: A comparison of accuracy, complexity, and data efficiency,” *Comput. Electron. Agric.*, vol. 215, no. November, p. 108424, 2023, doi: 10.1016/j.compag.2023.108424.
 - [17] M. Tshamaroh, N. S. Nasution, N. Nadhirah, R. A. Alfira, and Z. Xintong, “Amazon Stock Price Prediction Using Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU),” *Public Res. J. Eng. Data Technol. Comput. Sci.*, vol. 3, no. 1, pp. 1–9, 2025, doi: 10.57152/predatecs.v3i1.1656.
 - [18] N. H. Setiawan and Z. Zulkarnain, “Forecasting Palm Oil Production Using Long Short-Term Memory (LSTM) With Time Series Cross Validation (TSCV),” *Int. J. Soc. Serv. Res.*, vol. 4, no. 05, pp. 1237–1251, 2024, doi: 10.46799/ijssr.v4i05.780.
 - [19] K. E. ArunKumar, “Forecasting of COVID-19 using deep layer Recurrent Neural Networks (RNNs) with Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM) cells,” *Chaos Solitons and Fractals*, vol. 146, 2021, doi: 10.1016/j.chaos.2021.110861.
 - [20] M. F. Fayyad, V. Kurniawan, M. R. Anugrah, B. H. Estanto, and T. Bilal, “Application of Recurrent Neural Network Bi-Long Short-Term Memory, Gated Recurrent Unit and Bi-Gated Recurrent Unit for Forecasting Rupiah Against Dollar (USD) Exchange Rate,” *Public Res. J. Eng. Data Technol. Comput. Sci.*, vol. 2, no. 1, pp. 1–10, 2024, doi: 10.57152/predatecs.v2i1.1094.
 - [21] B. S. S. Ulama, R. A. Putra, F. Hibatullah, M. R. Habibi, and M. A. Nafis, “Comparison of Artificial Neural Network and Long Short-Term Memory for Modelling Crude Palm Oil Production in Indonesia,” *Int. J. Adv. Comput. Sci. Appl.*, vol. 16, no. 1, pp. 741–747, 2025, doi: 10.14569/IJACSA.2025.0160171.
 - [22] J. S. Turek, S. Jain, V. A. Vo, M. Capota, A. G. Huth, and T. L. Willke, “Approximating stacked and bidirectional recurrent architectures with the delayed recurrent neural network,” *37th Int. Conf. Mach. Learn. ICML 2020*, vol. PartF16814, pp. 9590–9600, 2020, doi: <https://dl.acm.org/doi/10.5555/3524938.3525832>.

- [23] G. A. Tardini and Suharjito, "Selection of Modelling for Forecasting Crude Palm Oil Prices Using Deep Learning (GRU & LSTM)," *Emerg. Sci. J.*, vol. 8, no. 3, pp. 875–898, 2024, doi: 10.28991/ESJ-2024-08-03-05.
- [24] A. Raup, W. Ridwan, Y. Khoeriyah, S. Supiana, and Q. Y. Zaqiah, "Deep Learning dan Penerapannya dalam Pembelajaran," *JiIP - J. Ilm. Ilmu Pendidik.*, vol. 5, no. 9, pp. 3258–3267, 2022, doi: 10.54371/jiip.v5i9.805.
- [25] R. Wardhani, N. Nafiiyah, and M. A. Haydar, "Algoritma Deep Learning dalam Memprediksi Hasil Panen Padi di Kabupaten Lamongan," *J. Inform. J. Pengemb. IT*, vol. 7, no. 1, pp. 13–17, 2022, doi: 10.30591/jpit.v7i1.2581.
- [26] L. C. Wanditra, I. M. Alamsyah, and D. Nasution, "Representation Theory of Recurrent Neural Network," *J. Indones. Math. Soc.*, vol. 31, no. 2, p. 1833, 2025, doi: 10.22342/jims.v31i2.1833.
- [27] A. Tomar and N. Gupta, "Prediction for the spread of COVID-19 in India and effectiveness of preventive measures," *Sci. Total Environ.*, vol. 728, p. 138762, 2020, doi: 10.1016/j.scitotenv.2020.138762.
- [28] A. Pranolo, S. Saifullah, A. Bella, U. Putra, R. Dreżewski, and A. Prasetya Wibawa, "Urban Traffic Volume Prediction using LSTM and Bi-LSTM: Performance Evaluation on the Metro Interstate Dataset," *Ilk. J. Ilm.*, vol. 17, no. 3, pp. 227–240, 2025, [Online]. Available: <http://dx.doi.org/10.33096/ilkom.v17i3.3001.227-240>
- [29] K. Kwanda, D. E. Herwindiati, and M. D. Lauro, "Perbandingan LSTM dan Bidirectional LSTM pada Sistem Prediksi Harga Saham Berbasis Website," *Ranah Res. J. Multidiscip. Res. Dev.*, vol. 7, no. 1, pp. 26–35, 2024, doi: 10.38035/rj.v7i1.1255.
- [30] V. Chittora and C. P. Gupta, "Dynamic spot price forecasting using stacked LSTM networks," *Proc. 3rd Int. Conf. Intell. Sustain. Syst. ICISS 2020*, pp. 1080–1085, 2020, doi: 10.1109/ICISS49785.2020.9315988.
- [31] A. Sagheer and M. Kotb, "Unsupervised Pre-training of a Deep LSTM-based Stacked Autoencoder for Multivariate Time Series Forecasting Problems," *Sci. Rep.*, vol. 9, no. 1, pp. 1–16, 2019, doi: 10.1038/s41598-019-55320-6.
- [32] Z. Niu *et al.*, "Recurrent attention unit: A new gated recurrent unit for long-term memory of important parts in sequential data," *Neurocomputing*, vol. 517, no. 1, pp. 1–9, 2023, doi: 10.1016/j.neucom.2022.10.050.
- [33] A. I. Putri, Y. Syarif, N. R. Aisyi, and N. Waeyusoh, "Implementation of Gated Recurrent Unit, Long Short-Term Memory and Derivatives for Gold Price Prediction," *Public Res. J. Eng. Data Technol. Comput. Sci.*, vol. 2, no. 2, pp. 68–80, 2025, doi: 10.57152/predatecs.v2i2.1609.
- [34] A. Kulkarni, Y. Wang, M. Gopinath, D. Sobien, A. Rahman, and F. A. Batarseh, "A review of cybersecurity incidents in the food and agriculture sector," *J. Agric. Food Res.*, vol. 23, pp. 1–34, 2025, doi: 10.1016/j.jafr.2025.102245.
- [35] M. Diqi, A. Wakhid, I. W. Ordiyasa, N. Wijaya, and M. E. Hiswati, "Harnessing the Power of Stacked GRU for Accurate Weather Predictions," *Indones. J. Artif. Intell. Data Min.*, vol. 6, no. 2, p. 208, 2023, doi: 10.24014/ijaidm.v6i2.24769.
- [36] Y. Xue, Y. Tong, and F. Neri, "An ensemble of differential evolution and Adam for training feed-forward neural networks," *Inf. Sci. (Ny.)*, vol. 608, pp. 453–471, 2022, doi: 10.1016/j.ins.2022.06.036.
- [37] Hajiar Yuliana, "Hyperparameter Optimization of Random Forest for 5G Coverage Prediction," *Bul. Pos dan Telekomun.*, vol. 22, no. 1, pp. 75–90, 2024, doi: 10.17933/bpostel.v22i1.390.