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Comparative Performance of LSTM and SARIMAX for Monthly Dengue Fever Forecasting in Sukabumi City

Author
[1]Muhammad George Elmar, [2]Asriyanik, [3]Winda Apriandari

Correspondence
[1,2,3]Universitas Muhammadiyah Sukabumi
[1]george088@ummi.ac.id
[2]asriyanik263@ummi.ac.id
[3]winda.apriandari@ummi.ac.id

Abstract:

Dengue Fever (DF) remains one of the most significant vector-borne diseases in Indonesia, including Sukabumi City, where the number of reported cases exhibits strong seasonal fluctuations influenced by climatic and demographic factors. Accurate forecasting is therefore essential to support early prevention and public health decision-making. This study compares the predictive performance of Long Short-Term Memory (LSTM) and Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) for forecasting monthly dengue cases in Sukabumi City. The forecasting models incorporate rainfall, temperature, humidity, and population density as predictor variables. The study follows the Cross Industry Standard Process for Data Mining (CRISP-DM) framework, consisting of business understanding, data understanding, data preparation, modeling, evaluation, and deployment. The dataset comprises 96 monthly observations collected between 2018 and 2025 and is divided into training and testing sets using an 80:20 ratio. Model performance is evaluated using Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Experimental results demonstrate that the SARIMAX model outperforms LSTM, achieving an MAE of 19.50 and a MAPE of 19.54%, whereas LSTM records an MAE of 20.96 and a MAPE of 21.13%. These findings indicate that SARIMAX is more suitable for forecasting dengue incidence characterized by strong seasonal patterns and relatively limited observations. The proposed comparison provides practical insights for selecting appropriate forecasting models to support evidence-based dengue prevention and public health planning in Sukabumi City.

Keyword: Dengue Fever; Long Short-Term Memory; SARIMAX; Time Series Forecasting; CRISP-DM; Machine Learning

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Introduction

Dengue Fever (DF) remains one of the most serious vector-borne infectious diseases affecting public health in Indonesia. The transmission dynamics of dengue are influenced by multiple environmental and demographic factors, including rainfall, temperature, humidity, and population density (Karo 2022; Mamenun et al. 2021). Consequently, the number of reported dengue cases often exhibits seasonal and fluctuating patterns, creating challenges for public health authorities in planning effective prevention and control strategies (Kementrian Kesehatan Indonesia 2025).

Accurate forecasting models are therefore required to anticipate future outbreaks and facilitate evidence-based decision-making (Khaira et al. 2020)

In Sukabumi City, dengue incidence has shown considerable variation in recent years. According to data from the Sukabumi City Health Office, 1,631 dengue cases and six related deaths were reported in 2024, representing the highest annual incidence recorded over the past decade. Although the number of reported cases declined to 538 by July 2025, the temporal pattern remains highly dynamic, indicating the need for forecasting approaches capable of accurately capturing disease trends and supporting early intervention (Anggraini, Huda, and Agushybana 2021; Awaludin 2025).

Various forecasting approaches have previously been employed to predict dengue outbreaks using both statistical and machine learning techniques. Logistic Regression has been applied for dengue prediction based on meteorological variables (Hariningsih, Candrasari, and Setyawati 2025), while Multivariate ARIMA has demonstrated satisfactory forecasting performance for multivariate epidemiological time-series data (Lestari and Witanti 2023). More recently, Long Short-Term Memory (LSTM) has gained considerable attention because of its capability to model nonlinear temporal dependencies in sequential datasets (Andromeda and Winarsih 2025; Khaira et al. 2020). Nevertheless, previous studies have primarily focused on climatic variables while giving limited attention to demographic factors such as population density, despite evidence suggesting that population density contributes to dengue transmission dynamics (Ayuningtyas 2023; Sari, Arlinda, and Nurhayati 2025). Furthermore, the incorporation of demographic variables, such as population density, together with climatic variables remains less extensively explored.

Therefore, this study compares the predictive performance of Long Short-Term Memory (LSTM) and Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) for monthly dengue forecasting in Sukabumi City using rainfall, temperature, humidity, and population density as predictor variables. Both models are developed using the same multivariate time-series dataset and evaluated using Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE), enabling an objective comparison of forecasting performance. The findings are expected to provide recommendations regarding the most appropriate forecasting approach for dengue surveillance while supporting data-driven decision-making in regional public health management.

Method

This study adopts the Cross-Industry Standard Process for Data Mining (CRISP-DM) as the research framework for developing and evaluating dengue forecasting models. CRISP-DM was selected because it provides a systematic and well-established methodology for data mining projects, covering the entire analytical process from problem identification to model evaluation. The framework consists of six sequential phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment (Kurniawan and Yasir 2022; Rianti, Majid, and Fauzi 2023). The overall research workflow is illustrated in Figure 1.

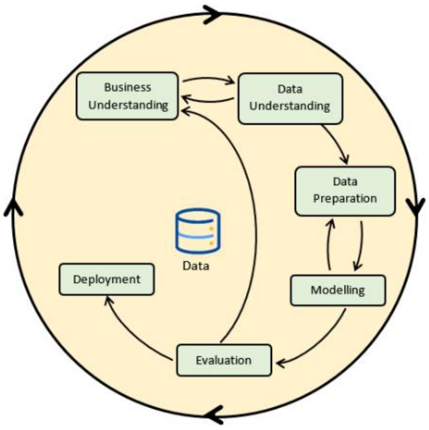

Figure 1. Tahapan CRISP-DM

Dataset

The dataset consists of 96 monthly observations collected from January 2018 to December 2025. The response variable is the monthly number of dengue fever cases reported in Sukabumi City. Four explanatory variables were incorporated into the forecasting models, namely rainfall, air temperature, relative humidity, and population density. Dengue case data were obtained from the Sukabumi City Health Office, while climate-related variables were collected from the Statistics Indonesia (BPS) Sukabumi City. Population density data were acquired from the Department of Population and Civil Registration of Sukabumi City. All variables were chronologically organized to construct a multivariate time-series dataset for both forecasting models.

Data Preparation

Data preprocessing involved several sequential procedures, including data quality assessment, missing value inspection, outlier detection, feature normalization, time-series sequence generation using the sliding window technique, and dataset partitioning. For the LSTM model, all predictor variables were normalized using the Min-Max Scaler to ensure comparable numerical ranges and improve neural network convergence during training (Khaira et al. 2020). Subsequently, sequential input data were generated using a three-month sliding window (time step = 3). Finally, the dataset was divided into 80% training data and 20% testing data, while preserving the chronological order to maintain the temporal characteristics of the time-series data.

Model Development

This study compares two forecasting approaches: Long Short-Term Memory (LSTM) and Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX). Both models were developed using the identical dataset to ensure a fair and objective performance comparison.

Long Short-Term Memory (LSTM)

The LSTM model was trained using normalized multivariate sequences with an input dimension of 3×5, representing three previous time steps and five variables for each observation. The network architecture consists of one LSTM layer, one Dropout layer, and one Dense output layer. To improve training stability and reduce overfitting, the model was optimized using the Adam optimizer and the Huber Loss objective function, while Early Stopping with a patience value of 20 epochs was applied during training. After the prediction process, all normalized outputs were transformed back to their original scale using inverse normalization before performance evaluation.

Table 1. Hyperparameter Configuration of the LSTM Model

Hyperparameter	Value
LSTM units	8
Dropout	0.2
Learning Rate	0.0005
Batch size	4
Epoch	200
Optimizer	Adam
Loss Function	Huber Loss
Early Stopping	Patience = 20
Validation Split	0.15

Seasonal ARIMA with Exogenous Variables (SARIMAX)

The SARIMAX model incorporates autoregressive, moving average, seasonal, and exogenous components simultaneously, enabling the model to capture temporal seasonality while accounting for external predictor variables (Hamzah et al. 2023). Unlike LSTM, the SARIMAX model was developed using the original dataset without normalization. The model incorporates four exogenous variables: rainfall, temperature, humidity, and population density, in addition to the historical dengue incidence data. The optimal SARIMAX configuration was determined using the Auto ARIMA procedure based on the Akaike Information Criterion (AIC). The selected configuration was ARIMA (1,0,0)(2,0,0)[12], which was subsequently used to construct the final SARIMAX forecasting model.

Model Evaluation

The predictive performance of both forecasting models was assessed using two commonly adopted error metrics: Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). MAE measures the average magnitude of prediction errors regardless of their direction, whereas MAPE expresses prediction errors as percentages, facilitating model comparison across different scales. Lower MAE and MAPE values indicate higher forecasting accuracy. These evaluation metrics served as the basis for determining the most suitable forecasting model for monthly dengue incidence prediction in Sukabumi City.

Results and discussions

Dataset Characteristics

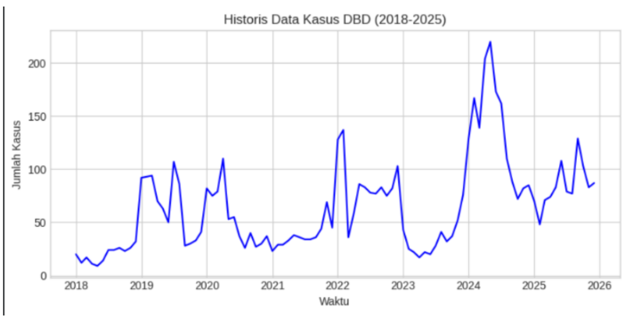

Figure 2. Historical Monthly Dengue Cases in Sukabumi City

The historical dengue dataset exhibits substantial temporal variability throughout the observation period. As illustrated in Figure 2, the monthly number of dengue cases demonstrates a pronounced seasonal pattern characterized by recurring increases and decreases across different periods. Several noticeable outbreak peaks are followed by rapid declines, indicating that dengue transmission is influenced by dynamic environmental and demographic conditions rather than remaining constant over time. Such characteristics justify the application of time-series forecasting models capable of capturing temporal dependencies.

Tabel 2. Descriptive Statistics of the Dataset

	curah_hujan	suhu	kelembaban	kepadatan	kasus
count	96.00	96.00	96.00	96.00	96.00
mean	764.53	24.04	87.55	7399.46	64.70
std	544.41	0.64	2.91	201.73	43.32
min	0.00	22.31	77.07	6995.00	9.00
25%	303.00	23.62	86.22	7269.00	30.00
50%	734.50	24.01	88.44	7366.50	54.00
75%	1094.25	24.50	89.47	7552.25	83.50
max	2740.00	25.45	91.44	7820.00	220.00

The descriptive statistics presented in Table 2 indicate considerable differences in the numerical ranges of the observed variables. Monthly dengue incidence exhibits the largest variability among all variables, whereas population density changes gradually throughout the observation period. These differences in measurement scales motivated the application of Min-Max normalization for the LSTM model, while SARIMAX utilized the original data values in accordance with its statistical assumptions.

Overall, the dataset demonstrates two important characteristics. First, the data contain a strong seasonal pattern, suggesting the presence of recurring temporal structures. Second, the relatively high variability in dengue incidence indicates that forecasting models must simultaneously capture seasonal behaviour and abrupt fluctuations to produce reliable predictions.

Data Preparation

Data preprocessing included missing value inspection, outlier detection, feature normalization, sequence generation using the sliding window technique, and chronological partitioning into training and testing datasets. The preprocessing results indicate that the dataset satisfied the requirements for time-series forecasting after these procedures were completed. For the LSTM model, all predictor variables were normalized using the Min-Max Scaler, ensuring that every feature shared a comparable numerical range during neural network training. Sequential samples were then generated using a three-month sliding window before the dataset was divided into 80% training and 20% testing subsets while maintaining temporal order.

Appropriate preprocessing is essential because prediction performance strongly depends on data quality. In particular, feature normalization improves convergence during neural network optimization, whereas the sliding window mechanism enables the LSTM model to learn temporal relationships from previous observations.

Model Performance

Forecasting Performance of the LSTM Model

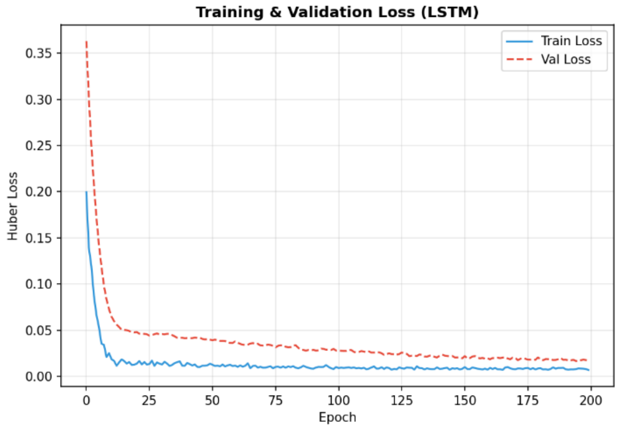

Figure 4. Training and Validation Loss of the LSTM Model

The LSTM model was trained using the normalized multivariate dataset. As shown in Figure 3, both the training loss and validation loss decreased steadily during the optimization process before converging to relatively stable values. The close agreement between both curves indicates that the model successfully learned the temporal characteristics of the dataset without exhibiting substantial overfitting. Furthermore, the implementation of Early Stopping prevented unnecessary training iterations once validation performance no longer improved.

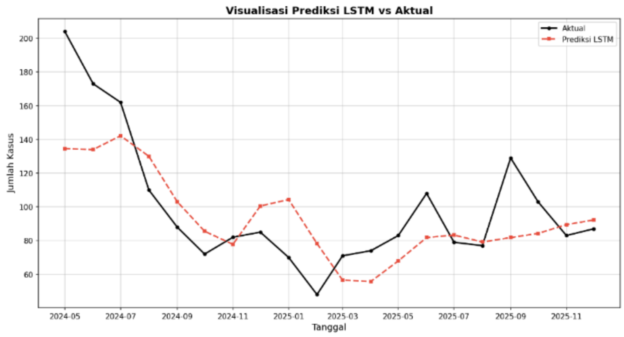

Figure 4. LSTM Forecasting Results

The forecasting results presented in Figure 4 demonstrate that the LSTM model successfully captures the overall temporal trend of monthly dengue incidence. Nevertheless, noticeable prediction deviations remain during periods with sharp increases or decreases in reported cases. This observation suggests that although LSTM effectively models temporal dependencies, its predictive capability becomes limited when representing highly fluctuating epidemiological data.

One possible explanation is the relatively limited dataset size, consisting of only 96 monthly observations. Deep learning models generally benefit from substantially larger datasets to learn complex nonlinear relationships. Consequently, despite employing the Adam optimizer, Huber Loss, and Early Stopping, the LSTM model was unable to fully capture all temporal variations observed in the historical dengue records.

Forecasting Performance of the SARIMAX Model

The SARIMAX model was developed using the optimal configuration identified through the Auto ARIMA procedure, namely ARIMA (1,0,0)(2,0,0)[12], combined with rainfall, temperature, humidity, and population density as exogenous variables.

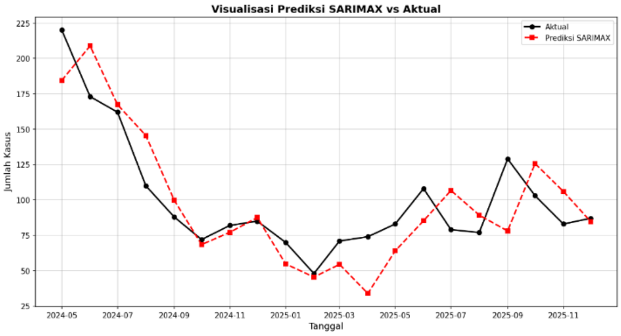

Figure 5. SARIMAX Forecasting Results

The forecasting results illustrated in Figure 5 indicate that SARIMAX closely follows the observed dengue incidence throughout the testing period. Compared with the LSTM model, the predicted values remain consistently closer to the actual observations, resulting in relatively smaller forecasting errors.

These findings suggest that integrating autoregressive components, seasonal structures, and exogenous variables enables SARIMAX to effectively represent the temporal behaviour of dengue incidence. For datasets characterized by strong seasonality and relatively limited observations, statistical forecasting approaches remain highly competitive and capable of producing stable predictions.

Performance Comparison

The quantitative comparison between the two forecasting models is summarized in Table 3.

Table 3. Comparison of Forecasting Performance

Model	MAE	MAPE (%)
LSTM	20.96	21.13
SARIMAX	19.50	19.54

Based on the evaluation results, SARIMAX achieved lower MAE and MAPE values than LSTM, indicating superior forecasting accuracy for the dataset used in this study. The visual comparison shown in Figure 6 further confirms that the SARIMAX predictions consistently align more closely with the observed dengue cases than those generated by the LSTM model.

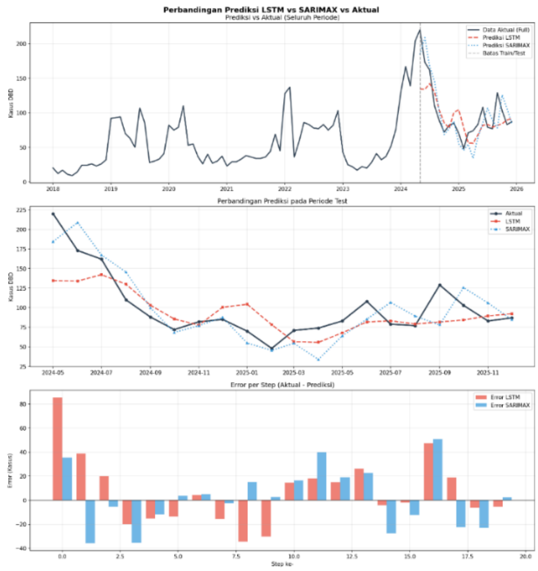

Figure 6. Comparison between LSTM and SARIMAX Forecasts

The results indicate that forecasting performance is strongly influenced by dataset characteristics rather than model complexity alone. Although LSTM possesses the capability to learn nonlinear temporal relationships, its effectiveness is constrained when only a limited number of observations are available. In contrast, SARIMAX explicitly models seasonality and incorporates exogenous variables, allowing it to produce more accurate predictions for the monthly dengue incidence dataset analyzed in this study.

Conclusion

This study compared the forecasting performance of Long Short-Term Memory (LSTM) and Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) for predicting monthly dengue incidence in Sukabumi City using rainfall, temperature, humidity, and population density as explanatory variables.

The experimental results indicate that SARIMAX achieved superior predictive performance, with an MAE of 19.50 and a MAPE of 19.54%, outperforming the LSTM model, which obtained an MAE of 20.96 and a MAPE of 21.13%. These findings demonstrate that SARIMAX is more effective in modelling monthly dengue incidence characterized by pronounced seasonal patterns and a relatively limited number of observations.

Although LSTM is capable of learning nonlinear temporal relationships, its performance was constrained by the size and characteristics of the available dataset. In contrast, SARIMAX successfully captured both seasonal behaviour and the influence of exogenous variables, resulting in more accurate and stable forecasting performance. The findings of this study provide practical evidence that statistical time-series models remain highly effective for dengue forecasting when historical observations are limited but exhibit clear seasonal characteristics. The developed forecasting models may serve as decision-support tools for local public health authorities in planning dengue surveillance and implementing preventive intervention strategies.

Future research may evaluate longer observation periods, incorporate additional environmental and socioeconomic variables, or investigate hybrid forecasting approaches that combine statistical and deep learning techniques to further improve prediction accuracy.

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