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Enhancing Weather Forecasting in Bandar Lampung: A Hybrid SARIMA-LSTM Approach

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ABSTRACT

Indonesia's tropical climate, marked by rainy and dry seasons, is increasingly affected by extreme weather events driven by climate change. Rising temperatures, shifting rainfall patterns, and sea-level rise have intensified health risks such as malaria, dengue hemorrhagic fever (DHF), and gastrointestinal infections. Accurate weather forecasting is essential for mitigating these challenges and informing risk management strategies. This study develops and evaluates a hybrid SARIMA-LSTM model for weather forecasting in Bandar Lampung, integrating time series analysis with deep learning to enhance predictive accuracy. SARIMA captures seasonal variations, while LSTM models nonlinear relationships, offering a robust approach to forecasting complex weather patterns. The SARIMA $(6,1,0)(3,1,0)_{26}$ model was selected for its effective seasonal representation and combined with LSTM to leverage its capability in modelling nonlinear dependencies. Hyperparameter optimization using grid search further improved model performance. Two data partitioning approaches were tested: 70%-30% and 80%-20% splits for training and testing, respectively. The SARIMA-LSTM hybrid model demonstrated superior performance with the 80%-20% split, achieving MSE, RMSE, and MAPE values of 0.1174, 0.3426, and 0.0104%, respectively. The model accurately forecasted weather conditions over 21 weeks, aligning closely with observed trends and effectively capturing seasonal patterns. These findings underscore the model's potential to support public health strategies, including disease outbreak mitigation for malaria and DHF, and enhance disaster preparedness in flood-prone areas.

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A. INTRODUCTION

Indonesia, known for its tropical climate and distinct seasons, has witnessed significant weather fluctuations attributed to climate change (M. Rizki et al., 2020). These changes encompass higher temperatures, altered rainfall patterns, rising sea levels, forest fires, droughts, and floods (Abbass et al., 2022; Ainurrohmah & Sudarti, 2022; Kulkarni et al., 2022; Lipczynska-Kochany, 2018; Michel et al., 2021; Murshed & Dao, 2022; Rocque et al., 2021). In Bandar Lampung City, climate change has notably increased the frequency of flood events. According to Kurniadi et al. (2020), seasonal flooding occurs almost annually, resulting in significant losses. Flood-prone areas demand targeted interventions, urging residents and local authorities to adopt proactive measures for prevention. Over the past decade, BNPB recorded 16 flooding incidents in Bandar Lampung, affecting 14,000 individuals, displacing over 500 people, damaging more than 900 homes, and impacting four public facilities.

Climate change has had a profound impact on public health, contributing to increased incidences of diseases such as malaria, Dengue Fever (DF), and gastrointestinal infections

(Ahmed et al., 2020; Fatmawati & Sulistyawati, 2019; Kaseya et al., 2024). These diseases thrive in environments affected by unpredictable weather patterns, creating favourable conditions for spreading and transmitting illnesses. The incidence of dengue, malaria, and diarrhoea in Bandar Lampung has demonstrated notable annual fluctuations. Dengue cases rose from 829 in 2017 to 1,198 in 2019, while diarrhoea cases increased from 18,136 in 2017 to 22,304 in 2019, reflecting a substantial rise. Conversely, malaria cases declined significantly from 932 in 2017 to 376 in 2019. Despite a marked decrease in 2022, with reported cases of dengue at 1, diarrhoea at 4, and malaria at 250, a resurgence has since occurred. Recent data from the Badan Pusat Statistik (2023) indicate 202 cases of dengue, 5,767 cases of diarrhoea, and 230 cases of malaria, underscoring the increasing variability and unpredictability of these diseases over time.

The two phenomena—floods and disease endemics—represent just a fraction of the broader impacts of weather changes in Bandar Lampung. Accurate weather forecasting is crucial for mitigating risks associated with extreme weather, providing vital support to governments and local communities. BMKG currently offers public services such as 3-day extreme weather forecasts, same-day alerts, and notifications for events expected within 2-3 hours (Nurpambudi & Aziz, 2023). These services present opportunities for improvement, enabling the daily dissemination of weather information. This study aims to develop long-term weather forecasts for Bandar Lampung.

Unfortunately, accurate weather forecasting is crucial in helping the government and the community manage risks associated with extreme weather events. Weather forecasting continues to pose a worldwide challenge owing to its inherent unpredictability and the complexities involved in time series forecasting (Kumar & Jha, 2013; Mung & Phyu, 2023). Time series forecasting, a field within predictive analytics, anticipates future values of a variable based on historical data or observations (Sandhya Arora, Milind Kolambe, 2024). Time series data are characterized by four main patterns: constant (horizontal), trend, cyclical, and seasonal (Nurfadila & Ilham Aksan, 2020). Weather data commonly exhibit seasonal patterns.

Time series data often contain both linear and nonlinear elements, yet neither linear nor nonlinear models fully capture the information within (Zhao et al., 2023). Consequently, researchers have proposed integrated models that incorporate both components. Linear models, such as the Seasonal Autoregressive Moving Average (SARIMA), are designed to identify and represent recurring seasonal patterns in data, including weekly, monthly, or annual cycles (Kumari & Muthulakshmi, 2024). SARIMA utilizes statistical methods to forecast future values by analyzing historical seasonal trends. Its primary strength lies in generating accurate short-term forecasts, assuming seasonal patterns will persist. However, SARIMA's effectiveness diminishes in long-term predictions, as seasonal trends may change over time, leaving residuals with nonlinear elements that are inadequately addressed (D. C. W. Wu et al., 2021).

In contrast, Deep Learning (DL) models like Long Short-Term Memory (LSTM) are adept at capturing nonlinear patterns and long-term dependencies in time series data. LSTM utilizes a feedback mechanism and memory components to learn complex temporal relationships effectively (Ni et al., 2020). This capability enables LSTMs to overcome challenges faced by SARIMA, particularly in long-term forecasting involving nonlinear patterns without seasonal repetition (Y. Wu et al., 2024). However, LSTMs present certain drawbacks, including extended processing times and high computational demands due to their complexity. This study combines SARIMA and LSTM to capitalize on the strengths of both methods, addressing their respective limitations. While SARIMA excels at identifying seasonal patterns, LSTM is more adept at capturing nonlinear relationships that SARIMA may miss. The integrated model aims to improve the accuracy and reliability of time series forecasts, particularly for weather data.

A previous study by Sun et al. (2020) combines SARIMA and LSTM models to forecast sea level changes caused by extreme weather events. The SARIMA model addresses linear data trends, while LSTM captures nonlinear patterns. Their study decomposes sea level anomalies (SLAs) into seasonal and random components, with SARIMA predicting the seasonal trends and LSTM forecasting the random elements. Using sea level data from 1993 to 2018, the SARIMA+LSTM model outperforms other models, achieving a minimum mean square error of 1.155 cm and a maximum R^2 of 0.89. The predicted outcomes align with SLA data, demonstrating the model's effectiveness in estimating sea level variability. Li & Yang (2023) proposed a hybrid model that integrates SARIMA and LSTM to improve air temperature forecasting accuracy. The model decomposes the temperature data into trend, seasonal, and residual components using the Loess technique. SARIMA handles the trend and seasonal components, capturing linear patterns, while LSTM models focus on the residuals to detect nonlinear patterns. This combination has demonstrated a 10.0–27.7% improvement in accuracy over other individual and hybrid models, as evaluated using metrics such as RMSE, MAPE, MAE, and the Kupiec index.

Amougou et al. (2024) developed a SARIMA-LSTM model to forecast climate change in the Sudo-Sahelian region of Cameroon, aimed at aiding climate adaptation strategy formulation. The model integrates two climate datasets—temperature and precipitation—derived from both in-situ measurements and spatial grid data. Using machine learning, the data were processed to create mathematical equations that capture the climate system's dynamics, enhancing forecasting accuracy for future climate scenarios and supporting adaptation planning. The results show that the SARIMA-LSTM model outperforms the standalone LSTM model, achieving a Mean Squared Error (MSE) of 0.19, compared to 0.31 for the latter.

Numerous studies demonstrate that integrating SARIMA and LSTM models enhances prediction accuracy and forecasting performance. However, their application in weather forecasting, particularly in tropical regions like Bandar Lampung, Indonesia, remains limited and underexplored. This study aims to fill this gap by developing a SARIMA-LSTM model tailored for weather forecasting in Bandar Lampung, focusing on improving prediction precision and aligning with local climate conditions. Additionally, the research explores enhancing public health strategies in Bandar Lampung, with a focus on dengue prevention and strengthening disaster preparedness in flood-prone areas.

B. RESEARCH METHODS

This study utilized two different methods for dividing the data: one allocated 70% for training and 30% for testing, while the other adopted an 80% training and 20% testing split. Hyperparameter tuning was implemented to enhance the model's performance. The optimized model's effectiveness was assessed using metrics like MSE, RMSE, and MAPE. Constructing the forecasting model encompassed data pre-processing, forecasting with the SARIMA model, employing the hybrid SARIMA-LSTM model for forecasting, and evaluating the model. Section 2 provides comprehensive descriptions of each of these steps.

1. Data Input

The data utilized in this research consists of daily weather information obtained from the BMKG website at http://dataonline.bmkg.go.id/home. The dataset includes 4,746 observations collected over 13 years from the Maritime Meteorology Station in Panjang, Tanjung Karang, Kota Bandar Lampung. It encompasses nine variables: minimum temperature, maximum temperature, average temperature, minimum humidity, rainfall, sunshine duration, maximum wind speed, maximum wind direction, and minimum wind speed. However, this study focuses specifically on one variable that exhibits seasonal patterns: the Daily Minimum Temperature (Tn). The selection of this variable aligns with the application of SARIMA, which is a univariate approach.

2. Data Pre-processing

Data pre-processing, or preparation, involves cleaning, transforming, and organizing raw data before analysis. This phase is critical as many forecasting techniques depend on assumptions about the data's characteristics (Meisenbacher et al., 2022). This study's pre-processing includes cleaning the data by addressing missing values and converting daily time series into weekly patterns. Missing values in time series data can arise from factors such as human error, technical issues, or equipment failures. Imputation is a standard method for handling these gaps, where missing values are estimated based on recent or historical data. This technique fills in missing values using information from adjacent time points (Petrusevich, 2021). Another method, interpolation, estimates missing values by averaging between nearby data points (Khattab et al., 2023). Both methods can be effective, but the choice should depend on the time series characteristics and the analysis objective (Liao et al., 2022). This study employs imputation techniques due to their versatility in handling both numerical and categorical data. Imputation estimates missing values using statistical or DL methods, aligning with the approach used here. In contrast, interpolation derives values based on mathematical relationships within the existing dataset. The chosen method significantly influences model outcomes, impacting both precision and reliability. Therefore, selecting the appropriate technique is crucial for ensuring the quality of the analysis and the accuracy of model predictions.

3. SARIMA Model

SARIMA, an advancement of ARIMA, is designed to analyze time series data with seasonal patterns (Chen et al., 2018). This method is renowned for its high accuracy in short-term forecasting. It employs two types of orders: non-seasonal, denoted as (p, d, q), and seasonal, represented as (P, D, Q, s). The non-seasonal order includes Autoregressive (AR) parameters, differencing level (d), and Moving Average (MA) parameters. The seasonal order extends these by incorporating seasonal AR (P), seasonal differencing (D), seasonal MA (Q), and periodicity (s). The seasonal differencing parameter (D) is an integer indicating the level of seasonal integration, while P and Q denote the seasonal lag for AR and MA. These values may be fixed or iterative, depending on the relevant seasonal lag (M. I. Rizki & Taqiyyuddin, 2021; Sirisha et al., 2022). The selection of SARIMA parameters was based on analyzing the time series data's patterns and characteristics. Non-seasonal parameters (p, d, q) were chosen to model the linear relationship (p), ensure stationarity (d), and address noise (q), identified through PACF and ACF graphs. Seasonal parameters (P, D, Q, s) were used to capture seasonal patterns (P), remove non-stationary seasonal trends (D), manage seasonal noise (Q), and define the seasonal period length (s) tailored to the data's characteristics.

a. Testing Stationarity

Before making predictions using the SARIMA model, it is crucial to verify that the data meets the assumption of stationarity, indicating stability without significant changes (Makridakis, S., Wheelwright S.C, 2017). That is important because many statistical forecasting methods assume time series are stationary, while those with trends or seasonal patterns are non-stationary due to changes in mean, variance, or both over time. Thus, appropriate transformations are necessary when applying these methods to non-stationary data (Meisenbacher et al., 2022). The stationarity of a time series can be assessed using the Augmented Dickey-Fuller (ADF) test, which determines whether a time series is stationary or non-stationary by examining the presence of a unit root. This test compares the current value with the series mean: if above the mean, the series tends to decrease; if below, it tends to increase (Ensafi et al., 2022). **Equation (1)** illustrates these changes, where μ is a constant, β is the coefficient on the time trend, k is the lag order of the autoregressive process, and $\Delta y(t)$ is defined as:

$$\Delta y(t) = \lambda y(t-1) + \mu + \beta t + \alpha_1 \Delta y(t-1) \pm \ldots + \alpha_k \Delta y(t-k) \quad (1)$$

The null hypothesis posits that the time series is non-stationary ($\lambda = 0$). Rejecting this hypothesis indicates that future movements ($\Delta y(\ t)$) are not purely random but depend on the current level, implying that the time series is stationary.

b. Differencing

Non-stationary data can be converted into stationary data through a differencing procedure. Differencing involves computing the disparity between data at one time period (Z_t) and the preceding period (Z_{t-1}), as illustrated in **Equation (2)**.

$$\Delta Z_t = (1 - B) Z_t \quad (2)$$

With Z_t represents the data post-first-order differencing, and notation B denoting the backward shift operator. This procedure ($\Delta \mathrm{Z_t}$) can be iterated up to n times until the data achieves stationarity (Makridakis, S., Wheelwright S.C, 2017). The equation for n-th order differencing can be defined by **Equation (3)**.

$$\Delta^n Z_t = (1 - B)^n Z_t \,, \quad n \geq 1 \quad (3)$$

c. SARIMA Model Forecasting

In this stage, stationary data are used to build an initial model by assessing the value of each parameter. The values of p and P are identified from the Autocorrelation Function (ACF) plot, while q and Q are observed from the Partial Autocorrelation Function (PACF) plot. Next, the preliminary SARIMA model undergoes parameter estimation, examining the significance of parameters and model diagnostics. A model is considered satisfactory if it exhibits characteristics of white noise and conforms to a normal distribution. White noise is a condition where residuals lack correlation, detected through autocorrelation tests during residual analysis (Wei, 2006). A model passes the white noise test if its residuals are random, indicating no autocorrelation or discernible patterns. **Equation (4)** illustrates the statistical test using the Ljung-Box test to identify autocorrelation within a model (Montgomery et al., 2012):

$$LB = n(n+2)\sum_{k=1}^{m}\frac{r_k}{n-k} \tag{4}$$

Meanwhile, the normality or residual distribution test evaluates whether residuals adhere to a normal distribution based on the collected data. The normality of residuals can be evaluated using the Kolmogorov-Smirnov test, as described in **Equation (5)** (Montgomery et al., 2012):

$$D = KS = max|F_0(X) - S_n(X)| \tag{5}$$

If multiple SARIMA models meet the criteria for parameter estimation, Akaike Information Criterion (AIC) values are then examined to assess model suitability. The SARIMA model with the lowest AIC value is considered the most suitable for forecasting purposes.

4. LSTM Model

Long Short-Term Memory (LSTM) is an advancement of the RNN model that has proven effective in tasks such as classification, processing, and prediction of unknown functional relationships within time series data (Yadav et al., 2020). The LSTM architecture typically includes a memory cell, an input gate, an output gate, and a forget gate. Each gate plays a specific role in determining which information to discard, retain, or incorporate into the model. In forecasting, LSTM aims to produce precise predictions with minimal errors (Wiranda & Sadikin, 2019). It achieves this by sequentially processing input data through its hidden layers, producing more accurate outputs (Farhah et al., 2021).

a. Data Normalization

Data normalization aims to decrease excessive variability, improve overall model performance, and reduce learning errors by mapping data values to a defined interval (Lattifia et al., 2022). In this research, the Min-Max Scaler method will be utilized, which is recognized as one of the most commonly employed scaling algorithms. This approach normalizes data by linearly transforming data values onto a scale ranging from 0 to 1, ensuring a uniform range of values across datasets (Larose & Larose, 2014). The normalized value X_n of the actual data X_0 can be computed using **Equation (6)**:

$$X_n = \frac{X_0 - X_{min}}{X_{max} - X_{min}} \tag{6}$$

b. Data Splitting
The data earmarked for LSTM processing will be split into training and testing sets, with a more significant portion allocated to training. The training set is used to construct and refine the LSTM model by identifying patterns in historical data. In contrast, the testing set evaluates the performance of the LSTM model after training. According to Nurhopipah & Hasanah (2020), the data distribution ratio significantly influences forecasting models' performance. Therefore, two distribution schemes will be employed to achieve optimal models. The first scheme divides the data into 70% for training and 30% for testing, while the second scheme allocates 80% for training and 20% for testing.

c. LSTM Model Forecasting
This study develops two LSTM models: the first uses SARIMA prediction data, while the second uses SARIMA residual data. Each model is tested using two different data partitioning schemes, resulting in four LSTM models. Determining the appropriate hyperparameters is essential before initiating model training to ensure optimal results. Hyperparameters are values that must be set prior to training (Yang & Shami, 2020). Hyperparameter tuning involves selecting the ideal model architecture by testing various combinations of hyperparameters. One practical approach for this is the Grid Search method (George & Sumathi, 2020), which systematically evaluates all predefined hyperparameter combinations in a grid. This method works by assessing the performance of different value combinations within the model (Belete & Huchaiah, 2022). The hyperparameters in this study include those used to configure the LSTM model, such as the LSTM units and batch size. The optimal model is constructed using the selected hyperparameter combination, which is then applied to generate weather forecasts.

5. Hybrid SARIMA-LSTM

The hybrid model marks a step forward by merging two or more individual methods in modelling. It aims to address nonlinear data that SARIMA finds challenging to handle to enhance accuracy (Rowan et al., 2022). The SARIMA-LSTM hybrid model integrates SARIMA's predictive data with LSTM and SARIMA's residual data with LSTM. Generally, the integration of time series models with linear and nonlinear autocorrelation structures is described according to **Equation (7)** (Zhang, 2003).

$$Z_t = L_t + N_t \tag{7}$$

6. Model Evaluation

Model evaluation assesses the precision of predictions by comparing predicted values against observed or actual values (Chen et al., 2018). The quality of predictions is assessed based on their level of accuracy; lower error rates indicate the best predictive accuracy. This study employs various metrics for model evaluation, which include:

a. MAPE: Measures the percentage of prediction errors by calculating the absolute mean difference between actual and predicted values relative to the actual data. A model with a MAPE <10% is considered excellent, indicating minimal error compared to the actual data.
b. MSE: Evaluates the mean prediction error by squaring the differences between actual and predicted values, then averaging them over the data set. A lower MSE indicates more minor prediction errors, suggesting better pattern capture by the model.
c. RMSE: The square root of MSE, which expresses prediction error in the same units as the original data. A lower RMSE indicates predictions that closely align with actual values.

Model performance was assessed by comparing MAPE, MSE, and RMSE values. Models with MAPE below 10% and MSE and RMSE values near zero demonstrate superior performance in capturing data patterns.

C. RESULT AND DISCUSSION

1. Data Input

The initial step includes importing data into Python version 3.0 using the pandas library. The research dataset is stored as a .csv file within the Python directory, containing daily weather data for Bandar Lampung City. The dataset consists of 4746 entries and nine columns, with the minimum temperature (Tn) column designated for analysis.

2. Data Pre-processing

This stage is designed to prepare the data for more efficient analysis. It begins with identifying and addressing missing values by imputing them using historical data, leveraging a DL model for the imputation process. Once the missing values are handled, the next step is to transform the daily minimum temperature data into weekly data using the function resample ('W').min(). This function calculates the minimum value for each week, from Monday to Sunday. As a result, the research dataset spans from January 4, 2010, to January 1, 2023. A comparison of the input data before and after the pre-processing stage is outlined in Table 1.

Table 1. Comparison of Input Data Pre and Post-preprocessing

Pre		Post	
Date	**Minimum**	**Date**	**Minimum**
04/1/2010	21,0	10/1/2010	19,0
05/1/2010	21,0	17/1/2010	18,0
06/1/2010	21,0	24/1/2010	18,0
07/1/2010	24,0	31/1/2010	19,0
08/1/2010	21,0	07/2/2010	20,0
...	...	...	...

Pre		Post	
Date	**Minimum**	**Date**	**Minimum**
30/12/2022	25,5	18/12/2022	24,4
31/12/2022	24,8	25/12/2022	23,5
01/1/2023	24,2	01/01/2023	24,0

After transforming the data into weekly patterns, the original dataset containing 4746 entries was condensed to 678. This subset was then depicted in a time series plot to visualize the variations in Bandar Lampung's minimum temperature data. Figure 1 presents a decomposition chart of the weekly minimum temperatures, emphasizing seasonal fluctuations.

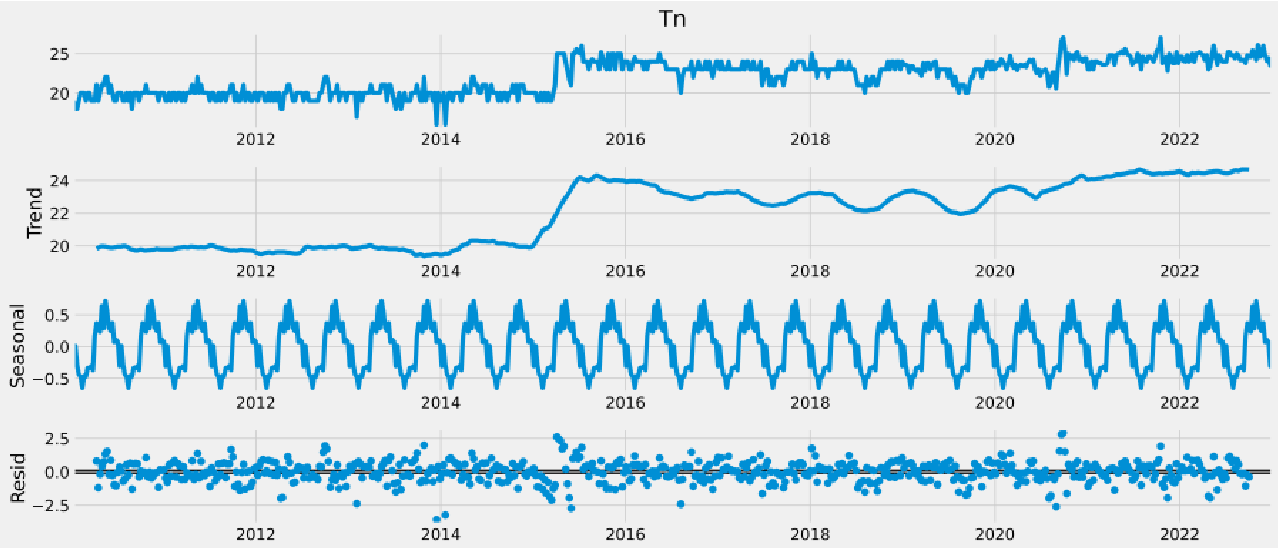
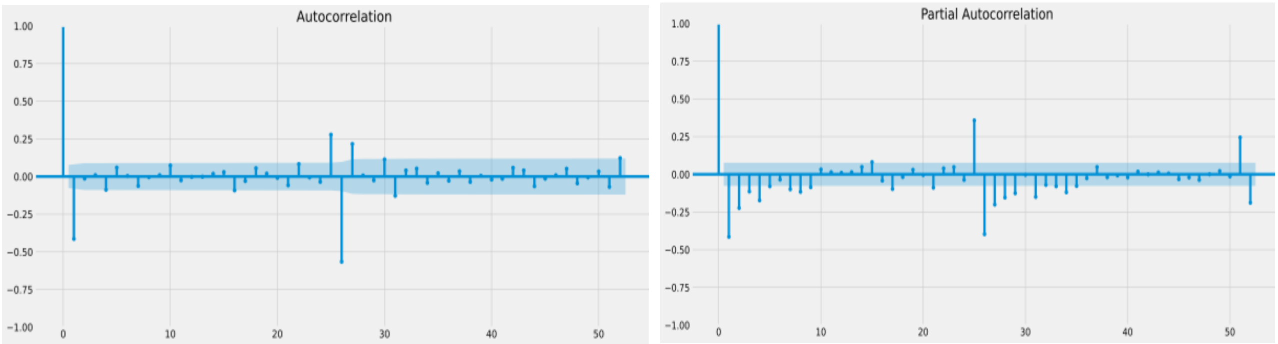


Figure 1. Weekly minimum temperature decomposition graph

3. SARIMA Model

The research findings show that the data does not meet the stationarity assumption due to mean, variance, or both changes across the seasonal pattern over time. Therefore, a differencing procedure is necessary for two specific components: the non-seasonal and seasonal components. After applying the differencing procedure, the resulting parameter values are d = 1 for the non-seasonal lag and D = 1 for the seasonal lag. The subsequent stage includes identifying the SARIMA model by examining the PACF and ACF plots depicted in Figure 2. The PACF plot is used to identify both the non-seasonal and seasonal AR orders, while the ACF plot is employed to determine the non-seasonal and seasonal MA orders.

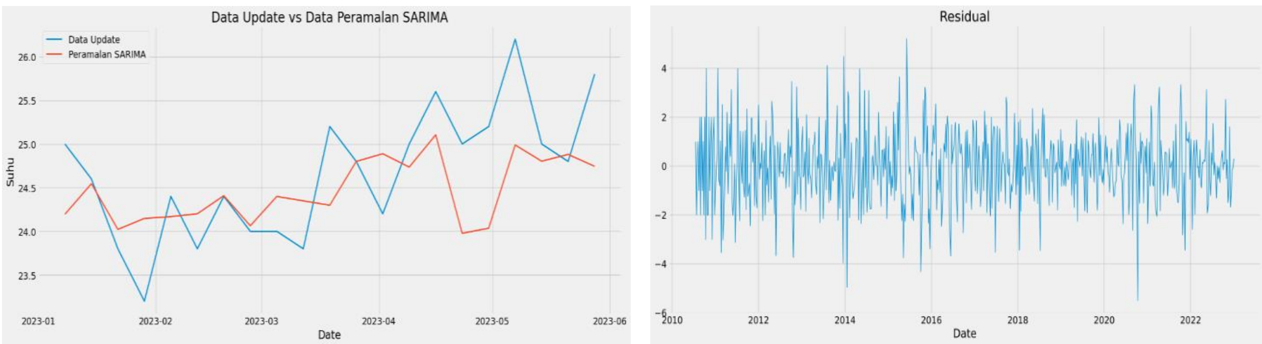
Based on the PACF and ACF plots illustrated in Figure 2, a preliminary model is formulated, which will later be assessed for the significance of its parameters and the overall feasibility of the model. An effective model is defined by residuals that demonstrate randomness and do not reveal any identifiable pattern. The results of the model parameter estimation produced 18 models that met the criteria of both the significance test and the white noise test, thus demonstrating that these models are adequate for predicting time series data. In order to ascertain the most optimal model, our focus was directed towards identifying the minimum value of the Akaike Information Criterion (AIC). The SARIMA model defined by the parameter configuration (6,1,0) $(3,1,0)_{26}$ was determined to be the optimal model based on its lowest AIC value compared to other models, suggesting a favorable balance between precision and complexity. The model with the lowest Akaike Information Criterion (AIC) is considered more effective, as it reduces the risk of overfitting by appropriately balancing complexity and retaining critical information in the dataset, as shown in Figure 2.



(a) (b)

Figure 2. Identification of SARIMA model using (a) PACF plot and (b) ACF plot

Forecasts generated by this SARIMA model will be utilized to predict outcomes for the next 21 weeks. After aggregating daily data into weekly summaries, these forecast results will be juxtaposed with the most recent data on weekly minimum temperatures sourced from the BMKG website. This graphical representation can be seen in Figure 3 (a). Figure 3 (a) illustrates that the SARIMA model's forecasts do not align with the observed data patterns. This discrepancy may arise from various factors, including the model's inability to capture seasonal variations beyond its fixed seasonal components and trends or its failure to account for more complex data fluctuations. Additionally, the SARIMA model may struggle to adapt to sudden structural changes or anomalies in recent data, such as irregular events or external influences affecting the data. Therefore, extracting the residuals of the SARIMA model by calculating the difference between the observed and predicted values is crucial. These residuals are visualized in Figure 3 (b).



(a) (b)

Figure 3. Results of the SARIMA model for (a) forecasting, and (b) residual

Figure 3 (b) illustrates that the residual plot exhibits a systematic pattern, suggesting that the SARIMA model fails to capture crucial data features, such as seasonal variations or unforeseen fluctuations. This highlights the need for integrating DL models to address the more complex dynamics and variations that SARIMA cannot account for.

4. Hybrid SARIMA-LSTM Model

At this stage, the forecasts and residual outputs from the SARIMA model are employed as inputs for the LSTM model. Before additional processing, both datasets undergo normalization using the Min-Max method and are divided according to predefined schemes. The first scheme allocates 403 data points for training and 144 for testing, while the second assigns 468 data points for training and 79 for testing. The data splitting significantly impacts the model's performance, particularly in terms of generalization and overfitting risks. The first schema, with limited training data, may lead to underfitting, as the model struggles to learn effectively from the data, hindering its ability to generalize and resulting in less accurate test predictions. Conversely, the second schema, with more training data, risks overfitting, where the model overly adapts to the training set, including noise and irrelevant variations, compromising its generalization ability on new test data. Furthermore, hyperparameter tuning procedures determine the numbers of LSTM units and batch sizes to attain an optimal model. The most influential parameter combinations identified for each dataset input are outlined in Table 2.

Table 2. Best Combination of LSTM Model Parameters

Data	Parameter	Splitting Data Schemes	
		First	Second
SARIMA Prediction	LSTM unit	16	16
	Batch size	8	8
SARIMA Residual	LSTM unit	64	128
	Batch size	16	16

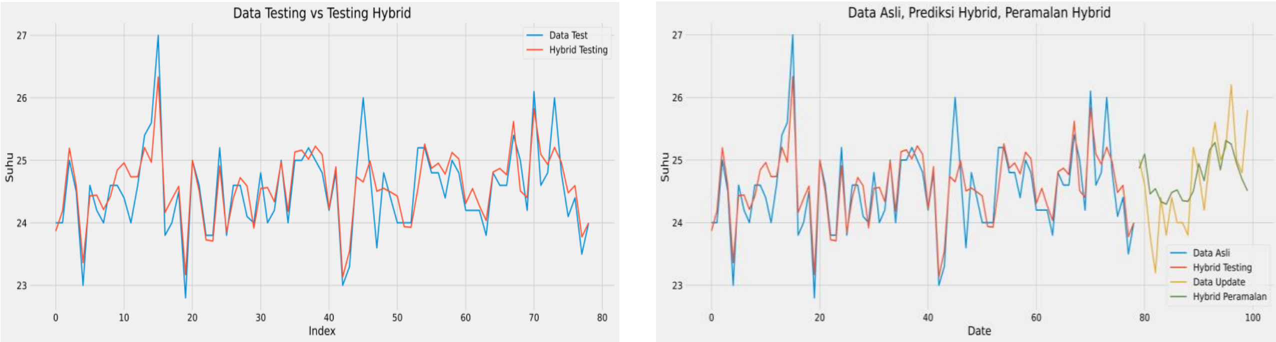
These parameters are combined to build an LSTM model, which inputs predictive and residual data. Predictions from both models are then integrated across each data partitioning scheme employed. Additionally, performance evaluations are carried out using MSE, RMSE, and MAPE metrics on the testing data to gauge the model's effectiveness. The assessment outcomes of the hybrid SARIMA-LSTM model are detailed in Table 3.

Table 3. Model Evaluation

Evaluation Metrics	Splitting Data Schemes	
	First	Second
MSE	1,5909	0,1174
RMSE	1,2613	0,3426
MAPE	0,0374%	0,0104%
Accuracy	99,9626%	99,9896%

Based on the analysis of the models detailed in Table 3, it can be inferred that the hybrid model employing the second scheme, with 80% of the data allocated for training and 20% for testing, exhibits better performance in forecasting weather over the next 21 weeks compared to the first scheme. That is evident from the lower MSE, RMSE, and MAPE values and higher accuracy rates. The forecasting outcomes using this scheme are depicted in Figure 4 (a) and (b). Based on Figure 4 (a), predictions made by the SARIMA-LSTM hybrid model show a robust ability to follow recent data trends. That suggests that the SARIMA-LSTM model effectively predicts weather patterns in Bandar Lampung over the next 21 weeks. Furthermore, Figure 4

(b) illustrates that the SARIMA-LSTM model provides precise forecasts that closely match the latest data trends. Given that these accurate forecasts align closely with current data trends, this model can significantly assist in planning and decision-making related to weather factors in the Bandar Lampung area.



(a) (b)

Figure 4. Results of the hybrid SARIMA-LSTM model for (a) predicion, and (b) forecasting

5. Comparison of SARIMA Model and SARIMA-LSTM Hybrid Model

The comparative performance of the SARIMA and SARIMA-LSTM models in terms of long-term forecasting capability and prediction accuracy reveals the distinct advantages of the hybrid approach. While the SARIMA model excels at capturing seasonal patterns and trends in time series data, it is less effective at forecasting data with complex dynamics or irregular fluctuations, such as those stemming from erratic seasonal changes. As shown in Figure 3, the SARIMA model captures specific patterns, but inconsistencies remain in its predictions, particularly with the most recent data, which may compromise long-term prediction accuracy.

In contrast, the SARIMA-LSTM hybrid model addresses these limitations by incorporating residuals as additional input for the LSTM component. These residuals, representing data components unexplained by SARIMA, provide valuable supplementary information for the LSTM, enhancing its capacity to model complex data fluctuations. This is reflected in the results in Table 3, where the MSE, RMSE, and MAPE values of the SARIMA-LSTM model are significantly lower than those of the SARIMA model, demonstrating a reduction in error rates and improved prediction accuracy. Moreover, the hybrid model’s integration of statistical and DL techniques enables it to handle non-stationary data dynamics and capture intricate patterns that SARIMA alone cannot. Through optimal normalization and data sharing, this model mitigates issues of overfitting and underfitting, which are common in time series forecasting. Overall, the SARIMA-LSTM hybrid model provides more accurate and dependable long-term predictions, positioning it as a superior method for forecasting dynamic weather patterns in Bandar Lampung.

D. CONCLUSION AND SUGGESTIONS

The SARIMA-LSTM hybrid model has proven effective for weather forecasting in Bandar Lampung, particularly for seasonal data like minimum temperatures. The SARIMA model, configured as ARIMA $(6,1,0)(3,1,0)_{26}$, initially predicts weather, and the residuals are processed further by LSTM. The LSTM model is optimized through hypertuning to identify the best unit parameters and batch sizes, ensuring optimal performance. An experiment with two data split schemes revealed that an 80%-20% training-testing ratio outperformed the 70%-30% split, likely due to a more stable data distribution and enhanced model capacity to understand complex patterns with larger training sets. With an MSE of 0.1174, RMSE of 0.3426, and MAPE of 0.0104%, the SARIMA-LSTM hybrid model achieved high accuracy. Predictions for the next 21 weeks demonstrated consistency with recent data, highlighting the model's capacity to capture seasonal patterns and adjust to emerging trends. This model shows promise for real-world applications in Bandar Lampung, such as preventing dengue outbreaks and improving disaster preparedness in flood-prone areas. However, further development is necessary to handle more complex data variations, such as extreme weather. Future research could explore ensemble learning or other DL models tailored to non-stationary or unpredictable seasonal changes.

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