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Weather Prediction Using CNN-LSTM-Based AI for Weather Pattern Analysis in Banten Province

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Abstract: Weather variability in Banten Province poses challenges across various sectors, including community activities, agriculture, and disaster preparedness, necessitating accurate weather prediction methods. This study proposes a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model to predict air temperature and rainfall based on historical weather time-series data. The dataset was obtained from the Open-Meteo API and BMKG for the observation period from January 2019 to May 2024. Input variables include air temperature, rainfall, wind speed, Sea Surface Temperature anomaly, and the El Niño–Southern Oscillation (ENSO) index. The data preprocessing stages involve data cleaning, normalization using Robust Scaler, and the construction of data sequences using the sliding window method prior to the model training process. Model performance was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), and compared against baseline models. The experimental results demonstrate that the CNN-LSTM model achieves an MAE of 0.60°C and an RMSE of 0.73°C for air temperature prediction, and an MAE of 6.15 mm and an RMSE of 8.31 mm for rainfall prediction. The prediction outcomes were subsequently integrated into a web-based dashboard to facilitate information visualization. Initial validation against BMKG observation data in South Tangerang showed a relatively low temperature deviation during the testing period. These findings confirm that the proposed approach has adequate potential to support short-term weather prediction systems in Banten Province.

Keywords: Weather Prediction, CNN-LSTM, Deep Learning, Robust Scaler, Time-Series Forecasting.

1. Introduction

Weather conditions have become increasingly difficult to predict and are often characterized by extreme variability. In Indonesia, particularly in Banten Province, fluctuations in rainfall intensity and drastic changes in air temperature can negatively affect various sectors, including agriculture, transportation, and disaster management. Excessive rainfall may lead to flooding, while prolonged periods of low precipitation can trigger drought conditions. Therefore, appropriate mitigation measures are required to reduce potential losses. One of the most critical mitigation efforts is the provision of accurate weather forecasting systems that enable communities and relevant authorities to take preventive actions in advance [1], [2].

Traditionally, meteorological institutions have relied on Numerical Weather Prediction (NWP) frameworks to simulate atmospheric conditions. Although NWP models are capable of representing atmospheric dynamics through physics-based formulations, they require substantial computational resources, high operational costs, and long execution times, particularly for high-resolution weather forecasting [3]. As an alternative, data-driven forecasting approaches based on artificial intelligence and deep learning have gained increasing attention due to their ability to learn complex patterns directly from historical observations while reducing computational demands [4]. Recent studies have also demonstrated the effectiveness of Transformer-based architectures in large-scale weather forecasting applications, highlighting the growing role of deep learning in meteorological research [5], [6]. Among various deep learning techniques, Long Short-Term Memory (LSTM) networks have shown strong performance in time-series forecasting because they are capable of retaining relevant information over long temporal intervals. This capability enables LSTM models to capture nonlinear dependencies more effectively than conventional statistical methods such as ARIMA [7], [8].

The effectiveness of LSTM architecture in time-series has been demonstrated in various studies. Previous research reported that a multivariate LSTM model achieved a Mean Absolute Percentage Error (MAPE) of 3.54% in household electricity consumption forecasting and outperformed conventional statistical approaches in capturing non-linear relationships and long-term temporal dependencies [9]. In addition, LSTM has been successfully applied to other forecasting tasks involving time-series data, demonstrating its capability to learn complex temporal patterns and improve prediction accuracy [10]. These findings suggest that LSTM is a promising approach for weather forecasting applications, which are characterized by dynamic interactions among multiple meteorological variables and nonlinear temporal dependencies.

Despite its effectiveness in modeling temporal dependencies, a standalone LSTM architecture may experience performance degradation when dealing with complex weather data characterized by local variations and noise. To address this limitation, the integration of Convolutional Neural Networks (CNNs) as feature extractors with LSTM networks has been widely adopted. One-dimensional CNN (1D-CNN) layers are capable of extracting salient patterns from weather-related variables before passing the learned representations to LSTM memory units, thereby reducing prediction errors in rainfall forecasting [11] and temperature anomaly prediction [12]. The effectiveness of the hybrid CNN-LSTM architecture has been demonstrated not only in subtropical climates but also in tropical archipelagic regions of Indonesia, including studies conducted in Batam [13], Medan [14], and South Tangerang [15]. By combining feature extraction and temporal learning capabilities, CNN-LSTM models can better represent complex weather dynamics and improve forecasting performance [16], [17].

Although deep learning has been widely applied in weather forecasting, the integration of local meteorological variables with large-scale climate indicators remains relatively limited, particularly in studies focusing on Banten Province. Therefore, this research proposes a hybrid CNN-LSTM framework that combines local weather observations, including temperature, rainfall, and wind speed, with broader climate indicators such as Sea Surface Temperature (SST) anomalies, the El Niño–Southern Oscillation (ENSO) Index, and the Indian Ocean Dipole (IOD) Index. Furthermore, a multi-output forecasting strategy is implemented to simultaneously predict temperature and rainfall up to 14 days ahead. The forecasting results are subsequently integrated into a web-based dashboard to facilitate real-time visualization and monitoring. Through the incorporation of both local and global climate drivers, this study aims to contribute to the development of more comprehensive weather forecasting systems for tropical regions.

2.Literature Review

Research on intelligent systems for meteorological applications has advanced considerably in recent years. Earlier studies primarily focused on the analysis of satellite and cloud imagery using CNN-based classification techniques [16], [19]. However, recent developments have shifted toward data-driven forecasting approaches that leverage spatio-temporal and multivariate time-series data to improve prediction accuracy [1], [4]. This transition has been driven by the increasing adoption of recurrent neural network architectures capable of modeling temporal dependencies from historical weather observations [7], [8]. Furthermore, several studies reported significant reductions in prediction errors when recurrent architectures were applied to historical precipitation datasets [15], [14]. In addition, the working mechanism of convolution also shows superior capabilities in filtering and extracting essential features from signal patterns and one-dimensional numerical data sequences [17], [18]. Recent surveys have highlighted the increasing adoption of 1D-CNN as feature extraction mechanisms in time-series forecasting tasks, particularly when combined with recurrent models to improve predictive performance [4].

Previous studies have explored various approaches to weather forecasting and climate-related prediction tasks. A comparative study between Numerical Weather Prediction (NWP) and artificial intelligence-based models using the ERA5 Reanalysis dataset demonstrated that AI models can significantly reduce computational time while maintaining forecasting performance for cyclone detection [3]. However, conventional NWP frameworks still require substantial computational resources and often lack sensitivity to localized microclimatic conditions. In another study, an LSTM-based approach applied to BMKG rainfall data showed promising results in capturing long-term sequential rainfall patterns [7]. Nevertheless, the model relied solely on local meteorological observations and remained vulnerable to overfitting when confronted with extreme weather anomalies.

Subsequent research comparing LSTM and CNN-LSTM architectures reported that the hybrid CNN-LSTM model achieved lower prediction errors than a standalone LSTM model by effectively extracting local features before temporal learning [15]. Despite these improvements, the study did not incorporate large-scale climate indicators such as ENSO or SST anomalies, nor did it provide an operational platform for delivering forecasting results to end users. Meanwhile, Transformer-based approaches have recently demonstrated strong performance in modeling long-term spatio-temporal relationships using global climate datasets [5]. Although highly accurate, these models are computationally intensive and may be difficult to deploy for practical regional-scale forecasting applications. Other machine learning methods, including XGBoost and Random Forest, have also been applied to flood risk classification using meteorological variables such as temperature, rainfall, and humidity [2]. However, these approaches are generally limited in capturing long-term temporal dependencies inherent in weather time-series data.

Based on the limitations identified in previous studies, there remains a research gap in integrating local meteorological variables with large-scale climate indicators within a unified forecasting framework that is capable of modeling long-term temporal dependencies while remaining practical for operational deployment. Therefore, this study proposes a hybrid CNN-LSTM model that combines local weather variables with SST Anomaly, ENSO Index, and IOD Index to support multi-output forecasting of temperature and rainfall up to 14 days ahead through an interactive web-based platform.

3.Methods

A. Data Description and Data Source

This study utilized a historical daily weather dataset obtained through the Open-Meteo public API, and BMKG covering the observation period from January 1, 2019, to May 31, 2024. The dataset consisted of 17,885 observations and included meteorological variables such as air temperature, precipitation, wind speed, SST anomaly, and the ENSO index. The SST anomaly and ENSO data were collected from international climate authorities, namely the National Oceanic and Atmospheric Administration (NOAA) and the Bureau of Meteorology (BOM). Data preprocessing involved data cleaning, missing value treatment using linear interpolation, and feature normalization using the Robust Scaler method to reduce the influence of outliers. Subsequently, the time-series data were transformed into sequential input samples using a sliding-window approach before being fed into the forecasting model. To preserve the temporal characteristics of the dataset, a chronological train–validation–test split strategy was applied, allocating 80% of the data for training, 10% for validation, and 10% for testing. Based on this configuration, 14,308 observations were used for model training, 1,788 observations for validation, and 1,789 observations for model evaluation.

B. Feature Parameter Extraction

The extracted numerical features consisted not only of basic meteorological observations but also incorporated large-scale climate indicators to provide additional environmental context for the forecasting model. In particular, ocean-atmosphere variability indicators, such as SST anomalies and climate oscillation indices, were included to capture broader climatic influences on regional weather patterns. The complete set of input features, including meteorological variables and climate anomaly indices, is presented in Table 1.

Table 1. Historical Weather Dataset Features

Feature Name	Description Units and Measurements
temperature_2m_mean	Average daily temperature at a height of 2 meters (°C)
precipitation_sum	Total accumulated precipitation or daily rainfall (mm)
windspeed_10m_max	Daily maximum wind speed at a height of 10 meters (km/h)
cape_proxy_radiation	Proxy of available convective potential energy radiation (J/kg)
sst_anomaly	Sea Surface Temperature Anomaly
enso_index	Macroclimate index related to the El Niño-Southern Oscillation phenomenon

C. CNN-LSTM Architecture and Hyperparameters

The proposed forecasting model was designed to accommodate the complexity of multivariate climate data. A sliding-window approach with a 31-day historical observation period was employed to predict weather conditions for the subsequent 14 days. The architecture begins with a one-dimensional convolutional layer (Conv1D) consisting of 96 filters, a kernel size of 3, and a Rectified Linear Unit (ReLU) activation function, which is responsible for extracting local temporal patterns and reducing short-term noise in the input sequences. The resulting feature maps are subsequently normalized using a Batch Normalization layer before being passed to two stacked LSTM layers. The first LSTM layer contains 192 memory units and incorporates a dropout rate of 0.2 to mitigate overfitting. The second LSTM layer consists of 64 units with a dropout rate of 0.3, enabling the model to capture deeper temporal dependencies from the extracted features. The learned representations are then processed through a fully connected Dense layer comprising 32 neurons before being fed into the final output layer. The output layer consists of two neurons that simultaneously predict daily air temperature and precipitation, thereby implementing a multi-output forecasting framework.

Model training and backpropagation optimization were performed using the Adam optimizer with a learning rate of 0.001. The training process was conducted iteratively for 50 epochs with a batch size of 32. To improve robustness against extreme weather variations and reduce the influence of outliers, the Huber Loss function was employed as the optimization objective. This loss function provides a balance between MSE and MAE, making it particularly suitable for meteorological forecasting tasks characterized by occasional extreme observations. The overall network architecture and data flow of the proposed CNN-LSTM model are illustrated in Figure 1.

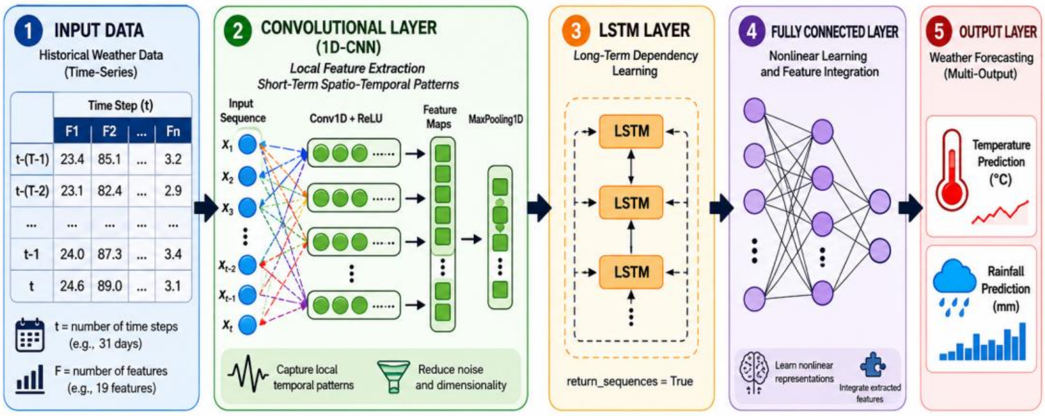

Figure 1. CNN-LSTM Hybrid Model Architecture

D. Web Operational Framework and Validation

The validated CNN-LSTM forecasting model was deployed within a Django-based back-end framework to enable operational implementation. The system integrates the forecasting engine with a web-based dashboard, where Chart.js is employed for dynamic data visualization and Leaflet is utilized for spatial weather mapping. This architecture facilitates the real-time presentation of forecasting results and enhances user accessibility. To assess the reliability of the proposed system, the generated forecasts were compared against observational data provided by the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG), including measurements collected from weather stations and satellite observations. This comparative evaluation was conducted to examine the consistency of the model outputs with reference meteorological data.

4.Results and Discussion

The implementation of the proposed hybrid CNN-LSTM model demonstrated reliable predictive performance on the weather time-series testing dataset. Prior to presenting the forecasting results of the proposed model, a comparative evaluation was conducted using two widely adopted performance metrics, namely MAE and RMSE. To provide a comprehensive assessment, the proposed approach was benchmarked against both a conventional statistical method, ARIMA, and a deep learning-based LSTM model. The comparative performance of these forecasting models on the Banten Province dataset is summarized in Table 2.

Table 2. Baseline Model Performance Comparison with CNN-LSTM (Test Data)

Model	MAE Temperature (°C)	RMSE Temperature (°C)	MAE Rainfall (mm)	RMSE Rainfall (mm)
ARIMA (Pure Statistics)	0.67	0.83	6.38	8.71
LSTM	0.64	0.78	6.11	8.74
CNN-LSTM (Study Proposal)	0.60	0.73	6.15	8.31

Based on the 14-day forecasting experiment conducted for the central region of Banten Province, as presented in Table 2, the proposed hybrid CNN-LSTM architecture achieved the lowest prediction errors among the evaluated models. For air temperature forecasting, the model attained a MAE of 0.60 °C and a Root Mean Square Error (RMSE) of 0.73 °C, outperforming both the ARIMA and standalone LSTM baseline models. The relatively low error values indicate that the proposed model was able to effectively capture daily temperature variations and underlying temporal patterns within the weather time-series data. Furthermore, the small difference between the MAE and RMSE values suggests that large prediction deviations were limited, indicating stable forecasting performance across the testing period.

For rainfall forecasting, a different performance pattern was observed. The standalone LSTM model achieved a slightly lower MAE of 6.11 mm compared with 6.15 mm obtained by the proposed CNN-LSTM model. However, when evaluated using RMSE, the CNN-LSTM model achieved a lower error value of 8.31 mm, outperforming the standalone LSTM model, which recorded an RMSE of 8.74 mm. Since RMSE assigns greater penalties to large prediction errors, these results suggest that the CNN-LSTM model was more effective in handling extreme rainfall events and reducing large forecasting deviations. While the standalone LSTM model performed comparably under normal rainfall conditions, its higher RMSE indicates greater sensitivity to unusual precipitation patterns. The incorporation of the 1D-CNN layer likely enhanced the model's ability to extract relevant local features associated with rainfall variability, thereby improving forecasting stability during periods of intense precipitation. These findings indicate that the proposed CNN-LSTM model provides a more balanced and robust performance for rainfall forecasting in Banten Province.

The experimental results indicate that the proposed CNN-LSTM model achieved better forecasting performance than the baseline models, namely ARIMA and standalone LSTM, for both temperature and rainfall prediction tasks. This improvement may be attributed to the complementary strengths of the two architectures. The CNN layer is capable of extracting salient local patterns from time-series data, whereas the LSTM layer effectively captures long-term temporal dependencies that are commonly present in meteorological observations. By combining these capabilities, the hybrid CNN-LSTM architecture can learn more complex relationships among weather variables than conventional statistical approaches such as ARIMA. Furthermore, the integration of feature extraction and temporal learning enables the model to better represent nonlinear patterns and dynamic interactions within weather time-series data, contributing to improved forecasting performance across the evaluation metrics.

In addition to daily meteorological variables, this study incorporated SST anomalies and the El Niño–Southern Oscillation (ENSO) index as input features. These large-scale climate indicators are known to influence climate variability across Indonesia, particularly through their effects on rainfall distribution and air temperature patterns. By integrating both local meteorological observations and global climate drivers, the proposed model was able to capture broader atmospheric and oceanic influences that may affect regional weather conditions. The inclusion of SST anomaly and ENSO information therefore provides additional contextual information that can enhance the model’s ability to identify weather patterns associated with large-scale climate variability.

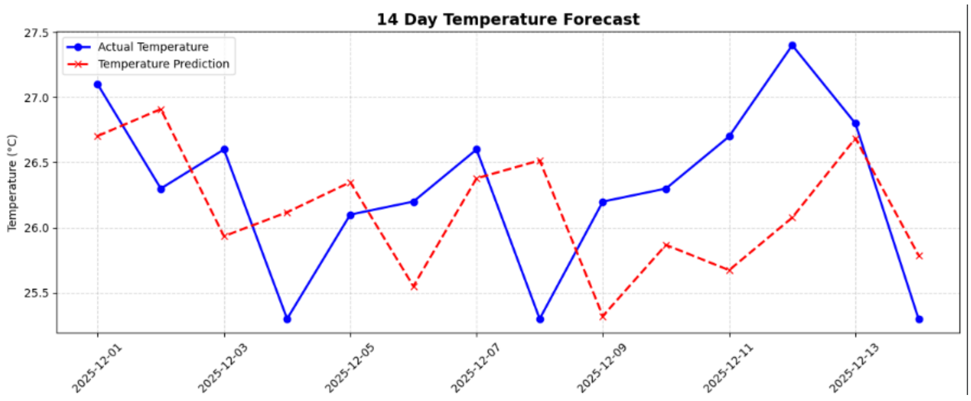

Figure 2. Comparison Visualization of Historical Data and Temperature Model Prediction Results

Figure 2 presents the comparison between the observed and predicted air temperature values over the 14-day forecasting period. Overall, the predicted temperature series follows the general trend of the observed data, indicating that the proposed CNN-LSTM model was able to capture the temporal variation of air temperature during the testing period. Although several deviations can be observed at specific time points, the differences between the predicted and observed values remained relatively small, which is consistent with the MAE and RMSE results reported in Table 2. The ability of the model to represent temperature dynamics may be attributed to the complementary roles of the CNN and LSTM components. While the 1D-CNN layer extracts relevant local patterns from the input sequence, the LSTM layers capture temporal dependencies from historical observations, enabling the model to learn underlying temperature trends more effectively.

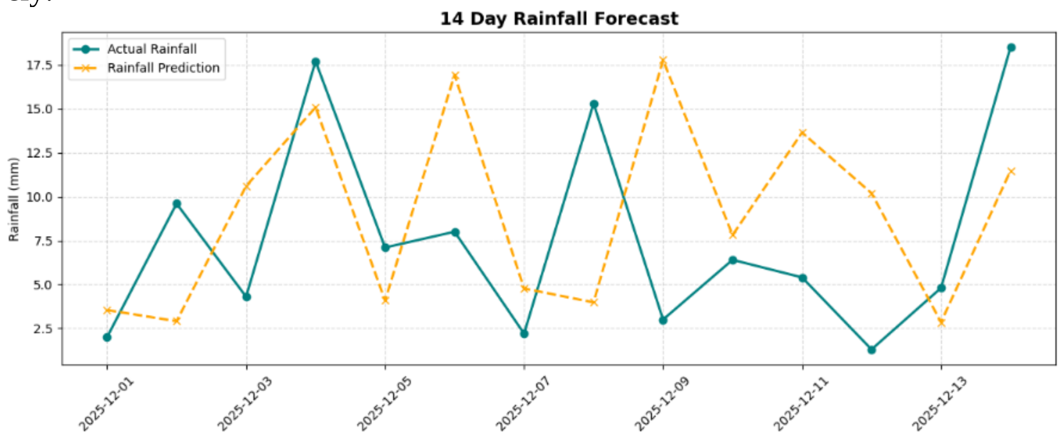

Figure 3. Comparison Visualization of Historical Data and Rainfall Model Prediction Results

Figure 3 illustrates the comparison between the observed and predicted rainfall values during the 14-day forecasting period. In contrast to temperature, rainfall exhibits higher variability and more irregular fluctuations, making it a more challenging variable to forecast. The predicted series was able to capture the general pattern of rainfall variation, including periods of relatively low and moderate precipitation. However, noticeable discrepancies were observed during several high-intensity rainfall events, where the model either underestimated or overestimated the observed values. This behavior is consistent with the inherently nonlinear and sporadic nature of precipitation data.

Despite these deviations, the CNN-LSTM model maintained a lower RMSE than the standalone LSTM model, as reported in Table 2, indicating a better ability to reduce large forecasting errors. The improved performance may be attributed to the feature extraction capability of the 1D-CNN layer, which helps identify relevant local patterns before temporal dependencies are modeled by the LSTM layers. Furthermore, the use of a 31-day sliding-window approach provided sufficient historical context for learning weather dynamics, enabling the model to capture the overall rainfall variability throughout the testing period. Nevertheless, the results suggest that forecasting extreme rainfall events remains challenging and could potentially be improved through the incorporation of additional climate variables or higher-resolution meteorological data in future studies.

The forecasting outputs generated by the CNN-LSTM model were subsequently integrated into a web-based weather information system developed using the Django framework. The system was designed to provide integrated access to key meteorological information, including air temperature, rainfall, and wind speed. To enhance data interpretation, the platform utilizes the Chart.js library to visualize historical observations and forecast results through interactive charts, enabling users to more easily identify weather trends and patterns. Furthermore, the integration of Leaflet-based mapping functionality provides spatial visualization of weather conditions across different regions of Banten Province, allowing users to explore weather information in a more intuitive and geographically contextualized manner. This implementation demonstrates the practical applicability of the proposed forecasting framework by transforming model outputs into an accessible decision-support and weather monitoring platform.

At a more localized level, the system provides a detailed weather analysis interface that presents meteorological information for specific observation locations. The interface includes key weather parameters, such as air temperature, humidity, and wind speed, together with short-term forecasting results displayed through time-series visualizations. The dynamic presentation of historical observations and forecast outputs enables users to monitor weather variations over time and examine the consistency between model predictions and observed conditions. Through this approach, the system serves not only as a platform for visualizing forecasting results but also as a practical tool for daily weather monitoring and information dissemination for both the general public and relevant stakeholders. Nevertheless, forecasting extreme rainfall events remains a challenging task due to the complex interactions among local meteorological conditions and large-scale climate variability. While the proposed CNN-LSTM model demonstrated satisfactory performance on the testing dataset, several high-intensity rainfall events were not fully captured. Future research may incorporate higher-resolution radar and satellite observations, as well as additional climate indicators, to enhance the model's ability to represent extreme weather conditions and improve forecasting robustness across different regions.

To evaluate the practical validity of the proposed forecasting system, an operational validation was conducted using a seven-day sequential observation period at a meteorological station in Tangerang City. The validation process involved a direct comparison between the weather forecasts generated by the CNN-LSTM model and the corresponding observational data provided by the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG). Both datasets were aligned using matching observation periods to ensure a fair and consistent evaluation. This comparative assessment was performed to examine the agreement between the model predictions and real-world meteorological observations under operational conditions. The results of the field validation are summarized in Table 3.

Table 3. Comparison of AI Web Dashboard Temperature Metrics with the Official BMKG Portal (7 Day Period in Tangerang City)

Day	Time Observation	Temperature CNN-LSTM Model (°C)	Actual Temperature BMKG (°C)	Deviation/Difference (°C)
Day 1	13:00 WIB	29.2	29	0.2
Day 2	13:00 WIB	30.5	30	0.5
Day 3	13:00 WIB	28.9	29	0.1
Day 4	13:00 WIB	29.6	30	0.4
Day 5	13:00 WIB	28.1	28	0.1
Day 6	13:00 WIB	31.2	31	0.2
Day 7	13:00 WIB	29.0	29	0.0

The comparative analysis presented in Table 3 indicates a relatively small discrepancy between the predicted and observed temperature values during the seven-day validation period in Tangerang City. The observed temperature deviations ranged from 0.0°C to 0.5°C, suggesting a good level of agreement between the CNN-LSTM forecasts and the corresponding BMKG observations. These results indicate that the proposed model was able to capture short-term temperature variations under the climatic conditions of the study area. Furthermore, the forecasting outputs were successfully delivered through the web-based platform, which provides responsive visualization and timely access to weather information. This implementation demonstrates the potential of the proposed system as a practical tool for weather monitoring and daily climate information dissemination.

5.Conclusions

This study demonstrates that a hybrid CNN-LSTM architecture integrating local meteorological variables with large-scale climate indicators, including Sea Surface Temperature (SST) anomalies, the ENSO Index, and the Indian Ocean Dipole (IOD) Index, can be applied to weather forecasting in Banten Province. Experimental results showed that the proposed model achieved an MAE of 0.60°C and an RMSE of 0.73°C for air temperature prediction, as well as an MAE of 6.15 mm and an RMSE of 8.31 mm for rainfall forecasting. Compared with the baseline models, the proposed approach demonstrated improved performance, particularly in rainfall prediction, where the RMSE was reduced by 4.9% relative to the standalone LSTM model. The contribution of this study lies in the integration of local and global climate variables within a hybrid CNN-LSTM framework, combined with Robust Scaler-based preprocessing and a multi-output forecasting strategy for simultaneous temperature and rainfall prediction. Furthermore, the forecasting outputs were successfully deployed through a web-based dashboard, and an initial validation using BMKG observational data indicated a satisfactory level of agreement, with an average temperature deviation of approximately 0.2°C during the evaluation period. Future work may incorporate high-resolution radar imagery and additional environmental variables, such as the Air Quality Index (AQI) and carbon emission indicators, to further improve forecasting capability and model generalizability.

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References

[1] J. Shi *et al.*, "Deep Learning and Foundation Models for Weather Prediction: A Survey," Jan. 2025, [Online]. Available: http://arxiv.org/abs/2501.06907

[2] S. Sandiwarno, "Penerapan Machine Learning Untuk Prediksi Bencana Banjir," *Jurnal Sistem Informasi Bisnis*, vol. 14, no. 1, pp. 62–76, Jan. 2024, doi: 10.21456/vol14iss1pp62-76.

[3] Y. Shi *et al.*, "Comparison of AI and NWP models in operational severe weather forecasting: A Study on Tropical Cyclone Predictions," Oct. 23, 2024. doi: 10.22541/essoar.172969651.17716955/v1.

[4] B. Lim and S. Zohren, "Time-series forecasting with deep learning: A survey," Apr. 05, 2021, *Royal Society Publishing*. doi: 10.1098/rsta.2020.0209.

[5] J. Gong, T. Han, K. Chen, and L. Bai, "WeatherFormer: Empowering Global Numerical Weather Forecasting with Space-Time Transformer," Sep. 2024, [Online]. Available: http://arxiv.org/abs/2409.16321

[6] A. Hasan, M. Roozbehani, and M. Dahleh, "WeatherFormer: A Pretrained Encoder Model for Learning Robust Weather Representations from Small Datasets," May 2024, [Online]. Available: http://arxiv.org/abs/2405.17455

[7] R. Farikhul Firdaus and I. V. Paputungan, "Prediksi Curah Hujan di Kota Bandung Menggunakan Metode Long Short Term Memory," *Jurnal Penelitian Inovatif*, vol. 2, no. 3, pp. 453–460, Nov. 2022, doi: 10.54082/jupin.99.

[8] D. D. Pramesti, D. C. R. Novitasari, F. Setiawan, and H. Khaulasari, "LONG-SHORT TERM MEMORY (LSTM) FOR PREDICTING VELOCITY AND DIRECTION SEA SURFACE CURRENT ON BALI STRAIT," *Barekeng*, vol. 16, no. 2, pp. 451–462, Jun. 2022, doi: 10.30598/barekengvol16iss2pp451-462.

[9] A. Faeda Insani, A. Mushawir, A. Adiaksa, S. Viridi, P. Studi Sains Komputasi, and F. Matematika dan Ilmu Pengetahuan Alam, "OPTIMISATION OF VARIABLE COMBINATIONS FOR HOUSEHOLD ELECTRICITY CONSUMPTION PREDICTION USING A MULTIVARIATE

TIME SERIES MACHINE LEARNING APPROACH OPTIMASI KOMBINASI VARIABEL UNTUK PREDIKSI KONSUMSI LISTRIK RUMAH TANGGA DENGAN PENDEKATAN MACHINE LEARNING MULTIVARIATE TIME SERIES."

[10] L. Aritonang, B. Aryowindo, R. Syarif, and E. Sabarita Barus, "FORECASTING RED CHILLI PLANT GROWTH USING TIME SERIES METHOD WITH LONG SHORT-TERM MEMORY MODEL FORECASTING PERTUMBUHAN TANAMAN CABAI MERAH MENGGUNAKAN METODE TIME SERIES DENGAN MODEL LONG SHORT-TERM MEMORY," vol. 10, no. 2, p. 2025.

[11] H. Al-Omari, M. A. Yaghi, and L. Alrifai, "An Enhanced Hybrid CNN–LSTM Model for Improved Precipitation Forecasting," *Algorithms*, vol. 19, no. 5, May 2026, doi: 10.3390/a19050394.

[12] Q. Guo, Z. He, and Z. Wang, "Monthly climate prediction using deep convolutional neural network and long short-term memory," *Sci. Rep.*, vol. 14, no. 1, Dec. 2024, doi: 10.1038/s41598-024-68906-6.

[13] Y. Christian and J. Agustio Liu Siaw Ping, "Designing a Hybrid Machine Learning Model for Weather Forecasting in Batam City Corresponding Author," 2026. [Online]. Available: http://creativecommons.org/licenses/by-sa/4.0/

[14] M. Alfandi and A. M. H. Sihite, "Penerapan Metode CNN-LSTM Dalam Memprediksi Hujan Pada Wilayah Medan," *Nasional Teknologi Informasi dan Komputer)*, vol. 6, no. 1, 2022, doi: 10.30865/komik.v6i1.5713.

[15] D. Kota, T. Selatan Uliyatunisa, and D. Supriatna, "Komparasi Model LSTM dan CNN-LSTM untuk Peramalan Curah Hujan," *Bulletin of Information Technology (BIT)*, vol. 6, no. 3, pp. 294–301, 2025, doi: 10.47065/bit.v5i2.2235.

[16] F. Hafeez *et al.*, "Hybrid LSTM-CNN Model with Temporal Feature Engineering and Genetic Algorithm Optimization for Temperature Forecasting," *Eng*, vol. 7, no. 5, May 2026, doi: 10.3390/eng7050224.

[17] L. Xiang, J. Xiang, J. Guan, L. Zhang, Z. Cao, and J. Xia, "Spatiotemporal forecasting model based on hybrid convolution for local weather prediction post-processing," *Front. Earth Sci. (Lausanne).*, vol. 10, Sep. 2022, doi: 10.3389/feart.2022.978942.

[18] R. A. Tilasefana and R. E. Putra, "Penerapan Metode Deep Learning Menggunakan Algoritma CNN Dengan Arsitektur VGG NET Untuk Pengenalan Cuaca," *Journal of Informatics and Computer Science*, vol. 05, 2023.

[19] S. A. Suryaman, "LAPORAN AKHIR PENELITIAN DASAR DAN TERAPAN Klasifikasi Cuaca dengan Metode Convolutional Neural Network (CNN)," 2021.