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Rainfall Intensity Prediction Using LSTM and Random Forest Hybrid Model

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Abstrak

Prediksi curah hujan yang akurat sangat penting untuk pengelolaan sumber daya air dan pengurangan risiko bencana. Variabilitas curah hujan harian yang tinggi memerlukan model peramalan berbasis data yang mampu menangkap dinamika temporal yang kompleks. Penelitian ini memperkenalkan kerangka hibrida residual yang mengintegrasikan jaringan Long Short-Term Memory (LSTM) dengan regresi Random Forest (RF) untuk meningkatkan estimasi curah hujan jangka pendek. Komponen LSTM berfungsi mengenali ketergantungan berurutan dalam data deret waktu, sedangkan RF digunakan untuk mempelajari pola kesalahan residual nonlinier yang tidak sepenuhnya tertangkap oleh LSTM. Sistem ini dilatih menggunakan beberapa variabel meteorologi, termasuk curah hujan, suhu, kelembapan, dan durasi penyinaran matahari. Evaluasi model dilakukan menggunakan metrik regresi seperti MAE, MSE, dan RMSE. Berdasarkan hasil eksperimen pada tiga stasiun BMKG di Jakarta, Medan, dan Manado, konfigurasi hibrida LSTM–RF menunjukkan tingkat akurasi dan kestabilan yang lebih baik dibandingkan model tunggal, sehingga dapat menjadi pendekatan yang andal untuk peramalan curah hujan di wilayah tropis.

Kata kunci— *Machine Learning, Curah hujan, Long Short-Term Memory, Random Forest, Hybrid Model, Prediksi cuaca, Time series.*

Abstract

Accurate rainfall prediction is vital for effective water resource management and disaster risk reduction. The high variability of daily rainfall patterns demands data-driven forecasting models capable of handling complex temporal dynamics. This research introduces a hybrid residual framework that integrates Long Short-Term Memory (LSTM) networks with Random Forest (RF) regression to enhance short-term rainfall estimation. The LSTM component captures sequential dependencies within the time series, while the RF model learns non-linear residual errors that remain after the initial LSTM predictions. The system is trained on several meteorological variables, including rainfall, temperature, humidity, and sunlight duration. Model evaluation employs common regression metrics such as MAE, MSE, and RMSE. Based on experimental results from three BMKG observation stations in Jakarta, Medan, and Manado, the hybrid LSTM–RF configuration consistently achieves higher accuracy and stability than single-model baselines, demonstrating its suitability for tropical rainfall forecasting applications.

Keywords— *Machine Learning, Rainfall prediction, Long Short-Term Memory, Random Forest, Hybrid Model, Weather Forecasting, Time Series.*

1. INTRODUCTION

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Indonesia is classified as a country highly prone to natural disasters due to its geographical and climatic conditions. Positioned between the Eurasian, Indo-Australian, and Pacific tectonic plates, the country faces frequent geological hazards such as earthquakes and volcanic eruptions, as well as hydrometeorological disasters like floods and landslides, which occur almost annually [1][2]. Data from the National Disaster Management Agency (BNPB) show a rising trend in disaster events in recent years [3], highlighting the urgent need for data-driven mitigation strategies.

The Indonesian National Disaster Management Agency (BNPB) reported 3,467 natural disaster events nationwide between January 1 and November 28, 2023. The most common disaster among them was flooding, which accounted for 978 incidents. Extreme weather, forest and land fires, and landslides followed with 975, 817, and 488 cases, respectively [4]. These disasters have had a very negative material and social impact, especially in places that are vulnerable like Sumenep Regency, Ambon City, and Bandar Lampung [5][6][7]. Regions with high rainfall intensity, such as the National Capital (IKN), which records an average of more than 2,600 mm each year [8], are highly susceptible to flash floods. Accurate rainfall prediction becomes crucial for early warning systems..

Floods and other hydrometeorological disasters are greatly impacted due to the increased frequency and severity of extreme weather events, such as excessive rainfall, brought on by global climate change [9]. Predicting rainfall and floods has therefore become crucial for managing water resources and preventing disasters in a number of disaster-prone regions. The complexity of hydrological systems and their dynamic spatiotemporal fluctuations are frequently difficult for traditional prediction techniques, such as physically based hydrological models, to capture [10]. Data-driven methods, especially those that use deep learning (DL) and machine learning (ML) techniques have grown in popularity in overcoming these constraints due to their capacity to uncover underlying nonlinear patterns in time series data [11][12]. In addition to enabling highly accurate short- and medium-term forecasts, models such as LSTM, CNN, and their hybrid variants have proven more effective in capturing temporal relationships than conventional methods[13].

The investigation demonstrates that despite the widespread usage of deep learning models like CNN and LSTM for flood and rainfall prediction, these models still have problems in capturing the spatiotemporal complexity of climatological data. Improving runoff prediction accuracy is hampered by suboptimal integration of temporal dependencies and characteristics, which is made worse by problems with long-term generalization and model interpretability, especially when it comes to identifying uncommon severe events [9][10]. Although hybrid techniques like LSTM-RF and LSTM-GBM have shown increased prediction flexibility and accuracy, they struggle with real-time prediction accuracy and adaption to local data sources like petabencana.id and regional variety [11][12]. Meanwhile, the SAE-BiLSTM model has shown improved performance in classifying rainfall intensity, but still lacks accuracy [13]. Consequently, a major obstacle in rainfall and flood prediction research is the creation of hybrid models that can interpretably and adaptively capture temporal and spatial relationships.

One of the major research issues that remains inadequately addressed is the lack of long-term evaluation and the limited generalizability of rainfall and flood prediction models across diverse geographical regions. Most previous studies have developed machine learning and deep learning-based models that were validated in only a single region. These models were not tested in locations with varying climates, topographies, and rainfall patterns, making it difficult to build robust and flexible models that can be applied across all tropical and subtropical areas.

For instance, the SA-CNN-LSTM model developed by [10] was tested exclusively in the Mazhou River Basin, China, without external validation in other regions. Meanwhile, the LSTM-GBM model by [11] and LSTM-RF by [12] focused on specific urban areas such as Manila and Jakarta, with limited spatial validation. [13] also underlined the need for more flexible models capable of handling diverse spatial data to effectively predict rainfall in topographically complex regions such as the Kathmandu Valley. Consequently, the scarcity of studies evaluating model generalizability across various contexts and climatic conditions highlights a significant research gap in the current body of literature.

This study used a hybrid residual technique, which combined the Long Short-Term Memory (LSTM) model with Random Forest (RF). LSTM was chosen for its ability to capture long-term temporal patterns, while RF was used to learn the residuals, or the differences between the initial LSTM predictions and the actual values [14][15]. By spotting non-linear patterns that are hard for LSTM to detect, this method increases accuracy. The study uses MAE, MSE, and RMSE measures to assess how well the LSTM-RF hybrid model predicts daily rainfall. It is anticipated to overcome the drawbacks of individual models and generate forecasts that are more accurate.

2. METHODS

2.1 Design and Overall System Architecture

The proposed model in this study integrates two predictive approaches Long Short-Term Memory with Random Forest in the form of a residual hybrid model. The overall system architecture consists of data preprocessing, LSTM model training, residual computation, and residual modeling using Random Forest.

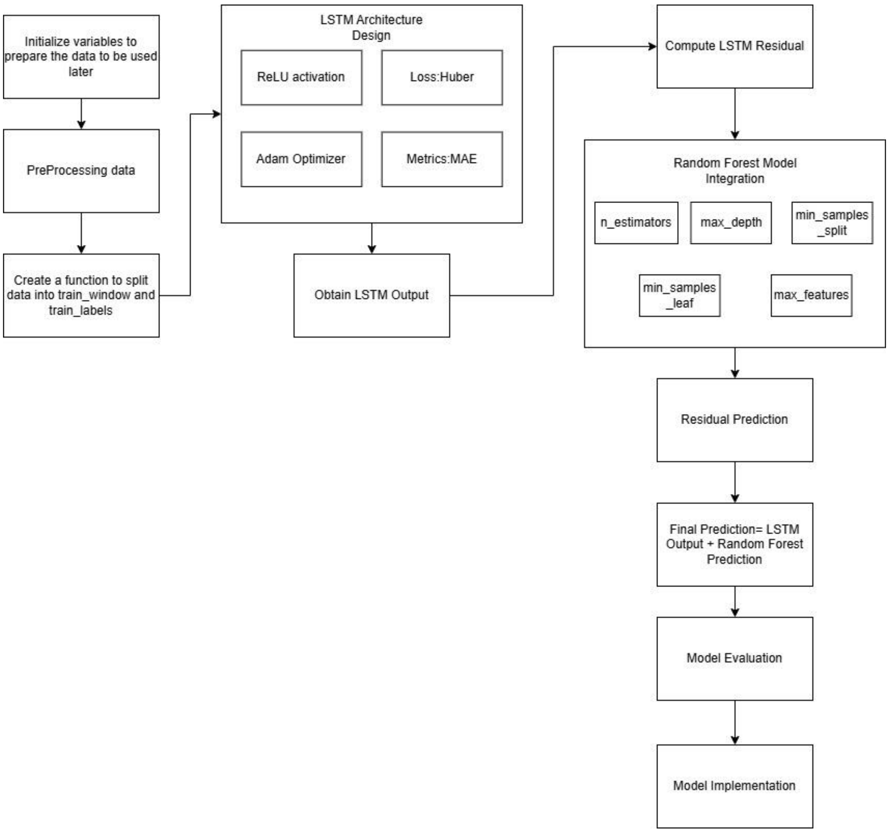

Figure 1. Flow LSTM-RF Hybrid Architecture

Figure 1 illustrates the architecture, which begins with data preprocessing, followed by training the LSTM model using the ReLU activation function, Huber loss, Adam optimizer, and

MAE as the evaluation metric. The LSTM predicted outcomes are contrasted with the actual data to obtain the residual, which is then predicted by the Random Forest using the parameters n_estimators, max_depth, min_samples_leaf, max_features, and min_samples_split. The final output is obtained by summing the LSTM output and the residual prediction generated by the RF model.

2.2 Theorical Framework

2.2.1 Long Short-Term Memory

Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) developed to address the challenge of capturing long-term dependencies that conventional RNNs often struggle with [16]. It can retain important information over time through an internal memory mechanism known as the "cell state," which makes it highly effective in processing sequential and time-series data [17]. The forget gate, input gate, and output gate are the three primary gates that make up an LSTM unit. These gates aid in controlling what data is stored in, taken out of, or added to memory [19]. As a result, LSTM is able to address the vanishing gradient problem commonly encountered in conventional RNNs [20].

The functions of the three main gates are as follows::

- Forget Gate (f_t): identifies the data that should be removed from the preceding cell state C_{t-1} [18].
- Input Gate (i_t) dan Candidate Value ($\widetilde{C_t}$): The type of new information used to update the current memory state is regulated [21].
- Output Gate (o_t): regulates the data that is transferred to the following time step from the memory [16].

The flow of information at each time step t is mathematically described by Equation (1) [21][19].

$$\begin{aligned}
f_t &= \sigma\left(W_f \cdot \left[h_{\{t-1\}}, x_t\right] + b_f\right) \\
i_t &= \sigma\left(W_i \cdot \left[h_{\{t-1\}}, x_t\right] + b_i\right) \\
\widetilde{C_t} &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \\
C_t &= f_t \odot C_{t-1} + i_t \odot \widetilde{C_t} \\
o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\
h_t &= o_t \odot \tanh(C_t)
\end{aligned} \tag{1}$$

The diagram demonstrates how the LSTM unit utilizes the input at time (x_t), along with the previous hidden state (h_{t-1}), and the cell state (C_{t-1}) to compute the updated hidden state (h_t) and the updated cell state (C_t). This process supports the efficient retention and handling of long-term dependencies in sequential data [17].

2.2.2 Random Forest

Random Forest (RF) is an ensemble learning algorithm based on decision trees that has proven effective in handling data with complex and non-linear characteristics [22]. Multiple regression trees are built on randomly sampled training data, and the predictions from each tree are then combined to produce the final output [23]. In regression tasks, the final result is obtained by averaging the predictions of all trees, leading to more consistent estimates that are less prone to overfitting [24].

Random Forest is capable of processing large datasets efficiently, including situations where the feature count greatly surpasses the number of data samples [25]. Additionally, this algorithm performs effectively with incomplete or sparse data, as it is relatively robust to noise and multicollinearity [26]. It also offers the capability to produce predictions accompanied by uncertainty estimates, using techniques such as out-of-bag (OOB) error estimation, structured cross-validation, and systematic parameter tuning [27]. For these reasons, Random Forest is widely applied in regression tasks across fields such as ecology, meteorology, and data science, due to its ability to construct stable, interpretable models and manage complex environmental variables[24]

In the context of regression, the prediction is obtained by averaging all individual predictions. This is mathematically represented in Equation (2).

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \tag{2}$$

Through this approach, Random Forest is able to produce more stable, accurate, and overfitting-resistant predictions. The random selection of feature subsets at each node further enhances the variety among trees and enhances the model's overall capacity for generalization.

2.3 Hybrid Long Short-Term Memory-Random Forest

This study used a residual-based hybrid approach to improve rainfall prediction accuracy. The method combines Long Short-Term Memory (LSTM) and Random Forest (RF), leveraging their complementary strengths. LSTM is effective in capturing temporal patterns and long-term dependencies in rainfall time series data. [14].

Meanwhile, Random Forest is used to learn the residuals, which are the differences between the actual values and the initial predictions generated by the LSTM. The role of RF is to capture non-linear patterns that cannot be fully learned by the LSTM, thereby refining and enhancing the overall prediction results [15].

Following the acquisition of the LSTM's first predictions, Equation (3) is used to compute the residual, which is the variation between the predicted and actual values

$$r_t = y_{train} - \hat{y}_{LSTM} \tag{3}$$

The calculated residuals, obtained only from the LSTM training data, are then used as the target for training the Random Forest (RF) model. The RF is trained to learn and predict these residual values using the same input features as the LSTM, specifically the most recent lagged weather variables from the last time step of each input window. This ensures that the RF model learns only from training residuals without accessing any test data, thereby preventing data leakage. Once the RF model generates the predicted residuals, the final rainfall prediction is obtained by summing the initial LSTM prediction with the RF-predicted residuals, as shown in Equation (4).

$$\hat{y}_{Hybrid=} \ \hat{y}_{LSTM} + \hat{y}_{RF} \tag{4}$$

This method makes it possible to combine the Random Forest (RF) model's capacity to correct residual mistakes based on multivariate patterns with the Long Short-Term Memory (LSTM) model's strengths in processing sequential information. As a result, compared to single-model methods, our hybrid model should generate rainfall projections that are more precise and consistent.

2.4 Pre-processing

The pre-processing stage begins with cleaning the dataset, including handling missing or inconsistent values across six weather variables like rainfall (RR), maximum temperature (Tx), minimum temperature (Tn), average temperature (Tavg), sunlight duration (ss), and average relative humidity (Rh_avg). After the data are cleaned and standardized, the Long Short-Term Memory (LSTM) model input is prepared using a windowing process.

For the LSTM, time-series data were converted into sequence-to-one sliding windows, where each set of past values predicts the next rainfall value. The Random Forest (RF) used the most recent features directly without windowing. Both models applied sample weighting to emphasize larger rainfall values, improving the focus on significant rainfall events. The dataset was divided into 80 percent for training and 20 percent for testing to ensure balanced model evaluation.

2.5 Eksperiment Configuration

The models were trained and evaluated using three random seeds (42, 123, and 314) to ensure consistent and reliable results across all experiments.

The LSTM model was tested with different parameter settings to achieve optimal performance. Batch sizes of 64 and 128 were used, with training epochs of 100 and 200. Learning rates of 0.001 and 0.005 were compared, and dropout values between 0.2 and 0.4 were applied to prevent overfitting. The number of LSTM units varied from 16 to 128 to evaluate memory capacity for long-term dependencies.

In the Random Forest experiment, two main parameters were tuned to assess their effect on prediction accuracy. The number of trees ranged from 100 to 500, and the maximum depth varied from 10 to 35, along with adjustments to min_samples_split, min_samples_leaf, and max_features. These settings were used to build several Random Forest and hybrid models to achieve an optimal balance between complexity and accuracy.

2.6 Model Evaluation

By contrasting the predicted outcomes with the actual values, the forecast results' accuracy was evaluated. Three widely used regression evaluation metrics were used in this study is Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).These metrics were selected because they offer a thorough assessment of the model's stability and accuracy in predicting time series [5,6,7].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y_i}| \tag{5}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{7}$$

3. RESULTS AND DISCUSSION

3.1 Preparing The Dataset

This study uses daily meteorological data from the Meteorology, Climatology, and Geophysics Agency (BMKG) for the period January 2021 to June 2025. The dataset covers three observation stations representing Indonesia's major islands: Stasiun Meteorologi Maritim Tanjung Priok (Station ID 96741) in Jakarta Utara, Stasiun Meteorologi Maritim Belawan (Station ID 96033) in Medan, and Stasiun Meteorologi Sam Ratulangi (Station ID 97014) in Manado. The data were obtained from the official BMKG online portal, and preprocessing ensured that missing values were handled properly and all records remained within climatologically valid ranges for each region.

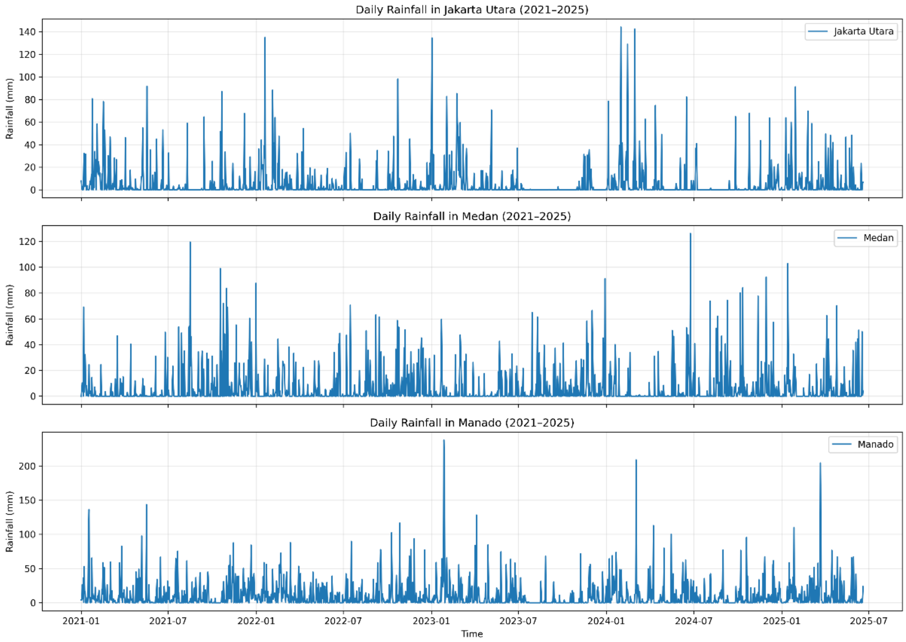

Figure 2. Daily Rainfall Variability (2021–2025) Across Three BMKG Observation Stations

Figure 2 illustrates the daily rainfall distribution at three BMKG observation stations, namely Jakarta Utara, Medan, and Manado, during the period from 2021 to 2025. The visualization highlights distinct regional rainfall patterns, where Jakarta Utara generally experiences shorter but more intense rainfall events, while Medan shows relatively moderate and evenly distributed rainfall occurrences. In contrast, Manado records higher rainfall magnitudes, particularly during the early and late months of each year.

3.2 Evaluation For Windowing

The selection of window size is a crucial step in time series modeling, as it determines how much historical information is utilized to predict future rainfall values. In this study, six different window sizes (3, 7, 14, 30, 60, and 90 days) were evaluated across three observation stations: Jakarta Utara, Manado, and Medan.

Table 1. Evaluate Windows

Window Size	Jakarta Utara (MAE / MSE / RMSE)	Manado (MAE / MSE / RMSE)	Medan (MAE / MSE / RMSE)
3	8.321 ± 1.814 / 262.249 ± 64.863 / 16.074 ± 1.970	12.270 ± 1.434 / 473.252 ± 74.242 / 21.689 ± 1.687	12.782 ± 0.893 / 357.329 ± 20.919 / 18.895 ± 0.559
7	**5.910 ± 0.647 / 183.033 ± 7.848 / 13.526 ± 0.292**	18.261 ± 4.919 / 806.504 ± 266.887 / 27.942 ± 5.076	**7.685 ± 0.151 / 291.070 ± 2.704 / 17.061 ± 0.079**
14	9.857 ± 1.981 / 276.881 ± 76.582 / 16.491 ± 2.221	**11.392 ± 0.983 / 475.698 ± 25.083 / 21.893 ± 0.589**	23.624 ± 16.177 / 1045.211 ± 947.280 / 29.146 ± 13.990
30	11.650 ± 4.916 / 346.670 ± 148.585 / 18.026 ± 3.969	13.317 ± 1.989 / 474.657 ± 59.713 / 21.731 ± 1.352	10.521 ± 2.534 / 312.608 ± 36.963 / 17.651 ± 1.028
60	7.395 ± 1.243 / 202.429 ± 22.999 / 14.205 ± 0.797	15.422 ± 5.420 / 628.524 ± 288.167 / 24.468 ± 5.461	11.412 ± 2.338 / 337.083 ± 66.737 / 18.274 ± 1.767
90	11.745 ± 3.888 / 319.847 ± 107.997 / 17.613 ± 3.104	11.661 ± 2.131 / 489.906 ± 51.338 / 22.104 ± 1.158	21.232 ± 13.697 / 863.678 ± 722.559 / 26.967 ± 11.681

Based on Table 1, window size performance differed across locations. Jakarta Utara and Medan achieved the best accuracy with a 7-day window, while Manado performed best with a 14-day window. These optimal configurations were used in later experiments to ensure accurate predictions for each region's rainfall pattern.

3.3 Baseline Model Experiments and Evaluation

In the baseline setup, the same hyperparameters were used for the LSTM, Random Forest (RF), and hybrid models. The LSTM had three layers with 128, 64, and 32 units, each followed by Batch Normalization and a 0.2 Dropout rate. It was trained with Huber loss ($\delta = 10.0$) using the Adam optimizer (learning rate 0.001) for 100 epochs and a batch size of 128. The RF used 100 trees with a maximum depth of 10 and standard parameters for feature selection and splitting. In the hybrid model, residuals from the LSTM were learned by the RF, and final predictions were obtained by adding the LSTM output and predicted residuals.

Table 2. Evaluation results of Baseline Model (LSTM, RF, and Hybrid).

Station ID	LSTM				RF				LSTM + RF			
	MAE	MSE	RMSE	TIME	MAE	MSE	RMSE	TIME	MAE	MSE	RMSE	TIME
96741 (Jakarta)	5.454 ± 0.154	190.883 ± 3.179	13.816 ± 0.115	26.75	4.848 ± 0.019	112.696 ± 1.539	10.616 ± 0.072	0.45	6.268 ± 0.012	167.267 ± 0.453	12.933 ± 0.018	0.16
96033 (Medan)	16.506 ± 8.313	549.160 ± 305.604	22.606 ± 6.175	27.45	7.589 ± 0.043	194.276 ± 1.052	13.938 ± 0.038	0.76	11.672 ± 0.053	315.861 ± 1.752	17.772 ± 0.049	0.25
97014 (Manado)	11.006 ± 0.420	399.315 ± 6.819	19.982 ± 0.170	39.81	11.651 ± 0.051	341.060 ± 2.463	18.468 ± 0.067	0.53	11.243 ± 0.046	402.015 ± 0.828	20.050 ± 0.021	0.16

Table 2 summarizes the baseline performance of the LSTM, RF, and Hybrid (LSTM–RF) models at three stations. The LSTM achieved stable accuracy (MAE 5.45–16.51) but required longer training (26–40 s) than RF (0.45–0.76 s). The hybrid model slightly improved results in Jakarta (MAE 6.27) and Medan (MAE 11.67), while Manado showed minimal change, suggesting that its benefits vary with local rainfall patterns.

3.4 Enhanced Model Experiments and Evaluation

The second configuration applied enhanced hyperparameters to improve baseline performance. The LSTM used a Bidirectional layer with 128 units and two stacked layers of 64 and 32 units, each followed by Batch Normalization and a 0.3 Dropout rate. A two-head Multi-Head Attention module (key dimension 32) was included for better generalization. The model was trained with Huber loss (δ = 10.0) and the Adam optimizer (learning rate 0.001) for 100 epochs and a batch size of 128. The Random Forest used 200 trees with a maximum depth of 10, while the hybrid model combined the best LSTM outputs with a residual RF using 400 trees and a depth limit of 12.

Table 3. Evaluation results of Enhanced Model (LSTM, RF, and Hybrid).

Station ID	LSTM				RF				LSTM + RF			
	MAE	MSE	RMSE	TIME	MAE	MSE	RMSE	TIME	MAE	MSE	RMSE	TIME
96741 (Jakarta)	8.714 ± 1.440	272.251 ± 57.952	16.402 ± 1.796	34.60	4.859 ± 0.018	108.642 ± 0.799	10.423 ± 0.038	0.47	6.983 ± 0.006	187.884 ± 0.157	13.707 ± 0.006	0.95
96033 (Medan)	7.640 ± 0.541	298.092 ± 16.091	17.259 ± 0.470	35.67	7.759 ± 0.068	193.395 ± 1.625	13.907 ± 0.058	0.80	10.954 ± 0.062	279.990 ± 1.065	16.733 ± 0.032	0.64
97014 (Manado)	10.816 ± 1.030	418.603 ± 21.966	20.453 ± 0.533	38.50	11.826 ± 0.010	355.104 ± 0.974	18.844 ± 0.026	0.49	11.571 ± 0.022	367.059 ± 0.915	19.159 ± 0.024	0.60

Table 3 summarizes the performance of the enhanced hybrid model at three Indonesian meteorological stations. The Random Forest (RF) produced the lowest errors overall, performing best in Medan (MAE = 7.76; RMSE = 13.91). The LSTM showed higher errors and longer training time (≈35–38 s), especially in Manado (RMSE = 20.45). The Hybrid LSTM–RF model improved upon the standalone LSTM, achieving the lowest RMSE of 13.71 in Jakarta, confirming its effectiveness in reducing residual prediction errors.

3.5 Optimized Model Experiments and Evaluation

In the third configuration, additional tuning was performed to improve model robustness. The LSTM was simplified into three layers of 64, 32, and 16 units with Batch Normalization and a 0.4 Dropout rate to prevent overfitting. It was trained using Huber loss (δ = 10.0) and the Adam optimizer with a 0.005 learning rate for 200 epochs and a batch size of 64. The Random Forest used 300 trees with a depth limit of 10, while the hybrid model refined LSTM residuals using an enhanced RF of 500 trees and depth 14, resulting in more stable and accurate rainfall forecasts.

Table 4. Evaluation results of Optimized Model (LSTM, RF, and Hybrid).

Station ID	LSTM				RF				LSTM + RF			
	MAE	MSE	RMSE	TIME	MAE	MSE	RMSE	TIME	MAE	MSE	RMSE	TIME
96741 (Jakarta)	5.876 ± 0.524	177.770 ± 17.285	13.317 ± 0.657	73.58	4.844 ± 0.015	108.481 ± 0.780	10.415 ± 0.037	0.78	6.117 ± 0.012	149.686 ± 0.126	12.235 ± 0.005	0.81

96033 (Medan)	12.596 ± 6.459	364.259 ± 126.243	18.821 ± 3.166	73.02	7.748 ± 0.069	192.850 ± 1.295	13.887 ± 0.047	1.08	11.292 ± 0.035	287.981 ± 0.768	16.970 ± 0.023	0.76
97014 (Manado)	15.036 ± 4.674	543.834 ± 113.560	23.193 ± 2.435	79.00	11.851 ± 0.030	356.556 ± 0.818	18.883 ± 0.022	0.69	11.806 ± 0.009	377.239 ± 0.750	19.423 ± 0.019	0.89

Table 4 presents the optimized model results across three Indonesian stations. The Random Forest (RF) showed lower errors than the standalone LSTM, with the best RMSE in Jakarta (10.42) and Medan (13.89). The Hybrid LSTM–RF achieved the highest accuracy, recording the lowest RMSE of 12.23 in Jakarta and effectively minimizing residual errors. While LSTM required longer computation time (around 73 s), the hybrid model retained RF's efficiency and improved predictive consistency across all stations.

3.6 Evaluation of Model Performance under Extreme Rainfall Conditions

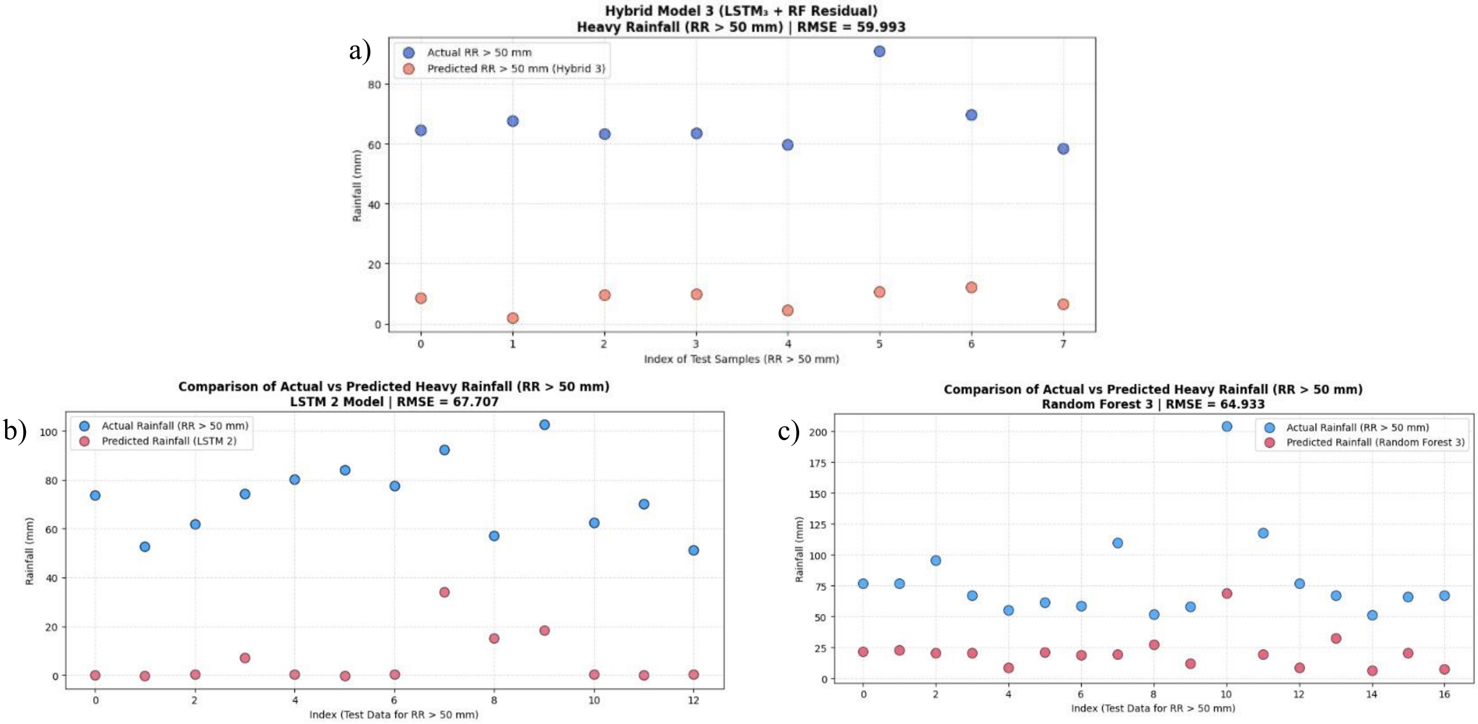

Figure 3. Comparison of actual and predicted rainfall exceeding 50 mm for three optimized models: (a) Hybrid Model 3 (Jakarta), (b) LSTM Model 2 (Medan), and (c) Random Forest Model 3 (Manado).

The figures show each model's ability to capture rainfall events above 50 mm. Hybrid Model 3 produced smoother and more consistent predictions, achieving the lowest RMSE (59.99 mm) and better generalization under heavy rainfall. LSTM Model 2 tended to underestimate peak values, staying below 40 mm when actual rainfall exceeded 80 mm (RMSE 67.71 mm). Random Forest Model 3 showed a similar underestimation pattern with slightly lower error (RMSE 64.93 mm). Overall, all models detected heavy rainfall occurrences but underestimated their intensity, suggesting a need for further calibration.

4. CONCLUSIONS

This study developed a residual-based hybrid model that integrates Long Short-Term Memory (LSTM) and Random Forest (RF) to predict daily rainfall intensity. The approach combines the temporal learning ability of LSTM with the nonlinear residual correction of RF, enabling a more accurate representation of rainfall dynamics based on historical data.

Experimental results from the three BMKG stations in Jakarta, Medan, and Manado showed that the hybrid model delivered better performance than both LSTM and RF individually. The optimized setup reached the lowest RMSE value of 12.23 mm in Jakarta and maintained computational efficiency close to that of RF. These results indicate that combining residual learning with temporal modeling effectively reduces prediction errors and enhances stability across different sites.

Moreover, the hybrid model exhibited better sensitivity to extreme rainfall events exceeding 50 mm, providing improved generalization compared to the baseline methods. This highlights its potential as a reliable forecasting framework for hydrometeorological applications in tropical regions. Future work should expand the model by incorporating spatial and meteorological variables such as humidity, temperature, and wind speed to enhance adaptability across diverse climatic conditions.

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