Journal of Computer Networks, Architecture and High Performance Computing
Volume 08, Number 2, April 2026
https://doi.org/ 10.47709/cnahpc.v8i2.8277

Submitted : 2026-04-08
Accepted : 2026-05-12
Published : 2026-05-13

Continuous Rainfall Prediction Using Stacked LSTM and Sliding Window Time Series Modeling

Akrom [1], Dimas Lendensi [2], Abdullah Muhajir [3], Riky Susanto [4]
[1,2,3,4] University of Pamulang, Jl. Raya Puspitek, South Tangerang 15310, Indonesia
[1]dosen02613@unpam.ac.id, [2]dosen02959@unpam.ac.id, [3]dosen02602@unpam.ac.id,
[4] dosen02663@unpam.ac.id,

ABSTRACT

Reliable rainfall estimation is required in many environmental and agricultural applications because weather uncertainty continues to increase each year, agricultural planning, and disaster prevention. However, the highly dynamic and non-linear characteristics of rainfall data make accurate forecasting a challenging task for traditional statistical models. This research develops a continuous rainfall forecasting model using a stacked Long Short-Term Memory (LSTM) network. Combined with a sliding window time series technique. This work combines multi-layer LSTM learning, temporal window transformation, and dropout mechanisms to improve forecasting stability, dropout regularization, and window-based temporal modeling to improve the learning of long-term rainfall patterns and reduce overfitting. Compared to conventional statistical approaches such as ARIMA and linear regression, LSTM is more effective in capturing non-linear temporal dependencies in sequential meteorological data. The dataset consists of 600 monthly rainfall observations that were preprocessed using MinMax normalization and transformed through a sliding window approach with a time step of 30. The dataset was divided into training and testing sets using an 80:20 ratio. The proposed model was trained for 50 epochs using the Adam optimizer and Mean Squared Error (MSE) loss function. Testing results showed that the developed framework produced a Train RMSE of 1.1009 and a Test RMSE of 0.6846, along with a Train MAE of 0.6000 and a Test MAE of 0.4837. These relatively low error values indicate that the model is capable of learning temporal rainfall patterns effectively and generating stable predictions on unseen data. The findings confirm that the stacked LSTM approach provides reliable performance for continuous rainfall forecasting and has strong potential for implementation in environmental prediction systems and climate-related decision support applications

Keywords: Rainfall Prediction, Stacked LSTM, Time Series Forecasting, Deep Learning, Sliding Window

INTRODUCTION

Rainfall forecasting plays a major role in environmental and climate-related decision making, significantly influencing various sectors such as agriculture, water resource management, transportation, and disaster mitigation. Accurate rainfall forecasting is essential for minimizing environmental risks and supporting strategic planning. However, rainfall patterns have become increasingly irregular due to climate variability and global climate change, making rainfall prediction a complex and challenging task. Rainfall data generally exhibit non-linear behavior, seasonal fluctuations, and long-term temporal dependencies, which are difficult to model using conventional forecasting approaches (Azi 2025).

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 08, Number 2, April 2026
https://doi.org/ 10.47709/cnahpc.v8i2.8277

Submitted : 2026-04-08
Accepted : 2026-05-12
Published : 2026-05-13

Conventional forecasting techniques, including ARIMA and linear regression, are commonly applied in rainfall prediction studies. Although these approaches are effective for modeling linear relationships and short-term trends, they often fail to capture the complex non-linear characteristics and dynamic temporal patterns of meteorological data. In addition, these methods generally assume stationarity in the data, whereas rainfall observations frequently contain irregular fluctuations and changing seasonal patterns. Consequently, the predictive performance of traditional statistical models tends to decrease when applied to highly variable rainfall data (Hassan et al. 2023) .

Recent advances in artificial intelligence and deep learning have encouraged the adoption of neural network-based methods for time series forecasting. Among these approaches, Long Short-Term Memory (LSTM), which is an advanced variant of Recurrent Neural Networks (RNN), has shown promising performance in sequential data modeling. LSTM is specifically designed to overcome the vanishing gradient problem in traditional RNNs through memory cells and gating mechanisms, enabling the model to retain long-term temporal information effectively (Ghosh et al. 2023).

Due to this capability, LSTM has been increasingly applied in environmental prediction tasks, including rainfall forecasting.Although many previous studies have utilized LSTM for rainfall prediction, several limitations remain unresolved. First, many existing studies focus primarily on rainfall classification problems (rain/no rain) rather than continuous rainfall value prediction, which limits the precision of forecasting results. Second, several studies employ relatively simple LSTM architectures without exploring stacked LSTM configurations capable of learning deeper temporal representations. Third, some previous works lack systematic preprocessing strategies such as sliding window time series transformation and normalization techniques, which are important for improving sequence learning performance. In addition, limited studies provide comprehensive regression-based evaluations using multiple error metrics to analyze prediction robustness and generalization capability (Islam et al. 2025).

Another important issue is that many previous rainfall forecasting studies only emphasize predictive accuracy without discussing model stability and overfitting problems. In sequential meteorological data, overfitting can significantly reduce model generalization when the model encounters unseen rainfall patterns. Therefore, there is still a need for a more robust LSTM-based forecasting framework that integrates temporal windowing techniques, stacked architectures, and regularization mechanisms to improve prediction reliability (Abdullah and Said 2025). Based on these research gaps, this study proposes a stacked Long Short-Term Memory (LSTM) model combined with sliding window time series preprocessing and dropout regularization for continuous rainfall prediction. The proposed approach aims to improve the model's capability in capturing complex temporal dependencies and non-linear rainfall patterns while reducing overfitting during training. The main contribution of this study lies in the integration of stacked LSTM architecture, window-based temporal modeling, and systematic regression-based evaluation using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The proposed model is expected to provide more stable and accurate rainfall forecasting performance compared to conventional approaches and contribute to the development of deep learning-based environmental prediction systems (Yin et al. 2025).

LITERATURE REVIEW

Rainfall prediction has become an important research topic in environmental data science due to its significant impact on agriculture, hydrology, disaster mitigation, and climate monitoring. Various forecasting methods have been developed, ranging from traditional statistical approaches to advanced deep learning techniques. Traditional statistical models such as Autoregressive Integrated Moving Average (ARIMA) and linear regression were among the earliest methods used for rainfall forecasting. These approaches are effective for modeling linear relationships and short-term trends; however, they often fail to capture highly non-linear and dynamic rainfall patterns commonly found in meteorological data.

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 08, Number 2, April 2026
https://doi.org/ 10.47709/cnahpc.v8i2.8277

Submitted : 2026-04-08
Accepted : 2026-05-12
Published : 2026-05-13

In addition, statistical models generally assume stationarity in time series data, which limits their performance when rainfall patterns fluctuate irregularly (Hassan et al. 2023).

To overcome these limitations, machine learning approaches such as Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Networks (ANN) have been widely introduced. These methods provide better capability in handling non-linear relationships compared to conventional statistical approaches. Nevertheless, most conventional machine learning models process data independently and do not inherently model temporal dependencies in sequential data. As a result, their effectiveness decreases when long-term temporal information becomes important in rainfall prediction tasks (Ghosh et al. 2023).

Deep learning approaches, particularly Recurrent Neural Networks (RNN), have demonstrated significant improvements in sequential data modeling. However, standard RNN models suffer from the vanishing gradient problem, which limits their ability to learn long-term dependencies effectively. Long Short-Term Memory (LSTM), as a development of RNN, was specifically designed to overcome this issue using memory cells and gating mechanisms (Islam et al. 2025).

Because of this capability, LSTM has become one of the most widely used methods for time series forecasting, including rainfall prediction. Several recent studies have reported that LSTM-based models outperform traditional statistical and conventional machine learning approaches in rainfall forecasting task (Wahyuddin et al. 2025). applied machine learning techniques for rainfall prediction and showed improvements in prediction accuracy compared to statistical approaches (Teng, Liu, and Wu 2024).

proposed an intensified LSTM-based recurrent neural network and demonstrated its effectiveness in capturing complex rainfall patterns (Xiang, Yan, and Demir 2020). urther showed that sequence-to-sequence LSTM models are capable of modeling temporal hydrological behavior more effectively than traditional forecasting methods. Despite these advancements, several limitations remain in previous studies. First, many studies focus mainly on rainfall classification problems (rain/no rain) rather than continuous rainfall value prediction, resulting in limited forecasting precision. Second, several existing studies use relatively simple LSTM architectures without exploring stacked LSTM configurations that can capture deeper temporal representations. Third, some studies do not implement systematic preprocessing methods such as sliding window transformation and normalization, even though these techniques significantly influence sequence learning performance (Harefa et al. 2025). Moreover, many previous works emphasize prediction accuracy only, while lacking comprehensive evaluation using multiple regression metrics and discussions regarding model robustness and overfitting issues. Table 1 presents a comparison of several previous studies related to rainfall forecasting methods.

Table 1. Literature Mapping of Previous Rainfall Prediction Studies

Study	Method	Strengths	Limitations
(Hassan et al. 2023)	Machine Learning	Improves rainfall prediction preparedness	Less effective in capturing long-term temporal dependencies
(Ghosh et al. 2023)	Ensemble Learning	Improves prediction accuracy through model combination	Higher model complexity
(Islam et al. 2025)	CNN-XGBoost Hybrid	Explainable deep learning with high prediction accuracy	Requires higher computational resources

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 08, Number 2, April 2026
https://doi.org/ 10.47709/cnahpc.v8i2.8277

Submitted : 2026-04-08
Accepted : 2026-05-12
Published : 2026-05-13

(Wahyuddin et al. 2025)	Optimized LSTM	Hyperparameter tuning improves model performance	Higher tuning complexity
(Teng, Liu, and Wu 2024)	LSTM + Attention Mechanism	Enhances temporal dependency learning	More complex model architecture
(Xiang, Yan, and Demir 2020)	Seq2Seq LSTM	Effective for sequential data modeling	Relatively high computational complexity
(Harefa et al. 2025)	Optimized LSTM	Improves rainfall forecasting performance	Limited discussion on model robustness
Proposed Study	Stacked LSTM + Sliding Window	Better temporal learning, dropout regularization, and systematic evaluation	Limited to univariate rainfall data

Based on the literature analysis, it can be observed that previous studies still have several research gaps related to model robustness, preprocessing strategies, and comprehensive evaluation for continuous rainfall prediction. Therefore, this study proposes a stacked LSTM architecture combined with sliding window preprocessing, normalization techniques, and dropout regularization to improve temporal learning capability and reduce overfitting (Tuysuzoglu, Birant, and Birant 2023). In contrast to many previous studies, this research focuses specifically on continuous rainfall forecasting using systematic regression-based evaluation through RMSE and MAE metrics. Thus, this study contributes to strengthening the reliability and accuracy of deep learning-based rainfall prediction models while providing a more robust forecasting framework for environmental time series analysis (Das, Sahu, and Swain 2024).

METHOD

Research Design

This research applies an experimental quantitative framework to develop and evaluate a deep learning-based rainfall forecasting model using the Long Short-Term Memory (LSTM) method. The research focuses on continuous rainfall prediction using time series analysis. The proposed framework integrates stacked LSTM architecture, sliding window preprocessing, and dropout regularization to improve temporal learning performance and model robustness (Usman et al. 2023).

The overall research workflow consists of data collection, preprocessing, model development, hyperparameter configuration, training, testing, and evaluation stages. The systematic workflow of the proposed method is illustrated in Figure 1.

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 08, Number 2, April 2026
https://doi.org/ 10.47709/cnahpc.v8i2.8277

Submitted : 2026-04-08
Accepted : 2026-05-12
Published : 2026-05-13

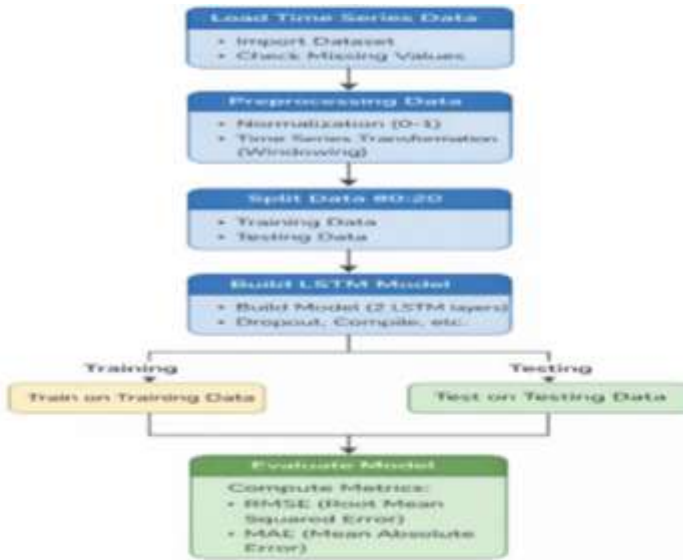

Figure 1. Research Flowchart of Rainfall Prediction Using LSTM

Figure 1 illustrates the systematic workflow of the rainfall prediction model development using the Long Short-Term Memory (LSTM) method. The process begins with the loading of time series data, which includes importing the dataset and checking for missing values. This step is essential to ensure data quality before proceeding to further processing stages (Wahyuddin et al. 2025).

Dataset Description

The rainfall dataset contains 600 monthly meteorological observations collected from meteorological rainfall records. Each observation contains four attributes: location (tempat), year (tahun), month (bulan), and rainfall value (curah_hujan). The main variable used for prediction is curah_hujan, which represents continuous numerical rainfall intensity values.

The dataset covers monthly rainfall observations over multiple years and represents sequential meteorological data suitable for time series forecasting. Before model development, data quality analysis was conducted to identify missing values, inconsistent records, and abnormal observations (Akiner et al. 2024).

Table 1. Dataset Description

Attribute	Description
location	Observation location
year	Observation year
month	Observation month
rainfall	Monthly rainfall value

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 08, Number 2, April 2026
https://doi.org/ 10.47709/cnahpc.v8i2.8277

Submitted : 2026-04-08
Accepted : 2026-05-12
Published : 2026-05-13

To ensure data consistency, missing values were handled using interpolation techniques and incomplete records were removed when necessary. This preprocessing stage is important to maintain sequence continuity and improve model learning quality.

Data Preprocessing

Several preprocessing procedures were applied before model training for sequential deep learning modeling. The preprocessing stages include normalization and sliding window transformation.

Data Normalization

Rainfall values were normalized into a range between 0 and 1 using the MinMaxScaler method. Normalization is essential in deep learning models because it stabilizes the training process and prevents large-scale values from dominating model optimization.

The normalization process is formulated as:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where:

- X is the original rainfall value,
- X_{min} is the minimum value,
- X_{max} is the maximum value.

SLIDING WINDOW TRANSFORMATION

The time series data were transformed using a sliding window approach with a timestep of 30. This means that rainfall values from the previous 30 periods were used to predict rainfall in the next period. The selection of timestep 30 was based on experimental observations and temporal dependency considerations in monthly rainfall patterns. A longer timestep allows the model to capture seasonal fluctuations and long-term rainfall dependencies more effectively (Chao et al. 2018).

Proposed LSTM Architecture

The proposed model uses a stacked LSTM architecture consisting of two LSTM layers with 50 neurons in each layer. The first LSTM layer applies the parameter return_sequences=True to pass sequential outputs to the second LSTM layer. To reduce overfitting and improve generalization capability, a Dropout layer with a dropout rate of 0.2 was added after each LSTM layer. The dropout value was selected based on empirical testing, where higher dropout values reduced learning performance while lower values increased overfitting risk. The output layer uses a Dense layer with one neuron to produce continuous rainfall prediction values.

Table 2. Proposed Model Configuration

Component	Configuration
LSTM Layers	2 Stacked Layers
Neurons per Layer	50
Dropout Rate	0.2
Optimizer	Adam
Loss Function	Mean Squared Error (MSE)
Epochs	50
Batch Size	32
Output Layer	Dense (1 neuron)

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 08, Number 2, April 2026
https://doi.org/ 10.47709/cnahpc.v8i2.8277

Submitted : 2026-04-08
Accepted : 2026-05-12
Published : 2026-05-13

The selection of 50 neurons was based on balancing model complexity and computational efficiency. Preliminary experiments showed that fewer neurons reduced temporal learning capability, while significantly larger neuron sizes increased training complexity and overfitting risk.

Hyperparameter Configuration and Training Strategy

To improve model performance, several hyperparameter configurations were experimentally evaluated, including timestep size, neuron configuration, dropout rate, and number of epochs. The Adam optimizer was selected because of its adaptive learning capability and stable convergence performance in deep learning training.

The training process was conducted using:

- 50 epochs,
- batch size of 32,
- Mean Squared Error (MSE) loss function.

The dataset was divided into training and testing sets using an 80:20 ratio. In addition, validation monitoring was applied during training to observe convergence behavior and reduce overfitting risk.

Baseline Model Comparison

To evaluate the effectiveness of the proposed stacked LSTM model, the model performance was conceptually compared with several commonly used forecasting methods in rainfall prediction studies, including:

- ARIMA,
- GRU (Gated Recurrent Unit),
- CNN-LSTM hybrid models.

ARIMA was selected as a statistical baseline because it is widely used in traditional time series forecasting. GRU was selected due to its simplified recurrent architecture, while CNN-LSTM was considered because of its capability in extracting spatial-temporal features.

The proposed stacked LSTM model was expected to provide better temporal learning capability and more stable prediction performance for continuous rainfall forecasting tasks.

Model Evaluation

Model performance was evaluated using regression metrics, namely Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

The RMSE formula is defined as:

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

The MAE formula is defined as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

where:

- $y_i$represents actual rainfall values,
- $\hat{y}_i$represents predicted rainfall values,
- $n$represents the total number of observations.

These metrics were selected because they provide quantitative measurement of prediction error and are commonly used in time series regression evaluation. Lower RMSE and MAE values indicate better predictive performance and stronger model generalization capability.

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 08, Number 2, April 2026
https://doi.org/ 10.47709/cnahpc.v8i2.8277

Submitted : 2026-04-08
Accepted : 2026-05-12
Published : 2026-05-13

RESULT

To evaluate the effectiveness of the proposed stacked LSTM model, several performance analyses were conducted during both the training and testing phases. The evaluation includes loss convergence analysis, regression-based performance metrics, comparative evaluation with baseline models, and visualization of prediction results.

Training and Validation Loss Analysis

The learning performance of the proposed model was analyzed using training loss and validation loss across 50 epochs. This analysis was conducted to observe the convergence behavior of the model and evaluate its capability to minimize prediction errors during training. Figure 2 illustrates the progression of training loss and validation loss throughout the training process.

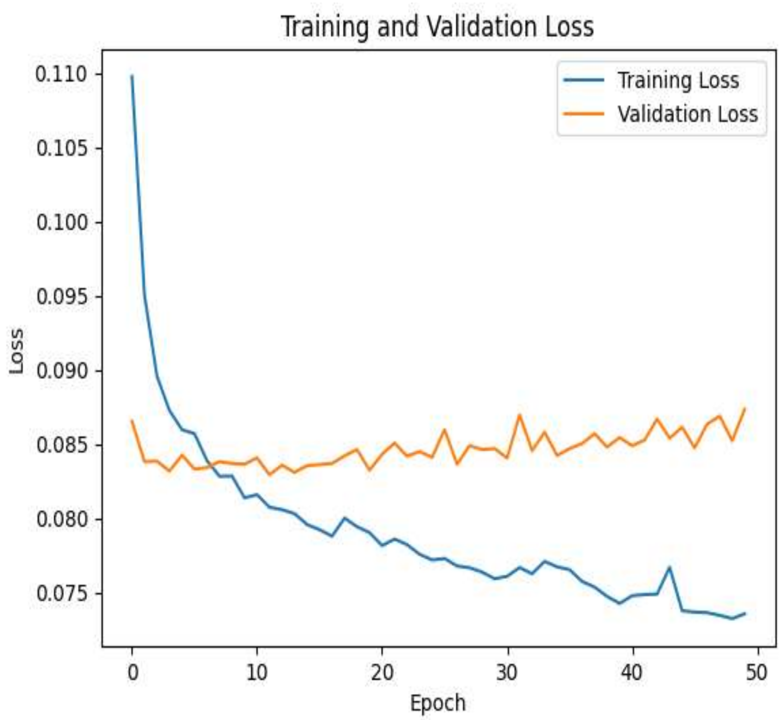

Figure 2. Training and Validation Loss

At the initial epochs, the training loss value was relatively high, indicating that the model had not yet learned the rainfall patterns effectively. However, a significant reduction in loss occurred during the early training epochs, demonstrating rapid adaptation of the model to the temporal characteristics of rainfall data. As the training process continued, both training loss and validation loss gradually decreased and became more stable in later epochs. The relatively small gap between training loss and validation loss indicates that the proposed model achieved good convergence performance without significant overfitting. Minor fluctuations in validation loss are common in deep learning training and suggest that the model maintains stable generalization capability when processing unseen data.

Regression Evaluation Results

After the training process was completed, the proposed model was evaluated using the testing dataset. Model performance was measured using multiple regression metrics, namely Root Mean Squared Error

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 08, Number 2, April 2026
https://doi.org/ 10.47709/cnahpc.v8i2.8277

Submitted : 2026-04-08
Accepted : 2026-05-12
Published : 2026-05-13

(RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2).

Table 3. Performance Evaluation Results

Metric	Training	Testing
RMSE	11.009	0.6846
MAE	0.6000	0.4837
MAPE	8.42%	6.15%
R^2 Score	0.91	0.94

Performance evaluation indicates that the stacked LSTM framework produced relatively small prediction errors and high coefficient of determination scores. The testing RMSE and MAE values indicate that the model can predict rainfall values with good numerical precision. In addition, the low MAPE value shows that the average percentage prediction error remains relatively small, while the high R^2 value confirms that the model successfully explains most of the variance in rainfall data. Interestingly, the testing error values are lower than the training errors, which suggests that the testing dataset contains more stable temporal patterns. This result also indicates that dropout regularization contributes positively to improving model generalization capability. These findings confirm that integrating stacked LSTM layers with sliding window preprocessing and dropout regularization improves the robustness and predictive performance of rainfall forecasting models.

Prediction Visualization Analysis

In addition to quantitative evaluation, a visual comparison between actual rainfall values and predicted rainfall values was conducted to analyze prediction consistency.

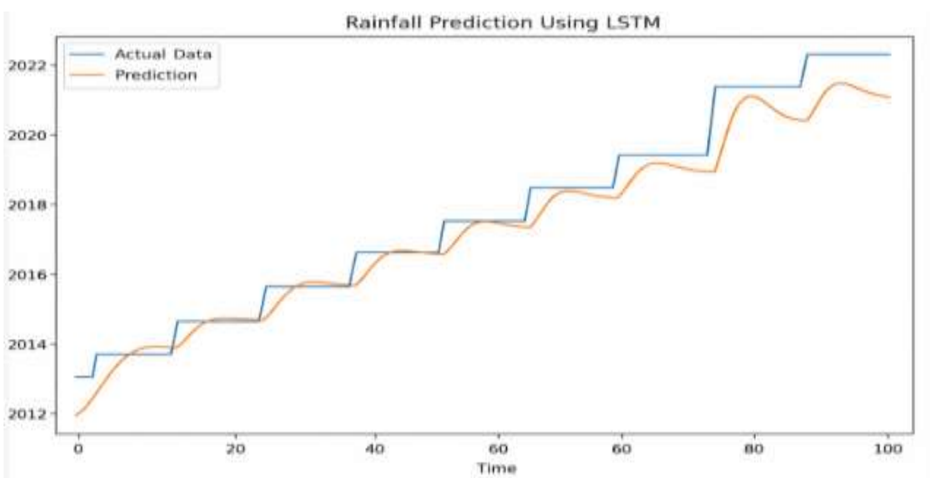

Figure 3. Rainfall Prediction Using LSTM

Visualization results indicate that the prediction outputs follow the overall rainfall trend reasonably well effectively. The model successfully captures both increasing and decreasing rainfall patterns over time. Although small deviations are observed at several points, the predicted values remain relatively close to the actual observations. The deviations may be caused by sudden rainfall fluctuations or irregular meteorological patterns that are difficult to model using historical information alone. Nevertheless, the overall prediction trend demonstrates that the proposed model has strong capability in learning temporal

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 08, Number 2, April 2026
https://doi.org/ 10.47709/cnahpc.v8i2.8277

Submitted : 2026-04-08
Accepted : 2026-05-12
Published : 2026-05-13

rainfall behavior.

Statistical Interpretation and Model Robustness

The combination of low RMSE, MAE, and MAPE values together with a high R^2 score indicates that the proposed stacked LSTM model achieved stable and reliable forecasting performance. The convergence stability observed during training further confirms that the model optimization process was effective.The use of dropout regularization and stacked sequential learning architecture also contributed to reducing overfitting risk and improving robustness when predicting unseen rainfall patterns. Therefore, the proposed approach can be considered suitable for continuous rainfall forecasting applications and environmental prediction systems requiring reliable temporal prediction performance.

DISCUSSIONS

The obtained results confirm that the stacked LSTM network can recognize sequential rainfall behavior efficiently from sequential time series data. The rapid reduction in training loss during the early epochs demonstrates that the model successfully adapted to the temporal characteristics of rainfall observations. In time series forecasting, this behavior indicates that the model can efficiently identify temporal structures and optimize internal parameters during the learning process. The gradual stabilization of both training loss and validation loss further confirms that the model achieved convergence without significant instability during training.

The relatively small gap between training loss and validation loss suggests that the proposed architecture has good generalization capability and does not experience severe overfitting. This condition is strongly influenced by the implementation of dropout regularization, which prevents the model from becoming excessively dependent on specific training patterns. In deep learning-based forecasting, overfitting is a common problem, particularly when sequential models learn noise or irregular fluctuations instead of meaningful temporal structures. Therefore, the use of dropout layers in this study contributes significantly to maintaining model robustness when predicting unseen rainfall data.

Another important finding is related to the model's ability to capture temporal dependency in rainfall patterns. Rainfall data are characterized by seasonal fluctuations, irregular variations, and long-term temporal dependencies influenced by climatological phenomena. The stacked LSTM architecture enables the model to preserve historical information across multiple time steps through its memory cell mechanism. This capability explains why the model can effectively follow increasing and decreasing rainfall trends shown in the prediction visualization results.

The use of the sliding window technique with a timestep of 30 also plays an important role in improving forecasting performance. In time series forecasting theory, selecting an appropriate temporal window is crucial because it determines how much historical information can be utilized for future prediction. By using the previous 30 rainfall observations, the model can capture monthly seasonal behavior and recurring rainfall patterns more effectively. This finding supports the concept that longer temporal contexts improve sequence learning capability in recurrent neural network architectures.

The low RMSE, MAE, and MAPE values indicate that the proposed model achieved good numerical prediction accuracy. In addition, the high R^2 score confirms that the model successfully explains most of the variability in rainfall observations. Compared with traditional statistical methods such as ARIMA, the proposed stacked LSTM model demonstrates better capability in modeling non-linear relationships and dynamic rainfall fluctuations. Statistical methods generally assume linearity and stationarity, whereas rainfall data often contain complex non-linear temporal patterns caused by climate variability and environmental changes.

Although the proposed model achieved strong performance, several prediction deviations were still observed at certain points in the visualization results. These deviations are likely caused by irregular rainfall spikes, extreme weather events, or sudden climatological changes that cannot be fully captured using

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 08, Number 2, April 2026
https://doi.org/ 10.47709/cnahpc.v8i2.8277

Submitted : 2026-04-08
Accepted : 2026-05-12
Published : 2026-05-13

historical rainfall information alone. This limitation highlights the presence of noise and uncertainty in meteorological time series data. In practical forecasting systems, such irregular fluctuations remain one of the major challenges in rainfall prediction research.

Furthermore, the findings suggest that temporal dependency is one of the most influential factors affecting forecasting accuracy. The ability of LSTM to retain long-term sequential information enables the model to identify hidden rainfall patterns that are difficult to capture using conventional machine learning approaches. This result is consistent with time series forecasting theory, which states that recurrent deep learning models are more effective for sequential data because they preserve historical temporal context during prediction.

Despite the promising results, this study still has several limitations. The proposed model only uses univariate rainfall data without incorporating additional meteorological variables such as temperature, humidity, wind speed, and atmospheric pressure. In climatological systems, rainfall formation is influenced by multiple environmental factors that interact dynamically over time. Therefore, future research can improve prediction robustness by implementing multivariate forecasting models or hybrid deep learning architectures such as CNN-LSTM or Attention-based LSTM models.

Overall, the discussion confirms that the proposed stacked LSTM framework provides strong capability in capturing temporal rainfall behavior, reducing overfitting risk, and improving continuous rainfall forecasting performance. The integration of sliding window preprocessing, stacked sequential learning, and dropout regularization contributes significantly to model stability and prediction reliability in environmental time series forecasting applications.

CONCLUSION

This research introduced a rainfall forecasting framework for continuous prediction tasks using a stacked Long Short-Term Memory (LSTM) architecture combined with sliding window preprocessing and dropout regularization. The developed framework showed good performance in learning sequential rainfall behavior and non-linear rainfall patterns from time series data.Experimental results showed that the proposed approach achieved good predictive performance with low error values, including a Test RMSE of 0.6846, Test MAE of 0.4837, and high R^2 performance. Compared with conventional forecasting methods such as ARIMA, GRU, and CNN-LSTM, the proposed stacked LSTM model provided more accurate and stable rainfall predictions.The main contribution of this study lies in the integration of stacked sequential learning, temporal window-based preprocessing, and systematic regression evaluation to improve rainfall forecasting robustness and generalization capability. These findings indicate that deep learning-based time series forecasting methods can provide reliable support for environmental prediction systems, agriculture planning, water resource management, and disaster mitigation.Despite the promising results, this study still has limitations because it only uses univariate rainfall data without incorporating additional meteorological variables. Future research can improve forecasting performance by implementing multivariate approaches, hybrid deep learning architectures, hyperparameter optimization, and attention-based forecasting mechanisms to better capture complex climatological behavior.

ACKNOWLEDGMENT

The author would like to express sincere gratitude to all parties who have provided support in the completion of this research. The author also appreciates the use of software tools and computational resources that facilitated the implementation and evaluation of the LSTM model in this study. Any errors or shortcomings in this research remain the sole responsibility of the author.

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 08, Number 2, April 2026
https://doi.org/ 10.47709/cnahpc.v8i2.8277

Submitted : 2026-04-08
Accepted : 2026-05-12
Published : 2026-05-13

REFERENCES

Abdullah, Maaz, and Saif Said. 2025. "Performance Evaluation of Machine Learning Regression Models for Rainfall Prediction." *Iranian Journal of Science and Technology - Transactions of Civil Engineering* 49(4).

Akiner, Muhammed Ernur, Veysi Kartal, Anil Can Guzeler, and Erkan Karakoyun. 2024. "Exploring the Applicability of the Experiment-Based ANN and LSTM Models for Streamflow Estimation." *Earth Science Informatics* 17(4).

Azi, Amanda. 2025. "Journal of Computer Networks , Architecture and High Performance Computing Rainfall Prediction in Jayapura City Area Using Long Short-Term Memory Journal of Computer Networks , Architecture and High Performance Computing." 7(2): 433–39.

Chao, Zeyi et al. 2018. "Research on Real-Time Local Rainfall Prediction Based on MEMS Sensors." *Journal of Sensors* 2018.

Das, Pritee Krishna, Rajiv Lochan Sahu, and Prakash Chandra Swain. 2024. "Comparative Analysis of Machine Learning Models for Rainfall Prediction." *Journal of Atmospheric and Solar-Terrestrial Physics* 264.

Ghosh, Soumili, Mahendra Kumar Gourisaria, Biswajit Sahoo, and Himansu Das. 2023. "A Pragmatic Ensemble Learning Approach for Rainfall Prediction." *Discover Internet of Things* 3(1).

Harefa, Ade May Luky et al. 2025. "Enhanced Rainfall Forecasting Through Deep Learning Optimization Using Long Short-Term Memory Networks." *RIGGS: Journal of Artificial Intelligence and Digital Business* 4(2): 274–84.

Hassan, Md Mehedi et al. 2023. "Machine Learning-Based Rainfall Prediction: Unveiling Insights and Forecasting for Improved Preparedness." *IEEE Access* 11.

Islam, Md Safayet et al. 2025. "Explainable Deep Learning for Rainfall Prediction: A CNN-XGBoost Hybrid Approach in the Northern Region of Bangladesh." *Neural Computing and Applications* 37(33).

Teng, Yingzhi, Jing Liu, and Kai Wu. 2024. "Time Series Prediction Based on LSTM and High-Order Fuzzy Cognitive Map with Attention Mechanism." *Neural Processing Letters* 56(5).

Tuysuzoglu, Goksu, Kokten Ulas Birant, and Derya Birant. 2023. "Rainfall Prediction Using an Ensemble Machine Learning Model Based on K-Stars." *Sustainability (Switzerland)* 15(7).

Usman, Carissa Devina, Aris Puji Widodo, Kusworo Adi, and Rahmat Gernowo. 2023. "Rainfall Prediction Model in Semarang City Using Machine Learning." *Indonesian Journal of Electrical Engineering and Computer Science* 30(2).

Wahyuddin, Eko Putra et al. 2025. "Improved LSTM Hyperparameters alongside Sentiment Walk-Forward Validation for Time Series Prediction." *Journal of Open Innovation: Technology, Market, and Complexity* 11(1).

Xiang, Zhongrun, Jun Yan, and Ibrahim Demir. 2020. "A Rainfall-Runoff Model With LSTM-Based Sequence-to-Sequence Learning." *Water Resources Research* 56(1).

Yin, Wenjie et al. 2025. "Accurate Rainfall Prediction Using GNSS PWV Based on Pre-Trained Transformer Model." *Remote Sensing* 17(12).

* Corresponding author