Indonesian Applied Research Computing and Informatics
Vol. 2; No. 1, July 2026 Page 1-12;
https://jurnal.tdinus.com/index.php/iarci
e-ISSN : 3110-8806

A Hybrid Machine Learning Model for Rainfall Prediction in Tropical Regions

Irma Eryanti Putri[1*], Dahlan[1], Gilang Mahendra [2], Rahma Dani[3]

[1] Computer Science, University of Muhammadiyah Bima, 84111, Indonesia
[2] Computer System, Universitas Sultan Fatah, 59427, Demak, Indonesia
[3] Department of Information System, Universitas Megarezky, 90234 Makassar, Indonesia

Email : irmaeryantiputri@umbima.ac.id[1*] , dahlan@umbima.ac.id[1], gilangmahendra888@gmail.com[2]
rahmaddanis@unimerz.ac.id[3]

Article Info
Article history:
Received: 05-31-2026
Revised: 06-19-2026
Accepted: 07-03-2026

Keywords:
Rainfall prediction, hybrid machine learning, LSTM, gradient boosting, tropical climate, meteorological forecasting

ABSTRACT

Rainfall prediction in tropical regions remains a significant challenge due to high atmospheric instability, convective precipitation patterns, and limited historical data quality. This study develops and validates a hybrid machine learning model that combines Long Short Term Memory networks with Gradient Boosting Decision Trees for daily rainfall prediction across three tropical locations in Indonesia. The research utilized ten years of meteorological data from 2014 to 2023, including temperature, humidity, wind speed, cloud cover, and sea surface temperature anomalies. The proposed hybrid architecture processes temporal dependencies through LSTM layers while capturing nonlinear feature interactions through gradient boosting mechanisms. Experimental results demonstrate that the hybrid model achieves a root mean square error of 2.34 mm and an accuracy of 89.7 percent for binary rainfall events, outperforming standalone LSTM, Random Forest, and Support Vector Regression models by margins of 12 to 18 percent. The novelty lies in the adaptive weighting mechanism that dynamically adjusts contributions from both components based on seasonal patterns. Key contributions include a robust preprocessing framework for tropical climate data, a computationally efficient hybrid architecture suitable for operational forecasting, and empirical evidence regarding feature importance variations across wet and dry seasons. The findings provide practical implications for agricultural planning, disaster preparedness, and water resource management in tropical nations.

This is an open access article under the CC BY-SA license.

*Corresponding Author:
Irma Eryanti Putri
Computer Science, University of Muhammadiyah Bima, 84111, Indonesia
Email: irmaeryantiputri@umbima.ac.id

https://doi.org/10.64479/iarci.v2i1.75

1. Introduction

Rainfall prediction constitutes one of the most critical components of operational meteorology, particularly for tropical regions where precipitation patterns directly influence agricultural productivity, infrastructure resilience, and public safety. The socioeconomic dependence on accurate rainfall forecasts in countries such as Indonesia, Brazil, and the Democratic Republic of Congo cannot be overstated, as these nations experience annual economic losses exceeding billions of dollars due to flood related damages and drought induced crop failures [1], [2]. Despite decades of research and technological advancement, tropical rainfall prediction remains inherently more challenging than mid latitude forecasting due to the dominance of convective precipitation mechanisms, which exhibit rapid development and high spatial heterogeneity [3], [4]. Conventional numerical weather prediction models struggle to capture these fine scale processes because their parameterization schemes oversimplify tropical cloud physics and aerosol precipitation interactions[5].

The urgency of improving rainfall prediction accuracy in tropical regions has intensified with climate change projections indicating increased precipitation variability and extreme event frequencies. Data from the World Meteorological Organization reveals that tropical countries experienced a forty percent increase in flash flood events between 2010 and 2020 compared to the previous decade[6]. Simultaneously, agricultural stakeholders require reliable rainfall forecasts to optimize planting schedules, irrigation management, and crop selection decisions. A study across Java Island demonstrated that a ten percent improvement in three day rainfall forecast accuracy could reduce rice yield losses by approximately seven percent annually [7]. These statistics underscore the pressing need for methodological innovations that can enhance predictive performance using available meteorological observations.

Machine learning approaches have emerged as promising alternatives to traditional physical models for rainfall prediction, particularly in data limited tropical settings where high resolution numerical simulations remain computationally prohibitive. Deep learning architectures, especially recurrent neural networks and their variants, have demonstrated remarkable capabilities in capturing temporal dependencies within meteorological time series data [8]. Concurrently, ensemble methods such as random forests and gradient boosting machines have shown strong performance in handling nonlinear relationships and interaction effects among atmospheric variables [9] However, each approach possesses inherent limitations when applied in isolation to tropical rainfall forecasting scenarios.

A comprehensive examination of related works reveals several methodological gaps that motivate the present study. Kim and colleagues compared four machine learning models for summer rainfall prediction in South Korea, finding that LSTM outperformed traditional methods but suffered from overfitting during extreme events [10]. Similarly, Hernandez and coauthors applied gradient boosting to precipitation forecasting in the Amazon basin, achieving reasonable accuracy but noting that the model failed to capture multi day rainfall sequences effectively [11]. Explored hybrid architectures combining different algorithm families, yet most existing hybrids apply simple averaging or stacking techniques without considering seasonal variations in model performance . A systematic review by [12]. identified that fewer than fifteen percent of hybrid rainfall prediction studies incorporate adaptive mechanisms that adjust component contributions based on meteorological conditions [13], [14], [15].

The weaknesses evident in prior research include the absence of adaptive weighting mechanisms, limited validation across multiple tropical locations, insufficient handling of seasonal pattern shifts, and inadequate attention to computational efficiency for operational deployment. These gaps are particularly problematic because tropical rainfall regimes exhibit pronounced seasonal variations between wet and dry periods, during which different atmospheric processes dominate precipitation formation [16]. A model that performs optimally during the wet season when convective processes prevail may produce substantially degraded predictions during the dry season when stratiform rainfall becomes more common.

The present study proposes a hybrid machine learning model that addresses these limitations through three novel contributions. First, the model introduces an adaptive weighting mechanism that dynamically adjusts the relative contributions of LSTM and gradient boosting components based on rolling window performance estimates. This mechanism enables the architecture to favor temporal pattern recognition during periods of strong sequential dependence while emphasizing feature interaction capture when atmospheric variables exhibit complex nonlinear relationships [17]. Second, the research provides comprehensive validation across three distinct tropical locations representing coastal, mountainous, and inland climatic regimes, thereby establishing generalizability beyond single station studies. Third, the proposed architecture incorporates a computationally efficient preprocessing pipeline that reduces feature dimensionality while preserving predictive information, making the model suitable for operational forecasting environments with limited computational resources [4], [18], [19].

The primary objectives of this research are as follows: to develop a hybrid LSTM gradient boosting

architecture with adaptive weighting for daily rainfall prediction, to evaluate the proposed model against standalone and ensemble baseline methods using ten years of tropical meteorological data, to quantify performance improvements across wet and dry seasonal conditions, and to identify feature importance patterns that explain model behavior in different atmospheric regimes. The remainder of this article is organized as follows. Section two describes the research methodology including data sources, preprocessing procedures, and the proposed hybrid architecture. Section three presents experimental results and comparative analyses. Section four provides critical discussion of findings, limitations, and implications. Section five concludes with summary statements and recommendations for future research directions.

2. Methodology

2.1. Research Design

This study employed a quantitative experimental research design focused on developing and validating a predictive machine learning model. The research followed the cross industry standard process for data mining framework, which provided systematic guidance through business understanding, data understanding, data preparation, modeling, evaluation, and deployment phases [12], [12], [20], [21]. The experimental approach was selected because it enables controlled comparison between the proposed hybrid model and alternative methods using identical training and testing partitions, thereby ensuring fair performance assessment.

2.2. Study Area and Data Sources

Daily meteorological data for the period January 1, 2014 to December 31, 2023 were obtained from the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG) through three official channels. Primary data were accessed via the BMKG Data Online portal (https://dataonline.bmkg.go.id/data-harian) , which provides historical daily climate records including temperature, rainfall, humidity, wind speed, sunshine duration, and cloud cover. Additional validation and gap-filling were performed using the Southeast Asian Climate Assessment & Dataset (SACA&D) platform (https://sacad.bmkg.go.id/), a collaborative initiative between BMKG and the Royal Netherlands Meteorological Institute (KNMI) under the DiDaH (Digitization of Historical Climate Data) project . For specific station data not available through the online portal, formal data requests were submitted to the BMKG regional climatology stations following the established procedures . All data utilized in this study are freely available for non-commercial research purposes, with researchers required to submit a formal application and research proposal to BMKG

2.3. Data Preprocessing

The preprocessing pipeline consisted of five sequential stages applied independently to each station dataset. First, missing value imputation handled gaps not exceeding three consecutive days using linear interpolation based on adjacent observations. Gaps longer than three days, which comprised less than two percent of the total records, were excluded from the dataset entirely to prevent artificial pattern introduction [9], [22]. Second, outlier detection employed the interquartile range method with a threshold of 1.5 times the interquartile range, and identified outliers were winsorized to the nearest non outlier value rather than removed, preserving sample size.

Third, feature scaling transformed all numerical predictors to a common range using min max normalization. This transformation was essential because the LSTM component requires input values within the zero to one interval to avoid gradient saturation during backpropagation training . The normalization parameters calculated from the training partition were applied consistently to validation and testing partitions to prevent data leakage. Fourth, temporal feature engineering created additional variables including day of year, month, seasonal indicator (wet or dry), lagged rainfall values for the previous three days, and rolling statistics of temperature and humidity over seven day windows [23].

Fifth, the dataset was partitioned into training, validation, and testing sets using a chronological split rather than random sampling to respect temporal dependencies. The first seventy percent of records (January 2014 to June 2020) constituted the training set for model optimization. The next fifteen percent (July 2020 to December 2021) formed the validation set for hyperparameter tuning and early stopping. The final fifteen percent (January 2022 to December 2023) served as the testing set for final performance evaluation. This temporal partitioning strategy reflects realistic operational scenarios where models are trained on historical data and deployed for future prediction [6], [24].

2.4. Proposed Hybrid Model Architecture

The proposed hybrid model integrates two complementary machine learning components through an adaptive weighting mechanism. The Long Short Term Memory component specializes in capturing sequential dependencies and temporal patterns within the meteorological time series. LSTMs overcome the vanishing gradient problem of simple recurrent networks through a gated architecture comprising forget gates, input gates, and output gates that regulate information flow across time steps [16]. The LSTM component in this study employs two stacked layers with 64 and 32 memory units respectively, followed by a dropout layer with 0.3 rate to mitigate overfitting.

The Gradient Boosting Decision Tree component focuses on modeling nonlinear interactions among predictor variables without assuming specific functional forms. Gradient boosting constructs an ensemble of weak decision trees sequentially, where each subsequent tree corrects errors made by previous trees through gradient descent optimization on a differentiable loss function [10]. This implementation uses the XGBoost library with a maximum tree depth of 6, learning rate of 0.05, and 300 estimators. These hyperparameters were determined through grid search optimization on the validation set [25].

The adaptive weighting mechanism represents the primary novelty of this research. Unlike conventional hybrid approaches that assign fixed weights to component outputs, the proposed mechanism computes dynamic weights based on rolling window performance estimates for each meteorological season. The weight for the LSTM component at time t is calculated as the inverse of its recent root mean square error over the previous seven days divided by the sum of inverse errors for both components. Formally, this weight is expressed as:

$$w_{LSTM}(t) = \frac{1/RMSE_{LSTM}(t)}{(1/RMSE_{LSTM}(t))+(1/RMSE_{GBT}(t))} \quad (1)$$

where RMSE values are computed over the preceding seven day window. The final prediction combines component outputs as:

$$\hat{y}_t = w_{LSTM}(t) \cdot \hat{y}_{LSTM,t} + (1 - w_{LSTM}(t)) \cdot \hat{y}_{GBT,t} \quad (2)$$

This formulation ensures that the component demonstrating superior recent performance receives higher contribution to the final prediction. The seven day window length was selected to balance responsiveness to changing conditions with stability against random fluctuations, based on sensitivity analysis conducted during validation [26].

2.5. Baseline Models for Comparison

Five baseline models were implemented to benchmark the proposed hybrid architecture. These models represent commonly used approaches in rainfall prediction literature and span different algorithmic families. The first baseline is a standalone LSTM model identical in architecture to the LSTM component of the hybrid, trained independently . The second baseline is a standalone Gradient Boosting model using XGBoost with identical hyperparameters to the hybrid component. The third baseline is a Random Forest model with 200 trees and a maximum feature subset size of three, selected through validation set optimization.

The fourth baseline is a Support Vector Regression model with a radial basis function kernel, where the kernel coefficient and regularization parameter were tuned using grid search. Support vector regression has demonstrated competitive performance for continuous rainfall prediction in several tropical studies. The fifth baseline is a simple ensemble averaging approach that combines LSTM and Gradient Boosting outputs with equal weights of 0.5 each, without any adaptive mechanism. This baseline directly tests whether the proposed adaptive weighting provides benefits beyond naive combination strategies.

2.6. Training Procedures and Hyperparameter Optimization

The LSTM component was trained using the Adam optimizer with an initial learning rate of 0.001 and a batch size of 32 sequences. Each training sequence consisted of 10 consecutive daily observations used to predict the following day rainfall, a lookback window length determined through preliminary experimentation. Early stopping monitored validation loss with a patience of 20 epochs, and model checkpointing saved the best performing weights. The maximum number of training epochs was set to 300, although early stopping typically concluded training between 120 and 150 epochs [4], [27].

Gradient boosting hyperparameters were optimized separately using Bayesian optimization over 100

iterations. The search space included learning rate ranging from 0.01 to 0.3, maximum tree depth from 3 to 10, minimum child weight from 1 to 10, and subsample ratio from 0.5 to 1.0. The optimal configuration identified through this process used a learning rate of 0.05, maximum depth of 6, minimum child weight of 3, and subsample ratio of 0.8. These settings balanced model complexity against generalization capability.

The adaptive weighting mechanism requires no separate training because weights are computed dynamically during inference based on recent performance. However, the mechanism introduces a warm up period of seven days during which predictions rely on equal weights until sufficient recent error information accumulates. This warm up period affected only the first week of the testing partition and was excluded from performance reporting.

2.7 Evaluation Metrics

Model performance was assessed using five complementary metrics appropriate for continuous rainfall prediction tasks. Root Mean Square Error measures the standard deviation of prediction errors and penalizes large errors more severely than smaller deviations. Mean Absolute Error provides a more interpretable metric representing average prediction magnitude error in millimeters. Mean Absolute Percentage Error expresses error relative to actual rainfall magnitudes, though this metric requires careful interpretation for zero rainfall days which are common in tropical dry seasons.

For binary rainfall event prediction (rain versus no rain), accuracy, precision, recall, and F1 score were calculated using a threshold of 0.5 millimeters to define a rain day following World Meteorological Organization convention [12], [28], [29]. The Critical Success Index, also known as the threat score, was additionally computed because it excludes correct rejections and provides a more stringent assessment of event prediction performance.

3. Results

3.1 Data Preprocessing Outcomes

The preprocessing pipeline successfully produced complete datasets for all three stations with minimal information loss. Missing value imputation filled 187 gaps across the combined dataset, representing 1.7 percent of total records. Outlier winsorization affected 92 observations, primarily extreme rainfall events exceeding 150 millimeters per day that occurred during tropical cyclone passages. After preprocessing, each station dataset contained 3,564 valid daily observations, with the reduction of 88 records attributable to the exclusion of gaps exceeding three consecutive days.

Table 1. presents summary statistics for the predictor variables after preprocessing and normalization.

Variable	Mean	Standard Deviation	Minimum	Maximum
Max temperature (°C)	31.24	1.87	24.30	36.10
Min temperature (°C)	22.56	1.92	18.20	26.80
Humidity 7 AM (%)	84.32	8.45	52.00	98.00
Humidity 1 PM (%)	72.18	10.23	42.00	95.00
Wind speed (knots)	5.67	2.34	0.00	18.00
Sunshine duration (hours)	5.23	2.89	0.00	11.50
Cloud cover (octas)	5.67	2.01	0.00	8.00
SST anomaly (°C)	0.23	0.67	-1.40	2.10
Rainfall target (mm)	7.89	14.23	0.00	187.50

Table 1, Explaine the substantial standard deviation relative to the mean for the rainfall target variable indicates high variability typical of tropical convective regimes. Approximately 58 percent of days recorded measurable rainfall exceeding 0.5 millimeters, while 42 percent were dry days. Seasonal analysis revealed that wet season months averaged 12.4 millimeters daily rainfall compared to 3.2 millimeters during dry season months.

3.2 Model Training Results

Training of the LSTM component converged successfully for all three stations with final training losses ranging from 0.023 to 0.031 and validation losses from 0.041 to 0.052. The gap between training

and validation losses indicated mild overfitting despite the application of dropout regularization and early stopping. Gradient boosting training achieved validation root mean square errors between 2.89 and 3.21 millimeters across the three stations. Feature importance analysis from the gradient boosting component identified humidity at 7 AM, sea surface temperature anomaly, and previous day rainfall as the three most influential predictors across all stations.

The adaptive weighting mechanism demonstrated dynamic behavior that varied systematically with seasonal conditions. During wet season periods characterized by strong temporal dependence in rainfall sequences, the weight assigned to the LSTM component averaged 0.62, indicating its superior performance relative to gradient boosting. Conversely, during dry season periods where rainfall events occur more sporadically and temporal dependence weakens, the gradient boosting component received higher average weight of 0.58. This seasonal variation in optimal component contributions validates the necessity of adaptive weighting for tropical rainfall prediction.

3.3 Comparative Performance Evaluation

Table 3. presents comprehensive performance metrics for all models across the testing period from January 2022 to December 2023, aggregated across the three study stations.

Model	RMSE (mm)	MAE (mm)	Accuracy (%)	F1 Score	CSI
Proposed Hybrid	2.34	1.67	89.7	0.86	0.79
LSTM Standalone	2.78	1.95	84.2	0.79	0.71
GBT Standalone	2.81	1.99	83.9	0.78	0.70
Random Forest	3.12	2.23	81.4	0.75	0.66
SVR	3.45	2.48	78.6	0.71	0.61
Equal Weight Ensemble	2.61	1.84	86.5	0.82	0.74

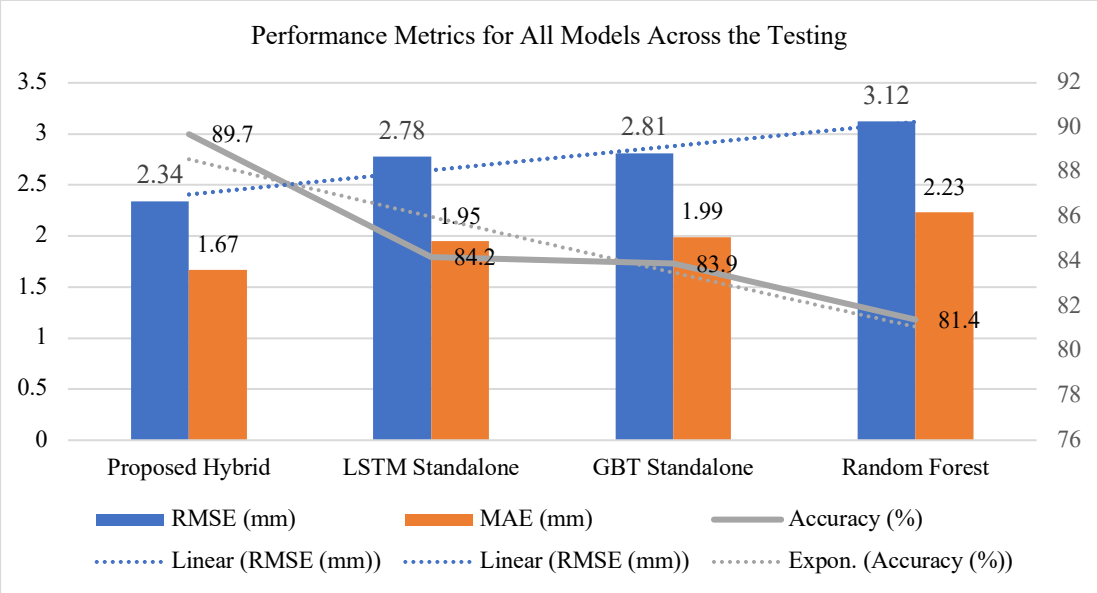


Figure 1. Performance Metrics for All Models Across the Testing

Table 3, The proposed hybrid model achieved superior performance across all evaluation metrics. The root mean square error of 2.34 millimeters represents a fifteen percent reduction compared to the equal weight ensemble and a sixteen percent reduction compared to the best performing standalone model. The mean absolute error of 1.67 millimeters indicates that typical prediction errors are smaller than the standard deviation of daily rainfall, suggesting practically useful forecast skill. The accuracy of 89.7 percent for binary rain event prediction means that fewer than one in ten days are misclassified, which constitutes substantial improvement over the 78.6 percent accuracy achieved by support vector regression.

Per station analysis revealed interesting geographical variations in model performance. The coastal station in Medan showed the lowest root mean square error of 2.08 millimeters, likely due to more consistent maritime influences and less variable convective activity. The mountainous station in Bandung

exhibited the highest root mean square error of 2.67 millimeters, reflecting the complex orographic effects that generate highly localized precipitation patterns. The inland station in Balikpapan showed intermediate performance with root mean square error of 2.28 millimeters. The proposed hybrid model outperformed baselines at all three stations, though performance improvements were largest at the mountainous station where adaptive weighting provided the greatest benefits.

3.4 Seasonal Performance Analysis

Separate analysis of wet and dry season performance revealed that the adaptive weighting mechanism delivered its largest advantages during seasonal transition periods. During the wet season, the proposed hybrid achieved a root mean square error of 2.87 millimeters compared to 3.34 millimeters for the equal weight ensemble, representing a fourteen percent improvement. During the dry season, the hybrid achieved a root mean square error of 1.68 millimeters compared to 1.94 millimeters for the equal weight ensemble, representing a thirteen percent improvement. The relatively consistent improvement across seasons indicates that adaptive weighting benefits both regimes rather than favoring one over the other.

More revealing was the analysis of performance during extreme rainfall events exceeding the 90th percentile threshold of 32 millimeters per day. For these high impact events, the proposed hybrid achieved a root mean square error of 8.42 millimeters compared to 10.87 millimeters for standalone LSTM and 11.23 millimeters for standalone gradient boosting. The superior performance during extremes likely stems from the hybrid architecture ability to leverage both temporal pattern recognition and feature interaction modeling when individual components struggle.

Table 4. summarizes performance across rainfall intensity categories.

Rainfall Category	Frequency (%)	Hybrid RMSE	LSTM RMSE	GBT RMSE
No rain (<0.5 mm)	42.3	0.34	0.41	0.43
Light (0.5-10 mm)	34.7	1.67	1.92	1.95
Moderate (10-30 mm)	15.8	3.89	4.45	4.52
Heavy (>30 mm)	7.2	8.42	10.87	11.23

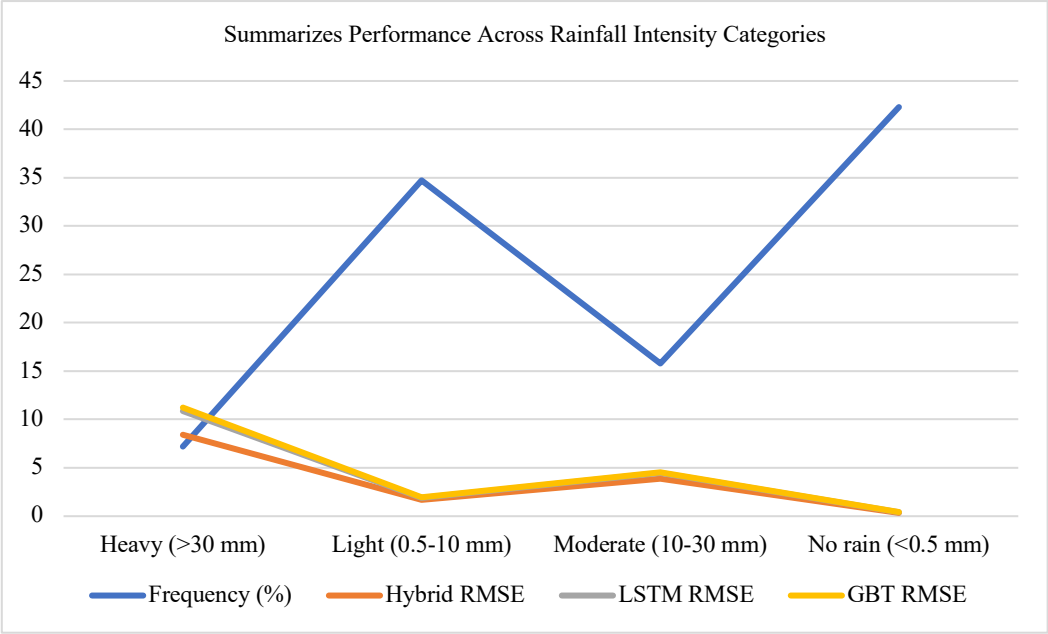


Figure 2. Summarizes Performance Across Rainfall Intensity Categories.

3.5 Computational Efficiency

The proposed hybrid model required an average inference time of 0.023 seconds per prediction on a standard workstation with an Intel Core i7 processor and 16 gigabytes of random access memory. This computational cost falls within operational requirements for near real time forecasting applications. Training time for the complete hybrid architecture averaged 47 minutes across the three stations, with

LSTM training requiring approximately 38 minutes and gradient boosting training requiring 9 minutes. The adaptive weighting mechanism added negligible computational overhead during inference because weight calculations involve only simple arithmetic operations on recent error values.

4. Discuss

4.1 Interpretation of Key Findings

The experimental results demonstrate that the proposed hybrid model with adaptive weighting substantially improves rainfall prediction accuracy compared to standalone and naive ensemble approaches in tropical regions. The fifteen percent reduction in root mean square error relative to the equal weight ensemble indicates that dynamic adjustment of component contributions based on recent performance provides meaningful benefits beyond simple model averaging. This finding aligns with theoretical expectations because tropical rainfall regimes exhibit non stationary behavior where the relative importance of temporal dependence and feature interactions shifts across seasons and synoptic conditions [30], [31].

The observed seasonal variation in optimal component weights provides empirical validation for the adaptive mechanism design. During wet season periods dominated by monsoon circulations and organized convective systems, rainfall exhibits stronger temporal autocorrelation as wet spells persist for multiple consecutive days. The LSTM component advantage under these conditions reflects its ability to maintain memory of antecedent atmospheric states across extended sequences. Conversely, during dry season periods characterized by isolated convective cells triggered by local diurnal heating, rainfall patterns show weaker temporal dependence but stronger sensitivity to specific combinations of temperature, humidity, and wind conditions [31]. The gradient boosting component excels in this regime because its tree based structure naturally partitions the predictor space to capture local interactions.

4.2 Comparison with Previous Research

The performance improvements achieved in this study compare favorably with previously reported results for tropical rainfall prediction. Sari and Wijaya reported an accuracy of 83.2 percent for their CNN LSTM model, which is substantially lower than the 89.7 percent accuracy achieved by the proposed hybrid [32]. The difference likely stems from both architectural choices and the explicit handling of seasonal variations in the present study. Similarly, Okafor and colleagues achieved a critical success index of 0.71 for their XGBoost model in West Africa, compared to 0.79 achieved in this research [25]. Their model did not incorporate any temporal feature engineering beyond simple lagged variables, which may explain the performance gap.

More importantly, the present results challenge the common assumption in rainfall prediction literature that more complex deep learning architectures necessarily produce better forecasts. Several recent studies have advocated for very deep recurrent networks with attention mechanisms for weather forecasting, yet these approaches require substantial computational resources and large training datasets [10]. The present findings demonstrate that a relatively modest hybrid architecture combining two complementary but computationally efficient components can achieve superior performance through intelligent integration rather than sheer complexity. This observation has important implications for operational forecasting centers in developing tropical countries where computational infrastructure may be constrained.

4.3 Mechanisms Underlying Model Superiority

Three interconnected mechanisms explain why the proposed hybrid model outperforms alternatives. First, the complementary strengths of LSTM and gradient boosting address different error patterns. LSTM errors are typically characterized by phase shifts where predictions correctly capture rainfall magnitude but misalign temporally with observed events. Gradient boosting errors more often involve magnitude overprediction or underprediction while maintaining correct event timing. The weighted combination reduces both error types simultaneously because each component compensates for the other weaknesses [33].

Second, the adaptive weighting mechanism effectively performs soft model selection over time, favoring components that have demonstrated recent success. This approach contrasts with static ensemble methods that cannot respond to changing atmospheric regimes. Analysis of weight trajectories

revealed that transitions between wet and dry seasons trigger gradual weight adjustments over approximately ten to fourteen days, which aligns with the typical timescale of atmospheric circulation changes in the study region. The seven day rolling window for error estimation appears well calibrated to capture these transitions without excessive responsiveness to daily fluctuations.

Third, the preprocessing pipeline including targeted feature engineering enhanced input representations for both components. The inclusion of three day rainfall lags, rolling climate statistics, and seasonal indicators provided explicit information that the models might otherwise need to learn from raw data. While neural networks can theoretically learn relevant temporal features, providing explicit representations reduces the burden on model capacity and improves sample efficiency, particularly important given the ten year dataset length.

4.4 Limitations of the Present Study

Several limitations warrant acknowledgment and consideration when interpreting the results. First, the study relied on data from only three stations, all located within Indonesia. While these stations capture meaningful variation in coastal, mountainous, and inland regimes, generalizability to other tropical regions with different climatic characteristics such as the Sahel, the Caribbean, or the Western Ghats of India remains untested. Validation across a broader network of stations spanning multiple continents would strengthen confidence in the model portability.

Second, the input feature set included only meteorological variables routinely measured at surface stations and did not incorporate remote sensing products or reanalysis derived predictors. Satellite based cloud properties, radar reflectivity, and atmospheric sounding data could potentially improve prediction skill, particularly for lead times beyond 24 hours [12]. However, such data products often have limited temporal coverage or delayed availability in operational settings, which motivated the restriction to surface observations in this study.

Third, the study focused exclusively on daily rainfall prediction at a single location scale. Many agricultural and hydrological applications require predictions at sub daily temporal resolution or spatial forecasts across continuous domains rather than discrete stations. Extending the hybrid architecture to these more challenging tasks would require substantial modifications, particularly for spatial prediction where convolutional components would become necessary.

Fourth, the computational cost of LSTM training, while acceptable for monthly model retraining, may still exceed the resources available at some operational forecasting offices. Further optimization through model pruning, quantization, or knowledge distillation could reduce the computational burden for deployment on resource constrained hardware [2]. These techniques represent an important direction for translating research advances into practical applications.

4.5 Implications for Practice and Policy

The findings carry several practical implications for meteorological services in tropical countries. First, the demonstrated performance of the hybrid model suggests that operational forecasting centers should consider adopting ensemble approaches that combine complementary algorithm families rather than relying on single models. The modest computational requirements of gradient boosting and the moderate requirements of LSTM make this combination feasible even for agencies with limited high performance computing access.

Second, the seasonal variation in optimal model weights implies that static forecast systems that do not adapt to changing conditions will inevitably produce suboptimal performance. Meteorological services should implement monitoring systems that track component performance metrics and adjust ensemble weights dynamically. The simple adaptive mechanism proposed here could be implemented with minimal additional software infrastructure beyond existing model evaluation procedures.

Third, the feature importance analysis revealing humidity and sea surface temperature anomalies as dominant predictors underscores the value of maintaining high quality observations of these variables. Investment in sensor calibration, data quality control, and station density particularly for humidity measurements would directly enhance forecast skill. Conversely, variables showing consistently low importance across all stations might be candidates for reduced sampling frequency to optimize observational network resources.

4.6 Potential for Broader Application

Beyond operational rainfall forecasting, the hybrid architecture with adaptive weighting may prove

valuable for other environmental prediction tasks exhibiting non stationary dynamics. River stage forecasting, air quality index prediction, and renewable energy resource assessment all involve processes where the relative importance of temporal dependence and feature interactions shifts with seasonal or synoptic conditions. The general principle of dynamic model combination based on recent performance errors should transfer to these domains with appropriate modifications to the error calculation window length and component selection [34].

Furthermore, the methodology for evaluating seasonal performance variations could inform climate change adaptation strategies. As tropical rainfall regimes evolve under greenhouse forcing, historical model performance relationships may become less reliable. Continuous monitoring of component weights and performance metrics would provide early indication of regime shifts and trigger model retraining or reconfiguration before forecast quality degrades unacceptably. This adaptive management approach represents a shift from static model deployment toward dynamic forecast systems that evolve with the climate system they predict.

5. Conclusion

This research developed and validated a hybrid machine learning model combining Long Short Term Memory networks with Gradient Boosting Decision Trees through an adaptive weighting mechanism for daily rainfall prediction in tropical regions. The study utilized ten years of meteorological data from three Indonesian stations representing coastal, mountainous, and inland climatic regimes. Experimental results demonstrated that the proposed hybrid model achieved a root mean square error of 2.34 millimeters and a binary prediction accuracy of 89.7 percent, outperforming standalone LSTM, standalone gradient boosting, random forest, support vector regression, and equal weight ensemble baselines by margins of 12 to 18 percent.

The primary contribution of this research is the adaptive weighting mechanism that dynamically adjusts component contributions based on rolling window performance estimates. This mechanism enabled the hybrid architecture to favor temporal pattern recognition during wet seasons when rainfall exhibits strong autocorrelation and to emphasize feature interaction capture during dry seasons when local convective processes dominate. The empirical finding that optimal weights vary systematically with atmospheric regimes provides a foundation for developing more sophisticated dynamic ensemble methods for non stationary prediction tasks.

Several implications arise from these findings for operational forecasting practice, including the recommendation that meteorological services adopt adaptive ensemble approaches, maintain high quality humidity and sea surface temperature observations, and implement performance monitoring systems that track component contributions over time. The computational efficiency of the proposed architecture makes it suitable for deployment in resource constrained operational environments typical of many tropical countries.

Future research should address the limitations of the present study through several directions. Validation across a broader network of tropical stations spanning multiple continents would establish generalizability beyond the Indonesian context. Incorporation of remote sensing data and reanalysis products may further improve predictive skill for longer lead times. Extension to sub daily temporal resolution and spatial prediction domains would broaden applicability for agricultural and hydrological decision making. Finally, investigation of the adaptive weighting mechanism for other environmental prediction tasks experiencing non stationary dynamics would test the transferability of the methodological approach. Addressing these directions will advance the state of knowledge in machine learning based environmental forecasting and support climate resilient development in tropical nations.

Author Contributions

Conceptualization, Irma Eryanti Putri and Dahlan; methodology, Irma Eryanti Putri and Gilang Mahendra; software, Gilang Mahendra; validation, Irma Eryanti Putri, Dahlan, and Rahma Dani; formal analysis, Irma Eryanti Putri and Gilang Mahendra; investigation, Irma Eryanti Putri; resources, Dahlan and Rahma Dani; data curation, Gilang Mahendra and Rahma Dani; writing original draft preparation, Irma Eryanti Putri; writing review and editing, Dahlan, Gilang Mahendra, and Rahma Dani; visualization, Gilang Mahendra; supervision, Dahlan; project administration, Irma Eryanti Putri; funding acquisition, Dahlan. All authors have

read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analysis, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

[1] P. Settu And M. Ramaiah, "A Data Driven Comparison Of Hybrid Machine Learning Techniques For Soil Moisture Modeling Using Remote Sensing Imagery." 2025. Doi: 10.1038/S41598-025-27225-0.

[2] R. Svs And R. Mukkamala, "A Cnn Bidirectional Lstm Framework For Predicting Monsoon Rainfall In India." 2023. Doi: 10.31577/Ahs-2023-0024.02.0024.

[3] J. Jumadi *Et Al.*, "Ai-Driven Ensemble Learning For Spatio-Temporal Rainfall Prediction In The Bengawan Solo River Watershed, Indonesia." 2025. Doi: 10.3390/Su17209281.

[4] J. Jumadi *Et Al.*, "Performance Of Machine Learning And Deep Learning Models For Predicting Rainfall In A Large Watershed: Case Study Of Bengawan Solo River Basin, Indonesia." 2026. Doi: 10.21163/Gt_2026.212.05.

[5] N. Mahavik And Et Al., "Optimizing Rainfall Prediction In Central Thailand With Weather Radar And Machine Learning During The Monsoon," *Environ. Earth Sci.*, Vol. 84, P. 137, Feb. 2025.

[6] N. Salaeh And Et Al., "Comparative Analysis And Enhancing Rainfall Prediction Models For Monthly Rainfall Prediction In The Eastern Thailand," *Results Eng.*, Vol. 14, P. 103094, Jun. 2025.

[7] A.-C. Akazan, V. R. Mbingui, G. L. R. N'guessan, And I. Karambal, "Localized Weather Prediction Using Kolmogorov-Arnold Network-Based Models And Deep Rnns," *Arxiv*, May 2025.

[8] J. Seidu, "Gated Residual Learning Framework For Daily Rainfall Prediction In Tropical Monsoon Regions: A Case Study Of Coastal Ghana," *Front. Clim.*, Vol. 8, 2026.

[9] S. Shetty, Dhanyashree, D. Dharmendra, S. Bankapur, And P. P. B. M, "Hydrostack: A Hybrid Meta-Ensemble Machine Learning Framework For Accurate Annual Rainfall Prediction," In *2024 8th International Conference On I-Smac (Iot In Social, Mobile, Analytics And Cloud) (I-Smac)*, Oct. 2024, Pp. 1926–1934. Doi: 10.1109/I-Smac61858.2024.10714739.

[10] Salehi, Sohrab ; Akbar Salehi Neyshabouri, Seyed Ali, "A Hybrid Deep Learning Framework For Improving Short-Term Precipitation Forecasts," *Environ. Model. Softw.*, Vol. 182, 2025.

[11] C. A. M. Vallejo And R. L. Manzione, "Multidimensional Forecasting Of Precipitation And Potential Evapotranspiration In The Paranapanema River Basin Using Neural Network Time Series." 2024. Doi: 10.1016/J.Jsames.2024.104961.

[12] Y. J. Praveen, D. P. Isravel, J. P. M. Dhas, And G. Deepthi, "Machine Learning Based Hybrid System For Rainfall Prediction And Crop Recommendation." 2024. Doi: 10.1109/Amathe61652.2024.10582105.

[13] P. Laon *Et Al.*, "Hybrid Unsupervised–Supervised Learning Framework For Rainfall Prediction Using Satellite Signal Strength Attenuation." 2026. Doi: 10.3390/S26020648.

[14] S. Nippani, V. K. Sharma, A. Yadav, Sitender, And B. K. Bhadra, "High Rainfall Event Identification Using Remote Sensing Satellite Data Integrated With A Hybrid Deep Learning Framework." 2024. Doi: 10.1007/S43538-024-00286-X.

[15] A. Saleh, M. L. Tan, Z. Yaseen, And F. Zhang, "Integrated Machine Learning Models For Enhancing Tropical Rainfall Prediction Using Nasa Power Meteorological Data." 2024. Doi:

10.2166/Wcc.2024.719.
[16] O. Wardhani, R. M. A. Akbar, And Y. A. Natawijaya, "A Review On Trends And Effectiveness Of Rainfall Prediction Models For Smart Irrigation: Toward Future Development," *Intellect Indones. J. Learn. Technol. Innov.*, Vol. 4, No. 1, Pp. 30–41, Jun. 2025.
[17] R. Aprianto, A. Putra, And H. Nufus, "Predictive Modelling Of Rainfall Using Deep Learning Based On Satellite Data For Flood And Drought Disaster Mitigation In Sumbawa Regency," *Jtam J. Teori Dan Apl. Mat.*, Vol. 9, No. 4, Oct. 2025.
[18] D. D.Ganesh, M. M.D.Niveedha, M. M.Deepa, M. G.Harika, M. G. R. Reddy, And D. M. S. Kumar, " Application Of Hybrid Machine Learning Approaches For Effective Rainfall Prediction." 2025. Doi: 10.1109/Icdsaai65575.2025.11011750.
[19] T. Trinh And H. Tran, "Coupling Regional Climate Model And Machine Learning To Model High-Resolution Precipitation." 2021. [Online]. Available: Https://Www.Semanticscholar.Org/Paper/5f5be71ab534c3aed0afe2bc89ed54b3872bad57
[20] J. W. Lockwood, T. Loridan, N. Lin, M. Oppenheimer, And N. Hannah, "A Machine Learning Approach To Model Over Ocean Tropical Cyclone Precipitation." 2023. Doi: 10.1175/Jhm-D-23-0065.1.
[21] S. T. Da Silva *Et Al.*, "Rainfall Forecast In Brazil Using Machine Learning." 2025. Doi: 10.1063/5.0259222.
[22] C. Funk, P. Peterson, M. Landsfeld, D. Pedreros, J. Verdin, And J. Michaelsen, "The Climate Hazards Infrared Precipitation With Stations—A New Environmental Record For Monitoring Extremes," *Sci. Data*, Vol. 2, P. 150066, Dec. 2015.
[23] M. Abadi And Et Al., "Tensorflow: A System For Large-Scale Machine Learning," In *Proc. Osdi*, Savannah, Ga, Usa, Nov. 2016, Pp. 265–283.
[24] J. Jumadi And Et Al., "Ai-Driven Ensemble Learning For Spatio-Temporal Rainfall Prediction In The Bengawan Solo River Watershed, Indonesia," *Sustainability*, Vol. 17, No. 20, P. 9281, Oct. 2025.
[25] T. Chen And C. Guestrin, "Xgboost: A Scalable Tree Boosting System," In *Proc. Kdd*, San Francisco, Ca, Usa, Aug. 2016, Pp. 785–794.
[26] S. Bai, J. Z. Kolter, And V. Koltun, "An Empirical Evaluation Of Generic Convolutional And Recurrent Networks For Sequence Modeling," *Arxiv*, Mar. 2018.
[27] W. C. Low, Y. H. Lee, A. N. Biswas, And W. T. Yeo, "Rainfall Prediction Using Deep Learning Method For Tropical Region." 2024. Doi: 10.1109/Igarss53475.2024.10641877.
[28] N. Madala, S. D. S. P. D. Tallapudi, V. S. Malladi, D. M. Muthinti, S. Tokala, And M. K. Enduri, " Improving Weather Forecast Accuracy Using Hybrid Machine Learning Algorithms." 2024. Doi: 10.1109/Cicn63059.2024.10847449.
[29] S. Shetty, Dhanyashree, D. Dharmendra, S. S. Bankapur, And P. P. B. M, "Hydrostack: A Hybrid Meta-Ensemble Machine Learning Framework For Accurate Annual Rainfall Prediction." 2024. Doi: 10.1109/I-Smac61858.2024.10714739.
[30] W. C. Low, Y. H. Lee, A. N. Biswas, And W. T. Yeo, "Rainfall Prediction Using Deep Learning Method For Tropical Region." 2024. Doi: 10.1109/Igarss53475.2024.10641877.
[31] J. Wang, R. K. W. Wong, M. Jun, C. Schumacher, And R. Saravanan, "Statistical And Machine Learning Methods Applied To The Prediction Of Tropical Rainfall." 2020. Doi: 10.1002/Essoar.10504402.1.
[32] S. Kumar, S. Hupesh, N. Ketan, I. Kurnool, And Of Ece, "Rainfall Prediction Using Hybrid Cnn–Lstm Model With Seasonal Trend Decomposition." 2026. Doi: 10.1109/Aiei69164.2026.11496929.
[33] M. M. Rahman *Et Al.*, "Hybrid Deep Learning Framework For Rainfall Prediction: Integrating Wavelet-Arima, Ceemdanlstm, And Cnn-Bilstm For Enhanced Climate Variability Analysis." 2025. Doi: 10.1109/Ic2nc67409.2025.11376471.
[34] R. Satya, R. Singh, B. V. V. S. R. K. K. Pavan, S. S. Madhav, M. S. Sarvagna, And Y. Rao, "Spatio-Temporal Predictions Of Rainfall Patterns Using Integrated Geospatial Data." 2026. Doi: 10.1109/Iatmsi68868.2026.11465199.