

Performance Evaluation of Multi Layer Perceptron Algorithm in Rainfall Prediction Based on AWS Station Topography Characteristics

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ABSTRACT

Accurate rainfall prediction is crucial for mitigating hydrometeorological disasters in Indonesia, where weather patterns are highly volatile and heavily influenced by topography. This study evaluates the performance of MLP algorithm in predicting rainfall intensity using high-resolution AWS data. The evaluation compares model accuracy across three contrasting topographical characteristics: coastal area (Serang Maritime Station), open lowland area (Cengkareng Meteorological Station), and mountainous area (Citeko Meteorological Station). The MLP model utilized historical rainfall, temperature differences, and humidity differences as input variables, trained over a three-year dataset (2022-2024). The results indicate that the MLP model possesses high nowcasting capabilities with an average MAE of 0.29 mm. The coastal area yielded the best prediction performance with RMSE 1.10 mm and MAE 0.22 mm, due to stable wind circulation patterns. Conversely, the open lowland area showed the highest RMSE of 2.14 mm due to sudden extreme rainfall spikes, while the mountainous region proved the most challenging to model with MAE 0.34 mm, due to highly dynamic orographic effects. Furthermore, the study identifies a structural limitation where the MLP underestimates extreme peak amplitudes, caused by data sparsity and the conservative nature of the MSE loss function. Ultimately, while the MLP is highly reliable as an early warning system for light to moderate rainfall, it requires further architectural modifications to accurately estimate extreme heavy rainfall.



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I. INTRODUCTION

Climate change and global warming have had a significant impact in various parts of the world, including an increase in extreme weather events [1]. In Indonesia, highly variable and intense rainfall is often the main trigger for destructive hydrometeorological disasters, such as floods and landslides [2]. Therefore, accurate rainfall intensity forecasts, especially on nowcasting scale, are a very important element in early warning and disaster risk mitigation efforts [3].

Conventional rainfall observations have generally relied on manual instruments such as Hellman-type rain gauges [4]. Although still widely used, Hellman rain gauges have a fundamental limitation in their low temporal resolution, which only provides daily accumulations [4] [5]. This resolution is insufficiently responsive to capture short-

duration extreme rainfall events that often trigger flash floods or urban flooding [6]. To overcome this, the Meteorology, Climatology and Geophysics Agency (BMKG) has been operating Automatic Weather Stations (AWS) equipped with automatic sensors to record weather parameters such as rainfall, temperature and humidity in real time at one-minute intervals [7] [8]. The availability of this high-resolution data opens up great opportunities for more precise weather prediction modelling.

However, the high fluctuations and complexity of non-linear relationships between weather variables in time-series data require advanced computational methods. The machine learning approach, particularly the Multi-Layer Perceptron (MLP) neural network architecture, has proven effective in processing unstructured data patterns [9]. MLP is capable of accepting multivariable inputs, such as historical rainfall

records, temperature dynamics, and air humidity, and then mapping them to predict the probability of rainfall in the future [10][11]. The feed-forward structure of MLP makes it reliable and computationally efficient for capturing basic patterns from weather data [12] [13].

On the other hand, rainfall characteristics in Indonesia are highly volatile and greatly influenced by differences in topography and geographical location [14] [15]. The characteristics of intense convective rainfall in coastal areas will have different time-series behaviour compared to low-lying open areas and mountainous regions that are prone to wind and orographic effects [11] [16]. While the application of the Multi-Layer Perceptron (MLP) algorithm for weather forecasting is well-established in the literature, its performance is often generalized without accounting for localized microclimates. Therefore, the primary contribution of this study is not the introduction of a novel algorithm, but rather a focused empirical evaluation of how specific topographical variations structurally affect the predictive reliability of a standard MLP model. Most existing studies focus on architectural optimization, leaving a critical gap in understanding how highly dynamic, localized convective weather in different terrains impacts a static feed-forward network.

To address this gap, this study aims to rigorously evaluate the performance of the MLP algorithm in predicting rainfall intensity using high-resolution AWS data across three contrasting topographical landscapes: Serang Maritime Meteorological Station (coastal region), Soekarno-Hatta Cengkareng Meteorological Station (open lowland region), and Citeko Meteorological Station (mountainous region). Through a comparative analysis of continuous error metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), this research provides critical insights into the spatial limitations and sensitivities of the MLP model. This empirical contribution is essential for supporting the strategic development of topography-adaptive disaster early warning systems.

II. METHOD

A. Data

This study utilises historical weather observation data sourced from AWS instruments belonging to BMKG. Weather parameters extracted include rainfall, air temperature and air humidity.

To examine the effect of topography on model performance, data was collected from three meteorological stations representing different regional characteristics, namely: Serang Maritime Meteorological Station representing coastal conditions, the Soekarno-Hatta Cengkareng Meteorological Station representing lowland or urban areas, and the Citeko Meteorological Station representing highland or mountainous areas. The data period used covers a three-year time span, from 1 January 2022 to 31

December 2024, with data resolution aggregated to hourly intervals.



Figure 1. Automatic Weather Station

While a three-year climatological timeframe may be relatively brief for capturing long-term macro-climate cycles, it yields approximately 26,280 hourly observation instances per station. For the specific purpose of hourly nowcasting, this high-frequency dataset provides a statistically sufficient volume for the MLP algorithm to optimize its weights and capture short-term convective patterns. Nevertheless, it is critically acknowledged that this three-year constraint naturally limits the presence of rare, extreme rainfall events in the training data, inherently contributing to the data sparsity challenge during model evaluation.

B. Pre-Processing Data

Pre-processing aims to prepare the dataset that will be used for modelling. serangkaian tahapan pra-pemrosesan dilakukan untuk memastikan kualitas data:

- 1) Data Cleaning: This includes removing *Not a Number* (NaN) values, unmeasured rainfall data (TTU), anomaly values of “9999”, negative rainfall data (< 0), and performing step checks and range checks on rainfall data [17].
- 2) Missing Data Imputation: Handling of missing temperature, humidity, and rainfall data on AWS is performed using the Multivariate Imputation by Chained Equation (MICE) algorithm, which produces estimated values based on observations of other variables through an iterative process [18]. To maintain the integrity of the time-based split and prevent data leakage, the MICE estimator was fitted exclusively on the training dataset, and the learned parameters were subsequently applied to impute the unseen test dataset.
- 3) Feature Engineering: In addition to historical rainfall records, the model also utilises additional features in the form of hourly temperature change differences and air humidity change differences. This is based on meteorological indications that a rapid decrease in temperature and an increase in humidity are primary thermodynamic precursors that often precede convective rainfall [19]. While other meteorological variables such

as wind speed, air pressure, and solar radiation are undoubtedly influential, this study intentionally restricts the input features to these three fundamental parameters to establish a baseline evaluation of the MLP's capability and to ensure data availability consistency across all three topographical stations. [19].

- 4) Data Normalisation: All input and output variables are transformed into a scale of 0 to 1 using the MinMaxScaler function for more efficient computation and homogeneous data dimensions. Similar to the imputation process, the scaler was fitted solely on the training data to ensure that future meteorological fluctuations remain entirely hidden from the model during the training phase. The normalization equation used is:

$$z = \frac{x_i - x_{min}}{x_{max} - x_{min}}$$

- 5) Specific Adjustments for Highly Fluctuating Meteorological Data: Tropical rainfall time-series data is highly fluctuating and severely zero-inflated (dominated by 0 mm during long dry spells). This extreme sparsity can cause gradient vanishing or 'dead neurons' when using the ReLU activation function. To technically adjust for this fluctuation, a small constant of 0.01 mm was temporarily added to all historical 0 mm data points during training. This constant was subsequently subtracted from the final prediction outputs to restore the original meteorological scale without disrupting the model's weight updates [20].

C. Flowchart

The stages of this research are systematically represented through a flowchart specially designed to model rainfall predictions using the Multi-Layer Perceptron (MLP) algorithm in Figure 2.

Figure 2 shows the flow of rainfall prediction modelling using *Multi-Layer Perceptron* (MLP), starting with the input of raw weather data (*Input Raw Dataset*) sourced from AWS instruments and Hellman Rain Gauge. The data then goes through a series of sequential preparation stages, starting from handling missing data values (Weather Data Imputation), cleaning and normalisation (Dataset Pre-Processing), to extracting additional predictor variables at the feature engineering stage (Feature Engineering).

Once the dataset is properly formatted, it undergoes a structuring process to convert the raw sequence into a supervised learning format. Specifically, a sliding window technique was applied with a lag feature of 1 hour ($t-1$) and a stride of 1 hour to predict the subsequent rainfall at time (t). Following this structuring, the flow continues to the dataset segmentation stage. To strictly prevent data leakage a common flaw in time-series modeling where future information inadvertently influences the training phase a chronological time-based split was implemented.

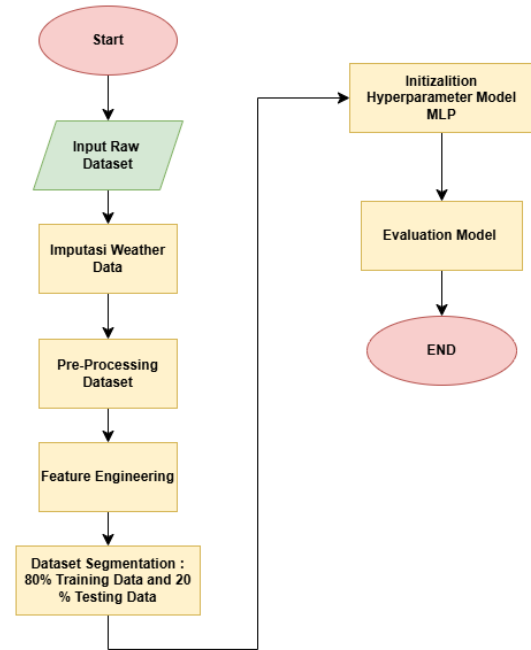


Figure 2. Research Flowchart

The first 80% of the historical time-series data was allocated sequentially as training data to form the algorithm's pattern recognition, while the remaining, most recent 20% of the chronological sequence was strictly reserved as an unseen test set. The training data is then used in the network architecture configuration and training stage so that the model is able to map the non-linear relationships between weather parameters. The model is then evaluated to analyse the performance of the MLP in each region in predicting rainfall.

D. MLP Model Architecture

The architecture was built to predict rainfall intensity using a feed-forward deep learning configuration with fully connected layers. This network was designed to receive three historical predictor variables, namely rainfall, temperature difference, and humidity difference, to map the probability of rainfall intensity at the next time.

The hyperparameter tuning strategy employed a systematic trial-and-error approach to identify the optimal configuration that balances computational efficiency and prevents overfitting on the highly sparse meteorological dataset. Based on this tuning strategy, the MLP model was constructed using two hidden layers, each initialized with 16 neurons [21]. The Rectified Linear Unit (ReLU) was selected as the activation function in the hidden layers because of its computational efficiency and its ability to capture complex non-linear interactions without suffering from the vanishing gradient problem. In the output layer, a linear activation function is utilized to produce continuous numerical rainfall intensity predictions. The training process is optimized using the Adaptive Moment Estimation (Adam) algorithm with a standard learning rate of 0.001, utilizing Mean Squared Error

(MSE) as the loss evaluation metric [22]. To further ensure training stability and optimal convergence, the model was configured with a batch size of 32 and trained over 50 epochs. Details of these final hyperparameter configurations are summarized in Table I.

TABEL I
HYPERPARAMETER MLP FOR RAINFALL PREDICTION

Component	Parameter	Value
Pre-Processing	Normalization	MinMaxScaler
	Segmentation	80% Training ; 20 Testing
	Input	3 Variables
Model Architecture	Hidden Layer 1	Dense (16 Units) , ReLU
	Hidden Layer 2	Dense (16 Units) , ReLU
	Output Layer	Dense (1 Units) , Linear
Training	Optimizer	Adam
	Loss Function	Mean Squared Error (MSE)
	Batch Size	32
	Epoch	50

E. Data Analysis

Data analysis was conducted to measure and validate the reliability of the trained Multi-Layer Perceptron (MLP) model. To establish a fundamental benchmark for the deep learning architecture, a Naive Persistence Model which conceptually assumes that the weather conditions and rainfall intensity at the next hour will be exactly identical to the current hour ($y_{t+1} = y_t$) was designated as the foundational baseline. Performance evaluation was carried out by comparing the output values of the model against actual observation data in the testing data. The evaluation parameters used were RMSE, and MAE. RMSE expresses the error value in units of solar radiation intensity. MAE measures the average absolute difference between the values predicted by the model and the actual observations. Unlike RMSE, MAE provides a linear average error without over-penalising outliers. The equations are expressed as follows [23]:

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

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (2)$$

III. RESULT AND DISCUSSIONS

A. Result of Pre-Processing Data

This study utilises a historical weather parameter dataset covering the period from 1 January 2022 to 31 December 2024, extracted from AWS. In the initial stage, observation data was recorded at one-minute intervals, with data

availability reaching approximately 500,000 rows per parameter for each station location. For the purposes of *Multi-Layer Perceptron* (MLP) modelling, this high-resolution data was aggregated to hourly resolution. This aggregation resulted in approximately 26,280 rows of active data per station over the three-year observation period.

This raw dataset then underwent a rigorous data cleaning process. Outlier detection was performed by removing data with Not a Number (NaN) values, unmeasured rainfall (TTU), instrument anomaly values “9999”, negative rainfall values (< 0), and unreasonable extreme daily rainfall (> 500 mm). The remaining missing data was handled using the Multivariate Imputation by Chained Equation (MICE) algorithm, which imputes values based on the patterns of other weather variables through an iterative process. Next, the entire dataset was normalised using the *MinMaxScaler* function into a range of 0 to 1. Since the majority of rainfall data had a value of 0 mm, which could trigger the death of neuron cells (*dead neurons*) during training, a small constant of 0.01 mm was added to each rainfall data value of 0 mm, which was later subtracted from the final result.

B. Evaluation MLP Model

Figure 3 illustrates the architectural form of the *Multi-Layer Perceptron* (MLP) network that has been trained and evaluated in this study.

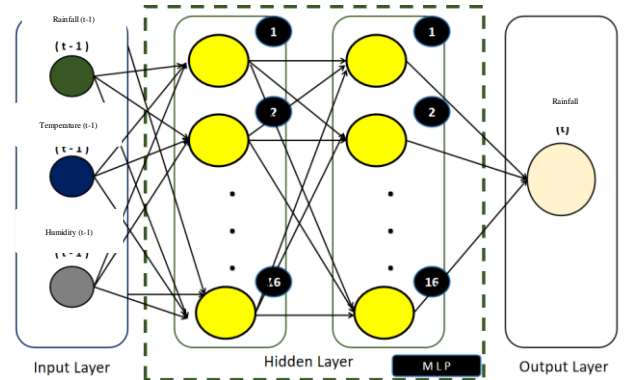


Figure 3. MLP Model Design for Rainfall Prediction

Based on this architecture, the model processes three historical weather parameters at time (t-1) in the input layer, namely rainfall intensity, temperature difference, and humidity difference. This information is then mapped non-linearly through two hidden layers, each consisting of 16 computational neurons, before finally converging on the output layer to produce rainfall predictions at time (t).

The prediction performance of this network architecture was then tested using 20% of the testing data from the three AWS stations separately. The testing was conducted to see how robust this feed-forward architecture is in dealing with different topographical characteristics. The evaluation results of the Root Mean Squared Error (RMSE), Mean Absolute

Error (MAE), and classification accuracy metrics are presented in Table II.

TABEL II
MLP MODEL PERFORMANCE BASED ON STATION LOCATION

Station Location	Characteristics	RMSE	MAE
Serang Maritime Station	Coastal Area	1.10	0.22
Soekarno-Hatta Cengkareng Meteorological Station	Open Area	2.14	0.33
Citeko Meteorological Station	Mountain Area	1.59	0.29

On average, the MLP algorithm produces highly capable *nowcasting* performance with an average MAE value of 0.29 mm, indicating a very minimal absolute error rate that is close to the *World Meteorological Organization* (WMO) minimum operational resolution standard of 0.2 mm [24]. This achievement confirms that MLP is very reliable in recognising non-rainy weather patterns and light to moderate rainfall intensity [25].

C. Discussion

Although the aggregate evaluation results show a high level of accuracy significantly outperforming the operational limits of a standard persistence baseline, which inherently fails to anticipate sudden convective rain onset or cessation, the MLP model responds to different topographical conditions with varying degrees of sensitivity. The differences in error metrics at the three AWS stations prove that geographical characteristics greatly influence the interaction patterns of weather parameters studied by the model.

In coastal areas (Serang Maritime Station), the model recorded the best evaluation with the lowest MAE of 0.22 mm. This indicates that coastal weather dynamics, which are strongly influenced by regular sea and land wind circulation patterns, have a relatively stable non-linear relationship between temperature, humidity, and rainfall. The stability of this pattern facilitates the feed-forward architecture of the MLP to perform precise function mapping. Conversely, in open lowland areas (Cengkareng Meteorological Station), the Root Mean Squared Error (RMSE) value spikes sharply to 2.14 mm. To interpret these metrics meaningfully, one must consider the zero-inflated distribution of the hourly rainfall dataset, where over 90% of the recorded data points are 0 mm (dry periods). In this quantitative context, an overall MAE of 0.33 mm appears exceptionally low simply because it is heavily diluted by thousands of non-raining hours. However, the significantly higher RMSE (2.14 mm) a metric that squares the errors mathematically confirms that when it does rain, the predictive errors are exceptionally large. This quantitative disparity between MAE and RMSE precisely indicates a high frequency of sudden, extreme rainfall spikes

(e.g., >20 mm/hour) that the model completely fails to capture.

Given the highly sensitive nature of RMSE calculations to outliers, this high value indicates a high frequency of extreme rainfall that is fluctuating and sudden in nature in the region. Meanwhile, the mountainous region (Citeko Station) proved to be the most difficult terrain to model. The combination of strong winds, orographic effects, and mountain microclimate condensation causes convective rainfall to fall in a highly dynamic and random manner. Consequently, Citeko produced the highest continuous baseline error (MAE = 0.34 mm). While the RMSE here (1.59 mm) is lower than Cengkareng's implying fewer catastrophic extreme outliers the high MAE quantifies a persistent, high-frequency baseline error. This quantitative behavior proves that the static MLP struggles continuously with the random, light-to-moderate microclimate fluctuations typical of mountainous orographic lifting, not just during extreme storms.

The phenomenon of the model's inability to achieve this peak amplitude value can be explained mathematically through two main technical factors related to severe data imbalance and algorithmic loss optimization. First, the hourly resolution rainfall dataset exhibits a massive class imbalance problem; the vast majority of the data instances represent dry spells (0 mm), while extreme convective spikes are exceedingly rare [26]. This severe data imbalance causes the neural network to heavily bias its weight updates toward the dominant majority class during backpropagation. Second, the standard Mean Squared Error (MSE) loss function used during training inherently minimizes the global average error. Because the dataset is heavily skewed towards zero, the MSE gradients continuously push the model to be mathematically 'conservative'. Predicting an extreme outlier carries the risk of a massive squared penalty if the prediction is a false positive; thus, the model adaptively suppresses its predictions to a safe, low baseline [27]. To technically overcome this fundamental limitation, future architectures must consider specific data imbalance handling techniques such as Synthetic Minority Over-sampling Technique for Regression (SMOTER) to artificially augment extreme events or adopt alternative loss functions. Utilizing asymmetric loss functions or weighted MSE, which impose significantly higher penalties for underestimating peak values rather than overestimating them, would force the network to prioritize extreme anomalies over global averages.

From these findings, claims regarding the operational deployment of the MLP model as a standalone early warning system must be approached with caution. While the algorithm is reasonably reliable as an initial indicator to predict the onset of rain and to estimate light to moderate precipitation, its structural unreliability during extreme conditions means it cannot be solely depended upon for critical disaster mitigation during heavy convective storms. However, for the needs of absolute quantitative estimation of extreme heavy rain, this architecture requires further modification, such as adjusting the loss function to be unbiased towards zero, or integration

with more complex sequential memory processing algorithms. Furthermore, the current reliance on a limited set of input variables represents a methodological constraint. Enriching the model with additional meteorological parameters specifically atmospheric pressure, wind speed, and solar radiation is highly recommended for future iterations. These variables govern the broader atmospheric kinematics that drive extreme weather systems and could significantly enhance the model's overall predictive performance.

IV. CONCLUSION

This study successfully evaluates the capability of MLP algorithm in forecasting hourly rainfall intensity using high-resolution AWS data. Overall, the MLP feed-forward architecture demonstrates robust nowcasting performance, achieving an average MAE of 0.29 mm, which closely aligns with WMO standard.

However, the evaluation reveals that topographical characteristics significantly dictate the model's predictive accuracy. The MLP performs exceptionally well in coastal areas (Serang) due to stable and structured weather dynamics. In contrast, open lowland areas (Cengkareng) suffer from high RMSE values caused by sudden, extreme rainfall fluctuations, while mountainous regions (Citeko) pose the greatest modeling challenge due to unpredictable orographic effects and microclimate condensations.

Additionally, a fundamental limitation of the MLP model was identified when handling extreme rainfall anomalies. The model tends to underestimate peak rainfall amplitudes due to the sparse nature of the dataset and the mathematical constraint of MSE loss function, which forces conservative predictions to minimize global errors. Therefore, it can be concluded that while the MLP algorithm serves as a useful baseline indicator for detecting the onset of light to moderate rainfall, claims regarding its use as a comprehensive early warning system must be heavily qualified due to its inherent inability to accurately forecast extreme heavy rain amplitudes. To provide a more comprehensive evaluation and address the sequential limitations of a static feed-forward network, it is highly recommended for future studies to directly compare the MLP with dynamic, sequential memory-based architectures such as Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRU). Such comparative future research, alongside the modification of loss functions to handle zero-biased data, is essential to develop a truly robust and adaptive hydrometeorological early warning system.

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