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A Multi-Layer Perceptron Regression and Variant Windowing for Estimating Rainfall Based on Weather Radar Data

F. E. Penalun[(1)], A. Hermawan[(2)], D. Avianto[(3)], A. Pramudwiatmoko[(4)]

[(1)] *Meteorological Climatology and Geophysics Agency, Indonesia*
[(1,2,3,4)] *Master of Information Technology, Yogyakarta University of Technology Indonesia*

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Correspondence:
Ferdinandus Edwin Penalun
6220211008.edwin@student.uty.ac.id

Abstract

Accurate rainfall information is crucial for various applications, including river flow estimation, water resource management, and flood warning system development. Traditional rain gauge networks, however, suffer from limited spatial coverage, leading to incomplete and biased data for large areas. This study proposes a novel approach for surface rainfall estimation using weather radar data and a MultiLayer Perceptron (MLP) Regressor machine learning model. Grid search was employed to explore model performance across different windowing configurations: no windowing, n-1 windowing, and n-2 windowing. The results demonstrate that n-1 windowing outperforms other configurations, achieving an average RMSE of 0.987, MAE of 0.263, and R-squared of 0.242 across five locations. This suggests that n-1 windowing effectively captures the temporal dynamics of rainfall patterns while improving the model's sensitivity to regularization. However, a tendency for underestimating high-intensity rainfall events remains. This research highlights the effectiveness of n-1 windowing with MLP Regressors for enhanced surface rainfall estimation using weather radar data. Further investigation is needed to address the underestimation bias, particularly for high rainfall events.

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1. Introduction

Technological advances and increased calculation capacity have strengthened atmospheric models using key variables as the basis for forecasting weather phenomena. Although current estimation models can provide information that can be extracted from atmospheric images, there are limitations in integrally processing large amounts of data [1]. One of the main challenges in forecasting is obtaining accurate baseline data especially when high spatial and temporal resolution is required [2]. Traditional rain gauge networks have limited spatial coverage, resulting in incomplete and biased rainfall data when used to represent large areas. Weather radar offers significant advantages. It provides high-resolution data over a large area during rain events, but its accuracy can be affected by noise, bright banding, anomalous propagation, beam blocking, and signal attenuation [3].

Rainfall estimation using radar data has played a significant role in improving the accuracy of rainfall measurements [4]. The main use of radar-based rainfall estimation is widely used in large-scale distributed hydrological models [5]. Accurate rainfall data is needed to estimate river water flow, calculate water resources, and build flood warning systems.

Information related to rainfall estimation produced by weather radar can meet the needs of high-resolution and up-to-date data in many areas, especially where rain gauge networks are sparse [6].

The traditional method for estimating rainfall based on radar data can be done with an empirical relationship between reflectivity value (Z) and rainfall rate (R). Marshall and Parmer introduced the R-Z relationship ($Z = 200R^{1.6}$) which describes the empirical relationship between Z and R. The R-Z relationship is sensitive to the variability of the drop size distribution which causes uncertainty in Quantitative Precipitation Estimation (QPE) [7]. The other alternative that is now most widely researched is using machine learning methods. One of the biggest advantages of machine learning algorithms is their applicability to non-linear relationships between dependent and independent variables [8].

A number of studies have been conducted in estimating rainfall utilizing machine learning (ML) technology based on radar data. In the research of Liao and Barros (2023) This study proposes a technique to enhance the resolution of rainfall data from dual-polarization weather radar imagery. The approach utilizes physics-guided Artificial Intelligence (PAI) and multi-layer perceptron models to downscale the resolution from 1 kilometer to 250 meters. Rainfall measurements serve as validation data to refine the creation of high-resolution Quantitative Precipitation Estimates (QPE) products [4]. In the research of Shin et al. (2021), dual-polarization radar data variables were used as independent variables in a regression tree and random forest model. These variables included differential reflectivity (ZDR), specific differential phase (KDP), cross coefficient (ρHV), reflectivity (ZH), along with additional data from two-dimensional video disdrometers that observed the size distribution of raindrops [8]. Tian et al. (2020) collected radar data at an altitude of 1200 meters above the surface using a 24 km × 24° beam matrix centered around the nearest grid point of the automatic rain gauge station[9]. esearch by Tan et al. (2017) used radar data at four spatial heights of 1km x 1km at several vertical levels of 1000, 2000, 3000, and 4000 meters [10]. In the research of Yo et al, (2021) using the maximum reflectivity value product to predict surface rainfall the model used is Convolutional Neural Network (CNN) [10]. The results of all previous studies show that the use of ML in estimating surface rainfall gives satisfactory results. The MultiLayer Perceptron Regressor (MLP Regressor) model is utilized in this study, employing feature selection through windowing variation to modify the independent variables, thereby enhancing the estimation performance.

2. Research Methodology

Figure 1 illustrates the research method's stages. The first stage is data preparation, where data is extracted and compiled into a usable dataset for the model. Next comes model selection, followed by data preprocessing using the windowing technique to select relevant independent variables. Finally, the model is trained and evaluated using a performance matrix.

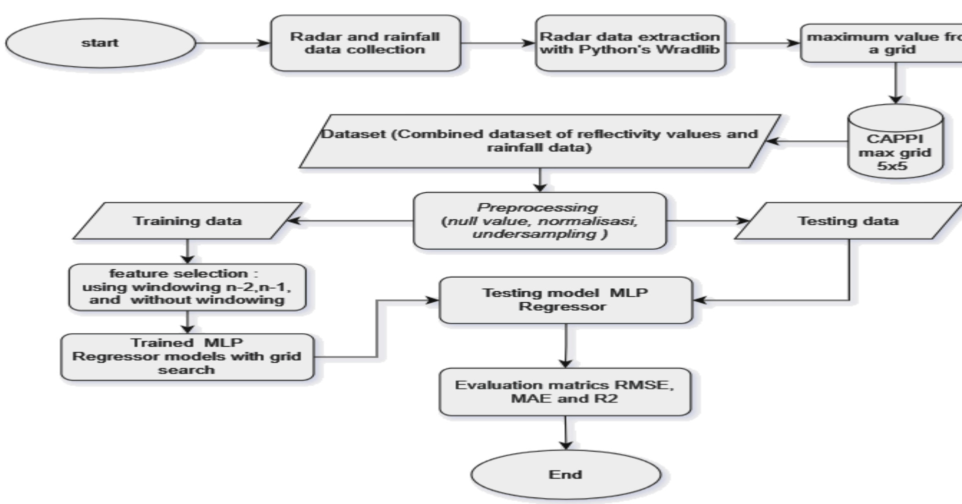


Figure. 1 : Research stages

2.1 Data Preparation

The primary data source for this research is a single-polarization radar located at the Climatology Station D.I Yogyakarta, situated at coordinates 7.73 S and 110.35 E in Indonesia. The weather radar operates by scanning the atmosphere for a duration of 228.5 seconds to generate one volumetric raw data, as depicted in Figure 2. This raw data is subsequently processed using the wradlib Python library for extraction[11].

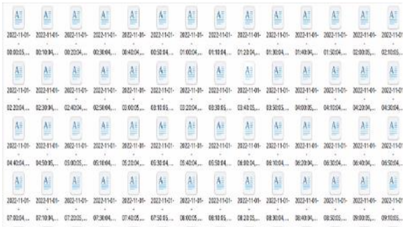


Figure 2. Sample of raw data

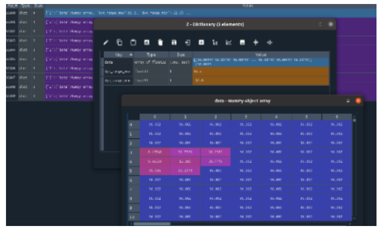


Figure 3. Reflectivity data from raw data at elevation 0

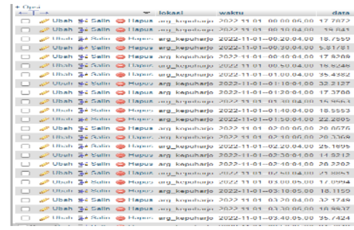
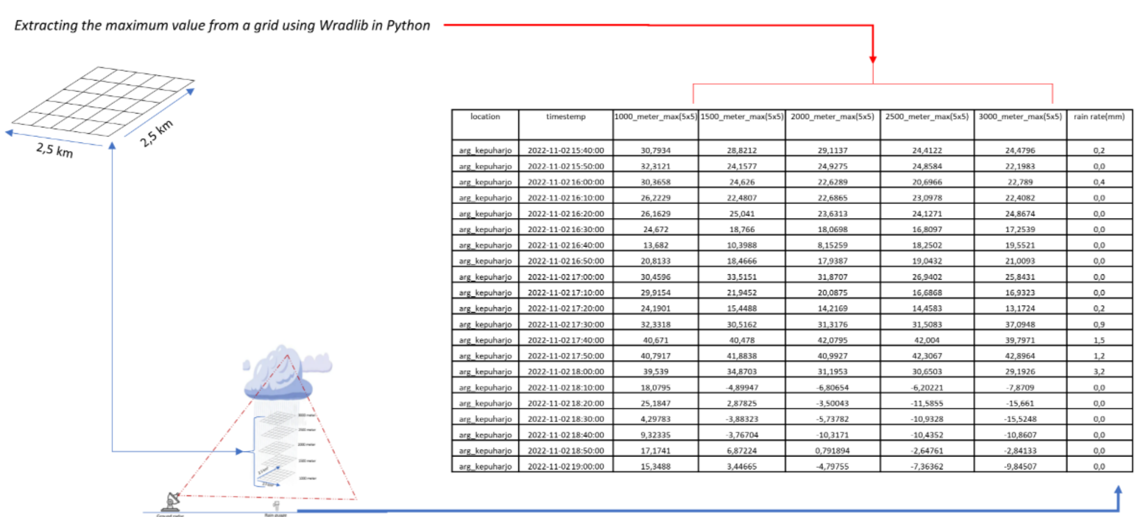


Figure 4. Data extraction results using wradlib into RDBMS MySQL

The volumetric radar data consists of nine elevations, containing reflectivity (Z) data. This data is stored in a structured format called a dictionary array. The reflectivity values for each elevation have different grid sizes, as shown in Figure 3. From these 9 elevations, the data will then be projected into latitude-longitude coordinates to form Constant Altitude Plan Position Indicator (CAPPI) data, which displays radar reflectivity values at specific altitudes [12]. CAPPI Product initially had a grid size of 800 x 800 with a 200 km range from the radar location. Then, a value retrieval was performed in a smaller grid size. The data extraction process was taken for five layers at altitudes of 1000 meters, 1500 meters, 2000 meters, 2500 meters, and 3000 meters. Each layer of the maximum value of the 5 x 5 grid on the radar represents a size of 2.5 km² on the Earth's surface. The extraction process has been adjusted to the latitude and longitude coordinates of the automatic rain gauge. Then the data is stored in the Relational Database Management System MySQL which can be seen in Figure 4. The rainfall measurement data on the surface has a measurement resolution of 0.2 millimeters (mm). The radar and rain gauge extraction data have the same data retrieval interval which is set every 10 minutes. The data acquisition period in this study has a span of 6 months during the rainy season from November 2022 to April 2023. There are five test locations used in this study: Automatic Weather Station (AWS) Kulonprogo, Automatic Rain Gauge (ARG) Kepuharjo, AWS Pakem, ARG SMPK Sleman, and AWS Geofisika Station Sleman. For more details, the data collection process can be seen in Figure 5.



location	timestemp	1000_meter_max(5x5)	1500_meter_max(5x5)	2000_meter_max(5x5)	2500_meter_max(5x5)	3000_meter_max(5x5)	rain rate(mm)
arg_kepuharjo	2022-11-02 15:40:00	30,7934	28,8212	29,1137	24,4122	24,4796	0,2
arg_kepuharjo	2022-11-02 15:50:00	32,3121	24,1577	24,9275	24,8584	22,1983	0,0
arg_kepuharjo	2022-11-02 16:00:00	30,3658	24,626	22,6289	20,6966	22,789	0,4
arg_kepuharjo	2022-11-02 16:10:00	26,2229	22,4807	22,6865	23,0978	22,4082	0,0
arg_kepuharjo	2022-11-02 16:20:00	26,1629	25,041	23,6313	24,1271	24,8674	0,0
arg_kepuharjo	2022-11-02 16:30:00	24,672	18,766	18,0698	16,8097	17,2539	0,0
arg_kepuharjo	2022-11-02 16:40:00	13,682	10,3988	8,15259	18,2502	19,5521	0,0
arg_kepuharjo	2022-11-02 16:50:00	20,8133	18,4666	17,9387	19,0432	21,0093	0,0
arg_kepuharjo	2022-11-02 17:00:00	30,4596	33,5151	31,8707	26,9402	25,8431	0,0
arg_kepuharjo	2022-11-02 17:10:00	29,9154	21,9452	20,0875	16,6868	16,9323	0,0
arg_kepuharjo	2022-11-02 17:20:00	24,1901	15,4488	14,2169	14,4583	13,1724	0,2
arg_kepuharjo	2022-11-02 17:30:00	32,3318	30,5162	31,3176	31,5083	37,0948	0,9
arg_kepuharjo	2022-11-02 17:40:00	40,671	40,478	42,0795	42,004	39,7971	1,5
arg_kepuharjo	2022-11-02 17:50:00	40,7917	41,8838	40,9927	42,3067	42,8964	1,2
arg_kepuharjo	2022-11-02 18:00:00	39,539	34,8703	31,1953	30,6503	29,1926	3,2
arg_kepuharjo	2022-11-02 18:10:00	18,0795	-4,89947	-6,80654	-6,20221	-7,8709	0,0
arg_kepuharjo	2022-11-02 18:20:00	25,1847	2,87825	-3,50043	-11,5855	-15,661	0,0
arg_kepuharjo	2022-11-02 18:30:00	4,29783	-3,88323	-5,73782	-10,9328	-15,5248	0,0
arg_kepuharjo	2022-11-02 18:40:00	9,32335	-3,76704	-10,3171	-10,4352	-10,8607	0,0
arg_kepuharjo	2022-11-02 18:50:00	17,1741	6,87224	0,791894	-2,64761	-2,84133	0,0
arg_kepuharjo	2022-11-02 19:00:00	15,3488	3,44665	-4,79755	-7,36362	-9,84507	0,0

Figure 5. Radar Data Collection Process

After both data are obtained, data adjustment is necessary when combining them. Data is sorted based on time criteria. Radar raw data at 00:00 UTC (Universal Time Coordinated) estimates the accumulated rainfall from 00:00 UTC to 00:10 UTC measured by the rain gauge. In general, radar data and rainfall values have a linear relationship. The lower the radar reflectivity value, the lower the rainfall intensity measurement. This is due to the direct relationship between radar reflectivity and rainfall intensity. The higher the backscatter energy received by the radar, the higher the reflectivity value, which is directly proportional to the higher rainfall intensity [13]. After collecting radar and rainfall data, preprocessing involves checking for missing values, data cleaning, and normalization. The first step focuses on handling missing rainfall data through value imputation using linear interpolation. This method estimates values for missing data points by assuming a linear relationship between two known data points that flank the missing value [14].

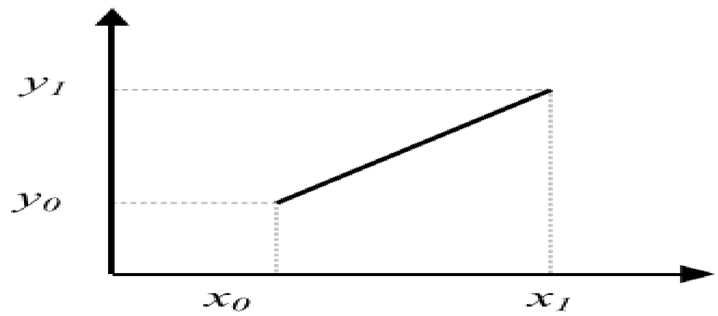


Figure 6. Linear interpolation

The points (x_0, y_0) and (x_1, y_1) represent the two points forming the straight line interpolation as shown in Figure 6. The equation for linear interpolation between the values at points P_1 (x_0, y_0) and P_2 (x_1, y_1) can be determined as shown in Equation 1 below:

$$y = \frac{y_1 - y_0}{x_1 - x_0}(x - x_0) + y_0 \quad \text{........ 1)}$$

After interpolating the missing rows in the rainfall data, we remove the corresponding data from the radar reflectivity data. This step is crucial because data representing no-rain events significantly outnumbers rain event data, creating an imbalanced dataset. By undersampling, the number of samples from the majority class (i.e., non-rain events) is reduced to achieve a balance between the two classes. It is important to note that many traditional machine learning methods assume that the target classes have the same distribution. For example, in weather forecasting and disease diagnostics, class imbalance often occurs because the majority of examples are labeled with one class while the number of examples of the other is smaller. By undersampling, we can improve the balance of the dataset and ensure that the machine learning model can learn well from both classes[15]. This class imbalance leads to a bias in the models, favoring the majority class and neglecting the minority class. Consequently, model performance on the minority class suffers, even when overall accuracy appears high. This phenomenon, known as the class imbalance problem, can be misleading. High overall accuracy doesn't guarantee the model generalizes well to the minority class.[16]. After achieving a more balanced dataset through undersampling, data normalization or standardization becomes even more important. Even a reduced majority class might have a wider value range compared to the minority class. These large variations in feature value ranges can lead to some features having an outsized influence on the model's learning process. Normalization or standardization helps mitigate this issue by ensuring all features have similar ranges[17]. Standardization is a specific type of normalization technique performed on the data to prevent features with large ranges from dominantly affecting the metrics used in machine learning models. Standardization transforms the data to have a zero mean and unit standard deviation. This ensures all features are on a similar scale and contribute equally during model training. MinMaxScaler is a commonly used approach for standardization, which scales the data to a range between 0 and 1[18]. The last phase of the preprocessing stage is the division of data into training and test data. It is important to separate the data that will be used to train the model (training data) and the data that will be used to test the performance of the model (test data). By dividing this data, we can evaluate how well our model works in generalizing patterns from previously unseen data.

2.2 Feature selection using windowing variation

Weather radars acquire data by performing scans that produce rain reflectivity values and information about height in the atmosphere. In contrast, rain gauges positioned at ground level directly measure the rainfall intensity reaching the Earth's surface. Because rain must fall through the atmosphere, there is a time lag between the time taken by the radar to measure the reflectivity of rain in the atmosphere and the time taken for rain to reach the rain gauges at ground level. As a result, the gauges record rainfall at ground level with a delay compared to the time when the rain reflectivity is recorded by the radar[19]. Several physical factors influence the relationship between measured radar reflectivity and surface rainfall, including natural differences in raindrop size distribution (larger drops scatter radar waves more efficiently). The presence of precipitation besides rain, such as melting hailstones, can also increase radar reflectivity due to the shape changes of melting hailstones, which are more reflective than spherical raindrops. Finally, changes in low precipitation levels caused by accretion (collision and merging of droplets) or evaporation can further complicate the relationship[20]. This research proposes exploring several data matrices in the selection of time-adjusted independent variables using windowing techniques. Windowing techniques involve dividing the data into smaller segments (windows) of a specific size to optimally determine the past data that affects the current data point[21]. The various windowing techniques to be explored, such as those visualized in Figure 7, can be used in this selection process.

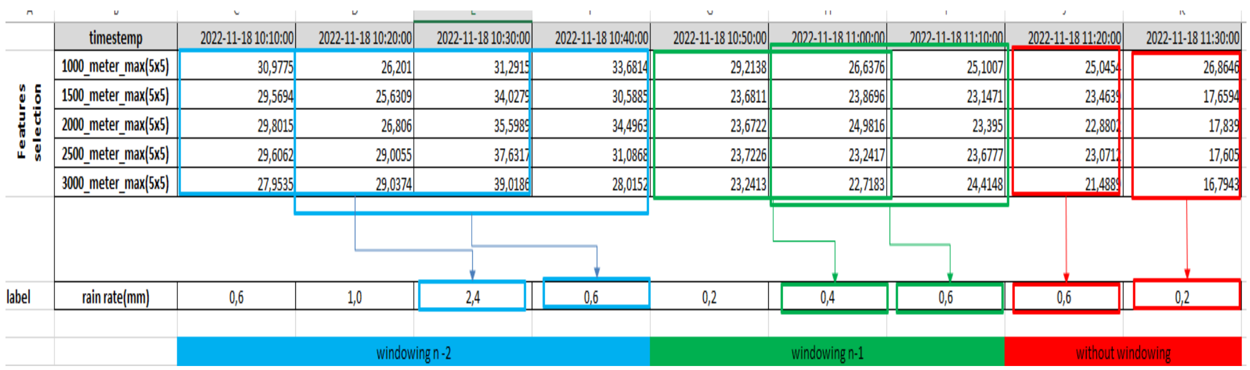


Figure. 7 *Windowing variation*

In Figure 7, there are three variations of the first technique for selecting time-adjusted features using windowing:

1. No Window (1 x 5 matrix): This approach only uses the current data point (1 row) and the five original features (5 columns) as independent variables.
2. n-1 Windowing (2 x 5 matrix): This method uses a window size of 1. It combines the current data point (row 1) with data from the previous time step (row 2) along with the 5 original features (5 columns) in each row. This creates a 2 x 5 matrix where each row represents a data point with previous data.
3. n-2 Windowing (3 x 5 matrix): This approach uses a window size of 2. It includes the current data point (row 1), data from the previous time step (row 2), and data from the previous two time steps (row 3) along with the original 5 features (5 columns) in each row. This results in a 3 x 5 matrix where each row captures the influence of the previous two data points on the current value.

2.3 Multilayer Perceptron (MLP) Regressor

A Multilayer Perceptron (MLP) is a type of artificial neural network architecture characterized by feedforward information flow. It consists of at least three layers of interconnected nodes: an input layer, one or more hidden layers, and an output layer. Each neuron in the hidden layers utilizes an activation function to transform the received input from the previous layer and generate an output that feeds into the next layer. This process iterates until the final output is produced. During training, the network employs the backpropagation algorithm to adjust the weights and biases associated with each neuron. This optimization aims to minimize the difference between the predicted and actual values, ultimately improving the model's performance. Using a set of features and targets, this algorithm can learn non-linear function approximators for both classification and regression tasks. This makes MLPs more versatile than logistic regression, as they can model complex, non-linear relationships between the input features and the output. Unlike logistic regression, MLPs can have one or more non-linear layers between the input and output layers, known as hidden layers (Figure 8). The layer on the left is the input layer, consisting of neurons representing the input features ($x_1,x_2,x_3.. x_n$). Each neuron in the hidden layer applies a weighted linear summation ($w_1x_1+w_2x_2...+w_nx_n$) to the values from the previous layer, followed by a non-linear activation function like a hyperbolic tangent function. Additionally, a bias value is added within each neuron in the hidden layer before applying the activation function. The final output layer, denoted by f(x), transforms the value from the last hidden layer into the network's prediction. The public coefs_ represent the weights connecting the layers of the network, while intercepts contain the vector of bias values added within each hidden layer neuron[22]. Hyperparameters in machine learning are parameters that govern how machine learning algorithms work. They are determined before training begins and affect the performance of the model. The grid search method is used to find the best hyperparameters by trying various combinations of hyperparameter values. By adjusting the hyperparameters appropriately, it is possible to obtain a well-balanced and well-generalized model[23]. Grid search is a concept used to search for hyperparameter combinations that result in the best model performance in prediction[24]. The grid search technique in GridSearch involves experimenting with hyperparameter combinations in testing. Hyperparameter optimization in grid search is a complex, time-consuming, and difficult to interpret process[25]. However, to optimize hyperparameters independent of windowing techniques, scikit-learn's Grid Search Cross Validation (GridSearchCV) library is used. It simplifies the process by integrating with scikit-learn's standard estimator API. GridSearchCV thoroughly evaluates all possible combinations of hyperparameter values defined in the param_grid parameter. The resulting combination that yields the best model performance is then selected[26]. Table 1 shows the list of hyperparameters used in grid search.

Table 1. List of hyperparameters in the MLP Regressor model

Hyperparameter	Param_grid parameter values	Description
hidden layer sizes	(50,), (100,), (50, 50), (100, 50)	Indicates the number and size of hidden layers in the neural network. For example, (50,) means one hidden layer with 50 neurons, and (100, 50) means two hidden layers, the first with 100 neurons and the second with 50 neurons.
activation	'relu', 'tanh'	Determines the activation function used for each neuron in the hidden layers. 'relu' refers to Rectified Linear Unit, while 'tanh' refers to hyperbolic tangent.
solver	'adam', 'sgd'	Determines the method used to optimize weights in the neural network. 'adam' and 'sgd' refer to optimization algorithms, namely Adam and Stochastic Gradient Descent.
alpha	0.0001, 0.001, 0.01	These values control the impact of regularization or loss function.

2.4 Evaluation metrics

Model performance measures are evaluated by comparing estimated values to observed values using statistical evaluation metrics like Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and coefficient of determination (R^2). RMSE and MAE values cannot stand independently. Output weights will then serve as evidence or support for one of the metrics [27]. RMSE values are used to distinguish model performance during calibration and validation periods and to compare performance between individual models and predictive models [28]. MAE exhibits lower sensitivity to outliers compared to certain RMSE metrics. It computes the average absolute variance between and actual values, disregarding their direction (positive or negative) [29]. For the value of R^2, value, if the value is closer to 0, it means that the independent variable has a very limited ability to explain the dependent variable. Conversely, a value close to 1 and far from 0 indicates that the independent variable is able to provide more information needed to predict the dependent variable [30].

3. Results And Discussion

A simple data analysis, such as correlation analysis, examining the linear relationship between the altitude layers (independent variables) and surface rainfall (dependent variable) suggests a linear trend. Figure 9 visualizes this relationship.

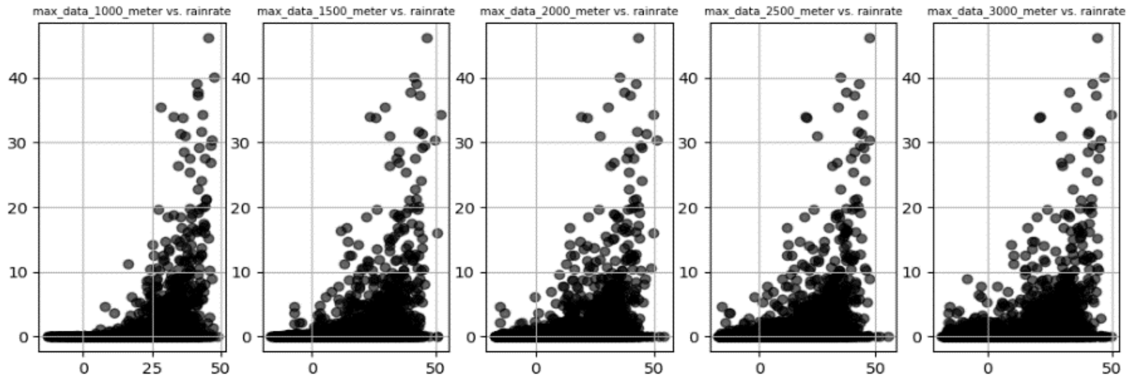


Figure 9. Radar Reflectivity vs. Rain Rate

After combining the data sets, there might still be some gaps where data is missing. Linear interpolation is a method used to estimate values for these missing data points. The following example shows how linear interpolation works to calculate a value at a specific time (2022-11-02 17:40:00) when data is available for times before (17:30:00) and after (17:50:00).

$$y = \frac{(2022-11-02\ 17:40:00 - 2022-11-02\ 17:30:00)}{(2022-11-02\ 17:50:00 - 2022-11-02\ 17:30:00)}(1{,}5-0{,}2) + 0{,}2$$
$$y = 0{,}5\ x\ (1{,}5-0{,}2) + 0{,}2$$
$$y = 0{,}65 + 0{,}2$$
$$y = 0{,}85$$

Table 2. Filling in blank data with linear interpolation

Time	Rain rate (mm) before Interpolation	Rain rate (mm) after Interpolation
02/11/2022 17:10	0	0
02/11/2022 17:20	0	0
02/11/2022 17:30	0,2	0,2
02/11/2022 17:40		0,85
02/11/2022 17:50	1,5	1,5
02/11/2022 18:00	1,2	1,2
02/11/2022 18:10	3,2	3,2

Undersampling was used by taking 20 data points before and 20 after each data point where the rain rate value exceeded 0 (indicating rain). Data for events without rain falling outside this range were excluded. Table 3 shows the change in the amount of data before and after undersampling. In this study, undersampling is employed with a radar data-based model to balance the majority class (no rain) and the minority rain class in our dataset, aiming to improve the model's ability to accurately predict rainfall intensity. The undersampling results show that the average amount of data before undersampling is about 23,482, with a decrease of about 67% in the amount of data after the application of undersampling, to about 7,800. This process was repeated for several different weather station locations, such as AWS Kulonprogo, Arg Kepuharjo, and others, with the percentage of data reduction ranging from 0.59% to 0.74%.

Table 3. Changes in the amount of data during preprocessing

NO	Location Name	Number of Data Before Undersampling	Percentage of data reduction (%)	Number of Data After Undersampling
1	AWS Kulonprogo	25070	0,74	6620
2	Arg Kepuharjo	24993	0,59	10323
3	Aws Pakem	21665	0,61	8358
4	Arg SMPK Sleman	22333	0,71	6530
5	AWS Stasiun Geofisika Sleman	23348	0,69	7167
	Mean	23482	0,67	7800

Once the dataset is prepared, the next step is data normalization. This process involves the use of MinMaxScaler which serves to simplify model training. The results of normalization can be seen in Table 4 as a sample example using the Kepuharjo ARG location.

Table 4. Sample data after normalization

Location	Time	1000_meter max(5x5)	1500_meter max(5x5)	2000_meter max(5x5)	2500_meter max(5x5)	3000_meter max(5x5)	rain rate(mm)
Arg_Kepuharjo	06/11/2022 09:10	0,705423	0,711613	0,708176	0,713092	0,72076	4,6
Arg_Kepuharjo	06/11/2022 09:20	0,811123	0,741737	0,72504	0,725528	0,783023	6,6
Arg_Kepuharjo	06/11/2022 09:30	0,801907	0,722978	0,736986	0,740026	0,782278	16,2

Following data pre-processing steps like normalization, data splitting is a common technique used to create training and testing sets for model development. In this study, we adopt an 80/20 split, allocating 80% of the data for training the model and 20% for testing its performance. Preserving the time series order throughout pre-processing is crucial for techniques like windowing to function effectively, as they rely on the sequential nature of the data.

Table 5. Best parameters and metrics evaluation results

Variant Windowing	Location	Output: Best Parameters Using Grid Search				Evaluation Metrics			Mean Evaluation Metrics		
		Activation	Alpha	Hidden layer sizes	Solver	RMSE	MAE	R-squared	RMSE	MAE	R-squared
Non windowing	ARG Kepuharjo	Relu	0.01	100,50	adam	1,719	0,431	0,101	1,012	0,274	0,212
	ARG Smpk Sleman	Tanh	0.01	50,50	adam	0,846	0,278	0,182			
	Aws Kulonprogo	Relu	0.01	100,50	adam	0,851	0,267	0,053			
	Aws Pakem	Relu	0.01	50,50	adam	0,736	0,193	0,458			
	Aws Stasiun Geofisika Sleman	Relu	0.001	100,50	adam	0,91	0,199	0,269			
windowing n - 1	ARG Kepuharjo	Relu	0.0001	100,50	sgd	1,618	0,317	0,203	0,987	0,263	0,242
	ARG Smpk Sleman	Relu	0.0001	50,50	sgd	0,845	0,281	0,183			
	Aws Kulonprogo	Relu	0.0001	100,50	adam	0,843	0,254	0,071			
	Aws Pakem	Relu	0.001	50,50	adam	0,772	0,184	0,402			
	Aws Stasiun Geofisika Sleman	Relu	0.0001	50,50	adam	0,858	0,277	0,35			
windowing n - 2	ARG Kepuharjo	Tanh	0.001	100,50	adam	1,669	0,477	0,152	1,018	0,302	0,197
	ARG Smpk Sleman	Tanh	0.01	50,50	adam	0,87	0,316	0,135			
	Aws Kulonprogo	Relu	0.01	100,50	adam	0,847	0,265	0,062			
	Aws Pakem	Relu	0.0001	50,50	adam	0,797	0,22	0,364			
	Aws Stasiun Geofisika Sleman	Relu	0.01	50,50	adam	0,908	0,232	0,272			

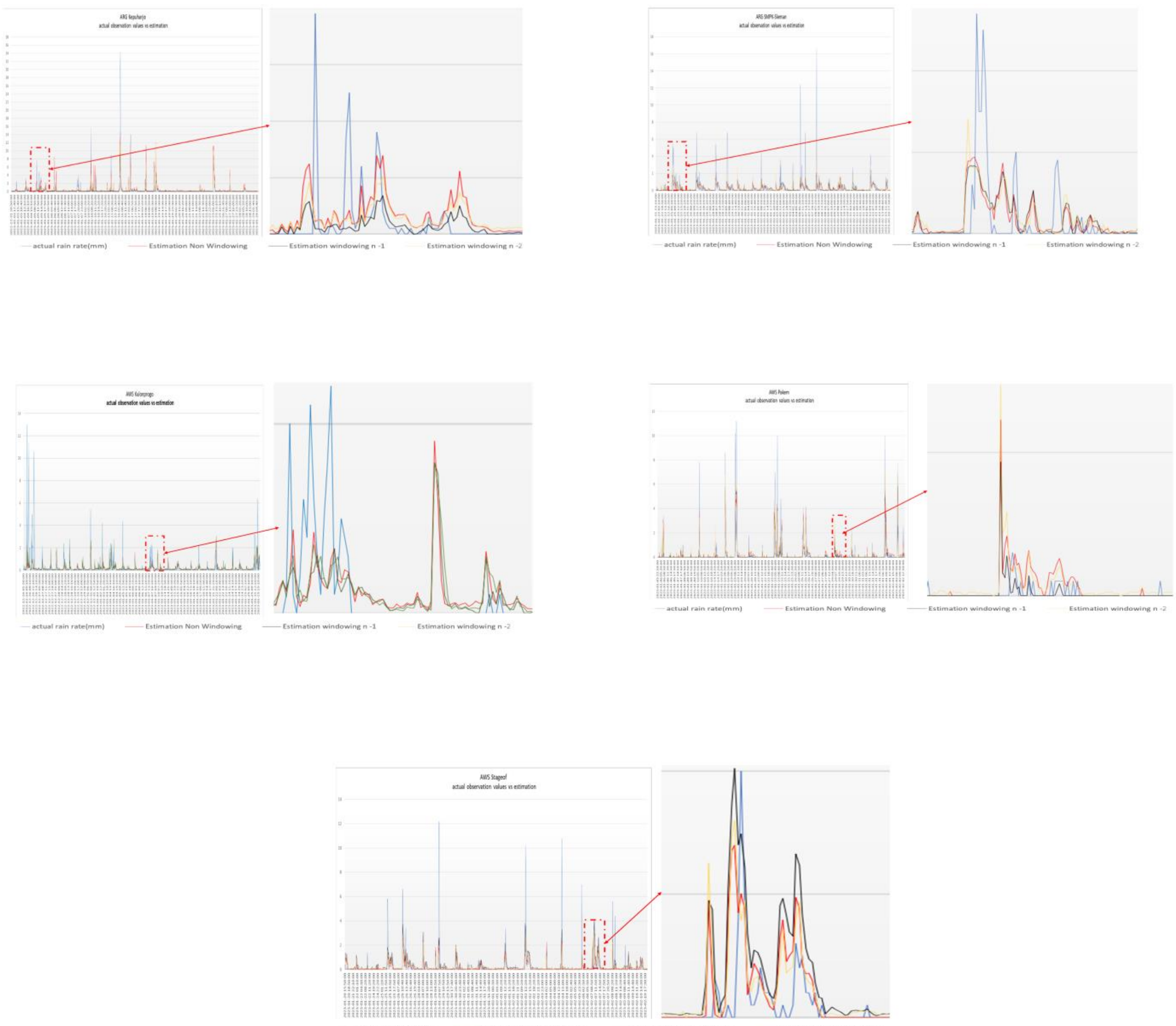


Figure 10. Actual vs. estimated results for non-windowing, n-1 windowing, and n-2 windowing.

From the results in Table 5, the use of grid search in this study allows extensive parameter exploration to improve the performance of MLP regression models in various variants, ranging from no windowing to using n-1 and n-2 windowing techniques. The variant without windowing produces the best parameters, including ReLU activation, alpha 0.01, and Adam solver. However, in the variant with n-1 windowing, it is seen that the use of the SGD solver becomes optimal for some locations. This suggests that the sensitivity of the model to regularization increases when applying n-1 windowing, which is reflected in the use of smaller alpha values. With a smaller alpha value, the model tends to focus on a tighter fit to the training data, reducing its complexity and reducing the risk of overfitting.

While in the n-2 windowing variant, despite the variation in optimal parameters, the model performance generally tends to be slightly lower compared to the other variants. This suggests that the use of n-2 windowing may introduce unnecessary complexity or reduce relevant information from the data. By using grid search, this study was able to adjust the model appropriately according to the characteristics of each location or dataset. This results in a significant performance improvement in surface rainfall estimation. These results significantly contribute to improving estimation accuracy, considering the model's sensitivity to regularization within the n-1 windowing technique. In this study, the best results of applying the windowing technique to the MLP Regressor model for surface rainfall estimation are detailed. From several locations observed, it appears that the windowing technique with size n - 1 consistently provides the best performance. For instance, at the Arg Kepuharjo site, the model employing n - 1 windowing demonstrated substantial enhancement, featuring a reduced RMSE value of 1.618 and a significantly higher R-squared value of 0.203, compared to the other configurations. A similar trend was seen at the Arg SMPK Sleman and AWS Kulonprogo sites, where the application of n - 1 windowing resulted in a slight but consistent improvement in estimation performance. At the Pakem AWS site, although the model without windowing has provided good results, the use of n - 1 windowing still shows high performance with the R-squared value remaining high (0.402) despite a slight increase in RMSE. Similarly, at the AWS Geophysical Station location, windowing n - 1 was able to achieve a balance between accuracy and model simplicity, which was reflected in the increased R-squared value.

The overall trend shows that the application of n - 1 windowing consistently gives the best results across locations. The n-1 windowing technique achieved lower average values for RMSE (0.987), MAE (0.263), and a higher R-squared (0.242), indicating improved estimation compared to other experiments. This improvement comes without significantly increasing model complexity. These findings suggest prioritizing the n-1 windowing technique for MLP regression models in similar weather radar applications. By successfully capturing the temporal dynamics of surface rainfall patterns, the n-1 windowing technique demonstrates its suitability. Further research to understand the reasons behind this success and explore alternative window sizes or adaptive strategies can lead to even better model performance in future studies.

From the graphical analysis in Figure 10, the tendency of all experiments follows the pattern of actual values. However, the model's response to estimate high rainfall tends to be underestimated. The need for more in exploration to improve the estimation is a weakness of the model in estimating rainfall with high intensity. Research by M. Schleiss et al. found similar results, indicating that rainfall estimation using radar data often underestimates values for predicting high rainfall [31]. Numerous factors bias the accuracy of research related to estimating rainfall using radar data. Rainfall can vary in intensity, type, and distribution, impacting the accuracy of radar measurements due to differences in reflectivity and wave reflection behavior [32].

4. Conclusion

Based on the analysis conducted, it can be concluded that the use of the n-1 windowing technique in the MLP Regressor model provides the best results in estimating surface rainfall. This technique consistently produced significant improvements in lower RMSE values and better R-squared values compared to other configurations. In addition, the use of n-1 windowing increases the sensitivity of the model to regularization, which is reflected in the use of smaller alpha values. This helps reduce model complexity and the risk of overfitting by focusing on a tighter fit to the training data. However, there are challenges in estimating high rainfall, where the model tends to underestimate the true value. This underestimation of high rainfall events contributes to a bias in the overall accuracy of the model, highlighting a limitation in its ability to capture extreme weather events. To address this bias and improve the accuracy of radar-based rainfall estimates, particularly for high-intensity events, further exploration is needed. Understanding the factors influencing measurement accuracy, such as variations in rainfall properties and wave reflection behavior, is crucial for future model development. These findings emphasize the value of n-1 windowing for improving MLP Regressor models in surface rainfall prediction, particularly when combined with further exploration to address the underestimation bias in high-intensity rainfall events. This conclusion paves the way for further research on mitigating the underestimation bias, potentially through incorporating additional data sources or exploring alternative model architectures alongside the effective n-1 windowing technique. Ultimately, this research contributes to the ongoing effort to improve the accuracy and reliability of rainfall estimation models in the context of weather radar data applications.

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انحدار مستقبلي متعدد الطبقات ومتغير الرياح لتقدير هطول الأمطار استنادًا إلى بيانات رادار الطقس

فرديناندوس إدوين إدوين بينالون [1*]، عريف هيرماوان [2]، دوني أفيانتو [3]، عارف براموودوياتموكو [4]

وكالة الأرصاد الجوية لعلم المناخ والجيوفيزياء، إندونيسيا[1*]
ماجستير في تكنولوجيا المعلومات، جامعة يوغياكارتا للتكنولوجيا في إندونيسيا[4،3، 2،2، 1*]

الخلاصة

دقة معلومات هطول الأمطار أمر بالغ الأهمية لتطبيقات عديدة، بما في ذلك تقدير جريان النهر وإدارة موارد المياه وتطوير أنظمة الإنذار المبكر بالفيضانات .لكن شبكات مقاييس المطر التقليدية تعاني من محدودية التغطية المكانية، مما يؤدي إلى بيانات غير مكتملة وغير دقيقة بالنسبة للمساحات الواسعة .تقترح هذه الدراسة نهجًا جديدًا لتقدير هطول الأمطار السطحية باستخدام بيانات رادار الطقس ونموذج الانحدار متعدد الطبقات (MLP)للتعلم الآلي .تم استخدام البحث الشبكي لاستكشاف أداء النموذج عبر تكوينات نوافذ مختلفة :بدون نافذة، ونافذة n-1، ونافذتين .n-2أظهرت النتائج تفوق استراتيجية النافذة n-1على التكوينات الأخرى، حيث حققت متوسط جذر خطأ التربيع المتوسط 0.987 (RMSE)ومتوسط الخطأ المطلق 0.263 (MAE)ومعامل التحديد 0.242 (R-squared)عبر خمسة مواقع .يشير هذا إلى أن استراتيجية النافذة n-1تلتقط الديناميكيات الزمنية لأنماط هطول الأمطار بشكل فعال مع تحسين حساسية النموذج للانتظام .ومع ذلك، لا يزال هناك اتجاه نحو التقليل من شأن أحداث هطول الأمطار الغزيرة .يسلط هذا البحث الضوء على فعالية استراتيجية النافذة n-1مع نموذج الانحدار متعدد الطبقات لتحسين تقدير هطول الأمطار السطحية باستخدام بيانات رادار الطقس .هناك حاجة إلى مزيد من التحقيق لمعالجة تحيز التقليل، خاصة بالنسبة لأحداث هطول الأمطار الغزيرة.