Machine Learning System for Rainfall Estimates from Single Polarization Radar

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Abstract: Rainfall becomes one of the weather parameters that is most widely considered because the phenomenon of its occurrence can significantly affect human activities, including in agriculture, plantations, fisheries, transportation and others. In addition, rainfall information is very important to do weather analysis, especially in analyzing the occurrence of floods caused by heavy rains so there is a need for accurate rainfall information. This study aims to obtain an optimal rainfall estimation system at locations where there is no direct rainfall observation data. Machine learning is one branch of artificial intelligence that provides a learning system for machines to learn automatically without explicit instruction. The machine learning used in this study is Multi layer perceptron (MLP), with backpropagation as a gradient value search algorithm and adam optimizer as an optimization function. The structure of the MLP used is 2 hidden layers which in the first hidden layer uses 7 neurons with a hyperbolic tangent activation function and the second hidden layer contains 3 neurons and the activation function is sigmoid and finally the output layer, the activation function used is pure linear. MLP system input data is radar data, reflectivity, radial velocity, spectrum width and radar rain estimation data which are validated with automatic rain observation data around the Single Polarization Radar observation in Yogyakarta. The results using MLP can improve rain detection accuracy by 79% and reduce the error value in the estimated rainfall.

1 INTRODUCTION

Indonesia is a humid archipelago and equatorial monsoon region (Tjasyono, B.H.K., and Harijono, S.W.B, 2007), many hydrometeorological natural disasters occur throughout the year, including Yogyakarta. Hydrometeorological disasters are disasters related to changes in the normal water cycle, such as flash floods (Minervino, A.C and Duarte, E.C, 2015). Hydrometeorological disasters in the current period show an increasing trend (Adi S. , 2013). Hydrometeorological disasters can seriously damage infrastructure, significant economic losses and often loss of life (Paul, S.H., Sharif, H.O., and Crawford, A.M.G, 2018). Rainfall is precipitate in liquid form which is largely a direct result of the condensation of water droplets in the clouds, followed by growth to a size large enough to overcome the effect of air buoyancy forces (Tjasyono, B.H.K., and Harijono, S.W.B, 2007) .

Single polarization radar is a remote sensing technology that can be used to determine the distribution of rain in locations where there is no rainfall measurement tool. A single polarization radar measures rainfall in real-time and provides high-resolution data for short-term rainfall forecasts, also known as nowcasting (Codo, M., and Rico-Ramirez, M.A., 2018). Radar emits electromagnetic waves at the frequency of microwaves in the form of pulses into the atmosphere through the transmitter. When a pulse hits an object, the electromagnetic wave is partly returned to the weather radar which is received as reflected energy called reflectivity. The amount of reflectivity depends on the physical parameters of the object.

Radar transmits microwaves and receives backscattering radiation from precipitation particles through radar reflectivity (Z), which is related to rainfall rate (R) using a semi-empirical equation of the form Z = aR^b (Germann, U., Galli, G. Boscacci, M., and Bolliger, M., 2006). However, parameters a

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and b of the Z-R relation equation are known to depend on rainfall type and rainfall size distribution. The use of the constant Z-R relation equation contributes to errors in the estimation of radar rainfall (Harrison,D.L., Driscoll,S.J., and Kitchen,M , 2000).

Radar has limitations that cause errors in estimating rain and rain forecasts by nowcasting, when the distance from the radar increases, naturally there is also an increase in the volume of radar sampling (Rico-Ramirez, M.A., and Cluckie, I.D, 2007). At higher altitudes, the distribution of the hydrometeor changes, causing a difference between the measured rainfall and the rainfall that actually falls to the ground, so it is necessary to determine the right technique for estimating using radar. The Single Polarization Radar in Yogyakarta is a Baron branded C-Band radar, which has a frequency of 5.2-5.9 GHz and a wavelength of 5-5.7 cm and Radar Yogyakarta began operations in 2016. In this research, a statistical / engineering based approach is used to improve the estimation of rainfall in Yogyakarta's Single Polarization Radar using VCP 21 with 9 elevations.

There are two classifications of rain estimation techniques using radar, namely: Physical-based techniques and statistical / engineering-based techniques (Bringi, V. N. and Chandrasekar, V, 2001). Physically based techniques are used to find the relationship between the observation radar and precipitation levels of observation, such as the use of relational equation Z-R precise in determining the estimated rainfall while using statistical techniques such as machine learning algorithms.

Machine learning is an application of artificial intelligence (AI) that provides a system of ability to learn automatically and improve from experience without being completely programmed (Chandrasekar, V., Tan, H., and Chen, H., 2017)(Chandrasekar, Tan, and Chen, 2017). Machine learning spends on developing computer programs that can be accessed and used for self-study. The machine learning used in this study is a multi-layer perceptron (MLP), with backpropagation as a gradient value search algorithm and adam optimizer as an optimization function. The structure of the MLP used is 2 hidden layers which in the first hidden layer uses 5 neurons with a hyperbolic tanget activation function and the second hidden layer contains 3 neurons and the activation function is sigmoid and finally the output layer, the activation function used is pure linear. MLP system input data is radar data, reflectivity, radial velocity, spectrum width and radar rain estimation data which are validated with automatic rain observation data around the Single Polarization Radar observation in Yogyakarta.

At the training stage of machine learning network will produce the best network and the best network will be tested with new radar data then verified. The results of the verification value will show and improve the rainfall estimation model using a single polarization radar around the study area. An optimal rainfall estimation system will further benefit weather forecasters in providing early warning information for heavy rainfall and in providing extreme weather analysis at locations where there is no direct rainfall observation.

2 STUDY AREAS AND DATASET

This study, the results of three radar data outputs are reflectivity, radial velocity, and width spectrum and the results of radar rain estimation using the Marshall-Palmer Z-R relation, will be used as input for MLP. The reflectivity data used are the CMAX(Z) product reflectivity, the CMAX(Z) product reflectivity deviation standard, the CAPPI(Z) product reflectivity 0.5 km and the CAPPI(Z) product deviation reflectivity standard 0.5 km. For radial velocity and spectrum width data used from CAPPI (V) 0.5 km and CAPPI (W) 0.5 km. The use of CAPPI 0.5 km product on reflectivity data, radial velocity data, and width spectrum data due to the closest surface, for CMAX products (taking maximum value) on the reflectivity value can represent conditions vertically at an altitude of 0.5-30 km (Ali, A and Hidayati,S, 2016). In addition, the distance between automatic rainfall data and radar is included as additional input. Furthermore, the 10 inputs are processed using MLP and automatic rain observation data from an automated weather station (AWS) will be used as a target / model validation.

Observation rainfall data used as a comparison of MLP is AWS data for 2017-2018 in 4 locations, namely Kulon Progo, Gajah Mada University, Bantul and Sleman. Data of Automatic rainfall observers is accumulated per hour. The following is the availability of AWS data shown in table 1.

Table 1. Automatic rainfall observation data used

Location	Coordinate	Total data (mm/hours)
Kulon-Progo	-7,890242; 110,100552	1342
Sleman	-7,75016; 110,419759	550
Bantul	-7,90736; 110,365048	3163
Gajah Mada University	-7,7704589; 110,3798372	3111

Radar data is processed using python with 2 (two) stages, namely the data extracting stage and the training model stage. Data extracting stage is the stage where the radar data value at the point of observation of rainfall is automatically extracted. After the radar product is extracted, the radar value is used as a predictor while the observed rainfall value is made a predictor in the MLP model.

The training stage of machine learning network will produce the best network and the best network will be tested with new radar data then verified. So the results of the verification value will show and improve the rainfall estimation model using a single polarization radar around the study area. An optimal rainfall estimation system will further benefit weather forecasters in providing early warning information for heavy rainfall and in providing extreme weather analysis at locations where there is no direct rainfall observation.

3 RESEARCH METHODOLOGY

3.1 Radar

A single polarization radar has three types of data output namely reflectivity, radial velocity and spectral width (Raghavan, 2003). Reflectivity (Z) states the amount of energy reflectivity returning from an object, depending on the size, shape and composition of the object. The amount of energy received by the radar is much smaller than the energy that was transmitted at the beginning. The following radar equation describes the calculation of the amount of energy returned by the radar, which is very dependent on the magnitude of the Power Transmit and the type of radar band used, the greater the object and the energy received, the greater the reflectivity value.

$$Pr = \frac{\pi^2}{1024 ln2}\left[\frac{Pt\, G^2 \theta\Phi}{\lambda^2}\right]\left([K]^2\,\frac{Z}{r^2}\right) \qquad (1)$$

Description:
Pr: average power of radio waves returned to radar (watts)
Pt: Peak wave power emitted by radar (watts)
G: Antenna gain
H: length of radar pulses in the air (m)
θΦ: radi wave width in vertical and horizontal (radians)
λ: wavelength emitted (m)
$[K]^2$: refractive index
r: distance from the radar to the target (m)
Z: Radar reflectivity factor (mm^6/m^3)

The first term of the equation above illustrates the geometrical composition which will be represented by the velocity of the electromagnetic waves which refers to the velocity of light propagation. The second term of the equation is about the parameters of the radar system, consisting of the type of polarization (horizontal and or vertical), antenna gain and wavelength, the amount of power transmitter and the amount of pulse used in operations. The resulting data resolution will be greatly influenced by the choice of sampling parameters, antenna speed and Pulse Frequency Repetition used which all depend on the radar system technical specifications. And the third term depends on the distance and characteristics of the target. The radar parameters are relatively fixed, and if the transmitter is operated and used with a constant output arrangement, the equation can be simplified to:

$$Pr = \frac{C[K^2]}{r^r}\, Z \qquad (2)$$

Where C is a radar constant. The value of Z can be calculated by the equation:

$$Z = \sum_{i=1}^{n} D_i^6 \qquad (3)$$

Z values vary between 0.001 and 10,000,000, to make it easier to understand, use a decibel scale:

$$Z(dBZ) = 10\, log_{10}(Z) \qquad (4)$$

$$\text{dBZ}=10 log_{10}\frac{Z\, mm^6 m^{-3}}{1\, mm^6 m^{-3}} \qquad (5)$$

The value of Z is proportional to the sum of the entire particle diameter raised to six in a sample volume, because the size of the drops is usually measured in millimeters (mm), and the volume is usually expressed in units of cubic meters (m^3), so Z has a unit of mm^6/m^3.

For the purposes of hydrology connecting signal strength with observed rainfall, an equation that combines radar reflectivity and rainfall is needed. This equation is the approach and empirical relationship between Z and R. The relationship between Z and R is drawn in exponential form, as follows:

$$Z = aR^b \qquad (6)$$

Where a and b are positive empirical constants whose value depends on the geographical location and climate conditions / type of rain. The coefficient a represents the condition for the median diameter of the drop size in a sample volume. The greater the value of a, the median size of drops in a sample volume indicates a larger diameter. While the coefficient b represents the equilibrium condition changes in the size of the drops. The results of rain estimation using the Marshall-Palmer Z-R relation is used to master regional variability in the distribution of raindrop sizes in Indonesia (M. Marzuki, H. Hashiguchi, M. K. Yamamoto2, S. Mori and M. D. Yamanaka, 2013).

Radar transmits electromagnetic waves using units of power transmit and operational frequency. Changes in frequency from higher droplets will be processed and recognized as movements approaching the radar, while changes in frequency from lower echo replies are recognized as echos moving away from the radar. Radar routinely measures speed and is used to detect wind speeds, tornadoes, and hurricanes. This echo movement data is called radial velocity (V) data. Velocity radial data can be used as a validation medium for echo reflectivity / intensity for the forecaster to recognize meteorological and non-meteorological echoes, because generally rain patterns have different patterns from other echoes. And especially for Ground Clutter echo has a zero radial speed value. V data not only describes the movement of rain particles, but Velocity data is very helpful in describing phenomena in two scales, namely the large scale (largescale) and small scale (mesoscale). Large scale (largescale) describes phenomena that occur in all regions and potential SHEAR that supports rotation while small scale (mesoscale) describes whether Converging, Divergent or rotating winds are also used to diagnose Couplets (two adjacent Inbound and outbound areas to detect Convergence , Divergence or rotation).

The spectral width (W) data produced by the weather radar is taken from processing the frequency signal reflected by the object and received by the weather radar. In one sampling volume each droplet has a different speed and direction of motion, the value of the deviation of each droplet is displayed by the spectral width data. Information obtained from the value of W in the form of air lability. A small width value indicates that in the sampling volume there is no difference in speed (stable) and a large width value indicates there is a difference in the speed of the hydrometeor in the sampling volume (unstable). W value gives information about the possibility of windshear, turbulence, mesocyclone.

Constant altitude plan position indicator (CAPPI) is a radar product that is made based on the height input desired by the user. The height referred to in this product is the height of the MSL. It is recommended to apply the Pseudo-CAPPI algorithm to maximize its output, the height of this cappi product has the same value both near and far from the radar. The CAPPI algorithm will only display data available at the desired height at each elevation available. When there is no data at the desired height then the data is blank.

The Maximum Reflectivity (CMAX) product represents the maximum reflectivity value between two heights for each cell of volume. In other words, able to show the maximum detectable reflectivity of each pixel between the selected user height, including the East-West and North-South profiles from the maximum in the side panel. This product was produced based on a volume scan. A minimum and maximum height set by the user and defaults to 0.5 and 30 kilometers. The advantages of MAX products include being able to display peaks and side views in the same window so as to give a three-dimensional (3D) impression of the weather situation. In addition, ground clutter will be reduced when choosing a bottom height that is higher than the radar installation height. However, this product is less useful for data speeds because only absolute speeds are displayed. The product is very useful especially for reflectivity data analysis to medium distances.

3.2 Multi Layer Perceptron (MLP)

MLP structure consists of input layer, hidden layer and output layer. The back-propagation algorithm is the most popular approach, which not only overcomes the weaknesses of the large network generated in the previous section, but also makes this network a powerful tool for a number of other applications, beyond pattern recognition (Theodoridis, S., Koutroumbas, K., Koutroumbas, K., & Koutroumbas, K. , 2008). This approach is usually to improve architecture and calculate synaptic parameters so as to minimize the appropriate cost function of the output. However, such an approach is a difficulty in the discontinuity of the step function (activation), promoting differentiation with respect to unknown parameters. Synaptic weight The perceptron multilayer architecture has so far been developed by Nouron McCulloch-Pitts (Theodoridis, S., Koutroumbas, K., Koutroumbas, K., & Koutroumbas, K. , 2008). The most complex task to implement the hardware artificial neural networks is the non-linear activation function. Common examples of activation function include hard-limiter, saturated linear, hyperbolic tangent function and sigmoid function (A. Armoto, L. Fanucci, E.P. Scilingo and D.De Rossi, 2011).

The most common non-linear activation functions, which are used in the artificial neural networks, are the sigmoid function and the hyperbolic, these functions are mainly used in statistics, bio-mathematics, physics, engineering, economic science, etc tangent (A. Armoto, L.

Fanucci, E.P. Scilingo and D.De Rossi, 2011). The general equation is as follows:

$$y = \frac{a}{1+e^{-bx-c}} + d \qquad (7)$$

where a, b, c and d are constants.

The sigmoid function is a particular case of Eq. (7) where we put a = 1, b = 1, c = 0 and d = 0. The equation thus becoming:

$$y = S(x) = \frac{1}{1+e^{-x}} \qquad (8)$$

On the other hand, when a = 2, b = 2, c = 0 and d = 1, the equation represents the hyperbolic tangent:

$$y = T(x) = \frac{2}{1+e^{-2x}} - 1 = \frac{e^{2x}-1}{e^{2x}+1} \qquad (9)$$

The following is a picture of MLP network architecture in this study:

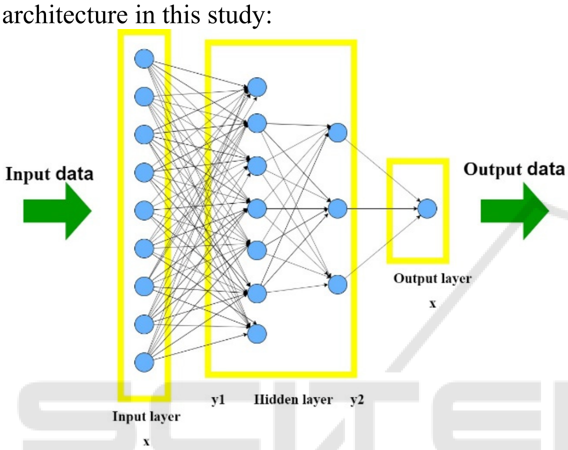

Figure 1. MLP network architecture

Adaptive Moment Estimation (Adam) is a very popular training algorithm for deep neural networks, implemented in many machine learning frameworks (Bock & Weis, 2019). Adaptive optimization algorithms, such as Adam and have proven better optimization performance than stochastic gradient descent (SGD) in several scenarios (Zhang, 2019). According to Kingma & Ba (2015), the Adam algorithm is a method that is easy to implement, computationally efficient, has few memory requirements, is not volatile for scaling gradients diagonally, and is suitable for large problems in terms of data and / or parameters. This method is also suitable for purposes and problems that are not stationary with gradients that have a lot of noise and data that are not continuous.

In this study, MLP used has 2 (two) hidden layers, which in the first and second hidden layers have different activation functions. The first hidden layer uses the sigmoid activation function and the second hidden layer uses the tangent activation function, with backpropagation as the gradient value finder algorithm and Adam optimizer as the optimization function. The structure of the MLP used 9 inputs, 2 hidden layers which in the first hidden layer uses 7 neurons with a hyperbolic tanget activation function and the second hidden layer contains 3 neurons and the activation function is sigmoid and finally the output layer, the activation function used is pure linear

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Based on the references above, the inputs used in MLP in this study are:

1. Maximum reflectivity / CMAX (Z)
2. CMAX(Z) standard deviation
3. reflectivity at an altitude of 0.5 km / CAPPI (Z) 0.5 km
4. standard deviation ofCAPPI (Z) 0.5 km
5. radial velocity at an altitude of 0.5 km / CAPPI (V) 0.5 km
6. standard deviation of CAPPI (V) 0.5 km
7. spectrum width at an altitude of 0.5 km / CAPPI (W) 0.5 km
8. standard deviation of CAPPI (W) 0.5 km
10. distance between AWS and radar

The study design is shown in Figure 2:

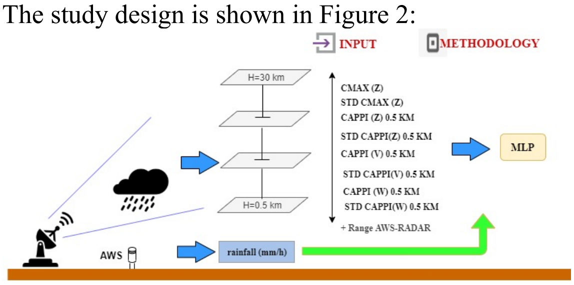

Figure 2: Conceptual diagram of the MLP based Machine Learning

In order to furter evaluate the rainfall perfornance, mean error (ME), mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and accuracy is used.

$$ME = \frac{1}{N}\sum_{i=1}^{N}(f_i - o_i) \quad (8)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|(f_i - o_i)| \quad (9)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(f_i - o_i)^2 \quad (10)$$

$$RMSE = \sqrt{MSE} \quad (11)$$

Description:
fi : Estimated rainfall from Radar/MLP
oi : rainfall from AWS

$$Accuracy = \frac{TP+TN}{n} \quad (12)$$

Description:

- True positive (TP) = the number of cases correctly identified as rain
- False positive (FP) = the number of cases incorrectly identified as rain
- n= the total amount of data

4 RESULT

Multi-layer perceptron (MLP) is a type of machine learning algorithm inspired by neuroscience (Tan et al., 2017) This technique has been widely applied in academia and industry such as computer vision, machine translation, neural language processing, and pattern recognition . The MLP algorithm consists of most neurons that are attached by interrelated weights (Hornik, Stinchcombe, & White, 1989). In a neural network, there are 3 (three) forming elements, namely (i) a set of connection lines that have different weight sets, a positive value will strengthen the signal while a negative value that weakens the signal underneath. The number of structure and relationship patterns will determine the network architecture and network model; (ii) the sum unit that determines the signal input multiplied by its weight, for example input = x_1, x_2, x_3 .... x_m, connecting weight = w_1, w_2, w_3 .... w_m, sum ouput = u_j = x_1 w_1 + x_2 w_2 + x_3 w_3 .... x_m w_m; (iii) an activation function that determines whether signals from neural inputs are forwarded to other neurons.

In this section will show the performance of MLP in estimating rainfall. The data used in this model are Radar and AWS data for 2017 and 2018 in Kulon-Progo, Bantul, UGM and Sleman. Rainfall estimation data from Radar and AWS are accumulated in 1 hour, containing rain data and no-rain data. Z-R relation used to estimate rain on radar in this study is the Marshall-Palmer Z-R relation. The results of this radar rainfall estimation will be compared with MLP and evaluated.

There is a difference in the time of rainfall calculation between AWS and Radar, where AWS will calculate continuous rainfall continuously for 10 minutes, while the results of measurement of radar rainfall estimation within 10 minutes there is a 4 minute pause to calculate the results of scanning some elevations (scaning 6 minutes, calculation 4 minutes). The estimated 10-minute rain from the radar / AWS will be accumulated to 1 hour. In addition, the rainfall measured by AWS is true rain falling to earth, while Radar calculates estimates of rain falling to the surface of the earth based on the results of scanning the atmospheric conditions in certain layers (depending on the product used).

Radar also has several limitations, one of which is the optimal results of the radar scaning representation when the object distance from the radar is far away. This happens because the earth is round, so the farther away the object is from the radar, the radar only gets scaning at the top layer (Rauber, R.M and Nesbitt, S.W, 2014)(Robert M. In this study, the distance between AWS and Radar locations is used as input in MLP.

Some of the above problems, require the approach to improve outcome radar rainfall estimates. There are 2 (two) classifications of rain estimation techniques using radar, namely: Physical-based techniques and statistical / engineering-based techniques (Bringi, V. N. and Chandrasekar, V, 2001). Physical-based techniques are used to find the relationship between radar observations and the rainfall rate of observations, such as the use of the Z-R equation equation that is appropriate in determining rainfall estimates while statistical techniques using algorithms such as machine learning models one of which is MLP.

Figure 3 and Figure 4 show the results of the distribution of data (scetterplot) between the results of variations in the MLP model compared to AWS as a rainfall observation / target model. The X-axis displays the results of the observed rainfall from AWS, while the Y-axis displays the results of the MLP model rain estimation. Black dotted line shows trend line / trend of MLP model. The sloping trend line to the right shows a positive correlation / correlation value, while the sloping tend line to the left shows the negative correlation value / correlation.

Based on Figure 3, the MLP rainfall results are compared with AWS data in 4 locations. The results of estimation of rain using MLP can increase the value of accuracy in detecting no-rain events to 79%. The existence of a sloping trendline to the right illustrates a positive correlation between estimated MLP rain and rain from AWS data.

However, there are some occurrences of rain with high intensity MLP unable to detect it. Figure 4 shows the estimation of radar rain using the Z-R Marshall-Palmer relation at 4 AWS locations. Based on Figure 4, radar rainfall estimates tend to underestimate rainfall estimates, this can be seen from the downward trend line..

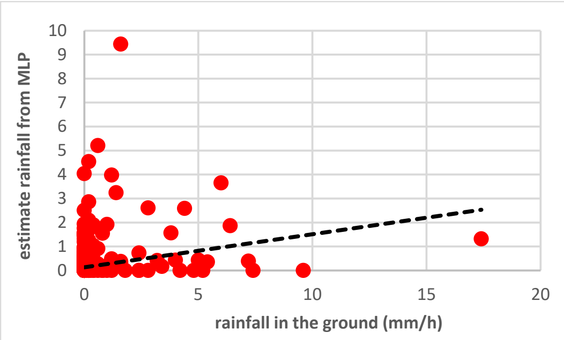

Figure 3. Scatter plot of estimated MLP rainfall and AWS rainfall

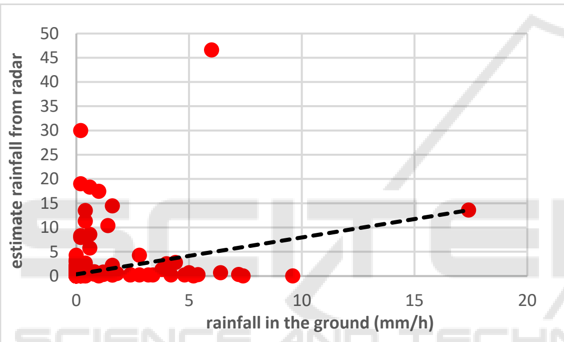

Figure 4. Scatter plot of estimated radar rainfall and AWS rainfall

ME value of a model, used to determine the tendency of the model in making estimates. The disadvantage of using ME verfication is that one error can cover the other's errors due to averaged error.

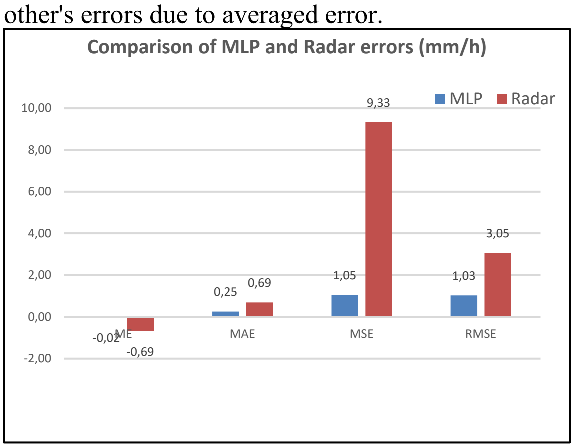

Figure 5. Comparison of MLP and Radar error values

Some relevant research methods use verification methods to evaluate the results of models that have been developed. An important aspect of the error metric used for model evaluation is its ability to distinguish between model results. A more discriminating measure that results in higher variation in model performance metrics among various sets of model results is often more desirable. In this case, MAEs may be influenced by a large number of average error values without adequately reflecting some large errors, RMSE is usually better at expressing model performance differences, but many researchers choose MAE over RMSE to present their model evaluation statistics when evaluating the results of the model (Chai & Draxler, 2014).

In measuring the performance of machine learning models in this study, the model output will be validated and verified, that is validating by measuring the accuracy of the model in predicting the occurrence and absence of rain and measuring the accuracy of the model in predicting rain events according to its category; while in verifying the model, you will see the model error from the value of mean error (ME), mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE). MAE is suitable for describing evenly distributed errors, whereas for normally distributed errors, RMSE is a better metric to present than MAE. ME value, is a bias value that can measure the tendency of the model in the form of underestimate if it is negative or overestimate is positive, but ME has a disadvantage because the error values can overlap. The MSE value can be analogized as a variant plus the bias squared of a model

Figure 5 shows the comparison of error values between estimated Radar and MLP rain, the error value closest to zero is MLP, ie with ME, MAE, MSE and RMSE values of -0.02 mm / h, 0.25 mm / h, 1.05 mm / h and 1.03 mm / h, while the ME, MAE, MSE and RMSE values of the radar rain estimate are -0.69 mm / h, 0.69 mm / h, 9.33 mm / h and 3.05 mm / h.

Based on the error value of the ME, MAE, MSE and RMSE values of the MLP model shown in Figure 5, the MLP model error values compared with the radar rainfall estimation results, the MLP model error values are smaller than the radar error values. this shows that the performance of the MLP model is better than the results of the estimation of radar rainforest and the MLP model is able to improve the rainfall estimation results from the single polarization radar data in Yogyajarta.

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