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ARTICLE ACCEPTANCE LETTER

Dear Sandi Ronggo Panji,

On behalf of the organizing committee of the ICGTD 2024, I am delighted to extend to you, our Letter of Acceptance to participate in the upcoming international conference, scheduled to be held from 26-27 September 2024 at Institut Teknologi Nasional Bandung Campus, West Java, Indonesia.

We are pleased to inform you that your submitted article: "**Implementation of the Backpropagation Algorithm for Predicting Relative Humidity in Digital Surface Weather Observation System"**, is ACCEPTED to be presented in ICGTD 2024. Your research and insights align perfectly with the conference's objectives, and we believe that your participation will greatly enrich the discussions and overall experience for all attendees.

Please register before 15th September 2024 in order to confirm your research using the publication options form at:
https://l1nk.dev/ICGTD2024

Should you have any questions or require further assistance regarding your participation, please do not hesitate to reach out to our conference secretariat at icgtd@itenas.ac.id.

Warm regards,
ICGTD 2024

Implementation of the Backpropagation Algorithm for Predicting Relative Humidity in Digital Surface Weather Observation System

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Abstract. Weather is the state of the atmosphere over a short period, influenced by various parameters such as temperature, air pressure, and humidity. Digital weather observation instruments have replaced conventional instruments, but operational challenges with sensors can disrupt data continuity and quality. Relative humidity is a critical parameter in weather forecasting, and a reliable prediction model is necessary to minimize the impact of sensor failures. This study developed a model for predicting relative humidity using an Artificial Neural Network (ANN) algorithm with backpropagation featuring two hidden layers and three different neuron combinations. The data was sourced from the Minangkabau Class II Meteorological Station with a measurement interval of one minute throughout June 2024. Data from one day in July 2024 with the same data interval as the training data was utilized for testing the prediction model. The Relative humidity prediction model with a 2-10-5-1 architecture emerged as the best model with a correlation (R) value of 0.9485. This R-value indicates a strong relationship between the parameters used. The Relative humidity prediction model had a prediction error of 0.3133% ± 3.014%. In testing, the prediction model exhibited a prediction error of 0.599072 ± 2.48%. The higher prediction error during testing compared to the model's prediction error may be attributed to the limited dataset used, as the number of datasets serves as the source of information for the model in predicting humidity values.

INTRODUCTION

Weather is the condition of the air in a region over a relatively short period, expressed through various parameters such as temperature, air pressure, wind speed, humidity, and other atmospheric phenomena [1]. Digital surface weather observation instruments are used in surface weather observation activities, whereas observation tools today are dominated by digital instruments or sensors for measuring atmospheric parameters. These tools have replaced conventional surface weather instruments such as mercury thermometers, OBS rain gauges, Campbell Stokes sunshine recorders, and mercury barometers [2]. Like other electronic devices, sensors face operational challenges that impact data continuity and quality, often due to issues in the sensor's structure that can lead to sensor damage or degradation in measurement accuracy [3].

Humidity is one of the critical elements in weather forecasting and early warning systems, as it provides information about the water vapor content in the air. In weather forecasting methods, the availability of atmospheric parameter data is crucial in influencing forecasting accuracy. Prediction is an estimation of future events based on existing data from the present and past [4]. A prediction model is needed to address this issue and minimize the impact of sensor structural damage. One commonly used model is the Artificial Neural Network (ANN) with the Backpropagation algorithm [1], [5], [6]. This is because the ANN backpropagation algorithm involves a training process through weight updates. The backpropagation algorithm is an artificial neural network architecture with forward training and error correction performed backward [1].

Previous studies have used the backpropagation algorithm to train and develop prediction models. In 2022, Seah Yi Heng et al. designed a model to predict solar radiation values using the backpropagation algorithm. The solar radiation prediction model used atmospheric parameters such as air temperature, humidity, and wind speed as input parameters. In this study, the relative humidity prediction model will be designed using an Artificial Neural Network (ANN) with the backpropagation algorithm, utilizing two hidden layers and three neuron combinations in the backpropagation algorithm architecture. The best model will be selected based on the correlation (R), root mean square error (RMSE), and mean absolute percentage error (MAPE) values.

DIGITAL SURFACE WEATHER OBSERVATION INSTRUMENT

The transition from conventional surface weather observation instruments (mercury and dial thermometers) to electronic instruments, specifically sensors, was initiated by BMKG in 2015 as a form of implementing the WMO's recommendation to prohibit the use of mercury in weather observation instruments. This surface weather observation instrument combines Automatic Weather Station (AWS) and observer-based observation, recording weather sequences interpreted into Synoptic code [2]. The concept or procedure for encoding and observing is regulated by the World Meteorology Organization (WMO), which includes the instrument layout, observation times, coding format and distribution, and criteria or specifications for the instrument used. The quality of observation with this instrument depends on the performance of the sensors used to measure air temperature (T), relative humidity (RH), air pressure (P), wind direction and speed (ddd and ff), and solar radiation (sss). This dependence often encounters issues in the continuity and quality of data produced by the sensors, which is caused by factors such as the sensor's lifetime and the atmospheric conditions in equatorial regions where dust (dry particles) is prevalent [3].

Humidity is a condition where the air becomes moist or wet, influenced by the amount of moisture in the atmosphere, which indicates the water vapor content that can be held in a volume of air. The measured humidity is the value of relative humidity, which is the ratio of the actual vapor pressure to the saturation vapor pressure. At the same time, air temperature is the degree of heat in a condition [7], [8]. Air pressure is the weight of the air over a unit area or volume of air, where the number of particles in a volume of air determines the air pressure value [9].

Air temperature, air pressure, and humidity are interrelated atmospheric parameters, where a change in one of these parameters will affect the value of the others. The equation for relative humidity is expressed as follows:

$$RH = \frac{es}{e_s} \tag{1}$$

Where relative humidity (RH) is the ratio of partial vapor pressure e to saturation vapor pressure e_s [10]. In 1967, using the Teten-Murray equation, the value of e_s at a specific air temperature (t) Was expressed as follows:

$$e_S(t) = 6{,}11\ x\ 10\ \left(\frac{7{,}5\ t}{t + 273{,}3}\right) \tag{2}$$

Climent Ramis, Romualdo Romero, and Sergio Alonso, members of the meteorology group in the faculty of physics at the University of the Balearic Islands, Spain, described the partial vapor pressure (e) ss follows:

$$e = \ e_S(t) - \frac{8C_P}{5L_V} pt \tag{3}$$

Cp is the specific heat at constant pressure for dry air, LV is the latent heat (C_P = 1005 $Jkg^{-1}K^{-1}$ dan L_V = 2,501 10^6 J kg^{-1}), and p is the pressure. Using equations (2) and (3) in equation (1), it can be expressed as follows:

$$RH = 100\% \left[\frac{e_S(t) - \frac{8C_P}{5L_V}pt}{e_S(t)}\right] \tag{4}$$

Thus, from equation (4), changes in air temperature (t) and air pressure (p) can affect relative humidity (RH). The R-value indicates the correlation between the parameters and represents the magnitude of the influence or relationship.

A commonly used approach in prediction model design is the Artificial Neural Network (ANN) with the backpropagation algorithm [1], [5], [6]. The prediction models developed by researchers typically use two types of parameters: input parameters and output parameters. The input parameters in the prediction model design include weather elements such as air temperature, humidity, pressure, and wind speed. The models are designed with one hidden layer and a combination of neurons in the hidden layer. For example, Seah Yi Heng et al.'s prediction model for solar radiation yielded a correlation value of 0.8113 between parameters for Kuala Terengganu, Malaysia. At the same time, Riri Diah Septiarini et al. achieved a MAPE value of 2.568% for their weather prediction model in Cilacap, Indonesia. Venkata R. Duddu et al. designed a model to predict fog weather phenomena using input parameters such as cloud cover, elevation, precipitation, air temperature, dew point temperature, wind speed, and rainfall, predicting fog conditions on road obstacles in North Carolina, USA.

In model design, values must serve as reliability/accuracy parameters for the created model. Generally, the accuracy of the model can be analyzed using the correlation (R), root mean square error (RMSE), and mean absolute percentage error (MAPE) values [11]. The equations for these three parameters are expressed as follows:

$$R = \frac{\sum_{i=1}^{m}(x_i - \bar{x})\sum_{i=1}^{m}(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{m}(x_i - \bar{x})^2 \sum_{i=1}^{m}(y_i - \bar{y})^2}} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - x_i)^2} \tag{5}$$

$$\mathrm{MAPE} = \frac{100\%}{\mathrm{m}}\sum_{\mathrm{i}=1}^{\mathrm{m}}\left|\frac{\mathrm{x_i}-\mathrm{y_i}}{\mathrm{y_i}}\right| \tag{5}$$

RMSE is an evaluation metric used to measure error, where a lower value indicates higher accuracy. MAPE expresses the error value as a percentage, with a lower MAPE value indicating higher prediction accuracy [12], [13].

METHODOLOGY

This study used data with a 1-minute interval from June 2024 at the Class II Meteorological Station Minangkabau—Padang Pariaman, West Sumatra. The data were collected from digital surface weather observation instruments, with 1-minute interval data for three measurement parameters: air temperature, humidity, and air pressure. The following steps were undertaken to develop a predictive model for humidity values using the backpropagation algorithm, as depicted in Figure 1.

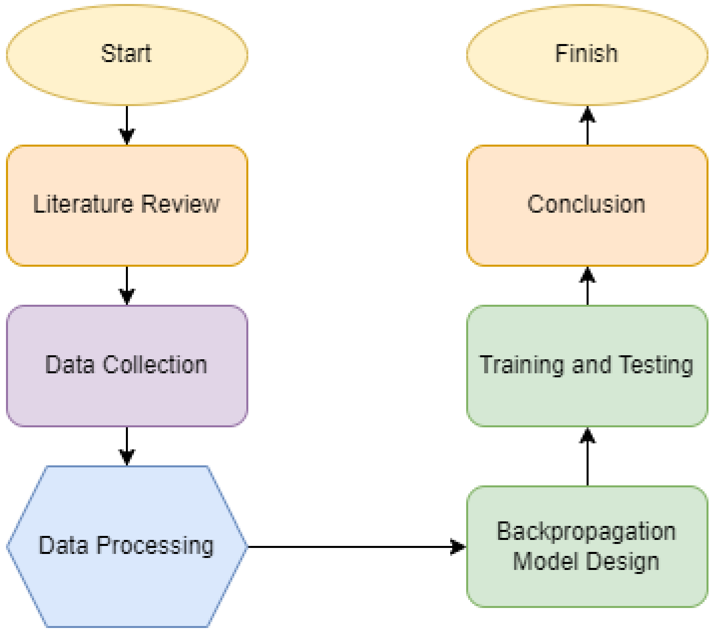

FIGURE 1. Research Flowchart

Several steps were undertaken to develop a predictive model for humidity values using the backpropagation algorithm. First, a literature review was conducted to address the problems related to the humidity sensor, which experienced challenges in data continuity and quality due to material damage and other factors. Data collection followed, gathering 1-minute interval data for air temperature, humidity, and air pressure throughout June 2024. During data processing, any 99999 values indicated sensor errors or data transmission disruptions were corrected or excluded.

The design of the backpropagation model involved creating an architecture with two input layers (air temperature and air pressure), two hidden layers, and one output layer (humidity). Three combinations of neurons in the hidden layers were tested: 2-4-2-1, 2-8-4-1, and 2-10-5-1. The model training and validation process was then carried out, with five repetitions for each combination to identify the best model. The data were split into 80% for training and 20% for validation, and the best model was selected based on the highest correlation (R) value or the lowest RMSE if R values were equal.

The best predictive model was tested using data from July 1, 2024, with RMSE and MAPE values used to evaluate the model's accuracy in predicting humidity. The model was further assessed based on the R-value, which indicated the strength of the relationship between the input and output parameters, and the RMSE and MAPE values, which measured the model's accuracy. Finally, the study concluded by determining whether the input parameters significantly impacted the output and whether the backpropagation algorithm model could effectively predict humidity values.

RESULT AND DISCUSSION

The data used for training and testing were collected from a digital surface weather observation instrument at 1-minute intervals in June 2024 at the Class II Meteorological Station Minangkabau - Padang Pariaman, West Sumatra. The details are as follows:

- Air temperature data: 41,794 records.
- Relative humidity data: 41,794 records.
- Air pressure data: 41,794 records.

The data for training and testing for each architectural combination are shown in the table below:

TABLE 1. Number of Training and Testing Data for Each Backpropagation Architecture Combination

Architecture	Training Data	Testing Data
2 – 4 – 2 – 1	80% (33,435)	20% (8,359)
2 – 8 – 4 – 1	80% (33,435)	20% (8,359)
2 – 10 – 5 – 1	80% (33,435)	20% (8,359)

As shown in the table, the training and testing data percentage was maintained at 80% and 20% of the total input data. Each combination was trained using the backpropagation algorithm with the following training parameters:

TABLE 2. Training Parameter

Parameter	Description
Epoch	1000 (Limits the maximum number of training iterations)
Goal	0.01 (Sets the error threshold for training)
Min. Grad	Ten^{-6} (Stops training if the weight updates become too small, indicating convergence)
Max. Fail	6 (Stops training if the validation error does not decrease after several iterations to prevent overfitting)
Iteration	5 (The number of training repetitions)

Training Results

After conducting the training process with a data split of 80% for training and 20% for validation across each architectural combination, the results were as follows:

TABLE 3. Training Results Table with 3 Training Combinations

Architecture Combination	Architecture	Iteration	R	RMSE	MAPE (%)
1	2 – 4 – 2 - 1	1	0.9432	0.3287	3.2116
		2	0.9434	0.3282	3.2097
		3	0.9440	0.3264	3.1893
		4	**0.9442**	**0.3262**	**3.1764**
		5	0.9435	0.3278	3.1989
2	2 – 8 – 4 – 1	1	0.9458	0.3213	3.1183
		2	0.9439	0.3268	3.1772
		3	**0.9447**	**0.3245**	**3.1440**
		4	0.9447	0.3246	3.1713
		5	0.9463	0.3198	3.1006
3	2 – 10 – 5 - 1	**1**	**0.9485**	**0.3133**	**3.0142**
		2	0.9476	0.3160	3.0451
		3	0.9459	0.3209	3.1039
		4	0.9475	0.3165	3.0536
		5	0.9479	0.3152	3.0585

Table 3 shows that the training results with 1000 epochs and five iterations showed the best results for each architectural combination. The best outcome for architecture combination one was achieved in the 4th iteration with an R-value of 0.9442, RMSE of 0.3262, and MAPE of 3.1764%. For architecture combination 2, the best result was achieved in the 3rd iteration with an R-value of 0.9447, RMSE of 0.3245, and MAPE of 3.1440%. For architecture combination 3, the best result was achieved in the 1st iteration with an R-value of 0.9485, RMSE of 0.3133, and MAPE of 3.014%.

TABLE 4. Training Results Table with the Best Architecture for Each Training Combination

Architecture Combination	Architecture	R	RMSE	MAPE
1	2 – 4 – 2 - 1	0.9442	0.3262	3.176%
2	2 – 8 – 4 – 1	0.9447	0.3245	3.144%
3	2 – 10 – 5 - 1	0.9485	0.3133	3.014%

Table 4 shows that the best humidity prediction model in training with three architectural combinations was the prediction model with the 2-10-5-1 architecture, which had a correlated (R) value of 0.9485, an RMSE of 0.3133, and a MAPE of 3.014%. The R-value indicates that changes in the input parameters (air temperature and air pressure) significantly impact changes in humidity values, showing a strong correlation. The prediction error for the humidity model is 0.3133% ± 3.014%.

Prediction Model testing

The best prediction model obtained from the training process, as shown in Table 3, was tested as follows: Testing was conducted on the combination architecture 2-10-5-1, with ten neurons in the first hidden layer and five neurons in the second layer. The test results were as follows:

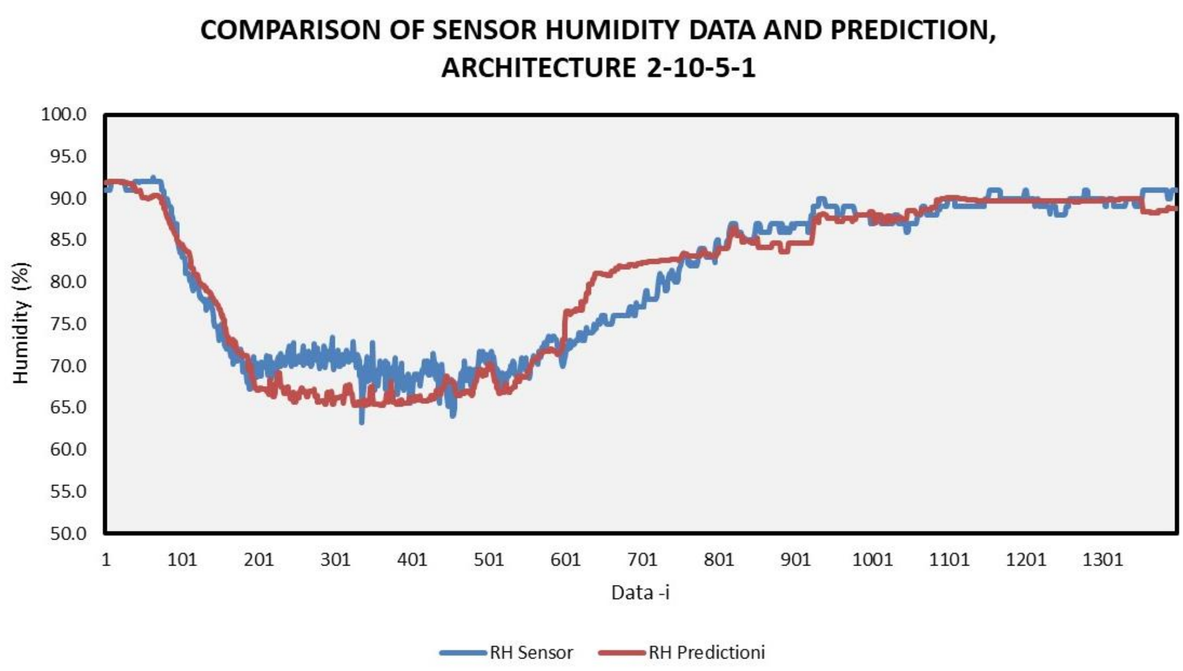

FIGURE 2. Comparison between RH values from the sensor and predicted RH

From the testing results, the RMSE was 0.599072, and the MAPE was 2.48%, with the maximum difference between the actual humidity values from the sensor and the predicted humidity values using the backpropagation algorithm. The results are as follows: maximum difference (ΔRH_max) of 7.4%, minimum difference (ΔRH_min) of

-6.6%, and average difference (ΔRH_mean) of 0.4%. Of the total test data, 7.58% or 106 records differed between sensor humidity values and predicted humidity values more significantly than ±5%, with 37 records above 5% and 69 below -5%. Thus, the prediction error is 0.599% ± 2.48%.

According to equation (4), relative humidity is influenced by air temperature and air pressure, indicating a correlation between the three parameters. The training results show that the R-value was 0.9485, meaning that the input and output parameters have a strong correlation, as indicated by the R-value. The relative humidity prediction model had a prediction error of 0.3133% ± 3.014%. In contrast, the model testing revealed a prediction error of 0.599% ± 2.48%. This discrepancy may be due to the model not fully capturing the changes between parameters, leading to different information in the test data compared to the model stored during training.

CONCLUSION

This study reveals that the relationship between the parameters used as inputs and outputs in the model is vital, as indicated by a high correlation coefficient (R) value of 0.9485. This suggests that the selected input parameters, such as air temperature and air pressure, significantly influence the predicted output of air humidity. The testing results for the Relative humidity prediction model with the 2-10-5-1 architecture demonstrate a prediction error of 0.599072 ± 2.48%. This level of accuracy indicates that the model is reliable for predicting air humidity, with a relatively low margin of error, underscoring the model's effectiveness in capturing the underlying patterns in the data.

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