# Weather Forecasting Using Neural Networks with Backpropagation and ADAM Optimizer for city of Lhokseumawe

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**Abstract**. Weather forecasting in Lhokseumawe is crucial due to its diverse climate and impact on community activities. It serves as an operational responsibility of the Meteorology, Climatology and Geophysics Agency (BMKG) worldwide. The method of forecasting currently employed by the BMKG involves meteorological teams observing and analyzing statistics based on principles of mechanics and physics. Artificial Neural Networks (ANN) can be utilized to forecast long-term weather conditions, with the backpropagation algorithm being an ANN algorithm employed for short-term weather prediction. This involves training the backpropagation architecture data, which includes an input layer with a size of 6 using Relu activation, one hidden layer with a size of 64 using Relu activation, and an output layer with a size of 3 using softmax activation. We also apply the ADAM optimizer, loss sparse categorical crossentropy, and accuracy metrics. However, the backpropagation algorithm displays weaknesses, including slow convergence, overfitting, and susceptibility to local minima, which can be addressed by utilizing the ADAM optimization algorithm. The research utilizes Artificial Neural Network (ANN) with the backpropagation algorithm and ADAM optimization to predict weather conditions in Lhokseumawe City with high accuracy. The research methods comprise of data collection, preprocessing, division, model building, and evaluation. The study outcomes present the weather conditions as sunny, cloudy, or rainy with an algorithm accuracy of 72%.

**Keywords:** Backpropagation, BMKG, Lhokseumawe, Weather prediction

## INTRODUCTION

Lhokseumawe is a low-lying region covering 181.06 km$^2$ above sea level, with an average elevation of +24 meters. It is situated at the coordinates of 04°54' North latitude, 05°18' South latitude, and 96°20' and 97°21' East longitude [1]. The weather conditions in Lhokseumawe fluctuate due to atmospheric conditions. Multiple community activities rely on the prevailing weather patterns in the area Weather conditions are affected by air temperature, air humidity, air pressure, wind, and other atmospheric factors [2],[3]. The following details the factors that influence weather conditions, including [4],[5]:

1. Air temperature is a measurement of the amount of heat in the atmosphere at a specific location and time. It is measured by a thermometer or another device capable of measuring temperature. The air temperature can

fluctuate throughout the day and vary from one place to another, and it is influenced by utilizing various factors, including altitude, geographic location, and human activity. Moreover, air temperature exerts a significant impact on weather conditions and contributes to occurrences such as wind, clouds, and precipitation. Temperature ranges in Celsius (°C) may vary depending on the geography and season of a location. Presented below are some general temperature categories :
a.Low temperature: Less than 0 ˚C
b.Cold temperature: 0 ˚C to 15 ˚C
c.Medium temperature: 15 ˚C to 25 ˚C
d.Heat temperature: 25 ˚C to 35 ˚C
e.Extremely hot temperature: More than 35 ˚C

2. Air humidity refers to the quantity of water vapor present in the atmosphere at a particular location and time. It can be measured using a hygrometer or similar device. Various factors, including temperature fluctuations, precipitation, and human actions, can impact air humidity, which can vary from extremely arid to excessively humid conditions. High humidity levels can produce cozy and comfortable weather while low humidity levels can result in warm and dry weather. The range of dew points in degrees Celsius (˚C) varies depending on both atmospheric conditions and relative humidity of a location. The following are typical dew point ranges
a.Low Dew Point: Below 0 ˚C
b.Medium Dew Point: 0 ˚C to 10 ˚C
c.High Dew Point: Above 10 ˚C

3. Air pressure is the force exerted by the mass of air on an object, and can be measured using a barometer in the atmosphere. It indicates the height of the air at a given location, and can vary throughout the day and from different locations. Temperature, humidity, and weather patterns can impact air pressure. As a result, air pressure significantly influences weather patterns, contributing to phenomena such as wind, clouds, and precipitation. The air pressure range is typically measured in millibars (mb) and can differ according to altitude and weather conditions. Here is a general mb air pressure range
a.Range of air pressure at sea level: About 1000 mb to 1013 mb
b.Air pressure range at high altitudes: Less than 1000 mb
c.Air pressure range in high pressure areas: More than 1013 mb

The movement of air in the atmosphere is defined as wind direction. Determination of wind direction can be accomplished by utilizing an anemometer or a vane anemometer. It is influenced by numerous factors including air pressure, temperature and topography, leading to changes throughout the day and geographical locations. Owing to its impact on the weather conditions, wind direction contributes significantly to phenomena like strong winds, clouds, and rainfall. Wind direction ranges are commonly measured in degrees (°) on a 360-degree scale, indicating the direction from which the wind is blowing. Common wind direction ranges include :

a. 0° or 360° : North
b. 90° : East
c. 180° : South
d. 270° : West

Viewing distance is the maximum horizontal range at which an object or objects are clearly visible to the human eye or observation device without significant interference or obstacles. The range of visibility (in kilometers) may vary depending on the environmental and weather conditions at a given location. Some common categories for visibility ranges in kilometers are as follows

a. Very poor: Less than 1 km
b. Bad: 1-4 km
c. Moderate: 4-10 km
d. Good: 10-20 km
e. Very good: More than 20 km

Wind speed is the rate at which air moves through the atmosphere. It can be measured with an anemometer. The speed varies by location, time of day, and is affected by several factors, including air pressure, temperature, and topography. Wind speed plays a critical role in shaping weather patterns and contributes to various phenomena, such as strong gusts, cloud formation, and precipitation. Wind speed is typically measured in knots (KT) and exhibits a varying range of values contingent upon the measurement scale employed. Below are some standard scales used to elucidate the range of wind speeds in KT:

a. 1-3 KT: Weak wind (Light air)
b. 4-6 KT: Light breeze
c. 7-10 KT: Gentle breeze
d. 11-16 KT: Moderate breeze
e. 17-21 KT: Fresh breeze
f. 22-27 KT: Strong breeze
g. 28-33 KT: Near gale
h. pp. 34-40 KT: Hurricane (Gale)
i. 41-47 KT: Strong gale
j. 48-55 KT: Storm
k. 56-63 KT: Violent storm
l. 63 KT: Cyclonic storm (Hurricane)

The process of selecting the most appropriate and effective method or technique to predict and determine future weather conditions is known as weather forecasting. This is a crucial task carried out by meteorological forecasters worldwide as it is one of the most important and demanding operational responsibilities. [7],[8]. Weather forecasting in Indonesia is carried out by the Meteorology, Climatology, and Geophysics Agency (BMKG) using meteorological models developed by other agencies worldwide, including the European Center for Medium-Range Weather Forecasts (ECMWF) [9]. The current approach relies on the observations and analysis of the meteorological forecasting team, who utilizes the Autoregressive Integrated Moving Average (ARIMA) technique to forecast short-term weather. The MAE, RMSE, and MAPE values for this method are 0.181, 0.254, and 0.159, respectively [10],[11],[12]. To accurately predict short-term weather conditions, a suitable and precise method is essential. One method proven to predict long-term weather conditions is the Artificial Neural Network (ANN) method [13].

One of the artificial neural networks (ANN) algorithms employed for weather forecasting is the backpropagation algorithm. Backpropagation exhibits drawbacks such as extended convergence time, overfitting, and a high likelihood of being trapped in local minima. To surmount these limitations, we can use the ADAM (Adaptive Moment Estimation) optimization algorithm, which combines gradient descent with strategies for modeling moving averages and gradient variances. The ADAM algorithm has the capability to overcome the issue of rotation at the local minimum and expedite convergence, making it superior to other forms of gradient descent in terms of avoiding the issue of becoming trapped at the local minimum [14].

Therefore, this study proposes to use ANN method with backpropagation algorithm and ADAM (Adaptive Moment Estimation) optimization in forecasting and prediction of weather conditions in Lhokseumawe city. This technique is expected to yield reliable results in accurately predicting weather conditions in the area. Based on what has been discussed, there are several problems for weather forecasting, namely: BMKG uses ARIMA model to predict weather with MAE accuracy 0.181, RMSE 0.254 and MAPE 0.159. To predict the weather this research uses ANN *Backpropagation* method. Backpropagation has disadvantages such as slow convergence, *overfitting*, and susceptibility to local minima. To solve these problems, this research uses the ADAM (*Adaptive Momen Estimation*) optimization algorithm, to accurately predict and predict weather conditions in Lhokseumawe City.

## METHODS

The research consists of several stages including data collection, preprocessing, sharing, backpropagation architecture, training, testing the model, and evaluating the results as depicted in Figure 1.

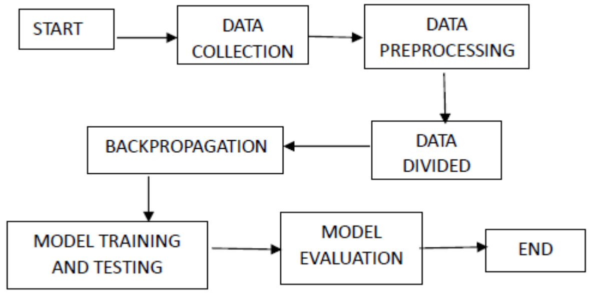


**FIGURE 1**. Research Flow

*A. Data Collection* This study adopts secondary data obtained from BMKG (Meteorology, Climatology, and Geophysics Agency) Malikussaleh Meteorological Station, North Aceh Regency with a span of 5 months totaling 3624 data. The data consists of 24-hour daily readings of temperature (in ˚C), dew point (in ˚C), air pressure (in ˚C), visibility (in km), wind speed (in KT), wind direction (in ˚), and weather conditions (sunny, cloudy, rainy). Table 1 shows the data as follows:

**TABLE 1.** Bmkg Raw Data Malikussaleh Meteorological Station, North Aceh District

| Wind direction (˚) | Wind speed (KT) | Visibility (km) | Temperature (˚C) | Dewpoint (˚C) | Air pressure (mb) | Weather |
|---|---|---|---|---|---|---|
| 120 | 8 | 7 | 27,4 | 24,3 | 1010,5 | cld decr |
| 90 | 12 | 8 | 28,8 | 23,5 | 1008,1 | cld unch |
| 120 | 6 | 6 | 24,6 | 23,3 | 1009,6 | cld unch |
| 140 | 5 | 5 | 23,9 | 22,8 | 1009,2 | haze |
| 130 | 5 | 5 | 25,3 | 24,2 | 1008 | haze |
| 0 | 0 | 5 | 24,2 | 23,5 | 1007,2 | haze |
| 150 | 3 | 5 | 24 | 23,3 | 1007,5 | haze |
| 120 | 6 | 6 | 24,4 | 23,1 | 1010,2 | inter slra |
| 120 | 7 | 6 | 25,5 | 23,8 | 1010,6 | rera |
| 160 | 3 | 5 | 25,6 | 24,4 | 1008,6 | rera |

*B. Data Preprocessing*

*Cleaning*, data cleaning by selecting data to be used, suchas deleting unwanted data or filling in *null data.*

1. *Encoding*, converting categorical data (non-numericaldata) into numerical data.
2. *Scaling*, creating input data with a range of 0-1 or datanormalization

*C.* Data Sharing

The data is divided into 2, namely, 80% training data as much as 2899 data and 20% test data as much as 725 data from 3624 data.

*D.* Establishment of Backpropagation Architectureipsum

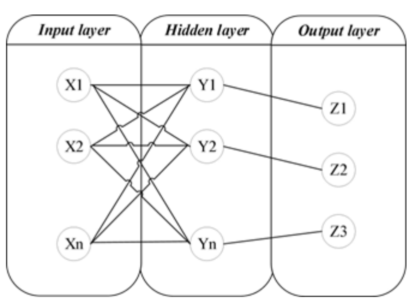


**FIGURE 2**. *Backpropagation* Architectur

Figure 2 is a *backpropagation* model by determining the input variables used, the number of hidden layers, the number of outputs, learning rate, activation function, ADAM optimization, momentum (between 0.1 and 0.9).

E. *Training and Testing the Model*

The training of the model is done with 2899 datasets to teach the model to recognize patterns. to test it with a separate dataset of 725. Notably, there was a significant variance between the model's accuracy during training and testing. Thus, additional experiments, such as retraining or adjustments to the model architecture, are required to prevent overfitting or underfitting.

F. Model Evaluation

Evaluation of model performance is obtained by creating a table confusion matrix on 3 classes to find accuracy asfollows in Table 2

**TABLE 2.** Confusion Matrix On 3 Classes

| **Actual** | **Prediction** | | |
|---|---|---|---|
| | Positive | Negative | Neutral |
| Positive | True Positive (TP) | False Negative (FNg) | False Neutral (FN) |
| Negative | False Positive (FP) | True Negative (TNg) | False Neutral (FN) |
| Neutral | False Positive (FP) | False Negative (FNg) | True Neutral (TN) |

## RESULTS AND DISCUSSION

The results of this study are in the form of weatherconditions viz: sunny, cloudy, and rainy:

| | Arah_angin | Kecepatan_angin | JarakPandang | Suhu | TitikEmbun | TekananQFF | Cuaca |
|---|---|---|---|---|---|---|---|
| **0** | 150 | 10 | 4.0 | 23.8 | 22.8 | 1010.1 | Hujan |
| **1** | 150 | 8 | 6.0 | 24.0 | 22.7 | 1010.8 | Hujan |
| **2** | 150 | 9 | 4.0 | 24.0 | 22.4 | 1011.7 | Hujan |
| **3** | 170 | 4 | 6.0 | 24.6 | 22.1 | 1011.9 | Hujan |
| **4** | 120 | 5 | 7.0 | 27.8 | 23.4 | 1011.7 | Berawan |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **3619** | 250 | 2 | 6.0 | 24.3 | 23.6 | 1006.8 | Berawan |
| **3620** | 220 | 3 | 6.0 | 24.0 | 23.3 | 1007.1 | Hujan |
| **3621** | 230 | 4 | 6.0 | 23.9 | 23.1 | 1007.1 | Hujan |
| **3622** | 220 | 4 | 7.0 | 23.9 | 23.1 | 1007.4 | Hujan |
| **3623** | 220 | 4 | 8.0 | 23.9 | 22.9 | 1007.8 | Hujan |

3624 rows × 7 columns

**FIGURE 3**. Data *Cleaning*

Figure 3 above is data that has been cleaned using interpolation, which is estimating the missing value based on the existing data before and after by dividing the two data because the data used is *timeseries data* so that each data is very influential in model accuracy.

| | Arah_angin | Kecepatan_angin | JarakPandang | Suhu | TitikEmbun | TekananQFF | Cuaca |
|---|---|---|---|---|---|---|---|
| 0 | 150 | 10 | 4.0 | 23.8 | 22.8 | 1010.1 | 2 |
| 1 | 150 | 8 | 6.0 | 24.0 | 22.7 | 1010.8 | 2 |
| 2 | 150 | 9 | 4.0 | 24.0 | 22.4 | 1011.7 | 2 |
| 3 | 170 | 4 | 6.0 | 24.6 | 22.1 | 1011.9 | 2 |
| 4 | 120 | 5 | 7.0 | 27.8 | 23.4 | 1011.7 | 1 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 3619 | 250 | 2 | 6.0 | 24.3 | 23.6 | 1006.8 | 1 |
| 3620 | 220 | 3 | 6.0 | 24.0 | 23.3 | 1007.1 | 2 |
| 3621 | 230 | 4 | 6.0 | 23.9 | 23.1 | 1007.1 | 2 |
| 3622 | 220 | 4 | 7.0 | 23.9 | 23.1 | 1007.4 | 2 |
| 3623 | 220 | 4 | 8.0 | 23.9 | 22.9 | 1007.8 | 2 |

3624 rows × 7 columns

**FIGURE 4**. Data *Encoding*

Figure 4 above is data that has been converted from the weather column which was previously categorical data, namely sunny, cloudy and rainy to numerical data, namely 0, 1, and 2

| | Arah_angin | Kecepatan_angin | JarakPandang | Suhu | TitikEmbun | TekananQFF | Cuaca |
|---|---|---|---|---|---|---|---|
| 0 | -0.033610 | 2.109407 | -0.018100 | -1.215647 | -0.769487 | 0.258568 | 2 |
| 1 | -0.033610 | 1.378157 | -0.016896 | -1.139213 | -0.862646 | 0.633818 | 2 |
| 2 | -0.033610 | 1.743782 | -0.018100 | -1.139213 | -1.142123 | 1.116282 | 2 |
| 3 | 0.171897 | -0.084344 | -0.016896 | -0.909912 | -1.421600 | 1.223496 | 2 |
| 4 | -0.341871 | 0.281281 | -0.016294 | 0.313031 | -0.210533 | 1.116282 | 1 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 3619 | 0.993925 | -0.815594 | -0.016896 | -1.024563 | -0.024215 | -1.510466 | 1 |
| 3620 | 0.685664 | -0.449969 | -0.016896 | -1.139213 | -0.303692 | -1.349644 | 2 |
| 3621 | 0.788418 | -0.084344 | -0.016896 | -1.177430 | -0.490010 | -1.349644 | 2 |
| 3622 | 0.685664 | -0.084344 | -0.016294 | -1.177430 | -0.490010 | -1.188823 | 2 |
| 3623 | 0.685664 | -0.084344 | -0.015692 | -1.177430 | -0.676328 | -0.974395 | 2 |

3624 rows × 7 columns

**FIGURE 5**. Data *Scalling*

Figure 5 above is the scaling data changing the data variables of wind direction, wind speed, visibility, temperature, dew point, and air pressure to be normalized using *StandardScaler* which has a mean of 0 and a standard deviation of 1.

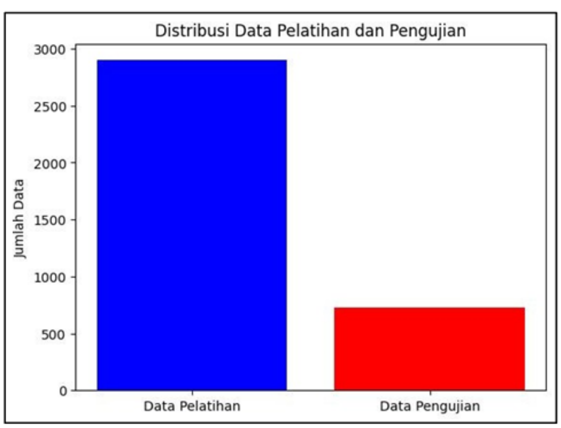


**FIGURE 6.** Split of Training and Test Data

Figure 6 above is the distribution of training data as much as 2899 data and test data as much as 725 data from 3624 data that will be used in the *backpropagation* model.


**FIGURE 7** Comparison Chart of *Accuracy Training* and *Testing*

Figure 7 above is a graph of testing accuracy higher than training accuracy, the better. However, perfect accuracy (100%) may not always be realistic or desirable, especially if the data is not balanced or there are acceptable errors.

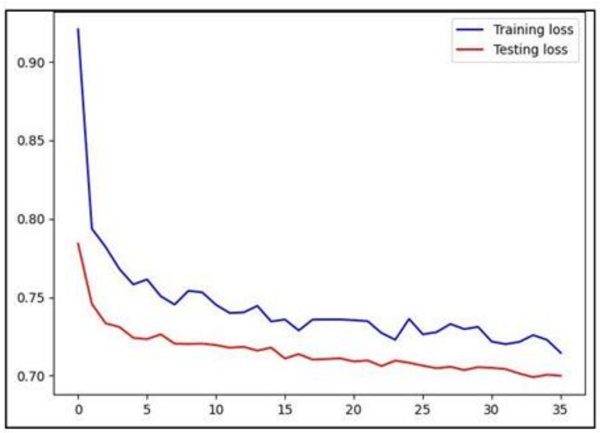


**FIGURE 8.** Comparison Chart of *Loss Training* and *Testing*

Figure 8 above is a graph of *testing loss* lower than *training loss*. The lower the *loss* value, the better. A low *loss* indicates that the model has the ability to produce predictions that are close to the true value. However, there are specific extensions to each task that may have a more specific interpretation for *loss*. For example, in *regression* problems, *MSE (Mean Squared Error) is* often used as a *loss function*, whereas in prediction *binary*, *binary cross-entropy* or *log loss is* often used

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| berawan | 0.73 | 0.97 | 0.83 | 506 |
| cerah | 0.00 | 0.00 | 0.00 | 53 |
| hujan | 0.60 | 0.20 | 0.30 | 166 |
| accuracy | | | 0.72 | 725 |
| macro avg | 0.44 | 0.39 | 0.38 | 725 |
| weighted avg | 0.65 | 0.72 | 0.65 | 725 |

**FIGURE 9**. *Confusion matrix*

The figure above is the *confusion matrix precision,recall*, *f1-score* and *accuracy* can be calculated as follows:

1. *Recall*

*Recall* measures the extent to which the positive classifications made by the model are correct.

$$Recall = \frac{TP}{TP + FP}$$

*The True Positives* (TP) for "Class 1" is 489 (the number of correct predictions for "Class 1").
*The False Positives* (FP) for "Class 1" is 0+17 = 17 (thenumber of incorrect predictions for "Class 1")

$$Recall = \frac{489}{489 + 17} = 0.97$$

2. Precision

*Precision* measures the extent to which the model can identifyall true positive classes

$$Precision = \frac{TP}{TP + FN}$$

*The False Negatives* (FN) for "Class 1" is 48+133 = 181 (the number of true but incorrectly predicted "Class 1" classes)

$$Precision = \frac{489}{489 + 181} = 0.7$$

*F1- Score*

*F1-score* is the harmonic mean of Precision and Recall,providing a balance between the two

$$\text{F1-score} = \frac{2\ x\ (precision\ x\ recall)}{precision\ x\ recall}$$

$$\text{F1-score (kelas 1)} = \frac{2\ x\ (0.73\ x\ 0.97)}{0.73 +\ 0.97}$$

$$\text{F1-score (kelas 1)} = \frac{2\ x\ (0.71)}{1.71} = 0.83$$

3. Accuracy

Accuracy measures how accurate the model is in making overall predictions:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

*True Negatives* (TN) is 0+33 = 33 (the number of correctpredictions for "Class 2" and "Class 3").
*The False Positives* (FP) are 48+133+0 = 181 (the number ofincorrect predictions for "Class 1" and "Class 2").
*The False Negatives* (FN) are 17+5+0 = 22 (the number ofincorrect predictions for "Class 2" and "Class 3")

$$\text{Accuracy} = \frac{489 + 33}{489 + 33 + 181 + 22} = 0.72$$

So, the calculation result is:
*Precision* (Class 1) ≈ 0.73
*Recall* (Class 1) ≈ 0.97
*F1-score* (Class 1) ≈ 0.83
*Accuracy* ≈ 0.72

## CONCLUSIONS

The conclusion that can be drawn from the use of the backpropagation algorithm and Adam optimization in predicting the weather in Lhokseumawe City is that it yields a 72% accuracy rate. To decrease the errors in MAE, RMSE, and MAPE, we utilize the backpropagation algorithm and ADAM optimization. This involves training the backpropagation architecture data, which includes an input layer with a size of 6 using Relu activation, one hidden layer with a size of 64 using Relu activation, and an output layer with a size of 3 using softmax activation. We also apply the ADAM optimizer, loss sparse categorical crossentropy, and accuracy metrics. Finally, we evaluate the model using testing data. Further research should utilize time series data and account for null data, as this can significantly impact the accuracy of the backpropagation method. In addition to traditional backpropagation, researchers may consider using other methods, such as CNN, Regression, SVM, or others, to predict weather conditions

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