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OPTIMAL HYPERPARAMETER TUNING 3BESTACC MULTILAYER PERCEPTRON ON RAINFALL DATA

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ABSTRACT

In this study, we classify the status of rain in Australia using the Multi-Layer Perceptron (MLP) method. The dataset has 23 features, but in this study 17 attributes were used which were of a numeric type, with 16 features as input and 1 feature as output, where the output was worth 2 conditions, namely Rain (1) and No Rain (0). The processed data does not contain a miss value of 56,420 records which are divided into 3 parts, namely training data, validation data and testing data. A total of 50,000 records from 56,420 records are divided into 5 folds randomly. Each fold contains 10,000 records. These five folds are used as training data, and validation data. With the K-Cross Validation principle, validation data is taken from one of the folds and the other 4 folds are used as training data. The remaining data of 6420 records are used as testing data. In the MLP method, there are two parameters to be tuned, namely the number of hidden layers and the number of nodes per hidden. In this study, the number of hidden layers tested was 1 to 12. Meanwhile, the number of nodes tested was 1 to 30. For each hidden layer, 3 structures were taken that had the highest accuracy to determine the structure of the next hidden layer. The results of the experiment show that the highest average accuracy is at 8 Hidden Layers with an accuracy of 0.854. The 8 Layer Hidden structure is (19, 24, 25, 25, 15, 3, 3, 26). This accuracy value is better than previous research conducted by Antonio SC in the article Prediction of Rainfall in Australia Using Machine Learning, with accuracy = 0.84. For this research, the accuracy value for testing data is 0.85586.

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Introduction

Weather is the condition of the atmosphere at a certain time and place. Weather is related to sunlight, air temperature, humidity, wind, and other air conditions, Lakitan (2002). Types of weather include rain, heat, snow, wind, and storms. These types depend on temperature, movement, and air pressure in an area. These types depend on temperature, movement, and air pressure in an area. Weather and climate play a role in various fields of life, including agriculture, transportation, industry, and telecommunication, Pratikto, Hariadi, and Aldrian (2014). The benefits of weather in agriculture include determining the time of planting and the appropriate type of plant. The benefits of weather in the field of transportation, especially air transportation, are weather conditions for smooth and safe flights. Besides the benefits obtained regarding weather conditions, the existence of the phenomenon of climate change has a broad impact on people's lives. The increase in the earth's temperature affects various aspects of natural changes and human life. Such as changes in the quantity and quality of water, changes in forest habitat and agricultural land, and other changes. Uncertainty of rainfall data is one of the most complex problems, Sethupathi, Ganesh, and Ali (2021). Rain is a parameter and a weather phenomenon. Rain comes from the evaporation of air containing water vapor. The air rises up and forms clouds. at a certain temperature. Next, the collected water vapor condenses into water droplets and falls to the earth as rain. As a rain parameter, its quantity can be measured and as a phenomenon, rain can be seen visually, as well as fog, smoke, and others. Rainwater plays an important role in preserving the environment and acts as a source of groundwater, Rejekiningrum (2009). Rainwater that falls on the surface of the earth will seep into the surface of the soil layer as a water reserve that is stored at a certain depth. Rain plays an important role in preserving the environment so that natural disasters do not occur, Suskha, Rusydi, and Wusqa (2020). Rainwater that falls to the surface of the earth will be absorbed by trees to maintain survival of trees for years because the presence of trees can minimize disasters, Respatiadi (2017). Conversely, heavy or continuous rainfall can cause landslides. Rain that continues to occur will cause the fertile soil to gradually erode so that over time the fertile soil will disappear. Erosion can cause natural damage and cause disasters that are very detrimental to humans. While the structure of the soil really needs water to always be able to maintain soil strength. So that in order for the soil construction system to survive, this is where the role of rainwater becomes important, in order to prevent the soil from experiencing prolonged drought. Rainfall greatly affects all aspects of life, so it is necessary to analyze rainfall data and rain status which includes forecasting or prediction of rainfall or rain status. The amount of data used to predict rainfall or rain status often uses monthly data so the amount of data is small and the information obtained is not detailed.

Rainfall forecasting information is an important requirement to support the management of water resources, especially when associated with climate change in tropical areas such as Indonesia. Currently, climate change is affecting rainfall patterns. The impacts of these effects include extreme floods and droughts. Therefore, the prediction of rainfall with a good and accurate method is needed to anticipate this impact as described by Anna, Priyono, Suharjo, and Priyana (2016) and Velasco, Serquiña, Shahin, Zamad, Juanico, and Lomocso (2019).

Many studies have used the SVM method by processing various data, including the MLP method for face detection, Uyun and Rahman (2013). MLP for breast cancer analysis, Agara (2018). Comparison of MLP and SVM methods on classification data, Zanaty (2012). MLP method on rainfall data in Brazil, Esteves, Rolim, and Ferraudo (2019), MLP on rainfall data in Johor, Nawaza, Haruna, Othman, and Heryansyah (2016), and MLP method for image annotations, Savita, Patel, and Sinhal (2013). The Tsukamoto FIS method for predicting rainfall in Tengger, Wahyuni, Mahmudy, and Iriany (2016) and several other machine learning methods have been used to predict rainfall data in various places, including the Extreme Learning Machine method with rainfall data in Poncokusuma, Simamora, Tibyani, and Sutrisno (2019), Support Vector Machine method and Naïve Bayes Classifier with BMKG Tanjung Priok data, North Jakarta, Laia and Setyawan (2020), K -Means with data in Australia, Kristiyanti, Saputra, and Rina (2021), Machine Learning (K-NN, Decision Trees, Random Forest, Neural Networks), Cabezuelo (2022). BNN with rainfall data in Tenggarong, East Kalimantan, Mislana, Haviluddin, Hardwinarto, Sumaryono, and Aipassae (2015), ANN with data from Tutiempo, Velasco, Serquina, Zamad, Juanico, and Lomocso (2019), ANN method with data from India, Nanda, Tripathy, Nayak, and Mohapatra (2013), ANN and SVM methods with data from Turkey, Tezel and Buyukyildiz (2016), LSTM with data from China, Zhang, Wang, Ma, and Chu (2019), machine learning and regression methods with data from Stanford, CA, Haupt, Cowie, Linden, McCandless, Kosovic, and Alessandrini (2018), MLP methods on data in China, Zhang, Jia, Gao, and Song (2020), ANN and ARIMA methods on data in Pinang, Masngut, Ismail, Mustapha, and Yasin (2020), machine learning methods (RF, SOI) on data in Australia, RNN method

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with data from India, Poornima and Pushpalatha (2019), Autoregressive Non-linear NN method with data from Vietnam, Le, Pham, Le, Ly, and Le (2019).

Existing hyperparameter tuning methods include Random Search, Mantovani, Rossi, Vanschoren, Bischl, and Carvalho (2015), GA, Samadzadegan, Soleymani, and Abbaspour (2010), GridSearch as described by Belete and Huchaiah (2022) and Braga, Carmo, Benatti, and Monard (2013), and EA, Friedrichs and Igel (2004). Iterated local search (ILS), Hutter, Hoos, and Stutzle (2007). Evaluation of many hyperparameters with large datasets will take a lot of time. Hyperparameter tuning is treated like an optimization problem, whose objective function is the predictive model performance with optimal hyperparameter configurations. A commonly used performance measure is predictive accuracy, Hutter, Hoos, and Stutzle (2007). The optimal hyperparameter value of one dataset may not necessarily give good results for other datasets.

This study predicts rain status using the Multi-Layer Perceptron method. The data used is data that has been cleaned (data cleaning) from the weatherAUS.csv daily data set so that the data is in complete condition with 16 independent variables (features). Each k-fold contains different and unrelated data indexes that are randomly generated. The authenticity/state of the art of this research is Optimal hyperplane-parameter tuning uses the three best accuracy values (3BestAcc) for each Hidden Layer. In Hidden Layer 1 generates nodes 1 until 30, then 3 nodes with the highest accuracy are selected. The next Hidden Layer Node structure is determined based on the current optimal Hidden Screen structure.

MATERIALS AND METHODS

Materials

The data set for this study was obtained from the kaggle.com platform at https://www.kaggle.com/datasets/jsphyg/weather-dataset-rattle-package (accessed on 2 February 2023). The dataset taken is daily rainfall data in 49 different cities in Australia over a 10-year period and stored in the form of a csv file. There are 145460 sample data with 22 (twenty-two) features, the names and descriptions of each feature are listed in Table 1 below:

Table 1: The WeatherAUS

No	Station Name	Information	type
1	Location	The location of the weather station is located	date
2	Min Temp	Minimum temperature (degrees Celsius)	strings
3	Max Temp	Maximum Temperature (degree C)	float
4	Rainfall	Recorded rainfall amount (mm)	float
5	Evaporation	Evaporation within 24 hours	float
6	Sunshine	Number (hours) of bright sunlight in 24 hours	float
7	Wind Gust Dir	The direction of the strongest wind gust in 24 hours	float
8	Wind Gust Speed	Speed of wind gust (km/h) strongest in 24 hours	strings
9	Wind Dir 9am	Wind direction at 09.00 local time	float
10	Wind Dir 3pm	Wind direction at 15.00 local time	strings
11	Wind Speed 9am	Wind Speed at 09.00 local time	strings
12	Wind Speed 3pm	Wind Speed at 15.00 local time	float
13	Humidity 9 am	Humidity (percent) at 09.00 local time	float
14	Humidity 3 pm	Humidity (percent) at 15:00 local time	float
15	Pressure 9 am	Atmospheric pressure (hpa) at 09.00 local time	float
16	Pressure 3 pm	Atmospheric pressure (hpa) at 15.00 local time	float
17	Cloud 9 am	Part of the sky covered with clouds at 09.00 local time.	float
18	Cloud 3 pm	Part of the sky covered with clouds at 15:00 local time.	float
19	Temp 9 am	Temperature (degrees C) measured at 09.00 local time	float
20	Temp 3 pm	Temperature (degrees C) as measured at 15.00 local time	float
21	Rain Today	Today's status (“Yes” means it is raining, “No” means it is not raining)	Strings
22	Rain Tomorrow	Tomorrow's status (“Yes” means rain, “No” means no rain)	Strings

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The processed data consists of 16 features with a numeric value and one output with 2 conditions, namely Rain ("Yes") and No Rain ("No"), but in this study 17 attributes of the numerical type were used, with 16 features as input and 1 feature as output. The processed data does not contain a miss value of 56564 records from 145460 records. Details of the NA (Not Available) value for each feature can be seen in Table 2 and Table 3 below:

Table 2. Information on the number of NAs in each feature

Name feature	amount of miss value		Name feature	amount of miss value	Fitur Name	amount of miss value
Date	0		Wind Gust Speed	2442	Pressure 3 pm	3113
Location	0		Wind Dir 9am	1921	Cloud 9 am	11255
Min Temp	175		Wind Dir 3pm	1053	Cloud 3 pm	11589
Max Temp	55		Wind Speed 9am	340	Temp 9 am	298
Rainfall	676		Wind Speed 3pm	683	Temp 3 pm	742
Evaporation	14018		Humidity 9 am	534	Rain Today	676
Sunshine	15056		Humidity 3 pm	964	Rain Tomorrow	3267
Wind Gust Dir	2467		Pressure 9 am	3103		

Table 3. Minimum, maximum and standard deviation values for each feature

No	Feature Name	units	min	Max	std
1	Min Temp	Celsius	-6,700	31,400	6,417
2	Max Temp	Celsius	4,100	48,100	6,971
3	Rainfall	mm	0,000	206,200	7,015
4	Evaporation	mm in 24 hours	0,000	81,200	3,696
5	Sunshine	hours	0,000	14,500	3,758
6	Wind Gust Speed	km/hour	9,000	124,000	13,335
7	Wind Speed 9am	km/hour	2,000	67,000	8,317
8	Wind Speed 3pm	km/hour	2,000	76,000	8,510
9	Humidity 9am	Procentage	0,000	100,000	18,513
10	Humidity 3pm	Procentage	0,000	100,000	20,197
11	Pressure 9am	Hpa	980,500	1040.400	6,909
12	Pressure 3pm	Hpa	977,100	1038,900	6,871
13	Cloud 9am	Oktas	0.000	8,000	2,797
14	Cloud 3pm	Oktas	0.000	9,000	2,647
15	Temp 9am	Celsius	-0.700	39,400	6,568
16	Temp 3pm	Celsius	3,700	46,100	6,837

In addition, weatherAUS.csv data has 16 numeric features and one target class with values 1 and -1. 16 features need to be converted into 1 feature which will be used as the abscissa of the histogram to be created. The ordinate axis states the frequency of data at a value. The transformation used in this research is Linear Discriminant Analysis (LDA) as shown in Figure 1. It can be seen that there is data that is close together but has a different class. This causes the accuracy value tends to decrease. Successively the amount of "NA" data is found in the Sunshine, Evaporation, and Cloud3pm features. There are some cities where some of the features do not contain or contain some data, one of them is the Evaporation and Sunshine features at Albury station have absolutely no value. This happens because the meteorological station in the city does not have a suitable sensor.

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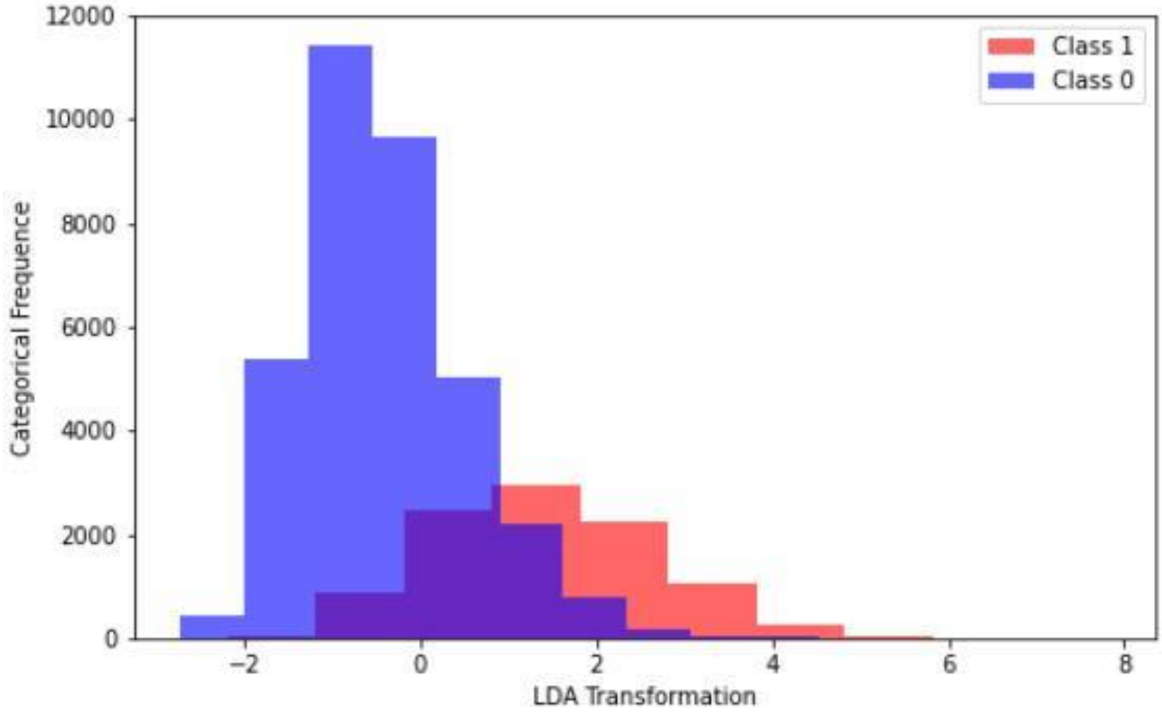
Figure 1. Class distribution of the rain tomorrow feature



Methods

The research scheme is shown in Figure 2 where the data reading process is the process of reading WeatherAUS.csv data, the data cleaning process is the process of deleting records containing "NA", the feature selection process is the process of selecting features, selecting 16 input features and 1 output feature. Furthermore, the function of the feature scaling process, the process of dividing the data into 2 (train and test), and the k-Fold process is the process of normalizing all input features to a value (0,1), the process of dividing the dataset into 2 parts sequentially, namely record 1 – record 50000 becomes training data, and record 50001 becomes record 56420 becomes test data, and the process functions to divide training data (80%) and validation data (20%) randomly. In addition, here are some explanations regarding the steps in Figure 2.

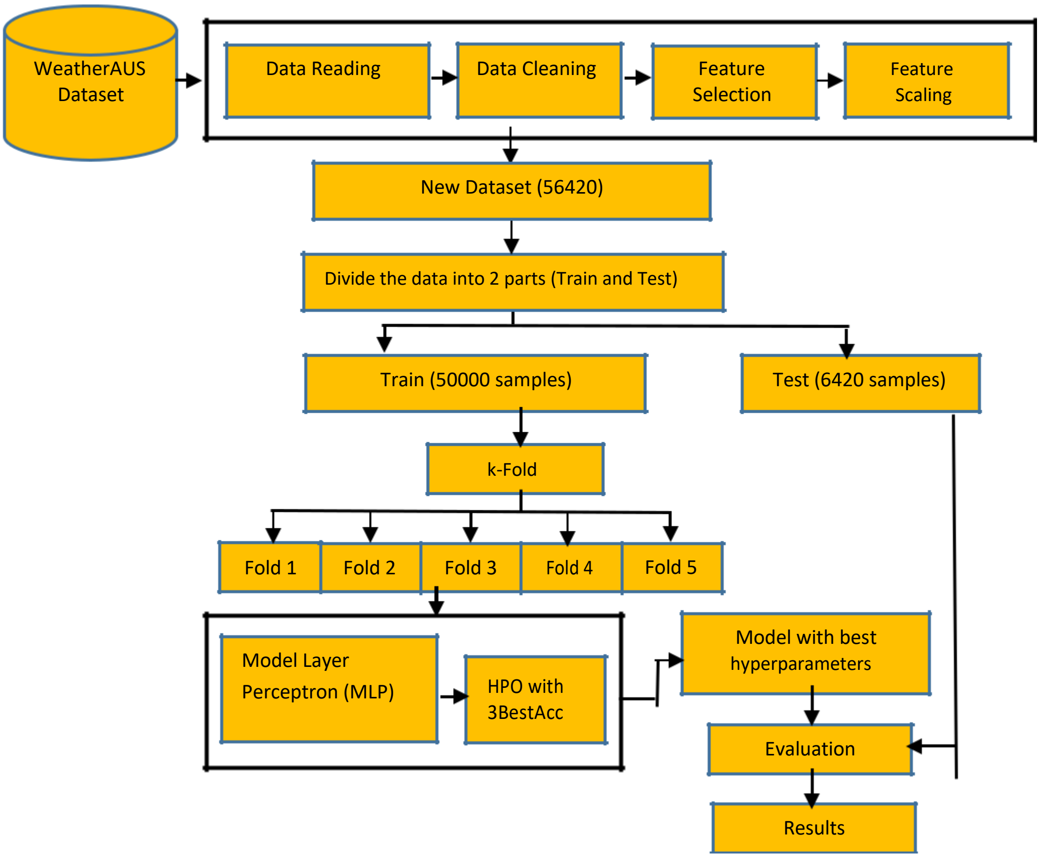
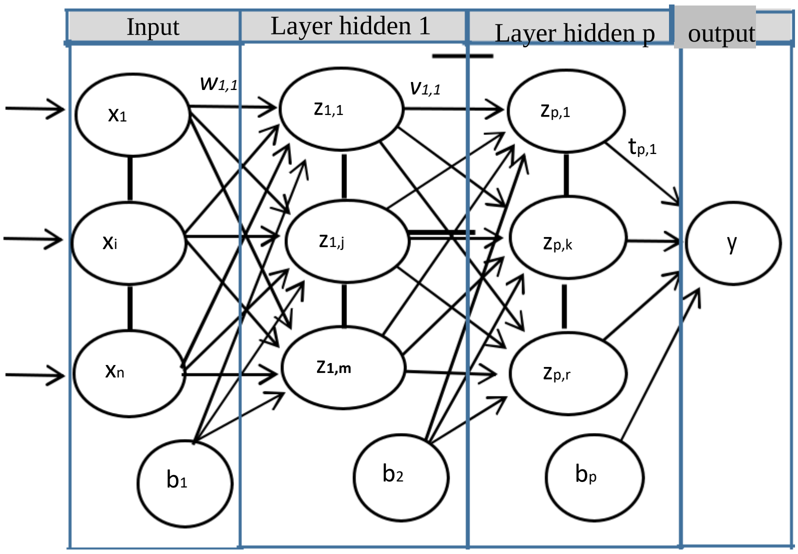


Figure 2. Research system diagram

Multi-Layer Perceptron Artificial Neural Network

The following is a form of a multi-layer perceptron network, where the number of nodes for each hidden layer varies.

Figure 3. Multi-layer perceptron network



with :

$z_{1,1} = \emptyset_1(b_1 + w_{1,1}* x_1 + w_{2,1}*x_2 + w_{3,1}*x_3 +\ldots+ w_{n,1}* x_n)$

$z_{1,2} = \emptyset_1(b_1 + w_{1,2} *x_1 + w_{2,2}*x_2 + w_{3,2}*x_3 +\ldots+ w_{n,2} *x_n)$

$z_{1,m} = \emptyset_1(b_1 + w_{1,m} *x_1 + w_{2,m}*x_2 + w_{3,m}*x_3 + \ldots + w_{n,m}*x_n)$

Otherwise, $y = t_{p,1}*z_{p,1} + t_{p,2}*z_{p,2} + t_{p,3}*z_{p,3} +\ldots+ t_{p,r}*z_{p,r}$ can be stated as follows:

$$\mathbf{z_{i,j}} = \emptyset_i\left(\sum_{i=1}^{n} \mathbf{w_{i,j} x_i} + \mathbf{b_i}\right)$$

$$\mathbf{y} = \emptyset_p\left(\sum_{j=1}^{r} \mathbf{t_{p,j} z_{p,j}} + \mathbf{b_p}\right)$$

Here, n and m are many input features and the number of nodes in the hidden layer 1, respectively. Furthermore, p,s is the number of hidden layers, r is the number of nodes in the hidden layer to p, and b is bias. After that w_{ij}, $\emptyset_i$, and R are weight from node i in one hidden layer to node j in the next hidden layer, the activation function on the hidden layer i, and the number of nodes in the hidden layer to p, respectively.

In general, a Neural network is an algorithm that models the relationship between a set of input values and a set of output values using a network of nodes called artificial neurons. Perceptron is usually used to classify a certain type of pattern which is often known as linear separation. Perceptron is used to perform simple classification and divide data to determine which data is included in the classification and which data is out of classification. Perceptron can be used to separate data into 2 classes.

Hyperparameter Optimization (HPO) using the 3 highest accuracy values (3BestAcc)

Following are the steps for MLP Hyperparameter Optimization with 3-BestAcc

1. Initialize the data and functions to be used, including the feature selection function as input and output features, delete records that have miss values, divide data into 5 folds sequentially random then determine training data, validation data, and test data, setting up the multi-function Perceptron Layers.

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2. There are 16 numeric types of input data features used, so many in this study the nodes tested are 1,2,3,…,30.

3. Experiment 15 times to get the number of Layer Hidden 1 nodes with the highest accuracy.

4. Choose the 3 nodes with the highest accuracy ($best_1$, $best_2$, $best_3$) obtained in step 3, then create a Layer Hidden 2 structure of 6 namely structure ($best_1$, i), (i, $best_1$), ($best_2$,i), (i, $best_2$), ($best_3$, i), (i, $best_3$), (i = 1,2,3,…,30). In each structure, 3 structures are taken with the highest accuracy, and 18 arrangements will be obtained.

5. With the same steps, to determine the 3 nodes of Layer Hidden n it is based on 3 nodes from Hidden Layers n-1. Formed 18 different structures, then chose 3 structures with the highest accuracy.

6. Calculating the accuracy of test data with optimal structure

Key Performance Metrics

In the section defining the metrics used to evaluate the results of the MLP method include:

1. Accuracy

   This metric has a numerical value that indicates the performance of the prediction model that can be used to evaluate the results of the MLP model, using the formula:

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

where:

TP : True Positive. The model can predict the positive class correctly
FP : False Positive. The model is wrong in predicting the positive class
TN : True Negatives. The model can correctly predict the negative class
FN : False Negatives. The model is wrong in predicting the negative class

2. Error

   The error value shows how far the predicted value is from the actual output. In this study, MSE was used with the formula:

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(y_k - t_k)^2$$

where :

N : Specifies the total number of samples
y_k: The class generated by the model
t_k: actual class

3. Proposed Tuning Hyperparameters 3BestAcc

   In this research, we are looking for the best hyperplane parameters (tuning hyperplane-parameters) using the Multi Layer Perceptron method. By using data records that have been cleaned (data cleaning), one part of the data will become training and validation data, while the rest of the data will be used as test data. The division of the dataset into training data, data validation using cross validation. The comparison of training data and validation data is 80:20, so the training data will be divided into 5 folds, namely Fold 1, Fold 2, Fold 3, Fold 4, and Fold 5, each of which contains random and different data (not intersecting) with the number records are the same.

RESULTS AND DISCUSSIONS

The data retrieved from https://www.kaggle.com/datasets/jsphyg/weather-dataset-rattle-package is divided into 3 parts. A total of 50000 records as data train and 6420 records are used as testing data. The 50 records used as training data and validation data with a ratio of 80:20. By means of k-cross validation, the data is divided into 5

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folds of the same size which are generated randomly. Each fold contains 10000 data records. One of the 5 folds is used as validation data and the other 4 folds are used as training data. Of the 56420 datasets, there are two classes, namely Rain Status with 12427 records, and status with no rain status with 43993 records.

Multilayer Perceptrons

The algorithm implemented in this study uses the Python MLPClassifier function in ScikitLearn. The modified parameters are:

- Hidden_layer_sizes contains the number of hidden layers and the number of nodes for each hidden layer
- random_state=1
- solver = "adam"
- learning_rate_init = 0.001
- max_iter=300
- toll = 0.000001

Furthermore for other parameters the default of the system. In this algorithm, one model accuracy value (number of Hidden Layers and number of nodes) is obtained by one fold as validation data and the other 4 folds as training data. This process is repeated five times so that the average accuracy can be obtained. The Hidden Layer structure that provides the highest accuracy is (19, 24, 25, 25, 15, 3, 3, 26). This structure is obtained from one of the fold compositions. If the composition of the folds is different, it is possible to obtain a different arrangement of the Hidden Layer structure but still has the highest accuracy in the arrangement of the folds. The accuracy value for testing data is 0.85586, this average value is higher than the accuracy value for obtaining optimal parameters, which is 0.8545. This value is slightly greater than that of A. Sarasa's research, namely there is an increase of 1,586% for accuracy and an increase of 1,365%.

Hyper Parameters Tuning

Hyper Parameter tuning is performed on the Multi-Layer Perceptron method on the parameters of the number of Hidden Layers and the number of nodes. In this study (19, 24, 25, 25, 15, 3, 3, 26) in the sense that the optimal MLP model has 8 Hidden Layers with the number of nodes on Hidden Layer 1 is 19, the number of nodes on Hidden Layer 2 is 24, and so on, and the number of nodes in Hidden Layer 8 is 26. This research tested up to 12 Hidden Layers, but it gives lower accuracy.

Table 4. Accuracy on a Hidden Layer

Hidd	Max. Accuracy
1	0.8484
2	0.8519
3	0.8526
4	0.8536
5	0.8528
6	0.8525
7	0.8536
8	0.8545
9	0.8537
10	0.8524
11	0.8532
12	0.8519

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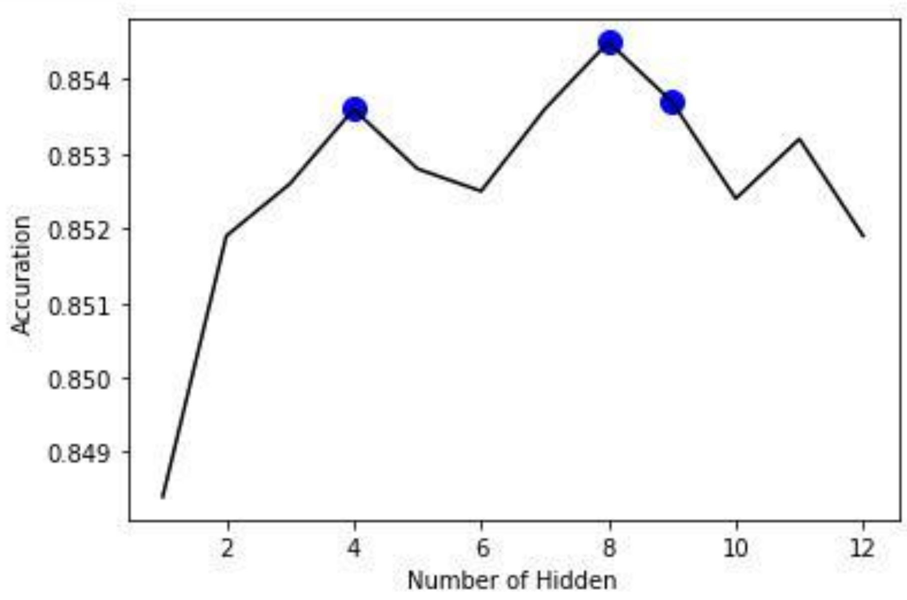
Figure 4. Accuracy on a Hidden Layer



Based on Figure 4. the highest accuracy value is on Layer Hidden 8.

CONCLUSION

The result of this research is the MLP method hyperparameter tuning with the 3BestAcc method. The 3BestAcc method can be used to find the Layer Hidden Multilayer Perceptron structure that gives optimal results. The working principle of 3BestAcc is to select 3 structures in a hidden layer with the highest accuracy, then these three structures are used to determine the structure of the next hidden layer. The further development of the 3BestAcc method still takes a lot of time, so the algorithm can be developed so that the selection of the Hidden Layer arrangement is more time efficient. Another possible research that can be developed is to look for the highest accuracy values at certain intervals. Further research is also possible on the dataset. Because the data records are large, the preprocessing stage can select representative data, reduce feature dimensions, or select the most influential features, so that fewer data is processed by the MLP model.

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COMPETING INTERESTS

The authors have no competing interests to declare.

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