# Comparison of Multi-layer Perceptron and Support Vector Machine Methods on Rainfall Data with Optimal Parameter Tuning

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***Abstract*—This study describes the search for optimal hyperparameter values in rainfall data in 49 cities in Australia, consisting of 145,460 records with 22 features. The process eliminates missed values and selects 16 numeric type features as input features and one feature (Rain Tomorrow) as output feature. It is processed using the Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM) methods based on Three Best Accuration (3BestAcc) and Best Three Nearest Neighbors (3BestNN). The results showed that the SVM kernel linear method gave an average accuracy value of 0.85586 and was better than the MLP method with an accuracy of 0.854.**

***Keywords—Rainfall; MLP; SVM; optimal***

## I. Introduction

Weather is the condition of the air at a certain time and place. Weather conditions are related to sunlight, air temperature, humidity, wind, and other conditions and play a significant role in various areas of life, such as changes in the quantity and quality of water, changes in forest habitat and agricultural land, and other changes. The weather for a short time must use the values of the weather elements that exist at that time. Meanwhile, weather statements in a more extended unit of time must use the values of weather elements with the lowest, highest, or most felt levels by the five senses as in [1].

Rain is one of the parameters and weather phenomena that comes from the evaporation of air containing water vapor and forms clouds at certain temperatures. Rain can be measured as a parameter, and rain can be seen visually as a phenomenon, such as fog, smoke, and others. Rainfall data information is very important for planning, especially for water structures such as irrigation, dams, urban drainage, ports, and docks, so data analysis is needed to predict it. In [2], rainfall is the amount of water that falls on a flat ground surface during a certain period which is measured in millimeters (mm) above the horizontal surface. Rain can also be interpreted as the height of rainwater that collects in a flat place, does not evaporate, does not seep, and does not flow.

One of the solutions for predicting rainfall is to analyze big data from the information obtained using the correct method to get the best accuracy. Big Data is a collection of data with super large data volumes and has a high diversity of data sources, so it needs to be managed with methods and assistive devices whose performance is appropriate as in [3]. However, the implementation of big data is still not good or requires a relatively long time to obtain the desired accuracy value, so it is necessary to reduce the feature dimensions by utilizing the Linear Discriminate Analysis and Principle Component Analysis methods to optimize the computational process.

This study will explain predictions of rain status based on a collection data set over a 10-year period that describes meteorological information from 49 different cities in Australia. Furthermore, the data is processed by eliminating missed values and selecting 16 numeric type features as input features and one feature (Rain Tomorrow) as output features and analyzed using the Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) methods. Then to get optimal results (maximum accuracy), an algorithm was developed to obtain hyperplane parameters using K-Fold cross-validation and developed through two schemes. The results of this study are the level of prediction accuracy in each city, which can be used as a supporting medium in urban planning and anticipation. In addition, the overall average accuracy can also be used as material for consideration in further research.

## II. Previous Research Study

Many methods have been used to predict rainfall data, including the Extreme Learning Machine Method on Artificial Neural Networks to predict rainfall in the Poncokusuma area of Malang district, using data from 2002 to 2015. The results of this study obtained a MAPE of 3.6852% with 4 features, 2 hidden layers, and the proportion of training data is 80% as in [4]. Research on clustering rainfall predictions in Australia using the K-Means algorithm in the WEKA and RStudio applications. The results obtained are the number of cluster 2 with an SSE of 28.0%, which is an ideal cluster to predict rainfall in Australia as in [5][6]. Research on rainfall prediction in Australia using Machine Learning by comparing the level of accuracy using several methods. The methods used are K-Nearest Neighbors, Decision Trees, Random Forests and Neural Networks. The results obtained by the best method are from Neural Networks with an accuracy rate of 85.5% as in [7].

- Multiple Face Detection Research using Hybrid Features with SVM Classifier: The data used is from two databases, namely the BAO database and the CMU database. The SVM classification method can recognize faces with an accuracy of 89% as in [8].

- Liver Cancer Analysis Research using SVM Data Mining Algorithm in MATLAB: The processed data is in images in the UCI machine learning repository. The accuracy obtained is 86.7% as in [9].
- Comparative Research of Naive Bayes and SVM Algorithms Based on Sentiment Analysis using Dataset Review: The data used is a dataset collected from the Twitter API. The SVM method achieves 77 per cent better accuracy than Naïve Bayes as in [10].

Research on hyperplane-parameter tuning for SVM, namely Hyper-parameter Tuning for Support Vector Machines with Distribution Algorithm Estimation, has been carried out using various methods, including Genetic Algorithms, Particle Swarm Optimization (PSO), Grid Search, and Random Search. This study will estimate hyperplane-parameter estimation using the Univariate Marginal Distribution Algorithm (UMDA) and Boltzmann Univariate Marginal Distribution Algorithm (BUMDA). Both methods are stochastic optimization techniques by building and taking samples from probabilistic models. The study's results obtained the best method using the Boltzmann Univariate Marginal Distribution Algorithm (BUMDA) as in [11].

Parameter optimization in SVM using the Taguchi Method for High Dimensional Data. In this study, optimal parameters were selected using the Taguchi method, which provides an increased level of accuracy compared to the Grid Search method as in [12]. Support Vector Machine (SVM) for Rainfall Forecasting on the Johor River, namely forecasting rainfall as a warning in the event of heavy rainfall resulting in flash floods. The data for the 60-year study period came from rainfall data in the Malaya Gum Field, Kota Tinggi, Johor, Malaysia. The method used is SVM. The research results on the SVM method with the Radial Basis Function RBF kernel has the best performance compared to sigmoid, linear and polynomial. The Root Mean Square Error (RMSE) value for the RBF 67.70 kernel is the best compared to other kernels as in [13]. Research on rainfall forecasting using the Support Vector Machine (SVM) has been conducted. The method used to predict rainfall is SVM regression. The research data used is rainfall data in Khurda District Orissa. The kernel that has the minimum Mean Square Error (MSE) is the Linear kernel which produces a minimum MSE average of 15.04% as in [14].

Sustainability plays an important role in enhancing the industry's competitive advantage. Continuous performance and application assessments face high dimensional data, robustness and imprecision. Machine learning is pressured to implement. This study aims to design a machine learning model to assess sustainability performance using SVM. Hyperplane-parameter tuning and k-fold validation are included for improved performance in SVM models. The research object was carried out in the bioenergy industry. The validation was carried out ten times. Tuning the hyperplane parameters gets 98.32% in testing the data. The final results show that SVM with a polynomial kernel model can classify sustainability performance accurately as in [15].

Problems related to hyperparameter tuning are still an interesting topic to be studied. Some of them are aspect-based sentiment analysis of iPhone users on Twitter using the SVM and GridSearch methods for hyperparameters C, gamma, and kernel as in [16], hyperparameter tuning of supervised learning algorithms for classification of families receiving rice food assistance using the grid search method, random search, and Bayesian optimization as in [17], and indoor pollutant classification modeling using relevant sensors under thermodynamic conditions with multilayer perceptron hyperparameter tuning using the GridSearch method as in [18].

## III. Material and Methods

### A. Materials

The data used in this study is secondary data related to daily rainfall in 49 different cities in Australia over a 10-year period Australia. The dataset was obtained from the kaggle.com platform accessed February 2, 2023. The sample data is 145,460 which consists of 22 (twenty-two) features.

They are the location of weather stations, minimum temperature (C), maximum temperature (C), recorded rainfall amount (mm), evaporation in 24 hours, number (hours) of bright sunlight in 24 hours, the direction of strongest wind gust in 24 hours, strongest wind speed (km/h) in 24 hours, wind direction at 09.00 local time, wind direction at 15.00 local time, wind speed at 09.00 local times, wind speed at 15.00 local time, humidity (per cent) at 09.00 local times, humidity (per cent) at 15.00 local time, atmospheric pressure (hpa) which decreases to an average sea level at 09.00 local times, reduced atmospheric pressure (hpa) to mean sea level at 15.00 local time, part of the sky covered with clouds at 09.00 local times. The unit size used is octas (a unit of eight), which records the number of clouds, the part of the sky covered by clouds, at 15.00 local time. The unit size used is octas (a unit of eight), which records the number of clouds, temperature (C) measured at 09.00 local time, temperature (C) measured at 15.00 local time, today's status (rain, notated 1 or not raining, given the notation -1), tomorrow's status (rain, given the notation 1 or not raining, given the notation -1).

### B. Methods

Based on the data obtained, the steps for preprocessing and analyzing the data are compiled as follows:

- Collect a data set over a 10-year period that describes meteorological information from 49 different cities in Australia and consists of 145,460 records with 22 features.
- At the preprocessing stage, the process carried out is the elimination of miss values and the selection of 16 features of a numeric type as input features and one feature (RainTomorrow) as an output feature. In the Python program, to delete all data miss values from a feature (e.g., the MinTemp feature), suppose df is a logical file containing the results of reading all data, with the statement: you can use the statement:

*df = df.loc[df[‘MinTemp’].isna()==False]* then the new df contains data with no missed values in the MinTemp feature. This process is carried out on all features.

- Using the Support Vector Machine method to determine the value of C that gives the best average accuracy, and the Multi-Layer Perceptron method to determine the hidden layer structure.

- Based on the data records that have been cleaned (data cleaning), the data will be divided using the k-cross validation principle into one part of the data (training and data validation). In contrast, the rest will be used as test data. The training and validation data will be divided into folds, fold1, fold2, fold3, fold4, and fold5, each containing random and different data (not intersecting) with the same number of records.

- Create a tuning method algorithm for Linear Kernel SVM and MLP with the principle of the three best accuration (3BestAcc) to find the 3 best accuracy values in a discrete hidden structure and three best nearest neighbor (3BestNN) to find the 3 best accuracy values in an interval.

- Displaying the Contour of the SVM method by carrying out the Principle Component Analysis (PCA) transformation so that two features are obtained, namely principal component 1 and principal component 2, which are used as abscissa and ordinate on a two-dimensional graph (cartesian graph). Based on the results of an experiment on 100 data, it was found that the contour hyperplane is a dividing line between the status of the two classes shown in Fig. 1.

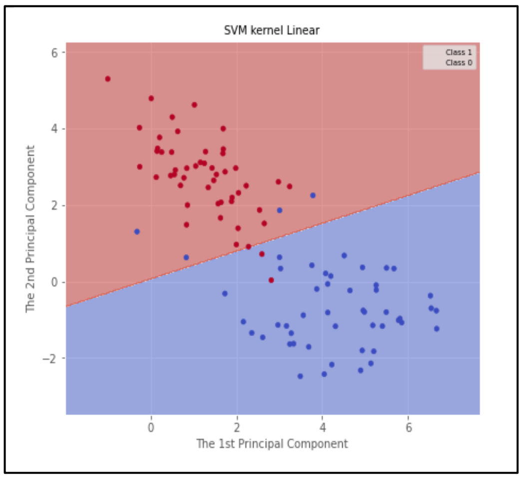


Fig. 1. Contour linear kernel hyperplane.

- Displaying the Histogram of Test Data Distribution by transforming 16 numeric features in the collected data into one feature, which will be used as the abscissa of the histogram created while the ordinate axis represents the frequency of data in a value. The transformation used in this study is Linear Discriminant Analysis (LDA). The distribution of data classes includes rain status for tomorrow in blue and non-rainy status for tomorrow in red. The histogram of the class distribution of tomorrow's rain status data is shown in Fig. 2.

- Output analysis is carried out after obtaining histogram graphs, accuracy, and Mean of Square Error (MSE) to obtain interpretations and conclusions from the results obtained.

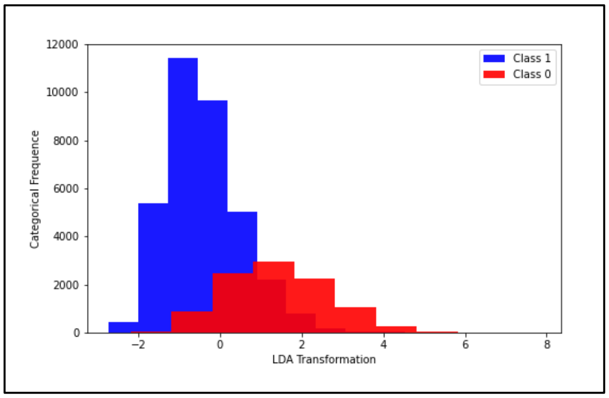


Fig. 2. Histogram of tomorrow's rain status distribution.

## IV. Results

### A. Research Data

The data retrieved from kaggle.com is divided into three parts. A total of 50,000 records were used as data (training and validation), and 6,420 records were used as test data. Of the 50,000 records used as training data and validation data with a ratio of 80:20. With the K-Cross Validation method, the data is divided into five folds of the same size, which are randomly generated. Each fold contains 10,000 data records. One of the five folds is used as validation data, and the other four are used as training data. Of the 56,420 datasets, there are two classes: Rain Status with 12,427 records and no rain status with 43,993 records.

### B. Support Vector Machine

The algorithm implemented in this study uses the Python SVM function in scikitLearn by Belete et al. as in [19]. The selected parameters are:

kernel='linear',

C=kC(input from user)

The default parameters of the system:

(*, C: float = 1, kernel: str = "rbf", degree: int = 3, gamma: str = "scale", coef0: float = 0, shrinking: bool = True, probability: bool = False, tol: float = 0.001, cache_size: int = 200, class_weight: Any | None = None, verbose: bool = False, max_iter: int = -1, decision_function_shape: str = "ovr", break_ties: bool = False, random_state: Any | None = None) -> None.

In obtaining the accuracy value of a certain linear C kernel SVM model, one fold is used as validation data and the other four folds as training data. This process was repeated five times to get average accuracy. This study used C ∈ (0.16), and the accuracy values were calculated at various initial intervals, as shown in Fig. 3. The C value with the highest accuracy is

0.08272, with an accuracy of 0.8538. This value is obtained from one of the folding compositions. If the composition of the wrinkles is different, it is possible to get other Cs, but the accuracy values are almost the same. The accuracy value for data testing is 0.85586; this average value is higher than the accuracy value for obtaining optimal parameters. This value is increasing by 1.586% compared to the results as in [20].

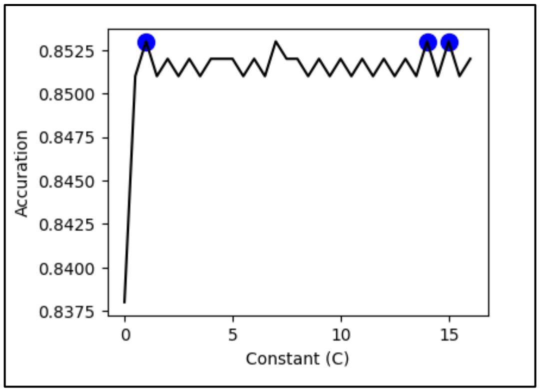


Fig. 3. Graph of accuracy calculation at interval [0.16].

### C. Multi-Layer Perceptron

The hyperparameter optimization (HPO) optimization steps for the MLP method use the three highest accuracy values or Three Best Accuration (3BestAcc) starting from the initialization of the data and functions to be used. Then from the 16 inputted numeric data, three nodes with the highest accuracy will be selected (best1, best2, best3) with 6 Hidden layer structures consisting of (best1, i), (i, best1), (best2, i), (i, best2), (best3, i), (i, best3), (i=1,2,3,…,30). Next, three structures with the highest accuracy were taken for each structure so that 18 arrangements were obtained.

The algorithm implemented in this study uses the Python MLPClassifier function in scikitLearn as in [21]. The modified parameters are:

- Hidden_layer_sizes contains the number of hidden layers and the number of nodes of each Hidden Layer

- random_state=1

- solver = "adam"

- learning_rate_init = 0.001

- max_iter=300

- toll = 0.000001

for other parameters, the default of the system.

Calculations are made from hidden layer 1 to hidden layer 12 because the accuracy value tends to decrease starting from hidden layer 9, as shown in Fig. 4, so the process is stopped at hidden layer 12.

Hyperparameter tuning is performed on the Multi-Layer Perceptron method on the parameters of the number of hidden layers and nodes. The process of getting one model accuracy value (number of hidden layers and number of nodes) uses one fold as validation data and the other four folds as training data. This process is repeated five times to obtain the average accuracy. The hidden layer structure that provides the highest accuracy is (19, 24, 25, 25, 15, 3, 3, 26) so it is obtained that the optimal MLP model has eight hidden layers with the number of nodes in the hidden layer 1 being 19, the number of nodes in hidden layer 2 is 24. and so on. This structure is obtained from one of the fold compositions. However, if the fold composition is different, it is possible to obtain a different Hidden Layer structure arrangement but still has the highest accuracy in the fold arrangement. The accuracy value for testing data is 0.85586; this average value is higher than the accuracy value for obtaining optimal parameters, which is 0.854. This value is 1.4% greater than the results as in [20].

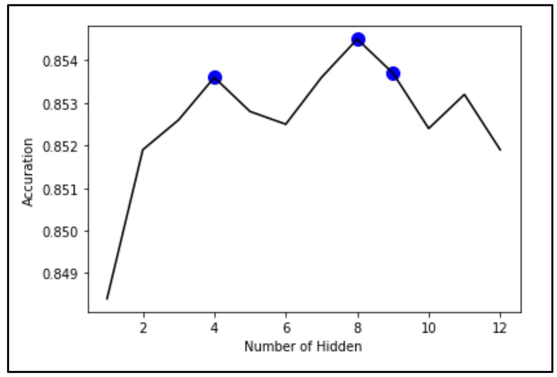


Fig. 4. Graph of the maximum accuracy value for each hidden layer.

TABLE I. ACCURACY PER STATION

| No | Station | Record | SVM Accuracy | MLP Accuracy |
|---|---|---|---|---|
| **1** | Darwin | 3062 | 0,857 | 0,859 |
| **2** | Perth | 3025 | 0,897 | 0,893 |
| **3** | Brisbane | 2953 | 0,856 | 0,853 |
| **4** | Melbourne Airport | 2929 | 0,839 | 0,826 |
| **5** | Perth Airport | 2913 | 0,901 | 0,891 |
| **6** | Sydney Airport | 2870 | 0,834 | 0,824 |
| **7** | Watsonia | 2730 | 0,826 | 0,823 |
| **8** | Mildura | 2594 | 0,935 | 0,912 |
| **9** | Mount Gambier | 2465 | 0,861 | 0,813 |
| **10** | Norfolk Island | 2464 | 0,804 | 0,785 |
| **11** | Cairns | 2444 | 0,826 | 0,786 |
| **12** | Townsville | 2419 | 0,895 | 0,873 |
| **13** | Wagga Wagga | 2416 | 0,881 | 0,881 |
| **14** | Alice Springs | 2223 | 0,957 | 0,953 |
| **15** | Nuriootpa | 2008 | 0,871 | 0,861 |
| **16** | Hobart | 1939 | 0,812 | 0,792 |
| **17** | Moree | 1913 | 0,912 | 0,912 |
| **18** | Melbourne | 1898 | 0,813 | 0,754 |
| **19** | Portland | 1863 | 0,783 | 0,598 |
| **20** | Woomera | 1734 | 0,969 | 0,938 |
| **21** | Sydney | 1690 | 0,814 | 0,838 |
| **22** | Sale | 1678 | 0,831 | 0,818 |
| **23** | Coffs Harbour | 1380 | 0,808 | 0,797 |
| **24** | William Town | 1198 | 0,805 | 0,789 |
| **25** | Canberra | 1078 | 0,851 | 0,811 |
| **26** | Cobar | 534 | 0,968 | 0,947 |
| **Average** | | | 0,862 | 0,840 |

Table I shows the average accuracy value for each station of the SVM methods and MLP methods. The accuracy information for each station can be used to determine which method to use for maximum accuracy. SVM kernel method C=0.08272, an accuracy of 0,85586 was obtained, while for the MLP method with a hidden layer structure (19, 24, 25, 25, 15, 3, 3, 26), an accuracy of 0,854 was obtained. Thus it can be concluded that the SVM kernel linear method is better than the MLP method with a difference of 0.00186.

### *D. Data Analysis for each Region*

Processing rainfall data at each station helps predict conditions where the results obtained are compared to obtain results with the best accuracy. Fig. 3 and Fig. 4 shows several stations whose station test data accuracy values are higher than the average accuracy of the SVM and MLP methods. In addition, Table II shows that the SVM method has a higher average accuracy than the MLP method, where the data for the "Rain" status is less than the data for the "No Rain" status. Therefore, the amount of testing data on the "Not Raining" status is used as much as 1.5 times of the "Raining" status data. An example is the data at the Darwin station, which consists of 789 data records for the “Rain” status. The number of testing data is 1.5 x 789 = 1183 records. The total number of records is 3062, so the total training data is (3062-1183) = 1879. Then the 1879 records are divided into five folds with the same number of records, each containing (1879/5) = 376 records.

TABLE II. STATION WITH AN ACCURACY OF MORE THAN 0.85586

| No | Nama Kota | Metode |
|---|---|---|
| 1 | Alice Springs | SVM |
| 2 | Cobar | SVM |
| 3 | Darwin | MLP |
| 4 | Mildura | SVM |
| 5 | Moree | MLP |
| 6 | Nuriootpa | SVM |
| 7 | Perth | SVM |
| 8 | Perth Airport | SVM |
| 9 | Townsville | SVM |
| 10 | Wagga Wagga | MLP |
| 11 | Woomera | SVM |

## V. CONCLUSION

This research results in the MLP method hyperparameter tuning with the 3BestAcc method. The 3BestAcc method can be used to find the structure of the Hidden layer Multi-Layer Perceptron which gives optimal results. The working principle of 3BestAcc is to select three structures in the hidden layer with the highest accuracy, and then these three structures are used to determine the structure of the next hidden layer. Further development of the 3BestAcc method still requires a lot of time, so algorithms can be developed to make the selection of the hidden layer arrangement more time efficient. Another research that might be developed is to look for the highest accuracy value at specific intervals. Further research is also possible on the dataset. Because the data records are extensive, the preprocessing stage can select representative data, reduce feature dimensions, or select the most influential features so that the MLP model processes fewer data.

Table II provides information that the SVM kernel linear method (C=0.08272) provides a better average accuracy value than the MLP method with a hidden layer structure (19, 24, 25, 25, 15, 3, 3, 26).

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