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Application of Backpropagation Neural Network in Predicting Mandatory Test Vehicle Parks

Rani Asmidewi[1], Yusuf Muhyidin[2], Minarto[3]
[1,2,3]Informatics Engineering, Wastukancana College of Technology
[1,2,3]Jl. Cikopak No 53 Purwakarta, Indonesia
e-mail: [1]raniasmidewi74@wastukancana.ac.id , [2]yusufmuhyidin@wastukancana.ac.id , [3]minarto@wastukancana.ac.id

Abstract
Backpropagation neural networks can be used in almost every aspect of human life, including the prediction of mandatory test vehicle parks. The goal of this study was to use BPNN (Backpropagation Neural Network) modeling to anticipate mandatory test vehicle parks based on the past data from the Department of Transportation at Purwakarta Regency, and to predict the results using the best model. This study makes use of mandatory test vehicle parks data from 2014 through 2023, which necessitates monthly testing. The test results show an accuracy level of 90.134% utilizing alpha 0.9, iteration number (epoch) of 10000, and MSE value 0.0064. Based on the best BPNN model into Matlab applications, the mandatory test vehicle park will be predicted from June 2023 to May 2024. The estimated value of the mandatory test vehicle park in December 2023 will be used to determine the requirement for proof of passing the periodic test in 2023 with a score of 7587.

Keywords: *Backpropagation, Neural Network, Mandatory test vehicle parks, forecast, MSE*

1. Introduction

Every year, the demand for transportation services in Indonesia is growing rapidly. According to data from Central Bureau of Statistics, the transportation industry will grow by 21.27% in the second quarter of 2022 after growing by 15.79% in the first quarter [1]. To achieve the "Zero Accident" vision, the government aims to reduce traffic accidents by monitoring motor vehicle testing and improving vehicle safety and roadworthiness [2]. Forecasting is required to plan the demand for proof of passing periodic tests, particularly at the Purwakarta Regency Transportation Service, given the significance of monitoring motor vehicle testing. The achievement and prediction statistics between 2018 and 2022 reveal considerable inequalities, resulting in stockouts and overstocks, which have an impact on shortages and high storage costs [3]. As seen in Table 1:

Table 1. Prediction Data and Achievement Data

No	Year	Prediction	Achievement
1	2018	3500	6727
2	2019	7000	6836
3	2020	6900	6637

No	Year	Prediction	Achievement
4	2021	7787	5959
5	2022	8021	5846

(Source: Department of Transportation at Purwakarta Regency, 2022)

The success of an agency or company relies on effective planning, including forecasting inventory needs for proof of passing periodic tests based on mandatory test vehicle park data. Accurate forecasting helps ensure the proper amount of proof is available, preventing stockouts and overstock. Forecasting is the art of anticipating something that has not yet occurred to predict future events by always requiring evidence from the past [4]. A neural network (ANN) is an information processing system based on biological neural networks that can analyze and recognize patterns in data to generate predictions [5]. The neural network is one method that can be used to make decisions, which Neural networks can produce accurate findings for predictions, recognizing patterns, classification, and a variety of other studies. Backpropagation is a supervised learning approach used in multi-layer Perceptrons to modify neuron weights in the hidden layers. It works by propagating errors backwards after forward propagation to reduce output errors [6]. Error backpropagation (BP) neural network analysis is a preferred approach for solving nonlinear issues [7]. A three-layer BP neural network can fit any continuous function, demonstrating its superior model learning capabilities [8].

One of the studies conducted by [9]. This study uses two classification data mining approaches, Neural Network and K-Nearest Neighbor (K-NN), to establish the optimum accuracy in standardizing child nutrition at Paiton Probolinggo Community Health Center. Following multiple trials, the Neural Network technique achieved its best accuracy of 97.74% in the third validation. The highest accuracy for the K-NN approach is 95.49% with an average validation multiple of 10 and at the third K. Furthermore, according to [10] research. The Backpropagation algorithm and the Firefly Algorithm are used in this study to detect the condition of human heart organs suffering from Premature Ventricular Contractions diseases utilizing the Multi Layer Perceptron approach. The Backpropagation method outperforms the Firefly method in terms of accuracy, scoring 99.48% versus 86.14%.

This study uses the Backpropagation method to determine the results of predictions for mandatory test vehicle parks based on the best model, resulting in data accuracy for predictions of mandatory test vehicle parks. The architecture of the Artificial Neural Network (ANN) influences the prediction results. The training procedure begins with the basic Backpropagation algorithm, which is then improved by include a learning rate and momentum coefficient to update the weights. System testing was performed with arbitrary weights to determine errors in the training data, and the error results exceeded the tolerance of 0.01 [11]. The research aims to use Matlab software to build the Backpropagation method for predicting mandatory test vehicle parks.

2. Research Methods

The methodology outlines the technical processes that will be carried out throughout the research stage.

2.1. Study Subject

The focus of this study was to predict mandatory test vehicle parks to plan for the need to demonstrate through regular testing. Secondary data received from Department of Transportation at Purwakarta Regency were used in this investigation. This study makes use of mandatory test vehicle parks data from 2014 to 2023.

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2.2. Research Techniques

The CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology was chosen to guide development due to its focus on data organization and the principles of motivating tool inter-operation and simplifying information treatment. This organization establishes a systematic and didactic approach for the company's analysts, who oversee operational activities [12]. The CRISP-DM method was utilized in this study to process mandatory test vehicle parks data, translate business challenges into data mining jobs, and carry out data mining projects that are independent of application area and technology used. This approach is a frequently utilized industry-oriented implementation of the Knowledge Discovery in Database (KDD) procedure [13].

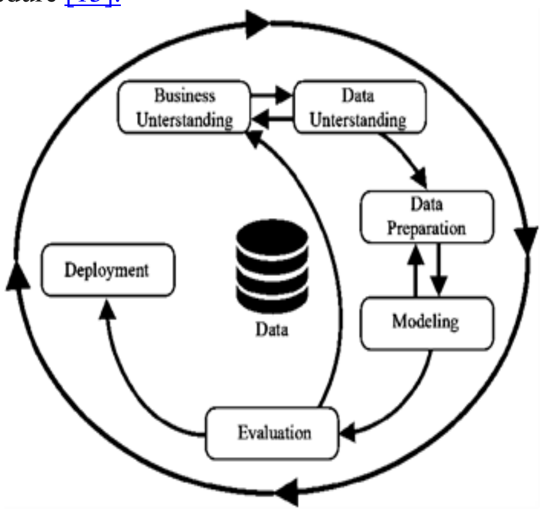

Figure 1. CRISP-DM method

1. Business Understanding
   In this study, the phase of getting to know the company is the first phase of the research and is directly related to the motor vehicle test data to formulate the research objectives. The primary goal of this study was to predict future mandatory test vehicle parks to determine the requirements for Electronic Test Pass (Blu-E). The Backpropagation Neural Network technique is used in this prediction.
2. Data Understanding
   This study relied on secondary data received from Department of Transportation at Purwakarta Regency. The information acquired is mandatory test vehicle parks between 2014 and 2023. Table 1 shows data from Department of Transportation at Purwakarta Regency on mandatory test vehicle parks.
3. Data Preparation
   The raw data received in the previous stage must be processed in the Data Preparation Stage. When processing data in research, the following steps should be followed:
   Stage 1: Data Cleaning. Data Cleaning is Filling in blanks, correcting data that does not match conditions, and modifying confirmation requirements data are all steps in the process [14]. The missing value technique is used to cleanse data in this investigation. The data gathered in this study consisted of 101 records, although not all of them could be used because several records had a value of 0. To overcome the missing value, either manually edit the data or remove records having the value 0. After the cleansing process, 99 records are available.
   Stage 2: Transformation. Normalization is one of the transformation data procedures. Data normalization is the process of scaling data so that it falls inside a specified range of values [15]. The goal of normalization is to make data processing more efficient. The min-max normalization formula will be used to do normalization in this investigation. The following predictions [16] can be used in data normalization calculations:

$$\boxed{x' = \frac{0.8\,(x - minvalue)}{maxvalue - minvalue} + 0.1} \quad (1)$$

Description: x : original value
x': the normalized value

Stage 3: Separation of Datasets. In this study, the training data and test data will be used in a ratio of 60:40.
Stage 4: Input and Output Determination. After the separation of Datasets, it identifies the input and output that will be used in this study. Twelve input nodes are used for training and testing. One output node is used.

The final stage is to put the variables to the test. After normalizing the data, the variables are tested with the settings shown in Table 2 to find the optimum architecture with the minimum MSE.

Table 2. Variable Test Parameters

Parameter	
Neuron Hidden layer	15,16,17
Learning Function	trainlm, traingd, traingdx
Learning Rate	0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9

4. Modeling
In the modeling phase, a Matlab application is used. Several tasks are completed during the modeling process, including selecting a modeling technique, creating a model, and evaluating the model [17]:
Stage 1: Select a modeling technique. Backpropagation with the Neural Network technique was employed as the data mining model in this investigation. Data mining modeling starts with specifying the input layer, hidden layer, and output layer so that the model can be used as a guide for developing the intended system [18].

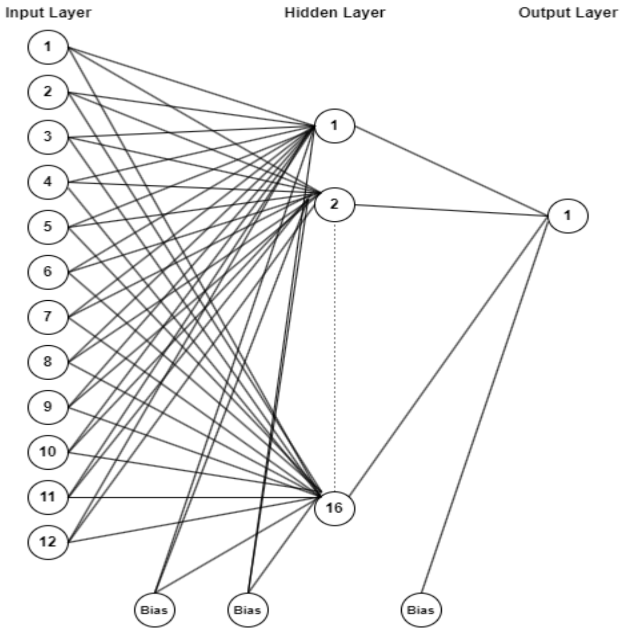

Figure 2. Backpropagation Neural Network Architecture

Stage 2: Create a model. The vehicle dataset being tested will be built using the Backpropagation model by the general provisions that have been implemented, by determining the initial weight using random numbers, conducting data mining training, and calculating the mean square error of the training results. The following is a high-level overview of the system design depicted in Figure 3:

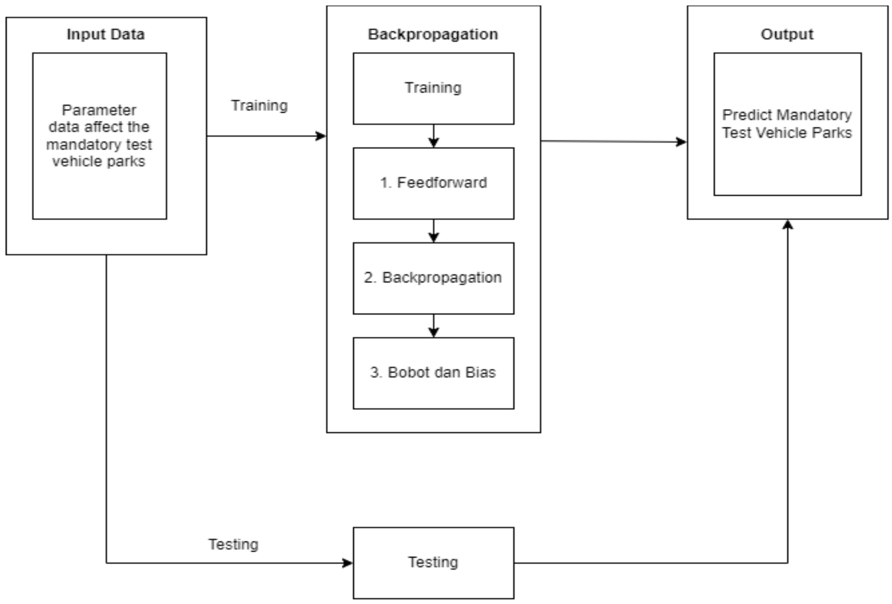

Figure 3. Modeling of Neural Network Backpropagation Systems

Stage 3: Model Evaluation (Assess Model). The Neural Networks algorithm is used to construct a neural network for modeling. With preset rules, the next step is Backpropagation training, which consists of three phases: forward, backward, and changing the weights to lower the error rate.

5. Assessment (Evaluation)
   The next step is to calculate the Mean Square Error (MSE) value after applying the model to the mandatory test vehicle parks dataset for the last ten (ten) years.

$$MSE = \sum_{t=1}^{n} \frac{(X_t + F_t)^2}{n} \quad (2)$$

Information: X_t : Actual
F_t : Forecast
n : number of items

MSE determines the average squared error in predictions. The lower the MSE number, the higher the model's quality.

6. Deployments
   At this point, deployment in all other fields of Department of Transportation at Purwakarta Regency is possible. However, in this study, the application, meaning the deployment step, was not carried out.

3. Results and Discussion

The data used in this study is secondary data acquired from the Motor Vehicle Testing Management Unit Department of Transportation at Purwakarta Regency, namely data on mandatory test vehicle parks between 2014 and 2023. Table 3 shows the following information on mandatory test vehicle parks.

Table 3. Mandatory Test Vehicle Parks Data

Year/ Month	January	February	…	December
2014	6388	6438	…	7106
2015	7136	7225	…	7691
2016	7715	7703	…	7408
Year/ Month	**January**	**February**	**…**	**December**
2018	6988	6904	…	6727
2019	6,725	6,691	…	6,836
2020	6852	6881	…	6637
2021	6532	6440	…	5959
2022	5886	5796	…	5846
2023	5879	5926	…	

Before entering the data into the network, it is first processed into interval data. These data are normalized so that they fall inside the range [0,1], using the Min-max normalization formula in equation 1, as shown in Table 4 below.

Table 4. Normalization Data

Year	January	February	…	December
2014	0.762	0.768	…	0.837
2015	0.840	0.849	…	0.898
2016	0.900	0.899	…	0.868
2017	0.867	0.859	…	0.822
2018	0.825	0.816	…	0.798
2019	0.797	0.794	…	0.809
2020	0.811	0.814	…	0.788
2021	0.777	0.768	…	0.718
2022	0.710	0.701	…	0.706
2023	0.710	0.714	…	

The data is separated into two categories: training data and test data. The training data accounts for 60% of the total, whereas the test data accounts for 40%. Table 5 following shows the training data and Table 6 shows the testing data:

Table 5. Data Training

Pattern	Input Data	Target
1	January 2014 - December 2014	January 2015
2	February 2014 – January 2015	February 2015
3	March 2014 - February 2015	March 2015
4	April 2014 – March 2015	April 2015
5	May 2014 - April 2015	May 2015
⋮	⋮	⋮
61	January 2019 - December 2019	January 2020

Table 6. Data Testing

Pattern	Input Data	Target
1	February 2019 - January 2020	February 2020
2	March 2019 – February 2020	March 2020

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3	June 2019 - May 2020	June 2020
4	July 2019 – June 2020	July 2020
5	August 2019 - July 2020	August 2020
⋮	⋮	⋮
38	May 2022 - April 2023	May 2023

The following stage is to discover the optimal model by running the training stage and adjusting the number of hidden units and learning rate to find the hidden units and learning rate that produce the minimum error value. The fewer iterations required, the better. At this level, the patterns investigated include 12-15-1, 12-16-1, and 12-17-1. Meanwhile, the learning rates examined ranged from 0.1 to 0.9 in increments of 0.1. The following outcomes have been obtained:

Table 7. Learning Rate Experiment Results Based on ANN Patterns

Pattern	Learning Rate	Iteration	MSE Training
12-15-1	0.1	2382	9.9525e-06
	0.2	3240	9.8531e-06
	0.3	3614	9.8617e-06
	0.4	2583	9.9641e-06
	0.5	2852	9.9206e-06
	0.6	5478	9.8607e-06
	0.7	1649	9.8863e-06
	0.8	4948	9.8915e-06
	0.9	4081	9.9603e-06
12-16-1	0.1	2424	9.8864e-06
	0.2	2821	9.8625e-06
12-16-1	0.3	2487	9.9184e-06
	0.4	2972	9.8717e-06
	0.5	4506	9.9333e-06
	0.6	3561	9.8928e-06
	0.7	1813	9.9421e-06
	0.8	2925	9.9378e-06
	0.9	3166	9.8432e-06
12-17-1	0.1	4203	9.9029e-06
	0.2	3467	9.8885e-06
	0.3	5465	9.8748e-06
	0.4	3518	9.8708e-06
	0.5	1645	9.9828e-06
	0.6	3936	9.8699e-06
	0.7	2246	9.9566e-06
	0.8	4805	9.9544e-06
	0.9	3170	9.9788e-06

The pattern and learning rate values with the lowest MSE values, namely 12-16-1 and 0.9 with MSE training 9.8432e-06, were achieved. Following that, we shall seek the momentum value that produces the least MSE value. Figure 4 shows the outcomes of epoch training with Matlab:

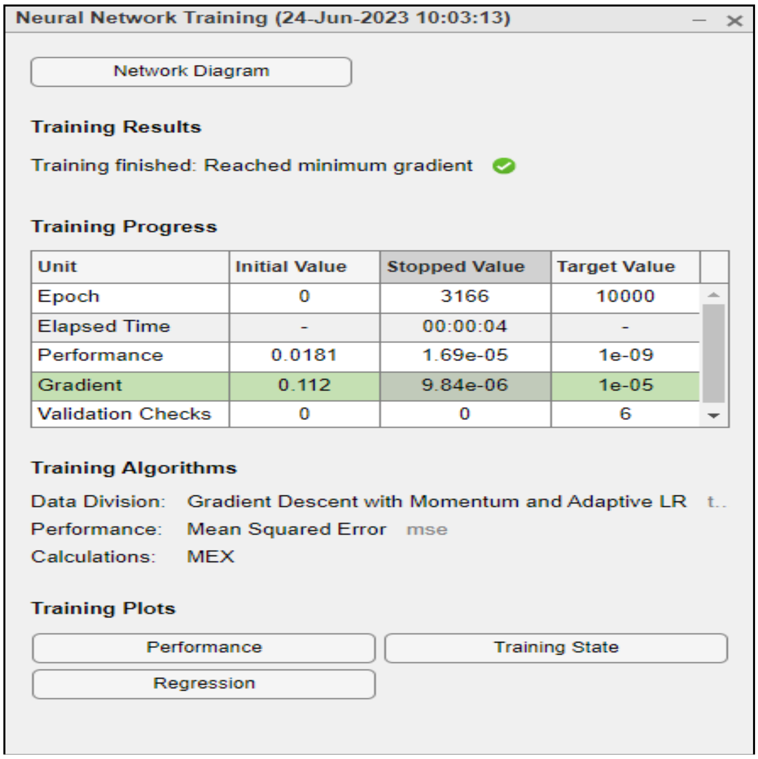

Figure 4. Neural Network Training Results

Figure 5 shows a graph of the output from training and training targets:

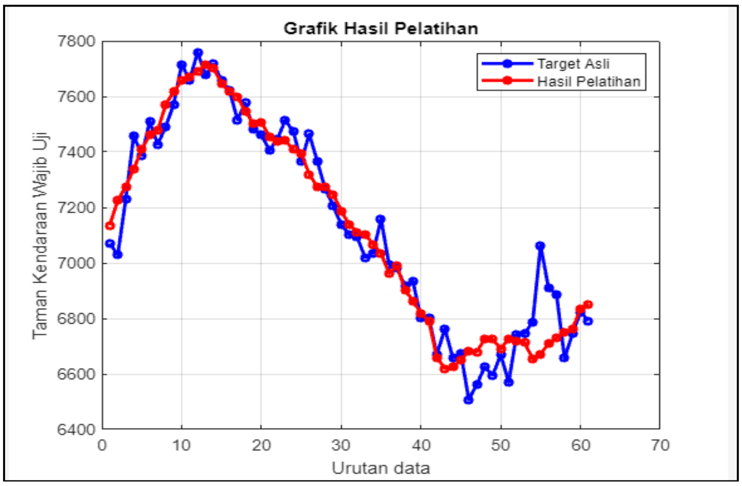

Figure 5. Graph of Training Results

Furthermore, the testing process is carried out utilizing the model described above. The feedforward stage is used for testing in the Matlab application. Furthermore, the testing process is carried out utilizing the model described above. The feedforward stage is used for testing in the Matlab application. The resulting MSE test value was 0.006367. Figure 6 shows a graph of the error value of the test results, and Figure 7 shows the ANN output graph with the target:

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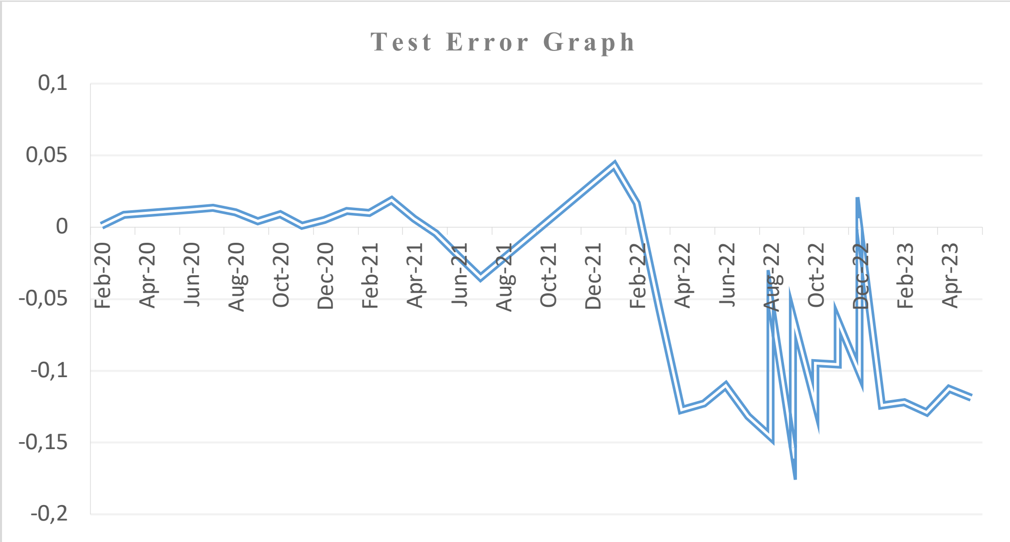

Figure 6. Test Error Graph

Figure 7. Graph of Testing Results

Experiment with system accuracy

The preceding experiment's combination of variables will subsequently be carried out with an experiment on the system's accuracy. The system accuracy is obtained by subtracting 100% from the MAPE value. Table 8: shows the MAPE value in this investigation.

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{x_t - y_t}{x_t}\right|}{n} \; x \; 100\% \tag{3}$$

$$MAPE = \frac{\left(\frac{6881-689.2}{6881} + \frac{6808-6891}{6808} + \cdots + \frac{6056-4908}{6056}\right)}{38} = 9.86\%$$

Description: X_t : Actual

Y_t : Forecast

n : numbers of items

As a result, the system accuracy equation is as follows:

Accuracy = 100% - 9.86% = 90.134%

In Table 8, the following is a comparison of the actual data and the prediction value of the test:

Table 8. Comparison of Actual Data Results and Test Prediction Values

No	Month	Actual Data	Prediction
1	Feb-20	6881	6892.3
2	Mar-20	6808	6891.4
3	Jun-20	6795	6912.6
4	Jul-20	6753	6883.4
5	Aug-20	6731	6833.6
6	Sep-20	6722	6762.9
7	Oct-20	6668	6753.5
8	Nov-20	6664	6676
9	Dec-20	6637	6684.7
10	Jan-21	6532	6643.4
11	Feb-21	6440	6537
12	Mar-21	6301	6483.1
13	Apr-21	6208	6267
14	May-21	6048	6005.2
15	Jun-21	5974	5780.7
16	Jul-21	5841	5504.2
17	Aug-22	5758	5257.2
18	Sep-22	5726	5121.9
19	Oct-22	5885	4971.2
20	Nov-22	6055	5429.1
21	Dec-22	5959	5946.2
22	Jan-22	5886	6301.6
23	Feb-22	5796	5955.6
24	Mar-22	5779	5235.7
25	Apr-22	5779	4551.9
26	May-22	5768	4584.7
27	Jun-22	5668	4605.4
28	Jul-22	5694	4425.6
29	Aug-22	5739	4330.9
30	Sep-22	5756	4272.8
31	Oct-22	5777	4591.1
32	Nov-22	5818	4893.7
33	Dec-22	5846	4869.2
34	Jan-23	5879	4682.8
35	Feb-23	5926	4750.1
36	Mar-23	5974	4729.5
37	Apr-23	5999	4915.3
38	May-23	6056	4908.7

to see a comparison of the actual data and the anticipated value in the picture below:

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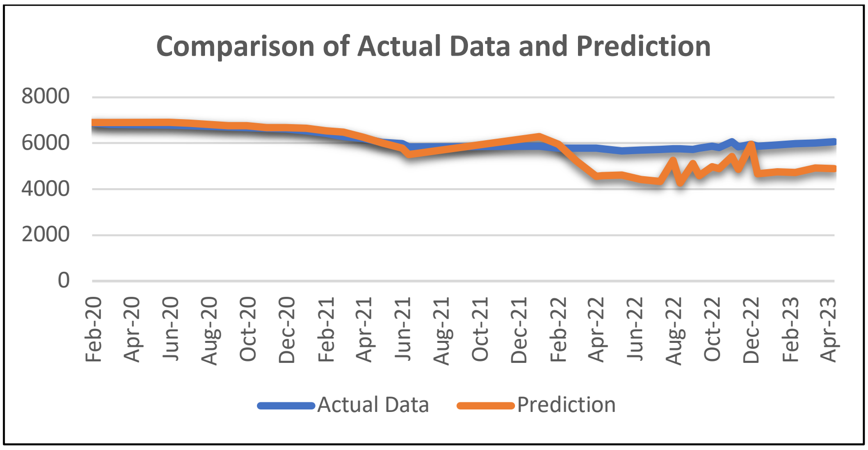

Figure 8. Comparison of Actual Data and Prediction

Prediction Outcomes

The feedforward step uses the best model to estimate mandatory test vehicle parks in the period to come. Predictions are made with the Matlab program. Table 9 shows the training output values, while table 10 shows the prediction output values:

Table 9. Training Output

Time	*X*	*Y* (Normalization)	Y_p (Normalization)	*Error*² (normalization)
January 2015	-30	0.839961115	0.838	0.001961115
February 2015	-29	0.84918989	0.8467	0.00248989
March 2015	-28	0.854270901	0.8566	-0.002329099
April 2015	-27	0.861011017	0.862	-0.000988983
May2015	-26	0.868165911	0.8689	-0.000734089
June 2015	-25	0.873661698	0.8756	-0.001938302
July 2015	-24	0.875320804	0.8725	0.002820804
August 2015	-23	0.884964355	0.8869	-0.001935645
September 2015	-22	0.889837978	0.8917	-0.001862022
October 2015	-21	0.893882048	0.8942	-0.000317952
⋮	⋮	⋮	⋮	⋮
January 2020	30	0.81051199	0.8106	-8.80104E-05
		Sum		-0.002640959

Table 10. Prediction Output

Time	*X*	Y_p (Normalization)
June 2023	39	0.7625
July 2023	40	0.7738
August 2023	41	0.8197
September 2023	42	0.9241
October 2023	43	0.9292
Time	***X***	**Y_p (Normalization)**
November 2023	44	0.9834
December 2023	45	0.9863

January 2024	46	0.9852
February 2024	47	0.9768
March 2024	48	0.9941
April 2024	49	0.9304
May 2024	50	0.9779

Denormalization

Denormalization, also known as post-processing, is the process of returning normalized output values to their original data form after producing values with a zero mean during simulation [19]. After obtaining the prediction output data, apply the denormalization formula to find the actual predicted value of mandatory test vehicle parks. Table 11 shows the denormalization results.

$$X = \frac{(X' - 0.1)\ x\ X_{max} - X_{min}}{0.8} + X_{min} \quad (4)$$

$$X = \frac{(0.7625 - 0.1)\ x\ 0.8 - 0.1}{0.8} + 0.1$$

Description: X' : Normalization value
X : Initial value
X_{max} : Initial maximum value
X_{min} : Initial minimum value

Table 11. Prediction Outcomes

Month	Prediction
June 2023	4698
July 2023	5882
August 2023	5970
September 2023	6324
October 2023	7130
November 2023	7169
December 2023	7587
January 2024	7609
February 2024	7601
March 2024	7536
April 2024	7669
May 2024	7178

After denormalizing or obtaining the actual prediction results, the predicted value of the mandatory test vehicle parks in December 2023 will be used to determine the need for proof of passing the periodic test in the following period.

4. Conclusion

The purpose of this study was to determine the results of forecasts for mandatory test vehicle parks using the best model, as well as to provide data accuracy for predictions of mandatory test vehicle parks at the Purwakarta Regency Transportation Service. This study used the backpropagation approach. The artificial neural network backpropagation method can be

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used to examine predictions of mandatory test vehicle parks based on the number of mandatory test vehicle parks from the previous year, ensuring that the network's pattern matches the intended pattern. The Backpropagation Neural Network model used in the study contains 12 input nodes, 16 hidden layer nodes, and one output layer. The Matlab application with 99 datasets is used to create a backpropagation neural network, which is then divided into two parts: training data and testing data. The prediction model training with the lowest MSE value is at the training variable alpha value of 0.9 with a total of 16 hidden layers, momentum of 0, maximum epoch 10000, and tolerance limit of 1e-05. The length of the training time is 00:00:04 seconds. The training MSE is 9.8432e-06 and the testing MSE is 0.006367, for a prediction model accuracy of 90.134%. The prediction results for the next 12 (twelve) months will be used as a reference in December 2023 to assess the necessity for proof of passing periodic tests in the subsequent period. The research has resulted in recommendations for future research, specifically that we expect to establish a model with a short number of iterations and develop research to determine predictions using the Python language.

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