Indonesian Journal of Artificial Intelligence and Data Mining (IJAIDM)
Vol. 7, No. 2, September 2024, pp. 392 – 403
p-ISSN: 2614-3372 | e-ISSN: 2614-6150

Application of the Artificial Neural Network Algorithm to Predict the Realization of the Duty Tax on the Name of Motor Vehicles in Lampung Province

[1*]Dian Kurniasari, [2]Putri Salsabila Ramadhani, [3]Wamiliana, [4]Warsono
[1,2,3,4]Departement of Mathematics, Faculty of Mathematics and Natural Sciences,
University of Lampung, Indonesia.
Email: [1]dian.kurniasari@fmipa.unila.ac.id, [2]putrisalsabila21@gmail.com,
[3]wamiliana.1963@fmipa.unila.ac.id, [4]warsono.1963@fmipa.unila.ac.id

Article Info
Article history:
Received May 4th, 2024
Revised May 31th, 2024
Accepted Jun 4th, 2024

Keyword:
Artificial Neural Network
BBNKB Tax
Lampung Province
Machine Learning
Predictions

ABSTRACT
Regional taxes, specifically the Motor Vehicle Name Return Tax (BBNKB), provide the primary source of revenue for regions from the several forms of taxes. The BBNKB tax is crucial in funding government and regional development due to its significant annual growth, encompassing four-wheeled and two-wheeled vehicles. Furthermore, the BBNKB tax catalyzes regional economic expansion and significantly contributes to the government's income. Hence, predicting and forecasting the BBNKB Tax in Lampung Province is necessary to monitor future tax rate fluctuations. That will enable the government to devise innovative tax payment systems and establish tax revenue targets. This study utilizes the Artificial Neural Network (ANN) methodology, using many approaches for distributing training and testing data to forecast. In addition, we utilize hyper-tuning on several factors to obtain the most favourable configurations. The ideal model achieved has a training data allocation of 80% and a testing data allocation of 20%. It was trained for 50 epochs and used a batch size of 16. The model has exceptional predictability, attaining an accuracy rating of 96.51%. Additionally, it showcases a low Root Mean Square Error (RMSE) of 0.246 and a minimal Mean Absolute Percentage Error (MAPE) score of 3.48%. Therefore, it is appropriate to predict the next two-year term. As a result, the forecast for the amount of tax collected from motor vehicle name returns in Lampung has fluctuated.

Corresponding Author:
Dian Kurniasari
Departement of Mathematics, Faculty of Mathematics and Natural Sciences
University of Lampung
Jl. Sumantri Brojonegoro No 1, Bandar Lampung, Indonesia.
Email: dian.kurniasari@fmipa.unila.ac.id
DOI: http://dx.doi.org/10.24014/ijaidm.v7i2.29456

1. INTRODUCTION

The tax sector is a promising source of domestic revenue with significant potential for further development [1]. Local taxes play a crucial role in local original taxes (PAD) and should be raised due to their substantial contribution to PAD. The Motor Vehicle Name Return Tax (BBNKB) is the primary municipal tax that generates the region's highest income. This phenomenon occurs due to an annual surge in individuals utilizing motorized vehicles, including four- and two-wheeled vehicles. BBNKB tax is levied on the transfer of ownership rights of motor vehicles as a result of a mutual agreement, unilateral actions, or situations arising from purchases, sales, exchanges, grants, inheritances, or involvement in a corporate entity.

The BBNKB tax plays a crucial role in financing the government and promoting regional development, as it stimulates economic growth in the region and serves as the primary source of state revenue. Hence, it is imperative to scrutinize and forecast the BBNKB tax in Lampung Province to comprehend forthcoming patterns of increase or fall and devise advancements in the tax payment system while establishing aims for tax revenue.

Predictions, as defined by Gosavi [2], refer to the techniques employed to identify future patterns based on available facts and limitations. An extensively employed approach for predicting and resolving intricate problems involving several factors is the Artificial Neural Network (ANN) [3]. An ANN is a computational technique designed based on human neurons' structure to model data [4]. The ANN comprises three distinct layers: the input, hidden, and output layers [5].

The application of ANN has been extensive across numerous domains [6–9], encompassing optimization, prediction, modelling, clustering, pattern recognition, simulation, and other disciplines. That can be attributed to its exceptional performance in self-learning, adaptability, and nonlinearity [10]. Furthermore, utilizing ANN models can significantly decrease research expenses and efficiently conserve computing resources [11, 12]. The ANN algorithm has been extensively implemented across many fields for prediction purposes. Fidan [13] constructed an ANN model to forecast the thermal properties of concrete based on its mechanical features. In order to optimize model performance, a range of activation functions, including sigmoid, tanh, and triangle functions, are employed. Furthermore, they employ cross-validation to guarantee robust generalization and mitigate the risk of overfitting. The results demonstrated that the suggested ANN model for forecasting the thermal characteristics of concrete can accurately carry out prediction tasks.

In his study, Naser [14] utilizes ANN to model trip creation, the initial phase of transportation planning. This study examined the performance of ANN using data collected from the Central Business Department (CBD) in Nasiriyah City. ANN models outperform statistical models, yielding higher performance. Kareem [15] assesses the efficacy of the Convolutional Neural Network (CNN) ANN in predicting weather forecasts by comparing their levels of accuracy. While both have distinct traits and features, ANN demonstrates higher performance when carrying out prediction tasks.

Yang [11] employed an ANN model to forecast the remaining durability of carbon fibre-reinforced composites (CFRCs) following low-speed impacts. They constructed an ANN model using the Backpropagation technique and successfully obtained favourable outcomes with an error rate of less than 5%. Baashar [16] constructed an ANN model to forecast student accomplishment and academic performance. The results demonstrate the efficacy and attain a high level of accuracy in predicting academic achievement, hence facilitating the evaluation of student performance in the academic domain.

According to the published studies, it may be inferred that ANN exhibits high accuracy. However, to achieve precise outcomes, it is necessary to undergo appropriate training in ANN [6]. Regrettably, prior studies have frequently neglected the optimization aspects of training ANN, particularly in fine-tuning hyperparameters essential for enhancing model performance. Thus, this paper specifically examines the implementation of hyperparameter tweaking in the Backpropagation algorithm, one of the techniques used in ANN. The objective is to identify the most favourable parameters to enhance the final model's performance.

2. RESEARCH METHOD

This study used an ANN-based Backpropagation algorithm. Backpropagation is one of the most popular ANN algorithms because of its efficiency and ease of implementation [17]. The data used is monthly data on the realization of the reverse duty tax on the name of motor vehicles in Lampung Province obtained from the Office of the Regional Revenue Agency of Lampung Province from January 2012 to June 2021. The forecasting method will involve multiple research steps, including:

1. Data input processing: the duty tax data for motor vehicles in Lampung Province will be inputted into the Python app running on Google Colab.
2. Data visualization: plots will be used to visually represent the data to find any patterns among the variables.
3. Data preprocessing: this stage involves finding and addressing missing values in the dataset.
4. Data transformation: the data will undergo normalization using the MinMaxScaler technique to guarantee that the variables have a consistent range of values.
5. Data splitting: the data will be split into three distinct schemes, precisely 60% for training and 40% for testing, 70% for training and 30% for testing, and 80% for training and 20% for testing. This partition will be used to evaluate the performance of the ANN model under varied data proportions.
6. Building of ANN model: the construction of the ANN model will involve utilizing a backpropagation method with the optimal parameters acquired during the hyperparameter tuning procedure. These parameters will include the number of nodes in the hidden layer, batch size, and epoch.
7. Prediction: the testing data will be utilized to generate predictions using three distinct methodologies, allocating 40%, 30%, and 20% of the testing data to each scheme.

8. Evaluation of prediction model: the effectiveness of the prediction model will be assessed by computing the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) values. These metrics will gauge the model's accuracy in predicting data.
9. Forecasting: the constructed model will forecast the reverse duty tax on motor vehicle names in Lampung Province for the upcoming 24 months. This forecast aims to offer information for future planning and policy-making.

The stages to be carried out in the research process can be seen in the Figure 1.

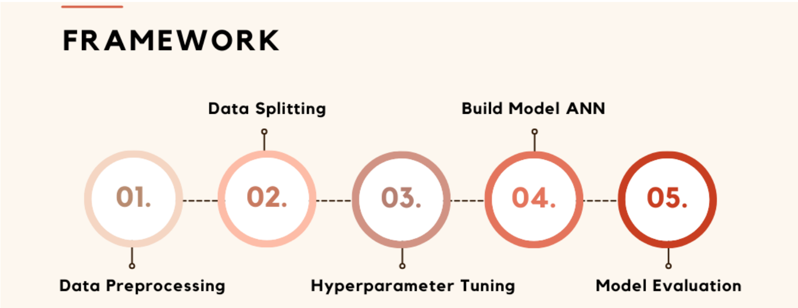


Figure 1. Proposed Model Framework

2.1 Data Preprocessing

Data preprocessing is the preliminary phase in the learning process, wherein data is manipulated or transformed into input that machines can readily process [18]. Furthermore, data preprocessing techniques can enhance ANN's performance and decrease complexity [19]. Data preprocessing is predicted to take up 50% to 80% of the time necessary for the learning process. Preprocessing has a crucial role in model construction, as demonstrated by Kadhim [20].

2.1.1 Data Cleaning

Data cleaning refers to the systematic procedure of identifying and rectifying mistakes and nonconformities in data sources to enhance their quality. Data cleaning encompasses the necessary steps to rectify incomplete and missing data, among other issues, to preserve the accuracy of prediction outcomes [21].

2.1.2 Data Transformation

Data scaling converts values from their original format to a different one to facilitate data analysis and processing. Although multiple data scaling approaches exist, identifying the appropriate scaling method is the primary difficulty. Several studies have demonstrated the impact of data scaling on various algorithms [22]. Sinsomboonthong 's research [23] specifically examined the performance of scaling techniques in the ANN model, such as statistical column, decimal scaling, and min-max normalization. Min-max normalization is widely regarded as the optimal method for scaling data due to its ability to yield the most precise outcomes. Consequently, this study will employ min-max normalization as a method of scaling. Min-max normalization, sometimes referred to as min-max scaling, is a straightforward method for scaling data by adjusting the range of feature values to either [0, 1] or [−1, 1] [24].

2.2 Data Splitting

Data splitting, or train-test split, refers to partitioning data into distinct subsets to train and evaluate models independently. That aims to prevent overfitting in the learning method, which might result in subpar model performance during testing [25]. Kumar [26] suggests that larger training sets are preferable to evaluation sets. Moreover, numerous studies propose using data training or testing schemes that partition datasets by ratios of 70:30 or 80:20. Pham et al. [27] found that enlarging the training data can enhance training performance and increase the stability of the model. Consequently, we employed a modified version of data splitting, allocating 60% of the data for training: 40% for testing, 70% for training: 30% for testing, and 80% for training: 20% for testing. That was done to get the best possible performance of the model.

2.3 Hyperparameter Tuning

Yang and Shami [28] define hyperparameter tuning as constructing an ideal model architecture by systematically exploring different parameter combinations. Hyperparameters are crucial in creating efficient learning models, particularly for tree-based and ANN models with numerous parameters [29]. The variables employed in this investigation were epoch and batch size. According to Vijayalakshmi [30], an epoch is the number of iterations needed throughout the training process. In this context, batch size denotes the number of training groups employed during a single iteration. These two factors heavily influence the learning process and are considered the most crucial hyperparameters [31].

2.4 Artificial Neural Network

2.4.1 Nodes in the Hidden Layer

The number of hidden layers applied impacts changes in learning outcomes. The criteria typically employed for determining the number of hidden layers are as follows:

1. The number of hidden layers exceeds the number of nodes in the input or output layers.
2. The number of hidden layers is calculated as two-thirds of the sum of the total nodes in the input layer and the number of nodes in the output layer.
3. The maximum number of hidden layers is twice the number of nodes in the input layer.

2.4.2 Activation Function

The activation function is also known as the transfer function. The activation function determines whether a neuron needs to be activated [32]. The activation function used in this study is the Rectified Linear Unit (ReLU). The ReLU activation function is employed to assign values collected from the layer. The ReLU function sets a threshold at zero so that when *x* is less than or equal to zero, *x* is equal to zero, and when *x* is more than zero, *x* remains unchanged. Equation (1) represents the mathematical expression that defines the activation function of the ReLU.

$$f(x) = \max(0, x) \tag{1}$$

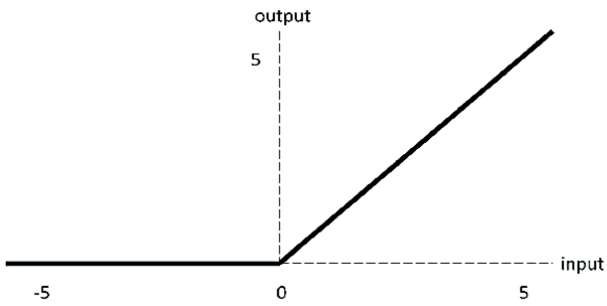


Figure 2. ReLU Activation Function

2.5 Validation Model

Hanke [33] asserts that forecasting approaches utilizing quantitative data with a specific temporal sequence can result in inaccuracies or mistakes. Hence, there is a want for methodologies that may be employed to assess inaccuracies in predicting methodologies. According to Kim [34], there are multiple techniques available for assessing models, such as [35]:

1. Mean Squared Error (MSE) is a metric that measures the average squared difference between the observed target value and the anticipated value.
2. Root Mean Squared Error (RMSE) is a statistic that quantifies the average discrepancy between projected and actual values.
3. Mean Absolute Percentage Error (MAPE) is a metric that quantifies the percentage difference between the anticipated value and the actual value. A model's prediction or forecasting is deemed accurate when the MSE, RMSE, and MAPE numbers approach zero.

The mathematical equations of MSE, RMSE, and MAPE are as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2 \tag{2}$$

$$RMSE = \sqrt{MSE} \tag{3}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - X_i}{Y_i}\right| \tag{4}$$

Where:

X_i : Predicted i-th value
Y_i : Actual value i-th
n : number of attempts

3. RESULTS AND ANALYSIS

3.1. Data Preprocessing

The first step in constructing an ANN model is to input data into a Python application using Google Colab. The provided data includes information on the motor vehicle name return tax in Lampung Province for ten years. The data is shown in Table 1, as depicted:

Table 1. Data Input

Year	BBNKB
01/01/2012	44.052.275.590
01/02/2012	45.563.869.025
01/03/2012	34.760.018.979
01/04/2012	55.549.557.892
01/05/2012	71.883.702.994
…	…
01/02/2021	45.784.629.500
01/03/2021	48.448.698.000
01/04/2021	49.976.513.500
01/05/2021	43.332.142.500
01/06/2021	66.763.390.500

Once the data is input, the subsequent task involves transforming the data into a time series format. Plots are used to visualize data in this style to detect patterns. Figure 3 illustrates a distinct trend pattern in the data, defined by periodic fluctuations in value that alternate between increases and declines over time.

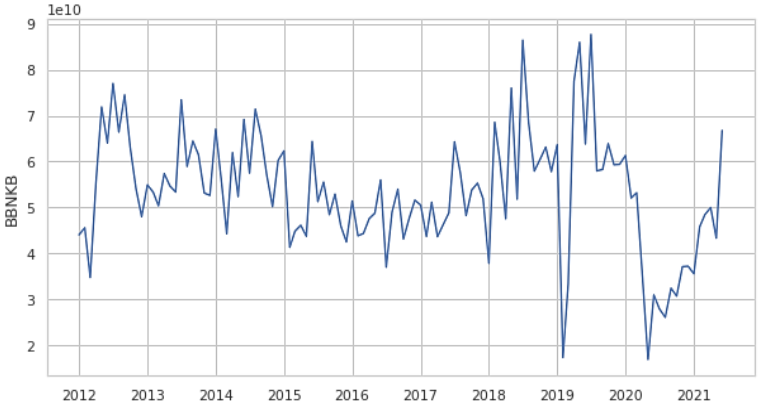


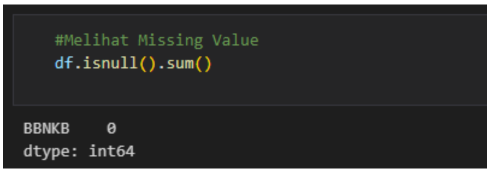
Figure 3. BBNKB Tax Data Plot

3.2. Data Preprocessing

Data preprocessing is crucial before constructing an ANN model. The preprocessing procedure encompasses multiple stages, specifically identifying missing data and the subsequent transformation or scale of the data. These procedures are crucial to guarantee that the data is prepared for processing using the ANN model with the highest possible quality.

3.2.1. Check Missing Value

This stage aims to determine the presence of missing data within the dataset. The execution of this stage is carried out using the subsequent syntax.



```
#Melihat Missing Value
df.isnull().sum()

BBNKB    0
dtype: int64
```

Figure 4. Syntax Check Missing Value

Figure 4 demonstrates no missing data in the reverse duty tax dataset on motor vehicles in Lampung Province. Nevertheless, subsequent actions can be undertaken in the event of any missing data. Firstly, the dropna() function can remove data rows with null values. Alternatively, the fillna () method can replace a null value with a different one.

3.2.2. Data Transformation

Data transformation is the systematic conversion of values in a dataset from its initial format to a different format, intending to enhance the data's utility for analysis. The data transformation method employed in this study involves the utilization of MinMaxScaler. MinMaxScaler is a normalization technique that transforms the original range of data values into a range between 0 and 1. Therefore, enhancing the dispersion of data can optimize its suitability for model construction and subsequent data analysis. The outcomes of data transformation are presented in Table 2.

Table 2. Data Transformation Results

Index	Transformation Results
0	0,3836388
1	0,40499657
2	0,25234544
3	0,54608774
4	0,77687836
…	…
109	0,4081158
110	0,445757
111	0,467344
112	0,3734638
113	0,7045317

3.3 Data Splitting

Once the data transformation procedure has concluded, the last phase involves partitioning the data into two subsets: training and testing data. The training data is utilized to train ANN algorithms, whilst the testing data is employed to assess the performance of the taught algorithms when making predictions. The generally utilized proportions for training and testing data are 80% training data and 20% testing data, 70% training data and 30% testing data, and 60% training data and 40% testing data. The proportions can be modified according to the requirements and intricacy of the constructed model.

Nevertheless, this study aims to evaluate multiple data-splitting strategies to identify the most optimal scenario for predicting. Various training and testing schemes will be examined to assess the model's effectiveness. Table 3 provides specific information regarding the data-splitting scheme that will be utilized.

Table 3. Splitting Training Data and Testing Data

Data Splitting	Amount of Data
60% data training and 40% data testing	54 data training and 36 data testing
70% data training and 30% data testing	63 data training and 27 data testing
80% data training and 20% data testing	72 data training and 18 data testing

3.4 Build model

The model built in this study is the ANN model utilizing the ReLU activation function. The ReLU activation function transforms the data values range from 0 to infinity. This function converts any negative input value to 0 while leaving positive values unchanged. Hence, the ReLU activation function is well-suited for time series data as it enhances the performance of neuron activation by preserving the actual value.

The model incorporates various parameters, such as the ReLU activation function, the number of input layers, two hidden layers, an output layer, the number of neurons or units in the hidden layer, the epoch, and the batch size. The parameter values utilized in this investigation are delineated in Table 4.

Table 4. Parameters Used

Parameter	Parameter Value
Epoch	50 and 100
Batch Size	16 and 32
Activation Function	ReLU

In machine learning and deep learning, an epoch is a singular iteration that encompasses the complete traversal of the training dataset. Batch size refers to the quantity of data samples fed to the model during each iteration of the training process. Choosing the appropriate number of epochs and batch size is a crucial aspect in training a model, as it can significantly impact the performance and stability of the resulting model. Therefore, it is crucial to ascertain the most advantageous configuration of parameters.

The ideal value for the parameter is determined through hypertuning, which includes deploying early stopping procedures. These strategies enable the automatic termination of the model learning process after the optimal parameter values have been identified, thereby preventing overfitting and conserving computational resources. Once the hypertuning procedure is finished, the optimal parameter value is derived from the analytical results. The outcomes of the process of hypertuning are shown in three distinct portions, specifically Table 5, Table 6, and Table 7, which are based on the implemented data-splitting method.

Table 5. Optimal Parameters for 60% Training Data and 40% Testing Data

Parameter	Parameter Value
Epoch	50
Batch Size	16
Activation Function	ReLU
Layer	Input: 1 layer Hidden: 2 layers consisting of 24 nodes and 17 nodes. Output: 1 layer

Table 6. Optimal Parameters for 70% Training Data and 30% Testing Data

Parameter	Parameter Value
Epoch	100
Batch Size	16
Activation Function	ReLU
Layer	Input: 1 layer Hidden: 2 layers consisting of 24 nodes and 17 nodes. Output: 1 layer

Table 7. Optimal Parameters for 80% Training Data and 20% Testing Data

Parameter	Parameter Value
Epoch	50
Batch Size	16
Activation Function	ReLU
Layers	Input: 1 layer Hidden: 2 layers consisting of 24 nodes and 17 nodes. Output: 1 layer

3.5 Model Testing

The model testing phase is conducted after identifying and implementing the optimal parameters. The loss and validation loss values are calculated as metrics to assess the model's performance. A lower loss number indicates a higher level of accuracy in forecasting unseen data for the model constructed. Therefore, a reduction in the loss value signifies an enhancement in the quality and precision of the constructed models.

Figures 5, Figure 6, and Figure 7 depict loss graphs for model test results using various data-splitting techniques. Refer to Figure 6 for a loss chart depicting 60% of the training data. Similarly, consult Figure 7 for a loss chart illustrating 70% of the training data and Figure 8 for a loss chart representing 80% of the training data.

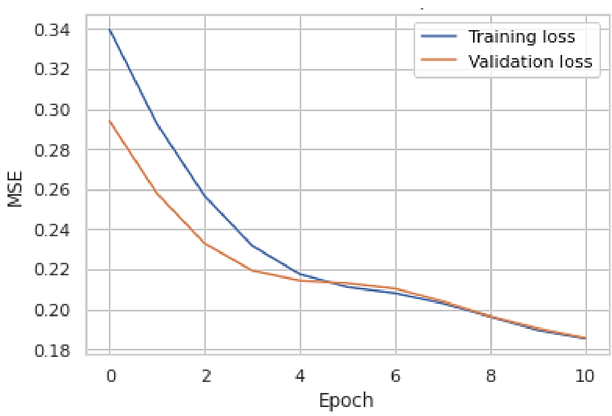


Figure 5. Loss Graph for 60% of Training Data

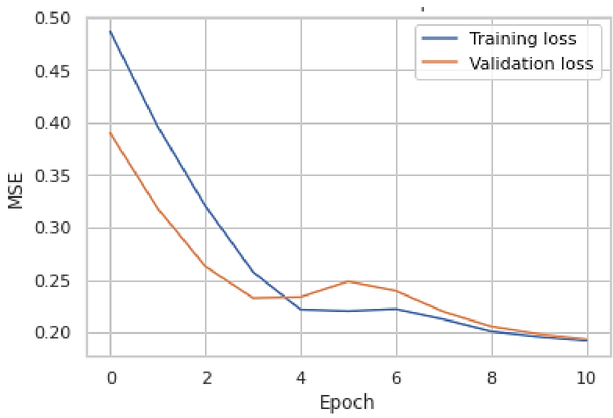


Figure 6. Loss Graph for 70% of Training Data

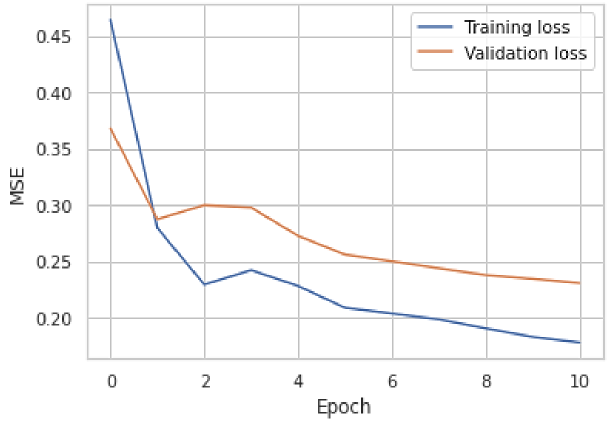


Figure 7. Loss Graph for 80% of Training Data

After analyzing Figures 5, 6, and 7, it can be inferred that all models created using training and testing data splitting methods, whether 60:40, 70:30, or 80:20, exhibit optimal outcomes without overfitting. That is evident from the convergence pattern of the loss and validation loss values at specific places on the graph, which suggests that the model can effectively generalize to previously unseen data.

3.6 Prediction

The model was employed to predict the imposition of inverse duty tax on motor vehicle designations in Lampung Province after the testing phase. An additional analysis is conducted on the derived predictions by comparing them with the actual data. Once the anticipated outcomes demonstrate a strong correspondence with the empirical data, the developed model may be a dependable instrument for predicting the forthcoming tax realization on motor vehicle names.

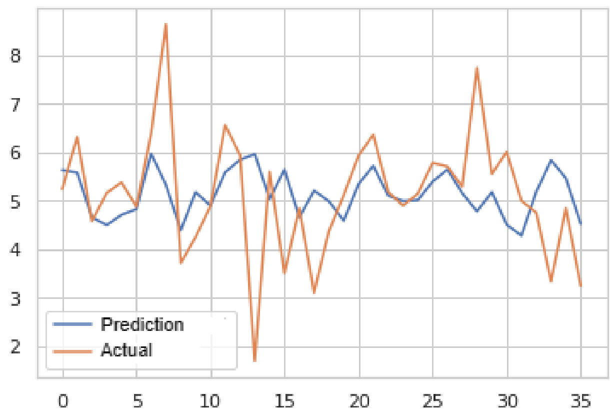


Figure 8. Plot 60% Training Data Prediction

Figure 8 displays two lines: the blue line represents the predicted results, while the orange line shows the actual data. Consequently, the results did not align with the data distribution when 60% of the training data was used for predictions. There were notable disparities between the predicted values and the actual data, indicating that the constructed model is insufficient for accurate forecasting.

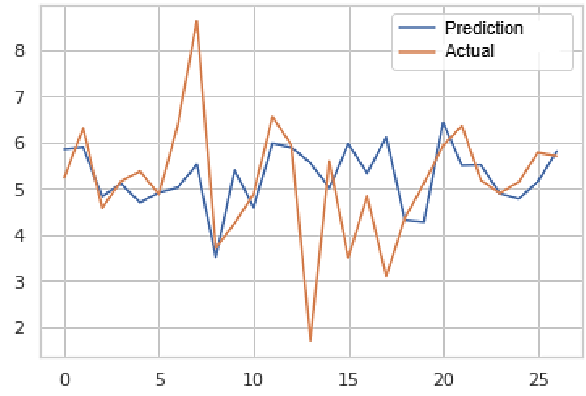


Figure 9. Plot 70% Training Data Prediction

The plot of prediction results utilizing 70% of the training data exhibits a striking resemblance to the actual data distribution pattern, as confirmed by Figure 9. Nevertheless, a disparity persists between the predicted values and the actual data, suggesting that the model's prognostications are reasonably precise.

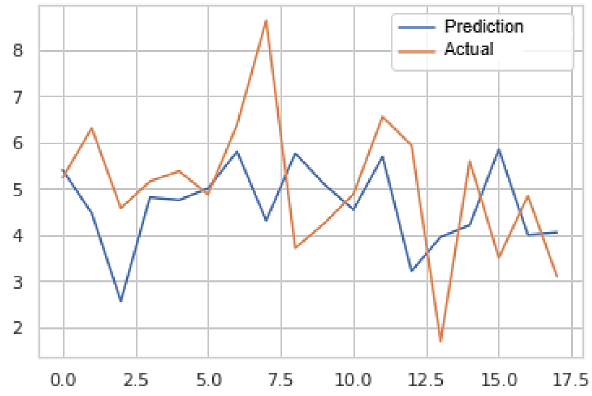


Figure 10. Plot 80% Training Data Prediction

The plot of prediction results utilizing 80% of the training data more closely than other models resembles the distribution pattern of the actual data, as indicated by Figure 10. This finding illustrates that the predicted value corresponds precisely to the actual data, suggesting that the developed model can be relied upon to foresee or predict BBNKB taxes.

3.7 Model Evaluation

RMSE and MAPE values are utilized in this study to evaluate the accuracy of prediction models. A comparison of the accuracy values acquired for each constructed model is presented in Table 8.

Table 8. Comparison of Accuracy Values

Data Schema	Model Evaluation		
	RMSE	MAPE	Accuracy
60% data training, 40% data testing	0.189	4.51%	95.48%
70% data training, 30% data testing	0.207	4.16%	95.83%
80% data training, 20% data testing	0.204	3.48%	96.51%

As shown in Table 8, the highest achievable accuracy was 96.51% when a data training scheme of 80% was utilized in conjunction with a 20% data testing scheme. This finding illustrates the model's exceptional predictive capabilities, attaining a 96.51% exact accuracy rate. Thus, this strategy for training data is exceptionally suitable for forecasting.

3.8 Forecasting

Once the accuracy number reaches a reasonable level, the next step is forecasting. Based on the existing findings, the model that yields the highest accuracy in forecasting future events employs an 80% data training and a 20% data testing approach. The following findings provide predictions on the implementation of the reverse duty tax on motor vehicles in Lampung province, on figure 11.

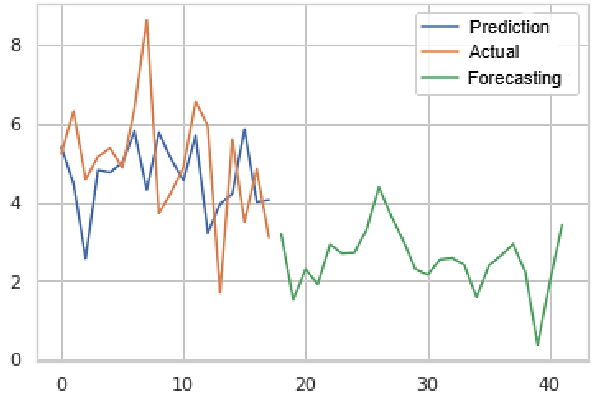


Figure 11. Plot Combination of Forecasting Results

Based on Figure 11, the forecasted results for the Lampung Province motor vehicle reverse tax name for two years have exhibited volatility, as depicted by the green line. The blue line corresponds to the projected outcomes, whereas the orange line corresponds to the factual facts.

4 CONCLUSION

This study used the backpropagation technique, an ANN, to predict the future occurrence of motor vehicle name return duty tax in Lampung for two years. The monthly data was acquired from the Office of the Regional Revenue Agency of Lampung Province from January 2012 to June 2021. Several data-splitting schemes are utilized: 60% for training, 40% for testing, 70% for training, 30% for testing, 80% for training and 20% for testing. Furthermore, hyperparameter optimization is conducted on the epoch and batch size to achieve the best possible parameters.

The findings indicated that the optimal parameters for predicting the occurrence of motor vehicle name reverse duty tax were 50 epochs and 16 batch sizes. The training data was divided into an 80% splitting scheme, while the testing data accounted for 20%. Additionally, the ReLU activation function was employed. The model's prediction capacity was excellent, with an accuracy of 96.51%, an RMSE of 0.246, and a MAPE value of 3.48%. Therefore, this model can be utilized to predict the occurrence of motor vehicle name return tax in Lampung in the next two years. The forecasted findings indicate oscillations in the motor vehicle name return duty tax collection in Lampung, with both increases and decreases observed.

REFERENCES

[1] D. R. Giovani and Y. Y. Padmono, *Faktor-Faktor yang Mempengaruhi Penerimaan Pajak Kendaraan Bermotor*. 1999.

[2] G. Gosavi and G. Gawde, "Prediction Techniques for Data Mining," 2022. [Online]. Available: https://www.researchgate.net/publication/357955350

[3] M. Arafat, T. Sjafrizal, and R. A. Anugraha, "An artificial neural network approach to predict energy consumption and surface roughness of a natural material," *SN Appl. Sci.*, vol. 2, no. 7, 2020, doi: 10.1007/s42452-020-2987-6.

[4] M. G. M. Abdolrasol *et al.*, "Artificial neural networks based optimization techniques: A review," *Electronics (Switzerland)*, vol. 10, no. 21. 2021. doi: 10.3390/electronics10212689.

[5] Z. E. Mohamed, "Using the artificial neural networks for prediction and validating solar radiation," *J. Egypt. Math. Soc.*, vol. 27, no. 1, 2019, doi: 10.1186/s42787-019-0043-8.

[6] M. Niazkar, "Revisiting the Estimation of Colebrook Friction Factor: A Comparison between Artificial Intelligence Models and C-W-based Explicit Equations," *KSCE J. Civ. Eng.*, vol. 23, no. 10, 2019, doi: 10.1007/s12205-019-2217-1.

[7] M. Niazkar, "Assessment of artificial intelligence models for calculating optimum properties of lined channels," *J. Hydroinformatics*, vol. 22, no. 5, pp. 1410–1423, 2020, doi: 10.2166/hydro.2020.050.

[8] H. R. Niazkar and M. Niazkar, "Application of artificial neural networks to predict the COVID-19 outbreak," *Glob. Heal. Res. Policy*, vol. 5, no. 1, 2020, doi: 10.1186/s41256-020-00175-y.

[9] M. Niazkar, N. Talebbeydokhti, and S. H. Afzali, "Bridge backwater estimation: A comparison between artificial intelligence models and explicit equations," *Sci. Iran.*, vol. 28, no. 2, pp. 573–585, Mar. 2021, doi:

10.24200/sci.2020.51432.2175.

[10] A. R. Florea and M. Roman, "Artificial neural networks applied for predicting and explaining the education level of Twitter users," *Soc. Netw. Anal. Min.*, vol. 11, no. 1, 2021, doi: 10.1007/s13278-021-00832-1.

[11] B. Yang, K. Fu, J. Lee, and Y. Li, "Artificial Neural Network (ANN)-Based Residual Strength Prediction of Carbon Fibre Reinforced Composites (CFRCs) After Impact," *Appl. Compos. Mater.*, vol. 28, no. 3, pp. 809–833, 2021, doi: 10.1007/s10443-021-09891-1.

[12] S. Kumar, V. Kumar, and A. K. Singh, "Prediction of maximum pressure of journal bearing using ANN with multiple input parameters," *Aust. J. Mech. Eng.*, vol. 20, no. 4, pp. 1069–1078, 2022, doi: 10.1080/14484846.2020.1769540.

[13] S. Fidan, H. Oktay, S. Polat, and S. Ozturk, "An Artificial Neural Network Model to Predict the Thermal Properties of Concrete Using Different Neurons and Activation Functions," *Adv. Mater. Sci. Eng.*, vol. 2019, 2019, doi: 10.1155/2019/3831813.

[14] I. H. Naser, A. M. Mahdi, and Y. H. Jasim, "Performance of Artificial Neural Networks (ANN) at Transportation Planning Model," in *IOP Conference Series: Materials Science and Engineering*, 2020. doi: 10.1088/1757-899X/928/2/022032.

[15] S. Kareem, Z. J. Hamad, and S. Askar, "An evaluation of CNN and ANN in prediction weather forecasting: A review," *Sustain. Eng. Innov.*, vol. 3, no. 2, pp. 148–159, 2021, doi: 10.37868/sei.v3i2.id146.

[16] Y. Baashar *et al.*, "Toward Predicting Student's Academic Performance Using Artificial Neural Networks (ANNs)," *Appl. Sci.*, vol. 12, no. 3, 2022, doi: 10.3390/app12031289.

[17] S. Setti and A. Wanto, "Analysis of Backpropagation Algorithm in Predicting the Most Number of Internet Users in the World," *J. Online Inform.*, vol. 3, no. 2, p. 110, 2019, doi: 10.15575/join.v3i2.205.

[18] K. Maharana, S. Mondal, and B. Nemade, "A review: Data preprocessing and data augmentation techniques," *Glob. Transitions Proc.*, vol. 3, no. 1, pp. 91–99, Jun. 2022, doi: 10.1016/j.gltp.2022.04.020.

[19] I. Pisa, I. Santín, J. L. Vicario, A. Morell, and R. Vilanova, "Data preprocessing for ANN-based industrial time-series forecasting with imbalanced data," in *European Signal Processing Conference*, 2019. doi: 10.23919/EUSIPCO.2019.8902682.

[20] A. I. Kadhim, "An Evaluation of Preprocessing Techniques for Text Classification," *Int. J. Comput. Sci. Inf. Secur.*, vol. 16, no. 6, pp. 22–32, 2018, [Online]. Available: https://sites.google.com/site/ijcsis/

[21] O. Azeroual, G. Saake, and M. Abuosba, "Data Quality Measures and Data Cleansing for Research Information Systems," 2019, [Online]. Available: http://arxiv.org/abs/1901.06208

[22] M. M. Ahsan, M. A. P. Mahmud, P. K. Saha, K. D. Gupta, and Z. Siddique, "Effect of Data Scaling Methods on Machine Learning Algorithms and Model Performance," *Technologies*, vol. 9, no. 3, 2021, doi: 10.3390/technologies9030052.

[23] S. Sinsomboonthong, "Performance Comparison of New Adjusted Min-Max with Decimal Scaling and Statistical Column Normalization Methods for Artificial Neural Network Classification," *Int. J. Math. Math. Sci.*, vol. 2022, 2022, doi: 10.1155/2022/3584406.

[24] D. Borkin, A. Némethová, G. Michaľčonok, and K. Maiorov, "Impact of Data Normalization on Classification Model Accuracy," *Res. Pap. Fac. Mater. Sci. Technol. Slovak Univ. Technol.*, vol. 27, no. 45, pp. 79–84, 2019, doi: 10.2478/rput-2019-0029.

[25] I. O. Muraina, "Ideal Dataset Splitting Ratios in Machine Learning Algorithms: General Concerns for Data Scientists and Data Analysts," *7th Int. Mardin Artuklu Sci. Res. Conf.*, no. February, pp. 496–504, 2022.

[26] S. Kumar, "Data splitting technique to fit any Machine Learning Model | by Sachin Kumar | Towards Data Science," Towards Data Science. [Online]. Available: https://towardsdatascience.com/data-splitting-technique-to-fit-any-machine-learning-model-c0d7f3f1c790

[27] B. T. Pham *et al.*, "A novel hybrid soft computing model using random forest and particle swarm optimization for estimation of undrained shear strength of soil," *Sustain.*, vol. 12, no. 6, pp. 1–16, 2020, doi: 10.3390/su12062218.

[28] L. Yang and A. Shami, "On hyperparameter optimization of machine learning algorithms: Theory and practice," *Neurocomputing*, vol. 415, pp. 295–316, 2020, doi: 10.1016/j.neucom.2020.07.061.

[29] F. Hutter, L. Kotthof, and J. Vanschoren, *Automated machine learning: Methods, Systems, Challenges*. 2020.

[30] V. Vijayalakshmi and K. Venkatachalapathy, "Deep neural network for multi-class prediction of student performance in educational data," *Int. J. Recent Technol. Eng.*, vol. 8, no. 2, pp. 5073–5081, 2019, doi: 10.35940/ijrte.B2155.078219.

[31] N. Rochmawati, H. B. Hidayati, Y. Yamasari, H. P. A. Tjahyaningtijas, W. Yustanti, and A. Prihanto, "Analisa Learning Rate dan Batch Size pada Klasifikasi Covid Menggunakan Deep Learning dengan Optimizer Adam," *J. Inf. Eng. Educ. Technol.*, vol. 5, no. 2, pp. 44–48, 2021, doi: 10.26740/jieet.v5n2.p44-48.

[32] J. Feng and S. Lu, "Performance Analysis of Various Activation Functions in Artificial Neural Networks," in *Journal of Physics: Conference Series*, 2019. doi: 10.1088/1742-6596/1237/2/022030.

[33] J. E. Hanke and D. Wichern, *Business Forecasting (Ninth Edition)*, vol. 5, no. 1. 2014.

[34] D. Kim, T. Kim, J. Jeon, and Y. Son, "Soil-Surface-Image-Feature-Based Rapid Prediction of Soil Water Content and Bulk Density Using a Deep Neural Network," *Appl. Sci.*, vol. 13, no. 7, 2023, doi: 10.3390/app13074430.

[35] K. Karunia, A. E. Putri, M. D. Fachriani, and M. H. Rois, "Evaluation of the Effectiveness of Neural Network Models for Analyzing Customer Review Sentiments on Marketplace," Public Research Journal of Engineering, Data Technology and Computer Science, vol. 2, no. 1, pp. 52–59, Apr. 2024, doi: 10.57152/predatecs.v2i1.1100.

BIBLIOGRAPHY OF AUTHORS

Dian Kurniasari is a Lecturer in the Mathematics Department of FMIPA at the University of Lampung. She obtained his bachelor's degree from Gadjah Mada University and his master's degree from Curtin University.

Wamiliana is a Lecturer in the Mathematics Department of FMIPA at the University of Lampung. She completed his bachelor's degree at the University of Indonesia, master's at Curtin University, and doctoral degree at the University of Montana.

Putri Salsabila Ramadhani completed his undergraduate education at the Mathematics Department of FMIPA, University of Lampung and graduated in 2022.

Warsono is a Lecturer in the Mathematics Department of FMIPA at the University of Lampung. He completed his bachelor's and master's degrees at IPB and his doctoral degree at the University of Alabama.