RESEARCH ARTICLE • OPEN ACCESS

Comparative Study of Multilayer Perceptron and Recurrent Neural Network in Predicting Population Growth Rate in Brebes Regency

Izzatul Yazidah and Emy Siswanah

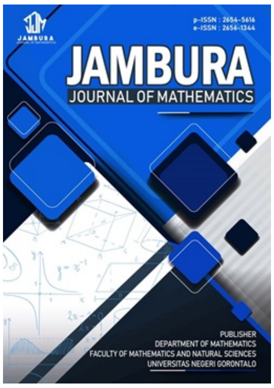
JAMBURA JOURNAL OF MATHEMATICS

Volume 7, Issue 1, Pages 71–78, February 2025

Received 15 January 2025, Revised 23 February 2025, Accepted 25 February 2025, Published 27 February 2025

To Cite this Article : I. Yazidah and E. Siswanah,"Comparative Study of Multilayer Perceptron and Recurrent Neural Network in Predicting Population Growth Rate in Brebes Regency", *Jambura J. Math*, vol. 7, no. 1, pp. 71–78, 2025, *https://doi.org/10.37905/jjom.v7i1.30199*

JOURNAL INFO • JAMBURA JOURNAL OF MATHEMATICS



Homepage	:	http://ejurnal.ung.ac.id/index.php/jjom/index
Journal Abbreviation	:	Jambura J. Math.
Frequency	:	Biannual (February and August)
Publication Language	:	English (preferable), Indonesia
DOI	:	https://doi.org/10.37905/jjom
Online ISSN	:	2656-1344
Editor-in-Chief	:	Hasan S. Panigoro
Publisher	:	Department of Mathematics, Universitas Negeri Gorontalo
Country	:	Indonesia
OAI Address	:	http://ejurnal.ung.ac.id/index.php/jjom/oai
Google Scholar ID	:	iWLjgaUAAAAJ
Email	:	info.jjom@ung.ac.id

Jambura Journal of Mathematics, Volume 7, Issue 1, Pages 71–78, February 2025 https://doi.org/10.37905/jjom.v7i1.30199

Research Article

Check for updates

Comparative Study of Multilayer Perceptron and Recurrent Neural Network in Predicting Population Growth Rate in Brebes Regency

Izzatul Yazidah[1] **and Emy Siswanah**[1,*]

[1]*Department of Mathematics, Universitas Islam Negeri Walisongo Semarang, Semarang, Indonesia*

ARTICLE HISTORY
Received 15 January 2025
Revised 23 February 2025
Accepted 25 February 2025
Published 27 February 2025

KEYWORDS
Prediction
Population Growth Rate
Multilayer Perceptron
Recurrent Neural Network

ABSTRACT. *Due to its ever-growing population, Brebes had the biggest population in Central Java from 2020 to 2022. The government of Brebes has to predict the growth rate of the population and prepare the resources and employment opportunities to anticipate this population growth rate. This research aims to analyze the result of growth rate prediction in Brebes using Multilayer Perceptron (MLP) and Recurrent Neural Network (RNN). These two methods are applied to determine the most suitable one to predict the population growth rate. This is determined by comparing the smallest MAPE value of these two methods. The analyzed data of the total population from 1991-2022 is taken from Badan Pusat Statistik (BPS) of Brebes. The percentage of division between training and testing data is 80%:20%. According to the research results, the recurrent neural network is the most suitable method, with the smallest MAPE being 1.9973%.*

1. Introduction

Indonesia is a country with a large population on earth with a population of 275,501,339 people. Indonesia is ranked fourth in the world in the list of large populations after India, China, and the United States. Every year, population growth in Indonesia always increases [1]. High population growth will disrupt the balance of natural resources, disrupt the availability of consumption, and affect the population structure in terms of quantity and quality [2]. Population growth can be a driving factor and a inhibiting factor for development. If the increase in population is not accompanied by development in quality, it will cause various problems such as limited employment opportunities, reduced Green Open Space areas, and decreased social welfare [3]. This will result in the failure to realize economic development.

Brebes Regency is a regency/city with an area of 1,902.40 km^2 and is ranked third in Central Java [4]. From 2020 to 2022, Brebes Regency became the regency with the largest population in Central Java with the following numbers: 1,978,759 people, 1,992,685 people, and 2,010,617 people [4]. Since 2019, Brebes Regency has also become one of the areas of extreme poverty [5]. So, Brebes Regency is one of the densely populated and extremely poor regencies. A large population can be both an opportunity and a challenge for Brebes Regency. In this case, a large population can be an opportunity for the development of Brebes Regency if the population is of good quality and will be a problem if the population is not of good quality. Therefore, it is necessary to conduct a study to predict the population density in the next few years in Brebes Regency so that the government can suppress the population growth rate and prepare/anticipate an increase in population. Some preparations that the government can make are preparing earth resources to balance increasing human needs and preparing jobs so that unemployment does not occur [2]. Several methods that can be used in predictive analysis, one of which is the artificial neural network method [6].

Artificial Neural Network (ANN) mimics the information processing in the human brain [7]. Generally, three neural networks are usually applied based on the type of network: Single-Layer Neural, Multilayer Perceptron Neural Network, and Recurrent Neural Network. Single layer networks are artificial neural networks that have the input layer connected directly with the output layer. A Multilayer Perceptron (MLP) Network is basically a type of artificial neural network that possesses a hidden layer between its input and output layers. A recurrent neural network is a type of neural network that has a connected pathway from its output back to its input [8].

MLP is a Neural Network method that is better than other methods in terms of prediction. MLP has characteristics, namely the weight value is determined better than other methods, MLP can be applied without prior information, and is able to overcome linear and nonlinear problems. This is supported by previous studies including Choubin et al. [9] which shows that the performance of the Multilayer Perceptron network is better than the Multiple Linear Regression and Adaptive Neuro-Fuzzy inference methods in predicting rainfall because it produces the smallest RMSE value of 0.86. In another study, Nooriansyah et al. [10] showed that the Artificial Neural Network method with Multilayer Perceptron (MLP) training obtained the smallest MAPE value of 6.88% compared to Support Vector Regression (SVR) which is 8.51% in predicting wave height. Research conducted by Aribowo et al. [11] showed that the Multilayer Perceptron method had the smallest MAPE value, namely 4.48%, compared to the Holt-

*Corresponding Author.

Email : emysiswanah@walisongo.ac.id (E. Siswanah)
Homepage : http://ejurnal.ung.ac.id/index.php/jjom/index / E-ISSN : 2656-1344

Winters method, namely 28.65% and the Auto Refressive Integrated Moving Average (ARIMA) method, namely 28.16% in predicting the price of quality III IR64 rice.

RNN is a Neural Network method that has several advantages. RNN is able to predict time series and nonlinear data accurately and has good convergence speed [12]. Conceptually, RNN has a strong memory for events that have occurred previously [13]. Hermawan's [14] using the Recurrent Neural Network and Recurrent Neuro Fuzzy methods in predicting the number of train passengers in Jabodetabek showed that the RNN method had the smallest MAPE value, namely 3.785%. Research by Achmalia et al. [15] which predicted cement sales using Backpropagation Neural Network and Elman type Recurrent Neural Network showed that the RNN method had a MAPE value of 28.9958%. Research conducted by Kusnanti et al. [16] in predicting the speed and direction of sea surface currents using the Elman Recurrent Neural Network method produced a MAPE value of 3.1253%. These studies show that the RNN method is an accurate method and has a small error in predicting data.

According to the previously mentioned research, the MLP method had the lowest error value when compared to other approaches. Similarly, the RNN approach outperforms other prediction methods in terms of predicting. These factors will be used in this study to compare the Recurrent Neural Network and Multilayer Perceptron approaches. Time series data is predicted using both approaches, and the resulting MAPE values are compared. The purpose of this research is to compare the accuracy level of population growth rate predictions in Brebes Regency using the Multilayer Perceptron and Recurrent Neural Network methods and to determine the outcomes of these predictions.

2. Methods

This research uses the applied method, which aims to solve or find the solution to a specific and particular problem [17]. Research is a structured or careful analysis to determine or find the truth [18]. The Multilayer Perceptron Method (MLP) and Recurrent Neural Network (RNN) are deep learning methods. In general, the flow in predicting using the MLP and RNN methods has the same steps. The difference between MLP and RNN lies in the number of layers that build the network architecture. The network architecture of the MLP method consists of 3 layers, namely the input layer, the hidden layer, and the output layer. The RNN method has 4 layers that make up the network architecture, namely the input layer, the hidden layer, the context layer, and the output layer. The network architecture that is built is used in the Network Training stage. Figure 1 and Figure 2 illustrate the network architecture of MLP and RNN.

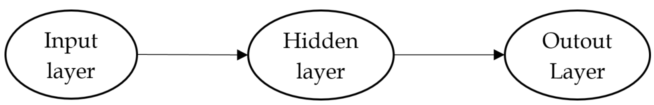


Figure 1. Network Architecture of MLP

RNN is similar to MLP with one or more context layers added. The number of neurons in the context layer is the same as the number of neurons in the hidden layer. In addition, the neurons in the context layer are connected to all neurons in the hidden layer. Neurons in the context layer are included because these neurons are the ones that serve as reminders of events in the previous network by storing the values of the hidden layer neurons. The stored values are returned one step and used in the next step as additional input to the network.

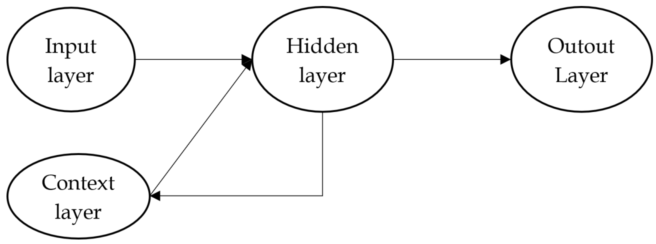


Figure 2. Network Architecture of RNN

The flow in predicting the population growth rate by comparing the Multilayer Perceptron and Recurrent Neural Network methods is as shown in Figure 3.

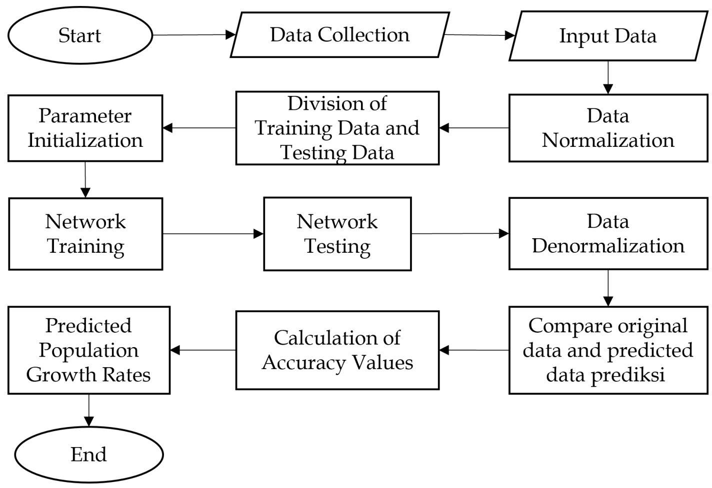


Figure 3. Research Flowchart

Here are the procedures for applying Multilayer Perceptron and Recurrent Neural Network methods:

1. Data Collectiing
   This research analyses the population growth rate of Brebes Regency from 1991-2022. For this research, the secondary data is obtained from previous research by other researchers and not by direct observation [19]. The data resource is the total population data from 1991-2022, and obtained from the website of Badan Pusat Statistik (BPS) Brebes [4].
2. Determining Input Value
   After collecting the data, the next step is to determine the input values by arranging the data in 5 years, namely X_1, X_2, X_3, X_4, X_5. Meanwhile, the target for the following year is (Y).
3. Data Normalization
   Essentially, normalization is changing the data to be in the range of 0 to 1.
4. Data Division
   The data is divided into two types: training data and testing data.
5. Parameter Initialization
   Determining network parameters to obtain the best model.
6. Network Training
   Forecasting using the MLP and RNN method focuses on train-

ing the network to be able to understand value patterns based on historical data in order to predict future values. The Multilayer Perceptron training stage is to identify the results of the input layer, hidden layer, and output layer on the training target. Meanwhile, the Recurrent Neural Network training stage is to identify the results of the input layer, recurrent layer, hidden layer, and output layer on the training target.

7. Network Testing
   Using obtained modeling from network training, such as architecture, parameter, activation function, and value.
8. Data Denormalization
   Reverting the data to the original number.
9. Comparing original data and prediction data from 1991-2022.
10. Calculating the Accuracy Value
    Determining the category of architecture model
11. Calculating the prediction result of the population growth rate for 2023-2026.
12. Comparing the MAPE of these methods to determine the most suitable one.
    Mean Absolute Percentage Error (MAPE) is the absolute value of the percentage error to the mean. MAPE is used to measure the error of the model's predicted value which is shown in the form of a percentage of the mean absolute error. The MLP and RNN methods are compared to find the best method by looking at the smallest MAPE value.

3. Results and Discussion

3.1. Data Collecting

The first step in this research is data collection. Population data in Brebes Regency was obtained from Badan Pusat Statistik [4]. Data on the population of Brebes Regency for 1991-2022 is shown in Table 1.

Table 1. Total population of Brebes

No.	Year	Population (Person)	No.	Year	Population (Person)
1	1991	1,536,534	17	2007	1,743,195
2	1992	1,542,775	18	2008	1,747,430
3	1993	1,548,928	19	2009	1,752,128
4	1994	1,555,424	20	2010	1,736,331
5	1995	1,561,329	21	2011	1,742,511
6	1996	1,567,044	22	2012	1,748,510
7	1997	1,572,878	23	2013	1,764,648
8	1998	1,577,631	24	2014	1,773,379
9	1999	1,583,426	25	2015	1,781,379
10	2000	1,698,635	26	2016	1,788,880
11	2001	1,705,433	27	2017	1,796,004
12	2002	1,711,657	28	2018	1,802,829
13	2003	1,717,103	29	2019	1,809,096
14	2004	1,722,306	30	2020	1,978,759
15	2005	1,727,708	31	2021	1,992,685
16	2006	1,736,401	32	2022	2,010,617

After the data is collected in Table 1, the data is then processed as input for each prediction method. The prediction process will be carried out using the Multilayer Perceptron method and the Recurrent Neural Network method.

3.2. Determening Input Value

Input value is an input value that describes a problem to be studied in the network in order to provide output value. Input pattern functions to divide data into training data and testing data. The time series pattern appears five times. It means there are five input data, and the desired output is after the fifth data. The appearing pattern refers to [20]. The time series pattern is shown in Table 2.

Table 2. Time series data of total population

No	X_1	X_2	X_3
1	1,536,534	1,542,775	1,548,928
2	1,542,775	1,548,928	1,555,424
3	1,548,928	1,555,424	1,561,329
4	1,555,424	1,561,329	1,567,044
5	1,561,329	1,567,044	1,572,878
⋮	⋮	⋮	⋮
27	1,796,004	1,802,829	1,809,096
No	**X_4**	**X_5**	**Y**
1	1,555,424	1,561,329	1,567,044
2	1,561,329	1,567,044	1,572,878
3	1,567,044	1,572,878	1,577,631
4	1,572,878	1,577,631	1,583,426
5	1,577,631	1,583,426	1,698,635
⋮	⋮	⋮	⋮
27	1,978,759	1,992,685	2,010,617

The pattern used to predict the output in Table 2 is to use input for the previous five years. The X value indicates the amount of data to be used as input, namely, X_i, $i = 1, 2, 3, 4, 5$. While the target or output in the training and testing process is indicated by the Y value.

3.3. Data Normalization

Data normalization is the scaling of input and target values so that they fall into a certain range. Normalization aims to ensure that input and target data are in accordance with the activation function used [21]. The activation function is a function that describes the relationship between the level of internal activation or summation function which can be linear or nonlinear. The purpose of the activation function is to replace the output signal with an input signal. The formula to calculate normalization [22]:

$$x'_i = \frac{0.8(x_i - x_{min})}{(x_{max} - x_{min})} + 0.1, \tag{1}$$

with

x'_i	=	data normalization result on *i* index
0.8	=	optimum default value of normalization
x_i	=	the data that will be normalized
x_{min}	=	lowest data value
x_{max}	=	highest data value
0.1	=	minimum default value of normalization.

The minimum data value and maximum data value based on the data in Table 2 are x_{min} = 1,536,534 and x_{max} = 2,010,617. The normalized value of X_1 is 0.1.

$$x'_i = \frac{0.8(1,536,534 - 1,536,534)}{(2,010,617 - 1,536,534)} + 0.1 = 0.1.$$

The results of data normalization calculations for all data in Table 2 are shown in Table 3.

Table 3. Data normalization

No	X_1	X_2	X_3	X_4	X_5	Y
1	0.1	0.11053	0.12091	0.13188	0.14184	0.15148
2	0.11053	0.12091	0.13188	0.14184	0.15148	0.16133
3	0.12091	0.13188	0.14184	0.15148	0.16133	0.16935
4	0.13188	0.14184	0.15148	0.16133	0.16935	0.17913
5	0.14184	0.15148	0.16133	0.16935	0.17913	0.37354
⋮	⋮	⋮	⋮	⋮	⋮	⋮
27	0.53785	0.54936	0.55994	0.84624	0.86974	0.9

The normalized data in Table 3 will be used in the training and testing process.

3.4. Data Division

The data used in this forecast is divided into two, namely training data and testing data. Training data is data used to train or form patterns in neural networks. While testing data is data used to determine the performance of patterns in previously trained neural networks, namely when obtaining new data that is not given in the training data. The results of data normalization in Table 3 are divided into training data and testing data. The percentage of data division for this research is presented in Table 4.

Table 4. MLP and RNN data division

Data Division	Percentage	Data
Training	80%	22
Testing	20%	5
Total	100%	27

The division of data in Table 4 refers to Hardiyanti's [23] that shows this 80:20 division will produce the lowest MSE than any other data comparisons.

3.5. Parameter Initialisation

Before carrying out the training process, it is necessary to determine the parameters that aim to form a network model. The network modeling process in Matlab is by selecting new then creating a new network. The research parameters used are as follows.

1. The number of input layer neurons is 5: X_1, X_2, X_3, X_4, X_5.
2. The number of hidden layer neurons: 5, 6, 7, 8, 9, and 10. The number of neurons models the network architecture and determines the lowest MSE value. There is no exact theory for choosing the number of hidden neurons [24]. Thus, the above numbers are used to obtain the best architecture model based on the lowest MSE value.
3. The number of neurons in the output layer is 1, Y.
4. The applied training function is Levenberg-Marquest (LM). *trainlm* is a training function with the best capacity in prediction [25].
5. The applied adaption learning function is *learngdm*. This function will achieve the optimum result [26].
6. The applied transfer function is sigmoid bipolar (*tansig*) and linear (*purelin*). The combination of these functions will achieve the lowest MSE value [25].
7. The maximum epoch is 1000. The number of 1000 will obtain the best MSE value [27]. The training process of each model is conducted 20 times as the weight of the data is changing [28].

3.6. Network Training

In the study using the MLP and RNN methods, 80% of the training data used was data from 1991 to 2017. The MLP and RNN training process used the 5-5-1, 5-6-1, 5-7-1, 5-8-1, 5-9-1, and 5-10-1 architectural models. Training the 5-5-1 architectural model means that there are 5 neurons in the input layer (X_1, X_2, X_3, X_4, X_5) plus a bias, 5 neurons in the hidden layer (z_1, z_2, z_3, z_4, z_5) plus a bias, 1 neuron in the output layer (Y). Training a 5-6-1 architecture model means there are 5 neurons in the input layer (X_1, X_2, X_3, X_4, X_5) plus a bias, 6 neurons in the hidden layer ($z_1, z_2, z_3, z_4, z_5, z_6$) plus a bias, 1 neuron in the output layer (Y). Training a 5-7-1 architecture model means there are 5 neurons in the input layer (X_1, X_2, X_3, X_4, X_5) plus a bias, 7 neurons in the hidden layer ($z_1, z_2, z_3, z_4, z_5, z_6, z_7$) plus a bias, 1 neuron in the output layer (Y). Training a 5-8-1 architecture model means there are 5 neurons in the input layer (X_1, X_2, X_3, X_4, X_5) plus a bias, 8 neurons in the hidden layer ($z_1, z_2, z_3, z_4, z_5, z_6, z_7, z_8$) plus a bias, 1 neuron in the output layer (Y). Training a 5-9-1 architecture model means there are 5 neurons in the input layer (X_1, X_2, X_3, X_4, X_5) plus a bias, 9 neurons in the hidden layer ($z_1, z_2, z_3, z_4, z_5, z_6, z_7, z_8, z_9$) plus a bias, 1 neuron in the output layer (Y). Training a 5-10-1 architecture model means there are 5 neurons in the input layer (X_1, X_2, X_3, X_4, X_5) plus a bias, 10 neurons in the hidden layer ($z_1, z_2, z_3, z_4, z_5, z_6, z_7, z_8, z_9, z_{10}$) plus a bias, 1 neuron in the output layer (Y).

3.7. Network Testing

The next stage after the training process is to test all models. Network testing was carried out on population data for Brebes Regency in 2018-2022. Table 5 and Table 6 are the of simulation results for testing 6 models using the MLP and RNN methods.

Table 5. Output (Y) of MLP Testing Results

Year	Target	Model					
		5-5-1	5-6-1	5-7-1	5-8-1	5-9-1	5-10-1
2018	0.54936	0.58578	0.54806	0.57927	0.57043	0.57164	0.55903
2019	0.55994	0.61441	0.55362	0.61918	0.5851	0.59966	0.5743
2020	0.84624	0.63927	0.55646	0.66062	0.59416	0.62784	0.58621
2021	0.86974	0.77802	0.59401	0.71935	0.59036	0.86161	0.53647
2022	0.9	0.78233	0.59327	0.61146	0.83949	0.97234	0.5676

Table 6. Output (Y) of RNN Testing Results

Year	Target	Model					
		5-5-1	5-6-1	5-7-1	5-8-1	5-9-1	5-10-1
2018	0.54936	0.54406	0.55531	0.55383	0.57536	0.5774	0.55321
2019	0.55994	0.55049	0.56929	0.56919	0.5994	0.60291	0.56055
2020	0.84624	0.55517	0.58133	0.58259	0.62193	0.62657	0.56476
2021	0.86974	0.71276	0.76134	0.92351	0.50614	0.85436	0.66462
2022	0.9	0.69969	0.72765	1.0065	0.45841	0.92107	0.54902

After obtaining the output value of the testing results using MLP and RNN, the MSE (Mean Square Error) value of the six models is then searched to obtain the best architectural model. The MSE error value for 6 models is shown in Table 7.

Table 7. The error value of MSE testing

Model	Error MSE MLP	Error MSE RNN
5-5-1	0.013877753	0.029921191
5-6-1	0.050824881	0.022351043
5-7-1	0.028946251	0.016770066
5-8-1	0.029267188	0.075950951
5-9-1	0.011014362	0.010313612
5-10-1	0.057894794	0.048901472

According to Table 7, the best architecture model of MLP and RNN is the 5-9-1 model. This model is the best one because the obtained MSE has the lowest than any other model. Furthermore, this 5-9-1 model is used to predict the population growth rate. Table 8 shows a comparison of testing the MLP and RNN methods with the 5-9-1 model previously obtained in Table 5 and Table 6.

Table 8. Output (Y) value of 5-9-1 testing result

Year	Target	MLP	RNN
2018	0.54936	0.57164	0.5774
2019	0.55994	0.59966	0.60291
2020	0.84624	0.62784	0.62657
2021	0.86974	0.86161	0.85436
2022	0.9	0.97234	0.92107

3.8. *Data Denormalization*

Data denormalization is the process of returning normalized data from a network with a value between 0.1 and 0.9 to the original data. In Table 8, the output of the 5-9-1 model is still in normalization form. These data will be converted to their original data with denormalization. The process will apply this formula:

$$x_i = \frac{(x'_i - 0.1)(x_{max} - x_{min})}{0.8} + x_{min}, \tag{2}$$

with

x_i	=	data denormalization result on i index
0.8	=	optimum default value of normalization
x'_i	=	the normalized data that will be denormalized
x_{min}	=	lowest data value
x_{max}	=	highest data value
0.1	=	minimum default value of denormalization.

The result of output denormalization is the prediction result from 2018-2022. Table 9 shows the prediction result of the total population from 2018-2022.

In Table 9, the comparison results of the MLP and RNN methods in 2022 show quite significant differences, namely differences reaching tens of thousands.

3.9. *Comparison of Original Data And Prediction Data From 1991-2022*

Table 10 and Table 11 are the results of the comparison of original data and predicted data in the training and testing

Table 9. The Prediction Result of the Total Population from 2018-2022

Year	Total Population	
	MLP	RNN
2018	$1,816,030$	1,819,443
2019	$1,832,634$	1,834,560
2020	$1,849,334$	1,848,581
2021	$1,987,867$	1,983,571
2022	$2,053,486$	2,023,103

process with the MLP and RNN methods before denormalization and after denormalization.

The comparison graph of prediction and original value using MLP and RNN are shown in Figure 4 and Figure 5.

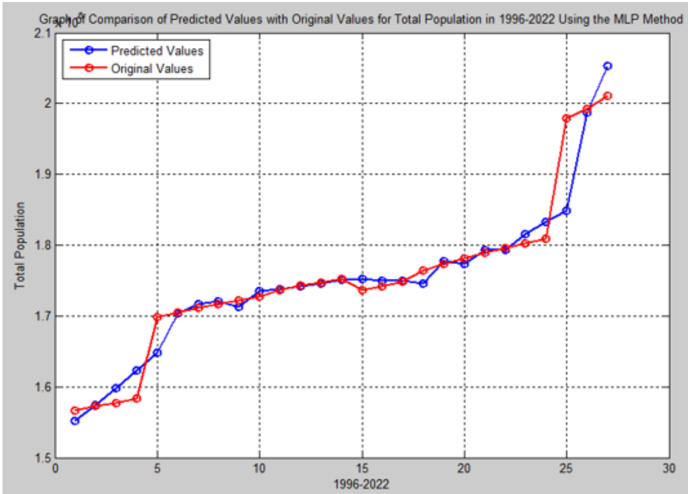


Figure 4. Comparison plot of MLP's prediction value and original value

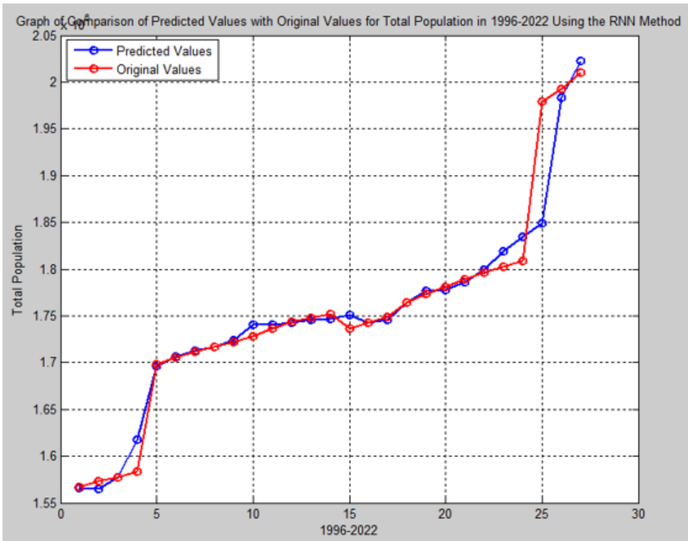


Figure 5. Comparison plot of RNN's prediction value and original value

Figure 4 and Figure 5 shows the plot line between prediction and original value are not much different. It can be concluded the prediction result of Brebes' total population from

Table 10. Comparison of MLP prediction value and RNN prediction value before denormalization

Year	Original Value	MLP Prediction Value	RNN Prediction Value	Year	Original Value	MLP Prediction Value	RNN Prediction Value
1991	0.15148	-	-	2007	0.4577	0.44563	0.44766
1992	0.16133	-	-	2008	0.48494	0.45339	0.45305
1993	0.16935	-	-	2009	0.49967	0.4622	0.45495
1994	0.17913	-	-	2010	0.51317	0.46523	0.4616
1995	0.37354	-	-	2011	0.52583	0.46109	0.44866
1996	0.38501	0.12672	0.15006	2012	0.53785	0.4598	0.45371
1997	0.39551	0.16467	0.14866	2013	0.15148	0.45436	0.48451
1998	0.4047	0.20471	0.16952	2014	0.16133	0.50756	0.50562
1999	0.41348	0.24747	0.2367	2015	0.16935	0.49999	0.50707
2000	0.4226	0.28937	0.36898	2016	0.17913	0.53294	0.52143
2001	0.43727	0.3822	0.38728	2017	0.37354	0.5338	0.54315
2002	0.44873	0.40495	0.39662	2018	0.54936	0.57164	0.5774
2003	0.45588	0.41093	0.40427	2019	0,55994	0.59966	0.60291
2004	0.46381	0.39719	0.41658	2020	0.84624	0.62784	0.62657
2005	0.43715	0.43652	0.44468	2021	0.86974	0.86161	0.85436
2006	0.44758	0.43978	0.4438	2022	0.9	0.97234	0.92107

Table 11. Comparison of MLP prediction value and RNN prediction value after denormalization

Year	Original Value	MLP Prediction Value	RNN Prediction Value	Year	Original Value	MLP Prediction Value	RNN Prediction Value
1991	1,536,534	-	-	2007	1,743,195	1,741,356	1,742,559
1992	1,542,775	-	-	2008	1,747,430	1,745,954	1,745,753
1993	1,548,928	-	-	2009	1,752,128	1,751,175	1,746,879
1994	1,555,424	-	-	2010	1,736,331	1,752,971	1,750,820
1995	1,561,329	-	-	2011	1,742,511	1,750,517	1,743,151
1996	1,567,044	1,552,368	1,566,200	2012	1,748,510	1,749,753	1,746,144
1997	1,572,878	1,574,858	1,565,370	2013	1,764,648	1,746,529	1,764,396
1998	1,577,631	1,598,586	1,577,732	2014	1,773,379	1,778,056	1,776,906
1999	1,583,426	1,623,925	1,617,543	2015	1,781,379	1,773,570	1,777,765
2000	1,698,635	1,648,755	1,695,933	2016	1,788,880	1,793,096	1,786,275
2001	1,705,433	1,703,767	1,706,777	2017	1,796,004	1,793,606	1,799,146
2002	1,711,657	1,717,249	1,712,312	2018	1,802,829	1,816,030	1,819,443
2003	1,717,103	1,720,792	1,716,846	2019	1,809,096	1,832,634	1,834,560
2004	1,722,306	1,712,650	1,724,140	2020	1,978,759	1,849,334	1,848,581
2005	1,727,708	1,735,957	1,740,793	2021	1,992,685	1,987,867	1,983,571
2006	1,736,401	1,737,889	1,740,271	2022	2,010,617	2,053,486	2,023,103

1996-2022 using RNN is close to the actual value.

3.10. Comparison of Original Data And Prediction Data From 1991-2022

After the testing process of the 2018-2022 data, the original data of the corresponding years will be evaluated. This evaluation aims to measure the model performance in predicting. MAPE, as the applied evaluation method, has the value is shown in Table 12.

Table 12. MLP's MAPE value result

Year	Total Population		Absolute Percentage Error
	Prediction Result	Original Data	
2018	1816030	1802829	0.732238
2019	1832634	1809096	1.301092
2020	1849334	1978759	6.540716
2021	1987867	1992685	0.241784
2022	2053486	2010617	2.132132
MAPE			2.189592

According to Table 12, the category of MAPE value for Multilayer Perceptron's prediction is very well as the result is below 10%. The MAPE test results using the RNN method are shown in Table 13.

Table 13. RNN's MAPE value result

Year	Total Population		Absolute Percentage Error
	Prediction Result	Original Data	
2018	1819443	1802829	0,921553
2019	1834560	1809096	1,407573
2020	1848581	1978759	6,578752
2021	1983571	1992685	0,457395
2022	2023103	2010617	0,621011
MAPE			2,189592

According to Table 13, the category of MAPE value for Recurrent Neural Network's prediction is very well as the result is below 10%.

3.11. The Prediction Result Of The Population Growth Rate For 2023-2026

The prediction results of the population growth rate for 2023-2026 after denormalization are shown in Table 14.

Table 14. The prediction results of the total population

Year	MLP Prediction	RNN Prediction
2023	2062478	2026372
2024	2073673	2027091
2025	2058963	2022253
2026	2069341	2023467

According to Table 14, the population growth rate from 2023-2026 can be calculated using the total population data of 2022; 2,010,617. Below is the formula to calculate the population growth rate with geometric method:

$$r = \left(\frac{P_t}{P_0}\right)^{\frac{1}{t}} - 1, \tag{3}$$

with

P_t = total population of t year

P_0 = total population of base year

r = population growth rate

t = time period between t year and base year (in year).

Population growth rate categories are shown in Table 15 [29].

Table 15. The category of population growth rate

Population growth rate (r)	Category
$r > 0$	Population increase
$r = 0$	Population stagnant
$r < 0$	Population decrease

Table 16 containing the prediction result of Brebes' population growth from 2023-2026.

Table 16. The MLP's prediction result of population growth rate

Year	MLP's Prediction Result	RNN's Prediction Result
2023	2.579%	0.784%
2024	1.556%	0.409%
2025	0.795%	0.193%
2026	0.722%	0.159%

According to Table 16 the value of the population growth rate for 2023, 2024, 2025, and 2026 is > 0. It can be concluded that there is a population increase in each year. The results of predicting the population growth rate of the Brebes Regency in 2023-2026 using the Multilayer Perceptron method are as follows.

1. The prediction result of the population growth rate in 2023 is 2.579%, which means that there is an increase in population of 51,861 people from 2022 to 2023.
2. The prediction result of the population growth rate in 2024 is 1.556%, which means that there is an increase in population of 63,056 people from 2022 to 2024.
3. The prediction result of the population growth rate in 2025 is 0.795%, which means an increase in population of 48,346 people from 2022 to 2025.
4. The prediction result of the population growth rate in 2026 is 0.722%, which means an additional population of 58,724 people from 2022 to 2026.

The prediction results of the population growth rate of Brebes Regency in 2023-2026 using the Recurrent Neural Network method are as follows.

1. The prediction result of the population growth rate in 2023 is 0.784%, which means that there is an increase in population of 15,755 people from 2022 to 2023.
2. The prediction result of the population growth rate in 2024 is 0.409%, which means that there is an additional population of 16,474 people from 2022 to 2024.
3. The prediction result of the population growth rate in 2025 is 0.193%, which means an increase in population of 11,636 people from 2022 to 2025.
4. The prediction result of the population growth rate in 2026 is 0.159%, which means that there will be an additional population of 12,850 people from 2022 to 2026.

3.12. Comparison of Multilayer Perceptron and Recurrent Neural Network

Comparing these two methods requires an analysis of the accuracy value to determine which method is the most suitable with the lowest MAPE error. The results of the comparison of MAPE values for the MLP and RNN methods are shown in Table 17.

Table 17. Comparison Result of MLP's and RNN's MAPE Value

Method	MAPE
MLP	2.1896
RNN	1.9973

The prediction results in Table 17 show that MLP and RNN methods have MAPE $< 10\%$, making these methods suitable for prediction. The accuracy value is calculated using MAPE value with the below equation:

$$Accuracy = 100\% - MAPE. \tag{4}$$

The comparison of the accuracy values of MLP and RNN is shown in Table 18.

Table 18. MLP's and RNN's Accuracy Value Comparison Result

Method	Accuracy
MLP	97.8%
RNN	98%

The RNN method is the most suitable for predicting based on the MAPE value shown in Table 17 and Table 18. Its MAPE is lower than MLP methods, and its accuracy is higher than MLP. Based on released data by BPS Brebes, the population of Brebes in 2023 is 2,043,077, so the population growth rate from 2022 to 2023 is 1.614%. The difference in the value of the original data population growth rate minus the MLP prediction data is -0.965%, and the difference in the value of the original data population growth rate minus the RNN prediction data is 0.83%.

4. Conclusion

According to the result and discussion, it can be concluded, namely comparison of the MAPE value of prediction results using the Multilayer Perceptron (MLP) and Recurrent Neural Network (RNN) methods with 80% training data division and 20% testing data resulted in the RNN method getting a smaller MAPE value of 1.9973% compared to the MLP method which is 2.1896%. The accuracy value for the RNN method is 98% and for the MLP method, the accuracy value is 97.8%. Based on the comparison of the MAPE values, the RNN method is better than the MLP method.

Author Contributions. **Izzatul Yazidah:** Conceptualization, methodology, software, formal analysis, investigation, resources, data curation, writing—original draft preparation, visualization, funding acquisition. **Emy Siswanah:** Conceptualization, validation, writing—review and editing, visualization, supervision, project administration. All authors have read and agreed to the published version of the manuscript.

Acknowledgement. We express our heartfelt thanks to the editors and reviewers for their meticulous review, insightful feedback, and constructive suggestions, which have greatly enhanced the quality of this paper.

Funding. This research received no external funding.

Conflict of interest. The authors declare no conflict of interest related to this article.

Data availability. Not applicable.

References

[1] WorldBank, "Population total," World Bank, 2022. [Online]. Available https://data.worldbank.org/indicator/SP.POP.TOTL.

[2] A. Akhirul, Y. Witra, I. Umar, and E. Erianjoni, "Dampak Negatif Pertumbuhan Penduduk terhadap Lingkungan dan Upaya Mengatasinya," *J. Kependud. dan Pembang. Lingkung.*, vol. 1, no. 3, pp. 76–84, 2020.

[3] P. Hardati, "Pertumbuhan Penduduk dan Struktur Lapangan Pekerjaan di Jawa Tengah," *Forum Ilmu Sos.*, vol. 40, no. 2, pp. 219–229, 2013, doi: 10.15294/fis.v40i2.5363.

[4] BPS, "Jumlah Penduduk Kab. Brebes Menurut Kecamatan (Jiwa)," BPS (Badan Pusat Statistik) Kabupaten Brebes, 2022. [Online]. Available: https://brebeskab.bps.go.id/id/statistics.

[5] T. A. Fauziyah and A. P. Utomo, "Angka Kemiskinan Brebes Turun 1,38 Persen, Wagub Taj Yasin: Gencarkan Lagi," 2023. [Online]. Available: https://regional.kompas.com/read/2023/01/13/201919078.

[6] Y. Arafat, "Penduduk Brebes Terbanyak di Jateng," 2021. [Online]. Available: https://jatengprov.go.id/beritadaerah/sp2020.

[7] T. Hafizah and D. K. Pane, *JST for Beginner: Memulai Belajar Konsep Dasar Jaringan Syaraf Tiruan*. Jambi: PT. Sonpedia Publishing Indonesia, 2023.

[8] F. Pakaja, A. Naba, and Purwanto, "Peramalan Penjualan Mobil Menggunakan Jaringan Syaraf Tiruan dan Certainty Factor," *J. EECCIS*, vol. 6, no. 1, pp. 23–28, 2012, doi: 10.21776/jeeccis.v6i1.162.

[9] B. Choubin, S. Khalighi-Sigaroodi, A. Malekian, and Ö. Kişi, "Multiple Linear Regression, Multilayer Perceptron Network and Adaptive Neuro-Fuzzy Inference System for the Prediction Of Precipitation Based On Large-Scale Climate Signals," *Hydrol. Sci. J.*, vol. 61, no. 6, pp. 1001–1009, 2014, doi: 10.1080/02626667.2014.966721.

[10] S. Nooriansyah, "Analisis Kinerja Metode Artificial Neural Network dan Support Vector Regression untuk Prediksi Significant Wave Height," *J. Teknol. Inf. dan Komun.*, vol. 13, no. 1, pp. 17–24, 2018, doi: 10.33005/scan.v13i1.1054.

[11] A. B. Aribowo, D. Sugiarto, I. A. Marie, and J. F. A. Siahaan, "Peramalan Harga Beras IR64 Kualitas III Menggunakan Metode Multilayer Perceptron, Holt-Winters Dan Auto Regressive Integrated Moving Average," *J. Tek. Inform.*, vol. 11, no. 2, pp. 60–64, 2019, doi: 10.31937/ti.v11i2.1246.

[12] J. Wang, J. Wang, W. Fang, and H. Niu, "Financial Time Series Prediction Using Elman Recurrent Random Neural Networks," *Comput. Intelligence Neurosci.*, vol. 2016, 2016, doi: 10.1155/2016/4742515.

[13] A. Farhah, A. L. Prasasti, and M. Paryasto, "Implementasi Recurrent Neural Network dalam Memprediksi Kepadatan Restoran Berbasis LSTM," *J. Media Inform. Budidarma*, vol. 5, no. 2, pp. 524–531, 2021, doi: 10.30865/mib.v5i2.2916.

[14] N. Hermawan, "Aplikasi Model Recurrent Neural Network dan Recurrent Neuro Fuzzy untuk Peramalan Banyaknya Penumpang Kereta Api Jabodetabek," Skripsi, Universitas Negeri Semarang, 2014.

[15] A. F. Achmalia, Walid, and Sugiman, "Peramalan Penjualan Semen Menggunakan Backpropagation Neural Network dan Recurrent Neural Network," *Unnes J. Math.*, vol. 9, no. 1, pp. 6–21, 2020, doi: 10.15294/ujm.v9i1.29970.

[16] E. A. Kusnanti et al., "Predicting Velocity and Direction of Ocean Surface Currents using Elman Recurrent Neural Network Method," *J. Inf. Syst. Eng. Bus. Intell.*, vol. 8, no. 1, pp. 21–30, 2022, doi: 10.20473/jisebi.8.1.21-30.

[17] E. Mulyatiningsih, *Riset Terapan Bidang Pendidikan dan Teknik*. Yogyakarta: Universitas Negeri Yogyakarta, 2011.

[18] M. A. Zakariah, *Metodologi Penelitian Kualitatif, Kuantitatif, Action Research, Research and Development (RnD)*. Kolaka: Yayasan Pondok Pesantren Al Mawaddah Warrahmah, 2020.

[19] A. Marisya and E. Sukma, "Konsep Model Discovery Learning pada Pembelajaran Tematik Terpadu di Sekolah Dasar menurut Pandangan para Ahli," *J. Pendidik. Tambusai*, vol. 4, no. 3, pp. 2189–2198, 2020, doi: 10.31004/jptam.v4i3.697.

[20] A. Y. Anggoro, "Aplikasi Jaringan Syaraf Tiruan dengan Algoritma Backpropagasi untuk Memprediksi Perubahan Harga Saham LQ 45," *Semnaptika*, vol. 1, no. 1, pp. 46–53, 2023.

[21] S. Kusumadewi, *Membangun Jaringan Syaraf Tiruan: Menggunakan MATLAB & Excel Link*. Yogyakarta: Graha Ilmu, 2004.

[22] A. P. Windarto et al., *Jaringan Syaraf Tiruan: Algoritma Prediksi dan Implementasi*. Medan: Yayasan Kita Menulis, 2020.

[23] A. F. Hardiyanti and D. Fitrianah, "Perbandingan Algoritma C4.5 dan Multilayer Perceptron untuk Klasifikasi Kelas Rumah Sakit di DKI Jakarta," *J. Telekomun. dan Komput.*, vol. 11, no. 3, pp. 198–209, 2021, doi: 10.22441/incomtech.v11i3.10632.

[24] J. J. Siang, *Jaringan Syaraf Tiruan dan Pemrogramannya Menggunakan Matlab*. Yogyakarta: CV. Andi Offset, 2009.

[25] M. B. El Houari, O. Zegaoui, and A. Abdallaoui, "Prediction of Air Temperature Using Multi-layer Perceptrons with Levenberg-Marquardt Training Algorithm," *Int. Res. J. Eng. Technol.*, vol. 02, no. 08, pp. 26–32, 2015.

[26] D. O. Deltania, "Prakiraan Kebutuhan Energi Listrik Wilayah Provinsi Jawa Tengah menggunakan Metode Backpropagation Neural Network dan Metode Ekstrapolasi Linier," *J. Simetris*, vol. 14, no. 2, pp. 351–365, 2023, doi: 10.24176/simet.v14i2.9487.

[27] W. Santoso, "Prediksi Volume Sampah di TPSA Banyuurip Menggunakan Metode Backpropagation Neural Network," *J. Media Inform. Budidarma*, vol. 7, no. 1, pp. 464–472, 2023, doi: 10.30865/mib.v7i1.5499.

[28] H. Mustafidah, M. Z. Budiastanto, and Suwarsito, "Kinerja Algoritma Pelatihan Levenberg-Marquardt dalam Variasi Banyaknya Neuron pada Lapisan Tersembunyi," *JUITA J. Inform.*, vol. 7, no. 2, pp. 115–123, 2019, doi: 10.30595/juita.v7i2.5863.

[29] D. Desriwendi, A. Hoyyi, and T. Wuryandari, "Pemodelan Geographically Weighted Logistic Regression (GWLR) dengan Fungsi Pembobot Fixed Gaussian Kernel dan Adaptive Gaussian Kernel," *J. Gaussian*, vol. 4, no. 2, pp. 193–204, 2015, doi: 10.14710/j.gauss.4.2.193-204.