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Forecasting Malaysian Exchange Rate using Artificial Neural Network

Ikhwan Muzammil Amran[1*], Anas Fathul Ariffin[2]

[1,2] Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA Cawangan Perlis, 02600 Arau, Malaysia

Authors' Email Address:anasfathul@gmail.com

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ABSTRACT

In todays fast paced global economy, the accuracy in forecasting the foreign exchange rate or predicting the trend is a critical key for any future business to come. The use of computational intelligence based techniques for forecasting has been proved to be successful for quite some time. This study presents a computational advance for forecasting the Foreign Exchange Rate in Kuala Lumpur for Ringgit Malaysia against US Dollar. A neural network based model has been used in forecasting the days ahead of exchange rate. The aims of this research are to make a prediction of Foreign Exchange Rate in Kuala Lumpur for Ringgit Malaysia against US Dollar using artificial neural network and determine practicality of the model. The Alyuda NeuroIntelligence software was utilized to analyze and to predict the data. After the data has been processed and the structural network compared to each other, the network of 2-4-1 has been chosen by outperforming other networks. This network selection criteria are based on Akaike Information Criterion (AIC) value which shows the lowest of them all. The training algorithm that applied is Quasi-Netwon based on the lowest recorded absolute training error. Hence, it is believed that experimental results demonstrate that Artificial Neural Network based model can closely predict the future exchange rate.

Keywords: *Artificial Neural Network, modelling, exchange rates, non-linear models.*

INTRODUCTION

Over the course of monetary history, the Malaysian monetary system has evolved into various forms since the breakdown of Bretton Woods system in the early 1970s. On August 1975, Malaysian currency which previously named as Malaysian Dollar has retitled as "Ringgit". But even Ringgit is an official action by the government, Malaysian legal tender is still called "Dollar". This is continued until 1993 when Government announced that the currency will be replaced as "Ringgit Malaysia" (Joe et al., 2016). The following events is vital to occur for Malaysian exchange rate.

Perhaps the most memorable event for Malaysian economic experienced is the year of 1997 which is Asian financial crisis. The countries who are affected greatly along with the crisis are Thailand, South Korea, and Indonesia while Malaysia, Philippine, Taiwan, and Laos had a moderate effect. The catastrophic event started at 30 September 1997 when US Dollar against Ringgit Malaysia currency

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exchanging at RM3.2250 per USD and it does not stop right there when momentous low on 7 January 1998, exchanging at RM4.8800 per USD (Yakob and Yaacob, 2000). Also by the same author, this disastrous event stays in a tough situation just before August, 1998 when Ringgit exchanging at RM4.0900 to RM4.2650 per USD. In September 2 1998, Malaysian government made a drastic move by pegging the Ringgit to US Dollar at RM3.80 per USD (Umezaki, 2007). This action has taken place 13 months right after the crisis began. After quite some time, in July Ringgit pegging to USD was changed to managed float system (Joe et al., 2016). This announcement was done right after China's Yuan ended pegging towards USD in 2005 (Azeem et al., 2017). Floating exchange rate decided by market forces, such as supply and demand with a little possibility intervene by the government (Mida, 2013). The justification of Malaysia transition from fixed exchange rate regime to managed float practices is because it is very difficult to deal with monetary policy autonomy, fixed exchange rate regime and open capital market alongside each other despite it may be achievable in temporary period (Joe et al., 2016).

RELATED WORKS

According to the study conducted by Chandrasekara and Tilakaratne (2009) about forecasting exchange rate, they were focused on finding a neural network model to forecast exchange rate of the US Dollar against Sri Lankan Rupee. Their study involved about ten years data of daily exchange rate of the LKR/USD from 1st January 1998 to 28th November 2008. For the input, the data of variable directly collected from Central Bank of Sri Lanka. For the study, they used three types of ANN models to predict the exchange rate which are feedforward neural network (FFNN) with backpropagation algorithm (BPR), FFNN with scaled conjugate gradient algorithm (SCG) and time delay neural network (TDNN). From the study, the result show that TDNN surpass the other model in term of performance and can be considered as the prime model to forecast exchange rate.

Kadilar et al. (2009) also carry out a research about predicting of exchange rate for Turkey. For the methodology, they used neural network as unorthodox forecasting method compare to periodic of autoregressive integrated moving average (ARIMA) and autoregressive conditional heteroskedasticity (ARCH). For the data, the duration of the data is from 3rd January 2005 to 28th January 2008 in weekly rates. The Turkish TL/USD data set acquired by 160 surveys from Central Bank of Turkey. The result concluded that ANN method is greater forecasting preciseness comparing to time series models such ARIMA and ARCH.

Besides, there are also previous study that has been conducted by Leung et al. (2000) about forecasting exchange rates. Based on their research article, the objective of their studies is analyzing the ability of forecasting for a particular neural network architecture that is general regression neural network (GRNN) and comparing the result to various model inclusive of multi-layered feedforward network (MLFN), multivariate transfer function, and random walk models. The set data for this study are obtained from AREMOS data base serve by Department of Education of Taiwan. The whole data contain 259 monthly time from January 1974 through July 1995. The empirical experiment results show that GNRR is prominent than variant neural network also economic approach contain in the research. The result also shows that forecasting capability of GRNN has possibility to solve financial forecasting problems.

Kamruzzaman and Sarker (2003) conducted a study to do a simulation forecast about currency of exchange rates of six currencies against Australian Dollar based on historical and moving average technical indicators. This study involved the use of three ANN based forecasting model using Standard Backpropagation (SBP), Scaled Conjugate Gradient (SCG) and Backpropagation with Baysian Regularization (BR). These models were evaluated on five widely used performance metrics namely, Normalized Mean Square Error (NMSE), Mean Absolute Error (MAE), Directional Symmetry (DS), Correct Up trend (CU) and Correct Down trend (CD). These criteria then are compared against traditional ARIMA. The results show that all neural network models generate superior achievement compare to linear ARIMA model demonstrating its acceptability for financial modelling. Among of three ANN based models, SCG based model present optimum statistic based on two best metrics.

Besides that, Erdogan and Goksu (2014) has done a study to predictive accuracy of ANN with normalized back propagation implementing exchange rates of Euro against Turkish Lira. Several factors act on the accuracy of neural network in executing procedure such as the instability nature of exchange rates. This study consists of exchange rates over the period from 2010 to 2013 ANN model are developed by rework the number of neuros, transfer functions and learning algorithms to obtain better statistical result. This empirical research continued comparative study of precision in different ANN method also in vary time horizons. The models were assessed based on Mean Squared Error (MSE) values and the results revealed that ANN actually capable to closely forecast the future exchange rates of Euro against Turkish Lira. Based on the observation they also found such network is more efficient in temporary predicting compared to long lasting forecast.

Artificial neural network provides better forecasting accuracy in short-term prediction method. Galeshchuk (2016) investigated the forecasting accuracy of artificial neural network using three time period of forecast namely daily step, monthly step and quarterly step with different time period of data collection respectively with the exchange rates of EUR against USD, GBP against USD and USD against JPY. The forecast values then were compared to actual value of exchange rate using prediction errors. The results revealed that daily step outperform other time period with average and maximum respective prediction errors are 0.2-0.4% for the exchange rate EUR/USD, 0.2-0.9% for the exchange rate GBP/USD and 0.3-1.3% for exchange rate USD/JPY respectively.

In another study, Philip et al. (2011) shows an artificial neural system study based model on forecasting the exchange rates of notable currencies against Nigerian Money. The authors then claim that current statistical models for forecasting incompetent to forecast the foreign exchange rate due to unpredictability and inconstancy character of foreign exchange data. An artificial neural network foreign exchange rate forecasting model (AFERFM) was used against the best known comparable model, Hidden Markov foreign exchange rate forecasting model (HFERFM) to forecast the future exchange rate. Standard Deviation and MSE are residual metrics have been applied to examine the action of the effect. Testing through actual data from http://www.oanada.com website is engaged to test the accuracy of the model. The outcome shows that AFERFM surpass the HFERFM mark in evaluating the foreign exchange rates.

Butt et al. (2019) made a paper namely "Prediction of Malaysian Exchange Rate Using Microstructure Fundamental and Commodities Prices: A Machine Learning Method''. The paper compared the accuracy of artificial neural network, RandomForest and support vector machine methods to forecast Malaysian Ringgit. Butt and her team found that, among these three methods, RandomForest technique is the method in term of model accuracy (error) followed by support vector machine. Which for model accuracy, the authors used Mean Squared Error (RMSE), Mean Absolute Error (MAE), Relative Absolute Error (RAE), and Relative Squared Error (RSE).

METHODOLOGY

The data of current exchange rate of Malaysia was obtained from the web page of Central Bank of Malaysia. The data showed the daily exchange rate from 25th August 2010 to 19th October 2018. Total data are based on 1999 days of exchange rate are used to forecast the exchange rate of Malaysia in 2018 with the information obtained.

The major issue in forecasting is the accurateness of the forecast. A fine forecast is a precise forecast. In statistic, the accuracy of prediction relies on the calculation of the error value of a model. Findings of the previous studies revealed that researchers are inclined to operate ANN as the method for forecasting. It is because ANN method delivers better accuracy of number in contrast to other old methods. The accuracy of the method will be judged by examining the error measure. Mathematical formulas and steps that are applied in this research are shown below:

Step 1: Data Analysis

The dataset has to be analysed first prior to running the data. In this stage, the data has to be transferred into the Alyuda software. The reason of the data analysis is to identify any data anomaly. Data anomaly will trigger the negative impression to the neural network potential capability. Before going to the next step, data anomaly complication has to be solved beforehand. The dataset then will be separated into three division which are training, validation and test set. The separate procedure can be done both in automatic or manual way (Hegde et al., 2015). The dataset then has to be converted into time series mode shows the period and look ahead that has to be set.

Step 2: Data Pre-processing

At data pre-processing step, window checks for pre-processing results. The dataset has to be adjusted first before step into the artificial neural network. The range of operating values for artificial neural neurons is limited, so the adjusting has to be done consistently with transformation of data. The scaling range used for the inputs of the network goes by [-1,1] by using hyperbolic tangent. Meanwhile the scaling range for output goes by [0,1]. The outputs of the network will depend on the activation function and this function known as sigmoid function. The sample signals will consistently be processed along each layer with the sigmoid function (Feng and Lu, 2010).

$$f\left(x\right)=\left(\frac{1}{1+e^{-x}}\right)$$

where *f(x)* is the sigmoid value, *x* represents the value of the data. The value is the total number of the input and weight value.

Step 3: Neural Network Design

At third stage, two characteristics to be decided which are the number of architecture and number of nodes in hidden layer. The number of nodes in hidden layer can be decided depending on Kolmogorov's Superposition Theorem.

$$h=2n+1$$

Where *h* characterizes the total nodes in hidden layer, *n* is the number of nodes in the input layer. The network architecture must be described. Within the stated range, the best network architecture will determine among each of the possible other alternatives.

Step 4: Training

This step will decide on which algorithm is the best and can be used. There are seven choices of algorithms that can be applied in Alyuda NeuroIntelligence namely Quick Propagation, Conjugate Gradien Descent, Quasi-Newton, Limited Memory Quasi-Newton, Levenberg-Marquardt, Online Back Propagation and Batch Back Propagation.

Step 5: Testing

All the data will be tested and validated during this step. The target and output value will be analyzed to attain the error that take place between them. Thus, it helps to obtain the MSE of the dataset.

FINDINGS AND DISCUSSION

Step 1: Data Analysis

Artificial neural network is a network that contains three layers, which are input layers, hidden node layer, and output layers. Software Alyuda Neurointelligence is used to assist the analysis and forecast the exchange rate in Malaysia. Total data input that analysed is 1999 data and separated into training, validation and test.

Step 2: Data Pre-processing

Table 1 shows the data accepted by the software and it consist of three data characteristics separately which is training, validation and testing. Training is present to the network that is an adjusted according to its error, while validation is to determine network generalization and to stop training when generalization stops get better. The last one is testing to evaluate network performance during and after training.

Table 1: Data Accepted for Processing

Data Partition Results of 1998 Row Accepted		
Training	1360	68.07%
Validation	319	15.97%
Test	319	15.97%

Step 3: Neural Network Design

After the data have been processed, the structure network of ANN is performed and all of the structure networks will be compared to each other to gain the best network for forecasting. Table 2 below shows network of [2-4-1] is the outperformed network based on the highest fitness and AIC value.

Table 2: Number of Network Architecture for Exchange Rate

ID	Architecture	Fitness	Train Error	Validation Error	Test Error	AIC	R-Squared
1	2-1-1	24.6886	0.03721	0.03792	0.04051	-14278.70	0.991745
2	2-7-1	126.7368	0.0126	0.0137	0.00789	-15703.71	0.998728
3	**2-4-1**	**136.5434**	**0.01255**	**0.01328**	**0.00732**	**-15732.96**	**0.998724**
4	2-5-1	131.1939	0.01259	0.0132	0.00762	-15720.40	0.998706
5	2-2-1	85.1237	0.01503	0.01509	0.01175	-15503.52	0.998326
6	2-3-1	126.2361	0.01257	0.01367	0.00792	-15739.13	0.998734

Table 2 shows network of [2-4-1] and it is the outperformed network based on the highest fitness and AIC value. The architecture network of [2-4-1] shows the fitness value is 136.543408 and Akaike Information Criterion (AIC) values is -15732.96. According to Akaike (1973), the AIC is a measurement of the relative quality of statistical models for a prescribed data. Given a selection of models for the data, AIC values the strength of each model, relatives to every one of the other models. Hence, the R-squared is 0.998724 are outperforming others because it indicates closest to value of one. Figure 1 illustrates the five best networks selected after designing the network architecture. The best network can be compared based on architecture network of all plotted network in the graph. Based on the lowest absolute error in the graph, network [2-4-1] is the best network.

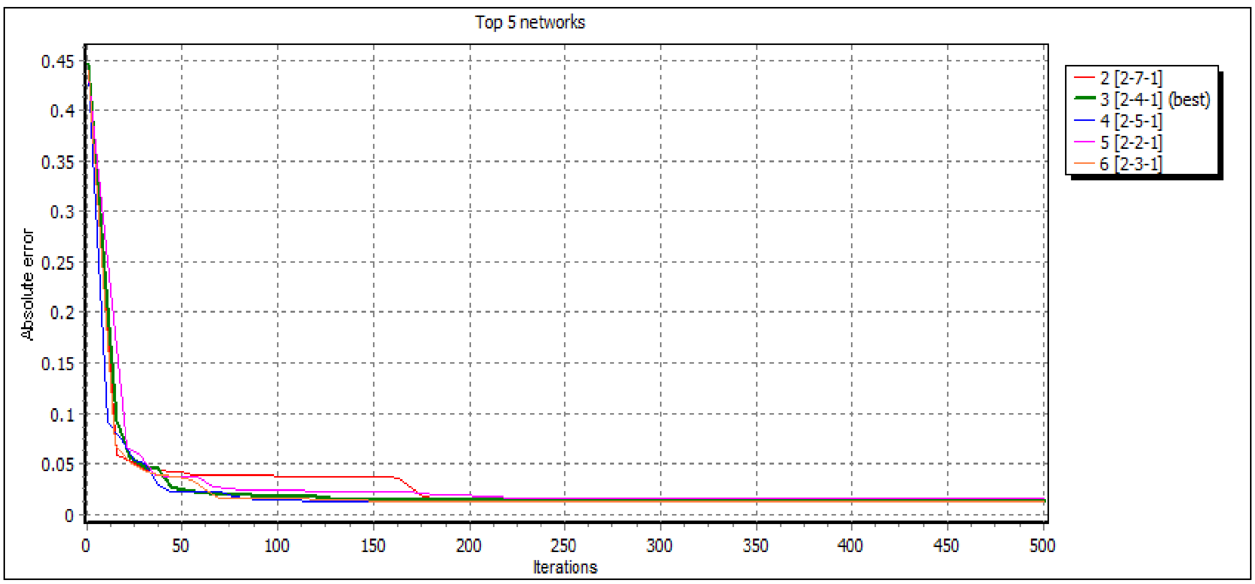

Figure 1: The Architecture Network of Selected Network

Step 4: Training

The simulation training is conducted based on the number of layers of the artificial neural network [2-4-1] selected in design unit. The overall results are shown in Table 3. After multiple simulation training, the Quasi-Newton algorithm has been selected because it has the smallest absolute error of training.

Table 3: Absolute Error (Training) of Training Algorithm

Training Algorithm	Absolute Error (Training)
Quick Propagation	0.041083
Conjugate Gradient Descent	0.016426
Quasi-Newton	**0.01238**
Limited Memory Quasi-Newton	0.014163
Levenberg-Marquardt	0.015989
Online Back Propagation	0.044559
Batch Back Propagation	0.426554

Figure 2 depicts the dataset errors and network for Quasi-Newton. It shows that the line of training set and validation set are both identical. The absolute error for decreasing dramatically from 0.44 until at 10 iterations and 0.08 absolute error. Then the graph decreases steadily until 501 iterations and 0.01 absolute error. The best network is when the absolute error 0.013 and 238 iterations.

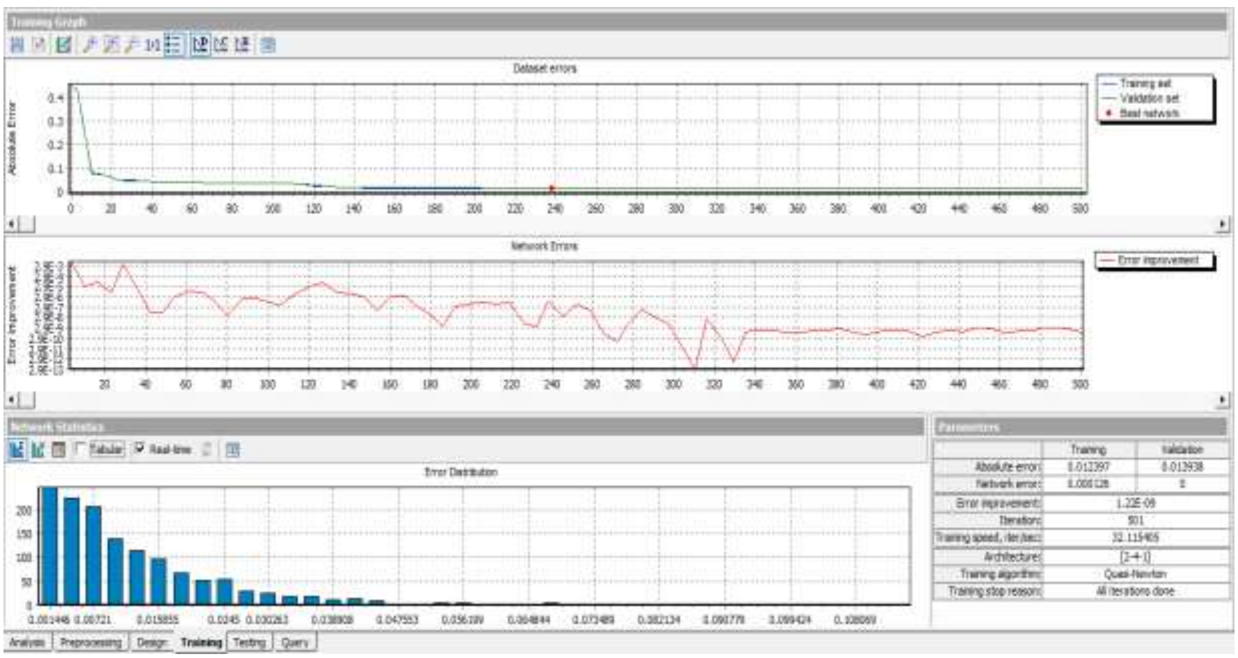

Figure 2: Dataset Error Distribution and Network Error Improvement of Quasi-Newton

Step 5: Testing

The dataset will be automatically tested. The result of Quasi-Newton which is selected in the simulation training. Based on the correlation in Table 4, the exchange rate is 0.999373 which indicates a strong positive relationship. The value coefficient determination (R-squared) is equal to 0.998744 also means that 99.87% or the model explains all the variability of the response data around its mean.

Table 4: Correlation and R-squared Values

	Target	Output	AE	ARE
Mean	3.485125	3.485358	0.012473	0.003518
Standard Deviation	0.498	0.497575	0.012461	0.00329
Min	2.9385	2.950462	0.000002	0.000000575
Max	4.4995	4.483242	0.093899	0.026076
Correlation: 0.999373 R-squared: 0.998744				

Based on Figure 3 shows the exchange rate values comparing to output values are directly proportional. These two values almost plot at the same position point. Then, if the target value increases, the output value also increases. It is showing that forecasting exchange rate using ANN method is suitable and accurate.

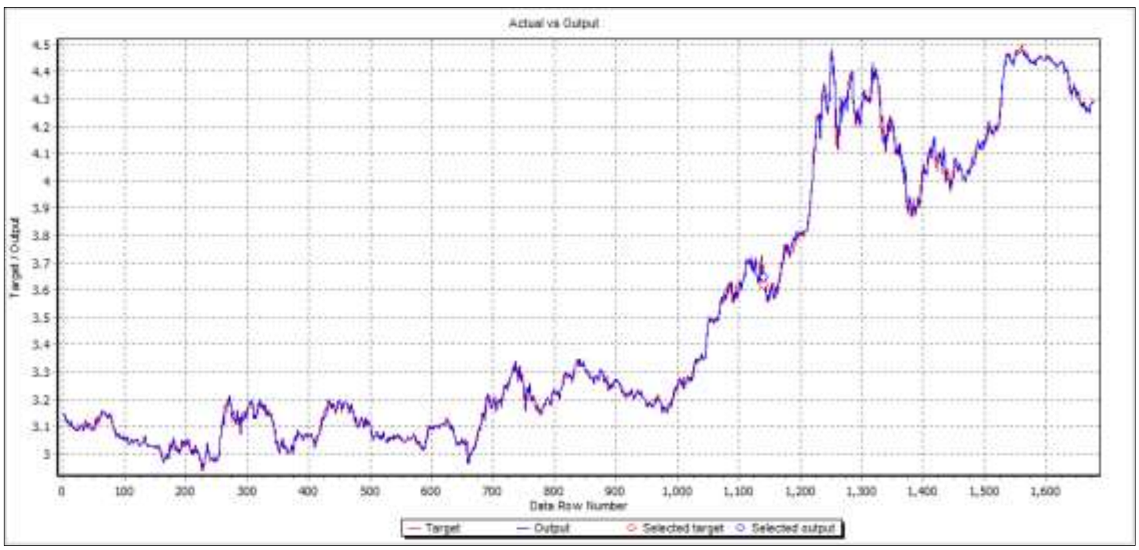

Figure 3: Comparisons Between Output Values and Target Values Exchange Rate

Table 5 shows network of [2-4-1] and it is the outperformed network based on the highest fitness and AIC value. The architecture network of [2-4-1] shows the fitness value is 136.543408 and Akaike Information Criterion (AIC) values is -15732.96. According to Akaike (1973), the AIC is a measurement of the relative quality of statistical models for a prescribed data. Given a selection of models for the data, AIC values the strength of each model, relatives to every one of the other models. Hence, the R-squared is 0.998724 are outperforming others because it indicates closest to value of one.

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Therefore, the simulation training is conducted based on the number of layers of the artificial neural network [2-4-1] selected in design unit. The overall results are shown in Table 6. After multiple simulation training, the Quasi-Newton algorithm has been selected because it has the smallest absolute error of training.

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Maximum	4.4995	4.483242	0.093899	0.026076

Correlation: 0.999373
R-squared: 0.998744

CONCLUSION

The particularity of the research towards real life event and this can enhance neural network as an alternative forecasting instrument for vastly unpredictable Malaysian exchange rate. In this study, the objective was to determine the best architecture model of the artificial neural network to forecast the Foreign Exchange Rate in Kuala Lumpur by a high point of accuracy. From viewing the past studies, the diverse data mining methods for forecasting exchange rate are considered. It is showed that Artificial Neural Network model is remarkably helpful in forecasting the Foreign Exchange Rate in Kuala Lumpur.

A diverse algorithm has been practising with neural network. The outcome can be concluded that network architecture [2-4-1] have been the most favourable architecture by outperforming other networks. The deciding factor is by evaluating several criteria for the network architecture such as fitness and AIC. It shows that it has the lowest value of AIC along with highest value of fitness compare to other networks. Meanwhile Quasi-Newton has been chosen as the best algorithm by producing lowest absolute training error.

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