Jurnal Informatika dan Rekayasa Perangkat Lunak ISSN 2656-2855
Vol. 7, No. 2, September 2025, Hal. 251-259 e-ISSN 2685-5518

Comparative Study of Recurrent Neural Network (RNN) and Extreme Learning Machine (ELM) in Predicting Bank Central Asia's Stock Price

Rizanatul Mukharomah[1], **Emy Siswanah**[2*]
[1,2] Department of Mathematics, Faculty of Science and Technology,
Universitas Islam Negeri Walisongo Semarang
[*]Email: emysiswanah@walisongo.ac.id

Abstrak

Memprediksi harga saham merupakan topik keuangan yang penting, terutama bagi investor yang ingin memaksimalkan keuntungan dan meminimalkan risiko. Penelitian ini membandingkan dua metode machine-learning, yaitu Recurrent Neural Network (RNN) dan Extreme Learning Machine (ELM), dalam memprediksi harga saham Bank Central Asia (BBCA). Kedua metode ini dipilih karena kemampuannya dalam menangani data runtun waktu. Penelitian ini menggunakan data harga harian BBCA selama periode tertentu dan melibatkan beberapa langkah seperti pengumpulan data, pra-pemrosesan data, pelatihan model, dan perhitungan nilai akurasi. Perhitungan akurasi dievaluasi menggunakan Mean Squared Error (MSE) dan Mean Absolute Percentage Error (MAPE). Penelitian ini menunjukkan bahwa ELM memiliki akurasi yang lebih baik dibandingkan RNN dalam memprediksi harga saham BBCA. ELM menunjukkan nilai MSE dan MAPE yang lebih rendah daripada RNN, yang mengindikasikan kemampuan ELM untuk memprediksi dengan kesalahan yang lebih kecil. Penelitian ini juga menyimpulkan bahwa ELM lebih akurat daripada RNN dalam memprediksi harga saham BBCA. Oleh karena itu, ELM adalah metode yang direkomendasikan untuk memprediksi harga saham.

***Kata kunci**: Artificial Neural Network, Bank Central Asia, Extreme Learning Machine, Prediksi Saham, Recurrent Neural Network.*

Abstract

Predicting stock prices is an important financial topic, especially for investors who want to maximize profit and minimize risk. This research compares two machine-learning capabilities, a Recurrent Neural Network (RNN) and an Extreme Learning Machine (ELM), in predicting Bank Cental Asia (BBCA) stock prices. These two are chosen for their capabilities in handling time-series data. This research uses the data of BBCA's daily prices over a certain period and involves several steps such as data collecting, data pre-processing, model training, and calculation of accuracy value. This accuracy calculation will be evaluated using Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). This research shows ELM has better accuracy than RNN in predicting BBCA's stock prices. ELM shows lower MSE and MAPE values than RNN, indicating the capability of ELM to predict with smaller errors. This research also concludes ELM is better in accuracy than RNN in predicting BBCA's stock prices. Thus, ELM is the recommended method to predict stock prices.

***Keywords**: Artificial Neural Network, Bank Central Asia, Extreme Learning Machine, Recurrent Neural Network, Stock Prediction.*

INTRODUCTION

Indonesia has been experiencing economic growth, and its growth is projected to surpass the past year. Investment can boost economic growth, where capital is invested for a long time with a chance to profit in the future (Paningrum, 2022). Stock is a promising instrument with a high risk (Auruma & Sudana, 2016). It is released security by a company/issuer, which states the stockholder is also a part of the company holder (Patricia, 2021).

According to BEI, the banking industry experiences significant growth in the stock market. PT Bank Central Asia resides at the top place as a private bank among other banks in

Bursa Efek Indonesia (BEI). BBCA is considered to have a big potential to be actively traded, making BCA an entity with the biggest valuation in BEI (Yuliyanti, 2013). Every time, the stock price fluctuates which is affected by many factors, making it an instrument with high risk. Thus, predicting stock prices is important for investors to minimize their losses.

Artificial neural network, an Artificial Intelligence method, is applied to predict stock prices. This method is chosen to predict stock prices because of its capability as an independent estimator and also can result in a prediction that matches the actual number (Agustina, Anggraeni, & Mukhlason, 2010).

Recurrent Neural Network (RNN) is an advanced evolution of feed-forward neural network architecture. With the distinctive feature of utilizing network outputs as inputs back into the system, RNN can produce another output based on previous information. This feature makes it very effective in processing sequential data (Hermawan, 2014).

Huang, Zhu, & Siew (2006) proposed Extreme Learning Machine in 2006 as an AI for a single-layer feed-forward neural network (SLFN). In ELM's algorithm, the input value of SLFN is randomly selected, while the output value is analytically selected. The biggest advantage of this algorithm is its efficiency in finding the network value than other methods (Arifianty, Mulyono, & Irzal, 2017). Considering this context, the researcher aims to compare RNN and ELM, for RNN in processing sequential data and having a recurring connection, and is compared to ELM as a single-layer feed-forward network.

This research aims to evaluate the prediction of BCA's stock price using two different methods, Recurrent Neural Network (RNN) and Extreme Learning Machine (ELM). This research wants to discover the RNN's and ELM's results in predicting BCA's stock closing price. The results from these two methods will also be compared. Each also will be evaluated to discover their accuracy, so the most suitable method can be chosen.

There are various advantages to this research. First, this study offers investors and Bank Central Asia insights into the application of mathematical ideas in predictive computations. This study offers more precise and scientific assistance for stock closing price prediction by leveraging artificial neural network systems and time-series analysis techniques.

Second, this study expands the knowledge of both authors and readers about prediction methods that use Extreme Learning Machines (ELM) and Recurrent Neural Networks (RNN). As a result, readers not only learn about the approaches taken but also acquire a thorough grasp of how these strategies are implemented within the stock market.

Thirdly, this study offers vital data on anticipated outcomes that can assist investors in making the best investment decisions. This information helps investors make better and more informed decisions by reducing the chance of loss when investing in a specific firm.

LITERATURE REVIEW

Recurrent Neural Network is a class of Artificial Neural Network where the units are connected recurrently. This allows them to use their internal memory to process input sequences. This type of artificial neural network utilizes previous stages to learn data and predict future trends. The initial stage of data must be remembered to predict and guess future values, in this case the hidden layer acts like a stock for past information from sequential data.

RNN can be seen as a "partially recurrent" network where most of the connections are simple. A certain group of neurons receive feedback signals from the previous time step. RNN in its recurrence only has a single screen (single layer), as in Figure 1.

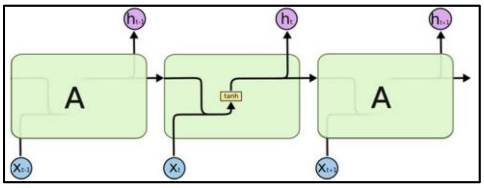

Figure 1. Recurrent Neural Network

The weakness of RNN regarding long-term dependency, this can be solved by the LSTM method (Yusuf, 2022). Long Short-Term Memory (LSTM) is one of the many types of Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) is able to capture data from past stages and use it for future predictions (Moghar & Hamiche, 2020).

LSTM has the ability to store data patterns used to make predictions. LSTM has the sensitivity to select and learn about data patterns so that it can conclude which data will be eliminated and which data will be retained because each neuron in LSTM uses several gates to manage memory in each neuron (Yusuf, 2022). The LSTM architecture consists of an input layer, an output layer, and a hidden layer which are presented in Figure 2.

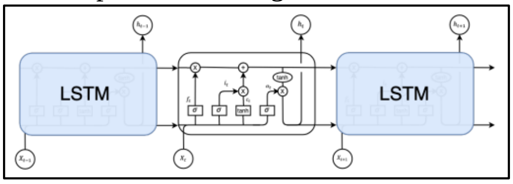

Figure 2. LSTM architecture

Extreme Learning Machine is presented by (Huang et al., 2006). ELM is a simple feedforward development method for neural networks using hidden layers or commonly called Single Hidden Layer Feedforward Neural Network (SLFN). The feedforward network uses manually determined parameters such as input weight and bias. These input weights and biases will be automatically generated randomly in certain areas. These random values can avoid stable forecasting results. In general, the ELM structure is shown in the Figure 3.

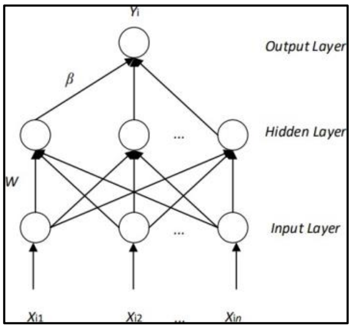

Figure 3. ELM structural

This research is different from previous studies because it does not only refer to the max epoch parameter and the number of hidden neurons as done by (Aldi, Jondri, & Aditsania, 2018), nor to the variations in batch size as researched by (Kristiana & Miyanto, 2023), but combines the testing of several parameters simultaneously (max epoch, the number of hidden neurons, batch size) with the addition of Z-score normalization methods. Furthermore, this study not only discusses the application of ELM as conducted by (Pratama, Adikara, & Adinugroho, 2018) but also expands the study by comparing the performance of RNN and ELM, thus producing a new contribution in the form of a cross-method comparison for daily stock price prediction.

RESEARCH METHOD

3.1 Research Type

The type of this research is quantitative research. It is an approach focusing on numerical analysis.

3.2 Research Data

This research uses secondary data, the stock daily closing price of PT Bank Central Asia Tbk. This data is obtained from Yahoo Finance. The time frame of data is from January 3, 2020, to December 29, 2023. This data is arranged as shown in Table 1.

Table 1. Input Data Structure

Pattern to-	Data Input (X_1)					
	X_1	X_2	X_3	X_4	X_5	X_6 (Target)
1	Data day 1	Data day 2	Data day 3	Data day 4	Data day 5	Data day 6
2	Data day 2	Data day 3	Data day 4	Data day 5	Data day 6	Data day 7
3	Data day 3	Data day 4	Data day 5	Data day 6	Data day 7	Data day 8
	.	.	.	.	.	.
n-5	Data day *n*-5	Data day *n*-4	Data day *n*-3	Data day *n*-4	Data day *n*-1	Data day *n*

3.3 Data Collecting Method

For this study, the documentation method was selected as the data collection method. The word "document," which describes a variety of written records, is the root of the term documentation. A researcher who employs the documentation method looks at a range of written sources, including printed materials like books and magazines, official archives like documents, rules, meeting notes, and other written sources (Setyawan, 2013).

3.4 Research Flow

3.4.1 Recurrent Neural Network

The RNN-LSTM Method's steps are as follows (Siregar & Widyasari, 2023):

1. Inserting the stock data of PT. Bank Central Asia Tbk.

2. Data normalization with Z-score is applied to equalize the range of values on each attribute with a certain scale, below is the formula (Aksu, Guzeller, & Eser, 2019):

$$x' = \frac{x_i - \mu_i}{\sigma_i} \quad (1)$$

Description:
x' : normalized data
x_i : data before normalization
μ_i : data average before normalization
σ_i : data standard deviation before normalization

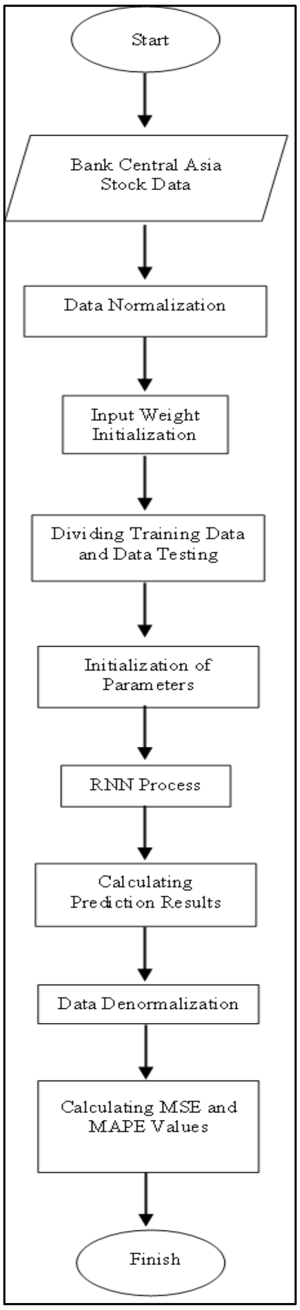

Figure 4. Flow Diagram of RNN Method

3. Initialising input weight randomly with a range of value -0.5 to 0.5.
4. The processed data is divided into the training set and testing set. The proportion for dividing this data is 80:20. It is based on the common standard practice of machine learning, and has been applied in several research in the past. This proportion also gives a sufficient example to train the model and provides enough data to test the model's performance. Ashar, Cholissodin, & Dewi (2018) explain the application of Extreme Learning Machine to predict the feasible pipeline production quantity.
5. Parameter initialization, which has been specified as follows:
   a) Maximum epoch: 50, 100, 500, 1000
   b) Hidden neuron: 5, 10, 15, 25, 30
   c) Batch size: 2, 4, 8, 16, 32, 64
6. The RNN method in MATLAB begins with training trials to identify the optimal parameters with the lowest MSE value. Once the parameters are identified, the RNN method is used to forecast using training data. The training stage will move on to the next level if it produces reasonable forecasting outcomes. The second step is testing, which involves forecasting using testing data and then examining the forecasting findings for the period following the testing data.
7. Calculating prediction results.
8. Data denormalization using the formula as follows:

$$d = (d' \times \sigma_i) + \mu_i \quad (2)$$

Description:
d : Denormalization result
d' : Normalization result
μ_i : data average before normalization
σ_i : data standard deviation before normalization

9. Evaluating the accuracy of the model with MSE and MAPE values
10. Data presentation and completion.

3.4.2 Extreme Learning Machine

This diagram shows the price prediction process of PT Bank Central Asia TBK stock using Extreme Learning Machine as illustrated in Figure 5. The applied steps in this method are as follows:

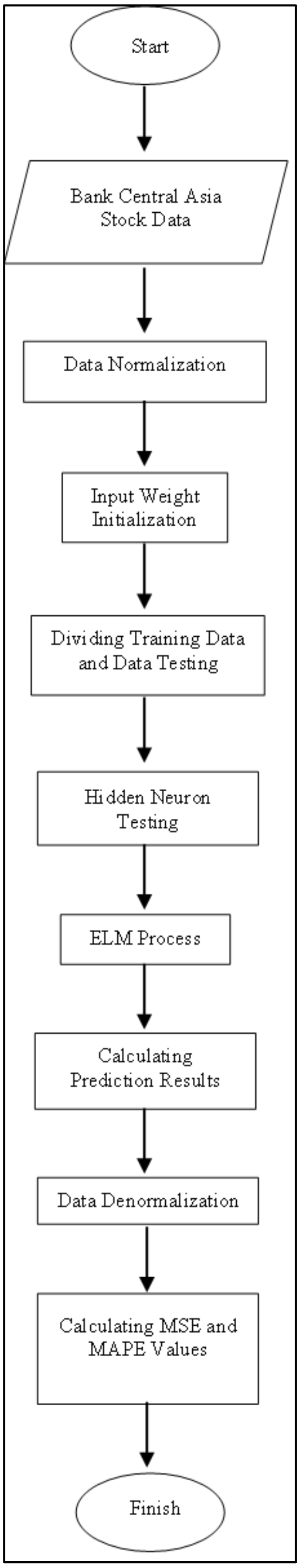

Figure 5. Flow Diagram of ELM

1. Inserting the stock data of PT. Bank Central Asia Tbk.
2. Data normalization with Z-score is applied to equalize the range of values on each attribute with a certain scale using formula 1.
3. Initialising input weight randomly with a range of value -0.5 to 0.5.
4. The processed data is divided into the training set and testing set. The proportion for dividing this data is 80:20.
5. The testing of the total neuron is applied with a hidden layer (neuron hidden testing), that consists of 2 to 10 neurons, to determine the best total neuron based on MSE (Mean Square Error).
6. The ELM method in R Studio begins with a training process to conduct prediction using training data. The training stage will move to the next level if it produces reasonable prediction outcomes. The second step is testing, which involves predicting using testing data and then examining the forecasting findings for the period following the testing data.
7. Calculating prediction results.
8. Data denormalization using the 2 formula.
9. Evaluating the accuracy of the model with MSE and MAPE values
10. Data presentation and completion

RESULT AND DISCUSSION

This research used the daily closing stock price of PT. Bank Central Asia as the primary data.

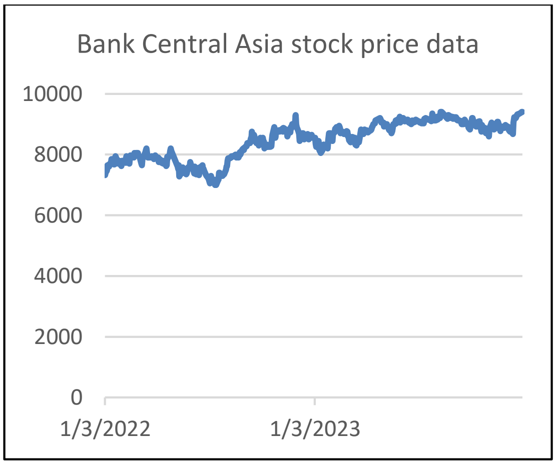

Figure 6. Chart of PT. Bank Central Asia's Stock Prices

Data normalization is first conducted before being divided. The division ratio is 80% training data and 20% testing data.

4.1 Recurrent Neural Network

RNN's model consists of three variables with the following testing:

1. Maximum epoch: 50, 100, 500, 1000
2. Hidden neuron: 5,10, 15, 25, 30
3. Batch size: 2, 4, 8, 16, 32, 64.

Below is the experiment result using various combinations of parameters:

Table 2. Hidden Neuron's Combination

Neuron hidden	Max epoch	batch size	MSE
5	50	64	0.03301
10	50	64	0.03643
15	50	64	0.03806
25	50	64	0.03733
30	50	64	0.03816

Table 3. Parameter Combination of Maximum Epoch

Neuron hidden	Max epoch	batch size	MSE
5	50	64	0.03301
5	100	64	0.03290
5	500	64	0.02589
5	1000	64	0.02438

Table 4. Parameter Combination of Batch Size

Neuron hidden	Max epoch	batch size	MSE
5	1000	2	0.02496
5	1000	4	0.02447
5	1000	8	0.02679
5	1000	16	0.02619
5	1000	32	0.02731
5	1000	64	0.02438

After the best parameter is obtained, the prediction for the training test is conducted. Below the prediction result of the training test:

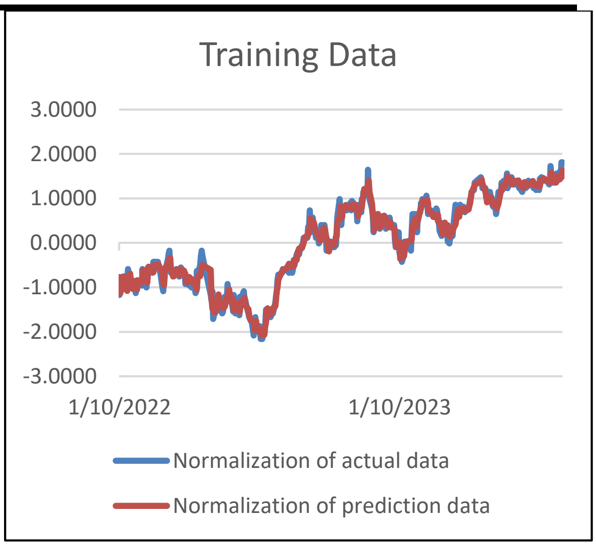

Figure 7. The Normalization Plot of Actual and Prediction Data for Training Test

Figure 7 shows the prediction plot following the actual data plot. The optimal parameter is obtained with a training and testing ratio of 80:20, 64 batch size, 5 hidden neurons, and a maximum epoch of 1000, with 0.02438 MSE.

After Recurrent Neural Network's prediction is obtained and the plot result is not far from the actual data, the prediction for 30 days forward is calculated after data testing, with the result as follows:

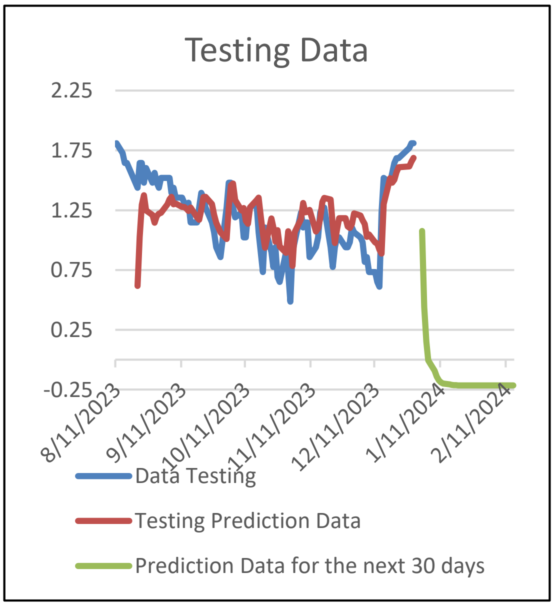

Figure 8. The Normalization Plot of Testing Actual Data, Plot of Prediction Result for Testing, and 30 Days Prediction Result with RNN

Using MSE and MAPE, accuracy calculation of the daily closing stock price's prediction is conducted to evaluate the compatibility of the Recurrent Neural Network.

Table 5. RNN's Accuracy Value

Parameter	Value
MSE	0.054232027
MAPE	18.170502

Table 5 shows that RNN obtains MAPE value below 20%. It means RNN has good capability in prediction.

4.2 Extreme Learning Machine

The testing of hidden layer neurons is conducted in the ELM method. This testing shows the mistake rate decreases as the number of neurons employed increases. This research will examine the number of hidden layer neurons from 2 to 10, to discover the optimum number of neurons based on MSE.

Table 6. Testing of Hidden Layer Neurons

Hidden Neuron	MSE
2	0.0554
3	0.0425
4	0.0372
5	0.0351
7	0.0342
6	0.0339
9	0.0331
8	0.033
10	0.0324

Table 6 shows the lowest error is 0.0324, associated with the smallest neuron, while 0,0554 error rate is achieved by the largest neuron. Thus, this research chooses 10 neurons.

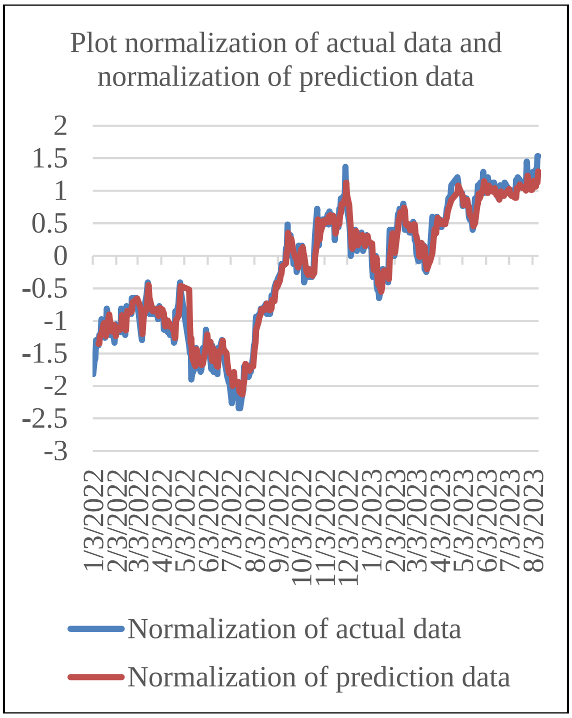

Figure 9. The Normalization Plot of Actual and Prediction Data for Training Test

After ELM's prediction on the training test is obtained, and the plot result is not far from the actual data, the prediction for 30 days forward is calculated after data testing, with the result as follows:

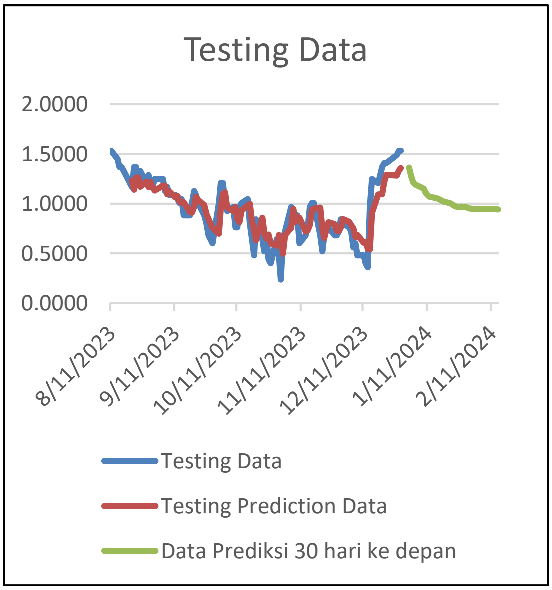

Figure 10. The Normalization Plot of Testing Actual Data, Plot of Prediction Result for Testing, and 30 Days Prediction Result with ELM

Figure 10 shows the pattern of prediction data closely following the pattern of actual data. The pattern only shows minor differences between the lines.

Using MSE and MAPE, accuracy calculation of the daily closing stock price's prediction is conducted to evaluate the compatibility of the Extreme Learning Machine.

Table 7. ELM's Accuracy Value

Parameter	Value
MSE	0.0241
MAPE	16.55443

Table 7 shows that ELM obtains MAPE value below 20%. It means ELM has good capability in prediction.

4.3 Comparison of RNN and ELM Methods

Using actual data and prediction results of PT Bank Central Asia Tbk's daily closing stock price, these two methods will be compared, which is shown in Figure 11.

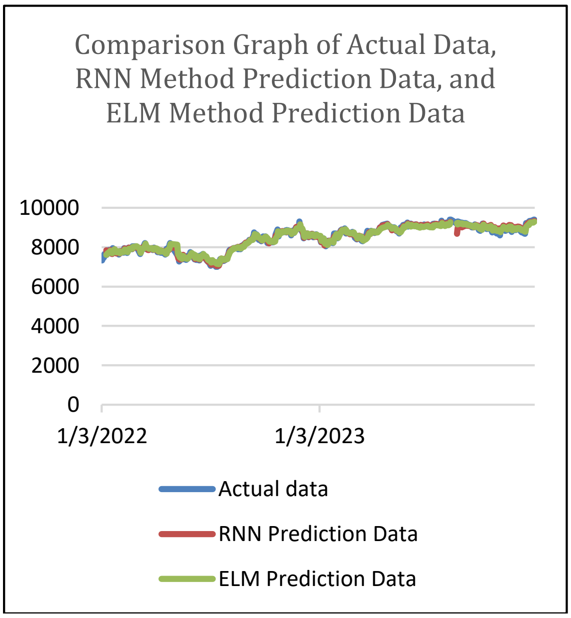

Figure 11. Comparison Graphic of Actual Data, RNN's Prediction Data, and ELM's Prediction Data

Figure 11 shows these two methods closely following the pattern of actual data. There is no significant difference between them.

Table 8. Accuracy Comparison of Recurrent Neural Network (RNN) and Extreme Learning Machine (ELM)

Model	**Accuracy Value**	
	MSE	**MAPE**
RNN	0.0542	18.1705
ELM	0.0241	16,5544
Best Model	**ELM**	**ELM**

Based on the analysis in Table 8, it can be seen that the Extreme Learning Machine (ELM) method is more effective in prediction because it has a lower error rate in the form of MSE and MAPE compared to the Recurrent Neural Network (RNN) method.

CONCLUSION

Prediction result of PT Bank Central Asia Tbk.'s daily stock price tends to decrease in the Recurrent Neural Network (RNN) method and the Extreme Learning Machine (ELM) method. Based on the accuracy, ELM is better than RNN. This study indicates that future research could focus on applying other types of RNN that may yield more accurate results, developing hybrid models between RNN and ELM, or integrating external variables (such as macroeconomic indicators, news, or market sentiment).

REFERENCES

Agustina, I. D., Anggraeni, W., & Mukhlason, A. (2010). *Penerapan Metode Extreme Learning Machine untuk Peramalan Permintaan. Undergraduate Thesis, Information system, RSSI 519.* 1–6.

Aksu, G., Guzeller, C. O., & Eser, M. T. (2019). The Effect of the Normalization Method Used in Different Sample Sizes on the Success of Artificial Neural Network Model. *International Journal of Assessment Tools in Education*, *6*(2), 170–192. https://doi.org/10.21449/ijate.479404

Aldi, M. W. P., Jondri, & Aditsania, A. (2018). Analisis dan Implementasi Long Short Term Memory Neural Network untuk Prediksi Harga Bitcoin. *E-Proceeding of Engineering*, *5*(2), 3548–3555.

Arifianty, A., Mulyono, M., & Irzal, M. (2017). Peramalan Indeks Harga Saham Gabungan (IHSG) dengan Metode Extreme Learning

Machine (ELM). *JMT : Jurnal Matematika Dan Terapan*, *1*(1), 22–32. https://doi.org/10.21009/jmt.1.1.4

Ashar, N. M., Cholissodin, I., & Dewi, C. (2018). Penerapan Metode Extreme Learning Machine (ELM) Untuk Memprediksi Jumlah Produksi Pipa Yang Layak (Studi Kasus Pada PT. KHI Pipe Industries). *Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer*, *2*(11), 4621–4628.

Auruma, T., & Sudana, I. M. (2016). Diversifikasi Investasi Saham: Perbandingan Risiko Total Portofolio Melalui Diversifikasi Domestik Dan Internasional. *Jurnal Manajemen Teori Dan Terapan| Journal of Theory and Applied Management*, *6*(1). https://doi.org/10.20473/jmtt.v6i1.2657

Hermawan, N. (2014). *Aplikasi Model Recurrrent Neural Network dan Recurrent Neuro Fuzzy untuk Peramalan Banyaknya Penumpang Kereta Api Jabodetabek. Skripsi*. Universitas Negeri Semarang, Universitas Negeri Yogyakarta.

Huang, G. Bin, Zhu, Q. Y., & Siew, C. K. (2006). Extreme learning machine: Theory and applications. *Neurocomputing*, *70*(1–3), 489–501. https://doi.org/10.1016/j.neucom.2005.12.126

Kristiana, L., & Miyanto, D. (2023). Penambahan Parameter PM2.5 dalam Prediksi Kualitas Udara : Long Short Term Memory. *Multimedia Artificial Intelligent Networking Database (MIND)*, *8*(2), 188–202. https://doi.org/https://doi.org/10.26760/mindjournal.v8i2.188-202

Moghar, A., & Hamiche, M. (2020). Stock Market Prediction Using LSTM Recurrent Neural Network. *Procedia Computer Science*, *170*, 1168–1173. https://doi.org/10.1016/j.procs.2020.03.049

Paningrum, D. (2022). Buku referensi investasi pasar modal - Destina Paningrum, S.E., M.M - Google Books. In *Lembaga Chakra Brahmana Lentera*.

Patricia, C. O. S. (2021). *The Effect of ROA, Capital, Growth Assets, LDR And DER on Share Prices in Registered Banking Sectors in Indonesia Stock Exchange Period 2010 - 2018*. *3*(2), 6.

Pratama, M. I., Adikara, P. P., & Adinugroho, S. (2018). Peramalan Harga Saham Menggunakan Metode Extreme Learning Machine (ELM) Studi Kasus Saham Bank Mandiri. *Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer*, *2*(11), 5009–5014. https://doi.org/http://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/3163

Setyawan, D. A. (2013). Data dan Metode Pengumpulan Data Penelitian. In *Metodologi Penelitian*.

Siregar, S. R., & Widyasari, R. (2023). Peramalan Harga Crude Oil Menggunakan Metode Long Short-Term Memory (LSTM) Dalam Recurrent Neural Network (RNN). *Lebesgue: Jurnal Ilmiah Pendidikan Matematika, Matematika Dan Statistika*, *4*(3), 1478–1489.

Yuliyanti, L. (2013). Pengaruh Profitabilitas terhadap Kebijakan Dividen. *Jurnal Pendidikan Akuntansi & Keuangan*, *1*(2), 10–20. https://doi.org/10.17509/JPAK.V1I2.15450

Yusuf, A. (2022). Prediksi Indeks Harga Saham Gabungan (IHSG) Menggunakan Long Short-Term Memory. *Epsilon: Jurnal Matematika Murni Dan Terapan*, *15*(2), 124. https://doi.org/10.20527/epsilon.v15i2.5026