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Stock price prediction using artificial neural network integrated moving average

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Abstract. Stock prices are always interesting to be a research topic because stock prices always change at any time. Stock price index is a benchmark for shareholders to sell, buy or maintain it. As in this study, the data used is the closing price of ANTM's share price which is then processed to predict future stock prices. The proposed method in this study is an integrated moving average which is used to transform data in order to improve data quality. So that it can improve the accuracy of predictions on the neural network. Based on the experiment conducted using 10 combinations of parameters on the neural network using integrated moving average, has been able to produce the RMSE value. And validation based on t-test also showed a significant difference compared to the previous model. So from the result of experiment use an integrated moving average proved to be able to improve neural network performance.

1. Introduction

A set of quantitative observations arranged in a chronological order is defined as a time series [1]. Many forecasting procedures are based on a time-series model [2]. Prediction is needed in various applications so time series forecasting is now very important area of research [3]. Determination of future stock prices has used a lot of time series forecasting, so to guide investor's decisions and trading, analysis and modeling of time series becomes an important task [4]. In line with this statement [5] that the stock price prediction is one of the most important topics in finance and business. Therefore stock price predictions are also always an interesting thing for researchers [6].

For its ability to identify nonlinear relationships, artificial neural network have also been used for modeling and analysis of time series in addition to traditional time series analysis with the Box-Jenkins model [7]. Artificial neural networks as approximators and flexible learning systems, has attracted growing interest to be used in modeling and forecasting time series [8]. Neural Network provides a promising tool for forecasters, neural network also has many desirable features that are very suitable for practical forecasting applications [9]. In addition, one of the advantages of neural networks is its ability to be applied to various applications [10]. Data input and output are very important in neural network modeling. Because the quality and distribution of sample learning sets is needed to generalize networks [11]. Besides that, in designing neural network modeling, parameters tuning are one of the important thing [12].

Data pre-processing is needed to extract redundant information from the original signal [13]. However, the potential for transformation to increase estimates is also sometimes ignored [14].



Popular method used to carry out the time series data smoothing process is moving average and exponential smoothing[15].

So, this research was conducted to develop the use of pre-processing data to improve the performance of neural network methods. which is applied to predict stock prices using integrated moving average data transformation.

2. Materials and methods

In this study, the data used is secondary data in the form of stock price data on Aneka Tambang Persero, Tbk.

2.1. Initial data processing

Historical ANTM's share price data is used in this study which is consisting of 2,699 records. The data is then taken from two entities in the form of a date and closing price and then the initial data is processed. In the first process, replace missing value is carried out to overcome some of the data that still contains missing value [16]. Then the second process is carried out a set of roles to change the regular attribute. The date attribute as a regular attribut is changed to the id attribute. In the third process the data is normalized using the binary sigmoid activation function. In the binary sigmoid function, the data are normalized in the range of 0 to 1 [17]. Then windowing is done to break the close attribute of the data into 5 data inputs and 1 data output. This close attribute is univariate data, which is data distribution that only involves one attribute or one variable [18]. After that, the data transformation process is carried out with an integrated moving average.

2.2. Proposed methods

This research focuses on developing methods in the pre-processing data process in the form of data transformation to improve the performance of neural network methods for making predictions. The proposed data transformation method is to integrate moving averages to improve neural network performance.

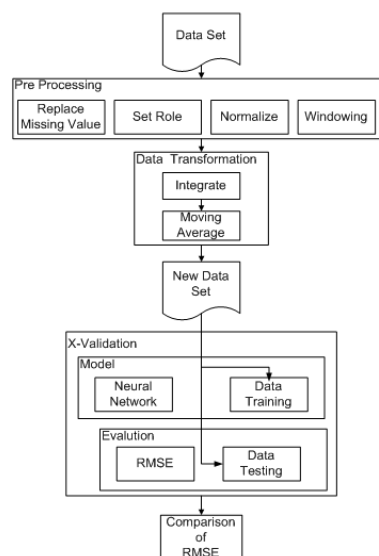


Figure 1. Proposed method.

The proposed method can be seen in Figure 1. In the proposed method, after pre-processing data and data transformation by integrating moving averages, it will produce a new data set which is then processed using the neural network method. Then the data will be split into training data and testing data using 10 fold cross validation. After that the RMSE value will be obtained. The RMSE value is then compared to the previous RMSE method.

3. Result and discussion

Based on the experiments that have been carried out, the summary results can be seen from Table 1, Table 2 and Table 3 as follows.

Table 1. Binary sigmoid neural network experiment

Number	Hidden Layer	TC	LR	Mom	Hor	RMSE
1	1	500	0.3	0.2	1	0.022
2	1	500	0.6	0.3	1	0.023
3	3	1000	0.6	0.3	1	0.023
4	3	1000	0.9	0.6	1	0.023
5	3	500	0.9	0.6	1	0.023
6	1	300	0.5	0.5	1	0.023
7	1	300	0.1	0.3	1	0.024
8	3	500	0.3	0.2	1	0.022
9	3	500	0.6	0.3	1	0.023
10	3	500	0.9	0.6	1	0.023

Table 2. Binary sigmoid neural network with discrete wavelet transform experiment

Number	Hidden Layer	TC	LR	Mom	Hor	RMSE
1	1	500	0.3	0.2	1	0.019
2	1	500	0.6	0.3	1	0.018
3	3	1000	0.6	0.3	1	0.18
4	3	1000	0.9	0.6	1	0.019
5	3	500	0.9	0.6	1	0.2
6	1	300	0.5	0.5	1	0.018
7	1	300	0.1	0.3	1	0.02
8	3	500	0.3	0.2	1	0.02
9	3	500	0.6	0.3	1	0.018
10	3	500	0.9	0.6	1	0.02

Table 3. Binary sigmoid neural network with integrated moving average experiment

Number	Hidden Layer	TC	LR	Mom	Hor	Window Wdth	Agregation Function	RMSE
1	1	500	0.3	0.2	1	5	Average	0.018
2	1	500	0.6	0.3	1	5	Average	0.016
3	3	1000	0.6	0.3	1	5	Average	0.011
4	3	1000	0.9	0.6	1	5	Average	0.004
5	3	500	0.9	0.6	1	5	Average	0.005
6	1	300	0.5	0.5	1	5	Average	0.016
7	1	300	0.1	0.3	1	5	Average	0.017
8	3	500	0.3	0.2	1	5	Average	0.017
9	3	500	0.6	0.3	1	5	Average	0.012
10	3	500	0.9	0.6	1	5	Average	0.005

Table 1 is the result of experiments on the neural network method with the binary sigmoid activation function. From this table, an average RMSE value of 0.0229 is obtained. Table 2 is the result of experiments on the neural network method with the binary sigmoid activation function which performed data transformation using a discrete wavelet transform and produced an average RMSE value of 0.019. And Table 3 is the result of experiments on the neural network method with the binary sigmoid activation function that is transformed using data integration moving averages. From table 3, the RMSE average value of 0.0121 is obtained. As for the comparison chart, it can be seen in Figure 2.

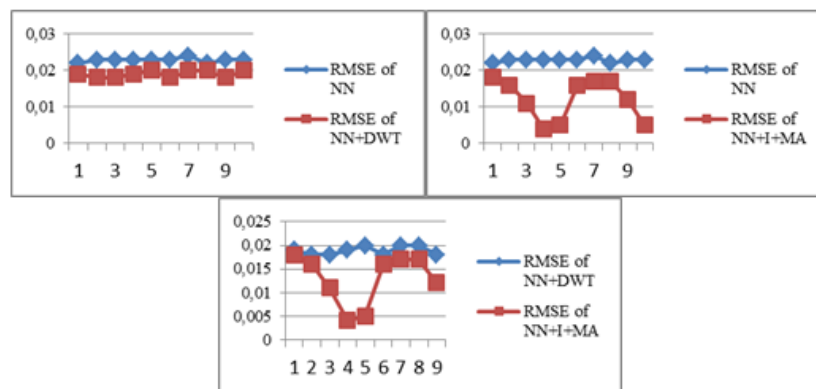


Figure 2. RMSE comparison

After the summary experiment results are obtained, the model validation is then performed. Validation is done to evaluate the prediction accuracy of a model [19]. The validation carried in this research was to use a t-test by comparing two variables the response variable and the predictor variable [20].

Table 4. T-Test result between neural network and neural network with discrete wavelet transform method

	Var 1	Var 2
Mean	0,0229	0,019
Var	3,22222E-07	8,88889E-07
Obs	10	10
PC	-8,24323E-18	
Hyp Mean Difference	0	
df	9	
t Stat	11,20656754	
P(T _i =t) one-tail	6,87957E-07	
t Critical one-tail	1,833112933	
P(T _i =t) two-tail	1,37591E-06	
t Critical two-tail	2,262157163	

Based on paired two sample t-tests that have been done, the results can be seen in Tables 4, 5 and 6. In Table 4, the RMSE values are compared to the ordinary neural network method, with the neural network method plus the discrete wavelet transform. From the results of these comparisons obtained the value of t count of 11.20656754 t table of 2.262157163 which means it can be concluded that H₀ is rejected and H₁ is accepted.

Table 5. T-Test result between neural network and neural network with integrated moving average

	Var 1	Var 2
Mean	0,0229	0,0121
Var	3,22222E-07	3,12111E-05
Obs	10	10
PC	0,206717452	
Hyp Mean Difference	0	
df	9	
t Stat	5,959266331	
P(T _i =t) one-tail	0,000106448	
t Critical one-tail	1,833112933	
P(T _i =t) two-tail	0,000212895	
t Critical two-tail	2,262157163	

In Table 5, the RMSE value is compared to the neural network method with the neural network method plus the moving average integration transformation. From the results of the T-test obtained t value of 5.959266331 and t table of 2.262157163. This means that the calculated t value is greater than t table. Then it can be concluded that H0 is rejected and H1 is accepted.

Table 6. T-Test result between neural network with discrete wavelet transform and neural network with integrated moving average

	Var 1	Var 2
Mean	0,019	0,01213,12111E-
Var	8,88889E-07	07
Obs	10	10
PC	-0,23204479	
Hyp Mean Difference	0	0
df	9	
t Stat	3,712444625	
P(T _i =t) one-tail	0,002413346	
t Critical one-tail	1,833112933	
P(T _i =t) two-tail	0,004826693	
t Critical two-tail	2,262157163	

In Table 6, a comparison of RMSE values to the neural network method with a discrete wavelet transform is compared the neural network method with moving average integration transformation . From the results of the T-test obtained t value of 3.712444625 and t table of 2.262157163. This means that the calculated t value is greater than t table. Then it can be concluded that H0 is rejected and H1 is accepted. It also obtained a probability value of 0.004826693 which means that there are significant differences between the two models.

4. Conclusion

In this study, the proposed method is the use of data transformation using a moving average in the neural network method. Evaluation of experimental results is done by determining the value of Root Mean Square Error (RMSE). The best RMSE value obtained was 0.004 and the average RMSE value was 0.0121. that is, from RMSE produced by the proposed method. After the evaluation, validation is then performed by comparing the RMSE results of the three models with the t-test. From the t-test conducted, showed significant differences between the proposed methods with the previous models. it means that transforming data using integrated moving averages proven to support an increase in Neural Network predictions when compared to previous models

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