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Comparison of Grid Search and Evolutionary Parameter Optimization with Neural Networks on JCI Stock Price Movements during the Covid 19

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Abstract

This study aims to determine the effect of covid 19 on the movement of the JCI Stock Price by testing various combinations of the input variables of closed price stock data on the JCI. The analysis is carried out to find the best RMSE value from the combination of these input variables using the neural network method. The best RMSE results are compared using the optimization of grid search and evolutionary parameters. The data used in this study was taken from the Yahoo.finance.com page on the JCI Historical Data, during the covid pandemic, from 12/11/2019 to 12/30/2021. The data obtained are 509 records. The input variable used is the closing price data (closed price) as a target. The preprocessing data used are data cleansing, filtering, and windowing until seven days before. The results obtained an RMSE value of 0.104 five days before Close t (P=5), training cycle 9000. Momentum 0.9 and learning rate 0.2 is then optimized using the grid search parameter to produce RMSE 0.101, training cycle 100. Learning rate 1 and momentum 0.1 are then compared with evolutionary parameters, which make RMSE 0.103 at learning rate 0.029, momentum 0.68, and training cycle 86. Based on this research, optimizing grid search parameters produces better RMSE than evolutionary parameter optimization. This small RMSE result shows that investors are still safe to invest.

Keywords: neural network, optimization, grid search, evolutionary, preprocessing, RMSE.

1. Introduction

2020 has been a challenging year for most people due to the COVID-19 outbreak. The World Health Organization (WHO) declared the Coronavirus Disease 19 (Covid-19) outbreak as a pandemic on March 9, 2020. This outbreak forced governments in various countries to make policies to prevent it from spreading or to overcome it, for example, by imposing lockdowns, and restricting large-scale business and travel activities, including for the people of Indonesia. WHO urges the public to maintain a safe distance (physical distancing), to prevent more comprehensive transmission of COVID-19. The pandemic has changed most business sectors to online, so their activities continue to run according to the protocol. This incident impacts the community's financial condition; salary cuts and termination of employment (PHK) occurred frequently. This situation necessitates people to find a new job or livelihood for living expenses. Investment activities such as investment in precious metals such as gold, investments in machinery and buildings, and financial assets, such as securities, deposits, stocks, and bonds [1] be an option.

Public statistical data from PT. Kustodian Sentral Efek Indonesia (KSEI), from the end of 2019, until January 2021, showed a significant increase in investors. The number of investors reached 3,880,753 even though the pandemic was still ongoing, and this shows that business in the capital market is an option. Community, rather than the real sector, slumped during this pandemic because of the Large-Scale Social Restrictions (PSBB).

Investors use this technology to seek profit and make a living through investment activities using company data. This data is used to predict the gains to be obtained. The movement of these data is fluctuating and dynamic, caused by certain factors[2]. Stock price movements depend on various factors such as political, economic, and global conditions, financial statements, and company performance.

So, to maximize profits and minimize losses, techniques or methods are needed to predict stock values that will

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occur in the future by analyzing trends from the last few years. It is helpful to get to know stock price estimation.[3]. This stock price movement was influenced by the Restrictions on Community Activities (PKM) during the COVID-19 pandemic around the world, especially in Indonesia. Coronavirus was first discovered in Wuhan, China, and then spread worldwide. For the first time in Indonesia, it was found that two people from Depok who had physical contact with Japanese citizens who were infected by the virus, came to Indonesia. Since then, the spread of this virus has been more evenly distributed throughout Indonesia. The government held a Large-scale Community Activity Restriction (PKMB) to prevent the further spread of the virus. This PKMB affects investment activities, and investors are more likely to hold back (wait and see)[4]. The Covid-19 outbreak has caused difficulties in various fields, such as the health sector, economic growth, industry, and tourism, due to restrictions on activities outside the home, including activities on the stock exchange. As a result, the stock price index at JKSE weakens[5].

Research has been done to predict stock prices using the Support Vector Machine (SVM) and Neural Network (NN) methods [6], which those methods have several advantages and disadvantages. The performance is very good for data series because it can solve overfitting problems and requires little data. The burden is that getting the optimal combination takes a long because it does trial and error. Other research [7] that examined the stock prices of FT100, DOW 30, and Nikkei 225 showed that Bayesian parameter optimization is more profitable than conventional methods.

Other researchers research optimizations performed on convolutional neural networks (CNN) on the random search and grid search[8][9]. The result is that unexpected and grid search results are the same but random computation time is better because the configuration is determined randomly. Then another study said that optimizing grid parameters is superior to optimizing other parameters[10]. Frequent overfitting and slow convergence are weaknesses of the neural network, which are then tried to overcome in this study by using optimization of grid search parameters and evolutionary parameters to get the best combination of inputs from the Neural Network to produce the most optimal RMSE. And fast convergence time.

Research that has been done [11] proposes three approaches, Long Short Term Memory (LSTM), Convolutional Neural Network, and algorithm Bayesian Optimize to forecast the effects of Covid-19, resulting in the optimal SMAPE for the next ten days at 0.25 And SMAPE 2.59. The same is true for predicting[12]stock price movement by using price movement data by using Convolutional Neural Network (CNN) and Bi-Directional Long Short-Term Memory (BLSTM) which results in a better accuracy of 66%. In addition, research conducted to predict stock prices using the genetic algorithm with grid optimization resulted in an increase of 10.9% from other approaches [13]. Another study [14] uses mean-variance (MV) with extreme gradient boost (XGBoost) with the algorithm Firefly (IFA). The result is method mean-variance superior to traditional methods (without stock prediction).

This aims to find the best combination of input variables to produce an optimal RMSE value using the neural network method. The results of this study were then compared using optimization grid search parameters and optimization with evolutionary parameter parameters to predict the movement of the Composite Stock Price Index (JCI) during the covid-19 pandemic.

2. Research Methods

The type of this research is experimental research, namely by conducting tests by looking for optimal accuracy resulting from the combination of the best parameters from the neural network method and optimization of grid search parameters, and optimization of evolutionary parameters to predict the movement of the Composite Stock Price Index (JCI) during the covid-19 pandemic in Indonesia. The flow of the research methodology is shown in Figure 1.

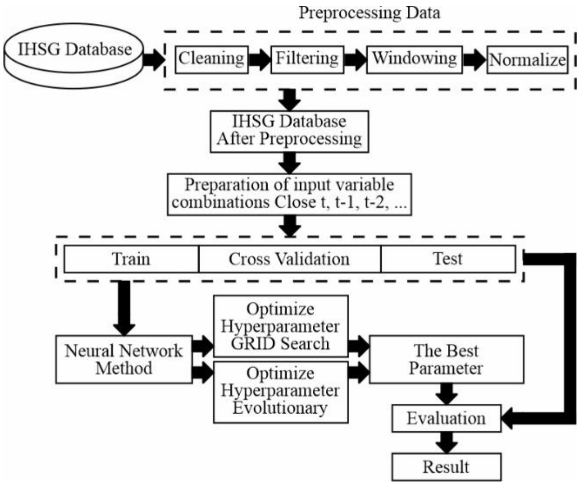

Figure 1. Flowchart of Grid Search Optimization and Evolutionary Optimization Stages on the Proposed Neural Network

2.1. Composite *Stock Price Index*

There are several indicators in measuring the performance of the stock exchange, namely the capitalization indicator and the index. The index often used by investors when investing in the Indonesia Stock Exchange (IDX) is the Composite Stock Price Index (JCI). Changes in stock market capitalization positively correlate with changes in the JCI; through the JCI, an investor can see whether market conditions are rising or falling. The rising JCI indicates a vibrant market

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condition and vice versa. This difference in conditions requires a strategy from investors in investing[15]. For investors who invest in the Indonesia Stock Exchange (IDX), JCI is a tool used as a benchmark or reference by investors in analyzing the development and movement of stock prices at any time. It was begun when the JCI was published to the public for the first time on April 1, 1983. The JCI can then be used as an indicator of stock price movements on the IDX and includes all shared and preferred stock prices. When the JCI can be calculated, namely on August 10, 1982, which at that time amounted to 13 shares, this was determined as the base day for calculating the JCI while the fundamental value is set at 100 for the general public for the first time[16].

2.2 Dataset Structure

The dataset used in this study is stock price movement data taken from public data. This data is from the Yahoo.com page regarding JCI share during the covid 19 pandemic, from 1 December 2019 to 31 December 2021. A total of 502 data were obtained. The data used is closing data, this data is very important because the closing price data is used as a benchmark for opening the following day, as shown in Table 1.

Table 1. JCI Closing Dataset

No	Date	Close
1	12/30/2021	6581.48
2	12/29/2021	6600.68
3	12/28/2021	6598.34
4	12/27/2021	6575.44
5	12/24/2021	6562.90
6	12/23/2021	6555.55
7	12/22/2021	6529.59
8	12/21/2021	6554.31
9	12/20/2021	6547.11
10	12/17/2021	6601.93
…	…	…
…	…	…
…	…	…
502	12/11/2019	6180.10

From Table 1, the line chart is obtained as shown in Figure 2.

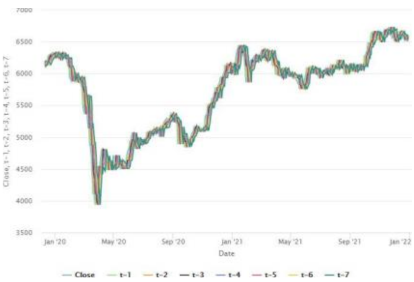

Figure 2. Line Chart of the Dataset

2.3 Preprocessing Data

Data preprocessing activity is an activity to clean data from data that is still in error, unclear or incomplete data. After obtaining the dataset from public data, then data preprocessing is carried out which includes data cleaning, filtering by changing the order from the newest date to the oldest date. Then, perform windowing (sliding window), namely by changing univariate data into multivariate data up to the previous seven days, as in the Table 2.

Table 2. Process Windowing Results Data

Date	Close t	Close t, t-1	Close t, t-2	Close t, t-3	Close t, t-4	Close t, t-5	Close t, t-6	Close t, t-7
12/30/2021	6581.48	6600.68	6598.34	6575.44	6562.90	6555.55	6529.59	6554.31
12/29/2021	6600.68	6598.34	6575.44	6562.90	6555.55	6529.59	6554.31	6547.11
12/28/2021	6598.34	6575.44	6562.90	6555.55	6529.59	6554.31	6547.11	6601.93
12/27/2021	6575.44	6562.90	6555.55	6529.59	6554.31	6547.11	6601.93	6594.80
12/24/2021	6562.90	6555.55	6529.59	6554.31	6547.11	6601.93	6594.80	6626.26
12/23/2021	6555.55	6529.59	6554.31	6547.11	6601.93	6594.80	6626.26	6615.64
12/22/2021	6529.59	6554.31	6547.11	6601.93	6594.80	6626.26	6615.64	6662.87
12/21/2021	6554.31	6547.11	6601.93	6594.80	6626.26	6615.64	6662.87	6652.92
12/20/2021	6547.11	6601.93	6594.80	6626.26	6615.64	6662.87	6652.92	6643.93
12/17/2021	6601.93	6594.8	6626.26	6615.64	6662.87	6652.92	6643.93	6603.80
…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…
12/11/2019	6180.10	6183.50	6193.79	6186.87	6152.12	6112.88	6133.9	6130.06

Then after that the next process is to normalize the data using the formula (1)

$$x' = \frac{x_{Old} - \bar{x}}{\alpha} \qquad (1)$$

x'= normalized data, x_{Old}= initial data, $\bar{x}$= average data, α= standard deviation. So, the data table after normalization is as in Table 3.

Table 3. Data After Normalization

Date	Close t, t-1	Close t, t-2	Close t, t-3	Close t, t-4	Close t, t-5	Close t, t-6	Close t, t-7
12/30/2021	1.312399	1.311677	1.278978	1.262353	1.253901	1.216186	1.257470
12/29/2021	1.308766	1.276079	1.259460	1.250899	1.213394	1.254806	1.246209
12/28/2021	1.273213	1.256586	1.248020	1.210443	1.251967	1.243557	1.331950
12/27/2021	1.253744	1.245161	1.207614	1.248967	1.240732	1.329202	1.320799
12/24/2021	1.242333	1.204807	1.246090	1.237746	1.326272	1.318063	1.370004
12/23/2021	1.202030	1.243233	1.234883	1.323178	1.315147	1.367213	1.353394
12/22/2021	1.240408	1.232041	1.320208	1.312066	1.364237	1.350621	1.427264
12/21/2021	1.229230	1.317257	1.309110	1.361093	1.347665	1.424408	1.411702
12/20/2021	1.314339	1.306174	1.358076	1.344543	1.421363	1.408864	1.397641
…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…
12/11/2019	0.664719	0.682814	0.674188	0.622195	0.563163	0.598003	0.59392

The variabel close t, close t-1, close t-2 to close t-7 are input variabels of the Neural Network process, while the output is the predict result. Artificial Intelligent Neural Network from Tabel 3 as in the Figure 2.

2.4 Selection Input Combination

After preprocessing the data, the input combination is selected from the alternative inputs. The combinations are close t, t-1 and t-2(P=1); close t, t-1, t-2 and t-3(P=2); close t, t-1, t-2, t-3 and t-4 (P=3); close t, t-1,t-2,t-3,t-4 and t-5(P=4); close t,t-1,t-2,t-3,t-4,t-5 and t-6(P=5) and close t,t-1,t-2,t-3, t-4, t-5, t-6 and t-7(P=6). Selection of this combination by using a neural network.

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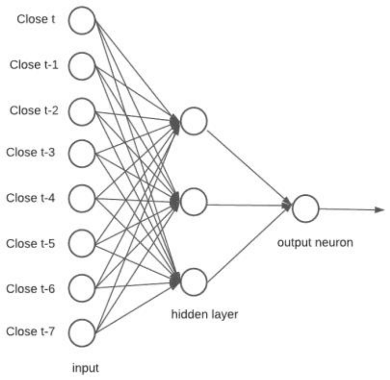

Figure 3. Artificial Intelligent Neural Network

2.5 Cross Validation

This study divides the data into training data and testing data. In this study, 10-fold validation is used, which separates 90 data sets for training and to find training data using neural network algorithms, to find training models, and then 10 data sets for testing data from training data models. This distribution is done randomly. Figure 4 is a schematic of 10-fold validation. The blue color represents the testing data and the white color represents the training data.

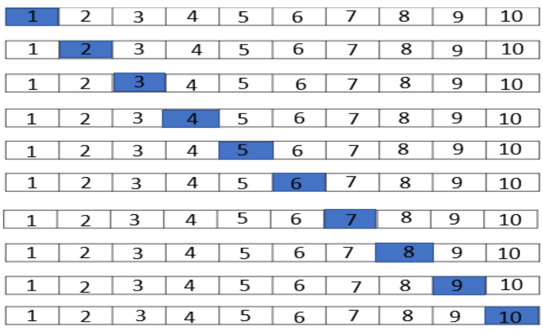

Figure 4. Schematic of 10-fold validation

2.6 Results Evaluation

RMSE or Root Mean Square Error is a method to find the error rate of the predicted value. The closer to the target, the better the prediction result. Based on equation 3, the best RMSE is obtained from the value of the neural network algorithm with grid parameter optimization compared to the value of the neural network algorithm with evolutionary parameters; the lowest RMSE value obtained is the most optimal RMSE value.[17].

$$\text{MSE} = \sqrt{\sum \frac{(Y' - Y)^2}{N}} \qquad (2)$$

Y'= Prediction value, Y= true value, N= amount of data. The category of an excellent RMSE value ranges from 0 to 1. The closer to 0, the better the RMSE. This means that the error value resulting from the evaluation is smaller than the one close to 1

2.7 Parameters Optimization

After obtaining RMSE results from the Neural Network algorithm, then optimized using grid search parameter optimization and evolutionary optimization to obtain more optimal results. Parameter Grid Search is often referred to as a complete search model on every combination of hyperparameters. Every variety of parameters specified will be tried to produce the best combination of values [10]. Evolutionary Parameter Optimization is Optimization techniques that follow biological evolution. According to the theory of evolution, a population has several individuals. From generation to generation, these individuals act as parents who reproduce to produce offspring. Better individuals tend to produce better offspring, too[18].

3. Results and Discussion

This stage describes the research results and explains the prediction of JCI stock price movements from JKSE during covid-19 to assist investors in making investment decisions. The implementation is by using JCI data. After going through the data preprocessing process, a search on the input combination that produced the most optimal RMSE value using a neural network algorithm optimized using a grid search parameter and compared again using evolutionary optimization. Which of these two optimizations is the better RMSE value? After getting the data on preprocessing, as shown in Table 1. The research was continued by dividing the data with various predetermined input combinations. Table 4 shows the combination of input variables P = 1,

Table 4. Combination P=1

closet t	Close t, t-1	Close t, t- 2
1.279822	1.312399	1.311677
1.309595	1.308766	1.276079
1.305966	1.273213	1.256586
1.270456	1.253744	1.245161
1.251011	1.242333	1.204807
1.239613	1.202030	1.243233
1.199358	1.240408	1.232041
1.237691	1.229230	1.317257
1.226526	1.314339	1.306174
1.311533	1.303270	1.355078
…	…	…
…	…	…
0.657418	0.664719	0.682814

Table 5 shows the combination of input variables P=2, consisting of t, t-1, t-2 and t-3

Table 5. Combination P=2

Closet, t	*Closet*-t-1	*Closet*, t- 2	*Closet*, t- 3
1.279822	1.312399	1.311677	1.278978
1.309595	1.308766	1.276079	1.259460
1.305966	1.273213	1.256586	1.248020
1.270456	1.253744	1.245161	1.207614
1.251011	1.242333	1.204807	1.246090
1.239613	1.202030	1.243233	1.234883
1.199358	1.240408	1.232041	1.320208
1.237691	1.229230	1.317257	1.309110

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1.226526	1.314339	1.306174	1.358076
1.311533	1.303270	1.355078	1.341547
…	…	…	…
…	…	…	…
0.657418	0.664719	0.682814	0.674188

Table 6 shows the input combination P=3, which consists of t, t-1, t-2, t-3 and t-4

Table 6. Combination P=3

Closet, t	*Closet*-t-1	*Closet*, t-2	*Closet*, t-3	*Closet*, t-4
1.279822	1.312399	1.311677	1.278978	1.262353
1.309595	1.308766	1.276079	1.259460	1.250899
1.305966	1.273213	1.256586	1.248020	1.210443
1.270456	1.253744	1.245161	1.207614	1.248967
1.251011	1.242333	1.204807	1.246090	1.237746
1.239613	1.202030	1.243233	1.234883	1.323178
1.199358	1.240408	1.232041	1.320208	1.312066
1.237691	1.229230	1.317257	1.309110	1.361093
1.226526	1.314339	1.306174	1.358076	1.344543
1.311533	1.303270	1.355078	1.341547	1.418146
…	…	…	…	…
…	…	…	…	…
0.657418	0.664719	0.682814	0.674188	0.622195

Table 7 shows the input combination P=4, consisting of t, t-1, t-2, t-3, t-4 and t-5

Table 7. Combination P=4

Closet, t	*Close t, t-1*	*Close t, t- 2*	*Close t, t- 3*	*Close t, t -4*	*Close t, t- 5*
1.279822	1.312399	1.311677	1.278978	1.262353	1.253901
1.309595	1.308766	1.276079	1.25946	1.250899	1.213394
1.305966	1.273213	1.256586	1.24802	1.210443	1.251967
1.270456	1.253744	1.245161	1.207614	1.248967	1.240732
1.251011	1.242333	1.204807	1.246090	1.237746	1.326272
1.239613	1.202030	1.243233	1.234883	1.323178	1.315147
1.199358	1.240408	1.232041	1.320208	1.312066	1.364237
1.237691	1.229230	1.317257	1.309110	1.361093	1.347665
1.226526	1.314339	1.306174	1.358076	1.344543	1.421363
1.311533	1.303270	1.355078	1.341547	1.418146	1.405837
…	…	…	…	…	…
…	…	…	…	…	…
0.657418	0.664719	0.682814	0.674188	0.622195	0.563163

Table 8 shows the input combination P=5, consisting of t, t-1, t-2, t-3, t-4, t-5 and t-6

Table 8. Combination P=5

Closet, t	*Close t, t-1*	*Close t, t- 2*	*Close t, t- 3*	*Close t, t -4*	*Close t, t- 5*	*Close t, t -6*
1.279822	1.312399	1.311677	1.278978	1.262353	1.253901	1.216186
1.309595	1.308766	1.276079	1.259460	1.250899	1.213394	1.254806
1.305966	1.273213	1.256586	1.248020	1.210443	1.251967	1.243557
1.270456	1.253744	1.245161	1.207614	1.248967	1.240732	1.329202
1.251011	1.242333	1.204807	1.246090	1.237746	1.326272	1.318063
1.239613	1.202030	1.243233	1.234883	1.323178	1.315147	1.367213
1.199358	1.240408	1.232041	1.320208	1.312066	1.364237	1.350621
1.237691	1.229230	1.317257	1.309110	1.361093	1.347665	1.424408
1.226526	1.314339	1.306174	1.358076	1.344543	1.421363	1.408864
1.311533	1.303270	1.355078	1.341547	1.418146	1.405837	1.394819
…	…	…	…	…	…	…
…	…	…	…	…	…	…
0.657418	0.664719	0.682814	0.674188	0.622195	0.563163	0.598003

Table 9 shows the input combination P=6, consisting of t, t-1, t-2, t-3, t-4, t-5, t-6 and t-7

Table 9. Combination P=6

Closet, t	*closet, t-1*	*closet, t-2*	*closet, t-3*	*closet, t-4*	*closet, t-5*	*closet, t-6*	*closet, t-7*
1.279822	1.312399	1.311677	1.278978	1.262353	1.253901	1.216186	1.257470
1.309595	1.308766	1.276079	1.259460	1.250899	1.213394	1.254806	1.246209
1.305966	1.273213	1.256586	1.248020	1.210443	1.251967	1.243557	1.331950
1.270456	1.253744	1.245161	1.207614	1.248967	1.240732	1.329202	1.320799
1.251011	1.242333	1.204807	1.246090	1.237746	1.326272	1.318063	1.370004
1.239613	1.202030	1.243233	1.234883	1.323178	1.315147	1.367213	1.353394
1.199358	1.240408	1.232041	1.320208	1.312066	1.364237	1.350621	1.427264
1.237691	1.229230	1.317257	1.309110	1.361093	1.347665	1.424408	1.411702
1.226526	1.314339	1.306174	1.358076	1.344543	1.421363	1.408864	1.397641
1.311533	1.303270	1.355078	1.341547	1.418146	1.405837	1.394819	1.334875
…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…
0.657418	0.664719	0.682814	0.674188	0.622195	0.563163	0.598003	0.593920

3.1 Experiment with Neural Network Algorithm

For each of these input combinations, an experiment was conducted to find a variety of parameters from the training cycle, momentum, and learning rate to produce an optimal RMSE using a neural network algorithm using RapidMiner. Table 10 shows the best RMSE values for the combination P=1.

Table 10. Combination of Neural Network Algorithm P=1

Training Cycle	Momentum	Learning Rate	RMSE
8000	0.9	0.01	0.130
		0.1	0.108
		0.2	0.106
		0.3	0.106
		0.4	0.106
		0.5	0.552
		0.6	0.509
		0.7	0.736
		0.8	48658
		0.9	0.601
		1.0	0.623

Table 10 shows that for the input combination P = 1, which produces the best RMSE value of 0.106, in the 8000-training cycle, the momentum is 0.9, and the learning rate is 0.2. Figure 5. Shows the neural network architecture based on Table 9.

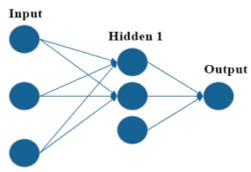

Figure 5. Architecture Neural Network P=1

As for the experiment at P=2, the experimental results are in Table 11.

Table 1. Combination of Neural Network Algorithm P=2

Training Cycle	*Momentum*	*Learning* Rate	RMSE
8000	0.9	0.01	0.133
		0.1	0.108
		0.2	0.107
		0.3	0.203
		0.4	0.183
		0.5	0.515
		0.6	0.586
		0.7	0.659
		0.8	0.675
		0.9	0.622

Table 11. shows the best RMSE for P=2 is in the training cycle of 8000, with a momentum of 0.9 and a

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learning rate of 0.2 with an RMSE of 0.107. Figure 6 shows the neural network architecture based on Table 10.

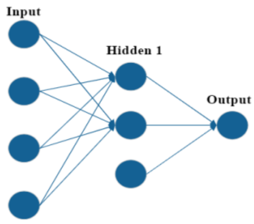

Figure 6. Architecture Neural Network P=2

The P=3 experiment's experimental results are shown in Table 12.

Table 12. Combination of Neural Network Algorithm P=3

Training Cycle	*Momentum*	*Learning* Rate	RMSE
9000	0.9	0.01	0.133
		0.1	0.107
		0.2	0.105
		0.3	0.113
		0.4	0.278
		0.5	0.376
		0.6	0.602
		0.7	0.510
		0.8	0.595
		0.9	19022

Table 12 shows that at P = 3, the best combination with a training cycle of 9000, a momentum of 0.9, and a learning rate of 0.2 will produce the best RMSE of 0.105. Figure 7 illustrates the neural network architecture based on Table 12.

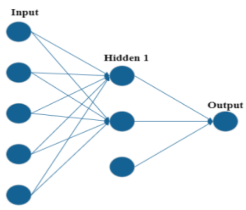

Figure 7. Architecture Neural Network P=3

For the experiment of searching for a combination of parameters of P=4, as in Table 13.

Table2. Combination of Neural Network Algorithm P=4

Training Cycle	*Momentum*	*Learning* Rate	RMSE
9000	0.9	0.01	0.130
		0.1	0.466
		0.2	0.105
		0.3	0.161
		0.4	0.437
		0.5	0.346
		0.6	0.513
		0.7	0.619
		0.8	0.432
		0.9	0.466

Table 13 shows that for P=4, the best combination to get the most optimal RMSE is the 9000-training cycle, 0.9 momenta, and 0.2 learning rate, which produces an RMSE of 0.105. Figure 8 illustrates the neural network architecture based on Table 13.

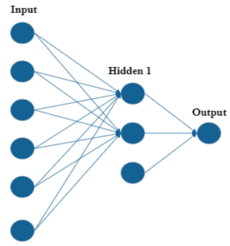

Figure 8. Architecture Neural Network P=4

Table 14. Experiments from searching the combination of parameters from P=5

Table 3. Combination of Neural Network Algorithm P=5

Training Cycle	*Momentum*	*Learning* Rate	RMSE
9000	0.9	0.01	0.126
		0.1	0.106
		0.2	0.104
		0.3	0.193
		0.4	0.379
		0.5	0.579
		0.6	0.460
		0.7	0.530
		0.8	0.599
		0.9	0.641

Table 14 shows that for P=5, the best RMSE value is generated in a combination of training cycle 9000, momentum 0.9, learning rate 0.2 with RMSE of 0.104. Figure 9 illustrates the neural network architecture based on Table 14.

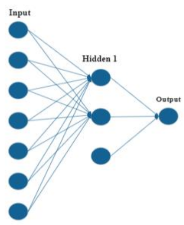

Figure 92. Architecture Neural Network P=5

Table 15. for the experiment to find the best combination of parameters from P=6, as in Table 15.

Table4. Experimental Combination of Neural Network Algorithm P=6

Training Cycle	*Momentum*	*Learning* Rate	RMSE
9000	0.9	0.01	0.124
		0.1	0.107
		0.2	0.141
		0.3	0.205
		0.4	0.460
		0.5	0.500
		0.6	0.601
		0.7	0.535
		0.8	0.451
		0.9	0.559

Table 15. For P=6, the best RMSE value is generated in the combination of training cycle 9000, momentum 0.9, learning rate 0.1 with RMSE of 0.107. Figure 10

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illustrates the neural network architecture based on Table 15.

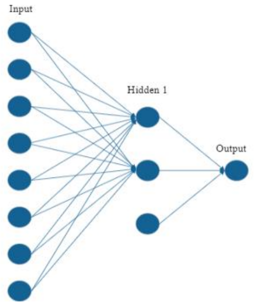

Figure 10. Architecture Neural Network P=6

Table 16 compares and selects the best attributes or variables using the Neural Network algorithm from P=1, P=2, P=3, P=4, P=5, and P=6.

Table5. Comparison Results of all Input Combinations

Input Combination	*Training Cycle*	*Momentum*	*Learning Rate*	RMSE
P=1	8000	0.9	0.2	0.106
P=2	8000	0.9	0.2	0.107
P=3	9000	0.9	0.2	0.105
P=4	9000	0.9	0.2	0.105
P=5	9000	0.9	0.2	0.104
P=6	9000	0.9	0.1	0.107

Based on Table 16, it can be concluded that the input combination, which produces the optimal RMSE of the neural network algorithm, is at P=5, with a variety of parameters, training cycle 9000, momentum 0.9, and learning rate 0.2, and produces an RMSE of 0.104.

3.2 Experiment with Grid Search Optimization and Evolutionary Parameters on Neural Networks

The following experiment, after obtaining the best RMSE value results from the combination of parameters using the neural network algorithm, then optimized using the grid search parameter. As a result, when using a neural network, the results obtained are RMSE 0.104, momentum 0.9, training cycle 9000, and learning rate 0.2, and after being optimized using a grid search value of RMSE 0.101, momentum 1, training cycle 100, and learning rate 1, so that it has an increase of RMSE 0.003. Figure 11 shows the grid search optimization architecture on a neural network.

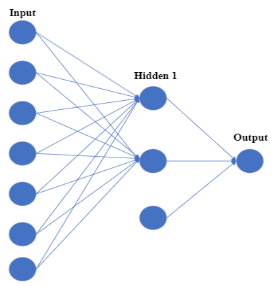

Figure 11. Grid Search Optimization Architecture on Neural Networks

In addition to being optimized by using the grid search parameter, this study also compares it with the optimization of evolutionary parameters, obtained RMSE 0.103, with a training cycle of 86, a learning rate of 0.029 and a momentum of 0.68. This result, when compared with the Neural Network, has a difference of 0.001. Figure 12 shows the evolutionary optimization architecture on a neural network.

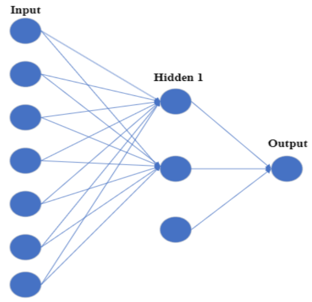

Figure 12. Evolutionary Optimization Architecture on Neural Networks

The experimental results of grid search optimization and evolutionary optimization on neural networks can be concluded in Table 17.

Table6. Comparison of Grid Search + Neural Network Optimization with Evolutionary + Neural Network Optimization

	GRID+ NN	Evolutionary+ NN	Neural Network
Training Cycle	100	86	9000
Momentum	1	0.68	0.9
Learning Rate	1	0.029	0.2
RMSE	0.101	0.103	0.104

Table 17 shows that using grid search optimization will produce a better RMSE than using the neural network algorithm, which is 0.101, meaning that there is an increase in RMSE of 0.003, while using evolutionary optimization makes an RMSE of 0.103, which means when compared to using a neural network. Alone will experience an RMSE optimization of 0.001.

For more details, it can be seen from the RMSE comparison image of grid search optimization with evolutionary optimization, as shown in Figure 13.

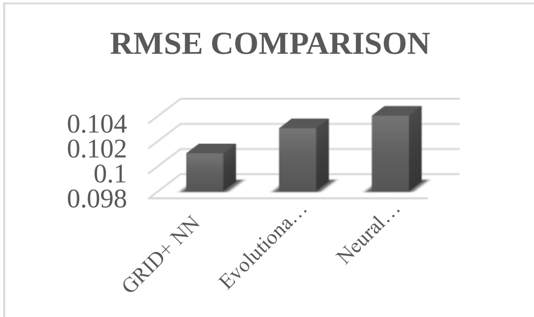

Figure 3. Bar Chart Comparison of Grid Search Optimization and Evolutionary Optimization

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The smaller RMSE value indicates that the prediction results from this experiment are getting better. Table 16 shows that the RMSE results from JCI stock price movements, using comparative price data as a reference for the next day's opening; the neural network method optimized by grid search will produce a smaller RMSE than evolutionary optimization. Thus, investors can still invest safely because the RMSE value is small.

This study also conducted experiments using datasets before covid 19 and after 2021 to find the RMSE value using a variable combination model from the neural network obtained previously. The dataset used for the experiment before covid 16 is from December 1, 2018, to December 31, 2019, and the dataset is from September 31, 2021, to September 27, 2022. The comparison of the results obtained is shown in Table 18.

Table7. Comparison of Grid Search + Neural Network with Evolutionary+ Neural Network before and now

	December 1, 2018 – December 31, 2019			September 31, 2021 – December 27, 2022		
	GRID+ NN	Evolutionary + NN	NN	GRID+ NN	Evolutionary + NN	NN
TC	51	94	9000	31	94	9000
momentum	0.4	0.692	0.2	0.2	0.692	0.2
LR	0.1	0.050	0.35	0.1	0.129	0.9
RMSE	0.206	0.214	0.35	0.198	0.219	0.391

The results of Table 18, compared with Table 17, can be seen in Figure 14.

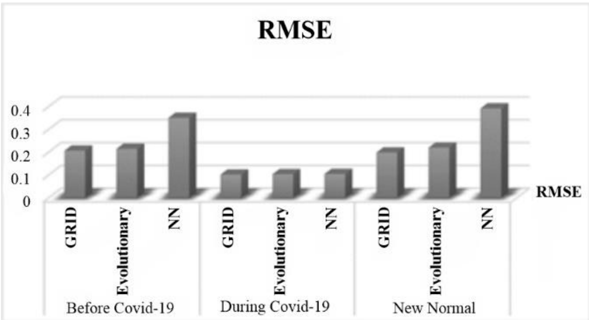

Figure 14. Comparison of RMSE Before, During Covid-19 and New Normal

Figure 14 shows that the RMSE on the neural network method during the covid-19 pandemic, namely in the period December 1, 2019, to December 31, 2021, was better than before the covid-19 pandemic or the new normal period, which was 0.104. Likewise, optimizing the grid and evolutionary means investment activities during the COVID-19 pandemic are better than before and the new normal. This is due to restrictions on community activities that impact investment activities carried out online. The cautious attitude of business people makes investment activities during the COVID-19 pandemic safer. The RMSE before the covid-19 pandemic was smaller than during the new normal due to the stability of the JCI price. Meanwhile, the RMSE value is higher during the new normal due to the desire of business people to dominate the market.

4. Conclusion

Based on the results of the discussion using the Composite Stock Price Index (CSPI) data from historical data on the Yahoo.com page using 502 data, which is implemented on the neural network algorithm, the results show that the best combination of inputs is the Close t, t-1, t combination. -2, t-3, t-4, t-5, and t-6 (P=5). The RMSE obtained is 0.104. With 9000 training cycles, 0.9 momenta and 0.2 learning rate. However, by optimizing the grid search parameter, the RMSE value is smaller, namely RMSE 0.101 and training cycle 100, momentum 1 and learning rate 1. When optimized using evolutionary parameters, the RMSE result is 0.103, with training cycle 86, momentum 0.68 and learning rate 0.029 when using the grid search parameter optimization.

Based on the discussion of the input combination model obtained between the neural network and the optimization of the grid search parameters, the RMSE value is better than the neural network with the optimization of evolutionary parameters. Still, for further research, the researcher suggests using other parameter optimizations to obtain a better RMSE.

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