IMPLEMENTATION OF THE CONVOLUTIONAL NEURAL NETWORK METHOD FOR PREDICTING LQ45 STOCK PRICES

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Abstract

Stock are securities of ownership of a company. Investments in the stock market on average can produce a return rate of 10-30% per year, this amount is about two to three times higher than the rate of return on deposits or savings in banks which are only 5-10 % every year. One problem is the stock price is fluctuating or changing due to certain factors. This study compares several window size data with different amounts of data, aiming to find window size data with a more accurate amount of data for stock price predictions. Convolutional neural network algorithm with window size data of 7 days, 14 days, 21 days and 28 days in the amount of data 1 year and 2 years for stock price predictions. The results of this study are the convolutional neural network algorithm with a data window size of 7 days at the amount of data 2 years is more accurate than the window size data and the amount of other data. Because the smallest error result is 0.000201587.

Keywords: *Predictions, Stocks, Window Size Data, Convolutional Neural Network.*

1. INTRODUCTION

The stock market is a place for buyers or investors to buy shares in a company. There are many ways that potential investors use to choose the right company, one of which is to analyze using the stock market index. The LQ45 index is an index consisting of 45 listed company stocks selected based on liquidity and market capitalization considerations. Companies that are included in the LQ45 index are companies that have good economic conditions.

Machine learning is a very useful tool to do some work in financial areas, which can be divided into two parts: supervised machine learning and unsupervised machine learning. The significant difference between the former and the latter is whether we have the label of the training data. One we should pay attention to is that deep learning is developed on the basis of machine learning, which shows that both concepts are very similar. Traditional deep learning way also includes two parts: Convolutional Neural Network and Recurrent Neural Network [2].

Convolutional neural network (CNN) is a deep learning algorithm which processes primarily images but also numerical data to find patterns. CNN are also referred as ConvNets and have little processing requirements than other classification algorithms. When we speak of CNN, primarily we think of image classification where CNN is feed with images and trains on these images using the

conventional techniques of Convolution, Pooling and Flattening and then tries to classify a new image from the features that it has learned [1].

In this journal, a deep learning model based on Convolutional Neural Network is proposed to predict the LQ45 stock price movement of Indonesian stock market. We use TensorFlow to help us design the model. At first, we will collecting data and normalize them because each feature has a big difference, otherwise it will affect the result. Then, because the stock data belongs to 1D time series data, we have used a 1D function to do the convolution and set one parameter is closing price as input.

2. RESEARCH METHODOLOGY

The flow of this research can be seen in Figure 1 below:

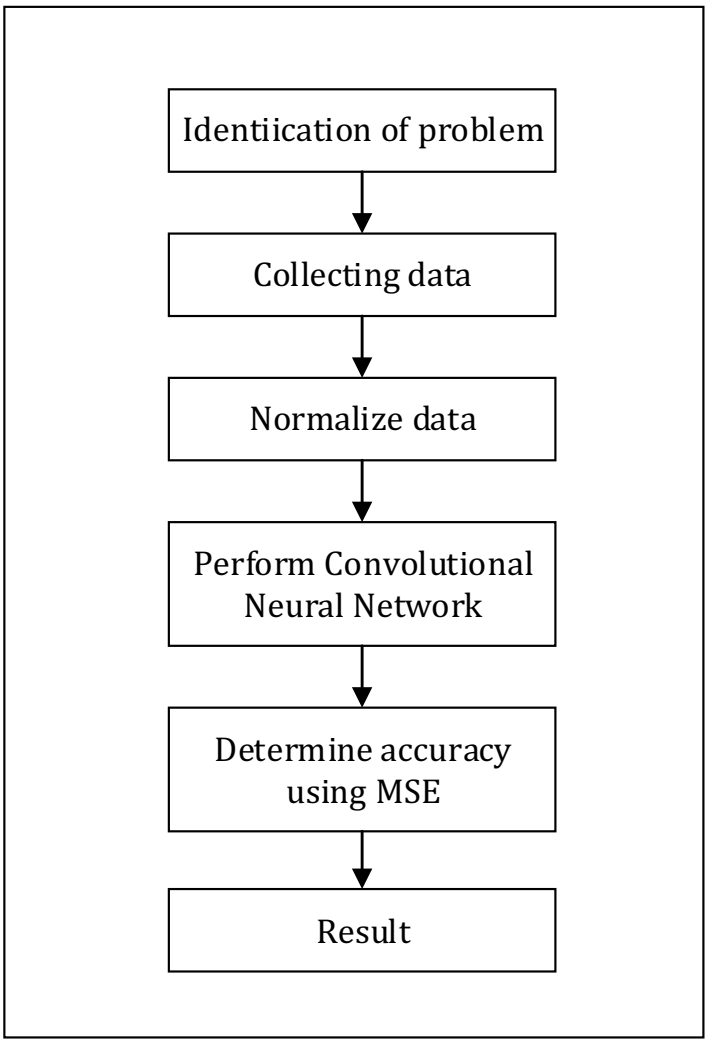

Figure 1. Research flow for stock price prediction

2.1 Identification of the problem

The initial step in this research is to identify problems by gathering various information related to research needs such as conducting a study of literature studies and observing cases.

2.2 Collecting Data

Collect and analyze data obtained from yahoo finance, such as stock closing

price data as a parameter used in stock price predictions.

2.3 Normalize Data

Normalization is the process of building a database structure so that most ambiguities can be removed. The objectives of normalization are as follows:

1. Eliminate duplication of data.
2. Reduce Complexity.
3. Simplify data modification [7].

The normalization formula is as follows:

$$Normalization = \frac{data_x - data_{min}}{data_{max} - data_{min}} \quad (1)$$

Information:

$data_x$ = Data to be normalized.

$data_{max}$ = Maximum data in that column.

$data_{min}$ = Minimum data in that column [5].

2.4 Perform Convolutional Neural Network

The Convolutional Neural Networks algorithm is a development of the Multi Layer Perceptron (MLP) which is designed to process two-dimensional data. The way Convolutional Neural Networks works is similar to MLP, but in Convolutional Neural Networks, each neuron can be represented in two dimensions, unlike MLP, where each neuron is only one dimension. In Convolutional Neural Networks, the data propagated on the network is two-dimensional data, so the linear operation and weight parameters on Convolutional Neural Networks are different. CNN steps as follows [8]:

1. Convolution Layer

   A convolution operation is an operation on two real-value argument functions. This operation applies the output function as a Feature Map of the input image. This input and output can be seen as two arguments of real value. Formally the convolution operation can be written with the following formula.

   $$s(t) = (x * w)(t) \quad (2)$$

   The function s(t) provides a single output in the form of a Feature Map, the first argument is the input which is x and the second argument is was the kernel or filter. If we view the input as a two-dimensional image, then we can assume t to be a pixel and replace it with i and j.
2. Pooling Layer

   Pooling Layer is a layer that uses a function with a Feature Map as input and processes it with various statistical operations based on the closest pixel value. Pooling layers inserted between successive convolutional layers in the CNN model architecture can progressively reduce the size of the output volume on the Feature Map, thereby reducing the number of parameters and calculations on the network, and for controlling overfitting.
3. ReLU Activation

   ReLU (Rectified Linear Unit) activation is an activation layer in the CNN model that applies the function

   $$f(x) = max(0, x) \quad (3)$$

   this function performs Thresholding with a zero value against the pixel value in

the image input. This activation causes all pixel values that are less than zero in an image to be set to 0.

4. Fully Connected Layer

   The Fully Connected Layer is the layer where all the activation neurons from the previous layer are all connected with the neurons in the next layer just like an ordinary artificial neural network. Each activation from the previous layer needs to be converted into one-dimensional data before it can be linked to all neurons in the Fully-Connected layer. The Fully-Connected Layer is usually used in the Multi Layer Perceptron method and aims to process data so that it can be classified [3]

2.5 Determine the accuracy of using MSE

Mean Square Error (MSE) is a parameter in forecasting to test the accuracy of the forecasting results that have been done. The smaller the Mean Square Error (MSE) value, the more accurate the forecasting results have been. The formula for calculating the Mean Square Error (MSE) is as follows [4]:

$$MSE = \frac{\sum Et^2}{n} \quad (4)$$

3. RESULTS AND DISCUSSION

3.1 Results

Data collection is obtained from yahoo finance in the form of closing price data for GGRM shares. The data is 1 year 2 years starting in 2018 and 2019. Data for 1 year closing share price can be seen in table 1 and data on stock closing for 2 years can be seen in table 2 below:

Table 1 Data on 1 year closing stock prices

No	Date	Price
1	01/02/2019	83000
2	04/02/2019	81000
3	05/02/2019	81000
4	06/02/2019	81500
5	07/02/2019	81300
6	08/02/2019	80900
7	11/02/2019	81000
8	12/02/2019	80775
9	13/02/2019	82575
10	14/02/2019	83000
...	...	...
267	14/02/2020	54575

Table 2 Data on 2 year closing stock prices

No	Date	Price
1	01/02/2018	81800
2	02/02/2018	81500
3	05/02/2018	81700
4	06/02/2018	82600
5	07/02/2018	83250
6	08/02/2018	83150
7	09/02/2018	81200
8	12/02/2018	79550
9	13/02/2018	80000
10	14/02/2018	80000
...	...	...
528	14/02/2020	54575

3.1.1 Normalize Data

The data were normalized for 1 year and 2 years. the results of 1 year data normalization can be seen in table 3 and the results of 2 years data normalization can be seen in table 4.

Table 3 Data on 1 year closing stock prices

No	Date	Price	Normalization
1	01/02/2019	83000	0,747648
2	04/02/2019	81000	0,703376
3	05/02/2019	81000	0,703376
4	06/02/2019	81500	0,714444

5	07/02/2019	81300	0,710017
6	08/02/2019	80900	0,701162
7	11/02/2019	81000	0,703376
8	12/02/2019	80775	0,698395
9	13/02/2019	82575	0,73824
10	14/02/2019	83000	0,747648
...	...	...	...
257	14/02/2020	54575	0,118428

Table 4 Data on 2 year closing stock prices

No	Date	Price	Normalization
1	01/02/2018	81800	0,721085
2	02/02/2018	81500	0,714444
3	05/02/2018	81700	0,718871
4	06/02/2018	82600	0,738794
5	07/02/2018	83250	0,753182
6	08/02/2018	83150	0,750968
7	09/02/2018	81200	0,707803
8	12/02/2018	79550	0,671278
9	13/02/2018	80000	0,68124
10	14/02/2018	80000	0,68124
...	...	...	...
528	14/02/2020	54575	0,105374

3.1.2 Window Size Data

This process forms the data into X and y, X is the data used for prediction and y is the reference data for prediction. The window sizes used in this study were 7 days, 14 days 21 days and 28 days. The data used is 2 years. The results of the window size data representation value can be seen in the following table.

Table 5 7-Day Data Representation of GGRM Stock Window Size Value

No	X	Y
1	[0,721084671, 0,71444383, 0,718871057, 0,738793581, 0,75318207, 0,750968456, 0,707802988]	[0,671278362]
2	[0,71444383, 0,718871057, 0,738793581, 0,75318207, 0,750968456, 0,707802988, 0,671278362]	[0,681239624]
3	[0,718871057, 0,738793581, 0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624]	[0,681239624]
4	[0,738793581, 0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624]	[0,695074709]
5	[0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709]	[0,695074709]
...	...	...
512	[0,193137797, 0,200885445, 0,178195905, 0,164914222, 0,16768124, 0,143331489, 0,144991699]	[0,138350858]

Table 6 14-Day Data Representation of GGRM Stock Window Size Value

No	X	Y
1	[0,721084671, 0,71444383, 0,718871057, 0,738793581, 0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709, 0,695074709, 0,723851688, 0,703375761]	[0,683453237]
2	[0,71444383, 0,718871057, 0,738793581, 0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709, 0,695074709, 0,723851688, 0,703375761, 0,683453237]	[0,673491976]
3	[0,718871057, 0,738793581, 0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709, 0,695074709, 0,723851688, 0,703375761, 0,683453237, 0,673491976]	[0,712230216]
4	[0,738793581, 0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709, 0,695074709, 0,723851688, 0,703375761, 0,683453237, 0,673491976, 0,712230216]	[0,660763697]
5	[0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709, 0,695074709, 0,723851688, 0,703375761, 0,683453237, 0,673491976, 0,712230216, 0,660763697]	[0,675705589]
...	...	...
505	[0,201438849, 0,192584394, 0,194798008, 0,200885445, 0,194244604, 0,172661871, 0,179856115, 0,193137797, 0,200885445, 0,178195905, 0,164914222, 0,16768124, 0,143331489, 0,144991699]	[0,138350858]

Table 7 21-Day Data Representation of GGRM Stock Window Size Value

No	X	Y
1	[0,721084671, 0,71444383, 0,718871057, 0,738793581, 0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709, 0,695074709, 0,723851688, 0,703375761, 0,683453237, 0,673491976, 0,712230216, 0,660763697, 0,675705589, 0,675705589, 0,6773658]	[0,681239624]
2	[0,71444383, 0,718871057, 0,738793581, 0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709, 0,695074709, 0,723851688, 0,703375761, 0,683453237, 0,673491976, 0,712230216, 0,660763697, 0,675705589, 0,675705589, 0,6773658, 0,681239624]	[0,663530714]
3	[0,718871057, 0,738793581, 0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709, 0,695074709, 0,723851688, 0,703375761, 0,683453237, 0,673491976, 0,712230216, 0,660763697, 0,675705589, 0,675705589, 0,6773658, 0,681239624, 0,663530714]	[0,675705589]
4	[0,738793581, 0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709,	[0,621472053]

	0,695074709, 0,723851688, 0,703375761, 0,683453237, 0,673491976, 0,712230216, 0,660763697, 0,675705589, 0,675705589, 0,6773658, 0,681239624, 0,663530714, 0,675705589]	
5	[0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709, 0,695074709, 0,723851688, 0,703375761, 0,683453237, 0,673491976, 0,712230216, 0,660763697, 0,675705589, 0,675705589, 0,6773658, 0,681239624, 0,663530714, 0,675705589, 0,621472053]	[0,680132817]
...	...	...
498	[0,107913669, 0,114001107, 0,14997233, 0,180962922, 0,176535695, 0,196458218, 0,201438849, 0,201438849, 0,192584394, 0,194798008, 0,200885445, 0,194244604, 0,172661871, 0,179856115, 0,193137797, 0,200885445, 0,178195905, 0,164914222, 0,16768124, 0,143331489, 0,144991699]	[0,138350858]

Table 8 28-Day Data Representation of GGRM Stock Window Size Value

No	X	Y
1	[0,721084671, 0,71444383, 0,718871057, 0,738793581, 0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709, 0,695074709, 0,723851688, 0,703375761, 0,683453237, 0,673491976, 0,712230216, 0,660763697, 0,675705589, 0,675705589, 0,6773658, 0,681239624, 0,663530714, 0,675705589, 0,621472053 0,680132817, 0,64360819, 0,617598229, 0,546209186]	[0,546209186]
2	[0,71444383, 0,718871057, 0,738793581, 0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709, 0,695074709, 0,723851688, 0,703375761, 0,683453237, 0,673491976, 0,712230216, 0,660763697, 0,675705589, 0,675705589, 0,6773658, 0,681239624, 0,663530714, 0,675705589, 0,621472053 0,680132817, 0,64360819, 0,617598229, 0,546209186]	[0,515218594]
3	[0,718871057, 0,738793581, 0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709, 0,695074709, 0,723851688, 0,703375761, 0,683453237, 0,673491976, 0,712230216, 0,660763697, 0,675705589, 0,675705589, 0,6773658, 0,681239624, 0,663530714, 0,675705589, 0,621472053 0,680132817, 0,64360819, 0,617598229, 0,546209186, 0,515218594]	[0,561704483]
4	[0,738793581, 0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709, 0,695074709, 0,723851688, 0,703375761, 0,683453237, 0,673491976, 0,712230216, 0,660763697, 0,675705589, 0,675705589, 0,6773658, 0,681239624, 0,663530714, 0,675705589, 0,621472053 0,680132817, 0,64360819, 0,617598229, 0,546209186, 0,515218594, 0,561704483]	[0,574986165]
5	[0,75318207, 0,750968456, 0,707802988, 0,671278362, 0,681239624, 0,681239624, 0,695074709, 0,695074709, 0,723851688, 0,703375761, 0,683453237, 0,673491976, 0,712230216, 0,660763697, 0,675705589, 0,675705589,	[0,570558937]

	0,6773658, 0,681239624, 0,663530714, 0,675705589, 0,621472053 0,680132817, 0,64360819, 0,617598229, 0,546209186, 0,515218594, 0,561704483, 0,574986165]	
...	...	...
491	[0,064194798, 0,085777532, 0,096292197, 0,092418373, 0,089097952, 0,083563918, 0,091311566, 0,107913669, 0,114001107, 0,14997233, 0,180962922, 0,176535695, 0,196458218, 0,201438849, 0,201438849, 0,192584394, 0,194798008, 0,200885445, 0,194244604, 0,172661871, 0,179856115, 0,193137797, 0,200885445, 0,178195905, 0,164914222, 0,16768124, 0,143331489, 0,144991699]	[0,138350858]

3.1.3 Calculation of the CNN method and MSE

This study compares 4 different window size data with 2 different amounts of data that are applied to the LQ45 stock price prediction. The parameters used in this study are epoch: 100, Convolutional layer 1: 128 filter, Convolutional layer 2: 128 filter, Pooling layer 1: 2, Pooling layer 2: 2, Activation Function: ReLu, Dense layer: 64.

a. Window Size Data 7 Days and Data 2 Year

Window Size data is 7 days, namely 7 days for prediction and the 8th day as prediction reference. The error results for window size data of 7 days and data for 2 year using MSE can be seen in the following table:

Table 9 Prediction Results and MSE Window Size Data 7 Days Data 2 Year GGRM Shares

No	Date	Actual	Prediction	Square Error
1	03/02/2020	0,138350858	0,135335	9,0971E-06
2	04/02/2020	0,142778085	0,136657	3,7463E-05
3	05/02/2020	0,154952961	0,129404	0,00065276
4	06/02/2020	0,172108467	0,144689	0,00075182
5	07/02/2020	0,158273381	0,171176	0,00016647
6	10/02/2020	0,143331489	0,154867	0,00013307
7	11/02/2020	0,143331489	0,144686	1,8339E-06
8	12/02/2020	0,13226342	0,136752	2,0145E-05
9	13/02/2020	0,13226342	0,123733	7,2775E-05
10	14/02/2020	0,118428334	0,105374	0,00017043
		MSE		0,00020159

b. Window Size Data 14 Days and Data 2 Year

Window Size data is 14 days, namely 14 days for prediction and the 15th day as prediction reference. The error results for window size data of 14 days and data for 2 year using MSE can be seen in the following table:

Table 10 Prediction Results and MSE Window Size Data 14 Days Data 2 Year GGRM Shares

No	Date	Actual	Prediction	Square Error
1	03/02/2020	0,138350858	0,1587329	0,000415427
2	04/02/2020	0,142778085	0,1412062	2,47069E-06
3	05/02/2020	0,154952961	0,1064791	0,002349712
4	06/02/2020	0,172108467	0,1114481	0,003679675
5	07/02/2020	0,158273381	0,1165703	0,001739149
6	10/02/2020	0,143331489	0,1039449	0,001551305

7	11/02/2020	0,143331489	0,1307949	0,000157166
8	12/02/2020	0,13226342	0,1331349	7,59396E-07
9	13/02/2020	0,13226342	0,1469406	0,000215421
10	14/02/2020	0,118428334	0,1341278	0,000246473
		MSE		0,001035756

c. Window Size Data 21 Days and Data 2 Year

Window Size data is 21 days, namely 21 days for prediction and the 22th day as prediction reference. The error results for window size data of 21 days and data for 2 year using MSE can be seen in the following table:

Table 11 Prediction Results and MSE Window Size Data 21 Days Data 2 Year GGRM Shares

No	Date	Actual	Prediction	Square Error
1	03/02/2020	0,138350858	0,129426	7,966E-05
2	04/02/2020	0,142778085	0,121691	0,0004447
3	05/02/2020	0,154952961	0,098734	0,0031605
4	06/02/2020	0,172108467	0,126555	0,0020751
5	07/02/2020	0,158273381	0,108096	0,0025177
6	10/02/2020	0,143331489	0,140956	5,642E-06
7	11/02/2020	0,143331489	0,153122	9,585E-05
8	12/02/2020	0,13226342	0,155553	0,0005424
9	13/02/2020	0,13226342	0,133276	1,024E-06
10	14/02/2020	0,118428334	0,143513	0,0006292
		MSE		0,0009552

d. Window Size Data 28 Days and Data 2 Year

Window Size data is 28 days, namely 28 days for prediction and the 29th day as prediction reference. The error results for window size data of 28 days and data for 2 year using MSE can be seen in the following table:

Table 12 Prediction Results and MSE Window Size Data 28 Days Data 2 Year GGRM Shares

No	Date	Actual	Prediction	Square Error
1	03/02/2020	0,138350858	0,110625	0,000769
2	04/02/2020	0,142778085	0,132101	0,000114
3	05/02/2020	0,154952961	0,129085	0,000669
4	06/02/2020	0,172108467	0,100784	0,005087
5	07/02/2020	0,158273381	0,13171	0,000706
6	10/02/2020	0,143331489	0,149078	3,3E-05
7	11/02/2020	0,143331489	0,137015	3,99E-05
8	12/02/2020	0,13226342	0,133027	5,84E-07
9	13/02/2020	0,13226342	0,104918	0,000748
10	14/02/2020	0,118428334	0,115803	6,89E-06
		MSE		0,000817

3.1.4 Calculation of accuracy values

To test the accuracy of the Convolutional Neural Network method, the predicted results are compared with the actual values. In addition, there is also an MSE calculation for all shares used with 1 year and 2 year data, the calculation results can be seen in the following table:

Table 13 MSE results from 1 year data

Window Size	GGRM	SRIL	SCMA	PGAS	BBNI
7 day	0,000408281	0,000965453	0,00186129	0,002687778	0,00142941
14 day	0,000879747	0,004547632	0,006139644	0,008349635	0,003238288
21 day	0,001185206	0,006036296	0,003640631	0,003659584	0,00285287
28 day	0,001872534	0,003578972	0,002520787	0,001829869	0,004369061

Table 14 MSE results from 2 year data

Window Size	GGRM	SRIL	SCMA	PGAS	BBNI
7 day	0,000201587	0,001229118	0,000768478	0,000653209	0,001364835
14 day	0,001035756	0,006419237	0,000651831	0,003744379	0,001858774
21 day	0,000955187	0,002514053	0,000673907	0,002647457	0,00345638
28 day	0,000817291	0,002464311	0,000289571	0,000834011	0,001982017

3.2 Discussion

The Convolutional neural network method was used with 4 different window size data and 2 different amounts of data. The window size data used was 7 days, 14 days, 21 hearts and 28 days. The data used is 1 year and 2 years for each share. In the table, it can be seen that GGRM shares with a window size of 7 days of data and 2 years of data have the lowest MSE, which is 0.000201587, this shows that the window size of 7 days and the amount of data for 2 years is the most effective.

4. CONCLUSION

The results of the accuracy using MSE in this study of 0.000201587 were obtained from the Convolutional neural network method with 4 different data size windows and 2 different amounts of data. This research can be developed using more varied parameters, but it can also be compared with a different window size and a different amount of data.

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