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Input Parameters Comparison on NARX Neural Network to Increase the Accuracy of Stock Prediction

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Abstrak

Transaksi saham adalah bisnis yang lazim di seluruh dunia. Untuk memperoleh keuntungan sebesar-besarnya, diperlukan analisis yang cermat agar pedagang saham dapat menentukan untuk melakukan pembelian atau penjualan di saat yang tepat dan pada harga yang tepat pula. Untuk itu, dapat dipakai analisis teknikal yang didasarkan pada data harga historis yang diproses secara matematis. Sejalan dengan perkembangan teknologi, analisis dan peramalan harga saham juga dapat dilakukan dengan menggunakan algoritma komputer seperti *machine learning*. Pada penelitian ini dilakukan simulasi jaringan saraf tiruan *Nonlinear Auto Regressive network with eXogenous inputs (NARX)* untuk memprediksi harga indeks saham. Eksperimen diimplementasikan menggunakan berbagai konfigurasi parameter input yang terdiri dari harga *Open, High, Low, Closed* bersama dengan beberapa indikator teknikal agar diperoleh akurasi yang maksimum. Simulasi dijalankan menggunakan data indeks saham yaitu JKSE (Indeks Indonesia Jakarta) dan N225 (Indeks Nikkei Jepang). Riset ini menunjukkan bahwa konfigurasi input terbaik dapat memprediksi harga-harga penutupan selama 13 hari mendatang dengan *mean absolute error (MAE)* sebesar 0,016 untuk JKSE dan 0,064 untuk N225.
Kata Kunci: Stock Prediction, Neural Network, NARX, Technical Indicator.

Abstract

The trading of stocks is one of the activities carried out all over the world. To make the most profit, analysis is required, so the trader could determine whether to buy or sell stocks at the right moment and at the right price. Traditionally, technical analysis which is mathematically processed based on historical price data can be used. Parallel to technological development, the analysis of stock price and its forecasting can also be accomplished by using computer algorithms e.g. machine learning. In this study, Nonlinear Auto Regressive network with eXogenous inputs (NARX) neural network simulations were performed to predict the stock index prices. Experiments were implemented using various configurations of input parameters consisting of Open, High, Low, Closed prices in conjunction with several technical indicators for maximum accuracy. The simulations were carried out by using stock index data sets namely JKSE (Indonesia Jakarta index) and N225 (Japan Nikkei index). This work showed that the best input configurations can predict the future 13 days Close prices with 0.016 and 0.064 mean absolute error (MAE) for JKSE and N225 respectively.
Keywords: Stock Prediction, Neural Network, NARX, Technical Indicator.

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I. INTRODUCTION

Predicting prices is one of the main challenges facing stock traders and investors around the world. This is because the more accurate the prediction, the greater the profits. In investing in stocks, high profits can be obtained with accurate analysis and a deep understanding of market conditions and the company's stock itself. Thus, before investors buy and sell shares, an in-depth analysis is carried out. In the area of stock trading, there are two sorts of analysis, namely fundamental and technical. Fundamental analysis aims to obtain the intrinsic value of a company's stock.

So, it is important for investors to evaluate the company's business such as financial performance, operations, even ownership and management. Usually this can be seen through financial reports and annual reports as well as news in the media. Meanwhile, in technical analysis, the assessment is based on historical stock prices. Buy and sell positions for shares are carried out based on an analysis of past stock price behaviour, trends, and possible repetition of price patterns. This technical analysis is usually displayed in the form of charts or graphs that show not only historical price data, but also several indicators calculated based on its historical data, which in turn can be used to predict future prices. By having that knowledge, the trader can determine to buy or sell stocks at the right moment and at the right price.

On the other hand, with the development of computer science, technical analysis and stock price predictions have become easier with various computational algorithms, one of which is machine learning. As stated by (Syukur & Istiawan, 2021), and the study done by (Li et al, 2017) shows that the utilization of machine learning in this area of stock price prediction can increase efficiency between 60-86 percent compared to the earlier methods.

Furthermore, there have been enough studies on the utilization of machine learning for this stock investment area. For example, authors in (Syukur & Istiawan, 2021) conducted a comparative study of machine learning techniques including Neural Networks, and Support Vector Machines. Then, (Vijk et al, 2020) used an Artificial Neural Network for predicting the closing price of the stock. In addition, (Jarrah & Salim, 2019) used Recurrent Neural Network and Discrete Wavelet Transform to foresee stock prices. Besides, (Lee et al, 2021) explored the effectiveness of Deep Neural Networks in conjunction with technical analysis indicators that were employed to stock market prediction.

Currently, there are quite a number of features or technical indicators used in making forecasting models by machine learning. For instance, (Alonso-Monsalve et al, 2020) studied several neural networks architecture in conjunction with various technical indicators to predict the intraday trend of cryptocurrencies. Likewise, research conducted by (Sezer et al, 2017) used Artificial Neural Network in conjunction with the features of the Relative Strength Index, Moving Average Convergence and Divergence, and Williams %R, to determine the right time to buy and sell, so that maximum profits can be obtained.

This paper studies the effect of various input parameters configurations on the Nonlinear Auto Regressive network with eXogenous inputs (NARX) Neural Network. According to (Ercan, 2017), NARX has several advantages i.e. firstly, learning is more effective where the gradient descent is better; and secondly, convergence is more accurate and faster. In order to improve the accuracy of stock price predictions, here, NARX were utilized by using the input parameters of Open, High, Low, Close prices and Volume of traded stocks, in conjunction with several technical indicators that are widely used by financial technical analysts.

There are some other researches that used NARX. For example, (Xiu & Chen, 2017) that used empirical mode decomposition (EMD) algorithm combined with nonlinear autoregressive models with exogenous inputs (NARX) neural network, for predicting the Shanghai Composite Index. Besides, (Indera et al, 2017) used NARX with Particle Swarm Optimization (PSO) to predict bitcoin price. Likewise, work by (Wibowo et al, 2017) studied the best structures of NARX for Indonesia composite index (IHSG)'s prediction. Also, research by (Alkhoshi & Belkasim, 2018) employed the NARX neural network, to predict the stock market index for the Dow Jones.

The dataset used in this paper are stock indexes from Indonesia and Japan taken from the Yahoo Finance website. Performance evaluation is done by measuring the Mean Average Error (MAE) of every configuration possibility, so that optimal results can be obtained. The simulations were done by using Matlab R2017b.

In the next section, the literature review that is relevant to this study, i.e technical indicators and NARX, will be presented. Then, the experiment method that was used in our work will be described. After that, a discussion of the results of this research is reported. Finally, the conclusions and suggestions for further research are shown.

II. LITERATURE REVIEW

A. Technical Indicators

Technical analysis in the stock market can be described as the study of prices, where charts being the main tool (Achelis, 1995). The chart not only shows the historical price data, but also some indicators that are mathematically calculated based on those previous data. These indicators can be employed to help stock traders to decide when to buy and sell, as well as to predict the upcoming prices. By knowing the next prices, a trader can take an action that is potentially beneficial for him. If the future prices are higher, he could buy now and sell later so he would get some gain. On the other hand, if the future prices are lower, he could make a short transaction (sell now, buy later) and would get some gain as well.

Several of the indicators that are widely used in technical analysis, are: Moving Average, Relative Strength Index, Momentum, Accumulation Distribution, Chaikin Oscillator, Volume Rate of Change, William's Accumulation Distribution, and Stochastic Oscillator, shown in Table 1.

Table 1. Technical Indicator Formulas

Indicators	Formulas
Moving Average	$MA_i = \frac{\sum_i^{i-n} Close}{n}$ where *n is the MA periods*
Momentum	$Mom_i = \left(\frac{Close_i}{Close_{i-n}}\right) * 100$
Relative Strength Index	$RSI_i = 100 - \left(\frac{100}{1+\left(\frac{U_i}{D_i}\right)}\right)$ where: U_i = *an average of upward price change* D_i = *an average of downward price change*
Accumulation / Distribution	$AD_i = \sum_{i=1}^{n}\left[\frac{(Close_i - Low_i)-(High_i - Close_i)}{(High_i - Low_i)}\right] * Vol_i$ where: Vol_i = *Volume of traded shares*
Chaikin Oscillator	$CO_i = EMA3_i\,(AD) - EMA10_i\,(AD)$ where: $EMAP_i = a * AD_i + (1-a) * MA(AD)_{i-1}$ *for* $P=3$, $a=0.50$ *for* $P=10$, $a=0.18$
Volume Rate of Change	$VROC_i = \left(\frac{Vol_i - Vol_{i-n}}{Vol_{i-n}}\right) * 100$ where: Vol_i = *Volume of traded stocks*
William's Accumulation Distribution	$WillAD_i = AD_i + WillAD_{i-1}$ where: $AD_i = Close_i - TRL_i$, (*if* $Close_i > Close_{i-1}$) $AD_i = Close_i - TRH_i$, (*if* $Close_i < Close_{i-1}$) $TRH_i = Close_{i-1}$ *or* $High_i$, *whichever is greater* $TRL_i = Close_{i-1}$ *or* Low_i, *whichever is less*
Stochastic Oscillator	$SchK_i = \left(\frac{Close_i - Lowest\ Low\ in\ K\ Periods}{Highest\ High\ in\ K\ Periods - Lowest\ Low\ in\ K\ Periods}\right)$ $SchD_i = MA\,(SchK_i)$ where *MA using D periods*

Source: Achelis (1995)

B. *Nonlinear Auto Regressive network with eXogenous inputs (NARX)*

As described by (Ezzeldin & Hatata, 2015) and (Boussaada et al, 2018), Nonlinear Auto Regressive network with eXogenous inputs (NARX) is a dynamic recurrent neural network which comprises some layers with feedback connections. In the NARX training, the output of the NARX network can be stated by the equation (1) as follows.

$$y(t) = f\big(x(t-1), x(t-2), \dots, x(t-D_x), y(t-1), y(t-2), y(t-D_y)\big) \quad (1)$$

where *f* is a nonlinear function estimated by a Multi-Layer Perceptron, *x(t)* and *y(t)* are the input and the output of the model at time step *t* respectively, while D_x and D_y are the input and the output order. The network predicted output *y(t)* is regressed on the available target input values. Figure 1 illustrates the 2 hidden layers NARX Neural Network (Ezzeldin & Hatata, 2018), while in our experiments, 5, 10, and 20 hidden layers were utilized. This implementation also permits a vector ARX model, in which the input and output can be multi-dimensional.

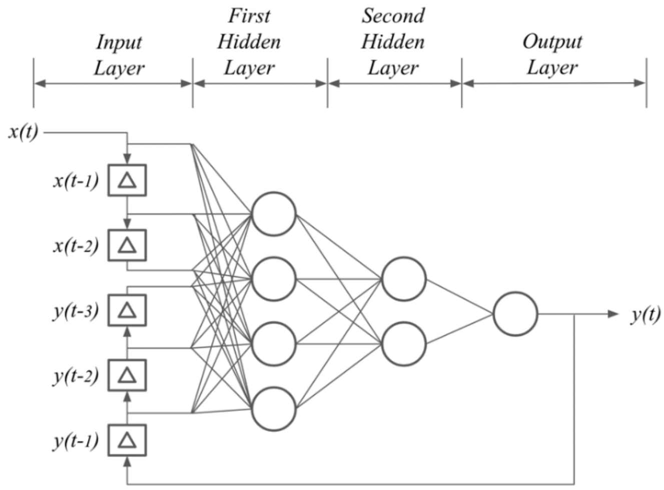

Figure 1. NARX NN with Two Hidden Layers
Source: (Ezzeldin & Hatata, 2018)

III. METHOD

In this study, experiments were carried out with the steps shown in Figure 2. First, raw data, namely stock trading history data that will be used as a data set, were prepared. The dataset used in this paper are stock indexes from Indonesia and Japan taken from the Yahoo Finance website. First, the data were examined to see whether all data are relevant. Then data cleansing can be done if needed. The data has several parameters in the form of stock prices at the opening of the stock exchange (Open), the highest price (High), the lowest price (Low), and the stock price closing (Close), the adjusted closing price (Adjusted Close) and the number of stocks transacted on that day (Volume).

Then, those data were used for calculating several technical indicators, namely Moving Average (MA), Relative Strength Index (RSI), Momentum (Mom), Accumulation Distribution (AD), Chaikin Oscillator (CO), Volume Rate of Change (VROC), William's Accumulation Distribution (WillAD), and Stochastic Oscillator (SchK and SchD), as shown in Table 1.

The next step is to normalise those data. Previous work by (Li et al, 2020), reported that the normalization can be utilized for refining accuracy, and the prediction accuracy is enhanced substantially. So, we applied the normalization to the inputs data, by using the formula that was suggested by (Anggoro & Novitaningrum, 2021), as stated in equation (2),

$$x_{normal} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (2)$$

where x is the value to be normalized; x_{normal} is the normalized value; x_{min} is the minimum value of the entire value to be normalized; and x_{max} is the maximum value of the entire value to be normalized.

Afterwards, the normalized data are split for training, validation, and prediction. As informed by (Zhang et al, 2022) the validation process is important as it can prevent the overfitting; therefore, in this experiment, 22.5% of data were used as validation dataset.

Then, the Nonlinear Auto Regressive network with eXogenous inputs (NARX) Neural Network (Ezzeldin & Hatata, 2015; Boussaada et al, 2018) was employed. During our experiments, as shown in Figure 3, the normalized Open, High, Low, Closed prices in conjunction with various Technical Indicators were used as inputs one configuration at a time; and then, the future Closed prices were predicted.

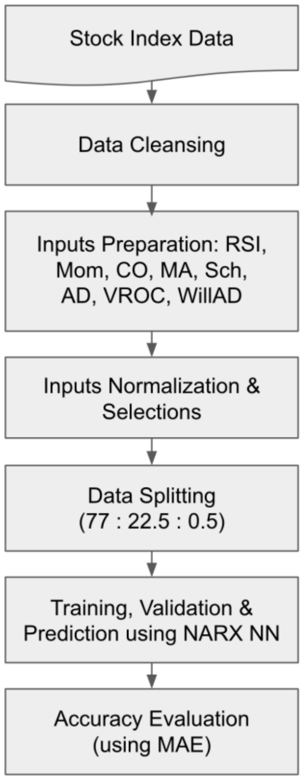

Figure 2. Experiment Steps

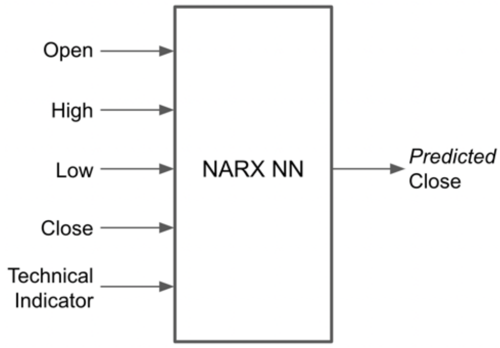

Figure 3. Inputs and Output Parameters of NARX NN

Finally, the prediction accuracy of each input configuration is evaluated by using the mean absolute error *(MAE)*, which can be expressed by the following equation (Farsangi et al, 2018),

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{A_t - P_t}{A_t} \right| \tag{3}$$

where A_t is the actual value, P_t is the predicted value, and n represents the number of the observations. From the results of this evaluation, which compare the predicted Close price with the actual Close price, it can be identified alternative input configurations that provide the highest accuracy.

IV. EXPERIMENT RESULTS AND DISCUSSION

Here are the main results in this paper, where the simulations were executed based on the steps on Figure 2. First, raw data, namely stock trading history data that will be used as a data set, downloaded from Yahoo Finance, consists of the Indonesian (JKSE), and Japan (N225) stock indexes. Stock data was taken for 11 years (2729 trading days), from January 3, 2011 to December 24, 2021. These data cannot be used directly, as there were some data with null value, so data cleansing was carried out.

Then, those data were used to calculate the 8 technical indicators that will be used, using Matlab, based on formulas shown in Table 1. Next, the Open, High, Low, Close prices and their technical indicators data were normalized. Subsequently, they were split for training, validation, and prediction with the portion of 77, 22.5, and 0.5 percent respectively. Afterwards, it was processed by the NARX NN, as illustrated in Figure 3. We decided to predict 0.5% from the 2627 of total data, or 13 days prediction. Because in real life, 13 days prediction is enough to help stock traders to gain, by using the swing trading style. Previous works usually used a higher portion of data for prediction, e.g. (Ercan, 2017) utilized 70, 15, and 15 percent of data for training, validation, and prediction respectively.

The mean absolute error (MAE) was calculated based on the error of prediction for the future 13 days Close prices. Each simulation was executed 20 times, then, the second quartile or median of those MAEs data was taken into account as our main result. In predicting the future of the Close price, the original data that we have are the previous Open, High, Low, and Close prices data. So, we consider the inputs of Open (O), High (H), Low (L), and Close (C) prices data as our baseline in measuring the prediction accuracy.

The following pictures show the performance of the simulations by using various input configuration possibilities. Figure 4 shows the performance of using the O, H, L, C, in conjunction with the Momentum technical indicator with several periods, n, from 6 to 96. The data was applied to NARX with 10 hidden layers. For JKSE, compared to the baseline (O, H, L, C), it can be seen that for n: 12, 24, 36, 48, 60, 84 the MAEs are lower. In other words, their performances are better than the baseline, where n: 12 gives the best accuracy. Meanwhile, for N225, for n: 6, 12, 24, 48, 60, 84 are lower than the baseline, where the n: 60 give the lowest MAE.

Likewise, Figure 5 presents the performance of using the O, H, L, C, and Moving Average with period n: 5 to 80. It can be seen that for JKSE, n: 20, 50, 70, 80 give better accuracy than the baseline, where n: 80 gave the best result. For N225, all MA periods (n) are lower than the baseline, where n: 30 is the best result.

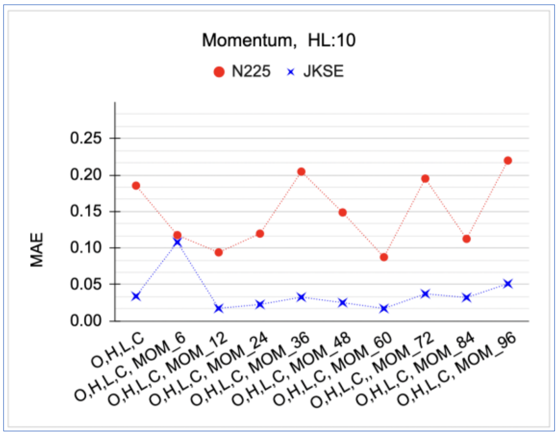

Figure 4. MAE of Predicted C, using O, H, L, C, and Momentum as inputs with Various Periods

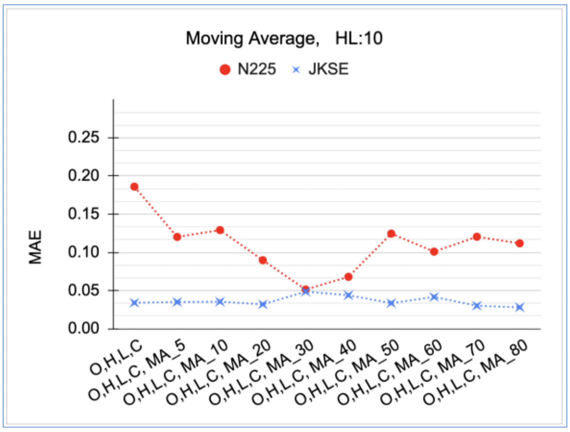

Figure 5. MAE of Predicted C, using O, H, L, C, and MA as inputs with Various Periods

Next, Figure 6 and Table 2 show the MAEs of JKSE Close price prediction using O, H, L, C; as well as O, H, L, C, V (Volume); and O, H, L, C in conjunction with technical indicators: RSI, Momentum 12, CO, MA 80, Stochastic D, Stochastic K, AD, VROC, and Will.AD. In this scenario, NARX with 5, 10, and 20 hidden layers (HL) were applied. It can be seen that for HL:5, the input configurations that are better than the baseline, given by the O, H, L, C, V, as well as by the following technical indicators: Mom. 12, CO, Stochastic D, VROC. For HL:10, the following technical indicators: RSI, Mom. 12, CO, MA 80, gave better results than the baseline. Meanwhile, for HL:20, the input parameters that are better than the baseline are: O, H, L, C, V and the indicators: RSI, Mom. 12, MA 80, AD, VROC. From all of the above, the best result is the O, H, L, C, RSI input configuration with HL:10, which gave MAE = 0.016 or equivalent to 98.4% accuracy.

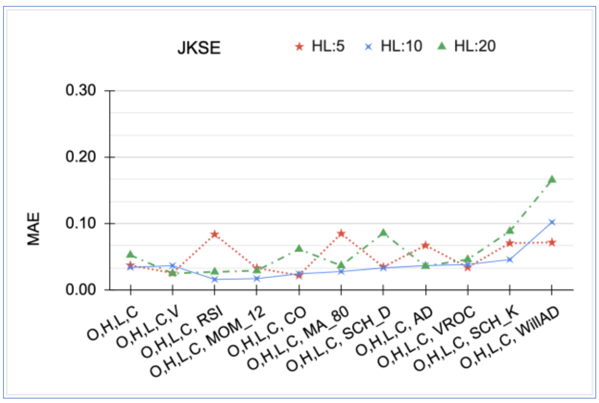

Figure 6. MAEs of JKSE Prediction with Various Inputs and Hidden Layers

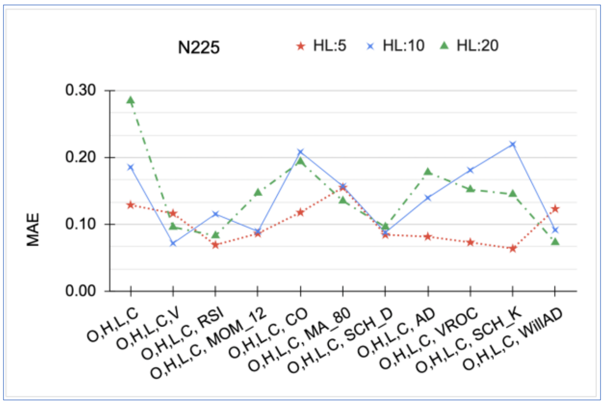

Figure 7. MAEs of N225 Prediction with Various Inputs and Hidden Layers

Table 2. MAEs of JKSE Prediction with Various Inputs and Hidden Layers

Input Configurations	MAEs		
	HL: 5	HL: 10	HL: 20
O,H,L,C	0.037	0.034	0.053
O,H,L,C,V	0.026	0.037	0.025
O,H,L,C, RSI	0.084	0.016	0.028
O,H,L,C, MOM_12	0.033	0.017	0.029
O,H,L,C, CO	0.022	0.025	0.062
O,H,L,C, MA_80	0.085	0.028	0.037
O,H,L,C, SCH_D	0.035	0.034	0.086
O,H,L,C, AD	0.067	0.037	0.036
O,H,L,C, VROC	0.034	0.039	0.046
O,H,L,C, SCH_K	0.071	0.046	0.089
O,H,L,C, WillAD	0.072	0.102	0.166

Table 3. MAEs of N225 Prediction with Various Inputs and Hidden Layers

Input Configurations	MAEs		
	HL: 5	HL: 10	HL: 20
O,H,L,C	0.129	0.186	0.285
O,H,L,C,V	0.117	0.072	0.096
O,H,L,C, RSI	0.069	0.116	0.083
O,H,L,C, MOM_12	0.087	0.090	0.147
O,H,L,C, CO	0.118	0.208	0.194
O,H,L,C, MA_80	0.155	0.157	0.135
O,H,L,C, SCH_D	0.085	0.088	0.096
O,H,L,C, AD	0.082	0.140	0.178
O,H,L,C, VROC	0.073	0.181	0.152
O,H,L,C, SCH_K	0.064	0.220	0.145
O,H,L,C, WillAD	0.123	0.092	0.073

For N225, as shown by Figure 7 and Table 3, it can be seen that for HL:5, the O, H, L, C, MA80 is the only input configuration that has worse performance than the baseline. For HL:10, the O, H, L, C, in conjunction with V, RSI, Mom.12, MA80, Sch.D, AD, VROC, WillAD have better performance than the baseline. Whereas for HL:20, all other input configurations are better than the baseline. From all of the above, the best result is the O, H, L, C, Sch.K input configuration with HL:5, which gave MAE=0.064 or equivalent to 93.6% accuracy.

It should be noted that our research is complementing previous works related to stock prediction using technical indicators and deep learning. Some of them can be summarized in the following Table 4, where (Lee et al., 2021) provided a method for predicting trend; (Sezer et al., 2017) gave a method for predicting trading action (Buy/Hold/Sell), (Alkhoshi & Belkasim, 2018) used NARX neural network, to predict the stock market, whereas this work proposed a method for predicting Close prices for the next 13 days.

Table 4. Related Works on Stock Prediction using Technical Indicators and Deep Learning

Authors	Methods	Main Results
Lee et al., 2021	Four layers Long Short-Term Memory (LSTM) model, with inputs O, H, L, C prices and technical indicators: KD, RSI, BIAS, Williams% R, and MACD; predicting trend (Rise/Fall/Flat); applied to TWSE 0050	The MACD obtained the highest estimation accuracy, i.e. 74%.
Sezer et al., 2017	Four layers artificial neural network (ANN), with inputs O, H, L, C prices and technical indicators: RSI, MACD, Williams %R; predicting Buy/Hold/Sell; applied to Dow30	The average success transaction is 67.33% (2 out of 3 transactions resulted in a profit).
Alkhoshi & Belkasim, 2018	NARX neural network, to predict the stock market index for the Dow Jones	A high accuracy by 98% of prediction for stable and moderately stable stocks
Our proposed method	NARX NN, with inputs O, H, L, C prices and technical indicators: MA, RSI, Mom., AD, CO, VROC, WillAD, SchK and SchD; predicting Close prices; applied to JKSE and N225	For JKSE, the best input configuration is O, H, L, C, RSI with HL:10 (MAE is 0.016 or equivalent to 98.4% accuracy). For N225, the best input configuration is O, H, L, C, SchK with HL:5 (MAE is 0.064 or equivalent to 93.6% accuracy).

V. CONCLUSIONS

As described in the previous sections, this work assessed a model for predicting Close prices of stocks, by using the Nonlinear Auto Regressive network with eXogenous inputs (NARX) neural network, with several hidden layers (HL). The inputs are the historical data of Open, High, Low, Close prices, and the option of Volume or technical indicators (Moving Average, Relative Strength Index, Momentum, Accumulation Distribution, Chaikin Oscillator, Volume Rate of Change, William's Accumulation Distribution, and Stochastic Oscillators).

This work was applied to predict for the next 13 days closing prices of JKSE and N225. The simulations showed that the best input configurations are O, H, L, C, RSI with HL:10 and O, H, L, C, SchK with HL:5, for JKSE and N225 respectively.

For future research, the use of various other technical indicators as additional inputs can be explored, as well as by utilizing other machine learning algorithms, to further improve the Close price prediction accuracy. Furthermore, its application to the trading scenarios or back-testing in order to simulate the profit/loss is also interesting to be investigated.

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