Artificial Neural Network-Based Machine Learning Approach to Stock Market Prediction Model on the Indonesia Stock Exchange During the COVID-19

Melina, Sukono, Herlina Napitupulu, Aceng Sambas, Anceu Murniati, and Valentina Adimurti Kusumaningtyas

Abstract—**The global COVID-19 pandemic has caused panic. In addition, it disrupted life and economic activities around the world. Prediction of the stock market during the COVID-19 pandemic became a major challenge because the data was not stationary, random, and complex nonlinear system. For this reason, an in-depth study of the following trends is required to develop an adequate predictive model to predict the stock market during the pandemic. This study designs a stock market prediction model during the COVID-19 pandemic on the Indonesia Stock Exchange using a deep learning approach based on artificial neural networks. The object of this research is the pharmaceutical industry in the health sector listed on the IDX. The input variables are the proposed model for predicting stock prices with daily stock price movements, including COVID-19 trend indicators, and the government's response tightness index to COVID-19 in Indonesia. The study results show that all proposed model systems achieve highly accurate forecasting for the stock market price prediction with MAPE $\leq$ 10%. Model 6-20-20-1 is the best model of all tested models, with MSE = 0.00055, RMSE = 0.007418, and MAPE = 1.17%.**

Index Terms—**artificial neural network; COVID-19; deep-learning; prediction; stringency index.**

I. INTRODUCTION

PANDEMIC is the number of cases in a certain population that has suddenly spread in various continents and countries, generally affecting many people. On March 11, 2020, COVID-19 was declared a pandemic by the World Health Organization (WHO) [1], which has caused enormous pressure on the global and national economy. In addition, the COVID-19 pandemic has an impact on the world economy through the closing of financial market indices, giving a huge impact and uncertainty on the world economic sector, resulting in many countries experiencing recession [2][3]. The COVID-19 pandemic in Indonesia was first discovered around early or mid-March 2020. After the first case was discovered, the trend of the Composite Stock Price Index (JCI) was declining, because there were issues regarding COVID-19, which began to spread. On March 16, 2020, the Jakarta Composite Index (JCI) tumbled by 33% from January 2020 to 3,918, which was the lowest point in eight years [4]. Prediction of market trends made before the pandemic was no longer following conditions during the pandemic because the data were not stationary and random [5][6][7][8].

In stock market, many internal and external factors can affect stock price fluctuations [9]. The main internal factor is the performance of the company issuing the shares. The company's external factors include sociopolitical, changes in interest rates, currency exchange rates, inflation, panic, and economic cycles [10]. Movements in stock markets are influenced by several factors, such as macro-economic factors, international events, and human behavior [11]. One of the most influential external factors is the COVID-19 pandemic panic that swept the world, triggering a dramatic change in stock market performance, where stock prices fell sharply and fluctuations were very large. Stock market prediction is a major challenge because the data are not stationary and random [12][13][14]. NN is one of the artificial intelligence techniques that has been used by researchers in various fields in this decade [15][16]. Prediction and analysis of stock market data have played an important role in today's economy. Various algorithms used for forecasting can be categorized into linear and non-linear models, one of which is NN [17][18]. Using deep neural networks is recommended for stock market index prediction [19]. Prediction models using multiple internal and external factors such as historical stock prices combined with data on external factors such as the situation of pandemic developments (panic), political factors, currency exchange rates, inflation, and the economy can be used to get better prediction results.

In this research, a stock market prediction model was designed during the COVID-19 pandemic using a deep learning approach based on an artificial neural network (ANN) [20][21]. ANN is used to predict because of its good approach to nonlinearity based on the parameters of the daily stock closing price in the IDX, the COVID-19 government response stringency index (Stringency Index) in Indonesia, and the COVID-19 trend indicator. The network is trained with input from factors and indicators that affect the daily stock price fluctuations of one of the companies listed on the IDX. The object of this research is the shares of PT. Kimia

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Farma Persero Tbk (KAEF), one of the drug manufacturers specialty and generic industry companies in the health sector listed on the IDX for the 2020-2021 period. The research results are expected to be a solution for decision-makers to be considered in determining investment policies in stocks by making the right decisions [22]. In addition, this study becomes the additional literature on the predictability of stock returns when a pandemic occurs. Thus, it can be used as a reference for potential investment opportunities for investors and minimize risk and stock returns as an investment tool [23].

II. METHODS

The stages of this study can be seen in Fig. 1 as follow:

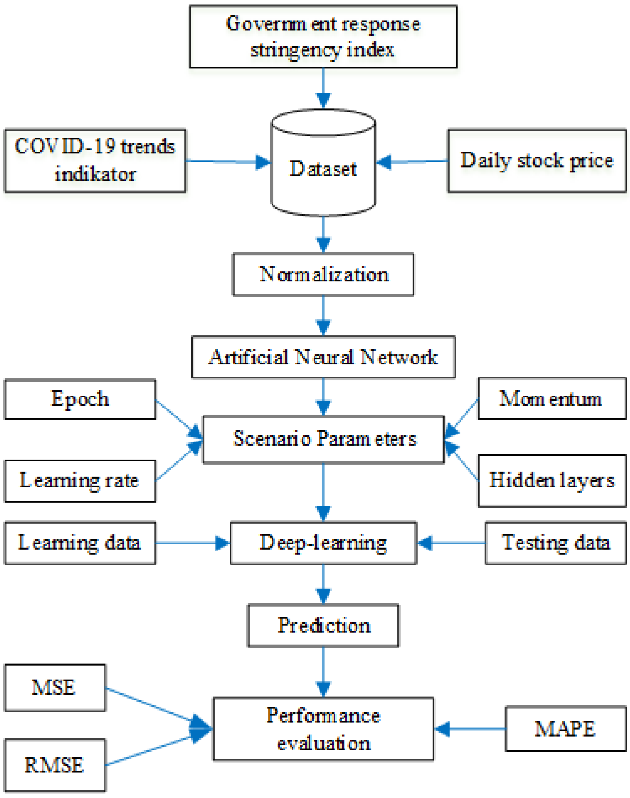

Fig. 1. Stages of Research

This section provides a detailed description of datasets used for prediction stock price movements as well as a brief overview, neural network concept, deep-learning approach, and mathematical description of prediction acurracy.

A. Dataset

In this project, we used three main datasets:

1 The input data are cumulative daily time-series data historical of Kimia Farma Persero Tbk (KAEF.JK) stock values from March 2, 2020 to July 16, 2021. The data was obtained using Yahoo Finance and includes the open, close, high, and low values for a given day.

2 Coronavirus trend indicator. The search for the keyword "corona virus" in Indonesia daily data between March 2, 2020, to July 16, 2021. The data was obtained using Google Trends.

3 COVID-19: Indonesia Government Response Stringency Index values from March 2, 2020, to July 16, 2021. The data was obtained using ourworldindata.org.

B. KAEF.JK stock time-series data

Health care stocks are one of the most significant sectors in the stock market during the COVID-19 pandemic [24]. We chose health sector stocks as the object of this research. PT Kimia Farma (Persero) Tbk produces and sells medicines, iodine, salts, quinine, vegetable oils, and herbal medicines, in Indonesia, the rest of Asia, Europe, Australia, Africa, and New Zealand. Herbal medicine uses plants to treat disease and enhance general health and wellbeing. For example, Cassia grandis is a tropical species belonging to Fabaceae. In Indonesia, this plant is known as "Johar Merah", which has been reported in Indonesian traditional medicines to heal wounds, scabies, and other skin medications [25].

PT. Kimia Farma (Persero) Tbk operates through manufacturing, distribution, retail, and other services segments. It also manufactures and markets chemicals, beta-lactam, and non-betalactam, antiretroviral, narcotic, hormone contraceptive, powder, oil castor, edible oil, cosmetics, over-the-counter, personal, and beauty care products, as well as food supplements, active pharmaceutical ingredients, and medical devices. In addition, the company manufactures, markets, distributes, trades in pharmaceutical products; and operates drug materials plants. As of December 31, 2020, it has operated 1,278 retail pharmacy outlets, 451 health clinic outlets, 75 clinical laboratories, 10 optics, 3 beauty clinics, and 24 international retail outlets. The company sells its products to pharmacies, drug stores, hospitals, and free traders through pharmaceutical wholesalers. The company was founded in 1817 and is headquartered in Jakarta, Indonesia [26]. We show a graph of the KAEF.JK stock time-series data, daily between March 02, 2020, to July 15, 2021, as shown in Fig. 2. The history of KAEF.JK stock prices is as follow [27]:

C. Trend Indicators of Corona Virus

Panic attacks are characterized by intense fear and a sense of feeling overwhelmed. When an investor gets a panic attack related to the covid-19 pandemic, he will instinctively seek information about the outbreak through the internet or other media. According to modern portfolio theory, financial markets are efficient and investors make rational decisions based on the available information [28]. Internet data are increasingly integrated into health informatics research and are becoming a useful tool for exploring human behavior. The most popular tool for examining online behavior is Google Trends (GT), This open tool provides information on trends and the variations of online interest in selected keywords and topics over time. The worldwide interest or concerns are reflected by all the keyword search [29].

GT is an online search tool that allows the user to see how often specific keywords, subjects, and phrases have been queried over a specific period. Numbers represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means there is not enough data for this term. We used GT value (GTV) to view and index the level of Coronavirus trend indicator before and after the World Health Organization issued a pandemic declaration on March 11, 2020. We found a major jump in searches related to anxiety and panic attacks, in the weeks following

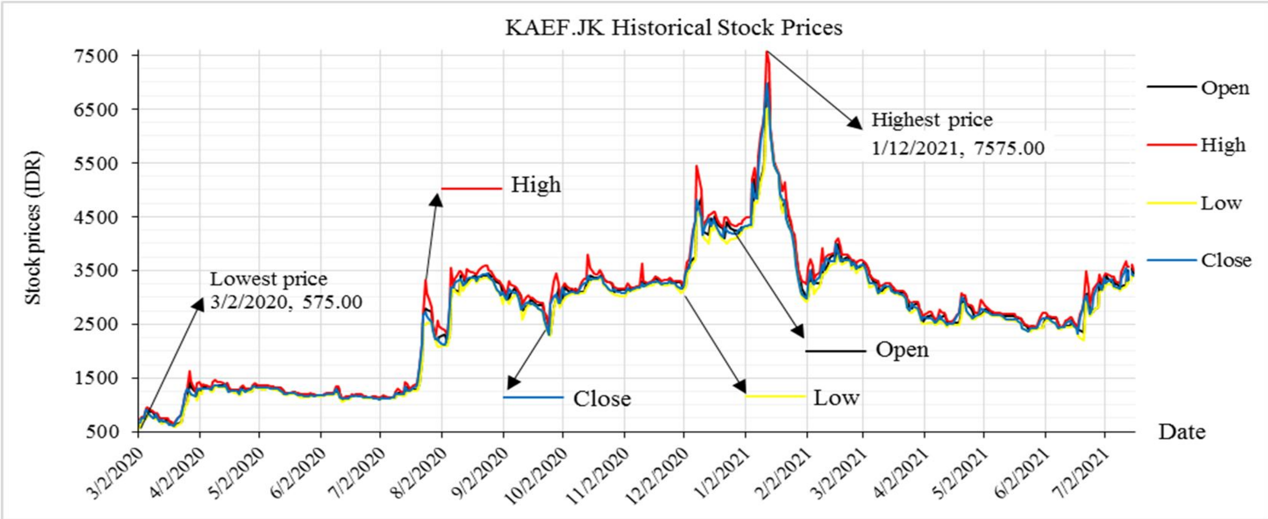

Fig. 2. The Historical of KAEF.JK stock prices

the pandemic declaration. The following graph shows the search for the keyword "corona virus" in Indonesia daily from March 2, 2020, to July 16, 2021 [30].

D. Governments Policy

To slow such pandemic confirmed cases, Indonesian local and central governments apply a lockdown-like policy. We call this Large-Scale Social Restriction (Pembatasan Sosial Berskala Besar), known as PSBB and PSBB-variant, i.e., expanded and tightened social restriction. After PSBB, enforcement of community activity restrictions applied. We call this PPKM (Pemberlakuan Pembatasan Kegiatan Masyarakat) applies. The starting dates for each city and province were as follows: City of Bandung: March 6, 2020, Province of West Java: March 2, 2020, Province of South Sulawesi: March 19, 2020, City of Jayapura: April 3, 2020, Province of Papua: March 22, 2020, City of Medan: March 27, 2020, Province of North Sumatera: March 17, 2020, City of Samarinda: April 4, 2020, and Province of East Kalimantan: March 14, 2020. It was known that the governments in the first three provinces and the corresponding capital cities / DKI Jakarta applied PSBB [31]. This composite measure is based on nine response indicators including school closures, workplace closures, and travel bans, which is rescaled to a value from 0 to 100 (100 = strictest). If policies vary at the subnational level, the index is shown as the response level of the strictest sub-region [32]. Large-scale social distancing and restrictions were imposed, affecting the distribution of some food products from the production areas. Large-scale social distancing also affects economic growth [33]. The government stringency index (GSI) in Indonesia [34], can be seen in Fig. 4 as follow:

E. Artificial Neural Network

Artificial Intelligence (AI) generally describes the implementation of several aspects of human ability [35]. ANNs are a family of mathematical methods inspired by the function of the human neural system and how neurons interact with each other [36]. Artificial neural network (ANN) is a technique of AI that tries to mirror how the brain works to perform more complex and dynamic tasks. A neural network is an interconnected assembly of simple processing elements, units, or nodes, whose functionality is loosely based on the animal neuron. The processing ability of the network is stored in the interunit connection strengths, or weights, obtained by a process of adaptation to or learning from, a set of training patterns [37]. ANNs are adaptive computational models inspired by the biological human brain system. A typical NN consists of multiple nodes organized in a layered fashion and connected to form an interdependent network [12].

ANN is an associate science system that works in the same method with biological neural networks that are believed to be highly accurate [38][39]. An ANN is an information processing system with certain performance characteristics in common with biological neural networks. ANN has been developed as generalizations of mathematical models of human cognition or neural biology, based on the assumptions that [15]:

1 Information processing occurs at many simple elements called neurons.
2 Signals are passed between neurons over connection links.
3 Each connection link has an associated weight, which multiplies the signal transmitted in a typical neural net.
4 Each neuron applies an activation function (usually nonlinear) to its net input (sum of weighted input signals) to determine its output signal.

F. Multilayer Perceptron

The following three points highlight the basic features of multilayer perceptrons [40][41]:

1 The model of each neuron in the network includes a differentiable non-linear activation function.
2 The network contains one or more hidden layers from both the input and output nodes.
3 The network exhibits a high degree of connectivity, which is determined by the synaptic weights of the network.

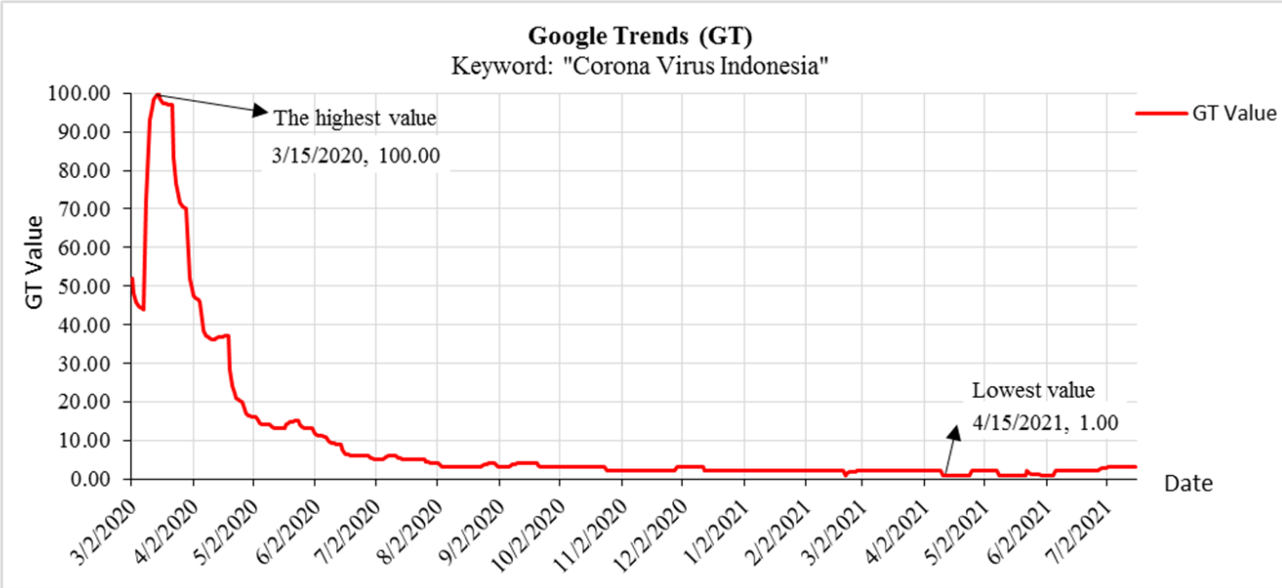

Fig. 3. The search for the keyword “Corona Virus Indonesia”

Fig. 4. COVID-19: Indonesia Government Response Stringency Index

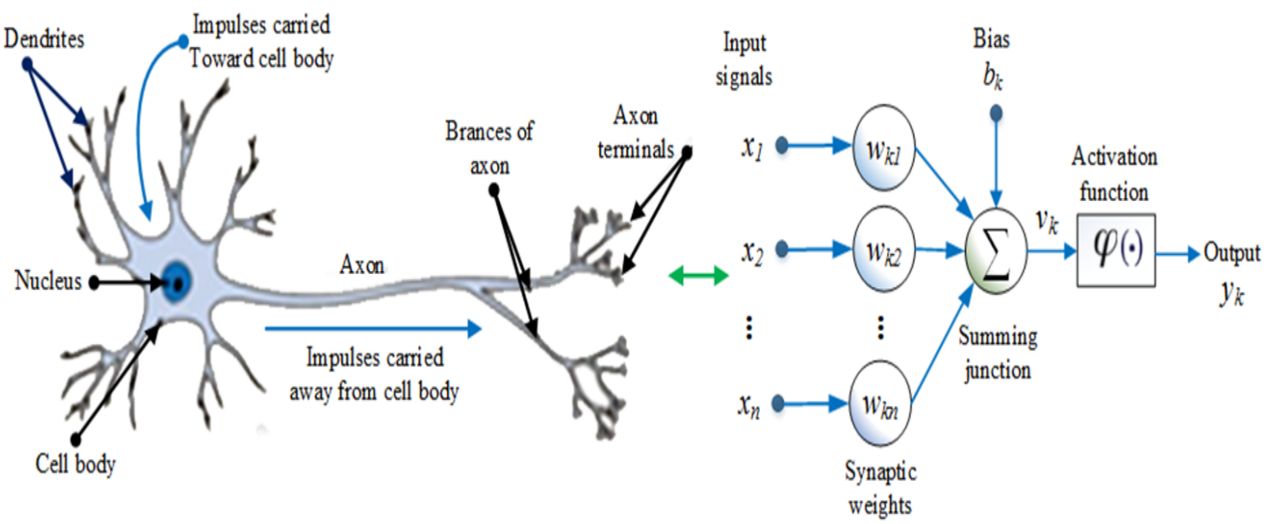

Fig. 5. Neural network conceps

G. Architecture

Examples of multilayer networks with the bias neurons are shown in Fig. 6:

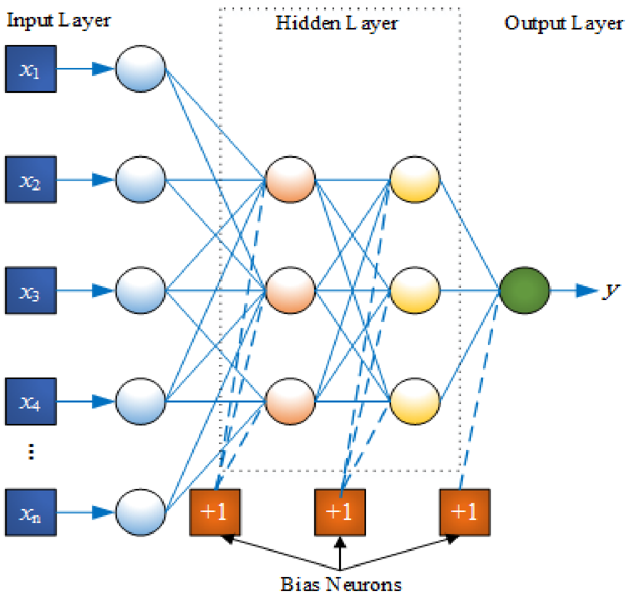

Fig. 6. Example of multilayer networks with the bias neurons

H. Activation function

An activation function for a backpropagation net should have several important characteristics, namely: continuous, differentiable, and monotonically nondecreasing. For the most commonly used activation functions, the value of the derivative (at a particular value of the independent variable) can be expressed in terms of the value of the function (at that value of the independent variable). Usually, the function is expected to saturate, i.e., approach finite maximum and minimum values asymptotically. One of the most typical activation functions is the binary sigmoid function, which has a range of (0, 1) and is defined as [14][22]:

$$f_1(x) = \frac{1}{1+\exp^{-x}} \tag{1}$$

This function is illustrated in Fig. 7:

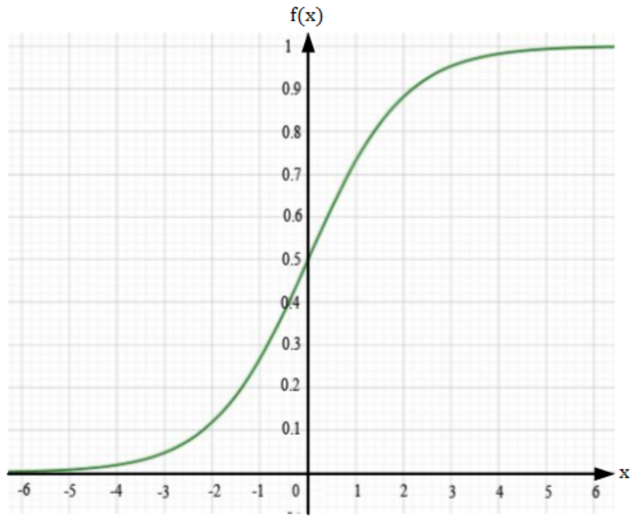

Fig. 7. Binary sigmoid, range (0, 1)

I. Back-propagation algorithm

A popular method for the training multilayer perceptrons is the back-propagation (BP) algorithm. The objective of the training is to minimize a defined error function, which implies that the neural network fits the input data, given the expected results as outputs [42]. The BP algorithm leverages the chain rule of differential calculus, which computes the error gradients in terms of summations of local-gradient products over the various paths from a node to the output. The BP algorithm is the most popular neural network training algorithm for financial forecasting. The BP network has been widely used in the area of financial time series forecasting because of its broad applicability to many business problems and its preeminent learning ability [43]. Another popular method in forecasting is Auto-Regressive Integrated Moving Average (ARIMA) is popular in the field of time-series forecasting because of its ability to give better and more reliable results than most known methods [44]. The Nonlinear Autoregressive Exogenous (NARX) method is implemented using a feed forward neural network. It is to optimize the stock market price prediction [45]. The long short-term memory (LSTM) method is also used to utilize big data in prediction using deep learning [46][47], However, a weakness of LSTM is that it tends to overfit to the training data and have unstable results [48]. The BP algorithm contains two main phases, referred to as the forward and backward phases, respectively. The forward phase is required to compute the output values and the local derivatives at various nodes, while the backward phase is required to accumulate the products of these local values over all paths from the node to the output [41]. The stages of the algorithm are as follows [15]:

1) Initialize weights. (Set to small random values). While the stopping condition is false, do Step 2-9.
2) For each training pair, do Step 3-8.
   Feed forward:
3) Each input unit ($X_i, i = 1, ..., n$) receives input signal Xi and broadcasts this signal to all units in the layer above (the hidden units).
4) Each hidden unit ($Z_j, j = 1, ..., p$) sums its weighted input signals,

$$z_{in_j} = v_{0_j} + \sum_{i=1}^{n} x_i v_{ij} \tag{2}$$

   applies its activation function to compute its output signal,

$$z_j = f(Z_{in_j}) \tag{3}$$

   and sends this signal to all units in the layer above (output units)
5) Each output unit ($Y_k, k = 1, ..., m$) sums its weighted input signals,

$$y_{in_k} = w_{0_k} + \sum_{j=1}^{p} z_j w_{jk} \tag{4}$$

   and applies its activation function to compute its output signal,

$$y_k = f(y_{in_k}) \tag{5}$$

Back propagation of error

6) Each output unit ($Y_k, k = 1, ..., m$) receives a target pattern corresponding to the input training pattern, computes its error information term,

$$\delta = (t_k - y_k) f^{'}(y_{in_k}) \tag{6}$$

calculates its weight correction term (used to update w_{ik} later),

$$\Delta w_{jk} = \alpha \delta_k z_j \tag{7}$$

calculates its bias correction term (used to update wok later),

$$\Delta w_{0_k} = \alpha \delta_k \tag{8}$$

and sends Elk to units in the layer below.

7) Each hidden unit ($Z_j, j = 1, ..., p$) sums its delta inputs (from units in the layer above),

$$\delta_{in_j} = \sum_{k=1}^{m} \delta_k w_{jk} \tag{9}$$

multiplies by the derivative of its activation function to calculate its error information term,

$$\delta_j = \delta_{in_j} f^{'}(z_{in_j}) \tag{10}$$

calculates its weight correction term (used to update V_{ij} later),

$$\Delta v_{ij} = \alpha \delta_j x_{ij} \tag{11}$$

and calculates its bias correction term (used to update V_{0_j} later),

$$\Delta v_{0_j} = \alpha \delta_j \tag{12}$$

Update weights and biases:

8) Each output unit ($Y_k, k = 1, ..., m$) updates its bias and weights ($j = 0, \ldots, p$):

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk} \tag{13}$$

Each hidden unit ($Z_j, j = 1, ..., p$) updates its bias and weights ($i = 0, ..., n$):

$$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij} \tag{14}$$

9) Test stopping condition

J. Accuracy Measures

A model's forecasts are rarely 100% accurate. A forecast may be slightly higher or slightly lower than the actual value, depending on how good the forecasting model is. The difference between a forecast value and its corresponding actual value is the forecast error:

$$e = Y - \hat{Y} \tag{15}$$

Where e is the Forecast error, Y is the actual value, and $\hat{Y}$ is the forecasted value.

The mean squared error (MSE) is a statistical indicator that measures the difference between real and predicted values. The MSE has been calculated as the average of the sum of the squares of forecast the errors as calculated below [49][50]:

$$MSE = \frac{1}{2} \sum_{n=1}^{n} (Y - \hat{Y})^2 \tag{16}$$

Where n = number of periods forecasted, Y = actual value, $\hat{Y}$ = forecast value. The smaller the MSE value, the better.

The root mean square error (RMSE) is one of the most commonly used measures for evaluating the quality of predictions. It shows how far predictions fall from measured true values using Euclidean distance as calculated below [11][51][52]:

$$RMSE = \sqrt{\frac{1}{2} \sum_{n=1}^{n} e_n^2} \tag{17}$$

Where, n = number of periods forecasted, e = forecast error. MSE and RMSE are measures of closeness that evaluates the predicted value's accuracy to the actual price [53].

A widely used evaluation of forecasting methods that does attempt to consider the effect of the magnitude of the actual values is the mean absolute percentage error (MAPE). The MAPE is calculated as the average of the absolute values of percentage errors [50]:

$$MAPE = \frac{1}{2} \sum \frac{|Y - \hat{Y}|}{|Y|} \tag{18}$$

Where n = number of periods forecasted; Y = actual value; $\hat{Y}$ = forecast value.

The lower the MAPE, the more accurate the forecast model. A scale of the judgment of forecast accuracy of MAPE [40], is shown in Table I:

TABLE I
A SCALE OF JUDGMENT OF FORECAST ACCURACY

MAPE	JUDGMENT OF FORECAST ACCURACY
$\leq$ 10%	Highly accurate
11% to 20%	Good forecast
21% to 50%	Reasonable forecast
$\geq$ 51%	Inaccurate forecast

III. RESULTS AND DISCUSSION

A. Data Preprocessing

Data processing is carried out to check whether there are outliers and missing data. Data imputation is then performed to generate the completecomplete initial dataset. The data obtained from the sources as mentioned above had to be pre-processed to make it suitable for reliable analysis. We pre-processed the datasets in the following manner: While tightness index data is available for all days during the award period, share price values obtained using Yahoo Finance are not available for weekends and other holidays when the market is closed. We estimate the missing values using the concave function to supplement these data. So, if the value of the stock price on a given day is x and the next available data point is y, then n is the missing value. We estimate the missing data by calculating the first day after it. This approach is justified because stock data usually follow a concave function [54]:

$$n = \frac{(y + x)}{2} \tag{19}$$

Then, the same method is followed recursively till all gaps are filled. The data used in this study are shown in Table II:

TABLE II
DATASET

DATE	STOCK PRICE				GTV	GSI
	OPEN	HIGH	LOW	CLOSE		
03/02/20	585	720	575	665	52.0	28.7
03/03/20	680	770	680	745	48.0	37.0
03/04/20	730	765	720	745	46.0	37.0
03/05/20	755	930	750	915	45.0	37.0
03/06/20	905	960	850	885	44.5	37.0
03/07/20	877	912	795	812	44.3	37.0
03/08/20	863	888	767	776	44.0	37.0
03/09/20	850	865	740	740	72.0	37.0
03/10/20	740	835	730	830	86.0	37.0
03/11/20	840	850	750	770	93.0	37.0
03/12/20	740	740	695	695	96.5	37.0
03/13/20	650	750	650	720	98.3	37.0
03/14/20	685	745	660	697	99.1	37.0
03/15/20	702	742	665	686	100.0	40.7
03/16/20	720	740	670	675	98.5	45.4
03/17/20	675	690	630	630	97.8	42.6
03/18/20	630	685	625	630	97.4	42.6
03/19/20	635	635	590	600	97.2	45.4
03/20/20	625	685	580	670	97.1	45.4
03/21/20	650	760	620	752	97.0	45.4
03/22/20	662	797	640	793	97.0	45.4
03/23/20	675	835	660	835	83.5	48.2
03/24/20	900	1040	870	1040	76.8	48.2
03/25/20	970	1170	955	1170	73.4	48.2
03/26/20	1040	1300	1040	1300	71.7	48.2
03/27/20	1425	1625	1210	1250	70.8	48.2
03/28/20	1335	1435	1187	1207	70.4	48.2
03/29/20	1290	1340	1176	1186	70.0	50.9
03/30/20	1245	1245	1165	1165	58.0	50.9
03/31/20	1160	1410	1085	1310	52.0	50.9
...	...	...	...	...	...	...
07/16/21	3450	3500	3390	3410	3.0	69.0

TABLE III
NORMALIZATION DATASET

DATE	STOCK PRICE				GTV	GSI
	OPEN	HIGH	LOW	CLOSE		
03/02/20	0.077	0.094	0.075	0.087	0.0067	0.0037
03/03/20	0.089	0.101	0.089	0.098	0.0062	0.0048
03/04/20	0.096	0.100	0.094	0.098	0.0059	0.0048
03/05/20	0.099	0.122	0.098	0.120	0.0058	0.0048
03/06/20	0.119	0.126	0.112	0.116	0.0057	0.0048
03/07/20	0.115	0.120	0.104	0.107	0.0057	0.0048
03/08/20	0.113	0.117	0.101	0.102	0.0057	0.0048
03/09/20	0.112	0.114	0.097	0.097	0.0094	0.0048
03/10/20	0.097	0.110	0.096	0.109	0.0112	0.0048
03/11/20	0.110	0.112	0.098	0.101	0.0121	0.0048
03/12/20	0.097	0.097	0.091	0.091	0.0126	0.0048
03/13/20	0.085	0.098	0.085	0.094	0.0128	0.0048
03/14/20	0.090	0.098	0.087	0.092	0.0130	0.0048
03/15/20	0.092	0.097	0.087	0.090	0.0131	0.0052
03/16/20	0.094	0.097	0.088	0.089	0.0129	0.0059
03/17/20	0.089	0.091	0.083	0.083	0.0128	0.0055
03/18/20	0.083	0.090	0.082	0.083	0.0127	0.0055
03/19/20	0.083	0.083	0.077	0.079	0.0127	0.0059
03/20/20	0.082	0.090	0.076	0.088	0.0127	0.0059
03/21/20	0.085	0.100	0.081	0.099	0.0127	0.0059
03/22/20	0.087	0.105	0.084	0.104	0.0127	0.0059
03/23/20	0.089	0.110	0.087	0.110	0.0109	0.0062
03/24/20	0.118	0.137	0.114	0.137	0.0100	0.0062
03/25/20	0.127	0.154	0.126	0.154	0.0096	0.0062
03/26/20	0.137	0.171	0.137	0.171	0.0093	0.0062
03/27/20	0.188	0.214	0.159	0.164	0.0092	0.0062
03/28/20	0.176	0.189	0.156	0.159	0.0092	0.0062
03/29/20	0.170	0.176	0.155	0.156	0.0091	0.0066
03/30/20	0.164	0.164	0.153	0.153	0.0075	0.0066
03/31/20	0.153	0.186	0.143	0.172	0.0067	0.0066
...	...	...	...	...	...	...
07/16/21	0.455	0.462	0.447	0.450	0.0003	0.0090

B. Normalization Dataset

Data are normalized to improve the function of the network which usually takes place before the network training, data are normalized. The extracted data were then normalized to unify the data range within 0 and 1. Normalization of data is done to bring all data into a common range. The formula used for the normalization of the initial data is as follows [50][55][56][57]:

$$x' = \frac{x-b}{a-b} \tag{20}$$

Where x' is normalized data, x is normal data, a is the maximum data with the largest value, and b is the data with the smallest value. Based on the maximum value dataset obtained from the stock price high-value data on December 24, 2021, with a value of = 7575.0, the drinking value is obtained from the GT Index column on April 15, 2021, with a value of = 1. Using equation (22), the data table displayed has normalized. Based on the data in table II, the normalization results will be obtained which are shown in Table III as follows:

C. Artificial Neural Network

Experiments are used to find significant model architecture that affects process outputs, and factor values that give the best output. Properly designing an experiment reduces time and cost and helps focus on the desired information. The objective of conducting experiments is to find which models are significant and which are not based on the smallest MSE and MAPE values. After designing and conducting the experiment, it is necessary to analyze the results and analyze them statistically. Statistical analysis of the experimental model is important to see how likely is it that a result obtained has occurred by chance alone. To properly design a NN, it is necessary to look at best practices to narrow the choice of variables to use. A thorough survey showed closing prices and technical indicators are commonly used as input variables [12]. Summary of split training and testing data is shown in Table IV and Table V:

TABLE IV
SUMMARY OF SPLIT TRAINING AND TESTING DATA

INPUT	PARAMETER	SPLIT DATA		TARGET
		TRAINING	TESTING	
GTV	X_1	80%	20%	NO
GSI	X_2	80%	20%	NO
OPEN	X_3	80%	20%	NO
MIN	X_4	80%	20%	NO
MAX	X_5	80%	20%	NO
CLOSING	X_6	80%	20%	YES

TABLE V
SUMMARY OF THE PARAMETER SETTINGS

PARAMETER	VALUE	STATUS
Input variables	$X_1, X_2, X_3, X_4, X_5, X_6$	Fixed
Target	X_6	Fixed
ANN type	BP Algorithm	Fixed
Max epochs	1000	Fixed
Learning rate (LR)	0.1 and 0.5	Experiment
Momentum	0.1	Fixed
Error Epsilon	0.00001	Fixed
Hidden Layers (HL)	1 and 2	Experiment
Number of neurons in HL	10, 15, 20	Experiment
Activation function	Binary sigmoid	Fixed

All models were trained separately for up to 1000 epochs using a binary sigmoid activation function with learning rates

TABLE VI
PREDICTION ACCURACY

NO	LR	INPUT	HL	NEURONS I	NEURONS II	OUTPUT	MSE	RMSE	MAPE
1	0.1	6	1	10	-	1	0.000060	0.007758	1.45%
2	0.1	6	1	15	-	1	0.000065	0.008041	1.30%
3	0.1	6	1	20	-	1	0.000057	0.007576	1.34%
4	0.1	6	2	10	10	1	0.000139	0.011797	2.91%
5	0.1	6	2	15	15	1	0.000074	0.008578	1.77%
6	0.1	6	2	20	20	1	0.000055	0.007418	1.17%
7	0.5	6	1	10	-	1	0.000081	0.009003	1.36%
8	0.5	6	1	15	-	1	0.000125	0.011175	2.22%
9	0.5	6	1	20	-	1	0.000081	0.008968	1.90%
10	0.5	6	2	10	10	1	0.000284	0.016841	4.46%
11	0.5	6	2	15	15	1	0.000061	0.007822	1.48%
12	0.5	6	2	20	20	1	0.000065	0.008039	1.66%

of 0.1 and 0.5. The activation function is used for the output layer of all architectures. The setup is presented based on table 5. The accuracy functions determined for all models are MSE, RMSE, and MAPE which are then calculated for evaluation. Here we have performed an analysis on KAEF stock price data. For this, we have used twelve deep neural network architecture models based on input number, number of hidden layers, and output number. The number of hidden layers used is 1 hidden layer and 2 hidden layers. They are combined with 10, 15, and 20 neurons in the hidden layer, respectively. All of these networks are trained with 80% of KAEF's daily closing price data, and these networks are tested using 20% of KAEF's closing price data. The results obtained are tabulated in Table VI-VIII, and Fig VIII-X:

Traditional techniques can hardly achieve better performance with the stock market development [58]. With deep learning development, a techniques like ANN proved to be effective in the finance field. From the research, we obtained prediction results with highly accurate. The models are evaluated using standard strategic indicators: MSE, RMSE, and MAPE [52]. The low values of these three indicators show that the models are efficient in predicting stock closing price based on Table VI. The 6-10-10-1 is the model with the smallest MSE value, where the MSE value = 0.000055, RMSE = 0.007418, and MAPE =1.17%, It illustrates that this model is the best of all tested models. Fig. 11, shows the Architecture 6-20-20-1 prediction model. All models tested, yielded very high prediction accuracy with MAPE $\leq$10%. The key to the prediction model so as to produce high accuracy, is the number of HL and neurons. The number of HL and neurons greatly affects the prediction accuracy. It can be seen that the number of HL and more neurons will produce better prediction accuracy results. However, the number of HL and too many neurons will also reduce the stability of the model and the length of the model execution time. Fig. 12 shows the relationship between the number of HL and neurons with the model execution time. This study uses three main datasets, daily stock price data GSI and GTV data. The GSI and GTV data are external factors in stock price fluctuations during the pandemic. GSI and GTV are very important factors in the network learning process, so that artificial neural networks can produce high accuracy predictions.

IV. CONCLUSION

The models are evaluated using standard strategic indicators: MSE, RMSE, and MAPE. The low values of these three indicators show that the models efficiently predict stock closing price. The obtained results show that all the deep learning models can generate highly accurate prediction. The MAPE values as low as 1.17% are observed. The proposed system also seems capable of producing correct predictions about the direction of stock price movements up to a maximum of 98.8%. It was found that the 6-20-20-1 model with LR 0.1 gave a better MSE to predict with MSE = 0.000055. In contrast, the 6-10-10-1 model with an LR of 0.5 gives the highest MSE and MAPE values for prediction. However, this model is still included in the category of highly accurate prediction, with MAPE $\leq$ 10%. Therefore, the ANN-based machine learning approach model can be used well to generate accurate forecasts for stock market predictions during COVID-19 with little data availability. Based on these results, we propose that using an ANN-based machine learning approach using historical stock price data plus GTV and GSI data is a very important factor influencing the stock market and can help improve prediction accuracy. A new method was proposed with Google trend and GSI features to get high accurate predictions for stock market predictions during COVID-19.

REFERENCES

[1] M. Scherf, X. Matschke, and M. O. Rieger. "Stock Market Reactions to COVID-19 Lockdown: A Global Analysis," Finance Research Letters, vol. 45, art. id. 102245, 2022.

[2] H. Hong, Z. Bian, and C. C. Lee. "COVID-19 and Instability of Stock Market Performance: Evidence from the U.S.," Financial Innovation, vol. 7, no. 1, pp. 1-18, 2021.

[3] M. Yousfi, Y. Ben Zaied, N. Ben Cheikh, B. Ben Lahouel, and H. Bouzgarrou. "Effects of the COVID-19 Pandemic on the US Stock Market and Uncertainty: A Comparative Assessment between the First and Second Waves," Technological Forecasting and Social Change, vol. 167, art. id. 120710, 2021.

[4] K. Kamaludin, S. Sundarasen, and I. Ibrahim, "Covid-19, Dow Jones and Equity Market Movement in ASEAN-5 Countries: Evidence from Wavelet Analyses", Heliyon, vol. 7, no. 1, art. id. e05851, 2021.

[5] Z. Machmuddah, S. D. Utomo, E. Suhartono, S. Ali, and W. Ali Ghulam. "Stock Market Reaction to COVID-19: Evidence in Customer Goods Sector with the Implication for Open Innovation," Journal of Open Innovation: Technology, Market, and Complexity, vol. 6, no. 4. art. id. 99, 2020.

[6] V. K. S. Reddy. "Stock market prediction using machine learning. International Research Journal of Engineering and Technology", vol. 5, no. 10, pp. 1033-1035, 2018.

[7] M. M. Rahman, A. Das Gupta, M. M. Uddin, M. Hossain, and M. Z. Abedin. "Impact of Early COVID-19 Pandemic on the US and European Stock Markets and Volatility Forecasting." Economic Research-Ekonomska Istraživanja, vol. 12, no. 1, pp. 1-18, 2021.

[8] M. A. Khattak, M. Ali, and S. A. R. Rizvi. "Predicting the European Stock Market during COVID-19: A Machine Learning Approach," MethodsX, vol. 8, art. id. 101198, 2021.

TABLE VII
RESULTS OF MODEL PREDICTION WITH LR 0.1

NO	DATE	TARGET	PREDICTION MODEL WITH LR 0.1					
			6-10-1	6-15-1	6-20-01	6-10-10-1	6-15-15-1	6-20-20-1
1	04/08/2021	0.337866	0.338016	0.332713	0.337157	0.343946	0.338658	0.334253
2	04/09/2021	0.352390	0.358813	0.353533	0.358150	0.364523	0.359266	0.354681
3	04/10/2021	0.343808	0.347641	0.342484	0.347000	0.354743	0.350245	0.346287
4	04/11/2021	0.339517	0.342101	0.336998	0.341457	0.349935	0.345734	0.342094
5	04/12/2021	0.335226	0.336552	0.331498	0.335916	0.345075	0.341242	0.337911
6	04/13/2021	0.328624	0.326983	0.321754	0.326139	0.334253	0.329391	0.325452
7	04/14/2021	0.332585	0.335879	0.330427	0.334911	0.341272	0.335427	0.330724
8	04/15/2021	0.331265	0.333308	0.327863	0.332335	0.338995	0.333318	0.328757
9	04/16/2021	0.331265	0.333779	0.328388	0.332867	0.339812	0.334234	0.329734
10	04/17/2021	0.343808	0.340739	0.335420	0.339950	0.347083	0.341684	0.337227
11	4/18/2021	0.350079	0.344237	0.338948	0.343510	0.350742	0.345425	0.340984
12	4/19/2021	0.356351	0.347737	0.342478	0.347072	0.354403	0.349168	0.344744
13	4/20/2021	0.395960	0.386866	0.381673	0.386603	0.394068	0.389717	0.385508
14	4/21/2021	0.395960	0.388677	0.383160	0.388132	0.395150	0.391272	0.387406
15	4/22/2021	0.381436	0.385570	0.380076	0.385021	0.392460	0.388866	0.385224
16	4/23/2021	0.364273	0.364209	0.358884	0.363635	0.371973	0.368384	0.364929
17	4/24/2021	0.354370	0.358082	0.352848	0.357550	0.366301	0.362665	0.359230
18	4/25/2021	0.349419	0.355020	0.349825	0.354523	0.363435	0.359842	0.356401
19	4/26/2021	0.344468	0.351972	0.346815	0.351495	0.360621	0.356998	0.353563
20	4/27/2021	0.348429	0.351867	0.346357	0.351090	0.357669	0.352300	0.347666
21	4/28/2021	0.351069	0.356453	0.350829	0.355619	0.361652	0.356156	0.351388
22	4/29/2021	0.351069	0.356615	0.351008	0.355806	0.362018	0.356629	0.351928
...	...	...	...	...	...	...	...	...
100	07/16/2021	0.450092	0.453520	0.447088	0.453566	0.459291	0.456300	0.451592

TABLE VIII
RESULTS OF MODEL PREDICTION WITH LR 0.5

NO	DATE	TARGET	PREDICTION MODEL WITH LR 0.1					
			6-10-1	6-15-1	6-20-01	6-10-10-1	6-15-15-1	6-20-20-1
1	4/8/2021	0.337866	0.332900	0.329061	0.338658	0.350886	0.337845	0.338457
2	4/9/2021	0.352390	0.352823	0.349545	0.357102	0.371119	0.358957	0.358807
3	4/10/2021	0.343808	0.342978	0.338537	0.348398	0.359596	0.347176	0.347480
4	4/11/2021	0.339517	0.337415	0.332481	0.344043	0.354131	0.341370	0.341912
5	4/12/2021	0.335226	0.332565	0.327075	0.339772	0.348399	0.335488	0.336272
6	4/13/2021	0.328624	0.321784	0.317027	0.329454	0.339772	0.326331	0.327502
7	4/14/2021	0.332585	0.329934	0.326325	0.336498	0.349592	0.336011	0.336807
8	4/15/2021	0.331265	0.327831	0.323949	0.334683	0.346995	0.333284	0.334210
9	4/16/2021	0.331265	0.327857	0.323839	0.334794	0.347180	0.333710	0.334632
10	4/17/2021	0.343808	0.334283	0.330239	0.340796	0.353667	0.340708	0.341350
11	4/18/2021	0.350079	0.337520	0.333456	0.343830	0.356938	0.344225	0.344741
12	4/19/2021	0.356351	0.340768	0.336690	0.346872	0.360212	0.347742	0.348135
13	4/20/2021	0.395960	0.380183	0.376703	0.383624	0.397852	0.386792	0.385996
14	4/21/2021	0.395960	0.386564	0.382589	0.390006	0.400773	0.388345	0.387565
15	4/22/2021	0.381436	0.384261	0.379816	0.388011	0.397674	0.385080	0.384414
16	4/23/2021	0.364273	0.362485	0.357178	0.367765	0.376369	0.363508	0.363457
17	4/24/2021	0.354370	0.355395	0.349878	0.361219	0.370002	0.357324	0.357483
18	4/25/2021	0.349419	0.352549	0.346849	0.358059	0.366574	0.354182	0.354457
19	4/26/2021	0.344468	0.348979	0.343164	0.354782	0.363401	0.351105	0.351497
20	4/27/2021	0.348429	0.347329	0.343237	0.352459	0.364900	0.352002	0.352337
21	4/28/2021	0.351069	0.352649	0.348821	0.357323	0.369850	0.356727	0.356892
22	4/29/2021	0.351069	0.352896	0.348929	0.357627	0.369910	0.356834	0.357010
...	...	...	...	...	...	...	...	...
100	7/16/2021	0.450092	0.457286	0.454539	0.454928	0.464476	0.453800	0.451588

[9] P. D. Yoo, M. H. Kim, and T. Jan. "Machine Learning Techniques and Use of Event Information for Stock Market Prediction: A Survey and Evaluation," IEEE Proceeding: International Conference on Computational Intelligence for Modelling, Control and Automation and International Conference on Intelligent Agents, Web Technologies and Internet Commerce 2005, 28-30 November, 2005, Vienna, Austria, pp835-841.

[10] B. Wu and T. Duan. "A Performance Comparison of Neural Networks in Forecasting Stock Price Trend," International Journal of Computational Intelligence Systems, vol. 10, no. 1, pp. 336-346, 2017.

[11] M. Mallikarjuna and R. P. Rao. "Evaluation of Forecasting Methods from Selected Stock Market Returns," Financial Innovation, vol. 5, no. 1, pp. 1-16, 2019.

[12] A. Lasfer, H. El-Baz, and I. Zualkernan. "Neural Network Design Parameters for Forecasting Financial Time Series," IEEE Proceeding: International Conference on Modeling, Simulation and Applied Optimization 2013, 28-30 April, 2013, Hammamet, Tunisia, pp1-4.

[13] D. P. Gandhmal and K. Kumar. "Systematic Analysis and Review of Stock Market Prediction Techniques," Computer Science Review, vol. 34, art. id. 100190, 2019.

[14] D. Selvamuthu, V. Kumar, and A. Mishra. "Indian Stock Market Prediction using Artificial Neural Networks on Tick Data," Financial Innovation, vol. 5, no. 1, pp. 1-12, 2019.

[15] L. Fausett, *Fundamentals of Neural Networks: Architectures, Algorithms, and Applications*. USA: Prentice-Hall, Inc., 1994.

[16] Sukono, Y. Hidayat, Suhartono, B. Sutijo, A. T. Bin Bon, and S. Supian. "Indonesian Financial Data Modeling and Forecasting by Using Econometrics Time Series and Neural Network," Global Journal of Pure and Applied Mathematics, vol. 12, no. 4, pp. 3745-3757, 2016.

[17] S. Zahroh, H. Hidayat, R. Septiani Pontoh, Sukono, A. Santoso, and A. Talib Bon. "Modeling and Forecasting Daily Temperature in Bandung," IEOM Prooceding: Proceedings of the International Conference on Industrial Engineering and Operations Management 2019, 26-28 November, 2019, Riyadh, Saudi Arabia, pp406-412.

[18] C. Hamzaçebi, D. Akay, and F. Kutay. "Comparison of Direct and Iterative Artificial Neural Network Forecast Approaches in Multi-Periodic Time Series Forecasting," Expert System Application, vol. 36, no. 2, pp. 3839-3844, 2009.

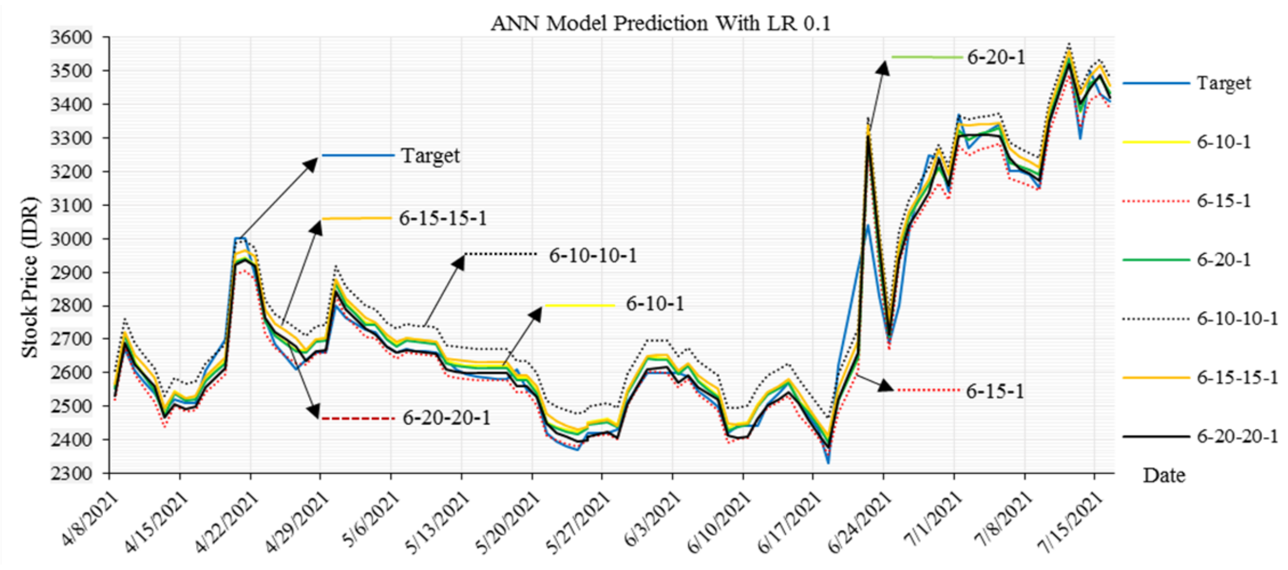

Fig. 8. Result of all models prediction with LR 0.1

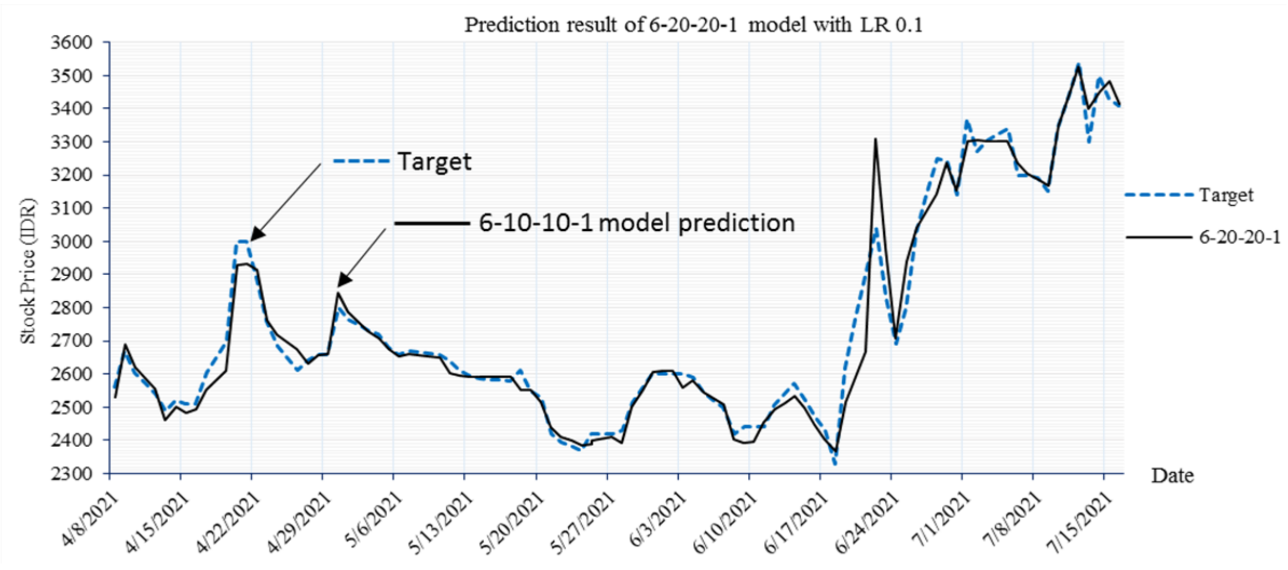

Fig. 9. Graph of prediction results of 6-10-10-1 model with LR 0.1

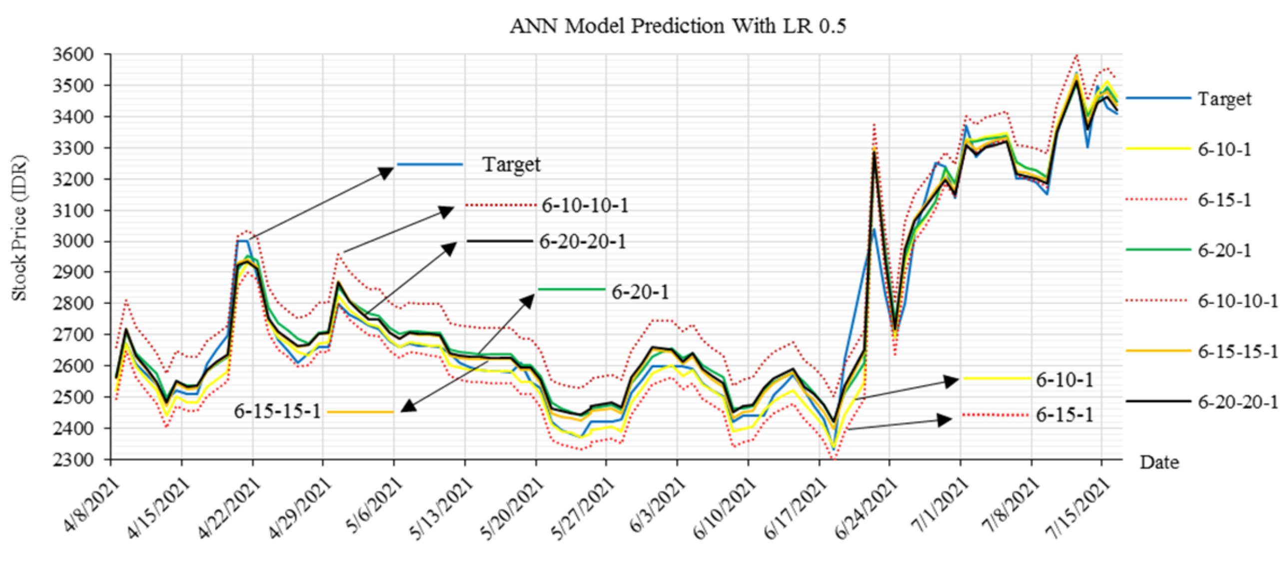

Fig. 10. Result of model prediction with LR 0.5

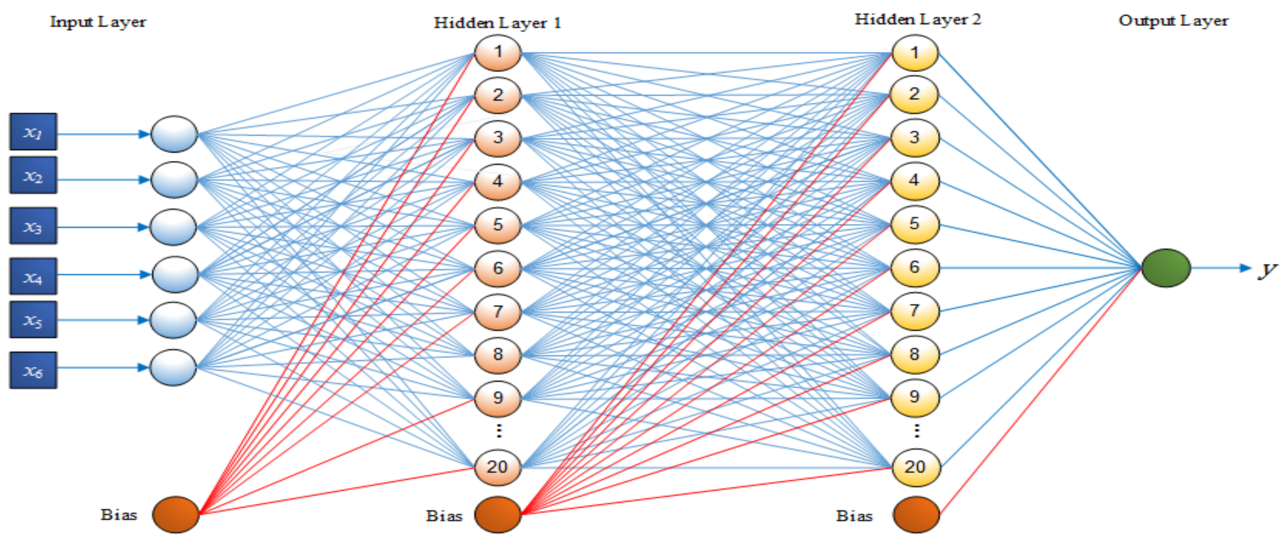

Fig. 11. The 6-10-10-1 model architecture

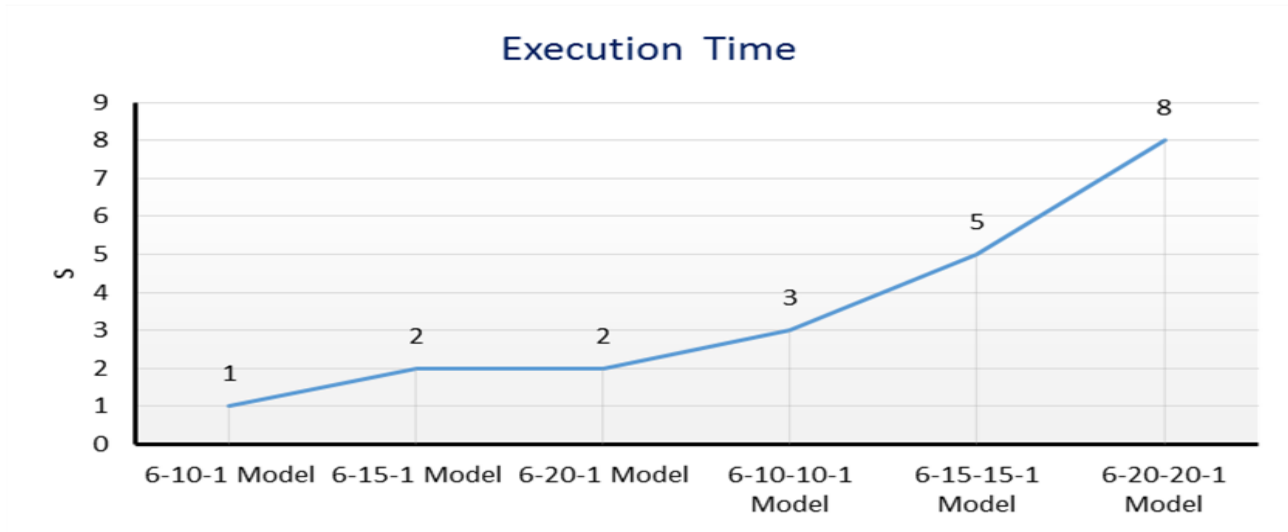

Fig. 12. The execution time of each ANN model

[19] S. Tekin and E. Çanakoğlu. "Prediction of Stock Returns in Istanbul Stock Exchange using Machine Learning Methods," IEEE Proceeding: Signal Processing and Communications Applications Conference 2018, 2-5 May, 2018, Izmir, Turkey, pp1-4.

[20] M. Obthong, N. Tantisantiwong, W. Jeamwatthanachai, and G. Wills. "A Survey on Machine Learning for Stock Price Prediction: Algorithms and Techniques," IEEE Proceeding: International Conference on Finance, Economics, Management and IT Business 2020, 5-6 May, 2020, Prague, Czech Republic, pp. 63-71.

[21] Y. Peng, P. H. M. Albuquerque, H. Kimura, and C. A. P. B. Saavedra. "Feature Selection and Deep Neural Networks for Stock Price Direction Forecasting using Technical Analysis Indicators," Machine Learning with Application, vol. 5, art. id. 100060, 2021.

[22] Sukono, E. Lesmana, D. Susanti, H. Napitupulu, and Y. Hidayat. "Estimating the Value-at-Risk for Some Stocks at the Capital Market in Indonesia based on ARMA-FIGARCH Models," Journal of Physics Conference Series, vol. 909, art. id. 12040, 2017.

[23] Sukono, D. Susanti, M. Najmia, E. Lesmana, H. Napitupulu, S. Supian and A. S. Putra. "Analysis of Stock Investment Selection based on CAPM using Covariance and Genetic Algorithm Approach," IOP Conference Series Material Sciences and Engineering, vol. 332, art. id. 12046, 2018.

[24] Nasdaq.com, "Are These The Best Health Care Stocks To Buy Right Now," Nasdaq, 2021. https://www.nasdaq.com/articles/good-stocks-to-invest-in-right-now-4-health-care-stocks-to-watch-2021-04-19 (accessed Jul. 28, 2021).

[25] V. A. Kusumaningtyas, Y. M. Syah, and L. D. Juliawaty, "Two stilbenes from Indonesian Cassia grandis and their antibacterial activities," Research Journal of Chemistry and Environment, vol. 24, no. 1, pp. 61–63, 2020.

[26] Investing.com, "Kimia Farma Persero Tbk Company Profile," kimia-farma-company-profile, 2021. https://id.investing.com/equities/kimia-farma-company-profile (accessed Jul. 16, 2021).

[27] Yahoo finance, "Historical Data KAEF.JK," PT Kimia Farma (Persero) Tbk (KAEF.JK), 2021. https://finance.yahoo.com/quote/KAEF.JK/history?p=KAEF.JK (accessed Jul. 16, 2021).

[28] A. Kliber and A. Rutkowska. "Can Google Trends Affect Sentiment of Individual Investors? The Case of the United States." Wydawnictwo Uniwersytetu Ekonomicznego we Wrocławiu, [Online]. Available: http://www.dbc.wroc.pl/Content/70311/Rutkowska_Kliber_Can_Google_Trends_affect_sentiment.pdf.

[29] A. Mavragani and G. Ochoa. "Google Trends in Infodemiology and Infoveillance: Methodology Framework," JMIR public health and surveillance, vol. 5, no. 2, art. id. e13439, 2019.

[30] Google Trends, "Google Trends 'Corona Virus,' " Google Trends, 2021. https://trends.google.co.id/trends/explore?date=2020-06-01 2021-07-21&geo=ID&q=corona virus (accessed Jul. 16, 2021).

[31] K. Syuhada, A. Wibisono, A. Hakim, and F. Addini. "Covid-19 Risk Data during Lockdown-Like Policy in Indonesia," Data Brief, vol. 35, art. id. 106801, 2021.

[32] T. Hale, N. Angrist, R. Goldszmidt, B. Kira, A. Petherick, T. Phillips, A. Webster, E. C. Blake, L. Hallas, S. Majumdar and H. Tatlow"A Global Panel Database of Pandemic Policies (Oxford COVID-19 Government Response Tracker)," Nature human behaviour,, vol. 5, no. 4, pp. 529-538, 2021.

[33] T. Perdana, D. Chaerani, A. L. H. Achmad, and F. R. Hermiatin. "Scenarios for Handling the Impact of COVID-19 based on Food Supply Network through Regional Food Hubs under Uncertainty," Heliyon, vol. 6, no. 10, art. id. e05128, 2020.
[34] Ourworldindata, "Indonesia Goverment Response Stringency Index," COVID-19: Stringency Index, 2021. https://ourworldindata.org/grapher/covid-stringency-index?tab=chart&country= IDN (accessed Jul. 16, 2021).
[35] Melina, E. K. Putra, W. Witanti, Sukrido, and V. A. Kusumaningtyas. "Design and Implementation of Multi Knowledge Base Expert System Using the SQL Inference Mechanism for Herbal Medicine," Journal of Physics Conference Series, vol. 1477, no. 2, pp. 1-9, 2020.
[36] J. Sandoval. "Computational Models of Financial Price Prediction: A Survey of Neural Networks, Kernel Machines and Evolutionary Computation Approaches," Ingeniería, vol. 16, no. 2, pp. 125-133, 2011.
[37] K. Gurney, "An Introduction to Neural Networks," USA: Taylor & amp; Francis, Inc., 1997.
[38] G. Piccinini. "The First computational theory of mind and brain: a close look at mcculloch and pitts's: logical calculus of ideas immanent in nervous activity" Synthese, vol. 141, no. 2, pp. 175-215, 2004.
[39] S. Z. Resa, S. Pontoh, Y. Hidayat, R. Aldella, N. M. Jiwani, and Sukono. "Covid-19 Modelling in South Korea using A Time Series Approach," International Journal of Advance Sciences Technology, vol. 29, no. 7 pp. 1620-1632, 2020.
[40] C. C. Aggarwal. "Neural Networks and Deep Learning," Cham: Springer, 2018.
[41] S. Haykin. "Neural Networks and Learning Machines," New York: Pearson Education, Inc, 2009.
[42] O. Coupelon. "Neural Network Modeling for Stock Movement Prediction, a State of the Art," 2007.
[43] M. Qiu and Y. Song. "Predicting the Direction of Stock Market Index Movement using an Optimized Artificial Neural Network Model," PLoS One, vol. 11, no. 5, art. id. e0155133, 2016.
[44] A. S. Girsang, F. Lioexander, and D. Tanjung. "Stock Price Prediction Using LSTM and Search Economics Optimization," IAENG International Journal of Computer Sciences, vol. 47, no. 4, pp. 758-764, 2020.
[45] Q. K. Al-Shayea. "Neural Networks to Predict Stock Market Price," Lecture Notes in Engineering and Computer Science: Proceedings of the World Congress on Engineering and Computer Science 2017, 25-27 October, 2017, San Francisco, USA, pp371-377.
[46] N. Yudistira. "COVID-19 Growth Prediction using Multivariate Long Short Term Memory," IAENG International Journal of Computer Sciences, vol. 47, no. 4, pp. 829-837, 2020.
[47] Z. Berradi, M. Lazaar, H. Omara, and O. Mahboub. "Effect of Architecture in Recurrent Neural Network Applied on the Prediction of Stock Price," IAENG International Journal of Computer Sciences, vol. 47, no. 3, pp. 436-441, 2020.
[48] Thayogo and A. Wibowo. "Weight-Dropped Long Short Term Memory Network for Stock Prediction with Integrated Historical and Textual Data," IAENG International Journal of Computer Sciences, vol. 47, no. 3, pp. 367-377, 2020.
[49] M. Jarrah and N. Salim. "A Recurrent Neural Network and a Discrete Wavelet Transform to Predict the Saudi Stock Price Trends," International Journal of Advanced Computer Science and Applications, vol. 10, no. 4, pp. 155-162, 2019.
[50] M. Hiransha, E. A. Gopalakrishnan, V. K. Menon, and K. P. Soman "NSE Stock Market Prediction Using Deep-Learning Models," Procedia computer science, vol. 132, pp. 1351-1362, 2018.
[51] R. S. Al-Gounmeein and M. T. Ismail. "Comparing the Performances of Artificial Neural Networks Models Based on Autoregressive Fractionally Integrated Moving Average Models," International Journal of Advanced Computer Science and Applications, vol. 48, no. 2, pp. 266-276, 2021.
[52] M. Vijh, D. Chandola, V. A. Tikkiwal, and A. Kumar. "Stock Closing Price Prediction using Machine Learning Techniques," Procedia Computer Sciences, vol. 167, pp. 599-606, 2020.
[53] X. Ji, J. Wang, and Z. Yan. "A Stock Price Prediction Method based on Deep Learning Technology," International Journal of Crowd Science, vol. 5, no. 1, pp. 55-72, 2021.
[54] A. Mittal. "Stock Prediction Using Twitter Sentiment Analysis," UK: Standford University, 2012.
[55] R. K. Klimberg, G. P. Sillup, K. J. Boyle, and V. Tavva. "Forecasting Performance Measures – What are Their Practical Meaning?," Advances in Business and Management Forecasting, vol. 7, pp. 137-147, 2010.
[56] O. D. Madeeh and H. S. Abdullah. "An Efficient Prediction Model based on Machine Learning Techniques for Prediction of the Stock Market," Journal of Physics Conference Series, vol. 1804, no. 1, art. id. 12008, 2021.
[57] A. J. Balaji, D. S. Harish Ram, and B. B. Nair. "Applicability of Deep Learning Models for Stock Price Forecasting An Empirical Study on BANKEX Data," Procedia Computer Sciemces, vol. 143, pp. 947-953, 2018.
[58] X. Jiawei and T. Murata. "Stock Market Trend Prediction with Sentiment Analysis based on LSTM Neural Network," Lecture Notes Engineering Computer Sciences: Proceedings of the International MultiConference of Engineers and Computer Scientists 2019, 13-15 March, 2019, Hong Kong, pp427-430.

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