The Model of Artificial Neural Network and Nonparametric MARS Regression for Indonesian Composite Index

Dodi Devianto¹*, Putri Permathasari², Mutia Yollanda³, Afridian Wirahadi Ahmad⁴

¹,²,³Department of Mathematics, Andalas University, Padang 25163, Indonesia
⁴Padang State Polytechnic, Padang 25163, Indonesia

*Corresponden Email: ddevianto@sci.unand.ac.id

Abstract. The Indonesian composite stock price index is an indicator of changes in stock prices as a guide for investors to invest in reducing risk. The regression model for Indonesian Composite Index (ICI) has the response variable as stock prices with fluctuation behavior and several financial predictor variables, the model tends to violate the assumptions of normality, homoscedasticity, autocorrelation and multicollinearity. This problem can be overcome by modeling the composite stock price index by using the Artificial Neural Network (ANN) and nonparametric regression of Multivariate Adaptive Regression Spline (MARS). In this study, the time series data from the composite stock price index starting from April 2003 to March 2018 with its predictor variables are crude-oil prices, interest rates, inflation, exchange rates, gold prices, Dow Jones price, and Nikkei 225 Index. The both methods give better goodness of fit, where the coefficient of determination ANN is 0.98925 and the MARS determination coefficient is 0.99427. While based on the Mean Absolute Percentage Error (MAPE) of ANN was obtained 6.16383 and the MAPE value of MARS is 4.51372. This means that the ANN method and nonparametric MARS regression method have good performance to forecast the value of the Indonesian composite stock price index in the future, but in this case of data the nonparametric MARS regression method shows the accuracy of the model is slightly better than ANN.

1. Introduction

The measures of the relationship between the predictors and response variables are necessary to obtain the regression model. The constant values as the coefficient in the regression model, which has not known are called parameters, and these values also have the role in prediction a model [1]. In each regression model, there is a residual obtained from the difference between the observed value and the model. A numerical approach can overcome the regression models that violate the residual assumptions. The numerical method is developed to modeling the data without regard to obey the classical statistical assumptions, where the Artificial Neural Network (ANN) and nonparametric regression of Multivariate Adaptive Regression Spline (MARS) are the alternatives model used to approach the model of Indonesian Composite Index (ICI).

The Indonesian composite index is an investment instrument that can be modeled in a regression equation with a numerical approach. An investment that is needed in running a business and some risks have to be accepted by investors as explained in [2]. To minimize risks in investing, the forecasting of stock prices is to be one of the alternatives to solve the risks. There are many things that
influence stock prices; they are Dow Jones price, Nikkei 225 index, inflation, interest rate, exchange rate, gold price, earning per-share, crude-oil price and many other observable variables. The historical data of stock prices and their fluctuation has discovered as described in [3][4]. Analyzing historical data of stock prices could be predicting the price fluctuation on the stock market.

There are many machine learning techniques that have been expanded to forecast stock prices as explained in [5] and also artificial neural networks [6]. While the nonparametric model of MARS was first popularized by [7] and it is one of the nonparametric regression methods which could be used to make a linear model. Regarding the forecast of stock prices index as in [8], they are comparing intelligent systems using a multilayer perceptron presents more reliable results than the other intelligent systems to forecast the stock exchange index. In this study, the Indonesian composite index would be forecasted by using ANN and nonparametric MARS regression as a response variable by using seven predictor variables. The methods will be compared based on their goodness of fit and Mean Absolute Percentage Error (MAPE) value to get the best model between them.

2. Methodology

A. Data Source

This research has used the historical data from April 2003 until March 2018, that is 180 data. The data were accessed formally via https://yahoofinance.com and http://www.bi.go.id. In this study, there is one response variable (Y) namely Indonesian Composite Index and there are seven predictor variables, namely crude-oil price (X1), interest rate (X2), inflation (X3), exchange rate (X4), gold price (X5), Dow Jones price (X6) and Nikkei 225 index (X7).

B. Stage of Research for Artificial Neural Network

Artificial neural networks were made in 1943 by McCulloch and Pitts as a mathematical model of the neuron for a basic switching element of the brain as in [7]. The neural networks are composed of nodes or units connected by directed links for providing to propagate the activation element of $x_i$ from the unit $i$ to $j$. Each link has weight $w_{ij}$ associated to the element of $x_i$, which determines the strength and sign of the connection. Each unit $j$ first computes a weighted sum of its inputs:

$$in_j = \sum_{i=0}^{n} x_i w_{ij}$$  \hspace{1cm} (1)

Then the activation function $g$ is applied to this sum to obtain the output $z_j = g(in_j)$ and continued to other neurons as a new set of input data.

According to [8], there are feed-forward and recurrent networks to make the network after deciding on the mathematical model of a neuron. The output of their layers is obtained through activation functions which unique after this transformation. These activation functions have to scale the output of the neural network into proper ranges. There are some activation functions provided which are explained in [9], wherein this study, it is used a sigmoid activation function defined as follows:

$$f(x) = \frac{1}{1 + \exp(-x)}$$  \hspace{1cm} (2)

The result of the sigmoid function is a value on the interval (0,1) where the sigmoid function only returns positive values. Based on [9], there are two steps to construct a model of the artificial neural network, they are training and validation. In the training neural network, the methods generally fall into the categories of supervised, unsupervised, and various hybrid approaches. The validating a neural network is a final step in ANN to determine if the additional training is required where the validation data is completely separate from the training data.

According to [10], during training neural network, the networks attempt to minimize the error. Error for $k$-th training data can be expressed in the following equation.
\[
Err_k(W) = \frac{1}{2} \sum_{j=1}^{\rho} (t_{kj} - y_{kj})^2
\]  
(3)

where \( t_{kj} \) is \( j \)-th output value which wants to be achieved or target value for \( k \)-th data and \( y_{kj} \) is \( j \)-th actual output for \( k \)-th data. The updating output layer for ANN can apply the chain rule to factorize the derivative \( Err_k(W) \) with respect to \( w^p_{jp} \), which is explained in [10] and [11]. The weights which have updated can be used in the next steps if the stopping criterion is not available on the process.

The backpropagation algorithm was the learning algorithm, and it uses gradient descent as the core learning mechanism. Based on [12], the learning network consists of the following steps. First, initialization of the network; the weights are generally initialized to be determined with random weights. Second, feed-forward; information process is passed forward through the network from input to hidden and output layer via node activation functions and weights. Third, assess the error; the output of the network is assessed relative to known output, if the error is below a pre-specified threshold the network is trained, and the algorithm terminated. Forth, propagation; the error at the output layers is used to re-modify the weights where the algorithm propagates the error backwards through the network and computes the gradient of the change in error with respect to changes in the weight values. Fifth, adjustment; adjustment is necessary to determine the weights by using the gradients of change to reduce the error.

The model of ANN for ICI is obtained in the following steps:
1. Define the input and output data that want to be obtained.
2. Normalization of data
3. Construct the architecture of the artificial neural network.
4. Training the networks of 134 data which consists of initialization, feed-forward, error assessment, propagation, and adjustment.
5. Validation the networks of 46 data to determine whether the process will be continued or be repeated the training process to get the error less than a threshold value.
6. Build the ICI model by using an artificial neural network.

C. Stage of Research for Multivariate Adaptive Regression Spline

The first step formation of the MARS model begins by determining the knots and basis functions of each predictor variable by plotting each predictor variable with the response variable. A good MARS model is determined by the location and the optimum number of knots. The MARS model is focused on overcoming high dimensional problems and discontinuities in the data. Besides, the MARS model is a development of the Recursive Partition Regression (RPR) approach that still has weaknesses, where the model that is later produced by this method is not continuous on knots. The MARS model can be written [13][14] as follows

\[
\hat{f}(x) = a_0 + \sum_{m=1}^{M} a_m \prod_{k=1}^{K_m} (S_{km}(x_{v(k,m)} - t_{km}))^{+}
\]

(4)

where \( a_0 \) is regression constant and \( a_m \) is the coefficient of the \( m \)-th basis function. The coefficient \( a_m \) is determined by the least squares method, where \( M \) is the maximum basis function. It is noted \( K_m \) as degree of interaction for \( m \)-th basis function, where \( S_{km} = +1 \) if the knot is located on the right subregion and \( S_{km} = -1 \) if the knot is left, the notation \( x_{v(k,m)} \) is the predictor variable of \( v \) for determining the \( k \)-th variable and \( m \)-th subregion. The \( t_{km} \) is the knot value of the predictor variable \( x_{v(k,m)} \). The MARS equation model in Equation (4) can be rewritten for simplicity understanding into the following equation

\[
\hat{f}(x) = a_0 + a_1 BF_1 + a_2 BF_2 + ... + a_M BF_M
\]

(5)

where \( BF_M \) is the \( m \)-th basis function.

The best model is determined based on the minimum Generalized Cross Validation (GCV) criteria, where the GCV function is defined as follows:
\[
GCV(M) = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{f}_M(x_i))^2 \left(1 - \frac{C(M^*)}{N}\right)^2
\]

where \(M\) is the number of basis functions, \(x_i\) is predictor variable and \(y_i\) is response variable, \(N\) is the number of observations, and complex model function of \(C(M^*)\) is defined as \(C(M^*) = C(M) + dM\) for \(d\) as the smoothing parameter and \(C(M)\) as the number of parameter on the model.

There are a number of measures of model accuracy, the most frequently used accuracy measures are Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) that can be formulated respectively as follows:

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} (t_i - y_i)^2
\]

\[
MAPE = \frac{1}{N} \sum_{i=1}^{N} \left|\frac{t_i - y_i}{t_i}\right| \times 100\%
\]

where \(N\) is the number of observational data, \(y_i\) is actual output data, and \(t_i\) is the output data using a particular method as in [15]. Beside these two measures, the coefficient of determination is also used to measure the accuracy of the model using certain forecasting methods in a given data set on the regression model [16]. The coefficient of determination \(R^2\) can be formulated as follows:

\[
R^2 = 1 - \frac{\sum_{i=1}^{N} (t_i - \bar{y})^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \times 100\%
\]

The model of MARS for ICI is obtained in the following steps:
1. Identification the behavior of the response variable and predictor variables.
2. Testing parameters for nonparametric regression models.
3. Standardization each variable which is involved in having the same value scale, and then determining the maximum number of basis functions (BF), maximum interaction (MI), minimum observation (MO). In this study it is selected BF = 14, 21, 28, MI = 1, 2, 3, and MO = 0,1,2,3. If more than three interactions, it will lead to a very complex interpretation of the model.
4. Determining the MARS model based on the smallest value of GCV and test of significance of the MARS.
5. Interpretation of the best MARS model and influential variables in the model.

3. Results and Discussion

A. The Model of Artificial Neural Network

In determining a nonlinear model of the artificial neural network with backpropagation method, after defining the input and output data and normalization of data. The next step is building the architecture of the artificial neural network. Based on the data, the architecture of the artificial neural network, which used is 7-4-3-1, it means that the network consists of seven input units, four hidden units in the first hidden layer, three hidden units in the second hidden layer, and one output unit.

The next step is training neural networks. Learning algorithms of the artificial neural network consist of initialization, feed-forward, error assessment, propagation, and adjustment.
1. Initialization. In the training process, the network has 134 data, learning rate \(\eta\) is 0.01, activation function which used is sigmoid function, and error assessment of 0.001 as a threshold value so far algorithm can be stopped.
2. Feed-forward. Each input unit \((x_{ki} = 1, 2, 3, \ldots, 7)\) accepts input data and distributes the data into each hidden unit. Based on the first data which is taken on April 2003 input values that are
normalized as follows $x_{11} = 0.11600$, $x_{12} = 0.99294$, $x_{13} = 0.29681$, $x_{14} = 0.09430$, $x_{15} = 0.00000$, $x_{16} = 0.09364$, $x_{17} = 0.01694$ and output value which want to be achieved or target value is $t_{11} = 0.00000$.

3. **Error assessment.** Because $|t_{11} - y_{11}| > 0$ for $k = 1$, then stopping criterion is not available, thus the training of the network has not finished being continued.

4. **Propagation.** The back propagation method used to find out the error information on the output unit and find out errors on each hidden unit. In the hidden layer, the propagation is used to find out the correction value of weights and bias.

5. **Adjustment.** The last step in learning algorithms of the artificial neural network, these are two steps to adjust the weights to get new weights, which will be used in the next process.

Before doing the next step, repeat the process of feed-forward, error assessment, propagation, until the error between the actual output or target and predicted output is less than a value that has determined. The following step is the validation neural network. In the validation process, data which used to test a network are 46 data. The following table is a model summary of the training and the testing process.

### Table 1. Model Summary

|         | Training | Testing |
|---------|----------|---------|
|         | Sum of Squares Error | 0.8259  | 0.1826  |
|         | Relative Error       | 0.0126  | 0.0065  |
| Dependent Variable: ICI. |

### Table 2. Parameter Estimates

| Predictor        | Predicted | Hidden Layer 1 | Hidden Layer 2 | Output Layer |
|------------------|-----------|----------------|----------------|--------------|
|                  | H(1:1)    | H(1:2)         | H(1:3)         | H(1:4)       |
| Input Layer      |           |                |                |              |
| (Bias)           | 1.086     | .288           | -.280          | -.246        |
| Crude-Oil Price  | .288      | .391           | -.153          | .160         |
| Interest Rate    | -.280     | -.420          | .325           | -.205        |
| Inflation        | -.246     | .160           | .600           | .009         |
| Exchange Rate    | .584      | .032           | -.064          | .977         |
| Gold Price       | 1.179     | -.217          | -.231          | -.320        |
| Dow Jones Price  | -.200     | .237           | -.534          | -.965        |
| Nikkei 225 index | -.087     | .099           | .131           | -.474        |
| Hidden Layer 1   | (Bias)    |                |                |              |
| H(1:1)           | .273      | .150           | -.283          |              |
| H(1:2)           | 1.311     | -.932          | .363           |              |
| H(1:3)           | .338      | -1.033         | -.520          |              |
| H(1:4)           | .427      | 1.239          | .729           |              |
| Hidden Layer 2   | (Bias)    |                |                |              |
| H(2:1)           | -.185     | .939           | 1.029          | .966         |
| H(2:2)           |           |                |                | 2.092        |
| H(2:3)           |           |                |                | -2.729       |
|                  |           |                |                | -1.402       |
Based on Table 1, the MSE value is obtained by using Equation (7) for the testing process, 0.0038 is less than the training process, 0.0063. It means that the artificial neural network has the ability to recognize new data. Finally, the obtained model can be used to forecast composite stock price index value. The last step is the modeling of the artificial neural network. After learning algorithms have finished, obtained new weights which will be used to make a nonlinear model of Indonesian composite index. Parameters estimation for the nonlinear model of ANN are shown in Table 2. The model of ANN is built by using two kinds of predicted hidden layer, the first hidden layer consists H(1:1), H(1:2), H(1:3) and H(1:4), while the second hidden layer consists H(2:1), H(2:2) and H(2:3), these structure are used to make prediction of Indonesian composite index as the output layer.

Based on the data, after forecasting the Indonesian composite index, it is obtained MAPE value of 6.16383, this is less than 10 and the coefficient of determination of 0.98925 approaches 1. It means that the model that has been obtained having a good performance to forecast composite stock price index in the future because it is almost approaching the real value.

B. The Model of MARS

After getting information about descriptive statistics and data behavior, furthermore, the regression model assumption is done, namely normality, homoscedasticity, autocorrelation, and multicollinearity test. This assumption is used as the strategy for testing parameters for nonparametric regression suitability. If there is an assumption that is not fulfilling the MARS method, which is a nonparametric regression model can be an alternative to solve the problem. A regression model assumption can be seen in the following Table 3.

| Table 3. Regression Model Assumptions |
|---------------------------------------|
|                                       |
|                                      |
| p-value | ABS RES | Durbin Watson | VIF  |
|--------------------------------------|
| Indonesian Composite Index            |
| 0.051                                |
| Crude-Oil Price                      |
| 0.001                                |
| 0.000                                |
| Interest Rate                        |
| 0.001                                |
| 0.617                                |
| Inflation                            |
| 0.000                                |
| 0.609                                |
| Exchange Rate                        |
| 0.000                                |
| 0.000                                |
| Gold Price                           |
| 0.001                                |
| 0.546                                |
| Dow Jones Price                      |
| 0.000                                |
| 0.000                                |
| Nikkei 225 Index                     |
| 0.003                                |
| 0.000                                |

Based on Table 3, for normality test, it is obtained p-value (2-tailed) for ICI (Y) is greater than \( \alpha = 0.05 \), which means that residuals are normally distributed. While, p-value (2-tailed) for the crude-oil price (\( X_1 \)), interest rate (\( X_2 \)), inflation (\( X_3 \)), exchange rate (\( X_4 \)), gold price (\( X_5 \)), Dow Jones Index (\( X_6 \)) and Nikkei 225 Index (\( X_7 \)) are lower than \( \alpha = 0.05 \) which means that residuals are not normally distributed. For the homoscedasticity test, the significant value of interest rate (\( X_2 \)), inflation (\( X_3 \)) and gold price (\( X_5 \)) are greater than significant level 5% in order that there is homoscedasticity. For autocorrelation test, if \( d < dL \) or \( d > 4-dL \) then there is exist an autocorrelation. If \( dL < d < dU < d < 4 \) then the conclusion could not be taken. Based on Table 4, it is obtained the value of \( d \) is 0.865 where from Durbin Watson’s table (\( N = 180, k = 7 \)), it obtained \( dU = 1.8374 \) and \( dL = 1.6761 \) in order that \( d < dL \). Based on a significant level 5% can be taken a conclusion that there is autocorrelation between residuals for each observation. For multicollinearity test, VIF value of \( X_1 \) and \( X_6 \) are greater than 10, which means that they are any correlation between the predictor variables, there is exist multicollinearity.
The classical regression model on the response variable of the Indonesian composite index does not meet the assumptions of autocorrelation and multicollinearity, so that an alternative MARS model can be used as a nonparametric statistical approach.

**Table 4. Results of Selection Model Using GCV**

| Model | BF | MI | MO | GCV   | Model | BF | MI | MO | GCV   |
|-------|----|----|----|-------|-------|----|----|----|-------|
| 1     | 14 | 1  | 0  | 0.01555| 19    | 21 | 2  | 2  | 0.01333|
| 2     | 14 | 1  | 1  | 0.01563| 20    | 21 | 2  | 3  | 0.01325|
| 3     | 14 | 1  | 2  | 0.01560| 21    | 21 | 3  | 0  | 0.01252|
| 4     | 14 | 1  | 3  | 0.01562| 22    | 21 | 3  | 1  | 0.01210|
| 5     | 14 | 2  | 0  | 0.01613| 23    | 21 | 3  | 2  | 0.01253|
| 6     | 14 | 2  | 1  | 0.01555| 24    | 21 | 3  | 3  | 0.01248|
| 7     | 14 | 2  | 2  | 0.01572| 25    | 28 | 1  | 1  | 0.01445|
| 8     | 14 | 2  | 3  | 0.01574| 26    | 28 | 1  | 1  | 0.01390|
| 9     | 14 | 3  | 0  | 0.01415| 27    | 28 | 1  | 2  | 0.01440|
| 10    | 14 | 3  | 1  | 0.01548| 28    | 28 | 1  | 3  | 0.01389|
| 11    | 14 | 3  | 2  | 0.01545| 29    | 28 | 2  | 0  | 0.01221|
| 12    | 14 | 3  | 3  | 0.01547| 30    | 28 | 2  | 1  | 0.01244|
| 13    | 21 | 1  | 0  | 0.01477| 31    | 28 | 2  | 2  | 0.01241|
| 14    | 21 | 1  | 1  | 0.01418| 32    | 28 | 2  | 3  | 0.01241|
| 15    | 21 | 1  | 2  | 0.01491| 33    | 28 | 3  | 0  | 0.01201|
| 16    | 21 | 1  | 3  | 0.01506| 34    | 28 | 3  | 1  | 0.01017|
| 17    | 21 | 2  | 0  | 0.01290| 35    | 28 | 3  | 2  | 0.01173|
| 18    | 21 | 2  | 1  | 0.01279| 36    | 28 | 3  | 3  | 0.01059|

In determining the MARS model using minimum GCV value, it is obtained by trial and error by combining the number of basis functions (BF), maximum interaction (MI), and minimum observation (MO) as the results in Table 4.

The best model of MARS based on the smallest value of GCV is 0.01017 with model equations as follows:

\[
Y = -0.763939 + 0.548287 \times BF_3 - 0.180626 \times BF_5 - 0.18591 \times BF_6 + 0.0887371 \times BF_9 - 0.515422 \times BF_{10} + 0.395404 \times BF_{11} + 1.6566 \times BF_{14} - 0.502737 \times BF_{17} - 0.264626 \times BF_{18} + 0.810037 \times BF_{19} - 0.129654 \times BF_{20} + 0.110508 \times BF_{21} - 0.317845 \times BF_{23} - 0.343702 \times BF_{24} + 0.122742 \times BF_{25} - 0.0379905 \times BF_{26} + 0.223046 \times BF_{27} + 0.123024 \times BF_{28}.
\]

where we have the basis function as follows

\[BF_1 = \max(0, ZX_1 + 0.0720768), BF_3 = \max(0, ZX_6 + 1.63949),\]
\[BF_4 = \max(0, ZX_5 - 0.641147), BF_5 = \max(0, 0.641147 - ZX_3),\]
\[BF_6 = \max(0, ZX_3 + 0.314867) \times BF_3, BF_9 = \max(0, 1.4938 - ZX_4) \times BF_4,\]
\[BF_{10} = \max(0, ZX_6 - 1.79433) \times BF_3, BF_{11} = \max(0, 1.79433 - ZX_3) \times BF_9,\]
\[BF_{14} = \max(0, ZX_1 - 1.09198) \times BF_3, BF_{17} = \max(0, -0.293419 - ZX_9) \times BF_5,\]
\[BF_{18} = \max(0, ZX_4 + 0.539429), BF_{19} = \max(0, -0.539429 - ZX_4),\]
\[BF_{20} = \max(0, ZX_1 + 0.03686) \times BF_{18}, BF_{21} = \max(0, -0.03686 - ZX_7) \times BF_{18},\]
\[BF_{23} = \max(0, 0.00555283 - ZX_9) \times BF_3, BF_{24} = \max(0, ZX_4 - 0.712028) \times BF_5,\]
\[BF_{25} = \max(0, 0.712028 - ZX_4) \times BF_6, BF_{26} = \max(0, ZX_2 + 1.42696) \times BF_5,\]
\[BF_{27} = \max(0, -1.42696 - ZX_3) \times BF_3, BF_{28} = \max(0, 0.712028 + 1.54936) \times BF_3.\]

From the best model which just have obtained, predictor variables that have effect Indonesia Composite Index (ICI) using the minimum GCV are $X_1, X_3, X_5, X_9, X_6$ and $X_7$. Based on the data, after forecasting ICI value, MAPE value of 4.53172 is less than 10, and also the coefficient of determination of 0.99427 approaches 1. It means that the model that has been obtained
having good performance to forecast composite stock price index in the future. Furthermore, the forecasting value of the Indonesia composite stock price index in the future is almost approaching the real value.

4. Conclusion

The both methods of ANN and nonparametric MARS regression can be used to forecast Indonesian composite index with better accuracy and goodness of fit respectively based on the MAPE value less than 10, and also the coefficient of determination approach 1, even though the nonparametric MARS regression method shows the accuracy of the model is slightly better than ANN. In order that the time series modeling by using ANN and nonparametric MARS regression methods can be an alternative to forecasting Indonesian composite index in the future.

References

[1] J. O. Rawlings, S. G. Pantula, and D. A. Dickey, *Applied Regression Analysis*. USA: Springer, 2001.
[2] F. K. Reilly and K. C. Brown, *Investment Analysis and Portofolio Management*. USA: Cangenga Learning Product, 2019.
[3] F. Liu and J. Wang, “Fluctuation prediction of stock market index by Legendre neural network with random time strength function,” *Neurocomputing*, pp. 12–21, 2012.
[4] D. Devianto, Maiyastri, and D. R. Fadhilla, “Time series modeling for risk of stock price with value at risk computation,” *Appl. Math. Sci.*, vol. 9(56), pp. 2779–2787, 2015.
[5] J. Patel, S. Shah, P. Thakkar, and K. Kotecha, “Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques,” *Expert Syst. Appl.*, pp. 259–268, 2015.
[6] M. Yollanda, D. Devianto, and H. Yozza, “Nonlinear Modeling of IHSG with Artificial Intelligence,” *IEEE Explor. ICAITI 2018*, pp. 85–90, 2019.
[7] J. H. Friedman, “Multivariate Adaptive Regression Spline (With Discussion),” *Ann. Stat.*, vol. 19, pp. 1–141, 1991.
[8] E. Guresen, G. Kayakutlu, and T. U. Daim, “Using artificial neural network models in stock market index prediction,” *Expert Syst. Appl.*, pp. 10389–10397, 2011.
[9] K. Wong, T. A. Bodnovich, and Y. Selvi, “A bibliography of neural network business applications research: 1988–September 1994,” *Expert Syst. Appl.*, pp. 253–262, 1995.
[10] S. Russel and P. Norvig, *Artificial Intelligence: A Modern Approach*. New Jersey: Pearson Education, 2019.
[11] J. Heaton, *Introduction to Neural Networks for C*. America: Heaton Research, Inc, 2018.
[12] J. L. McClelland and D. E. Rumelhart, *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*. Cambridge: MIT Press, 2016.
[13] J. A. Freeman and D. M. Skapura, *Neural Network: Algorithms, Applications, and Programming Techniques*. America: Company, Addison-Wisley Publishing, 2014.
[14] N. D. Lewis, *Build Your Own Neural Network Today!: With Step by Step Instructions Showing You How to Build Them Faster than You Imagined Possible Using R*. Create Space Independent Publishing Platform, 2015.
[15] J. D. Andres, F. Sanchez-Lasheras, P. Lorca, and F. J. De Cos Juez, “A hybrid device of self organizing maps (SOM) and multivariate adaptive regression splines (MARS) for the forecasting of firms “bankruptcy,” *Account. Manag. Inf. Syst.*, vol. 10(3), pp. 351–374, 2011.
[16] S. Makridakis, S. C. Wheelwright, and V. E. McGEE, *Forecasting: Methods and Applications*. New York: Wiley, 1997.