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# Multilayer Perceptron and Long Short-Term Memory for Predicting Indonesian Composite Stock Price Index Using Macroeconomic Factors

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***Abstract*—Capital markets are complex and dynamic, so they have risks and uncertainties. The main activity in the capital market is investment. There are several instruments for investing, namely gold, land, savings, deposits, bonds and stocks. Investors need a variety of information to help determine the right momentum to invest, one of which is the stock price in the future. By making predictions, investors can minimize the risk of loss in investing. The purpose of this study is to compare the Multilayer Perceptron and Long Short-Term Memory algorithm in predicting Indonesian Composite Stock Price Index in the future based on macroeconomic factors. This study uses Dow Jones Industrial Average, Shanghai Stock Exchange, world gold prices, world oil prices, USD to IDR exchange rate, inflation, BI Rate, and money supply as macroeconomic factors to predict the price of the Indonesian Composite Stock Price Index. The time series used for the research data is monthly, from January 1991 to December 2018. Based on the results of the evaluations that have been conducted, this study found that modeling using the Multilayer Perceptron algorithm has a better performance than Long Short-Term Memory. Evaluation using Root Mean Squared Error and R-squared each produces a value 86.86% and 3.19% for Multilayer Perceptron; 74.24% and 3.94% for Long Short-Term Memory.**

***Keywords—Stock Price Prediction, Multilayer Perceptron, Long Short-Term Memory, Indonesian Composite Stock Price Index, Macroeconomic Factor***

## I. INTRODUCTION

The capital market is one of the most important parts of the economy. At present, the capital market has a major influence on the economic situation. The main activity in the capital market is investment. There are several instruments for investing, namely gold, land, savings, deposits, bonds and stocks. Stocks provide the greatest growth when compared to other investment instruments [1]. Based on the Stock Price Index value, the condition of companies listed on the stock exchange can be known. The Stock Price Index also reflects the economic conditions of a country. The sharp decline of the Stock Price Index indicates a country is experiencing an economic crisis [2].

Capital markets are complex and dynamic markets, so they have high risks and uncertainties. Many factors influence stock price movements, such as economic policy, political events, investor sentiment, and macroeconomic conditions. In predicting stock price movements in the future, the right factors are needed as a foundation. One of the factors that influence the movement of the Stock Price Index is macroeconomic conditions. In the study [3] stated that macroeconomic information is very important in the stock market prediction.

Investors need a variety of information to serve as a basis for making decisions in determining the right momentum to invest so that investors can get optimal profits. One of the information that is often used as the basis of investment is the stock price index in the future. The Stock Price Index can reflect the performance of the stock prices of all companies listed on the Stock Exchange of each country, so to make investors easier in investing, predicting the future Stock Price Index is needed.

Capital market data is complicated and non-linear, so the best method is needed to predict future Stock Price Indexes. The Stock Price Index prediction involves an analysis of the time series because it has time-series type data. One method that can be used to predict future Stock Price Indexes is Deep Learning. The Deep Learning method can identify hidden patterns and data dynamics through an independent learning process [4].

Macroeconomics was successfully used as a feature in predicting the Indonesian Composite Stock Price Index by implementing an Artificial Neural Network (ANN) [5]. Multilayer Perceptron (MLP) provides better predictive results when compared to Long Short-Term Memory (LSTM) in predicting stock prices with technical financial indicators as features [6], as well in [7] MLP provides better prediction results when compared to Simple Recurrent Neural Network (SRNN), Gated Recurrent Unit (GRU), and LSTM in predicting stock prices with historical stock prices as features.

In other research [8], LSTM gets better results than MLP to predict the daily closing price of Facebook, Google, and Bitcoin based on the calculation of the Mean Squared Error value. [9] in predicting stock prices with historical prices as features, LSTM with multivariate inputs provides better predictive results, when compared to univariate inputs. LSTM provides good prediction results with strong adaptability to data with different stability in predicting stock prices with historical prices as features [10]

In this study, we propose a stock price prediction model in the future using data from macroeconomic factors. The object used is the Indonesian Composite Stock Price Index, while the macroeconomic factors used are the Dow Jones Industrial Average (DJIA) [11-13], Shanghai Stock Exchange (SSEC) [12-13], world gold prices [13], world oil prices [13], USD to IDR exchange rate [11] [13-15], Inflation [14], BI Rate [14-15], and Money Supply [16-17]. Deep learning algorithms used are Multilayer Perceptron (MLP) and Long Short Term Memory (LSTM).

## II. Literature Review

Macroeconomics (exchange rate, interest rate, inflation rate, and money supply M2) are successfully used as a feature in predicting the Indonesia Composite Stock Price Index by applying ANN. The time series of data used is monthly. Based on evaluations using the Regression value (R-value) and Mean Squared Error (MSE) each obtained an accuracy of 96.38% and an error of 0.0046 [5].

MLP, SRNN, GRU and LSTM algorithms were used to predict the daily stock prices of companies listed on the Colombo Stock Exchange (CSE). The results of this study, if referring to Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE), modeling with MLP produces the lowest error rate when compared with other algorithms, therefore the MLP model produces the best results [7]. MLP and LSTM algorithms were used to predict short-term stock prices (per minute) listed on the New York Stock Exchange. The results of this study indicate that the LSTM model is successful in predicting the future price trend, upward or downward, at almost all the points. However, the model fails to predict the exact price with the required accuracy. While the MLP model can capture the future trends, upward or downward, while also predicting the prices with an extremely high level of accuracy as compared to the LSTM model [6].

LSTM is used to predict three stocks with similar trend and different stability in terms of P values. This research shows that LSTM has strong adaptability to data with different stability. Based on the evaluation results using Root Mean Squared Error (RMSE), LSTM obtained a small error that is equal to 0.0374 [10]. In the case of [9], predicting Apple stock with two input conditions, namely multivariate and univariate. Based on evaluations using Mean Absolute Error (MAE), LSTM with multivariate feature input produces a smaller error that is equal to 0.033, compared to univariate features with an error of 0.155.

In [18] LSTM algorithm was used to predict the daily stock price of S & P500. Referring to the evaluation of errors using Mean Absolute Percentage Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Average Mean Absolute Percentage Error (AMAPE), LSTM produced a relatively small error. While in [8], the MLP and LSTM algorithm were used to predict the daily closing prices of Facebook, Google, and Bitcoin. Based on the calculation of the Mean Squared Error value obtained by the two algorithms, LSTM gets better results than MLP.

## III. Theoretical Framework

### A. Multilayer Perceptron (MLP)

Multilayer Perceptron (MLP) is a class of Feedforward Artificial Neural Network (ANN). In MLP, the output of each layer is used as input for the next layer [19]. MLP consists of at least one hidden layer other than the input layer and the output layer. Each node of a layer other than the input layer is called a neuron that uses a nonlinear activation function. MLP uses supervised learning techniques called backpropagation for training while minimizing the loss function. It uses the optimizer to set parameters (weight and bias). A multilayer perceptron is the basic form of the deep neural network [20].

### B. Long Short-Term Memory (LSTM)

LSTM is a special kind of RNN, capable of learning long-term dependency. LSTM is designed to avoid long-term dependency problems by having a design by which it is natural to remember information for a long period of time. The LSTM does have the ability to remove or add information to the cell state, carefully regulated by structures called gates. An LSTM has three of these gates, to protect and control the cell state [21]. Figure 1 shows the repeating module in LSTM.

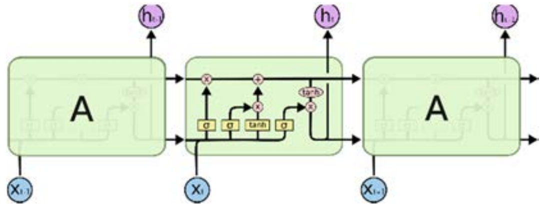


Fig. 1. Repeating Module in LSTM [21].

The first step in LSTM is to decide what information will be removed from the cell state. This decision is made by a sigmoid layer called the forget gate layer. The equation used for the first step is as follows [21]:

$$f_i=\sigma\left(W_f.[h_{t-1},X_t]+b_f\right) \quad (1)$$

The next step is to decide what new information will be stored in the cell state. At this stage, it has two parts. First, the sigmoid layer called the "input gate layer" decides which values will be updated. Next, the tanh layer creates a new candidate values vector, which can be added to the state. Then the two parts are combined to make an update to the state. The equation used for this step is as follows [21]:

$$i_t=\sigma(W_i.[h_{t-1},x_t+b_i]) \quad (2)$$

$$\hat{C}_t = \tanh(W_c.[h_{t-1},x_t]+b_c) \quad (3)$$

$$C_t=f_t * C_{t-1}+i_t * \hat{C}_t \quad (4)$$

The last step, the sigmoid layer determines which parts of the cell state going to output. Then, the cell state placed through tanh (to push the values to be between −1 and 1) and multiply it by the output of the sigmoid gate, so only the decided parts that becomes the output. The equation used for the last step is as follows [21]:

$$O_t=\sigma(W_o[h_{t-1},x_t]+b_o) \quad (5)$$

$$h_t=O_t * \tanh(C_t) \quad (6)$$

## IV. Methodology

### A. Collection of Data

This research using past data from the Indonesian Composite Stock Price Index and macroeconomic factors. The macroeconomic factors used consist of the Dow Jones Industrial Average (DJIA), the Shanghai Stock Exchange (SSEC), world gold prices, world oil prices, USD to IDR exchange rate, Inflation, BI Rate, and Money Supply.

Indonesian Composite Stock Price Index, DJIA, SSE, world gold prices, world oil prices, and USD to IDR exchange rate data were obtained from investing.com. Inflation data is obtained from inflation.ue. BI Rates data are obtained from bi.go.id. Money Supply data obtained from

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kemendag.go.id. The time series of data used is monthly, from January 1991 to December 2018 with a total of 336 rows of data for each variable.

Figure 2 shows a sample of the data set that has been collected. The data set has a range of different data values. This data will be used in the selection of the data variables stage.

| Date | IHSG | DJIA | SSEC | GOLD | OIL | IDRUSD | MS | BIRATE | INFLATION |
|---|---|---|---|---|---|---|---|---|---|
| Jan, 1991 | 383.02 | 2882.18 | 129.97 | 365.8 | 18.90 | 1912.0 | 83649.0 | 0.1925 | 0.0971 |
| Feb, 1991 | 391.33 | 2913.86 | 133.01 | 367.4 | 18.68 | 1920.0 | 84364.0 | 0.1925 | 0.0901 |
| Mar, 1991 | 408.11 | 2887.87 | 120.19 | 357.1 | 19.44 | 1932.0 | 81738.0 | 0.2355 | 0.0952 |
| Apr, 1991 | 413.71 | 3027.50 | 113.94 | 355.9 | 20.85 | 1939.0 | 85114.0 | 0.2050 | 0.1029 |
| May, 1991 | 397.60 | 2906.75 | 114.83 | 361.4 | 22.11 | 1947.0 | 86478.0 | 0.1901 | 0.0961 |

Fig. 2. Data Set

## B. *Selection of Data Variables*

Indonesian Composite Stock Price Index data is used as the dependent variable, while macroeconomic factor data is used as an independent variable. With the Pearson method, the results of the correlation show that all independent variables correlate with the dependent variable. The value of the Pearson correlation coefficient is always in interval [−1, +1]. Its value indicates the strength of the linear relationship between the features: values close to -1 indicate a strong negative relationship, while values close to +1 indicate a strong positive relationship [22].

Figure 3 shows the results of the correlation. DJIA, SSEC, world gold prices (GOLD), world oil prices (OIL), USD to IDR exchange rate (IDRUSD), Money Supply (MS), BI Rate (BIRATE), and Inflation (INFLATION), each has a correlation value with the Indonesian Composite Stock Price Index (IHSG) of 0.88, 0.71, 0.91, 0.66, 0.7, 0.97, -0.48, and -0.31. So that all macroeconomic factors can be used in this research.

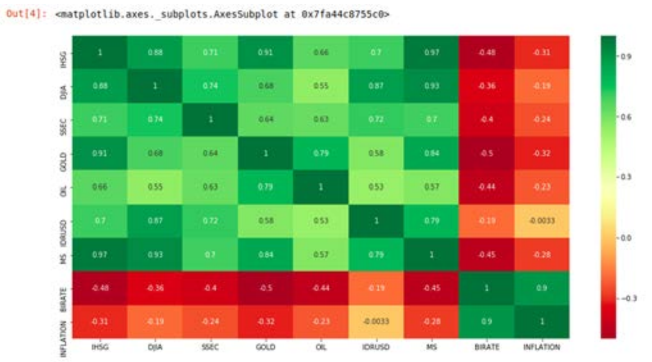


Fig. 3. Result of Data Correlations

## C. *Modeling of Data*

The data was split into three parts, namely train, validation, and test, each with 80%, 10%, and 10% percentages. Based on the percentage of data splitting, data train, validation, and test, each has data of 269, 34, and 33. Splitting of data sets is done sequentially from the first index to the last index. Data train and validation are used in the training stage, while the test data is used at the testing stage. Figure 4 shows the results of data splitting.


Fig. 4. Result of Data Splitting

Then, all variables in the data train, validation, and test are normalized using MinMaxScaler in the range [0,1]. The purpose of this normalization is to make the value of each variable in the data have the same range of values so that the data becomes uniform and no variable dominates other data variables. Other than that, normalization is done because Neural Network is sensitive to unnormalized data [6]. The equation used for the MinMaxScaler is as follows [6]:

$$x_{std} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (7)$$

$$x_{scaled} = x_{std} * (max - min) + min \quad (8)$$

The normalized data is then modeled according to the MLP and LSTM algorithms. The two algorithms have different types of input, where MLP has a two-dimensional input type, while LSTM has a three-dimensional input type because it takes time steps.

The data model used for prediction with the MLP algorithm is that the independent variable data at month "t" is used to predict the value of the dependent variable month "t+1". Figure 5 shows the data model for the MLP algorithm.

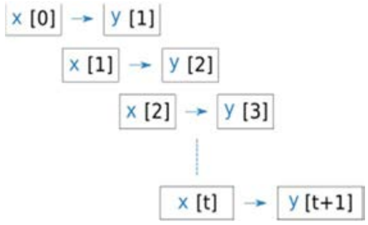


Fig. 5. Data model of MLP algorithm

While the data model used for prediction with LSTM uses the sliding windows method with three time steps, where the independent variable data at month "t-3", "t-2", and "t" are used to predict the value of the dependent variable month "t+1". Figure 6 shows the data model of the LSTM algorithm.

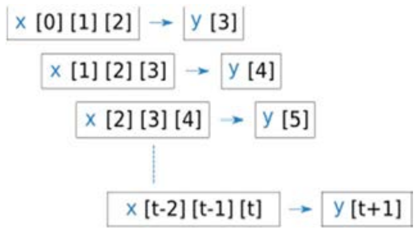


Fig. 6. Data Model of LSTM algorithm

## D. *Modeling of Neural Networks*

The modeling for Neural Network using two algorithms, namely Multilayer Perceptron (MLP) and Long Short Term Memory (LSTM). Both algorithms have the same layer architecture, which consists of three layers, namely one input layer, two hidden layers, and one output layer. While the parameters of each algorithm have different settings so that each algorithm can achieve the best performance. The tuned parameters consisted of the number of neurons and the type of activation function. The parameters used in the Neural Network model for each algorithm are shown in Table I. Figure 7 shows the MLP model, while Figure 8 shows the LSTM model.

TABLE I. ALGORITHM MODELING PARAMETERS

| **Model** | | **Parameter** | | |
|---|---|---|---|---|
| **Algorithm** | **Layers** | **Number of Neurons** | **Activation Function** | **Recurrent Activation Function** |
| **MLP** | **Hidden 1** | 7 | Tanh | - |
| | **Hidden 2** | 3 | Tanh | - |
| | **Output** | 1 | Relu | - |
| **LSTM** | **Hidden 1** | 8 | Tanh | hard sigmoid |
| | **Hidden 2** | 4 | Tanh | hard sigmoid |
| | **Output** | 1 | Relu | - |

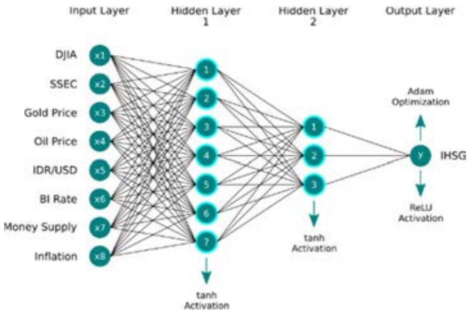

Fig. 7. MLP Model

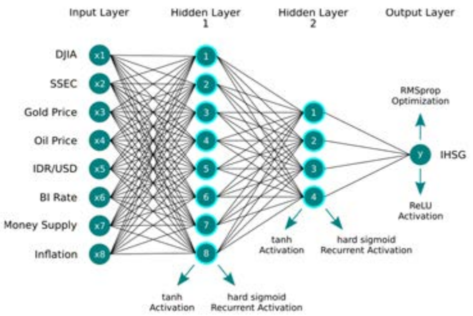

Fig. 8. LSTM Model

## E. *Training of Neural Networks*

MLP and LSTM model training using data train and validation. Training is carried out in several literacies until it reaches the smallest validation loss. The training process will be stopped if the value of validation loss does not indicate an improvement or is more likely to rise. The parameters used in the training process of each algorithm are shown in Table II.

TABLE II. TRAINING ALGORITHM PARAMETERS

| **Parameter** | **Model** | |
|---|---|---|
| | **MLP** | **LSTM** |
| **Iteration** | 200 | 200 |
| **Patience** | 20 | 20 |
| **Batch Size** | 7 | 7 |
| **Loss Function** | MSE | MSE |
| **Optimizer** | Adam | RMSprop |

## F. *Performance Evaluation of Neural Networks*

After the training process is complete, the best model for each algorithm is used to predict the test data. The predictive results of each algorithm will be evaluated using the Root Mean Squared Error (RMSE) and R-squared (R ^ 2). RMSE is defined as the sum of the squares of the difference between the real values and the predicted values. The closer the predictions are to the real values, the lower the RMSE is. A lower RMSE means a better, more accurate prediction [23]. R-squared measures how well a model can predict the data, and falls between zero and one. The higher the value of the coefficient of determination, the better the model is at predicting the data [24]. The equation used for the RMSE and R-squared is as follows [23-24]:

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y-y)^2} \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i-\hat{y})^2}{\sum_{i=1}^{N}(y_i-y_{\text{mean}})^2} \quad (10)$$

# V. RESULT AND ANALYSIS

In this section, performance in the training and testing stages of the two modelings using MLP and LSTM algorithms will be analyzed and evaluated.

## A. *Training Evaluation*

In Figure 6 and 7, the training process of MLP and LSTM algorithm models is carried out in 200 literacy, but the MLP training process stops at 109th literacy, while LSTM on 93th literacy is because the value of validation loss does not show any improvement or more likely to rise at the last 20 iterations. In the 89th literacy, the MLP model achieves the smallest validation loss value with MSE of 0.00373, while the LSTM in 73th literacy with MSE of 0.00448. So that the model at that point is used as the best model of MLP and LSTM to make predictions on the test data.

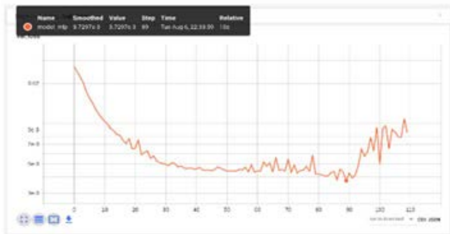

Fig. 6. Validation Loss of MLP Training Process

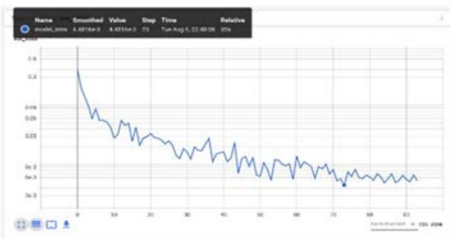

Fig. 7. Validation Loss of LSTM Training Process

## B. *Testing Evaluation*

Figure 8 shows the results of predictions from the MLP and LSTM algorithm models using the best results from the training process. Based on the results of these predictions, the MLP and LSTM models succeed in predicting the Indonesian Composite Stock Price Index movement trend in the future but did not accurately predict the actual price. Both models are unable to predict prices that have changed drastically, as happened at points 311, 325, 330 and 334.

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Overall, both models are able to predict actual prices closely. Compared to the LSTM model, the prediction results of the MLP model are closer to the actual price.

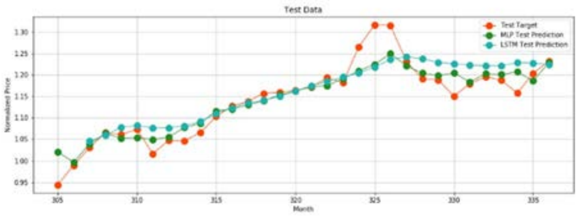


Fig. 8. Predictions Result of MLP and LSTM Model

### C. RMSE and R-squared Evaluation

Figure 9 shows the percentage of RMSE values for each algorithm model obtained at the testing stage. The MLP model gets 3.19% while LSTM gets 3.94%. So based on the RMSE evaluation, the MLP model has a better performance than LSTM.

Figure 10 shows the percentage value of R-squared. The MLP model gets 86.86% while LSTM gets 74.24%. So based on the evaluation of R-squared, MLP model has a better performance than LSTM.

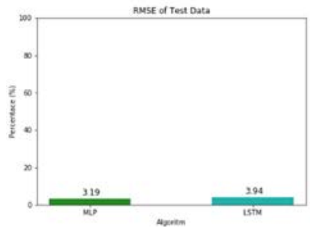


Fig. 9. RMSE Percentage of MLP and LSTM Model

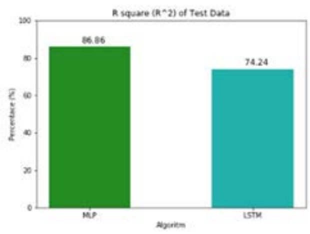


Fig. 10. R-squared Percentage of MLP and LSTM Model

## VI. Conclusions

Based on the research that has been done, where aims to compare the performance of Multilayer Perceptron (MLP) and Long Short-Term algorithms (LSTM) to predict Indonesian Composite Stock Price Index in the future with macroeconomic factors. The results of this study found that modeling using the MLP algorithm has a better performance than LSTM based on the evaluation that has been done. Evaluation using RMSE and R-squared produces values 86.86 % and 3.19 % for MLP; 74.24 % and 3.94 % for LSTM. In general, the two algorithmic models are able to predict the trend of the movement of the Composite Stock Price Index in the future, but are unable to accurately predict the actual price.

This study use monthly time series data, macroeconomic factors as a feature to predict Indonesian Composite Stock Price Index, and feature selection using Pearson statistical method. For future research, the time series can be narrowed down to daily or even minutes, using other features such as market sentiment to predict market prices, and other statistical methods as feature selection.

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## OF APPRECIATION

Awarded to :

**Muhammad Nizar Yoga Pratama and Ernastuti**

**Titled: Multilayer Perceptron and Long Short-Term Memory for Predicting Indonesian Composite Stock Price Index Using Macroeconomic Factors**

for his/her participation as a **Authors** in
The Fourth International Conference on Informatics and Computing (ICIC 2019)
at Dian Nuswantoro University (UDINUS), Semarang Indonesia
on 23-24 October 2019

**Prof. Zainal A. Hasibuan, PhD**
Ketua APTIKOM

**Assoc. Prof. Dr. Media A. Ayu, SMIEEE**
General Chair

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IEEE INDONESIA SECTION
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