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THE UTILIZATION OF DEEP LEARNING IN FORECASTING THE INFLATION RATE OF EDUCATION COSTS IN MALANG

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ABSTRACT

The public needs information about the predicted inflation rate for education costs to manage family finances and prepare education funds. This information is also beneficial for the government to create policies in education. Malang is one of the educational cities in Indonesia, but research on the prediction of the inflation rate of education costs in the city still needs to be made available. Besides, the researchers have yet to find previous studies on forecasting that used the specific inflation rate for education costs in Indonesia by applying the Deep Learning method, especially those using the Consumer Price Index (CPI) data for the Education Expenditure Group. This research aims to develop a model to forecast the inflation of education costs in Malang using the Deep Learning Method. This research was conducted using Consumer Price Index (CPI) data for the Education Expenditure Group in Malang during 1996-2021s taken from the Central Bureau of Statistics (BPS) Malang. The forecasting method used is the Long and Short-Term Memory (LSTM) method, which is a development of the Recurrent Neural Network (RNN). The results showed that it achieved the best accuracy by a model with one hidden layer and four hidden nodes, namely MAPE=2.8765% and RMSE=8.37.

Keywords*: deep learning, education cost, inflation, long short-term memory.*

I. INTRODUCTION

SETTING up an education fund is vital in planning and managing family finances. Education costs are high and tend to increase occasionally, forcing people to prepare education funds as early as possible. A good education is needed to improve human resources in Indonesia; thus, people can compete globally. Decision-related to children's education in Indonesia is often mainly due to the high cost of education [1]. The increase in education costs is a factor influencing the decisions of economic actors in carrying out their economic activities.

Information about the inflation rate of future education costs is needed to make family financial planning more effective. Considering that inflation is one of the main reasons behind economic decisions, inflation in education costs is included in the determinants of economic activity in household groups [2]. As it greatly influences the number of education costs in the future, information on the inflation rate of education costs significantly contributes to people's decisions when choosing a school for their children or setting up education funds. The cost of education itself is the cost incurred by the community to pursue education, both direct and indirect.

In the research conducted by Hapsari and Tyas, the demand for education in Malang, especially in tertiary institutions, has increased effectively within seven years, between 2005-2012 [3]. The level of need for higher education is considered equivalent to other economic goods, considering that education is also an economic good in the service sector. As the characteristics of other economic interests, the price of educational services is determined by the amount of demand and the increase in the cost. According to the Central Bureau of Statistics data for the City of Malang, the Cumulative Inflation Rates

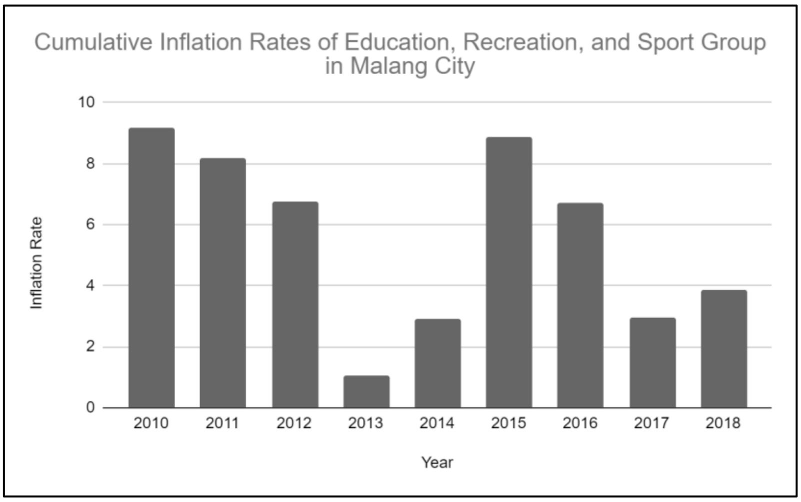

Figure 1. Cumulative Inflation Rates of Education, Recreation, And Sports Group In Malang City [4]

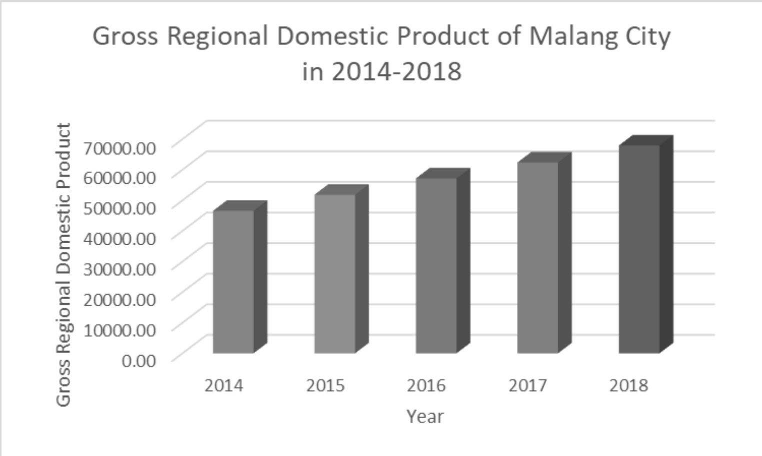

Figure 2. Gross Regional Domestic Product of Malang City in 2014-2018 [4]

of the Education, Recreation, and Sports Groups in Malang City in 2010-2018 are shown in Figure 1.

The inflation rates of Recreation and Sports Group tend to be stable. Thus, the Cumulative Inflation Rates of the Education, Recreation, and Sports Group can show the condition of education cost inflation well. From Figure 1, we can see that the Cumulative Inflation Rates of Education, Recreation, and Sports Groups in Malang City from 2010-2018 are above 0, which means that during that period, the education cost in Malang City increases yearly.

People's income per capita in Indonesia, as recorded by GRDP (Gross Regional Domestic Product), has consistently increased from year to year. Along with this, there is a consistent increase in tuition fees or inflation. The response given to the demand for higher education services to the increase in people's income in general and the cost of higher education services is shown through the coefficient of income and price elasticity of demand for higher education.

Malang City recorded an increase in GRDP from 2014 to 2018, as shown in Figure 2. The diagram presents an increase in income in Malang, whose trend has been increasing from year to year. It is assumed that people's purchasing power also increases along with the increase in GRDP. The implication is that the demand for educational services has also increased. However, each household/economic actor still has their budget constraint (expenditure limit) depending on their income.

Malang is one of the educational cities in Indonesia. Data from the Central Bureau of Statistics for the City of Malang show that currently, there are thousands of educational institutions, from preschool to higher education levels, in Malang [4]. This becomes a magnet for people to study in the city. Government policies to control inflation in Malang to provide affordable educational facilities will determine the development of the education sector. Education has a significant contribution to economic growth, where existing human capital or Human Resources (HR) will drive the Gross Domestic Product (GDP) level in a country [5] [6]. Therefore, education is also a critical Human Resources (HR) investment for the country.

Studies on the cost of education in Indonesia have been carried out in scientific fields, such as education, management, and information technology. However, research on predicting the inflation rate of education costs in Malang is still rare. This is the research gap we want to solve. Prediction or forecasting of the inflation rate of education costs is very important as it will affect the decision of the community as economic actors to select certain educational facilities. In addition, forecasting the inflation rate of education costs can also help the government make policies in the field of education.

There are many forecasting methods in economics, including naïve techniques, smoothing, decomposition, trend, Box-Jenkins, and ARCH-GARCH. Information technology has also supported the development of various other forecasting methods, for example, those based on Machine Learning and Deep Learning. In previous research, Machine Learning has been widely used in prediction systems. The accuracy obtained by Machine Learning is higher than the classical method. According to a study conducted by Baja et al., the Machine Learning method produces high accuracy, 93.53%, for forecasting sales [7]. Research conducted by Ensafi et al. shows that the Machine Learning method based on Artificial Neural Network (ANN), that is, Stacked Long Short-Term Memory (LSTM), produces a higher level of forecasting accuracy than the classical methods with the value of MAPE 17.34% [8].

Machine Learning technology based on Artificial Neural Networks (ANN) is also widely used to develop inflation rate prediction systems. In the research conducted by Yang and Guo, the Deep Learning method has a better level of accuracy than classical methods in predicting inflation rates [9]. The RMSE value obtained by the deep learning model in this research is 0,359. In addition, in a study conducted by Alfiyatin et al., the Deep Learning method also produces very good accuracy in predicting the inflation rate in Indonesia [10]. However, the authors have yet to find previous studies on forecasting that used the specific inflation rate in Indonesia data using the Deep Learning method, especially for education costs, by using the data of the Consumer Price Index (CPI) for the Education Expenditure Group.

Based on these considerations, this research aims to create a model to forecast the inflation rate in education costs in Malang using the Deep Learning Long Short-Term Memory (LSTM) Method. The data used in this research are the Consumer Price Index (CPI) for the Education Expenditure Group in Malang from 1996-2021. This research is expected to help the community carry out family financial planning regarding education costs. In addition, the results of this study can also be used as a consideration for policymakers in formulating wiser regulations on education costs in Malang.

II. Research Method

A. Time Series Data

Time Series data are historical data usually consisting of a series of observations over time. Fluctuations in time series data are generally only affected by time and slightly or not influenced by other factors. Examples of data with a time series pattern are world gold prices, inflation rates, and the spread of endemic cases.

From those data, the pattern can be analyzed to see its tendency to continue in the future [11]. Forecasting on time series data is a type of quantitative forecasting involving statistical analysis called a one-variety time series model. One-variety time series models focus on observing the sequence of data patterns chronologically for a particular variable, for example, naïve techniques, smoothing, decomposition, trends, and the Box-Jenkins Methodology (ARIMA-SARIMA), and ARCH-GARCH [12].

B. Long Short-Term Memory

Long Short-Term Memory (LSTM) is one of the Deep Learning methods. LSTM is an improvement of the Recurrent Neural Network (RNN) with adding memory cells. The general architecture of the LSTM consists of input layers, output layers, and hidden layers with memory cells, input gates, output gates, and forget gates [13]. A memory cell in an LSTM can store values for a longer time duration than an RNN.

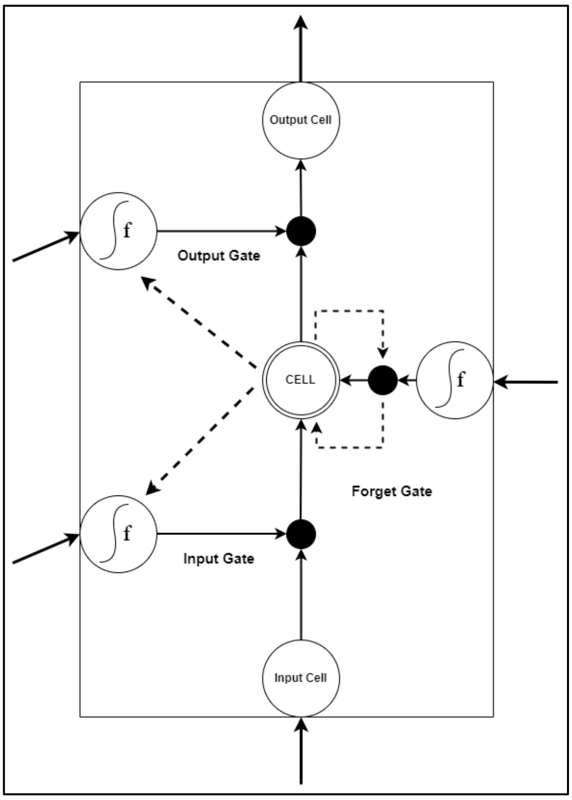

Figure 3. Architecture Of A LSTM's Memory Cell [16]

LSTM is the most suitable type of RNN method for use on time series data because this method is suitable for application to data that has a long-term trend pattern [14]. In recent years, many researchers have used deep learning, such as RNN, instead of classical methods, such as Autoregressive Integrated Moving Average (ARIMA) for time series prediction, due to the disadvantage of ARIMA in capturing a rapidly changing process in time series data [15]. The limitation of RNN is that the influence of the given input on the hidden layer leads to the network output either decaying or blowing up exponentially as it cycles around the recurrent connections [16]. To solve this problem, LSTM improves the RNN's hidden layer by adding memory cells.

Figure 3 shows the architecture of an LSTM's memory cell whose three gates are named Forget Gate (f_t), Input Gate (I_t), and Output Gate (O_t). A forget gate controls the extent to which fixed values are stored. A forget gate is a sigmoid layer that takes the output value at t-1 and the input value at t then combines them and implements them as the inputs of the logistic sigmoid activation function [13]. The output of a sigmoid function is 0 or 1. When f_t = 1, the previous state will not be changed, and the data will be saved; when ft = 0, the last state will be forgotten. The formula of f_t is described as (1) [17] where Wf is the weight of forget gate, $S_{(t-1)}$ is the previous S or S of t-1, X_t is actual data in time t, and σ is the tanh function.

$$f_t = \sigma(W_f S_{t-1} + W_f X_t) \tag{1}$$

Input gates (I_t) function to control the amount of memory that must be stored. An input gate uses a tanh function (σ) as the activation function. The formula of I_t is described in (2) [17] where W_i is weight of the input gate.

$$I_t = \sigma(W_i S_{t-1} + W_i X_t) \tag{2}$$

The value of the input gate is multiplied by the output of the candidate layer ($\hat{C}$) [18]. The formula of $\hat{C}$ is described as (3) and (4) where $\hat{C}$ is the intermediate cell state and W_c is the weight of the cell state.

$$\hat{C} = \sigma(W_c S_{t-1} + W_c X_t) \tag{3}$$

TABLE 1
DESCRIPTION OF EVERY RANGE OF MAPE

MAPE	Description
<10%	Excellent significance
10%-20%	Good significance
20%-50%	Moderate significance
>50%	Low significance

$$c_t = i_t \hat{C}_t + f_t c_{t-1} \tag{4}$$

The output gates (O_t) function controls the extent to which the value in the cell is used to calculate the output activation value. This gate uses a logistic sigmoid activation function. The formula of O_t is described in (5) [18], where W_o is the weight of the output gate.

$$O_t = \sigma(W_o S_{t-1} + W_o X_t) \tag{5}$$

C. Forecasting Models Accuracy Measurements

The accuracy of forecasting results can be measured with standard and relative statistical measures. This subsection will explain theories and equations about statistical measures used to measure the accuracy of the models simulated in this research. In general, those measures are carried out based on the error values (e_t), calculated using (6) where X_t is actual data, and Y_t is forecasting results.

$$e_t = X_t - Y_t \tag{6}$$

In addition, testing is also carried out based on the relative error values of forecasting (re_t). Relative error values are calculated using (7).

$$re_t = \frac{X_t - Y_t}{X_t} \times 100 \tag{7}$$

A standard statistical measure commonly used to measure forecasting model accuracy for n amount of data is the Root Mean Squared Error (RMSE). The smaller the RMSE value, the better the accuracy of the model created. The RMSE is calculated by (8).

$$MSE = \sqrt{\frac{\sum_{t=1}^{n} e_t^2}{n}} \tag{8}$$

One method of measuring the accuracy of the forecasting model which is included in the relative statistical measure is the Mean Absolute Percentage Error (MAPE), according to (9) [5].

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} |re_t| \tag{9}$$

The smaller the MAPE value, the better the accuracy of the forecasting model. The quality of forecasting for each range of MAPE values can be seen in Table 1 [19]. Table 1 describes the significance of each range of MAPE values. The table above shows that models are considered to have excellent significance if the MAPE values are below 10%. The models are considered to have good significance if the MAPE values are between 10%-20%. Thus, the MAPE value expected to gain in this research is below 20%. Based on other studies about deep learning forecasting, it is common to use RMSE and MAPE to assess deep learning models [17] [8].

TABLE 2
DATA ON THE CONSUMER PRICE INDEX (CPI) FOR THE EDUCATION EXPENDITURE GROUP IN MALANG DURING 1996-2021

No.	Year	Month	CPI of Education Group
1	1996	January	125.66
2	1996	February	125.66
3	1996	March	125.66
4	1996	April	125.66
5	1996	May	125.66
6	1996	June	125.66
7	1996	July	132.48
8	1996	August	132.48
9	1996	September	132.48
10	1996	October	132.48
11	1996	November	132.48
12	1996	December	132.48
13	1997	January	132.48
14	1997	February	132.48
15	1997	March	132.48
…	…	…	…
312	2021	December	105.97

TABLE 3
CONFIGURATION OF THE SIMULATED DEEP LEARNING MODELS

Configuration	Model 1	Model 2	Model 3	Model 4
Input	1	1	1	1
Input node	5	5	5	5
Hidden layer	1	5	10	15
Hidden node	10	10	10	10
Output node	1	1	1	1
Activation Function	Tanh	Tanh	Tanh	Tanh
Normalization Method	Min-Max	Min-Max	Min-Max	Min-Max
Training Data	209	209	209	209
Testing Data	103	103	103	103

D. Data and Research Method

This study aims to apply deep learning technology in a forecasting system for Indonesia's inflation rate of education costs. Different from previous studies, this research uses data on monthly Consumer Price Index (CPI) values for the education expenditure group in Indonesia, especially in Malang. Data were taken from the Malang City in Figures reports which are published by the official website of the Central Bureau of Statistics for East Java Province. The Malang City in Figures can be downloaded via the link https://jatimprov.bps.ac.id. The data were taken from January 1996 to December 2021. An overview of CPI value data in Malang can be seen in Table 2.

Table 2 shows the CPI of the Education Group in Malang during 1996-2021, which is used in this research. The Consumer Satisfaction Index (CPI) is one of the components used to calculate the inflation rate. The Consumer Price Index (CPI) value itself describes price increases in expenditure groups, for example, food and beverages, health, sports, recreation, and education. For this reason, the CPI value can be utilized in the analysis of fluctuations in the inflation rate in the education expenditure group.

The deep learning method applied in this study is Long Short-Term Memory (LSTM) with time series data. The input layer in the created model consists of 1 node, and the output layer consists of 1 node. There arefour4 simulated models, each with a different number of hidden layers. To determine the number of hidden layers and nodes, we try and error each number in simulation, from the smaller number to the more. The configurations of the models created can be seen in Table 3.

Table 3 shows the configurations of 4 models which are simulated, each with 1, 5, 10, and 15 hidden layers and ten nodes in each layer. The models aim to predict the CPI of the Education Group one month ahead of each data. Using those configurations, we want to test which model produced better results in MAPE and RMSE.

After the training process is carried out, a testing process is also performed to test the model created. In the training process, 67% of the data are used, and the remaining 33% is for the testing process. The model's accuracy is measured using statistical measures of Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). The flow of the experimental process carried out can be seen in Figure 4.

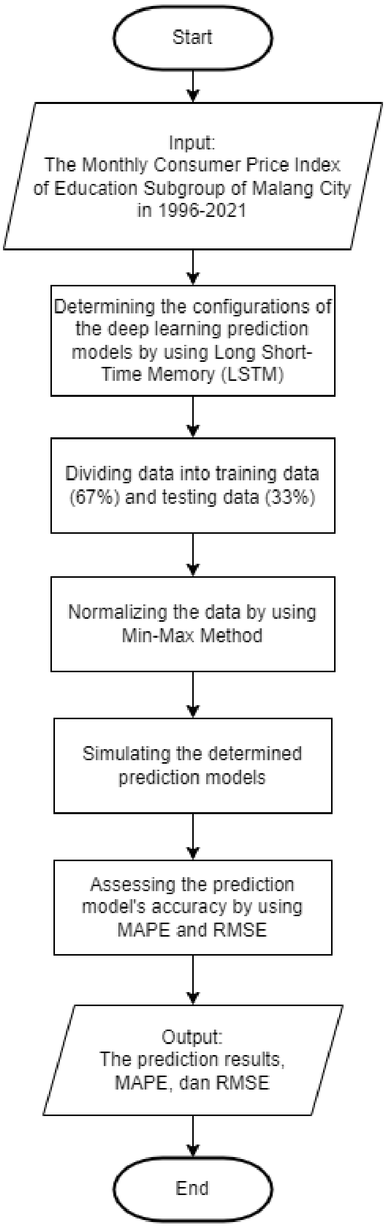

Figure 4. Experimental Process Flow in Research

The flowchart shows the steps of the experiment, which are collecting the input data of the model, determining the configurations of the models which are simulated, assessing the data dependence on time, dividing the data into training and testing data, normalizing the data, simulating the models, and assessing the models. The outputs of the experiment are the prediction results, MAPE, and RMSE.

In this study, an experiment was done using the Consumer Price Index (CPI) data for the Education Expenditure Group in Malang from 1996-2021. The time series data are divided into two parts. They are training and testing data. Of the total data, 67% is used as training data, while the remaining 33% is for data testing. Next, forecasting simulations were carried out using the Long Short-Term Memory (LSTM) Method, including the stages of normalization, training, testing, and measuring accuracy with Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE).

III. Result and Discussion

The articles must consist of at least eight pages. Do not change the font size or line spacing to insert more text on a limited number of pages. Use italics for emphasis; do not use underscores.

This section describes the results obtained from the simulations that have been carried out. The model configurations used, and the experiment stages that are run have been described in the previous section.

```
# Starting LSTM
Inputs: Time series
Outputs: MAPE and RMSE of the forecasted data
# Split data into:
# 80% training and 20% testing data
1. size ← length(series)
2. train_size ← 80/100*length(series)
3. train ← series[0...train_size]
4. test ← series[train_size...size]
# Set the random seed to a fixed value
5. set random.seed(7)
# Fit an LSTM model to training data
Procedure fit_lstm(train, epoch, neurons)
6. X ← train
7. X2 ← test
8. model ← Sequential()
9. model.add(LSTM(neurons, input_shape=(1, 1), activation="tanh"))
   model.add(Dense(10))
   model.add(Dense(1))
10. model.compile(loss='mean_squared_error', optimizer='adam')
11. res ← model.fit(X, epochs=200, batch_size=1)
# Make a one-step forecast
# Forecast the training dataset
12. trainPredict ← model.predict(X)
13. testPredict ← model.predict(X)
# Validations on the test data
20. rmse = sqrt(mean_squared_error(Y, testPredict))
21. m ← 0
    for each i in range(length(Y)):
    m ← m+abs((testPredict[i]-Y[i])/Y[Ii])
    end for
22. mape ← m/length(testPredict)*100
23. return rmse
    Return mape
```

Figure 5. The Training and Testing Algorithm Used in Simulations

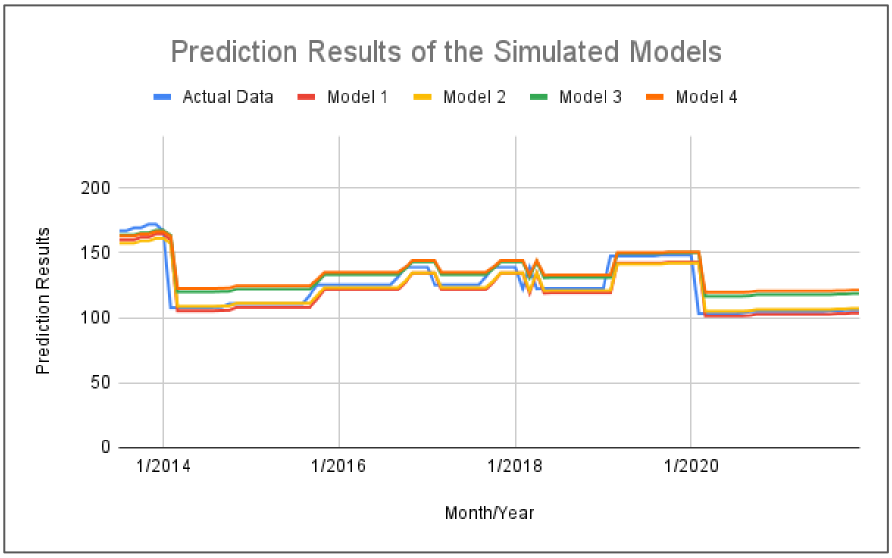

Figure 6. Prediction Results Of The Simulated Models

In the simulations, we used each row of data to predict the monthly Consumer Price Index (CPI) values for the education expenditure group of the next month (1 step). The training and testing algorithm used in simulations is described in Figure 5. The comparison of the prediction results in Model 1, Model 2, Model 3, and Model 4 with the actual data in the testing process can be seen in Table 4 and Figure 6. From the assessment process, we obtained the values of Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and the number of epochs the models need to reach convergence, which is shown in Table 5.

Based on the test results in Figure 6, Table 4, and Table 5, it is revealed that the best simulation results are obtained by Model 1 with one hidden layer, seen from the resulting Mean Absolute Percentage Error

TABLE 4
FORECASTING RESULTS OF THE SIMULATED MODELS

Month	Actual Data	Model 1	Model 2	Model 3	Model 4
7/2013	166.97	160.1376	157.3558	163.8112	163.1169
8/2013	166.97	160.1376	157.3558	163.8112	163.1169
9/2013	169.16	160.1376	157.3558	163.8112	163.1169
10/2013	169.16	162.1465	159.1203	165.3922	164.5694
11/2013	171.85	162.1465	159.1203	165.3922	164.5694
12/2013	171.85	164.6098	161.2815	167.3273	166.3461
1/2014	166.67	164.6098	161.2815	167.3273	166.3461
2/2014	107.81	159.8621	157.1137	163.5942	162.9175
3/2014	107.81	105.4832	108.8358	119.9074	122.6638
4/2014	107.81	105.4832	108.8358	119.9074	122.6638
5/2014	107.81	105.4832	108.8358	119.9074	122.6638
…	…	…	…	…	…
12/2021	105.97	103.7972	107.3278	118.5296	121.3940

TABLE 5
ASSESSMENT RESULTS FROM THE SIMULATED MODELS

Statistics Measurements	Model 1	Model 2	Model 3	Model 4
MAPE	2.67%	2.774%	8.9987%	10.861%
RMSE	8.774	8.53	12.7999	14.7509
Epoch	10	20	-	-

TABLE 6
MAPE AND RMSE VALUES FROM MODELS WITH DIFFERENT NUMBERS OF HIDDEN NODES

Testing Method (1 Hidden Layer)	2 Node	4 Node	6 Node	8 Node	10 Node	12 Node
MAPE	3.244%	2.8765%	3.7354%	4.1278%	3.8765%	4.2555%
RMSE	8.5258	8.37	8.6049	8.716	8.6240	8.7666

TABLE 7
EXECUTION TIMES OF THE MODELS SIMULATED

Amount of Neurons	Execution Time (ms) in this research	Execution Time (ms) in other research
20	8,6835	9,1331
40	8,7447	8,9873
60	7,4906	8,6651
80	8,0687	8,3544
100	8,5253	8,2127

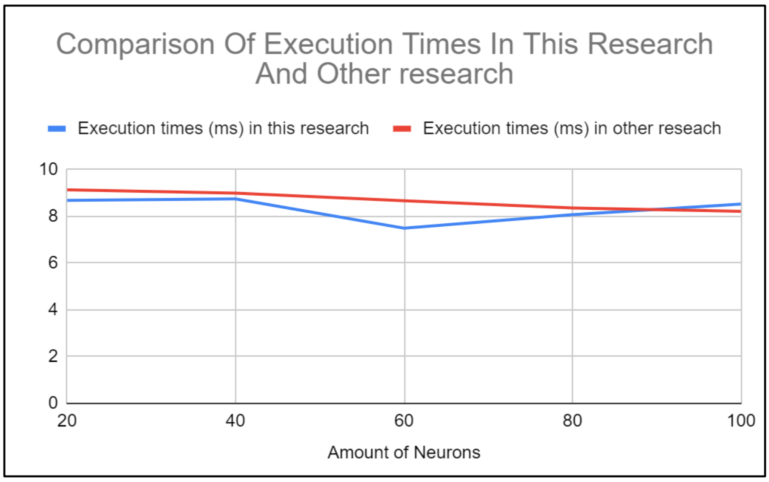

Figure 7. Comparison Of Execution Times In This Research And Other Research

(MAPE) and Root Mean Squared Error (RMSE) values. The MAPE value of Model 1 is 3.925%, and the RMSE value is 8.6623. The simulations show that the MAPE value increases with the increase in the number of hidden layers, from 1 to 15 hidden layers. The model that produces the highest MAPE and RMSE values is Model 4, with MAPE = 10.8608% and RMSE = 14.7509. The minimal epoch needed to reach the convergence state was obtained by Model 2, while Model 3 and Model 4 produce unstable loss (never reaching the convergence state).

Furthermore, model simulations were also carried out with 1 hidden layer with hidden nodes totaling 2, 4, 6, 8, 10, and 12. The MAPE value of each simulation carried out can be seen in Table 6. From the simulation results in Table 6, it is known that the best MAPE and RMSE values are obtained by the model with 1 hidden layer and 4 nodes. The MAPE value of the model is 2.8765% and the RMSE value is 8.37. Based on Table 1, the model is said to have very high accuracy when the MAPE value is below 20%. Therefore, a model with 1 hidden layer and 4 nodes has very high accuracy. Yet, compared to other studies, the RMSE values of those models are still worse than the model built in other studies which used the GRU-RNN method and Extreme Learning Machine Method [Chang and Guo][Alfiyatin]. On the other hand, the execution time of those models is better than the model in other studies though they have more hidden nodes (neurons). For instance, Model 3 with 100 neurons has the same execution time as the model built in other research with 20 neurons. The execution times of the models simulated in this research are shown in Table 7 and Figure 7.

Table 6 and Figure 7 show the execution times of the models with 20 to 100 neurons. The execution times vary from 7,4906-9,5253 ms. This is better than the execution time generated by the model in other research with 20 neurons.

This model can forecast the inflation of education costs as well as show the fluctuation of the inflation properly. The forecast can be used as a consideration for people to make decisions regarding education fund preparation. In addition, it also serves as a basis for the government to develop better policies in education.

IV. CONCLUSION

Based on the simulations and analyses performed in this study, there are two concussions. First, from the research results, it is revealed that the lowest MAPE and RMSE values are obtained by Model 1 with 10 hidden layers. The MAPE value obtained is 3.925% and the RMSE value obtained is 8.6623. Second, the number of nodes in the hidden layer that produces the highest level of accuracy is 4 nodes. The model with 1 hidden layer consisting of 4 nodes produces MAPE = 2.8765% and RMSE = 8.37.

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