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GRU-RNN Model to Analyze and Predict the Inflation by Consumer Price Index

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Abstract: - The general population need data on the expected rate of inflation for educational expenses to plan for and manage family budgets. When formulating educational policy, this data is also useful for the government. Chennai serves as one of Indonesia's educational hubs, yet there is a lack of publicly accessible data on the city's inflation rate for education expenses. Furthermore, there is a lack of prior studies on forecasting that specifically used the Education Expenditure Group's Consumer Price Index (CPI) information to determine inflation rates in education prices utilizing the Deep Learning approach. The goal of this study is to utilize the Deep Learning Method to create a model that can predict how much tuition will rise in Chennai. The Education Expenditure Group in Chennai relied on Consumer Price Index (CPI) information for its study. An improvement in the Long and Short-Term Memory (LSTM) and Recurrent Neural Network (RNN), approach is used for predicting purposes. A method with four hidden nodes and a single hidden layer produced the best results, with RMSE=8.38 and MAPE=2.8766%.

Keywords: Inflation Rate, Educational Expenses, CPI, Deep Learning Method, LSTM Method.

I. INTRODUCTION

A family's financial planning and management should prioritize the establishment of an education fund [1]. Due to the high and unpredictable expense of higher education, individuals should start saving for it as soon as feasible. For Indonesia to have better human resources and be more competitive on a global scale, more people need to have high education [2]. A major factor in decision-making about the education of children in Indonesia is the exorbitant expense of schooling [3]. Economic actors' choices to engage in economic activity are impacted by the rise in schooling expenses [4]. For families to make better use of their financial resources, they need to know how much future education expenditures are likely to increase due to inflation. Included among the factors that determine economic activity in family groups is inflation in education expenses, which is significant since it is one of the primary reasons why people make economic choices [5-7]. Knowing the inflation rate for educational prices is helpful for parents and guardians when making choices about schools and saving for their children's education since it affects the total amount of money needed for their children's education in the future [8]. Whether direct or indirect, the community as a whole bear the brunt of the expense of education [9].

Chennai has seen a significant growth in education demand, particularly in higher institutions, between 2006-2013. Higher education, as a service sector economic good, is regarded equally important to other economic goods [10-12]. Similar to other economic interests, educational service prices depend on demand and cost increases. The statistics for the City of Chennai's Recreation, Education, and Sports Groups from 2011 to 2019 are shown in Figure 1, according to the Chennai Central Bureau of Data [13-15]. Leisure and Sports Group usually has somewhat consistent inflation rates. As a result, the state of education cost inflation may be well shown by the Educational institutions Recreation, and Sports Group's total inflation [16]. The Education, Recreation, and Sports Group's cumulative Inflation Rates were more than zero, indicating that the expense of education in Malang City increased annually during that time [17].

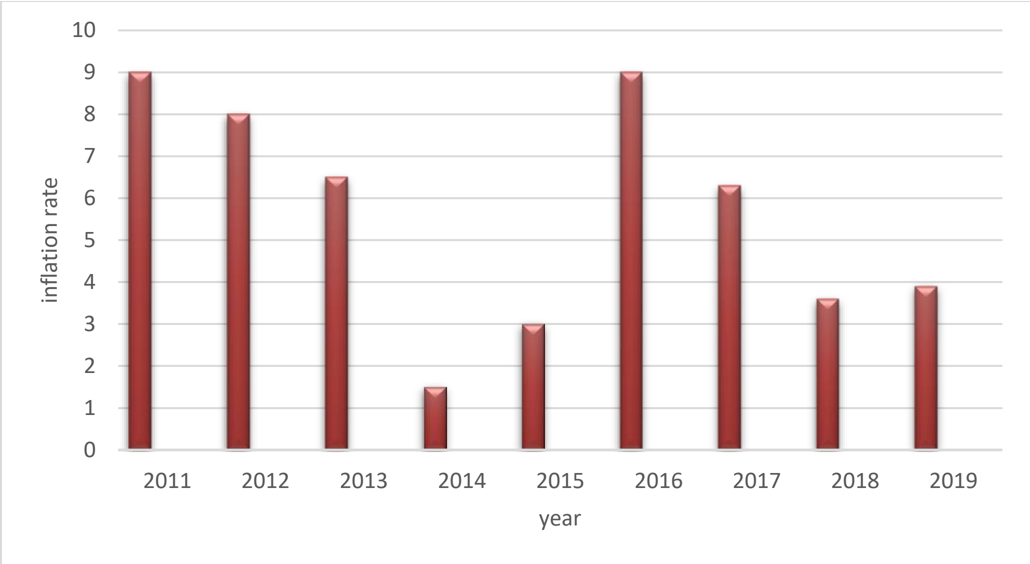

Figure 1. Chennai's Educational Institutions Recreation, and Sports Groups Inflation Prices

As shown by the Gross Regional Domestic Product (GRDP), the income per capita of the Indonesian people has been steadily rising over the last several years [18]. Inflation or the cost of tuition goes hand in hand with this. The price and income elasticity of demand for higher educational institutions reveal how demand is affected by changes in both the cost of services for higher education and overall people's income [19].

Figure 2 shows that between 2015 and 2019, Chennai City's GRDP increased. The graph shows that Malang's revenue has been on the rise during the last several years [20]. As GRDP rises, it is believed that people's buying power also rises. That educational services are in high demand follows naturally. Nevertheless, regardless of their wealth, every family or economic player still has a budget limitation or spending limit.

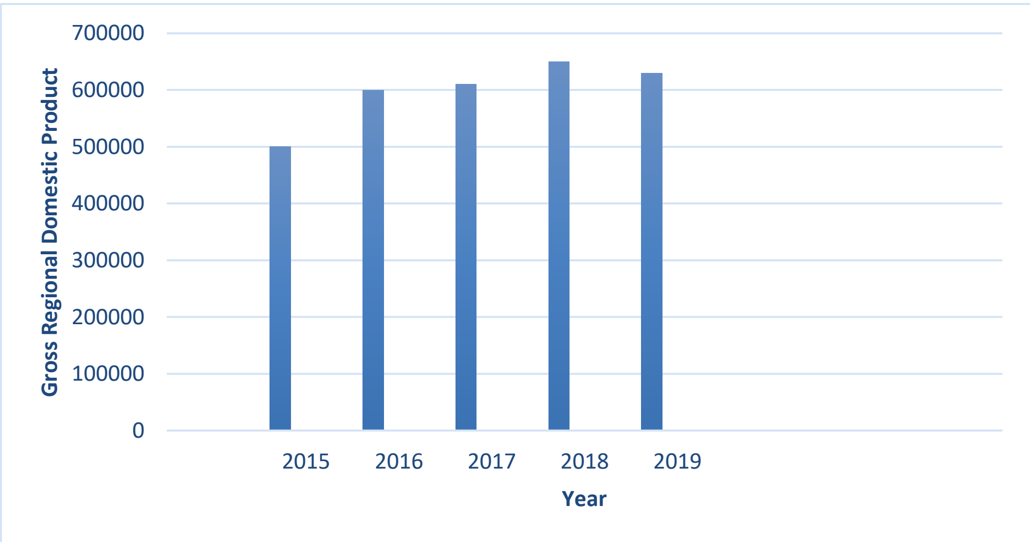

Figure 2. Chennai City's 2015–2019 GRDP

Several Indonesian universities have campuses in Chennai. The Central Bureau of Statistics reports that there are hundreds of educational institutions in the city of Chennai ranging from preschools to universities. This draws more and more students to the city for their academic pursuits.

The education sector's growth would be dictated by the government's policies aimed at controlling inflation in Chennai and making educational facilities affordable. Human Resources (HR), often known as a country's current human capital, is the primary factor that determines the GDP level, and education plays a key role in this process. Consequently, the nation's investment in education is a vital HR strategy.

Academic disciplines in Indonesia, including education, administration, and IT, have investigated the country's educational expenditures. Predicting the pace of inflation in Chennai's education prices, however, remains an uncommon area of study. This paper aims to fill this knowledge vacuum in the research. Since society as a whole makes purchasing decisions based on economic factors, accurate predictions of the rate of inflation for educational expenditures are crucial. Another way that governments might use inflation rate forecasts to inform education policy is by looking at historical data.

Numerous approaches exist in economics for making predictions, such as smoothing, naïve techniques, trend, decomposition, ARCH-GARCH and Box-Jenkins. Machine learning and deep learning-based forecasting methods are only two examples of how information techniques have facilitated the improvement of new approaches to this problem. Prediction systems have made extensive use of Machine Learning in prior studies. Compared to the traditional approach, the results produced by Machine Learning are more precise. Research shows that when it comes to sales forecasting, the Machine Learning technique yields very accurate results (93.56%). According to studies, a Machine Learning approach using an ANN, specifically Stacking Long Short-Term Memory (LSTM), outperforms traditional approaches in terms of predicting accuracy (MAPE 17.35%).

Building systems to forecast inflation rates also makes extensive use of machine learning techniques based on ANN. According to the study, when it comes to forecasting inflation rates, the Deep Learning technique outperforms the traditional methods. In this study, the method of deep learning yielded an RMSE value of 0.360. Furthermore, the rate of inflation in Tamil Nadu may also be accurately predicted using the Deep Learning approach. Nevertheless, prior predicting research using the particular inflation rate in Indonesian data via the use of Deep Learning techniques, particularly concerning education expenditures as measured by the CPI, has not been located by the authors.

This study's overarching goal is to use these factors to inform the development of an LSTM (Deep Learning) model for predicting the value of inflation in Chennai’s educational expenses. CPI data for the Educational Group Expenditure in Chennai from 1997 to 2022 is used in this study. The study results should be useful for families as they budget for their children's college expenses. Furthermore, authorities in Chennai might use the study's findings to inform the development of more prudent rules at the expense of schooling.

II. METHODOLOGY

A. Data from time series

Data collected over some time is known as a time series, and it often includes a sequence of observations. Time is the sole component that often influences the variations in time series data; other variables tend to have a little or non-existent impact. Data that follows a period pattern includes things like inflation rates, the global price of gold, and the development of endemic diseases. The pattern may be examined using those data to determine its likelihood of continuing in the future. An example of quantitative forecasting that makes use of statistical analysis is the one-variable time series model, which is applied to time series data. Examples of one-variety time series models include naïve approaches, decomposition, smoothing, trends, and the ARCH-GARCH and Box-Jenkins Methods, which each concentrate on studying the sequential patterns of data for a certain variable.

B. LSTM

The LSTM technique is a subset of Deep Learning. LSTM is an enhanced version of RNN that incorporates memory cells. The long short-term memory architecture consists of input layers, output layers, and buried layers with memory cells, input gates, and forgetting gates. RNN memory cells are less capacious than LSTM cells.

LSTM RNNs are ideal for processing time series data with long-term trend patterns. Recent time series forecasting researchers have switched from classical methods like ARIMA to deep learning methods like RNN due to ARIMA's inability to capture time series data changes. Because the input affects the hidden layer in RNNs, the network's output may decline exponentially or explode as it cycles through the recurring influences. LSTM trains RNNs to overcome this issue by enhancing their hidden layers with memory cells.

Three gates, the Forget Gate (f_t), the input gate Gate (I_t), and the Output Gate (O_t), make up an LSTM memory cell, as shown in Figure 3. The degree to which predetermined values are retained may be adjusted using a forget gate. To implement a forget gate, a logistic sigmoid activation function, which is a layer of sigmoid, accepts the input rate at t and the output rate at t-1 to combine them.

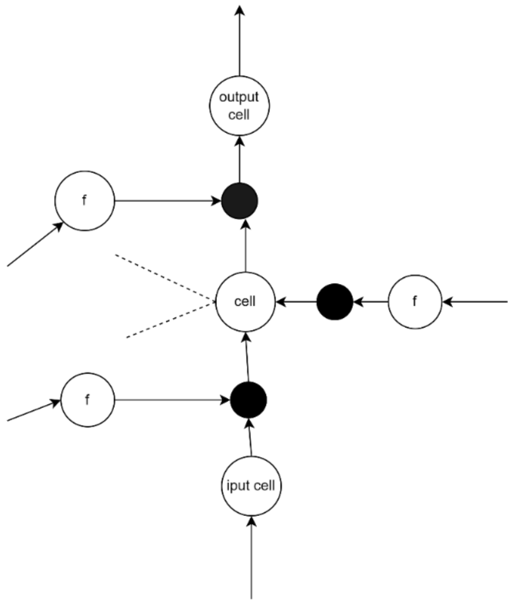

Figure 3. Memory Cell Architecture of LSTM

A sigmoid function returns a value between zero and one. If f_t= 1, the information will be stored without changing the prior state; if$f_t = 0$, the information will be erased from memory. This is the formula forf_t: (1), the forget gate's weight denotes Wf, $S_{(t-1)}$ is the prior S or S of t-1, X_t is the actual data at time t, and F is the function of tanh.

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

The quantity of memory that has to be stored may be controlled by input gates (I_t). The activation function for an input gate is the tanh function (σ). Where $W_i$the mass of the input gate, the formula for is I_t may be found in (2).

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

Calculate the input gate's rate by multiplying it with the candidate layer's output (). Where denotes the midway state cell and W_c represents the cell state weight, the formula for is defined as (3) and (4).

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

$$c_t = \sigma\left(i_t \hat{C}_t + f_t c_{t-1}\right) \qquad (4)$$

The amount of which the amount stored in the cell is utilized to determine the input activation rate may be controlled by the output gates functionality (O_t). The activation function used by this gate is a logistic sigmoid. The output gate's weight, W_o , is defined in the 0t formula by equation (5).

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

C. Measurements of the Accuracy of Forecasting Models

Conventional and relative statistical metrics may assess prediction accuracy. This section will review statistical metrics theories and formulae to assess the simulation models' dependability. For these activities, the conventional operating procedure is to employ the error (e_t) values from (6), where X_t is the actual data and Y_t is the forecast.

$$e_t = X_t - Y_t \qquad (6)$$

Testing uses anticipated relative error levels. Formula (7) calculates relative error numbers.

$$re_t = \frac{X_t - X_t}{X_t} \times 100 \qquad (7)$$

The Root Mean Squared Error (RMSE) is a prominent statistical measure for measuring the accuracy of a forecasting model with respect to n data points. Reduced RMSE immediately improves model accuracy. RMSE is calculated using the formula after entering the numbers. (8).

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

As stated in (9), the Mean Absolute Percentage Error (MAPE) is one way to evaluate the predictive model's precision that is part of the relative statistical metric.

$$MAPE \frac{1}{n} \sum_{t=1}^{n} |re_t| \qquad (9)$$

A lower MAPE score indicates that the model is more accurate in making predictions. Tabulated are the predicted quality levels for all MAPE value ranges. The relevance of each MAPE value range is shown in Table 1. Following the guidelines laid forth in the above table, methods are deemed to possess exceptional impact when the values of MAPE fall below 10%. Assuming MAPE values in the 10%-20% range, the models are deemed to possess good relevance. Because of this, the anticipated increase in MAPE value from this study is less than 20%. It is usual practice to evaluate deep learning models using RMSE and MAPE, according on previous research on deep learning forecasting.

Table 1 Every MAPE Range Description

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

D. Research Methods and Data

Implementing a system to predict the rate of inflation in Tamil Nadu's education prices using deep learning is the goal of this work. The monthly CPI numbers for the education spending category in Tamil Nadu, particularly in Chennai, are used in this study, which differs from earlier studies. The data used in this study came from the Central Bureau of Statistics' (CBS) Chennai in Figures reports, which can be found on the East Java Province official website. The data was collected between January 1997 and November 2022. The CPI value statistics in Chennai shown in an overview. The Education Group of CPI in Chennai from 1997 to 2022 is shown in figure 4, which is used in this study. When determining inflation, CPI is one of the factors taken into account. Values in the CPI reveal overall rate rises across categories of spending, including food and drink, healthcare, transportation, and education. Consequently, changes in the education spending group's inflation rate may be analysed using the CPI index.

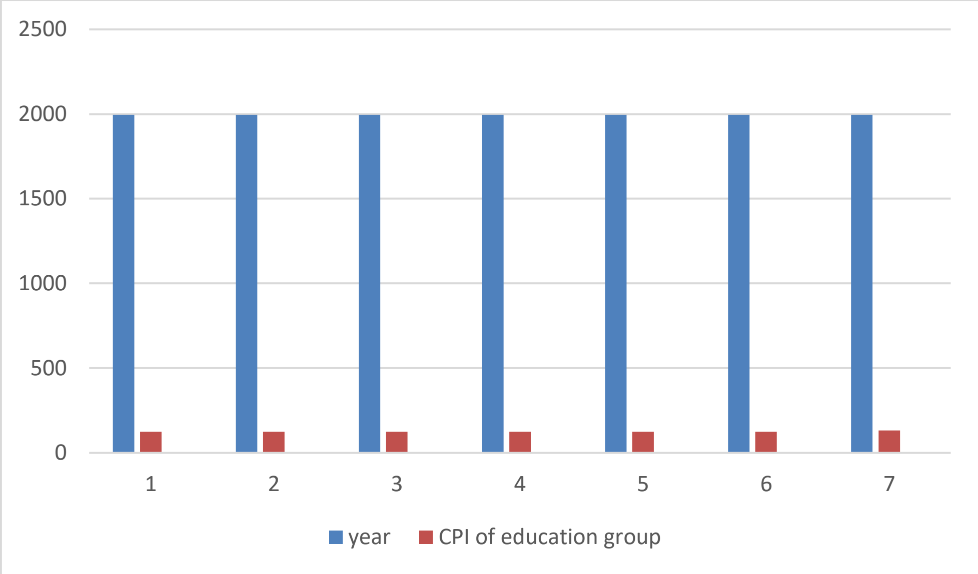

Figure 4. Chennai Education Expenditure Group Cpi 1997–2022.

This research used the Long Short-Term Memory (LSTM) deep learning approach using time series data. The generated model has a single node each in the input and output layers. Each of the four virtual models has a unique number of hidden layers. Find out how many concealed layers and nodes there are by experimenting with different numbers in simulation, starting with the smallest and working your way up to the largest.

Figure 5 displays the configurations of four methods, with various numbers of hidden layers and nodes. The models range from one to fifteen with ten levels in each. Using data collected one month in advance, the models hope to forecast the Education Group's CPI. The goal is to compare the models' MAPE and RMSE scores using those settings to see which one performed better. The built model is subjected to testing when the training procedure has concluded. The data is divided between the training and testing processes, with 68% utilized for training and 34% for testing. Methods like Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) are used to assess the method's precision. Figure 6 displays the procedure of the method of experimentation.

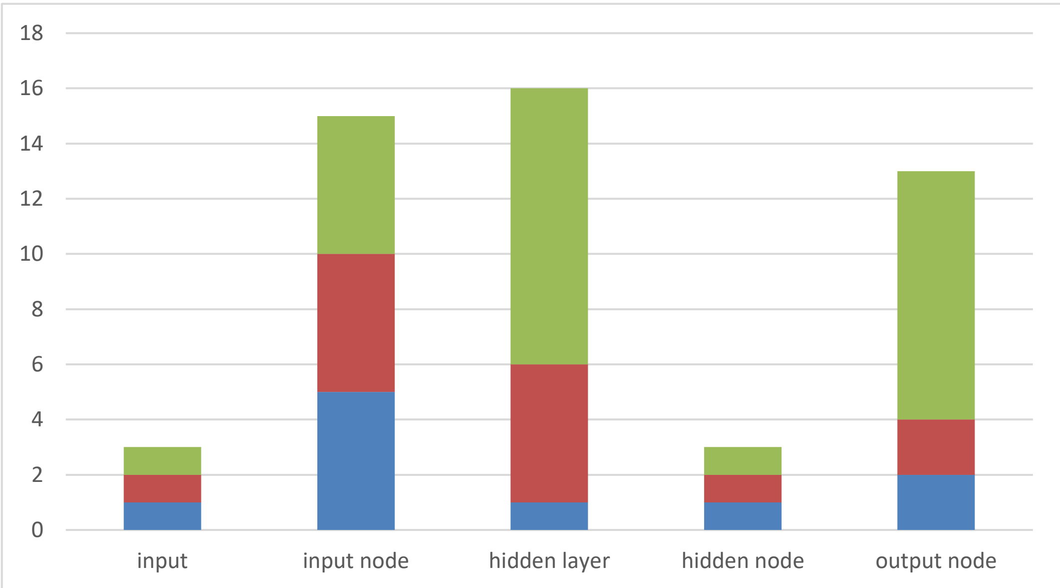

Figure 5. Configuring Simulation Deep Learning Models

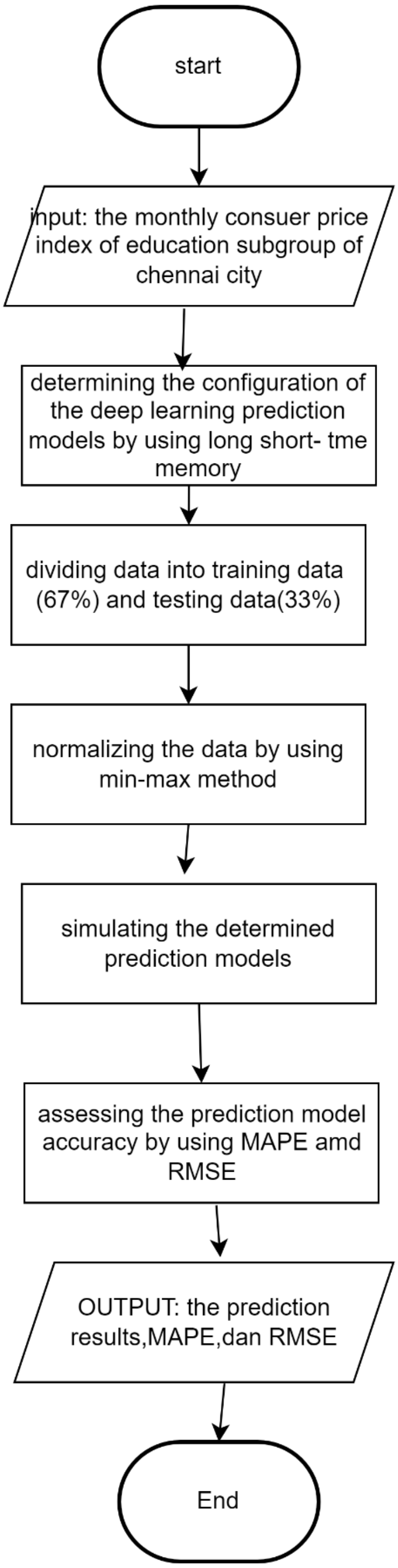

Figure 6. Research Experimental Process Flow

Data collection, model configuration determination, data dependence assessment, data normalization, data division into sets for training and testing, model simulation, and model assessment are all shown in the flow diagram of the experiment. The experimental outcomes, including the predictions, RMSE and MAPE, are the outputs. This research experimented using Malang's Education Expenditure Group's Consumer Price Index (CPI) data from 1997 to 2021. There are two sections of the time series data. All of these numbers are used for training and testing purposes. The data used for training accounts for 68% of the total, whereas the data used for testing accounts for 34%. Next, the LSTM Method was used to simulate forecasting, which included standardization, training, testing, and accuracy measurement using MPE and RMSE.

III. Discussion and Results

A minimum of eight pages is required for the articles. Avoid cramming more content into a small number of pages by adjusting the size of the font or line spacing. Emphasize using italics; underscore not to be used. The outcomes of the run simulations are detailed in this section. This section has detailed the model setups and experimental steps.

The simulations included one stage, utilize each row of data to forecast the following month's CPI values for the education spending category. Figure 7 explains the method used for testing and training. Figure 8 and 9 show the results of comparing the actual data from the testing procedure with the predictions from Models 1, 2, 3, and 4. Results of the evaluation, which included the Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the amount of epochs required for the methods to achieve convergence.

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

Figure 7. Method Used for Training and Testing in the Simulations

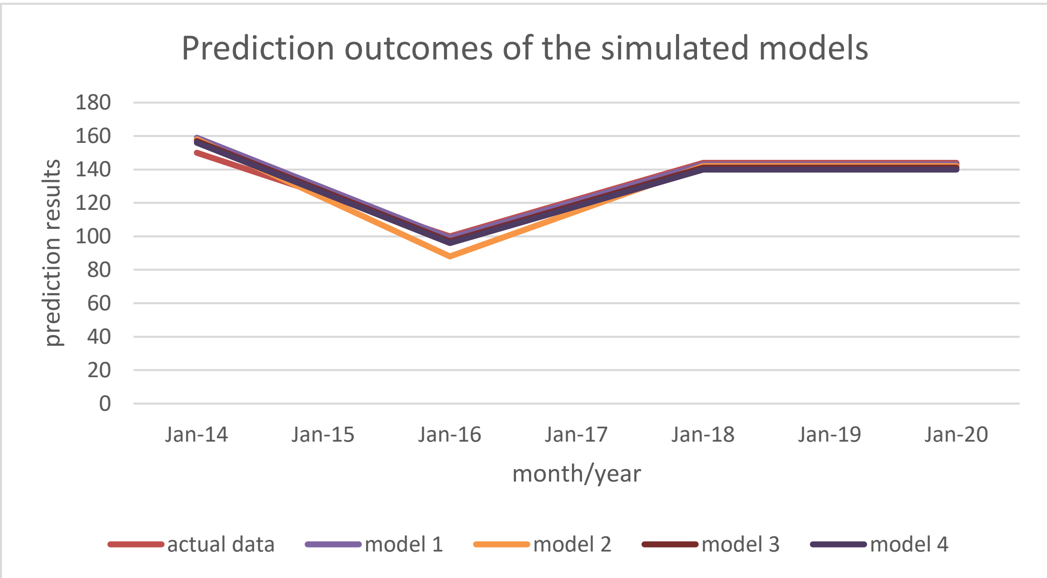

Figure 8. Simulated Model Prediction Results

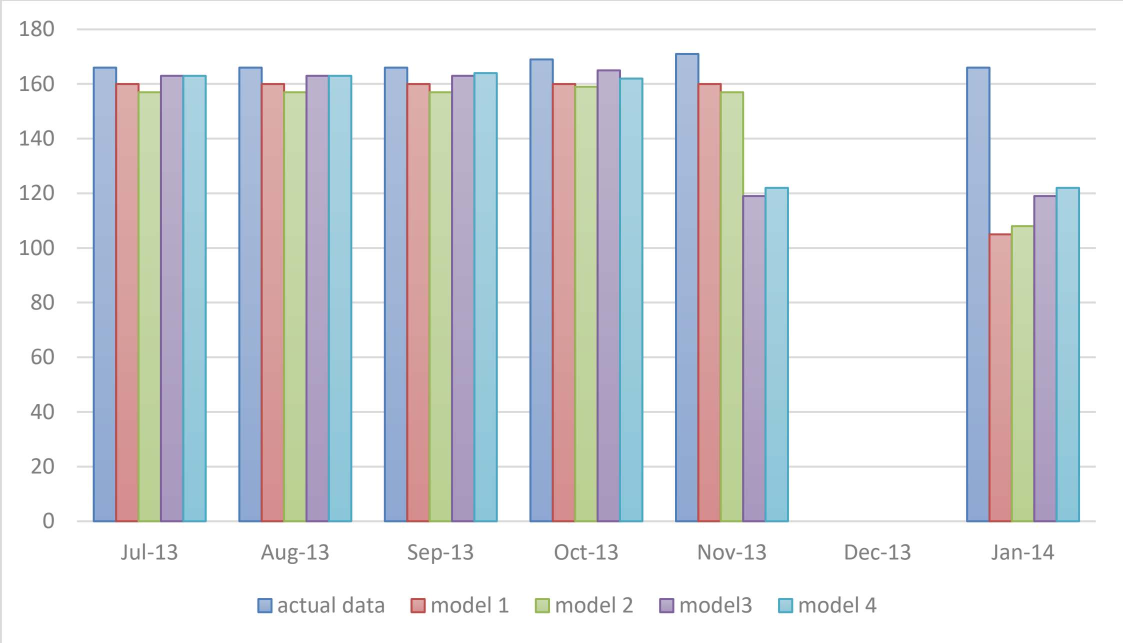

Figure 9. Simulated Model Predictions

Figure 10 show the test results. The RMSE and Mean Absolute Percentage Error (MAPE) figures show that Model 1 with one secreted layer gets the best outcomes. Model 1 has an RMSE of 8.6624 and a MAPE of 3.926%. According to the results of the simulations, the MAPE value rises as the number of layers that are hidden grows, ranging from 1 to 15.

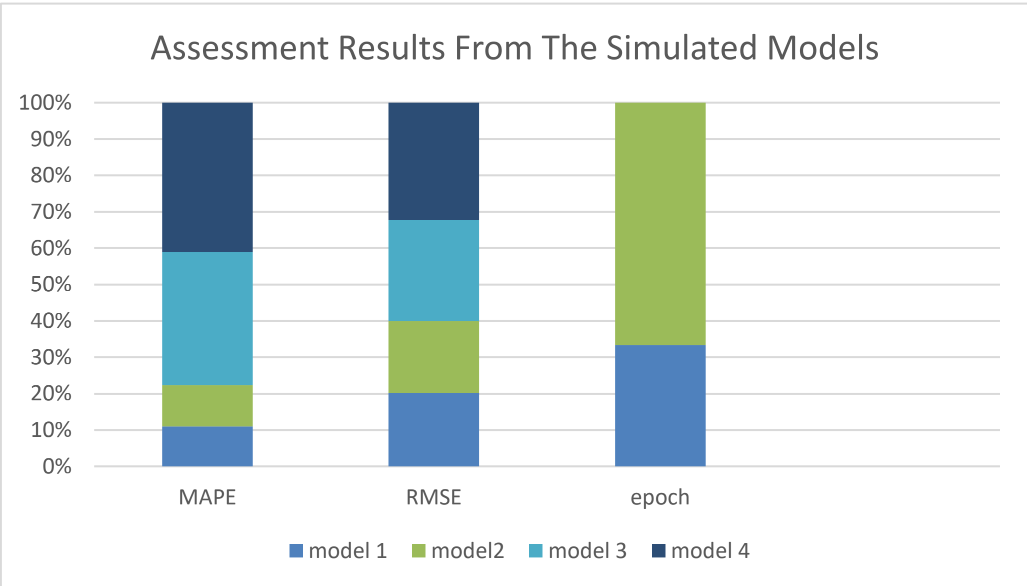

Figure 10. Simulated Model Assessment Results

Model 4 has the highest MAPE and RMSE values, coming in at 10.8609% and 14.7510, respectively. While Model 2 achieved the smallest timeframe required to attain the convergence state, Model 3 and Model 4 result in instability loss. An additional set of model simulations included a single hidden layer with2, 4, 6,8,10, and 12 hidden nodes, respectively. Figure 11 shows that the highest RMSE and MAPE rates were achieved by the design with 1 layer that was hidden and four nodes after running the simulation. The model has an RMSE of 8.38 and a MAPE of 2.8766%. According to Table 1, a MAPE score below 25% indicates that the model has extremely good accuracy. Consequently, the accuracy of a method with just four nodes and one hidden layer is very good. RMSE values of such models are lower than those of GRU-RNN and Extreme Learning Machines models from past studies.

However, despite having more hidden nodes (neurons), such models outperform the model in other experiments in terms of execution time. Examples include Model 3, which uses 100 neurons yet takes the same amount of time to execute as a 20-neuro model from another study.

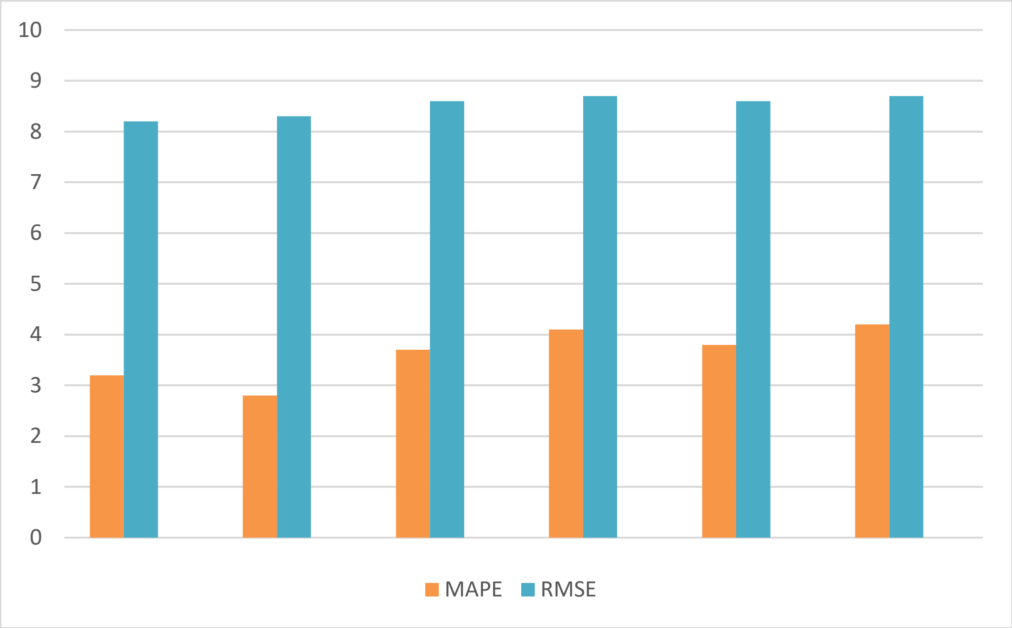

Figure 11. Models with Different Hidden Nodes' MAPE and RMSE Values

Models ranging from twenty to one hundred neurons display their execution durations in Figure 12 and 13. From 7, 4900 to 9, 5200 milliseconds, the execution times might range. Compared to prior studies that used 20 neurons, this represents an improvement in the model's execution time. This model accurately shows the ebb and flow of inflation and can predict how much college will cost in the future. Individuals may take the prediction into account while making choices about saving for college. Furthermore, it provides the government with a foundation to formulate more effective educational policy.

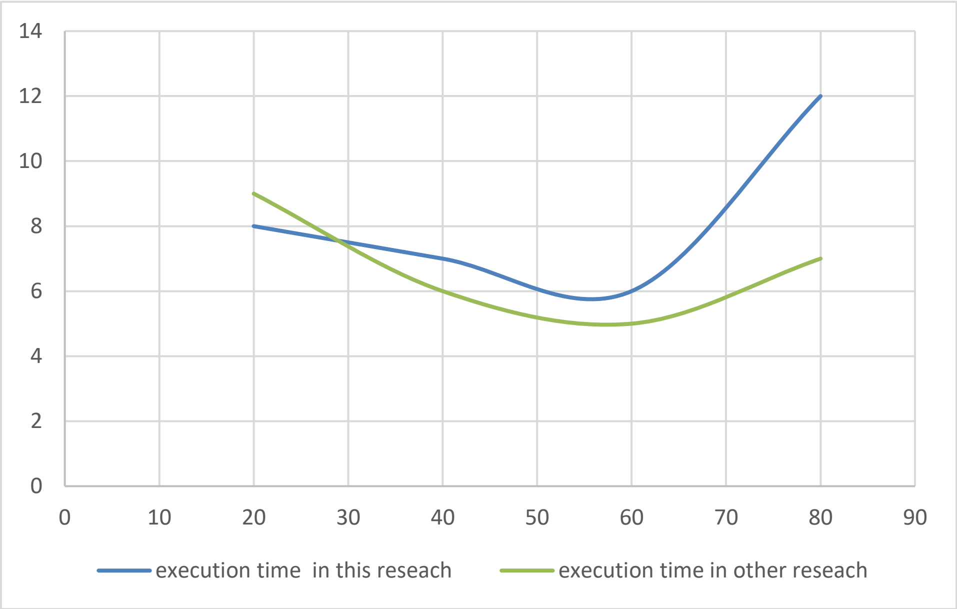

Figure 12. Compared to Other Research: Execution Times

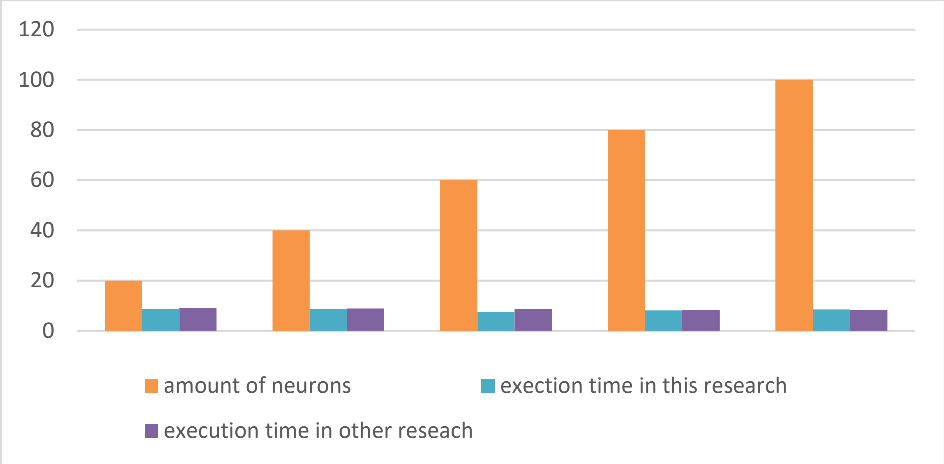

Figure 13. Simulated Model Execution Times

IV. Conclusion

In this research, there are two concussions, as determined by the simulations and analysis that were carried out. To begin, the findings of the study indicate that Model 1 with ten hidden layers is the one that achieves the lowest values for both MAPE and RMSE. 3.926% is the number that was acquired for the MAPE, and 8.6624 is the value that was found for the RMSE. In the second place, the nodes in the layer that is hidden that results in the maximum degree of accuracy is four specific nodes. The MAPE value of 2.8766% and the RMSE value of 8.38 are produced by the model that has one layer that were hidden and consists of four nodes.

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