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Python-Powered Precision: Unraveling Consumer Price Index Trends in Makassar City through a Duel of Long Short-Term Memory and Gated Recurrent Unit Models

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Abstract

This research aims to carry out a predictive analysis of the Consumer Price Index in the city of Makassar to anticipate possible impacts on inflation and deflation in the future. The Consumer Price Index is an indicator that can be used as a basis for measuring changes in the prices of goods and services purchased by consumers, which have an impact on inflation in a region. The CPI is very useful for knowing the level of increase in prices, services, and income, as well as measuring the amount of production costs. This data was obtained through the official website of the Central Statistics Agency (BPS) for the Makassar city area. The methods used in this research are Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). The results of this research show that based on analysis and testing, the LSTM model has an MAE of 1.0849 and the GRU model has an MAE of 0.9915, which shows that there is no significant difference between the two methods and both methods can work very well, however, The lowest error value was obtained in the GRU model using a 70:30 dataset ratio, 9 number of sequences, 16 neurons in hidden layer 1 and 32 neurons in hidden layer 2, and 1000 number of epochs.

Keywords: Prediction; Long Short Term Memory; Gated Recurrent Unit; Consumer Price Index; Mean Absolute Error.

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Introduction

Deep learning approaches are very effective in solving very complex problems and processing data on a large scale. Deep learning has made extraordinary contributions in various fields, including computer vision, natural language processing, and speech recognition, and has shown promising results in fields such as medicine, materials science, and other sectors. The use of deep learning requires large amounts of training data and powerful computing resources, such as GPU (Graphics Processing Unit) or TPU (Tensor Processing Unit), to train complex neural networks. Nevertheless, the advantage of deep learning lies in its ability to overcome problems that were previously difficult or impossible to solve by traditional methods and continues to be the focus of research and technological development in the modern era.

The price index is an indicator used to measure general economic conditions (Maharani, 2022). The price index has a very important role in measuring the level of economic progress in a region for the government (Arif, 2014). CPI, which stands for Consumer Price Index, is one of the price indices that is often used as the main reference in Indonesia(Raya et al., 2022). CPI is one of the economic indicators used as a basis for measuring inflation and deflation in the prices of goods and services consumed by people in urban areas from time to time (Sumantri & Latifah, 2019). Factors that contribute to the CPI in general are foodstuffs, water, gas, fuel and electricity, health, sports, prepared food, education, recreation, and housing (Hamdan, 2018).

The Consumer Price Index (CPI) is closely related to inflation and deflation because it will experience deflation when the CPI decreases, while it will experience inflation when the CPI increases for goods and services (Cui et al., 2023), (A et al., 2023). When prices increase due to inflation, it will be difficult for them to fall again, and this will also affect

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the increase in prices of other goods (Ningsih & Andiny, 2018), (Fitriyana et al., 2023). By knowing the price index first, you can measure inflation in an area (Noor & Komala, 2019). Based on the Official Statistical News (BRS) issued by BPS Makassar City, the Consumer Price Index value in August 2023 was 116.05 which resulted in a deflation of 0.08 percent from the previous month, namely June 2023 with a CPI of 116.14 (BPS, 2023).

Because the Consumer Price Index (CPI) is fluctuating, efforts need to be made to anticipate impacts that may cause inflation or deflation in the future (Rahmawati & Setyobudi, 2023), (Cahyono et al., 2019). One effective approach in dealing with this problem is to conduct a predictive analysis of the Consumer Price Index (CPI) in the future. Therefore, the research will compare the Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) methods to make predictions based on historical data in previous years (Carnegie & Chairani, 2023), (Egi Nuraini, 2022). Thus, it is hoped that this research will be able to contribute to efforts to help policymakers from the Makassar city government in the economic sector to anticipate the possible impacts of inflation in the future.

Method

In conducting this research Python is used to analyze and test algorithms, while the method used to predict the consumer price index uses Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) algorithms for Predicting the Consumer Price Index in Makassar City.

1. Research Stages
   The following are the research stages carried out in analyzing LSTM and GRU in predicting the Consumer Price Index in the city of Makassar.

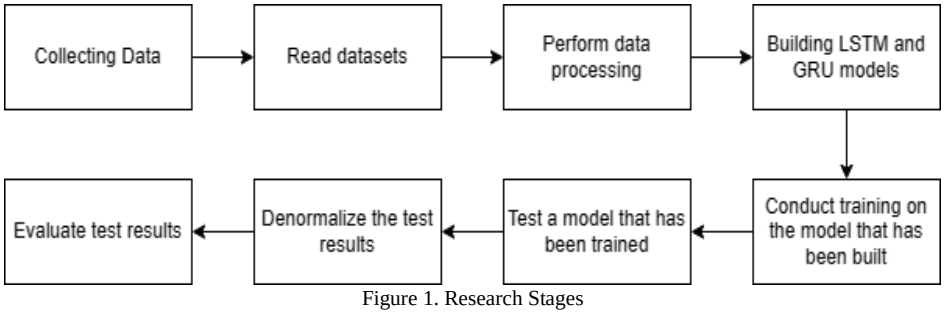

Figure 1. Research Stages

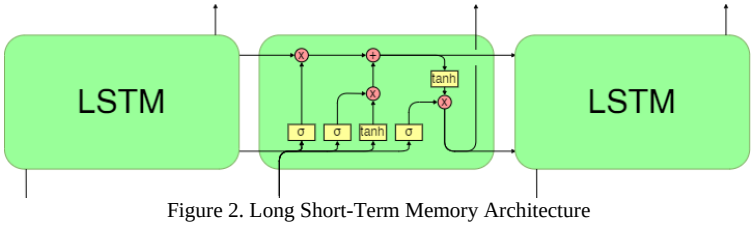

Figure 2. Long Short-Term Memory Architecture

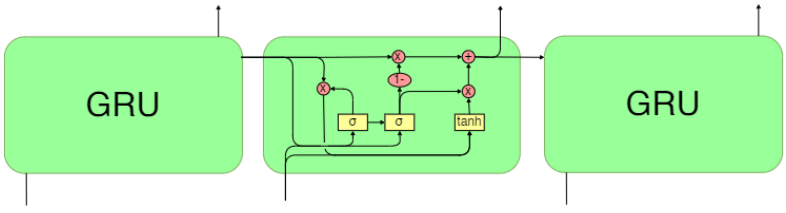

Figure 3. Gated Recurrent Unit Architecture

Figure 1 shows the research stages which begin with the data collection process, then prepare the data at the data pre-processing stage which consists of the data normalization process. Data normalization (scaling) is a process to

transform original data or actual data into another form. This process is done to produce the smallest possible error value. Next, the segmentation process, and data splitting (KILINÇ & Polat, 2022). Further, build and train the LSTM and GRU models using the training data that has been prepared, and the test data used for the testing process for the LSTM and GRU models that have been built (Tussifah, 2023), (Yudistira et al., 2023). After that, the prediction results are denormalized so that the resulting output can be easily read and the next evaluation process is carried out using Mean Absolute Error (MAE) to determine the performance of the model that has been created (Wijaya et al., 2021).

2. Datasets

The dataset for this research uses secondary data obtained from the official website of the Central Statistics Agency (BPS) for the Makassar city area. This dataset has 2 attributes, namely month and consumer price index value (Wanto & Windarto, 2017). An overview of the data used can be seen in Table 1.

Table1. Research Dataset

Month	CPI
January 1979	120.53
February 1979	120.60
March 1979	121.92
April 1979	124.80
May 1979	128.56
…	…
April 2023	115.75
May 2023	115.79
June 2023	116.05
July 2023	116.14
August 2023	116.05

The total data for this research from January 1979 to August 2023 is 536 data containing 2 attributes, namely the Month attribute and the CPI (Consumer Price Index). This data will be processed using LSTM and GRU models so that predictions can be made accurately.

Results and Discussion

Results

Before testing the performance of the Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) methods (Alkahfi & Chiuloto, 2021). First, hyperparameters are tested so that the two proposed methods can produce the best performance in predicting the consumer price index (Ardi, 2023), (Nagakusuma et al., 2022). The hyperparameters that will be tested in this research are dataset ratio testing, testing the number of sequences, testing the number of neurons and hidden layers, and testing the number of epochs.

Table 2. Dataset Ratio Testing

Ratio	LSTM	GRU
80:20	5.4772	4.9837
75:25	5.5910	4.5417
70:30	**4.0352**	**3.1601**
60:40	6.3097	4.1615

Table 2 shows the best dataset ratio obtained by using 70% training data and 30% test data from both models with an MAE of 4.0352 for LSTM. Meanwhile, GRU obtained results with an MAE of 3.1601.

Table 3. Sequence Length Testing

Sequence	LSTM	GRU
3	5.8907	3.6963
6	**4.3509**	3.6531
9	6.5161	**3.2188**
12	7.4744	4.9310

Table 3 shows the best performance for the LSTM model with an MAE of 4.3509 using 6 sequence lengths. Meanwhile, the GRU model obtained an MAE of 3.2188 using 9 sequence lengths.

Table 4. Testing the Number of Neurons and Hidden Layers

Neurons	LSTM	GRU
8	6.7148	5.3358
16	5.3499	5.1066
32	5.9772	4.0405
8, 8	8.6787	8.5970
8, 16	4.7337	3.9153
8, 32	5.9685	3.5695
16, 8	**4.4436**	4.7568
16, 16	5.4480	5.1532
16, 32	6.4285	**3.1270**
32, 8	5.0740	3.2710
32, 16	4.8090	3.4471
32, 32	5.2416	3.5836

Table 4 shows the best results for 16 neurons in hidden layer 1 and 8 neurons in hidden layer 2 with an MAE value of 4.4436. Meanwhile, the test results carried out on the GRU model obtained the best results for 16 neurons in hidden layer 1 and 32 neurons in hidden layer 2 with an MAE value of 3.1270.

Table 5. Epoch Testing

Epoch	LSTM	GRU
50	4.9010	4.3956
100	4.5788	3.9182
150	5.1491	4.0863
250	3.6476	3.5577
500	3.4614	3.6478
1000	**3.2267**	**3.1515**

Table 5 shows that the best results were obtained with 1000 epochs from both LSTM and GRU models. In the LSTM model, the MAE value is 3.2267, while in the GRU model, the MAE is 3.1515. After testing the hyperparameters, the best hyperparameters were obtained for both methods. The hyperparameter results obtained can be seen in Table 6.

Table 6. LSTM and GRU hyperparameters

Hyperparameters	LSTM	GRU
Dataset ratio	70:30	70:30
Sequence length	6	9
*Neurons*and hidden layers	16, 8	16, 32
Epoch	1000	1000

The prediction results obtained from test data for both models produce very good performance and are close to the actual values. A comparison of predicted values with actual values can be seen in Table 7.

Table 7. Comparison of actual and predicted values of LSTM and GRU

Month	Actual	LSTM Prediction	GRU Predictions
2010-06-01	119.33	118.817139	119.118958
2010-07-01	121.85	119.389954	119.676323
2010-08-01	123.71	121.779434	122.178207
2010-09-01	124.21	123.726723	124.064835
2010-10-01	123.65	124.378128	124.595757
…	…	…	…
2023-04-01	115.75	115.464760	115.837387
2023-05-01	115.79	115.749077	116.079155
2023-06-01	116.05	115.811310	116.122810
2023-07-01	116.14	116.060013	116.380569
2023-08-01	116.05	116.166069	116.473946

For a graph of the actual and predicted values for the two models, see Figure 4.

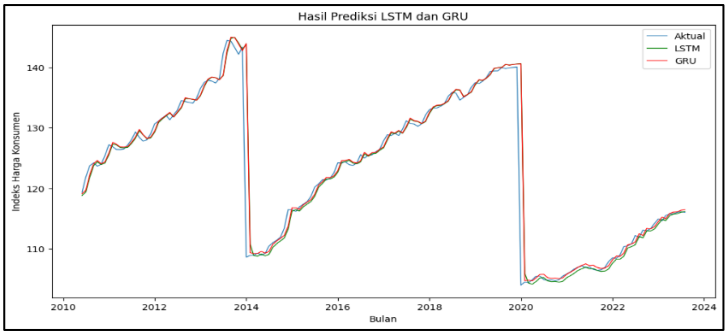

Figure 4. Graph of actual and predicted values of LSTM and GRU

After obtaining the prediction results from testing using test data, an evaluation of the two proposed models was carried out by comparing the difference between actual and predicted values. The results of the evaluation carried out using Mean Absolute Error can be seen in Table 8.

Table 8. LSTM and GRU Evaluation Results

Model	MAE
LSTM	1.0849
GRU	0.9915

In table 8, it can be seen that the evaluation results obtained show that there is no significant difference between the two methods and both methods can work very well, but the lowest error value is obtained in the GRU model with an MAE value of 0.9915.

Discussion

This research aims to conduct a comparative analysis between the Long Short Term Memory and Gated Recurrent Unit methods to predict the Consumer Price Index in the city of Makassar. Long Short-Term Memory and Gated Recurrent Units are types of Recurrent Neural Networks that work sequentially and are able to remember information from the past to be able to make predictions in the future (Iman & Wulandari, 2023), (Sen et al., 2020).

Long Short Term and the Gated Recurrent Unit effectively overcomes the problem of Recurrent Neural Networks which are usually affected by vanishing gradients when dealing with data series with long time intervals (Siregar & Widyasari, 2023). LSTM can resolve correlations in time series for short-term and long-term information (Banerjee et al., 2022), (Johny et al., 2022). Gated Recurrent Unit is similar to LSTM, but has a simpler architecture compared to LSTM (Seth et al., 2022).

The results achieved in this research were carried out by evaluating each method so that the resulting performance works optimally and can make accurate predictions (Paputungan & Jacobus, 2021). From the evaluation results, both methods can work very well and the difference in performance between the two methods is not too significant, however, the Gated Recurrent Unit produces a lower error value than Long Short Term Memory (Meliana & others, 2021).

It is hoped that this research will be able to contribute to efforts to help policymakers from the Makassar city government in the economic sector to anticipate the possible impacts of inflation or deflation in the future.

Conclusions and Suggestions

Conclusions

In building the LSTM and GRU models, this research builds and analyzes both models using Google Colab(Sautomo et al., 2021). This research carried out several stages of test analysis to determine hyperparameters to obtain the best results. In testing the epoch and dataset ratio, both models got the best results using 1000 epochs and a ratio of 70% training data and 30% test data. To test the number of sequences, LSTM uses 6 sequences while GRU uses 9 sequences. The test results on the number of neurons and hidden layers were also carried out with 16 neurons for hidden layer 1 and 8 neurons for hidden layer 2 in the LSTM model, 16 neurons for hidden layer 1, and 32 neurons for hidden layer 2 in the GRU model.

The results of the analysis of the two models show that there are no significant differences between the two methods and both methods can work very well, but the lowest error value is obtained in the GRU model with an MAE value of 0.9915 using a 70:30 dataset ratio, 9 number of sequences, 16 neurons for hidden layer 1 and 32 neurons for hidden layer 2, as well as 1000 epochs.

Suggestions

Based on the results obtained in this research, several suggestions for further research for predicting the Consumer Price Index in the city of Makassar:

1. Conduct comparative analysis using other methods.
2. Implementing the method into an application to monitor the Consumer Price Index value in the city of Makassar in the future.

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