THE GEORGE WASHINGTON UNIVERSITY

WASHINGTON, DC

INFLATION FORECASTING USING LSTM NETWORKS: CASE OF TURKEY

Overview

- Introduction and Motivation
- Description of the dataset used in traning
- Experimental Setup
- Result
- Conclusion

Introduction and Motivation

- Inflation forecasting is a critical component of economic decision-making and policymaking (James H Stock, 1999).

- Thus, accurate inflation forecasting is essential to make informed decisions that can impact the overall economic health of a country (Jan J. J. Groen, 2013)

- Fortunately, advances in machine learning and artificial intelligence have provided new and more sophisticated methods for forecasting economic time series data, including inflation (Nakamura, 2005)

- One such method that has shown promise is Long Short-Term Memory (LSTM) networks, which belong to the family of recurrent neural networks (RNNs)

- The primary objective of this project is to leverage the power of LSTM networks to forecast inflation in Turkey accurately.

- To achieve this goal, the project will utilize historical data on inflation, macroeconomic variables, and other relevant factors.

- By utilizing cutting-edge machine learning techniques such as LSTM networks, this project has the potential to contribute to the development of more accurate and reliable methods for forecasting inflation, which can lead to more informed economic decision-making and better policymaking.

Description of the Dataset

- The data utilized for both the training and testing phases of the neural network is a comprehensive time series, sourced from esteemed organizations including the Turkish Statistical Institute, Federal Reserve Economic Data, and the World Bank

- Series is comprised of monthly observations spanning a remarkable period, commencing in January 1994 and culminating in January 2023.

- The variables utilized in the analysis are diverse, including the inflation rate, policy rate established by the esteemed Central Bank of Turkey, the prevailing value of the Turkish Lira relative to the US dollar, the M2 money supply, the industrial production index, the business tendency index, and the registered unemployment figures within the Turkish economy.

Experimental Setup

- We will be using data from the beginning to 2021 for training and from 2021 to 2022 for validation.
- We plan to predict a 12-step out forecast, using 12 input time steps, we will leave the last 12 observations (2022-2023) for out-of-sample testing later.
- The first step will be to preprocess the data. Next, we will define the architecture of the LSTM network, including the number of memory cells, the number of hidden layers, and also the loss function and the optimization algorithm used to train the network.
- To judge the performance of the network, we use metrics such as mean squared error (MSE), mean absolute error (MAE), and root mean squared error (RMSE) to compare the predicted inflation rates to the actual inflation rates

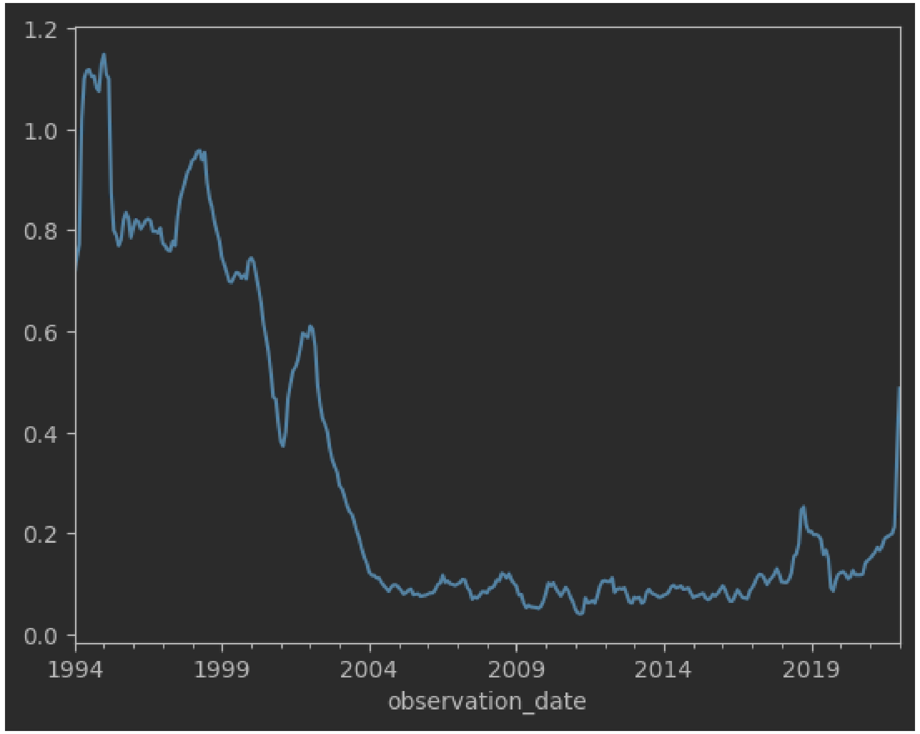
Results

- The graphical representation of the inflation data over the time period of 1994-2023 reveals some interesting patterns in the behavior of inflation in Turkey.

- Notably, from 1994 to 2004, there was a significant decline in inflation.

- From 2004 to 2018, there was a period of relative stability in inflation, with the inflation rate hovering around 0.15. This period was characterized by a stable political environment and the implementation of sound macroeconomic policies, which contributed to the overall economic stability of Turkey.

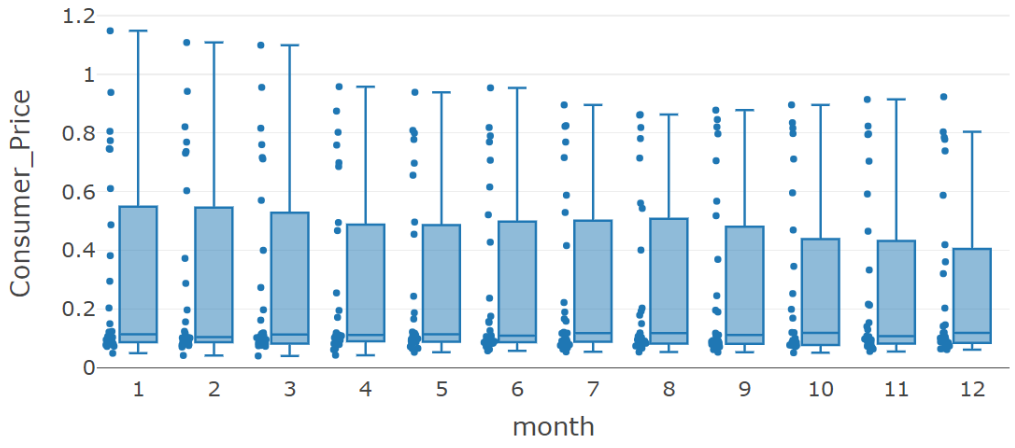
- However, there was a structural break in 2019, which led to a sharp increase in inflation.



- To gain a deeper understanding of the behavior of inflation in Turkey, it is important to analyze the data at a more granular level.

- One way to do this is to examine the inflation on each month over time and looking at its distribution categorized by each month.

- There appears to be a higher degree of volatility in inflation in the earlier part of the year compared to the latter part. This suggests that there may be seasonal factors or other drivers that contribute to increased uncertainty in inflation during this time.



- As the goal is to forecast future trends/values in a time-series dataset, one approach that can be used is the Autoregressive Integrated Moving Average (ARIMA) model, which combines AR and MA models.

- We set ARIMA model as a benchmark to compare how LSTM performs relatively on the same task.

- One potential limitation of ARIMA models, however, is the assumption of stationarity, which may not hold in time-series data.

- Therefore, before running the ARIMA model, we check the stationarity of the inflation time series data. One commonly used method for testing stationarity is the Augmented Dickey-Fuller (ADF) test, which tests the null hypothesis that a unit root is present in a time series sample.

- After running the ADF test on the inflation time series data, we fail to reject the null hypothesis that a unit root is present in the series. Therefore, we take the first difference and run the test again which concludes that differenced series is stationary.

- Following that, we check PACF and ACF to determine the optimal number of lags and the order of the MA term for the ARIMA model, which happens to be 1.

- These results suggest that an ARIMA(1,1,1) model might be appropriate for fitting the inflation time series data

- Since CPI exhibits exponential growth (variance increases), we build the model on the ln(inf)

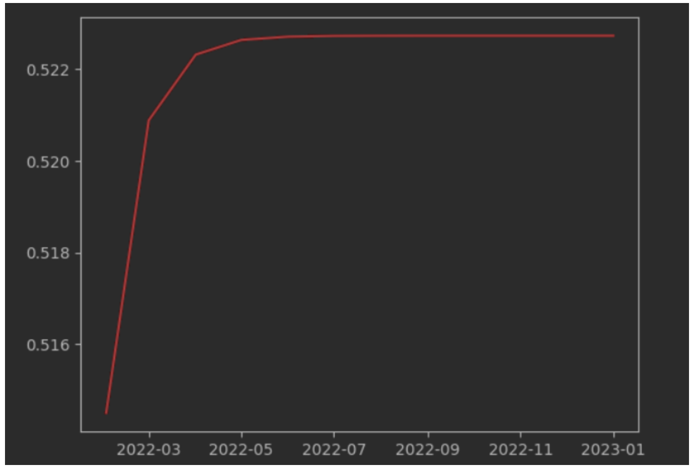
- To evaluate the performance of the ARIMA (1,1,1) model on the test set, we can calculate the mean squared error (MSE).

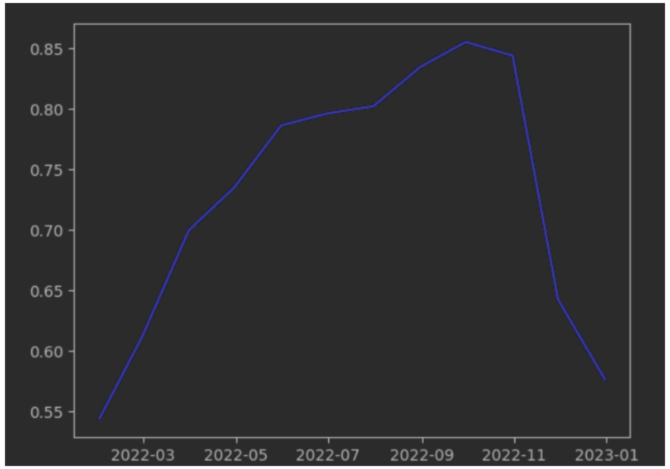
- The calculated MSE is 0.014. As it can be seen from the plots below, the model underpredicts inflation over the specified time period.

Dep. Variable:	Consumer_Price	**No. Observations:**	325
Model:	ARIMA(1, 1, 1)	**Log Likelihood**	318
Date:	Thu, 20 Apr 2023	**AIC**	-630
Time:	18:40:11	**BIC**	-619
Sample:	01-01-1994	**HQIC**	-625
	- 01-01-2021		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.0392	0.169	-0.232	0.817	-0.371	0.292
ma.L1	0.3359	0.158	2.120	0.034	0.025	0.646
sigma2	0.0082	0.000	23.145	0.000	0.008	0.009

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	340.30
Prob(Q):	1.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	4.25	**Skew:**	0.13
Prob(H) (two-sided):	0.00	**Kurtosis:**	8.01





- After running ARIMA(1,1,1) model as a benchmark model we see that it does not produce strong results in terms of forecasting.

- Following that we run LSTM network with no covarities, in other words, univariate.

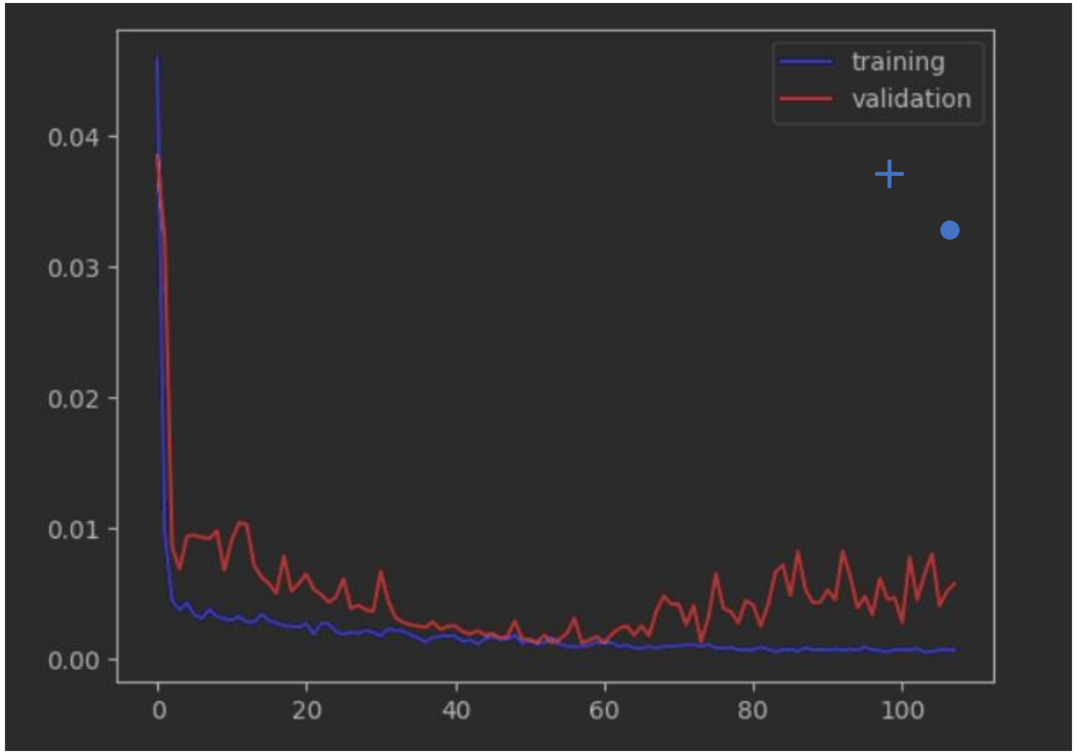
- The univariate LSTM model architecture was designed with a single layer and 100 neurons.

- Dropout regularization was not employed due to the simplicity of the problem, with only one layer present in the neural network, and the limited size of the dataset. It was found that adding dropout regularization for LSTM significantly decreased the model's performance on the test set.

- To ensure that the model did not overfit, the train and validation loss were closely monitored throughout the training process. A small learning rate of 0.0001 was selected to account for the size of the neural network and the limited size of the dataset.

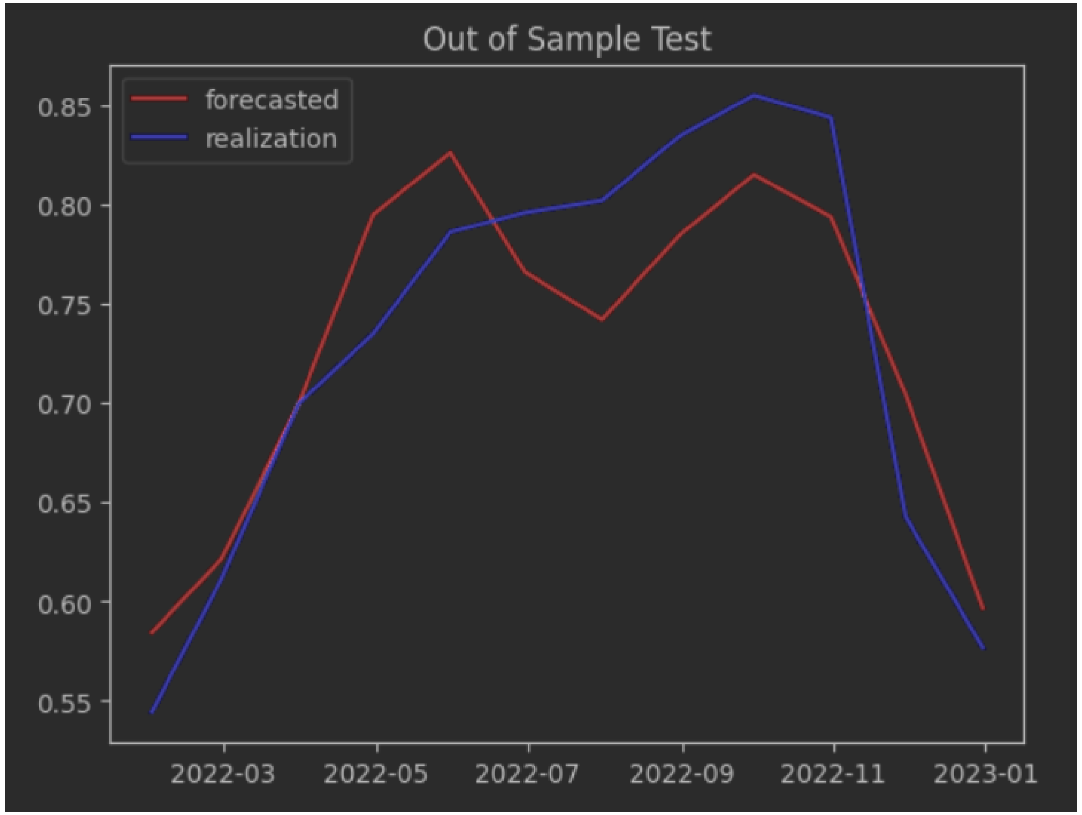
- The model is trained to forecast one step ahead, given the previous 12 time steps as input.

- The MSE for the univariate LSTM network is 0.00219, indicating that the model has a relatively low prediction error.



- Despite these fluctuations, the model overall captures the underlying movement of the inflation between the periods of 2022-2023.

- Overall, compared to the benchmark ARIMA(1,1,1) model, the LSTM network shows a significant improvement in terms of its forecasting power, indicating that the use of deep learning techniques can result in more accurate predictions of time series data.



- In order to improve the accuracy of the inflation rate forecast, it is common practice to include other relevant variables that may affect its behavior.

- In the case of the analysis in question, several variables have been identified as potentially influential, including the policy rate established by the Central Bank of Turkey, the value of the Turkish Lira relative to the US dollar, the M2 money supply, the industrial production index, the business tendency index, and the registered unemployment figures within the Turkish economy.

- To determine which of these variables may play a significant role in forecasting inflation, a Granger causality test is conducted.

- This test examines the causality relationship between two variables by analyzing whether the past values of one variable can be used to predict the future values of the other variable.

- It is important to note that one of the main assumptions of the Granger causality test is that the data is stationary. Therefore, prior to conducting the Granger causality test, the Augmented Dickey-Fuller (ADF) test is employed to determine whether the variables of interest are stationary.

- After preparing the data, the Granger causality test is conducted to examine the causal relationship between the variables and inflation rate. The output of the test is then examined using a significance level of 0.05 to determine whether the null hypothesis can be rejected

	Consumer_Price_x	interest_rate_x	M2_x	Real_ef_Ex_x	Ind_Prod_x	registered_unemp_x	Buisness_ten_x
Consumer_Price_y	1.0000	0.0000	0.0000	0.0000	0.4261	0.5353	0.6765
interest_rate_y	0.0004	1.0000	0.7439	0.8312	0.0190	0.7908	0.1315
M2_y	0.0140	0.0664	1.0000	0.0000	0.0000	0.1059	0.7490
Real_ef_Ex_y	0.0061	0.0723	0.0000	1.0000	0.0000	0.0765	0.3308
Ind_Prod_y	0.7907	0.5307	0.0000	0.0001	1.0000	0.0095	0.1002
registered_unemp_y	0.8525	0.7101	0.0256	0.1856	0.0417	1.0000	0.7163
Buisness_ten_y	0.2476	0.2184	0.3100	0.2890	0.1682	0.1114	1.0000

- The Granger causality test results show that for the industrial production index, the number of registered unemployed, and the business tendency index, we fail to reject the null hypothesis at the 0.05 significance level. Therefore, it can be concluded that these variables do not Granger cause inflation rate and can be excluded from the analysis.

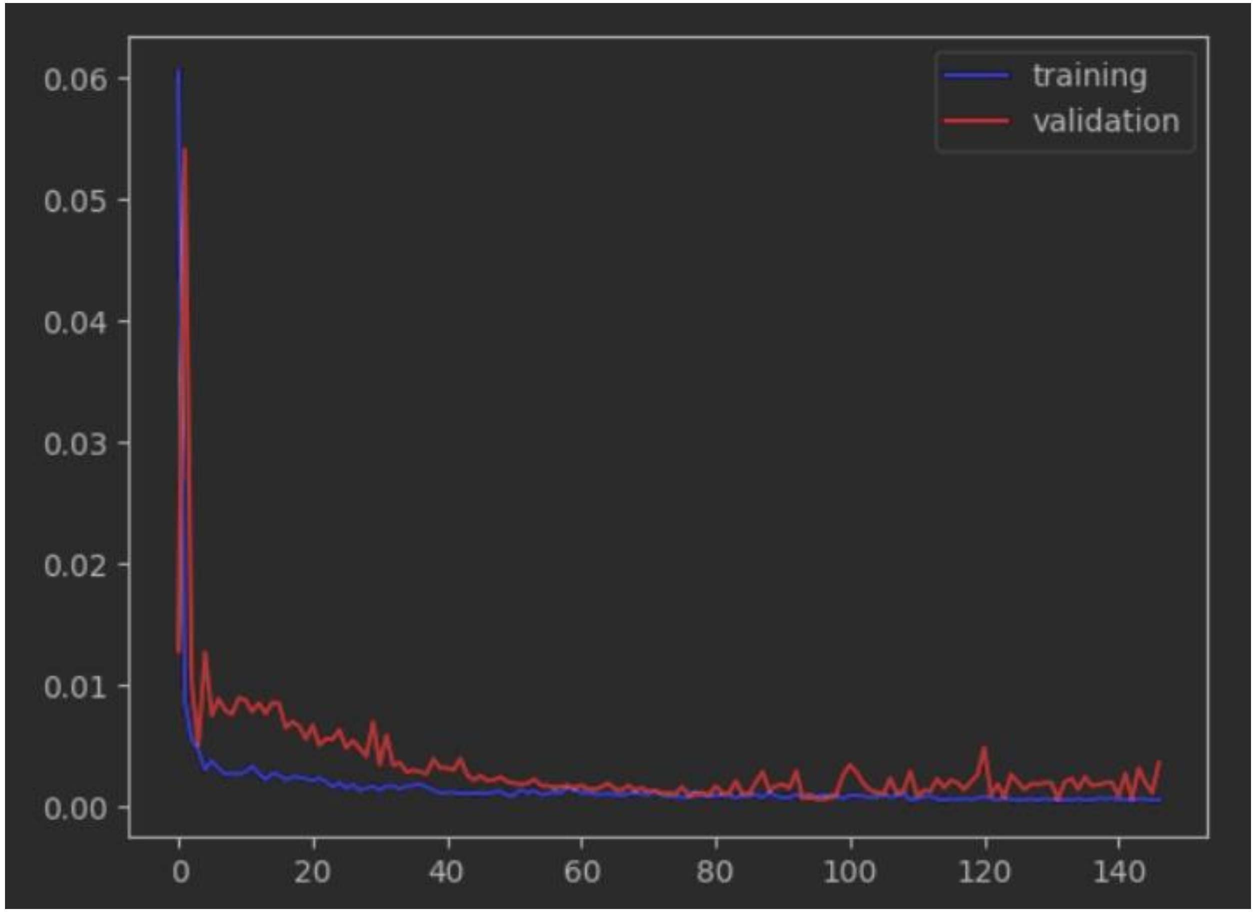
- The number of nodes in each LSTM layer was varied to find the optimal configuration that provided the best performance in terms of forecasting accuracy. After several experimental runs, it was found that the final model architecture consisting of two LSTM layers with 64 and 32 nodes respectively, followed by a Dropout layer with a rate of 20%, and a Dense output layer provided the best results.

- The model was then trained for 500 epochs, and the EarlyStopping and Dropout techniques were implemented to address the overfitting issue.

- To further fine-tune the hyperparameters, we use different combinations of hyperparameters to find the optimal configuration that provided the best performance

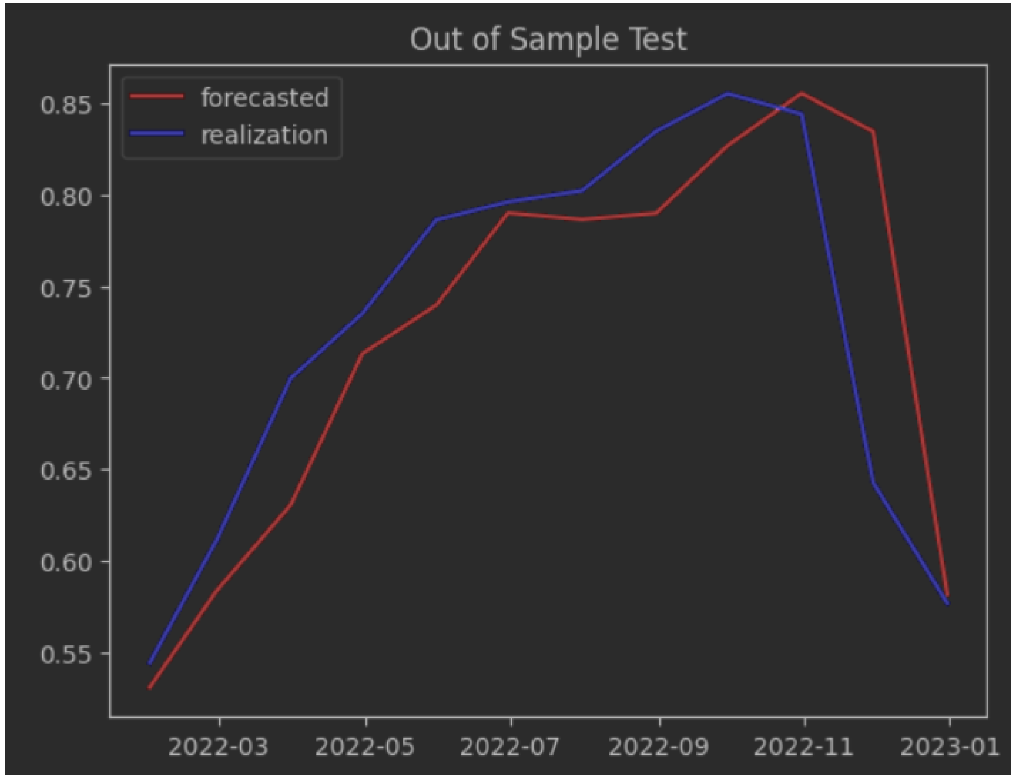
- The performance of the multivariate model compared to the univariate model appears to be quite impressive, as it captures the shape of inflation better and has a lower test mean squared error (MSE).

- Specifically, the test MSE for the model is 0.00035 whereas for univariate model it was 0.00219.



- This suggests that the multivariate model may be capturing more of the complex relationships between the various input features and the target variable.

- Overall, the results suggest that the multivariate LSTM model has a significant improvement over the univariate model for forecasting inflation, and could be a useful tool for decision-making in areas such as monetary policy and financial forecasting.



Summary and Conclusion

- The primary aim of this project was to employ LSTM networks for accurate inflation forecasting in Turkey, compare them with traditional methods like ARIMA, and evaluate both univariate and multivariate LSTM models.

- Three models were considered and compared in the analysis, namely ARIMA(1,1,1), univariate LSTM, and multivariate LSTM.

- Firstly, the ARIMA(1,1,1) model had a calculated MSE of approximately 0.014.

- Next, we trained a univariate LSTM network, which showed a significant improvement in forecasting power compared to the benchmark ARIMA(1,1,1) model. The MSE of the univariate LSTM was 0.00219.

- The final model considered in this study was the multivariate LSTM network.

- The MSE was found to be approximately 0.00035, suggesting that the multivariate LSTM model is able to forecast inflation rates with a reasonable level of accuracy. Compared to the benchmark ARIMA(1,1,1) model and the univariate LSTM network, the multivariate LSTM network exhibited a significant improvement in terms of its forecasting ability.

- This highlights the potential benefits of using multivariate LSTM models in forecasting time series data, as it allows for the incorporation of multiple variables that may have a causal relationship with the target variable.

- In terms of future improvements, this report can be further augmented by also including Bidirectional LSTMs into analysis and comparison to see whether BiLSTM models provide better predictions compared to ARIMA and LSTM models.

- Furthermore, the Gated Recurrent Unit can also be put into the analysis to see how it performs on the same task.