Inflation Forecasting for Pakistan using Artificial Neural Networks

By

Muhammad Jawwad

Fall 2017-MS(IT)-18-00000203885

Supervisor

Dr. Muhammad Muneeb Ullah

Department of Computing

A thesis submitted in partial fulfillment of the requirements for the degree of Masters of Science in Information Technology (MSIT)

In

School of Electrical Engineering and Computer Sciences (SEECS)
National University of Sciences and Technology (NUST)
Islamabad, Pakistan

August 2021

Approval

It is certified that the contents and form of the thesis entitled "Inflation Forecasting in Pakistan with Artificial Neural Networks" submitted by MUHAMMAD JAWWAD ASLAM have been found satisfactory for the requirement of the degree

Advisor : Dr. Muhammad Muneeb Ullah

Signature: ______________________

Date: 07-Aug-2021

Committee Member 1:Dr. Muhammad Latif Anjum

Signature:

06-Aug-2021

Committee Member 2:Dr. Muhammad Imran Malik

Signature: ______________________

Date: 06-Aug-2021

Signature: ______________________

Date: ______________________

THESIS ACCEPTANCE CERTIFICATE

Certified that final copy of MS/MPhil thesis entitled "Inflation Forecasting in Pakistan with Artificial Neural Networks" written by MUHAMMAD JAWWAD ASLAM, (Registration No 00000203885), of SEECS has been vetted by the undersigned, found complete in all respects as per NUST Statutes/Regulations, is free of plagiarism, errors and mistakes and is accepted as partial fulfillment for award of MS/M Phil degree. It is further certified that necessary amendments as pointed out by GEC members of the scholar have also been incorporated in the said thesis.

Signature: ______________________

Name of Advisor: Dr. Muhammad Muneeb Ullah

Date: 07-Aug-2021

Signature (HOD): ______________________

Date: ______________________

Signature (Dean/Principal): ______________________

Date: ______________________

Dedication

I dedicate everything to my parents for their love and affection. Also, to economists who are working hard for the country and its people. Further, to media and politics who brought my attention towards this topic by discussing it so frequently about it.

Robert Kiyosaki also deserves my special praise for the books he wrote which totally changed the way I used to think about money. It was a total mind shift.

Certificate of Originality

I hereby declare that this submission titled "Inflation Forecasting in Pakistan with Artificial Neural Networks" is my own work. To the best of my knowledge it contains no materials previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any degree or diploma at NUST SEECS or at any other educational institute, except where due acknowledgement has been made in the thesis. Any contribution made to the research by others, with whom I have worked at NUST SEECS or elsewhere, is explicitly acknowledged in the thesis. I also declare that the intellectual content of this thesis is the product of my own work, except for the assistance from others in the project's design and conception or in style, presentation and linguistics, which has been acknowledged. I also verified the originality of contents through plagiarism software.

Student Name:MUHAMMAD JAWWAD ASLAM

Student Signature: _______________

Acknowledgements

The work would never have been completed if it was not the support of my supervisor, friend (Sulman Shoukat) and the prayers of my parents. Further, I would like to acknowledge the support of my sister who helped me in my research work.

Table of Contents

List of Figures

List of Tables

Abstract

Inflation forecasting is an important activity at central banks to formulate forward looking monetary policy. So the interest rate can be adjusted in order to curb inflation in the country. For this various techniques and models are proposed, machine learning is one of those. In machine learning, artificial neural network (ANN) is a popular tool. Further, RNN-LSTMs are special type of artificial neural networks that learn better from sequential data. In the past, researchers used both regular and RNN based artificial neural networks, but either they used only inflation data for training or their model was implemented for any other country. While there are other factors too that influence the inflation rate. Therefore, we attempted to solve the same problem in context of Pakistan. Not only we implemented RNN-LSTM but used other relevant features such as oil prices and exchange rates to train the model. We found best network architecture for our RNN-LSTM based neural network and the baseline model by exhaustively trying different number of nodes and layers. Then we trained both models first using only year-on-year monthly inflation and after that using all available features. Thus we got

univariate and multivariate versions of both models i.e 4 models in total. Further, we ran all 4 models on Pakistan and the other four countries' datasets. At the end, our RNN-LSTM based model clearly outperformed the baseline model not only in case of Pakistan but for other countries as well.

1. Introduction

Inflation is a decrease in the purchasing power of money, reflected in a general increase in the prices of goods and services in an economy.[1] Doing its forecast is considered a significant exercise in central banks for devising forward looking monetary policy. Like in other areas, machine learning is finding its way to make forecasts; inflation forecasting is not any exception.[2] In machine learning, most popular tool for forecasting is artificial neural network (ANN).

Due to availability of large and high frequency data and advancements in computing, forecasters have started using Machine Learning for better predictions, particularly to account for structural break(s) in the series and nonlinearities in the underlying relationships. Machine Learning (ML) has different philosophy behind it compared to Traditional Statistics (TS). There is huge difference in approach and applications of the two: ML is a branch of Artificial Intelligence (AI) which aims to discover regularities in data through pattern recognition so that these regularities can be generalized (with purpose). It heavily relies on computing power whereas TS techniques were mostly developed when currently available computing powers were not available and statisticians had to rely on small samples and relatively slow computations that forced them to make heavy assumptions about data and its distributions (Hassibi, 2016).[3]

Central banks are also using ML for policy related analysis yet there is a little evidence for use of these techniques for inflation forecasting as regular tool. Only 22% central banks use ML tools according to a survey from 50 central banks.[2] These tools are data driven and are able to identify the underlying data generating process of a time series making them very effective in forecasting. One of the tools to forecast inflation under the broader umbrella of ML is Artificial Neural Networks (ANN). It keeps a part of the data for testing its own ability to identify the pattern(s) for prediction, and uses backpropagation to reach a trained network. The trained network is later used for forecasting.

1.1 Motivation

Purpose of macroeconomic policy formation is to make sustainable economic growth possible in low inflation environment. In addition to survey reports, central banks also consider short to medium term inflation forecasts, to define their monetary policy, particularly the interest rate. The accuracy of these inflation predictions matter significantly in effectiveness of monetary policy. During the last years, central bankers have devised many inflation forecasting models including theoretic and a theoretic. These models are not so reliable, at least occasionally, due to structural break(s) and unaccounted for nonlinearities in structural relationships. Further, each country has its own dynamics and nature, thus inflation also occurs in different way in different countries. For this, we are proposing RNN-LSTM neural network based solution that deals with sequential data very well.

1.2 Contribution

In 2018, Nadim et al. tried forecasting inflation in Pakistan using neural networks, which makes their research quite relatable to us. They first tried to find best network architecture by running different combinations of number of layers and nodes. Using the best architecture settings, they trained several models and averaged their prediction results to resolve the random weights initialization issue. As they average out the predictions of multiple networks, therefore they name their model as thick artificial neural network.[2] However, their model was univariate and they did not include other features that correlate very well with inflation such as oil price and exchange rate. Further, their model was not as sophisticated as RNN-LSTM to handle non-linearities and outliers. Given all that, we proposed methodology based on RNN-LSTM neural network and used additional features other than the CPI.

Along with that, we implemented our proposed model and Nadim Hanif et al model for four other countries i.e Canada, China, India and Sri lanka, to gauge their performance and ability to generalize.

1.2.1 RNN-LSTM Neural Network

LSTM represents a particular type of a recurrent neural network which is in turn a specific type a simple fully connected neural network. The difference between the NN and the recurrent neural network (RNN) comes from the recurrent nature of the latter. An RNN consists of a NN which is repeated as many times as there are data lags in the input.

1.2.2 Additional Features

Other than Year-on-Year monthly inflation, we used oil prices, exchange rates and other inflationary data deduced from consumer price index to train our model.

We performed features engineering and extracted multiple inflationary features from CPI. There details are mentioned below:

$$\text{Month} - \text{on} - \text{Month Inflation} = \frac{\text{Current Month CPI} - \text{Previous Month CPI}}{\text{Previous Month CPI}} * 100$$

$$\text{Quarter} - \text{on} - \text{Quarter Inflation} = \frac{\text{Current Month CPI} - \text{Previous 3rd Month CPI}}{\text{Previous 3rd Month CPI}} * 100$$

$$\text{Year} - \text{on} - \text{Year Inflation} = \frac{\text{Current Month CPI} - \text{Same Month CPI of Previous Year}}{\text{Same Month CPI of Previous Year}} * 100$$

1.2.3 Other Countries' Data

Along with Pakistan, we gathered data of 4 other countries with same features. The countries are Canada, China, India and Sri lanka. At the end, we were running the best performing models on the other countries dataset. We did it for both RNN-LSTM models and the Nadim et al.'s model.

1.3 Outline

First we discuss the work already done to solve this problem in chapter 2. Within that chapter we discuss our proposed methodology as well. Further, in chapter 3 we share details of the data we are working with and its collection. Then we talk about the experiments we ran and the results we got. Finally we summarize, conclude and propose future work that can be done to get better results.

2. Literature review

Artificial neural networks have been used for making predictions in many fields including rainfall (Chang, Rapiraju, Whiteside & Hwang, 1991)[4], airborne pollen (Arizmendi, Sanchez, Ramos & Ramos, 1993)[5], industrial production (Aiken, Krosp, Vanjani & Govindarajulu, 1995)[6], wind pressure profile (Turkkan & Srivastava, 1995)[7], and international airline passenger traffic (Nam and Schaefer, 1995)[8]. However, they may be used by financial institutions and applied to economic variables like commodity prices (Kohzadi, Boyd, Kermanshahi & Kaastra, 1996)[9], bankruptcy and business failure (Odom & Sharda, 1990[10]; Coleman, Graettinger & Lawrence, 1991[11]; Salchenberger, Cinar & Lash, 1992[12]; Tam & Kiang, 1992[13]; Fletcher & Goss, 1993[14]; Wilson & Sharda, 1994)[15], and credit scoring (Blanco, Pino-Mejías, Lara & Rayo, 2013[16]; Khashman, 2011[17]). Similarly, Anna Almosova et al.(2019) implemented RNN-LSTM neural network to forecast inflation for US. It was found that neural network outperformed linear autoregressive model (AR), the random walk model (RW), seasonal autoregressive model (SARIMA) and Markov switching model (MS-AR). Further, the RMSE for neural network was almost one third of the RMSE of random walk. However, their model was specifically designed to predict inflation for US only.[18] RNN-LSTM is one of the kind of fully-connected neural networks where prediction is computed sequentially after each time step of the input. Intermediate output, which is called the ”state” of the network, is used as an additional input at the next time step.

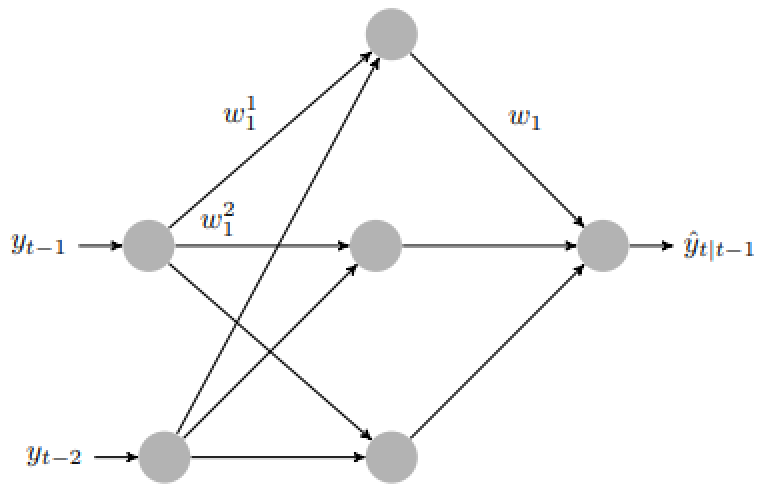

Figure 1: Fully-connected Neural Network (p=2)

The RNN's structure has two important features. First, the network is explicitly informed that the input lag y_{t-2} comes before the lag y_{t-1}. More recent lags are likely to be more influential for the final prediction. This stands opposite to the regular Neural Network that treats all the lags equally regardless of their sequence. Second, the network memorizes information about the distant input lags when predicting the final output. In text analysis, for example, if an RNN is used to guess the last word in the sentence, the first few words can tell the network about whether the sentiment of the sentence is positive or negative. In our application, the state of the RNN can potentially extract the information about trend or seasonality.

The LSTM network is used in a sequence similar to the aforementioned RNN of which it is a special kind. It is distinct through its internal structure consisting of so called "gates". These allow the network to decide on its own what part of the network state and the input it wants to remember on the next iteration and what part it can forget.

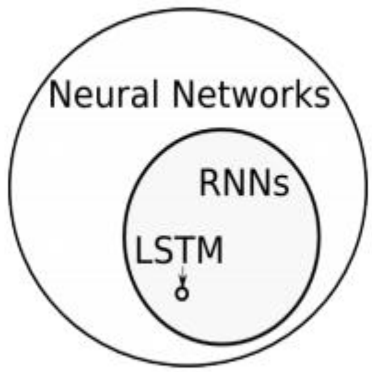

Figure 2.1 Classification of Artificial Neural Networks

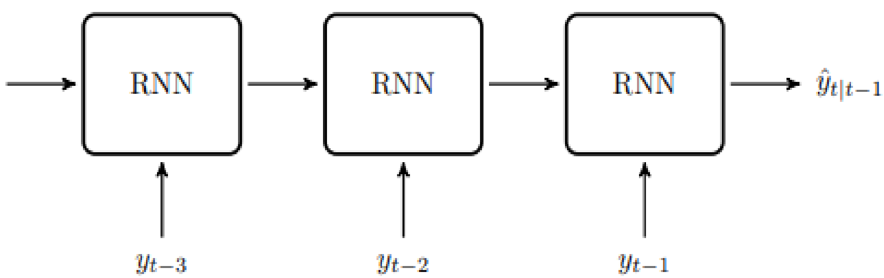

Figure 2.2 Recurrent Neural Network Representation

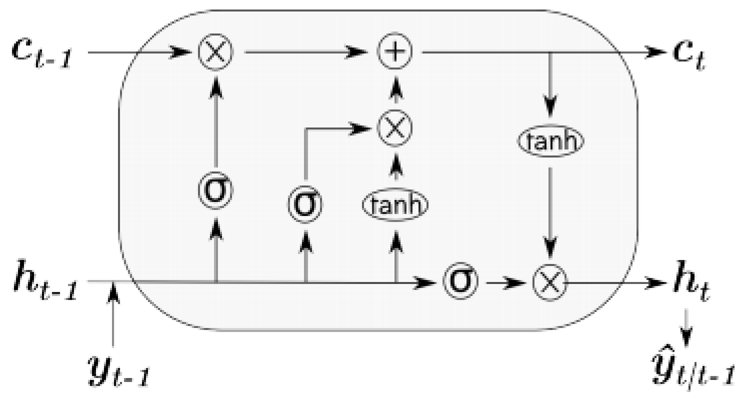

Figure 2.3 LSTM Cell Representation

Here y_{t-1} represents the input at the time step t (for example a lagged inflation value). c is the "state" of the network which represents its memory about the past. ht denotes the output of the LSTM at the step t. σ and tanh represent the gates which are small neural networks that have the sigmoid function or the hyperbolic tangent function as activations at the output. On the left of the diagram one can see that the prediction of the network for the period t that was computed on the previous step (h_{t-1}) and the input value at this step (y_{t-1}) are combined and then filtered through the four gates. These determine what part of the state c_{t-1} should be forgotten, what and how much information should be added to the state and how the prediction for the step t should be adjusted based on the state. On the right side of the diagram the output of the cell is presented: it is a new updated value h_t , and $\hat{y}$ that is computed from it.(Anna Almosova et al 2019) [4]

Prior to this, . Ahmed et al. (2010) and Stock & Watson (1998) judged linear and nonlinear methods for macroeconomic forecasting by averaging their performance over a large number of macro time series[19]. These studies also found that simple Neural Networks perform well at short forecasting horizons.[12] Similarly, Chen et al. (2001), Nakamura (2005) and McAdam & McNelis (2005) carried out studies that show that Neural Networks outperform benchmark linear models for shorter horizons based on various evaluation metrics.[20]

Elger et al. (2006) implemented recurrent neural network but of a different class than the LSTMs analyzed here. They show that for shorter horizons recurrent NNs are comparable with Markov switching autoregressive models and at longer horizons Markov switching models are more accurate. However, they used a different type of recurrent neural network, different cross-validation and forecast evaluation procedures. Moreover, they used GDP inflation data while we relied on Consumer Price Index based inflation. [21]

In 2015, Malik et al carried out a study and compared different inflation forecasting models in context of Pakistan. They used RMSE as an evaluation metric and found out the 3 models that give best results when predicting inflation for Pakistan. Those three models are External Structural VAR, Bayesian External VAR model, and Bayesian Credit VAR model. As that was a recent study that time and it was quite relevant, so Nadim et al considered 3 models as baseline models for their work[22].

Nadim et al. implemented artificial neural network for predicting inflation in Pakistan. They first created neural networks by using different number of layers and neurons. Then, they used monthly YoY inflation to train those models. The models were then tested and the network architecture that gave best results was selected. After resolving the best architecture setting problem, another problem was of random weights initialization. For this, they used best architecture settings to design/train multiple neural networks and then predicted inflation for last 2 years (24 forecasts). Those predictions of each models were then averaged out. Hence the random weights initialization problem was taken care of.

3. Datasets

We used monthly historical data of consumer price index, oil prices and exchange rate of 5 countries including Pakistan. In addition to that we included monthly inflation rate, quarterly inflation rate, 12 Months Moving Average Inflation and monthly Year on Year inflation in our dataset.

3.1 Data Collection

3.1.1 Pakistan

We gathered consumer price index data from Pakistan Bureau of Statistics website.[23] The data ranges between Jan 1959- Dec 2020. Thus, we have 744 rows of monthly CPI data i.e 62 years. Using the data we calculated Monthly, Quarterly, 12-Months Moving Average and YoY monthly inflation. In addition to that, exchange rates data of the same period was collected from ceidata website.

3.1.2 Canada

The consumer price index data for Canada was collected from OECD.[24] It ranged from Jan 1962 to June 2018 and comprised of 678 rows i.e 56.5 years. Similarly exchange rate data of the same period was fetched from federal reserve board. [25]

3.1.3 China

The CPI data of China was collected from Federal Reserve Economic Data website.[25] It belonged to the period of Jan 1995 - June 2018 and contained 282 rows i.e 23.5 years. Further, the exchange rate data of the same period was taken from International Monetary Fund. [26]

3.1.4 India

The exchange rate and CPI data of India was fetched from International Monetary Fund.[26] It ranged from Jan 1960 to June 2018 and consisted of 702 rows i.e 58.5 years.

3.1.5 Sri Lanka

The CPI data of Sri Lanka was collected from World Bank.[27] It belonged to the period of Jan 1962-Mar 2021 and composed of 744 rows i.e 59.25 years. Exchange rate data of the same period was taken from International Monetary Fund.

The international oil price data was same for all countries and it was collected from Federal Reserve Bank of St.Louis website.[25]

3.2 Sample Data

The data we worked on had 8 features in it. Such as Time, Consumer Price Index, Month-on-Month Inflation (MoM), Quarter-on-Quarter Inflation (QoQ), 12 Months Moving Average Inflation, Exchange Rate, Oil Price and Monthly Year-on-Year inflation. Let's describe them briefly below:

3.2.1 Consumer Price Index (CPI)

The Consumer Price Index measures the average change in prices over time that consumers pay for a basket of goods and services. In case of Pakistan, Pakistan Burea of Statistics publishes the details about it.

3.2.2 Crude Oil

Crude oil is a naturally occurring petroleum product composed of hydrocarbon deposits and other organic materials. A type of fossil fuel, crude oil is refined to produce usable products including gasoline, diesel, and various other forms of petrochemicals. Its price was used as a feature in model.

3.2.3 Exchange Rate

An exchange rate is the value of a nation's currency in terms of the currency of another nation or economic zone. It varies with time according to the market dynamics, economy and polices of that country.

3.2.4 Extracted Features

Other features such as MoM, QoQ, 12 Months Moving Average and YoY inflation are calculated from Consumer Price Index.

Time	CPI	MoM	QoQ	12 Month Moving Average	Exchange Rate	Oil – Crude Prices	YoY
Jan-95	41.96	1.46	3.92	12.71	17.99	30.92	15.38
Feb-95	41.94	-0.06	2.42	12.86	18.53	30.97	13.84
Mar-95	42.31	0.88	2.30	13.05	18.55	30.97	14.32
Apr-95	42.36	0.12	0.95	12.93	19.87	30.95	11.80

Table 3.1 Pakistan Dataset

Time	CPI	MoM	QoQ	12 Month Moving Average	Exchange Rate	Oil - Crude Prices	YoY
Jan-95	68.42	0.35	1.05	0.11	1.41	17.99	0.58
Feb-95	68.74	0.46	0.93	0.25	1.40	18.53	1.87
Mar-95	68.90	0.23	1.04	0.41	1.41	18.55	2.11
Apr-95	69.13	0.34	1.04	0.59	1.38	19.87	2.46

Table 3.2 Canada Dataset

Time	CPI	MoM	QoQ	12 Month Moving Average	Exchange Rate	Oil - Crude Prices	YoY
Jan-95	62.14	2.89	5.07	24.48	17.99	8.46	24.10
Feb-95	62.70	0.91	5.28	24.39	18.53	8.46	22.40
Mar-95	62.88	0.28	4.11	24.25	18.55	8.45	21.30
Apr-95	64.01	1.79	3.01	24.12	19.87	8.44	20.70

Table 3.3 China Dataset

Time	CPI	MoM	QoQ	12 Month Moving Average	Exchange Rate	Oil - Crude Prices	YoY
Jan-95	2.42	-42.49	-26.10	-30.70	17.99	49.87	-76.35
Feb-95	1.04	-56.96	-62.40	-37.14	18.53	49.90	-91.39
Mar-95	-0.89	-185.41	-121.14	-49.31	18.55	49.63	-106.12
Apr-95	0.71	-179.21	-70.88	-63.31	19.87	49.37	-95.85

Table 3.4 Sri Lanka Dataset

Time	CPI	MoM	QoQ	12 Month Moving Average	Exchange Rate	Oil - Crude Prices	YoY
Jan-95	9.89	4.39	-4.07	55.15	17.99	31.37	8.29
Feb-95	9.81	-0.76	0.00	46.30	18.53	31.38	-1.48

Mar-95	9.74	-0.74	2.83	39.95	18.55	31.59	-1.41
Apr-95	9.67	-0.75	-2.24	34.91	19.87	31.41	-1.34

Table 3.5 India Dataset

Further, we divided the data into 70% training, 15% validation and 15% test set.

4. Experiments & Results

In this chapter, we present quantitative analysis of our models performance against baseline and state of the art architectures.

4.1 Experimental Protocol

We implemented state of the art model and compared it with our proposed model. Both univariate and multivariate versions of the models with best architectures were tried. To find the best architecture, we first divided Pakistan's dataset in 70% training, 15% validation and 15% test set, then trained our model using different number of nodes, epochs and hidden layers. The settings with best results were selected to be later used in testing phase. As activation function, tanh was used for all models except RNN Multivariate model where relu was used.

After finding best performing models, we used them to predict inflation of other countries i.e Canada, Srilanka, India and China.

As we already have historical data of inflation, so to gauge the performance of models, we used root mean square error. Further, we relied on HIM metric which was used by Hamid et al to check the performance of models.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \quad (O-P)^2}$$

O - Observed Values

P - Predicted Values

N - Number of Observations

$$HIM = \frac{1}{2} * \left(\frac{1}{e^{RMSE}} + \frac{c}{h-1}\right)$$

h - No. of forecast horizons

c - No. of times forecast series crosses the actual series

4.2 Results

After performing validation on all 4 models, we got following results. The figures in layer columns indicate the number of neurons in that layer. Tanh was used as an activation function for all models except RNN Multivariate's case where Relu was used instead. Further, the best performing architecture is highlighted with bold in the table.

4.2.1 Validation Results

4.2.1.1 Nadim et al.'s Univariate Model [2]

Sr.No	Layer 1	Layer 2	Layer 3	RMSE	HIM
1.	4	-	-	0.925	0.453
2.	8	-	-	0.936	0.442
3.	16	-	-	0.937	0.441
4.	32	-	-	0.943	0.422
5.	64	-	-	0.938	0.432
6.	**128**	**-**	**-**	**0.924**	**0.435**
7.	4	4	-	0.937	0.455
8.	8	8	-	0.926	0.443
9.	16	16	-	0.957	0.428
10.	32	32	-	0.935	0.423
11.	64	64	-	0.937	0.455
12.	128	128	-	0.941	0.451

13.	4	4	4	0.939	0.436
14.	8	8	8	0.940	0.441
15.	16	16	16	0.977	0.424
16.	32	32	32	0.942	0.431
17.	64	64	64	1.169	0.391
18.	128	128	128	1.173	0.248

Table 4.1 Baseline Univariate Model Validation Results

During validation, it was found that RMSE increases with the number of layers. However, the HIM value was improving but at the cost of RMSE. After applying various combinations of number of neurons and layers, the best setting found was of 1 layer and 128 neurons along with tanh activation function as shown in Table 4.1. The RMSE of 0.924 and HIM value of 0.435 was achieved on that settings.

4.2.1.2 Nadim et al.'s Multivariate Model [2]

Sr.No	Layer 1	Layer 2	Layer 3	RMSE	HIM
1.	**4**	**-**	**-**	**0.130**	**0.476**

2.	8	-	-	0.223	0.428
3.	16	-	-	0.294	0.438
4.	32	-	-	1.702	0.091
5.	64	-	-	1.249	0.143
6.	128	-	-	2.576	0.047
7.	4	4	-	0.131	0.438
8.	8	8	-	0.426	0.377
9.	16	16	-	1.459	0.116
10.	32	32	-	1.746	0.110
11.	64	64	-	4.902	0.004
12.	128	128	-	4.933	0.003
13.	4	4	4	0.318	0.392
14.	8	8	8	0.552	0.316
15.	16	16	16	1.058	0.211
16.	32	32	32	0.742	0.358
17.	64	64	64	5.392	0.053

18.	128	128	128	5.692	0.051

Table 4.2 Baseline Multivariate Model Validation Results

As visible from Table 4.2, the performance was degrading in this case with increasing number of layers and nodes. The best results were achieved on settings with 1 layer, 4 nodes and tanh used as activation function. RMSE and HIM of 0.130 and 0.476 was achieved on this setting.

4.2.1.3 RNN-LSTM Univariate Model

Sr.No	Layer 1	Layer 2	Layer 3	RMSE	HIM
1.	4	-	-	0.027	0.639
2.	8	-	-	0.026	0.649
3.	16	-	-	0.025	0.659
4.	32	-	-	0.022	0.725
5.	64	-	-	0.022	0.725
6.	128	-	-	0.022	0.762
7.	4	4	-	0.038	0.587
8.	8	8	-	0.025	0.659

9.	16	16	-	0.023	0.678
10.	32	32	-	0.023	0.753
11.	64	64	-	0.022	0.743
12.	128	128	-	0.023	0.725
13.	4	4	4	0.038	0.569
14.	8	8	8	0.027	0.648
15.	16	16	16	0.024	0.659
16.	**32**	**32**	**32**	**0.023**	**0.752**
17.	64	64	64	0.023	0.725
18.	128	128	128	0.022	0.734

Table 4.3 RNN-LSTM Univariate Model Validation Results

In this scenario, the performance of model degrades as we increase the number of layer both RMSE and HIM wise. However, increasing the number of neurons, significantly improves the results as shown in Table 4.3. Therefore, the best result was found on architecture with 3 number of layers, 32 neurons in each layer and tanh used as an activation function.

4.2.1.4 RNN-LSTM Multivariate Model

Sr.No	Layer 1	Layer 2	Layer 3	RMSE	HIM
1.	4	-	-	0.151	0.457
2.	8	-	-	0.049	0.522
3.	16	-	-	0.047	0.569
4.	32	-	-	0.088	0.485
5.	64	-	-	0.125	0.469
6.	128	-	-	0.056	0.491
7.	4	4	-	0.136	0.436
8.	8	8	-	0.090	0.494
9.	16	16	-	0.092	0.479
10.	32	32	-	0.046	0.542
11.	64	64	-	0.045	0.580
12.	**128**	**128**	**-**	**0.038**	**0.597**
13.	4	4	4	0.218	0.402
14.	8	8	8	0.220	0.401
15.	16	16	16	0.215	0.403

16.	32	32	32	0.085	0.478
17.	64	64	64	0.077	0.481
18.	128	128	128	0.068	0.536

Table 4.4 RNN-LSTM Multivariate Model Validation Results

As you can see in the Table 4.4, the model was depicting a random behavior with increase in number of layers and neurons. However, the best combination found was of 2 layers with 128 neurons in each layer with relu used as an activation function. We got RMSE of 0.038 and HIM of value 0.597 on this best found architecture.

4.2.2 Optimized Models

Following models and settings were found to be best after performing validation.

Nadim et al.'s Univariate Model		**Nadim et al.'s Multivariate Model**	
Layers	1	Layers	1
Nodes	128	Nodes	4
Epochs	500	Epochs	400
Activation Function	tanh	Activation Function	tanh
RNN-LSTM Univariate Model		**RNN-LSTM Multivariate Model**	
Layers	3	Layers	2
Nodes	32,32,32	Nodes	128,128
Epochs	200	Epochs	500
Activation Function	tanh	Activation Function	Relu

Table 4.5 Optimized Models Summary

4.2.3 Test Results

Best architecture from every model was selected and all four models were run on the remaining 15% test data set using the same architecture.

Sr.No	Model Name	RMSE	HIM
1	Nadim et al.'s Univariate Model	1.111	0.401
2	Nadim et al.'s Multivariate Model	0.162	0.458
3	RNN-LSTM Univariate Model	0.020	0.685
4	RNN-LSTM Multivariate Model	0.141	0.496

Table 4.6 Test Results

As shown in Table 4.5, both univariate and multivariate models of RNN-LSTM outperformed the Nadim et al.'s model. However, out of all 4 models, the RNN-LSTM univariate model gave the best results. Further, it was observed that by adding features in RNN-LSTM model, the RMSE increase hence the overall performance degrades. While in case of Nadim et al.'s model, the performance significantly improves as we add more features for training the model.

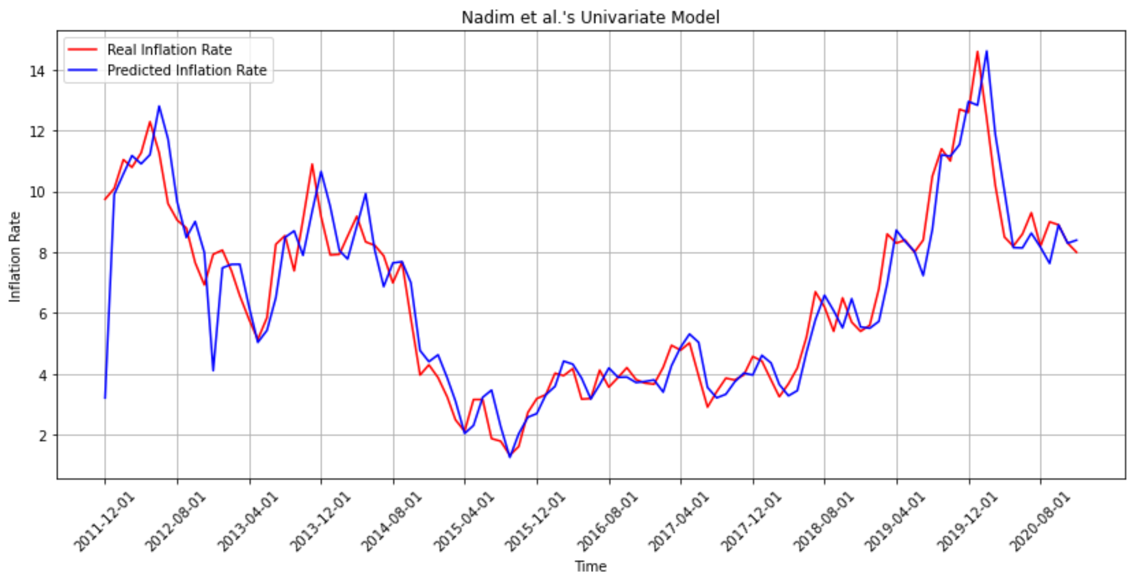

Figure 4.1 Baseline Univariate Model

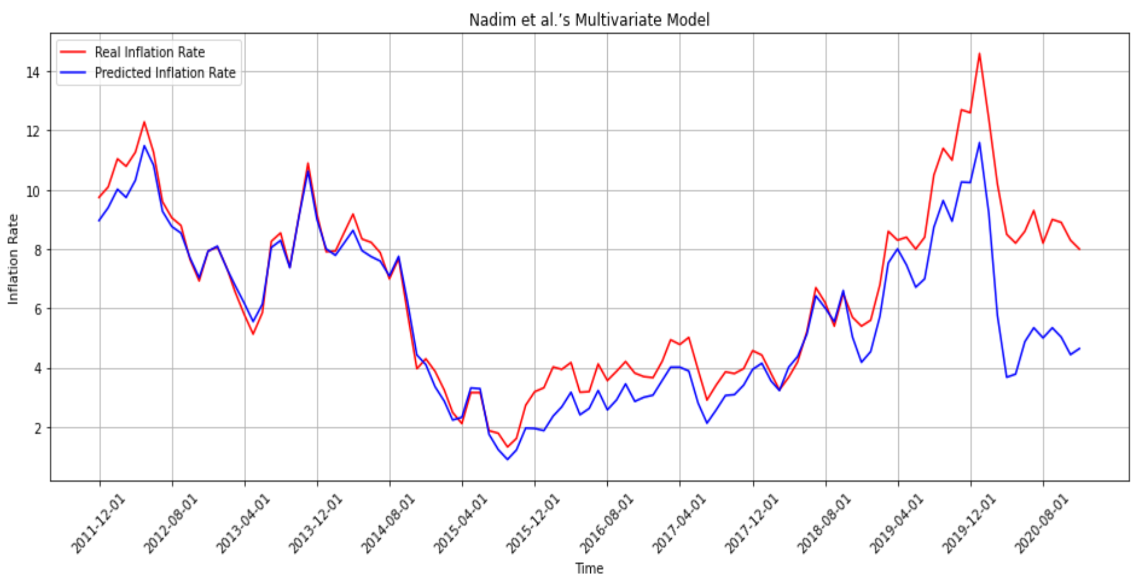

Figure 4.2 Baseline Multivariate Model

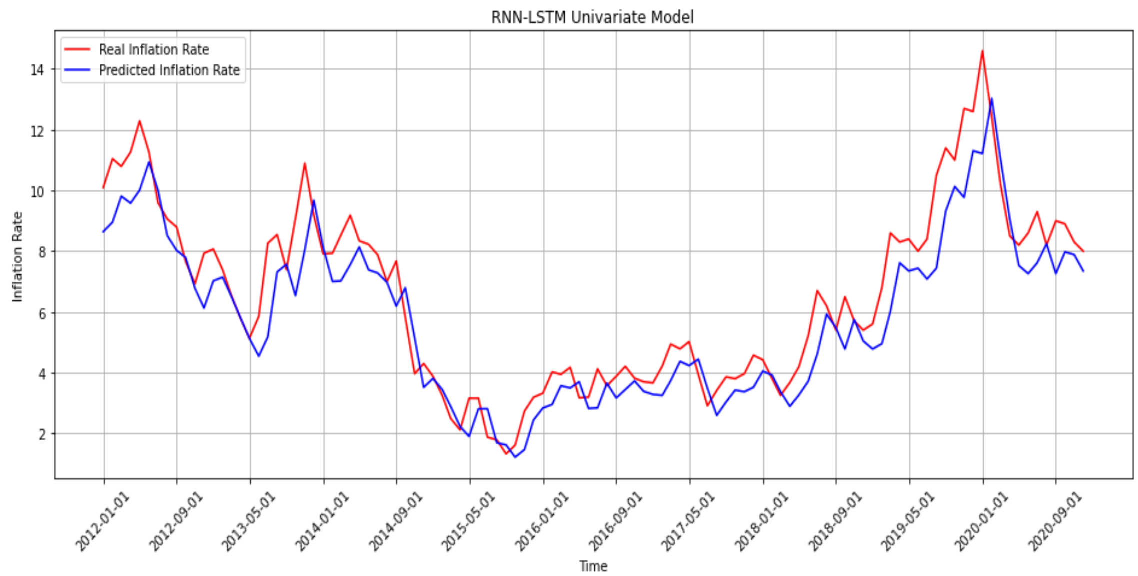

Figure 4.3 RNN-LSTM Univariate Model

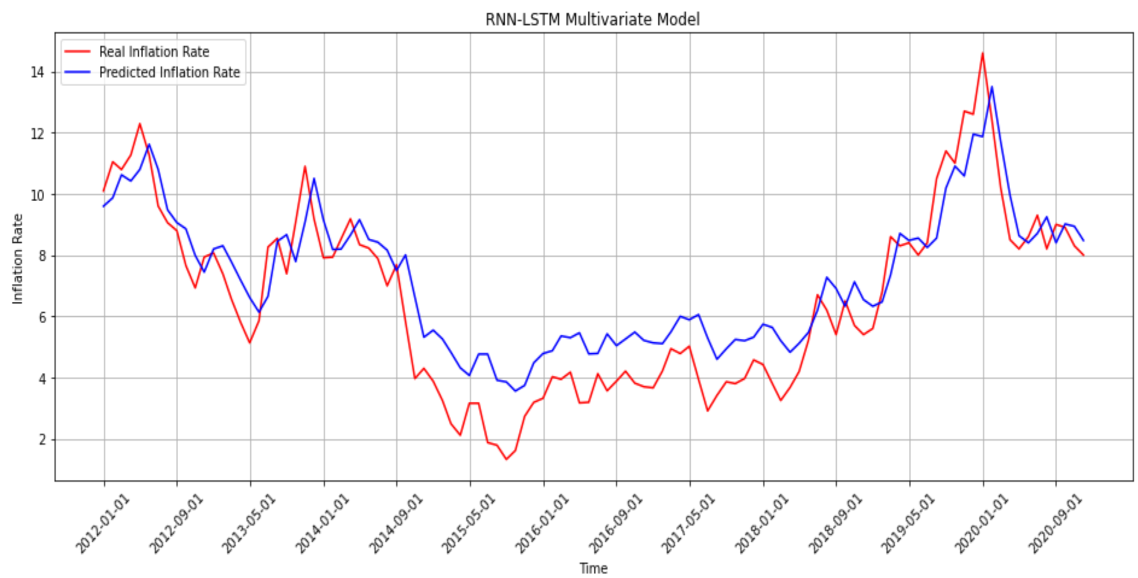

Figure 4.4 RNN-LSTM Multivariate Model

The results showed that RNN-LSTM univariate model is giving best results, followed by it's multivariate version with a narrow margin. However, one thing to note here is the difference between performance of Nadim et al univariate and multivariate models. It indicates that adding features to Nadim et al.'s model significantly improves its performance.

4.2.4 Other Countries Results

Subsequently after running our models on Pakistan's dataset, we ran the best models on other four countries' dataset without validation. Their results are as follows.

4.2.4.1 Nadim et al.'s Univariate Model [2]

Sr. No	Country	RMSE	HIM
1	Canada	0.358	0.601
2	China	0.404	0.611
3	India	9.579	0.268
4	Sri Lanka	7.872	0.041

Table 4.7 Baseline Univariate Model Results

The model's performance was satisfactory in case of Canada and China dataset. However, the results varied with a large margin in case of India and Sri Lanka from the ground truth.

4.2.4.2 Nadim et al.'s Multivariate Model [2]

Sr. No	Country	RMSE	HIM
1	Canada	0.997	0.535
2	China	0.088	0.503
3	India	3.101	0.030
4	Sri Lanka	8.689	0.036

Table 4.8 Baseline Multivariate Model Results

After adding different features in the training set, the results were improved for China and India dataset. While overall the model performed best for China and worst for Sri Lanka dataset.

4.2.4.3 RNN-LSTM Univariate Model

Sr. No	Country	RMSE	HIM
1	Canada	0.029	0.711

2	China	0.018	0.696
3	India	4.873	0.111
4	Sri Lanka	0.073	0.553

Table 4.9 RNN-LSTM Univariate Model Results

The model performed comparatively better than the Nadim et al.'s model for all 4 countries. It gave best results for Canada and worst result for India dataset. However, its performance was best for India data set compare to other models.

4.2.4.4 RNN-LSTM Multivariate Model

Sr. No	Country	RMSE	HIM
1	Canada	0.037	0.659
2	China	0.019	0.723
3	India	4.930	0.079
4	Sri Lanka	0.064	0.551

Table 4.10 RNN-LSTM Multivariate Model Results

It gave best results for China and Sri Lanka dataset compare to other models. However, it performed worst for India data set. Also, from the Table 4.8 and

4.9, it is clear that adding more features to RNN-LSTM univariate model improves the performance for China and Sri Lanka dataset. However, its performance degrades for Canada and India dataset.

The best result for each country is underlined in above tables for reference. Further, by deliberating upon the above results, one might see that India models are not performing well on India dataset. It can be attributed to the existence of some outliers in the data.

5. Conclusion and Future Work

We considered Nadim et al.'s model as a baseline mode because their work was latest, relatable and also it was in context of Pakistan. Further, they also used neural networks to forecast inflation for Pakistan. While we used RNN-LSTM based model to predict inflation for Pakistan. Further, unlike Nadim et al, we did not rely only on monthly YoY inflation, we included additional features like oil price and exchange rate too in the training data. We divided the data in 70-15-15 data split and trained all 4 models i.e Nadim et al's univariate & multivariate models and RNN-LSTM based univariate & multivariate models, on the 70% data. We made multiple neural networks by changing the number of layers and nodes. Then we performed validation for every model on 15% validation data. After doing that we found out the best architecture settings for every model and then ran the models on remaining 15% of the data by using those settings.

At the end, RNN-LSTM neural network significantly outperformed Nadim et al model in forecasting inflation. Not only it learns more from sequential data, but also handled outliers comparatively better. However, adding more features like oil price and exchange rate etc degraded its performance. While, Nadim et al model performance was clearly improved after including those features. Other than Pakistan, RNN-LSTM performed better also in case of Canada, Sri Lanka, India and China. However, in case of China and Sri Lanka, its performance was improved by adding oil price and exchange rate features.

5.1 Future Work

As mentioned earlier, performance of RNN-LSTM model degraded upon adding more features. Therefore, we propose features selection exercise. Also, we did not perform model validation selection exercise for other 4 countries' dataset. Which can be done to improve results for their scenario. Further, we suggest implementation of transfer learning to benefit from the existing and already trained models. In addition to that, other features like credit to private sector, government borrowings and currency notes printing may be included in training data as they significantly impact inflation.

6. References

1) Inflation Definition: Formula & How to Calculate (investopedia.com)

2) Nadim et al. (2018) A Thick ANN Model for Forecasting Inflation (repec.org)

3) Hassibi, K. (2016). Machine Learning vs. Traditional Statistics: Diffrent philosophies, Different Approaches. Retrieved from:https://www.datasciencecentral.com/profiles/blogs/machine-learning-vstraditional-statistics-different-philosophi-1

4) Chang, I., Rapiraju, S., Whiteside, M., & Hwang, G. (1991). A neural network to time series forecasting. Proceedings of the Decision Science Institute (Vol. 3, pp. 1716-1718)

5) Arizmendi, C. M., Sanchez, J. R., Ramos, N. E., & Ramos, G. I. (1993). Time series predictions with neural nets: application to airborne pollen forecasting. International journal of biometeorology, 37(3), 139-144

6) Aiken, M., Krosp, J., Vanjani, M., & Govindarajulu, C. (1995). A neural network for predicting total industrial production. Journal of End User Computing, 7, 19-19

7) Turkkan, N., & Srivastava, N. K. (1995). Prediction of wind load distribution for air-supported structures using neural networks. Canadian Journal of Civil Engineering, 22(3), 453-461

8) Nam, K., & Schaefer, T. (1995). Forecasting international airline passenger traffic using neural networks. Logistics and Transportation Review, 31(3), 239

9) Kohzadi, N., Boyd, M. S., Kermanshahi, B., & Kaastra, I. (1996). A comparison of artificial neural network and time series models for forecasting commodity prices. Neurocomputing, 10(2), 169-181

10) Odom, M. and R. Sharda, 1990. A neural network model for bankruptcy prediction. Proceedings of the IEEE International Conference on Neural Networks (San Diego, CA) 163-168

11) Coleman, K. G., Graettinger, T. J., & Lawrence, W. F. (1991). Neural networks for bankruptcy prediction: The power to solve financial problems. AI Review, 4, 48-50

12) Salchenberger, L. M., Cinar, E., & Lash, N. A. (1992). Neural networks: A new tool for predicting thrift failures. Decision Sciences, 23(4), 899-916

13) Tam, K. Y., & Kiang, M. Y. (1992). Managerial applications of neural networks: the case of bank failure predictions. Management Science, 38(7), 926-947

14) Fletcher, D., & Goss, E. (1993). Forecasting with neural networks: an application using bankruptcy data. Information & Management, 24(3), 159-167

15) Wilson, R. L., & Sharda, R. (1994). Bankruptcy prediction using neural networks. Decision Support Systems, 11(5), 545-557

16) Blanco, A., Pino-Mejías, R., Lara, J., & Rayo, S. (2013). Credit scoring models for the microfinance industry using neural networks: Evidence from Peru. Expert Systems with applications, 40(1), 356-364

17) Khashman, A. (2011). Credit risk evaluation using neural networks: Emotional versus conventional models. Applied Soft Computing, 11(8), 5477-5484

18) Anna Almosova et al. (2019) Nonlinear inflation forecasting with recurrent neural networks (europa.eu)

19) Ahmed, Nesreen K, Atiya, Amir F, Gayar, Neamat El, & El-Shishiny, Hisham. 2010. An empirical comparison of machine learning models for time series forecasting. Econometric Reviews, 29(5-6), 594–621.

20) Chen, Xiaohong, Racine, Jeffrey, & Swanson, Norman R. 2001. Semiparametric ARX neural-network models with an application to forecasting inflation. IEEE Transactions on neural networks, 12(4), 674–683.

21) Elger, Thomas, Binner, Jane, Nilsson, Birger, & Tepper, Jonathan. 2006. Predictable non-linearities in U.S. Inflation. 93(02), 323–328.

22) Hanif, M., & Malik, M. J. (2015). Evaluating the Performance of Inflation Forecasting Models of Pakistan. SBP Research Bulletin, 11, 43-78

23) Consumer Price Index data: Pakistan Bureau of Statistics (pbs.gov.pk)

24) Organization for Economic Co-operation and Development, Consumer Price Index: Total, All Items for Canada [CPALCY01CAM661N],

retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPALCY01CAM661N, July 27, 2021.

25) Federal Reserve Board: https://www.federalreserve.gov

26) International Monetary Fund: https://www.imf.org

27) World Bank: https://www.worldbank.org/