Inflation Forecasting using HYBRID ARIMA-LSTM Model

By

Hira Jamil

A thesis submitted in partial fulfillment

of the requirements for the degree of

Master of Science (MSc) in Computational Sciences

The Faculty of Graduate Studies
Laurentian University
Sudbury, Ontario, Canada

THESIS DEFENCE COMMITTEE/COMITÉ DE SOUTENANCE DE THÈSE
Laurentian Université/Université Laurentienne
Office of Graduate Studies/Bureau des études supérieures

Title of Thesis Titre de la thèse	Inflation Forecasting using HYBRID ARIMA-LSTM Model
Name of Candidate Nom du candidat	Jamil, Hira
Degree Diplôme	Master of Science
Department/Program Département/Programme	Computational Sciences
Date of Defence Date de la soutenance	January 07, 2022

APPROVED/APPROUVÉ

Thesis Examiners/Examinateurs de thèse:

Dr. Kalpdrum Passi
(Supervisor/Directeur(trice) de thèse)

Dr. Ratvinder Grewal
(Committee member/Membre du comité)

Dr. Oumar Gueye
(Committee member/Membre du comité)

Dr. MV Druga Prasad
(External Examiner/Examinateur externe)

Approved for the Office of Graduate Studies
Approuvé pour le Bureau des études supérieures
Tammy Eger, PhD
Vice-President Research (Office of Graduate Studies)
Vice-rectrice à la recherche (Bureau des études supérieures)
Laurentian University / Université Laurentienne

ACCESSIBILITY CLAUSE AND PERMISSION TO USE

Abstract

Prediction of time series is one of the most demanding research areas due to the nature of various time series i.e., stocks, inflation, stock indexes etc. Various methods have been used in the past to forecast such time series, however, Machine Learning (ML) methods have been suggested in the academic literature as alternatives to statistical ones for time series forecasting. Yet, scant evidences are available about their relative performance in order of their accuracies and computational requirements. In this thesis, a hybrid model consisting of ARIMA and LSTM is proposed and compared with individual models ARIMA, LSTM, and PROPHET for inflation forecasting. Two Scale-dependent metrics namely mean absolute error (MAE) and root mean square error (RMSE), one Percentage-error metric, mean absolute percentage error (MAPE) and coefficient of determination (R^2) are used to evaluate the variance between dependent and independent parameters for inflation forecasting in developed and developing countries. Consumer Price Index (CPI) data is collected monthly to reflect the effect of price inflation at consumer level. Most of the central banks depend on inflation forecast to inform their respective monetary policy makers and to enhance the efficacy of monetary policy. The publicly available CPI data is presented for analysis and evaluation of price inflation effects on developed and developing countries. For this research work, six developed countries (Canada, United States, Australia, Norway, Poland and Switzerland) and six developing countries (Colombia, Indonesia, Brazil, South Africa, India and Mexico) with different durations are targeted to evaluate the performances of proposed machine learning model and the individual models to forecast inflation (CPI). The proposed HYBRID model with one-step ahead forecasting outperformed every other model for forecasting inflation (CPI) of developed and developing countries regardless of duration. The best performance was observed by taking 90% training data and 10% testing data. All

forecasting models performed better on data of six developed countries with overall average errors of 1.023796 in MAE, 0.009648 in MAPE and 1.222454 in RMSE when taking 10% as test data. While in the case of developing countries overall average errors of MAE, MAPE and RMSE was 1.361308, 0.011847, and 1.562288 respectively. Also, in the case of 20% and 30% test data, the performance of all models on developed countries data was better than developing countries in terms of least errors in MAE, MAPE and RMSE.

Keywords: Inflation (CPI); Forecasting; ARIMA; LSTM; Hybrid; Prophet; Scale-Dependent Metrics; Percentage-Error Metric; R^2; Developed and Developing Countries

Acknowledgments

First and foremost, I am thankful to God for my good health and well-being, which enabled me to graduate and finish this thesis.

Prof. Kalpdrum Passi has been an excellent instructor, mentor, and thesis supervisor, providing insightful and humorous advice and support. My experience working with him is something I'm proud of, and I'm grateful for it. He was always available to clear all my doubts and handled all the queries with patience. He helped me a long way since I started my academic journey with Laurentian.

In addition, I want to express my gratitude to my brother, aunt and uncle for their sound advice and sympathetic care. You are always inclined to assist me. They helped me to achieve my dream goal by providing mental as well as financial support throughout this roller coaster ride.

Finally, I could not have finished this dissertation without the help of my friends, who provided fascinating talks as well as enjoyable distractions from my study.

Table of Contents

List of Tables

List of Figures

LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
DNN	Deep Neural Network
ML	Machine Learning
CPI	Consumer Price Index
SVM	Support Vector Machines
RF	Random Forest
RNN	Recurrent Neural Network
LSTM	Long Short Term Memory
GDP	Growth Domestic Product
WPI	Whole Price Index
PPI	Producer Price Index
ARIMA	Autoregressive Integrated Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
RMSE	Root Mean Squared Error
SES	Simple Exponential Smoothing
AR	Autoregressive
MA	Moving Average
LASSO	Least Absolute Shrinkage and Selection Operator
SVR	Support Vector Regressor

VAR	Vector Autoregression
ARMA	Autoregressive Moving Average
KNN	K-Nearest Neighbors
ELM	Extreme Learning Machines
BP	Back Propagation
MAD	Median Absolute Deviation
MSE	Mean Square Error
ANN	Artificial Neural Network
PE	Percentage Error
OECD	Organization for Economic Co-operation and development
BPNN	Back Propagation Neural Network
SARIMA	Seasonal Autoregressive Integrated Moving Average
AIC	Akaike Information Criteria

CHAPTER 1

Introduction

1.1 Background

Everyone has an eye on when prices increase and by how much it can be increased therefore inflation is main focus of consumers for goods and services. Estimation of future prices are required to make good steps towards household budget and business investments. An accurate forecast for inflation is needed especially for policy makers, whose job is to provide right steps regarding maintaining prices and make course corrections when these are required [1]. The inflation prediction has a vital role in the successful monetary policy. It is hard to eliminate the importance of inflation forecasting especially for rationally thinking and economic agents such as various economic obligations, wages and interest rate, are usually expressed in nominal prices. It is being widely practiced by central banks to implement forecasting to guide monetary policy; it is mainly based on expectations that how inflation would be in both short term and medium term. Current values are quite helpful to forecast future inflation predictions because inflation data does not immediately vary. Its trend demonstrates the tightening or easing of monetary policy along with some errors. Hence, inflation predictions depict that it is important for both households and businesses, and for regulatory bodies to overcome the apparent effects of inflation [2]. Many activities are inflation based which has a direct adverse impact on these activities such as contracts concerning employment, sales, tenancy, and debt. In addition, many banks and other policy makers depend on inflation forecasts not only to structure new monetary policy but also to curb the expected inflation and enhance policy efficacy [3]. The consequences of inflation are well understood, it can cause a decline in the national currency due to weak purchasing powers [4]. Noticeably, the forecasting of economic and financial time series data is a difficult task mainly due to the

unprecedented challenges in economic trends and conditions on one hand and on the other hand, incomplete information is also a challenging task in this area [5].

Lot of research work has been done via intelligent algorithms, as we know that computers are more reliable to formalize problems and minimize the time and chances of human errors. Indeed, computers could guide and formalize tasks and it is quite easy approach for computers to comprehend those tasks [6]. Intelligent models are like a hierarchy; they always learn from their experience and work in terms of layers and they are able to learn concepts from complex to easier ones. Artificial Neural Networks (ANN) have an input and output layer connected by hidden layers, whereas deep neural networks (DNN) have many layers due to this reason it is known as deep learning [6]. Machine learning (ML) is a part of Artificial intelligence field which learns automatically from a given task which is assigned through developed algorithms. Modeling through ML uses the previous data for developing the model and computing forecast values. ML finds the best fit for particular problems and determines the pattern, parameters and the functions. The models predict future values of the variables from the known lag values [7].

In this study, Machine Learning (ML) methods for economic and financial time series forecasting are considered. Over the few past decades, ML methods have become an important estimation tool to select model and forecast for applied researchers in economics and finance. Big and vast datasets are producing reliable and robust forecasts and introducing a great importance of machine learning [8].

To forecast data, it is important to consider the causal relationship between the dependent variables and independent variable of inflation [9]. The Consumer Price Index (CPI) is one of the dependent variables of economic indicators and can measure the changes over time in the prices of consumer goods and services.

Consumer Price Index (CPI) is a fundamental tool for macroeconomic analysis of a country [10]. The CPI data is based on time series data due to depending on a time sequence, changes happen with respect to time. The main advantage of time series data set is that it can be used for forecasting. CPI time series has an internal

dynamic system that is dependent on fluctuation data set. There are plenty of studies on time series data, still accuracy and data management has room for researchers to explore this area [4].

In this study, it is aimed to forecast inflation under two sets of countries developed and under-developed and different machine learning models will be applied. In this study, historical monthly Inflation (CPI) data is extracted of six developed and six developing countries from the Federal Reserve Bank of St. Louis. This thesis conducts empirical examination of the pattern and relation of inflation and economic growth in multiple-nations using monthly data. Developed countries including Canada, United States, Australia, Norway, Poland and Switzerland and developing countries including Colombia, Indonesia, Brazil, South Africa, India and Mexico have been considered to forecast inflation using different models.

1.2 Inflation

The inflation rate is widely used as an indicator to help government to manage economy and plenty of alternative measures are available for the economy, including the unemployment rate, industrial production growth, housing starts, capacity utilization rates in manufacturing, and the numbers of "help-wanted" postings, all are comprehended to have some predictive power for consumer price inflation [11]. Recently big data environment and machine learning methods have gained an attention in the field of economic analysis. As far as macroeconomic forecasting is concerned, common factors were taken from large number of variables (see Fig.1) [12]. In this thesis, we extend the analysis to perform a thorough comparative analysis of factor models and machine learning methods for forecasting the developed and developing economies by using updated macroeconomic data [12]. There are many related studies on macroeconomic forecasting based on factor models and machine learning [12]. All these forecasts come from relatively traditional econometric methods [13].

The inflation forecast is possibly divided into two parts: short-term and long-term forecasting. There are certain limitations when it comes to forecasting macroeconomic data. On the one hand, potentially

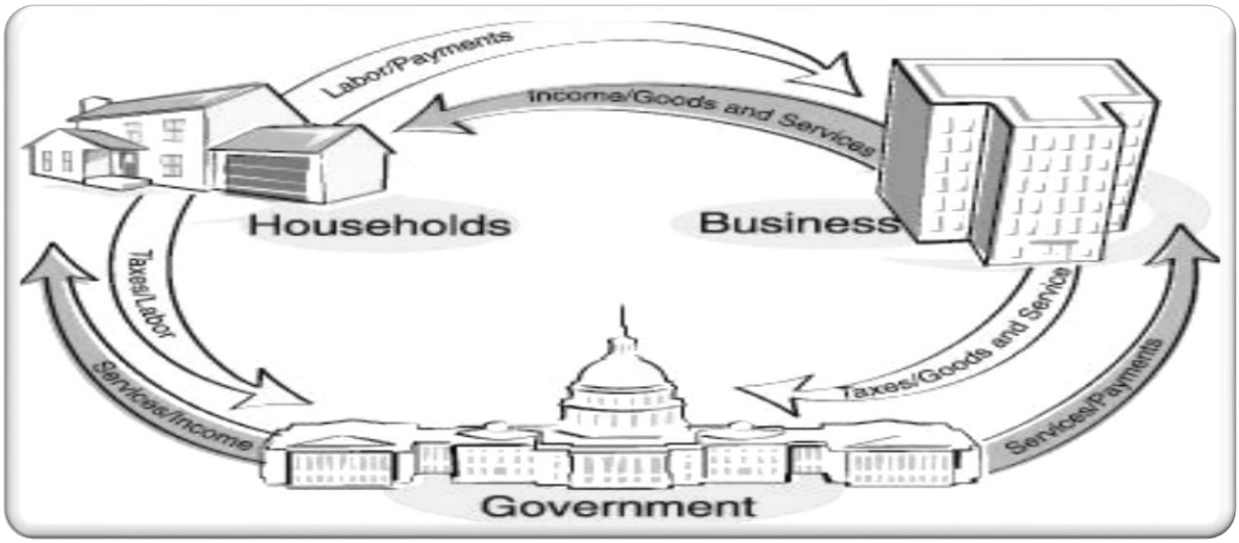

Figure 1. Diagram of Macroeconomic variables [14]

informative predictors are available, and on the other hand, the limited duration of the time series is available, which leads to the so-called 'curse of dimensionality'. For example, if there are more features than observations, the risk of over fitting of model is a possibility. Monthly data for most of the developed countries is about 700-time observations and in the developing countries it is less than the developed countries. Therefore, the forecasting with more than one macroeconomic variable may not be a good idea as compared to considering single-factor model. In other words, because of the overfitting problem, univariate model provides more accurate forecasting as compared to multivariate model. As more predictors are added, the accuracy of forecasting will be compromised, apparently multivariate time series looks very attractive because of having many predictors but in reality, univariate is more proficient and provide more accurate forecast because of its simplicity and more centered [33]. Machine learning-based techniques such as Support Vector Machines (SVM), Random Forests (RF) and deep-learning models such as Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM) have attracted lots of attentions in recent years with their

applications in many disciplines including finance [5]. It is comprehended a great success has been achieved by intelligent algorithms and is mainly due to the fact that ML models have potential to forecast the inflation which would be an apparent support to pSolicy makers, banks and businesses.

1.2.1 Consumer Price Index – CPI

Consumer price index (CPI) is the most common economic indicator which measures the changes in prices of a group of goods with respect to time [15]. Mostly, CPI is measured through basket, same sort of items are picked in baskets under different groups; these groups are made to classify items such as commodities, equities, household goods, industrial goods etc. CPI data is a time series data and can be predicted because its relationship pattern with variables is based on time. ML models and numerical tests demonstrate that the CPI is directly proportional to the exchange rate. Moreover, many researchers have shown the effective connection between inflation and exchange rate and envisaged that there is dependence between them [10] [12] [4]. It has been noticed that the time series of CPI change rate and GDP change rate have a similar trend of values in quarter and similar periodic behavior over the years.

1.2.2 Selected Countries for the Study

Developed and developing countries macroeconomic data may have different in nature. If we consider developed and developing macroeconomic indicators to forecast inflation or deflation, we might have difficulty because of different data trends. Noticeably, CPI based data is common factor among developed and developing countries economy, which is being widely used to forecast inflation. This study forecasts a multi-countries empirical examination of the pattern and relation of inflation and economic growth using monthly data. The sample includes developed and developing economies over the world. Twelve countries are selected to forecast inflation under two outstanding groups; Developed Countries such as Canada, United States, Australia, Norway, Poland and Switzerland and developing countries like Colombia, Indonesia, Brazil, South Africa, India and Mexico. Inflation and economic growth are two significant macroeconomic variables

for the policymakers which shows apparent relationship between exchange rate and inflation. Inflation is the rate of change in prices. If we have the last year price level P_0, present year price level P_1 then inflation (ɣ) is measured by ɣ = $\frac{P_1 - P_0}{P_0}$ [16]. There are several measures of inflation, among them consumer price index (CPI) will be used for this study. Multiple types of baskets of goods, depend on chosen sets of services and baskets are calculated and targeted as price indexes. Usually, consumer price index and wholesale price index are most popular price indexes. The CPI is a weighted average of prices of a basket of services and goods that is associated directly with the primary needs of consumers. The considered cost of services and goods are the retail prices of each item which are directly available in the market to buy for individual citizens. The price changes in the CPI reflects the cost of living, therefore it is one of the most effective indexes to identify the durations of deflation or inflation. Another popular measure of inflation is the wholesale price index (WPI) that is the stage of tracing the changes in the prices of the goods before the retail level. The WPI items may be different from one country to other, items at the producer or wholesale level are mostly included. The producer price index (PPI) calculates the average changes in selling prices that are received by domestic producers of goods and services as the time passes. The PPI depicts the price changes with respect to the seller while the CPI measures the price changes with respect to the buyer. Each index indicates the average weighted price change, which may be applied at the overall economy, commodity or sector level. CPI calculates the expenditure of purchasing a specific bundle of commodities by the town people [17]. Many factors can influence economic growth, inflation is one of them, therefore it is important to study developed and developing countries inflation. Both groups have different historical data and require different approaches to forecast inflation to overcome its imminent threat. ML models are being widely used for inflation forecasting. Forecasting different countries inflation using ML models still can contribute to the research [16].

1.2.3 Effects of Inflation

If we leave this area untreated, the negative effects of inflation will not be negligible. It could be responsible for decline in the national currency's purchasing power that can cause to deteriorating socioeconomic conditions and living standards in the country's economy [4]. The consequences of inflation are very wide therefore it is divided into six groups which might cause significant side effects on their routine and included:

- Distribution of Income
- Production
- Employment
- Business and Trade
- Government Finance
- Economy Growth

Inflation makes business and trade uneasy which is considered as the backbone of the economy. Simultaneously, it raises many uncertainties among investors and organizations. The middle-class people suffer most in such circumstances and standpoint of the economy is that new investment gets stopped because of fear of instability. Most of the central banks depend on inflation forecasting to inform and enhance their respective monetary policy. However, traditional methods of forecasting have become inaccurate and challenging and they render monetary policy environment uncertain. In this research, we use different ML methods to forecast the inflation rate and come up with more reliable ML model for informing the monetary policy.

1.3 Objectives

This work was highly inspired by the literature on Economic and Financial time series forecasting with classical and deep learning models. Sima et al. 2018 [16] used secondary sources of historical monthly financial time series data from 1985 to Aug 2018 collected from the World Bank development indicator (WDI) and Federal Reserve Bank of St. Louis [5] [18].

The main objective of our study is to use different machine learning models to forecast the inflation or deflation growth ties in 12 countries over the world. To forecast inflation, the main challenge is to manage and use huge volume of historical data and to distinguish the relationship between parameters for appropriate information extraction. ML models do not depend on the distribution of data; they perform on time series data to understand the nonlinearity in the data to forecast the future trend. In spite of this efficient performance of ML models, there is very scant work in literature of forecasting, especially for univariate time series cases. But it is noticed that univariate time series provides sufficient evidences via statistical methods on linear processes usually performs well [19]. Hence, in this research, one variable of financial time series is chosen to be fed into the ARIMA, PROPHET, LSTM and HYBRID models using monthly CPI inflation data.

Our objective is to build a robust and accurate predictive framework that contains a suite of machine learning-based regression models with walk-forward validation. For forecasting CPI inflation, we have chosen a very realistic value of the prediction horizon as one month for our proposed models. We hypothesize that the performance of different machine learning models will be different on monthly CPI inflation data for developed countries (Canada, United States, Australia, Norway, Poland and Switzerland) and developing countries (Colombia, Indonesia, Brazil, South Africa, India and Mexico) because of low and high level of per capita income difference. In case of our data sets, a rolling forecast will be applied as the dependency is on past lags. At the time of adding new observation, a rolling forecasting will be applied and it's also called "walk-forward validation". In this study, four different machine learning-based regression models have been

compared on three different sets of training and testing data with walk forward validation. While one of the proposed model (HYBRID) is built by combination of classical and deep learning and individual performance of ARIMA and LSTM is also part of this study. The newly developed model PROPHET, with its features of reasonable forecasting without manual efforts on messy data is compared with classical and deep learning models. ML models for forecasting provide a great benefit in form of accuracy of the outcome, such as difference between the actual and predicted values.

1.4 Outline of the Thesis

This thesis has the following organization.

Chapter 1 includes a background on inflation forecasting based on CPI, an overview of the research, and a discussion of the problem statement.

Chapter 2 reviews previous research work of ML models performances for financial time series.

Chapter 3 presents the inflation forecast data, mathematical background of ML models of data.

Chapter 4 presents the analysis of data and discusses the results obtained by different models. It discusses the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and R^2 to assess the results for accurate inflation forecasting.

Chapter 5 presents the conclusions and directions for future work.

CHAPTER 2

Literature Review

2.1 Related Work

Inflation is an important feature to forecast accurately for each country whether it is developed or developing as the currency may be devalued over a period of time. Hence, inflation forecasting is very challenging and literatures shows that the consumer price index (CPI) metric for forecasting inflation is studied less and there is room for further study and improvement in forecasting [20]. It seems that the inflation is engineered in the developed countries more-or-less in all the main aspects which has a strong influence, for example demand side factors (government spending, population), monetary factors (money growth, interest rate), supply side factor (oil prices), and external factors (nominal effective exchange rate). In addition, it is found that in developing countries inflation is more affected by the demand side effect (government spending), supply side (oil prices) and the external factor (nominal effective exchange rate) than the monetary variables. Thus, many regulatory bodies use inflation forecasting to control inflation through effective fiscal policy (through government expenditures), it also help to mitigate imports by improving their trade position and introduce the suitable exchange rate policy [21].

Inflation was noticed at its peak in 2008 and 2011 in developed countries which were caused by high prices of food and energy (when oil prices increased). After this year inflation got stabilized to some extent. Though deflation was noticed in the same year in Japan, on the other hand low inflation was found in U.S and Germany and high level of inflation found in Canada [22].

Badreldin-Abdulrehman et al. 2018 [23] envisaged that inflation is a main cause of many problems not only in developing countries but also in developed countries. This is monetary

phenomenon and continuously raises the overall prices. This study specifically examined the use of ARIMA forecasting and tested its ability to create accurate baselines. Specifically, as a retrospective from the partial auto correlation function it was seen that the coefficient of AR = 1 and degree of difference = 2. It helped the authors to validate residue properties in ARIMA (1, 2, and 1), $P > 0.05$ and passed beyond the testing phase and diagnosis. It is evident in this study that it is well integrated with predictive values and actual values during the period (1970-2016). Also, it forecasted that there would be more inflation in coming years (2017-2026).

Sima et al. 2018 [5] examined that forecasting time series data is an imperative area of study especially in the field of economics, business, and finance. Traditionally, there are a number of techniques available to forecast the next lag of time series data such as univariate Autoregressive (AR), univariate Moving Average (MA), Simple Exponential Smoothing (SES), and noticeably Autoregressive Integrated Moving Average (ARIMA) with its variants. The empirical study was done and reported to demonstrate that deep learning-based algorithms such as LSTM outperformed traditional-based algorithms such as ARIMA model. More specifically, there was mitigation in error rates obtained by LSTM which were between 84% - 87% than ARIMA. Furthermore, it was noticed that the number of training times, known as “epoch” in LSTM has no significant effect on the performance of the trained forecast model and it exhibits a truly random behavior.

Marcelo et al. 2019 [3] has conducted research on forecasting of inflation using different machine learning methods. He suggested that inflation forecasting could bring outstanding results due to the availability of big data environment and machine learning methods which improved forecasting of inflation. He concluded in this study that machine learning techniques such as Random Forest and Least Absolute Shrinkage and Selection Operator (LASSO) models produced

better forecasting results than conventional methods of inflation forecasting. According to this study, Random Forest helps to reduce smallest errors than the other machine learning methods.

Milunovich et al. 2019 [24] forecasted log prices using forty-seven ML models with multi-equation and single equation algorithms, integrated with conventional methods of machine learning and deep learning neural networks. He concluded that available data from 1 to 2 quarter ahead was forecast with multiple algorithms which results in exceeding accuracy than random forest. It was seen that support vector regressor (SVR) with 4 to 8 quarter ahead forecast was one of the most efficient techniques, while VAR and ARMA forecast well for 1 quarter ahead. Notwithstanding, deep neural networks models were tested and it was found that these neural networks are more suitable for forecasting with medium and long-time horizons.

Rodríguez et al. 2020 [13] studied that mostly machine learning models for inflation forecasting depends on the performance of average univariate inflation. The author made a comparison of performance of different models of machine learning from optimum forecast literature. According to the author, the following best models were obtained including LSTM, univariate KNN, and random forest. Furthermore, it was examined that the combination of forecast models performed better than individual forecast. Also, the study depicted that combined model reduces bias and improve the forecasting accuracy.

Baybuza et al. 2018 [2] used several machine learning methods such as LASSO, Elastic Net, Random Forest, Ridge, and Boosting methods to predict Russian inflation. The study suggests that random forest and gradient boosting models gave the best inflation prediction amongst all the models on Russian economy. These models gave the potential forecasting as compared to conventional random walk and auto-regression.

Richardson et al. 2021 [25] posed the question "whether Machine learning models can help central Banks on forecasting of macroeconomics variables"? They applied 600 predictors to evaluate potential forecast of New Zealand GDP. Their results depicted that machine learning models render significant improvement in forecasting than traditional methods that were used by central banks i.e. autoregressive benchmark and dynamic factor model. Moreover, they evaluate from this study that machine learning models help to improve official forecasts in New Zealand's central Bank i.e. Reserve Bank of New Zealand.

Szafranek et al. 2019 [8] worked on thick modelling approach and combined bagged single hidden layer feed forward artificial neural network to validate the forecast on Poland's economy. According to the author, accuracy models were very helpful to curb the inflation rate of Poland and brought low inflation rate in the country. The techniques and model which was used in this study is comparably best from traditional benchmark methods. Linear and nonlinear models were brought in contact with multi variate and univariate approaches to generate more assumptions to reduce errors. It was emphasized that central banks should use machine learning methods along with conventional benchmark methods for forecasting of inflation.

Maehashi et al. 2020 [12] conducted a comparative time series research on Japanese macroeconomics forecasting using traditional factor models and machine learning methods. Their results suggest that mostly machine learning and factor models performed better than the traditional autoregressive models. Secondly, it was noticed in this study that machine learning models are comprehended as good for medium to long term forecasting of macroeconomic variables. Furthermore, they found that nonlinearity is important for machine learning models,

additionally, they found that combined forecasting is better than using traditional and machine learning models alone.

Acosta et al. 2018 [26] in this research applied k-mean clustering to predict inflation. His results showed that this approach performed better at forecasting Mexican inflation, and it was better to obtain by trimmed mean method except food and energy.

Sokolov et al. 2016 [27] applied back propagation learning or BP including extreme learning machine (ELM) to predict the GDP. It was a comparative study of BP and ELM; their results suggest that ELM is better at predicting GDP than BP.

Li-Wang et al. 2013 [28] proposed a hybrid model, which has a distinctive approach of ARIMA and artificial neural networks (ANN) in modeling the linear and nonlinear behaviors in the data set. Hybrid model was examined on three sets of actual data namely; Wolf's sunspot data, the Canadian lynx data and the IBM stock price data respectively. There was an improvement in forecasting on the first 35 periods which was integrated with the multiplicative model based on Median Absolute Deviation (MAD) over the ARIMA, ANN and the additive model was 55.43%, 44.72% and 50.02%, respectively. If we consider multiplicative model, MSE (Mean Square Error) and MAPE (Mean Absolute Percentage Error) would provide more accurate results as compared to other models. For the longer term on 67 periods, the multiplicative method produced better predictions by MSE of 50.47%, 46.68% and 46.76% and by MAD (Median Absolute Deviation) of 40.28%, 36.13% and 35.60% over the ARIMA, ANN and additive model, respectively.

Bashar Al-hnaity et al. 2016 [29] proposed a hybrid method along with SVM, SVR and BPNN. These models were used to forecast stock prices of FTSE 100, S&P 500 and Nikkei 225 based on their closing prices. BPNN topology was set according to trial-and-error techniques, two hidden layers along with back propagation approach were engaged with 20 neurons for the first

hidden layer and 5 neurons for the second hidden layer. The best forecast model for FTSE100 was obtained with 20, and 5 neurons in the first and second hidden layers, respectively. Similarly, for S&P 500 the best model was obtained with 10, and 5 neurons in the first and second hidden layers, respectively with a learning rate of 0.3 and momentum kept constant at 2. For Nikkei225 the best model was obtained with 10, and 5 neurons in the first and second hidden layers, respectively with a learning rate of 0.7 and momentum kept constant at 10. This study depicts that hybrid combination models performs better than conventional models.

Ashish et al. 2020 [30] studied the prediction of stock markets prices based on their stock exchange forecasting. SARIMA and Prophet Models are the machine learning models which are rendered outstanding predictions for some time series. Since stock market data is dynamic data therefore the machine learning models can predict the dynamic change in data points. Stock market data does not have seasonality or trend, usually it relies on the current prices of the stock, which may go high or become low. The percentage error showed that PROPHET performed better as compared to SARIMA for the stock prices case study.

Emir et al. 2020 [31] investigated regarding sales which were conducted on Facebook's Prophet algorithm and back testing strategy. This study was done on the Real-world sales data obtained experimentally from biggest retail companies in Bosnia and Herzegovina. To measure a reliable estimation and accuracy in terms of percentage error for this expanding window, back testing strategy was implemented. To predict sales forecast with the help of historical data, a relation between the past and present information is established. In this research, the back testing experiment was cycled 12 times with monthly sales data of products. At each step, historical data was fitted into Prophet model (i.e., observation horizon) and monthly sales forecast for the next three months (i.e., forecasting horizon) for the same period was performed in order to calculate

percentage error (PE) at monthly and quarterly times. Then, the expected mean absolute percentage error (MAPE) was measured over repeated back testing experiments to quantify the expected level of forecasting. Approximately 50% of the product portfolio was predicted with MAPE < 30% on a monthly available data. On the other hand, approximately 70% of the product portfolio with MAPE < 30% on a quarterly basis (40% of products with MAPE < 15%) were noticed in this research.

Ozan-Kozan et al. 2018 [32] performed forecasting over Bitcoin data set available from May 2016 to March 2018, meanwhile comparison of changes in other currencies. Both ARIMA and PROPHET models were used by three-fold splitting technique on the time series data set. The three-fold splitting technique provided adequate ratios for training, validation, and test sets. Finally, two different models were compared for their performances. It was noticed that PROPHET outperforms ARIMA with R^2 value of 0.94 for Prophet and 0.68 for ARIMA.

Doruk et al. 2021 [19] worked on the data of monthly inflation rate of 28 countries those were member of Organization for Economic Cooperation Development (OECD). He found that neural network models' performance was better than Autoregressive models. Arithmetical combination of an ensemble model through multiple networks is also suggested to improve accuracy.

Time series is called a temporal data of objects which is available in the fields of science and finance. The time series data includes quantity, dimensionality and necessary updates according to the requirements [33]. The various papers [20] [13] [3] prove the power of machine learning methods for financial time series data with various models. However, machine learning methods used in combination with more conventional methods can give better forecasting results. Noticeably, Inflation (CPI) forecasting is mostly researched with classical methods such as

univariate Autoregressive (AR) model, univariate Moving Average (MA) model, Simple Exponential Smoothing (SES), and Autoregressive Integrated Moving Average (ARIMA). Very few works are done for forecasting the inflation with different properties of models. This research explores the hybrid model with ARIMA and LSTM to forecast inflation in developing and developed countries and compares the performance with individual models ARIMA, LSTM and PROPHET.

CHAPTER 3

Data and Methods

3.1 Methodology

In this Chapter, an introduction of the methodology of the empirical experiment is described. It includes the tools used to conduct the execution with, the workflow of experiment implementation, basic information about the dataset, variables selection, model selection and evaluation metrics for model comparison.

Secondary Data source is used for the study and data was collected for 1960 to 2021 from the FRED database of the Federal Reserve Bank of St. Louis, which is publicly available in csv format. CPI monthly data is extracted for 12 different countries such as Canada, United States, Australia, Norway, Poland, Switzerland, Colombia, Indonesia, Brazil, South Africa, India and Mexico from developed and developing countries group. Monthly inflation rates are obtained for CPI indices by calculating the monthly difference of the observations divided by last month's price level. Table 1 represents the Work Flow for forecasting the inflation. We aim to research with monthly inflation rate because this data is directly related to the influence of inflation at consumer level or at end-user level. CPI data reflects the real impact of inflation on end users and this way the CPI data is very helpful for monetary policy makers to determine the minimum wages and compensation. The data was split in different ratios for training and testing, such as 90% for training and 10% for testing, or 80% for training and 20% for testing or 70% for training and 30% for testing. This was done to ascertain the best training-to-testing ratio.

Table 1. Work Flow Chart

CPI DATA	• Time series as .CSV • Training DATASET : Testing DATASET • 70 : 30, 80 : 20, 90 : 10
BUILD ML MODELS	• ARIMA • LSTM • PROPHET • HYBRID (ARIMA+LSTM)
RESULTS	• PERFORMANCE INDICES (MAE, RMSE, MAPE, R^2) • PLOTS AGAINST ACTUAL OUTCOMES

3.2 Tools

3.2.1 The Jupyter Notebook

The Jupyter Notebook is available in the Python environment to process the data. It is an open-source web application that favors the workflow of scientific computing from the combination of live coding, an execution of mathematical options, plotting, visualizing and explanatory texting to rich media [24]. According to requirement a programmer uses the Jupyter Notebook for the process of experiments, including data integration, data pre-processing, data shifting, data cleaning, feature engineering, model building and statistical validation [23].

3.2.2 Machine Learning Toolkit

The Scikit-learn projects in Python are used for the Machine Learning application. It is efficient library designed for diverse kind of users in terms of expertise. The top advantage of Scikit-learn is its user-friendly and easy-to-apply characteristics. The primary goal of this project is to provide forecasting performance through different methods and well-established machine

learning regression models. It includes tools for building machine learning models and predictions, as well as tools or model evaluation and selection. It gives efficient execution of state-of-the art algorithms, accessible to non-machine learning experts, and reusable across scientific disciplines and application fields [23].

Table 2 presents the python libraries for the proposed models

PYTHON LIBRARY	**ARIMA**	**LSTM**	**PROPHET**	**HYBRID**
from pandas import read_csv	✓	✓	✓	✓
from statsmodels.tsa.arima.model import ARIMA	✓			✓
from pandas import to_datetime	✓	✓	✓	✓
import matplotlib.pyplot as plt	✓	✓	✓	✓
from keras.models import Sequential		✓		✓
from keras.layers import Dense		✓		✓
from keras.layers import LSTM		✓		✓
from sklearn.preprocessing import MinMaxScaler		✓		✓
from sklearn.metrics import mean_squared_error	✓	✓	✓	✓
import math	✓	✓	✓	✓
from sklearn.metrics import r2_score	✓	✓	✓	✓
from fbprophet import Prophet			✓	

3.2.3 Statsmodels Library

For statistical and econometric analysis Statsmodels library is available in Python. It is developed for statisticians, econometricians, Python users and developers in multiple disciplines. In past, the main focus has been in economics side but with the passage of time it is brought in use in many fields. Current progress is making this tool more user-friendly for developing the codes and statistical modeling. The main idea behind the design is that a model is itself an object to be used for data reduction [34]. Statsmodels is quite helpful in performing several options to work with Autoregressive Integrated Moving Average (ARIMA) time-series model i.e. simulation and estimation code. It becomes very easy when there is need to compare theoretical properties of ARIMA process along with empirical counterparts [35].

3.2.4 Keras using Theano

The Keras can be used for TensorFlow, CNTK, and Theano as a back-end, it is high-level neural networks API interface. It was mainly introduced as an Open-ended Neuro-Electronic Intelligent Robot Operating System (ONEIROS). It includes multiple benefits, especially during researches and developments. Theano is available in Python which is deep learning structure and known for its speed [2]. This library is used with different techniques to obtain the speed and connect with a GPU. We decided to use this, since it is fast and quick drop-in replacement for Keras backend framework. In our experiments, we used CPU for Keras framework using Theano as backends.

3.2.5 PROPHET Library

The PROPHET library is available in Python which is developed by Facebook team under an open-source license for predicting the time series. A data set should be in numeric form and can be calculated. As the PROPHET library is introduced for the needs of business forecasts by Facebook team, following characteristics show the need of using PROPHET library. For instance, hourly,

daily, weekly or monthly observations; seasonality behavior; prediction irregularity that exist within predefined intervals; large missing values; trend behavior and situations when the trend's behavior is based on non-linear curves when it is reached to natural limits [36]. By changing the parameters, we can obtain improved results, as it is not fully automatic.

3.3 CPI Dataset

This research work proposes the machine learning models to investigate the inflation-economic growth relationship in 12 countries including six developed and six developing countries over the world. The 6 developed countries used in this research include Canada, United States, Australia, Norway, Poland and Switzerland and 6 developing countries include Colombia, Indonesia, Brazil, South Africa, India and Mexico.

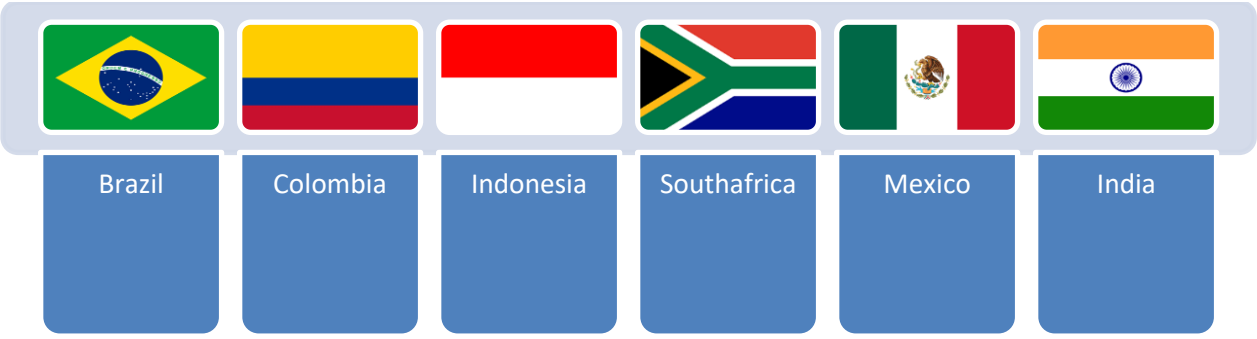

Figure 2 List of Developing countries [37]

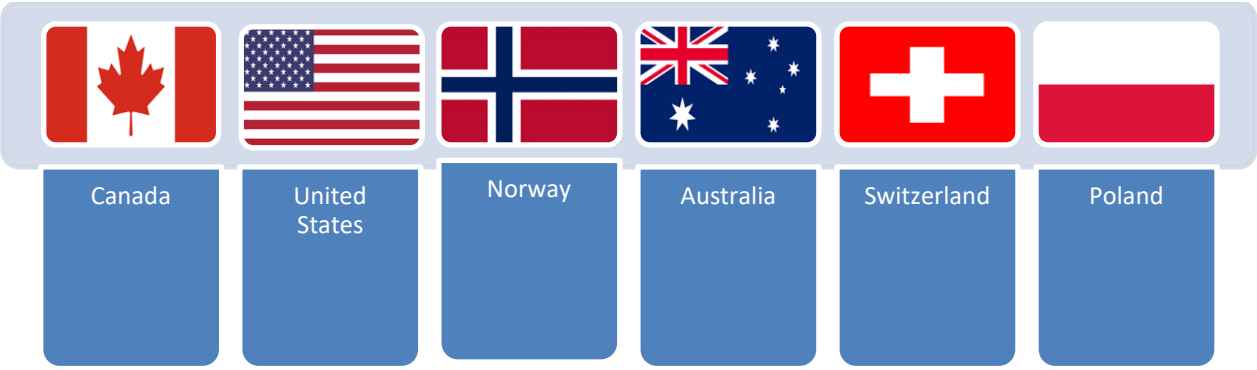

Figure 3 List of developed countries [38]

This study is using secondary sources for historical monthly Inflation (CPI) data collected from Federal Reserve Bank of St. Louis [39].

3.4 Methods

The models for time series techniques in the research work are described in this section. The mathematical formulation of Autoregressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), HYBRID and PROPHET models are explained.

3.4.1 Autoregressive Integrated Moving Average (ARIMA)

Autoregressive Integrated Moving Average (ARIMA) combines the terms of Autoregressive (AR) process, Integrated process and Moving Average (MA) processes, and constructs a model for the time series. These terms are explained below [5]:

- AR: Autoregression. It explains the dependencies on number of lags (previous) observations and is denoted by (p).

- I: Integrated. It represents the difference order of observations at different time to remove non-stationarity in time series and is represented by (d).

- MA: Moving Average. It represents the dependency on the residual error terms (q). The mathematical formulation for Autoregressive (AR) term, i.e., AR (p), is taken as a linear process given by:

$$x_t = c + \sum_{i=1}^{p} \emptyset_i \, x_{t-i} + \varepsilon_t \qquad (1)$$

where the stationary variable is mentioned as x_t, c is taken as constant, the term in $\emptyset_i$ is autocorrelation coefficients at previous observations 1, 2, …, p and ε_t represents the residuals with variance σ_ε^2 and mean zero. MA model of order q, i.e., MA (q), can be described in the form:

$$x_t = \mu + \sum_{i=0}^{q} \theta_i \; \varepsilon_{t-i} \qquad (2)$$

Where μ is the expectation of x_t which is generally equal to 0, the θ_i terms indicate the weights which are applied to the current and prior values in the time series, where $\theta_0 = 1$. Assuming that ε_t is a Gaussian white noise series with mean zero and variance σ_ε^2. A white noise time series cannot be predicted because of a 0 mean, constant variance and 0 correlation, ε_t are uncorrelated therefore it is difficult to forecast future values with the help of previous values. By combining Autoregressive and Moving average (p, q), it can be written as below:

$$x_t = c + \sum_{i=1}^{p} \emptyset_i \, x_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \; \varepsilon_{t-i} \qquad (3)$$

Where $\theta_i \neq 0$, $\emptyset_i \neq 0$, and $\sigma_\varepsilon^2 > 0$, ARIMA forecasting is also known as Box and Jenkins forecasting, the integrated part of ARIMA easily deals with non-stationary part of time series data. Actually, the process of transforming the non-stationary time series data into stationary time series data is due to integrated component of ARIMA model which is mentioned as ARIMA (p, d, q).

3.4.2 Artificial Neural Network (ANN)

There are three layers in neural network such as, input, hidden and output layers. The variables in a dataset constitute the number of nodes in the input layer which is also known as dimensionality. Hidden layer(s) are used to develop these nodes and integrate the nodes with the links “synapses”. The synapses links between each node in the input layer and the hidden layer have weights. The role of the weights is to make a decision on which input signals should pass through the hidden layer. The weights represent the strength or extent to the hidden layer. Usually, neural networks define the ability of fixing the weights for synopsis. Nodes in the hidden layers pass through an activation function e.g., sigmoid or tangent hyperbolic (tanh) on the weighted sum to transform the inputs into outputs, or forecasted values. The various outputs of vector of probabilities are computed for output layer and one of the best output with its minimum cost or error rate is obtained. The errors which are obtained through the network training for the first time may not be accurate. For finding the best favourable values for errors, from the output layer towards the hidden layers, back propagation is used into the network and consequently the weights are managed. It is repeated several times, i.e., epochs, on the same observations and the weights are fitted according to need until any correction is found in the predicted values and in the cost as well. Once the cost function is reduced, the model is considered trained.

3.4.3 Long Short-Term Memory (LSTM)

LSTM is considered a type of Recurrent Neural Network (RNN), it can remember the values from initial stages to use in future for forecasting [5].

3.4.3.1 Recurrent Neural Network (RNN)

We can define a recurrent neural network as a special kind of neural network and the main goal is to forecast the next step in the sequence of observations regarding previous steps that is observed in the sequence. The main focus of RNNs is to use sequential series for understanding the previous values to forecast future values. According to this, observations should be remembered by initial stages during forecasting the future steps. The hidden layers in RNNs play an action of internal storage for remembering the date which is stored in previous stages from sequential data. RNNs are known as “recurrent” because of its function which performs the uniform task for each element of the defined sequence, with the properties of given information defined earlier to predict the unseen data. The main problem of RNNs is just to remember short term sequence observations instead of memorizing long term sequence observations. This challenge can be coped with the “memory line” which is presented in the Long Short-Term Memory (LSTM) recurrent network.

3.4.3.2 Long Short-Term Memory (LSTM)

We associate LSTM with RNNs and consider it as a type of RNN with the option of remembering the long sequences of data. The record of the long sequences data is only possible by adding some gates with a memory line which is the feature of typical LSTM. The mechanism of internal working of a LSTM cell is in Figure 4:

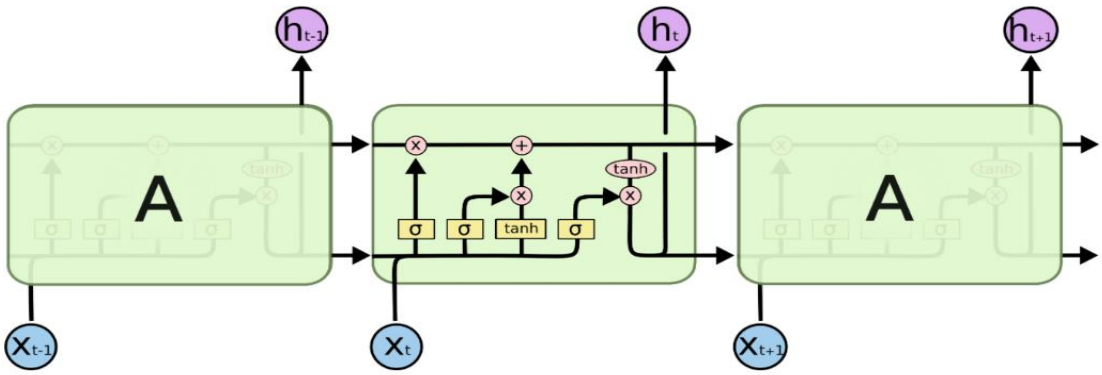

Figure 4 Structure of LSTM [40]

There are different features in LSTM which is an advanced type of RNN to process the long sequence of time series data. LSTM consists of set of cells or system modules, where observations are noted and saved. LSTM cells are like transport lines, especially the upper line which is in every cell that introduces the connection of one module to another one; it plays the role of carrying data from previous cell and collect them for the present one. The role of gates in every cell is to decide about discarding the data, filtering or passing to the next step. These gates are dependent on sigmoidal neural network layer that allows the cells to let the information dispose or keep. The range of 0 and 1 is generated from each sigmoid layer and depicts the quantity of data for keeping or discarding. A 0 value depicts that information should not be forwarded for further steps while a 1 indicates that the information is ready to pass through. There are three gates involved with the main focus of handling the different states:

- **Forget Gate** outputs a number of 0 and 1, where 1 represents “it will be carrying” while 0 indicates that “it will not be carrying”.

- **Memory Gate** is used to save new data into the cells. First layer, a sigmoid layer, which is basically known as "input door layer" selects the values for modification. Next, a (tanh) layer builds a vector of new candidate values which are included to the state.

- **Output Gate** represents the final results from each cell. The final outcome is dependent on the cell state with its refined and currently added information.

3.4.4 HYBRID Model

A HYBRID model is proposed in this research to combine classical and deep learning models on financial time series. These two models are decided because combination of the models can decompose a time series in linear and nonlinear trends and it can be represented by the following equation:

$$x_t = L_t + N_t + \varepsilon_t \qquad (4)$$

Here, L_t represents the linearity in the time series 'x_t' at time step t, N_t is representing the nonlinearity in the time series 'x_t' and ε_t represents the error term in the time series 'x_t' [41]. According to study, HYBRID models are improving the forecasting as compared to individual models' performance. We are inspired by the researches on these techniques and provide the answer for Inflation forecasting performance using this combined model.

3.4.5 PROPHET Model

PROPHET only accepts the information as a dataframe with columns: "ds" or date stamp (in datetime format), and "y" which is the variable that is used for prediction. To make a dataframe with the dates for which we need a prediction, futuredataframe() function is used. At that point, there is a need to determine the number of days to calculate using the period's parameter. A

function call to the predicting function stores it in the estimated dataframe. It is preferred that the dataframe is reviewed and the predictions are seen as the lower and upper limits of the vulnerability interim [9]. PROPHET equation is written as:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon(t) \qquad (5)$$

where,

I. g(t) provides information of trend

II. s(t) indicates the periodic components in time series

III. h(t) is occasional or holiday event in time series and ε(t) depicts error term.

Generally, PROPHET forecasts accurately for a maximum of ¼ of the data. It is the best results within the range, for example if we have 100 observations, then only next 25 observations can be predicted with good accuracy. Noticeably, other ranges for results can also be chosen but ¼ of the data is good target to get accuracy [1].

3.5 Comparison of the models

For the purpose of comparing ARIMA, LSTM, PROPHET and HYBRID models, a series of experiments were performed on the inflation (CPI) time series data of some selected developed and developing countries. The following research questions are answered:

1. **RQ1**. Which model provides more accurate forecasting of time series data?

2. **RQ2**. Which opted ratio for training and testing samples is the best choice for forecasting CPI based inflation?

3. **RQ3**. Do the models perform differently for CPI based inflation of the developed and developing countries?

4. **RQ4**. Does the HYBRID model of ARIMA and LSTM improve the results as compared to individual models?

3.6 Data Preparation

The variable of financial time series was used as input to the ARIMA, PROPHET, LSTM and HYBRID models. The data was divided into training and test sets. The training set is used by the models to learn the patterns present in the data and to train the model. The dataset was divided into training-testing sets in the following ratios: 90:10, 80:20, and 70:30. This was done to find the best training-testing ratio for the CPI based inflation time series data.

3.7 Evaluation Metrics

The ARIMA, LSTM, HYBRID (ARIMA-LSTM) and PROPHET algorithms for forecasting the time series are based on "Rolling Forecasting Origin". The predictions which are based on rolling forecasting origin emphasise the single step forecasting, i.e., next observation to forecast from the data set [5]. This approach uses training set and predictions are added one by one in training set, one-month look-ahead view in our case. Multiple variations of rolling forecast are there [5] which are listed below.

- One-step forecasts without re-estimation: The evaluation of a single set of training data is done and after this, on the rest of data set one-step forecasts are generated.

- Multi-step forecasts without re-estimation: In the same way of one-step forecasting, multiple steps are performed for next forecast.

- multi-step forecasts with re-estimation: the model is re-adjusted at each iteration before computing the next forecasting.

In case of our data, the dependency is on previous observations of time series, and therefore, multi-step forecast with re-estimation is applied. The basic method to use the rolling forecast is to reconstruct the model when a new observation is added to the training set each time. An approach of rolling forecast is often called "walk-forward model validation".

Two performance measures are used to evaluate the performance of the proposed models; these are scale-dependent metrics, mean absolute error (MAE) and root mean square error (RMSE) as shown in equations (6) and (7) below.

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \qquad (6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}} \qquad (7)$$

where y denotes the actual value and $\hat{y}$ denotes the estimated value.

To demonstrate the variance between dependent and independent parameter, R^2 is well-defined in Eq. (8) where y denotes the actual value, $\bar{y}$ denotes mean value and $\hat{y}$ denotes the estimated value:

$$R^2 = 1 - \sum_{i=1}^{N} \frac{|y_i - \hat{y}_i|}{|y_i - \bar{y}_i|} \qquad (8)$$

Another performance measure used to evaluate the performance of our proposed models is percentage-error metric, mean absolute percentage error (MAPE), where y denotes the actual value and $\hat{y}$ for estimated value and is shown in Eq. (9):

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \left| \frac{yi - \widehat{yi}}{yi} * 100 \right| \qquad (9)$$

3.8 The ARIMA algorithm

ARIMA model is a linear regression-based forecasting approach and uses temporal structures in time series data to predict. The inflation (CPI) is taken as an input in the algorithm to provide the outcome in the form of forecast with the errors. The data set was divided into three types of ratios of training and testing i.e. 70:30, 80:20 and 90:10, respectively. Two data structures are constructed to receive the added training data at each iteration called "history", and the continuous forecasted values for the testing data, called "prediction."

Earlier p,d,q were defined as constructive parts of ARIMA where:

- p is the number of lag observations used in training the model (i.e., lag order).
- d is the number of times differencing is implemented (i.e., degree of differencing).
- q is the size of the moving average (i.e., generated from white noise series).

3.8.1 Pseudo Code for ARIMA

```
Input: inflation (CPI)
Outputs: MAE, MAPE, RMSE, R^2 # errors of forecasted data
1. Split the time series data into 70%, 80%, 90% training and 30%, 20%, 10% testing
2. fit model = ARIMA(time series, order=(3,1,0)) #summary of fit model
# Walk forward validation on test data
3. do
        { for each i in range(time series(test))
```

```
    model → ARIMA(history, order=(3, 1, 0)) #model.fit()
    hat (variable) → model_fit.forecast()
    predictions.append(hat (variable))
    observed values → test[i]
    history.append(observed values)
    end for}
4. Return: MAE, MAPE, RMSE, R^2
```

According to statistical criteria, the comparative performance of ARIMA models (p=1, d=1, q=0), (p=2, d=1, q=0) and (p=3, d=1, q=0) are checked for minimum AIC (Akaike information criteria) [22]. AIC (Akaike information criteria) is very popular measure of a statistical model and it quantifies the goodness of fit. By comparing different order (p,d,q) of model, lowest AIC value is selected which suggests that the model fulfils the requirement of goodness of fit and highest values of AIC indicate the worst model of order (p,d,q). Order (3, 1, 0) is selected as it gives the lowest AIC value and is considered as baseline to model the forecast inflation rate for six developed and six developing countries. The data of two countries is tested for considering the best order (p, d, q) model based on lower AIC values as given in Table 3.

Table 3 AIC values based on parameters of ARIMA (p, d, q)

Country	**Order (p,d,q)**	**AIC**
Canada	(1,1,0)	241
	(2,1,0)	219
	(3,1,0)	**200**
Brazil	(1,1,0)	273
	(2,1,0)	275
	(3,1,0)	**271**

The algorithm fixes $ARIMA$ (p=3, d=1, q=0) model for the testing data. The ‘q’ (moving average) zero indicates constant mean and constant variance which further indicates that moving average is not considered. The model is adjusted by keeping two parameters changeable to obtain more accurate values and the third parameter is kept constant. The $ARIMA$ with orders (3, 1, 0) indicates that the lag value which is ‘p’ considered with order 3. The difference order ‘d’, which is 1, chosen for making the time series stationary from non-stationary. Now, the expected value (hat) can be forecasted and adds the expected values (hat) to the prediction, then the actual value is collected to test data for re-adjusting the model. After building the history and predictions data structures, MAE, MAPE, RMSE and R^2 are generated as the performance metrics for measuring the accuracy of the forecasted values.

3.9 The LSTM Algorithm

In time series data, there is dependence among the observations. Recurrent Neural Networks can powerfully handle the connection among the input variables. LSTM is a type of Recurrent Neural Network (RNN) which is able to keep and learn the relationship of long sequence of observations in time series data. Developed algorithm is a one- step univariate forecasting model [5]. For implementing the algorithm, Keras library along with Theano were used.

3.9.1 Pseudo Code for LSTM

Inputs: series
Outputs: MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), RMSE (Root Mean Square Error), R^2 (Coefficient of determination) # errors of the forecasted data
1. Split the time series data into 70%, 80%, 90% training and 30%, 20%, 10% testing
2. set → random.seed (7)
3. fit_lstm(train, epoch, neurons) #LSTM for training data with 1500 epochs and 4 neurons
5. model.compile → loss function = mean_squared_error, optimizer = adam
6. do

```
        { for each t in range (epoch)
         model.fit → X, Y, epochs=n, shuffle=False
         model.reset_states()
        end for }
#Walk-forward validation on the test data
7. do

        { for each i in range(length(test))
          forecast(lstm_model, X) → yhat
          predictions.append(yhat)
          expected values → test[i]
          end for }
8. Return: MAE, MAPE, RMSE, R^2
```

For comparing with ARIMA, it is divided into training and testing data sets 70:30, 80:20 and 90:10, respectively. The seed number is selected to fix '7' and this is advised to keep the random number to ensure the reproduction of the outcomes. "fit_lstm" is a function in the algorithm that constructs and trains the LSTM model. Training dataset is received through the function called fit_lstm, the number of epochs, i.e., the number of times for which data is adjusted to the model, and the number of neurons, i.e., the number of memory blocks or units. The LSTM hidden layer is created, and having constructed the network, it should be composed and parsed to relate with the mathematical notations and conventions used in Theano. For the loss function and the optimization algorithm, "mean squared error" and "ADAM" are applied. When the compilation is done, next the model is fit to train dataset. As the network model is stateful, the network should be adjusted according to number of epochs, especially if epochs are more than one. In order to improve the learning mechanism, shuffling parameter needs to be adjusted to false. For the next iterations, i.e., epochs, algorithm resets the internal states of the training for making it ready for next epoch. To call the LSTM model, a small function is constructed and is used to predict the next step (one-month ahead forecast) in the data. Construction of LSTM model with given training

data, number of epochs and neurons is operational part of the algorithm and forecasts the test dataset and report the obtained MAE, MAPE, RMSE and R^2 values.

3.10 HYBRID Algorithm

3.10.1 HYBRID

Individual experiments are defined earlier for ARIMA and LSTM models. Having fitted a model on input time series, the residuals are collected from the ARIMA predictions. Noticeably, the ARIMA model forecasting is considered for providing explanation about linear relationships in the time series data and Residual part provides information about non-linear relationship in the time series data as a second section of the HYBRID model. Details we have discussed earlier, the residual values from ARIMA model are used as input for the LSTM model. The residual data is divided so that the last time step is treated as a target value and the model is trained on the remainder of the previous observations.

3.10.2 Pseudo Code for HYBRID

```
# ARIMA
Inputs: series
Outputs: residuals
1. Split data into 70%, 80%, 90% training and 30%, 20%, 10% testing data
2. fit model = ARIMA(series, order=(3,1,0)) #summary of fit model
# Walk forward validation on test data
3. do
        { for each i in range(series(test))
         model → ARIMA(history, order=(3, 1, 0)) #model.fit()
         hat (variable) → model_fit.forecast()
         predictions.append(hat (variable))
         observed values → test[i]
         history.append(observed values)
         end for}
Return: residuals #ARIMA results
```

```
# LSTM
Inputs: Residuals #ARIMA results
Outputs: MAE, MAPE, RMSE, R^2 of the forecasted data
1. set → random.seed(7)
2. fit_lstm(train, epoch, neurons) #LSTM for training data with 1500 epochs and 4 neurons
3. model.compile → loss function = mean_squared_error, optimizer = adam
4. do
      { for each t in range (epoch)
       model.fit → X, Y, epochs=n, shuffle=False
       model.reset_states()
      end for }

# Walk-forward validation on the test data

7. do

      { for each i in range(length(test))
        forecast(lstm_model, X) → yhat
        predictions.append(yhat)
        expected values → test[i]
        end for }
8. Return: MAE, MAPE, RMSE, R^2
```

3.11 The PROPHET Algorithm

Time is used as a regressor in FBPROPHET model and tries to fit linear and nonlinear function of time as components. FBPROPHET fits the data using a linear model by default but from its arguments it can be changed to the nonlinear model (logistics growth).

Generally, FBPROPHET Model have the following arguments:

Interval_width	0.95
Yearly_seasonality	True
Weekly_seasonality	True
Daily_seasonality	True

Holidays	None
Changepoint_prior_scale	0.05

95% confidence interval, which is interval width, at default we will set the uncertainty interval to produce a confidence interval around the predicted value. By default, Yearly_seasonality / Weekly_seasonality / Daily_seasonality are fit, but we can bring changes according to the component of our time series by adding other seasonality. Holidays or event dates is an additional feature that is included if holidays are part of time series, Changepoint_prior_scale is a flexible option which is adjusted for how the model should behave against trend changepoints.

3.11.1 Pseudo Code for PROPHET

Inputs: series

Outputs: MAE, MAPE, RMSE, R^2 of the forecasted data

```
1. Split data into 70%, 80%, 90% training and 30%, 20%, 10% testing data
2. df = df.reset_index()
3. predictionsFbP = list()
4. do
        { for t in range(len(test)):
        model = Prophet(yearly_seasonality=False) # yearly seasonality false since data is
monthly
model.fit(train);
        output → model.predict(test)
        yhat → output['yhat'][t]
        predictionsFbP.append(yhat)
        obs → test.loc[[t+len(train)]]
        train.append(obs)
        print('Month → %d, Predicted = %f, Expected=%f'% (t+1, yhat, test1[t]))
#('predicted=%f,          expected=%f' % (yhat, obs))
end for }
```

5. Return: MAE, MAPE, RMSE, R^2

The data set is divided into training and testing sets, 70:30, 80:20 and 90:10 respectively. Use of PROPHET model is pretty straightforward. We needed to prepare the dataset and built a data frame with only two columns: “ds” or date stamp (in datetime format), and “y” which is the variable that is used for prediction and must be in numerical values. In our case, the dataframe “ds”, which is used for the datestamp, is receiving the “’date” and “y” is being used as input to the ‘CPI Inflation’ from the dataset. Then, we are required to develop an object from the Prophet() class, in which the data frame is fitted into the object. The dataframe is built via PROPHET.make-future-dataframe and modify into the future forecasting for a predefined one-step forecasting. There is a step of computation of expectations on a “ds” column called dataframe having the dates of forecasted values. At this time, we only looked at ‘ds’ and ‘yhat’ columns and ignored further details as they were not required in this work. As, ‘yhat’ column contains the predicted values of ‘y’ in the historical data frames ‘ds’ and ‘yhat’ column are plotted to depict the features, for instance seasonality or trend.

CHAPTER 4

Results and Discussion

This chapter presents the results for forecasting of inflation (CPI) of developed and developing countries and discusses the comparative analysis of ARIMA, LSTM, PROPHET and HYBRID (ARIMA+LSTM) methods. There are a total of twelve countries out of which six are developed and six are developing countries. Each algorithm is implemented for monthly inflation (CPI) forecasting of each country using different training and test ratios for data, namely 70:30, 80:20 and 90:10. Developed countries include Canada, Poland, Australia, Norway, Switzerland and USA, whereas developing countries include Brazil, India, Colombia, Indonesia, Mexico and South Africa. Evaluation metrics to calculate the performance of algorithms are R^2, Scale-dependent metric MAE (mean absolute error), Percentage-error metric MAPE (mean absolute percentage error) and Scale-dependent metric RMSE (root mean square error). After adjusting order (p, d, q) for ARIMA, number of neurons and number of epochs for LSTM and yearly seasonality (False) for PROPHET, the results and discussion is divided into three main parts as per the train-to-test ratio. The walk forward validation method for one step ahead (monthly) is used for performance validation.

4.1 Training-to-testing ratio 70:30

Inflation (CPI) forecasting of developed countries Canada, Poland, Australia, Norway, Switzerland and U.S is shown in Figures 5, 6, 7, 8, 9 and 10. In figures “Actual” represents the inflation forecasting of test data, “HYBRID” represents the inflation forecasting using ARIMA+LSTM model, “LSTM” represents the forecasted data by LSTM model, “ARIMA”

represents the inflation forecasted by ARIMA model and “PROPHET” using PROPHET model to forecast inflation (CPI).

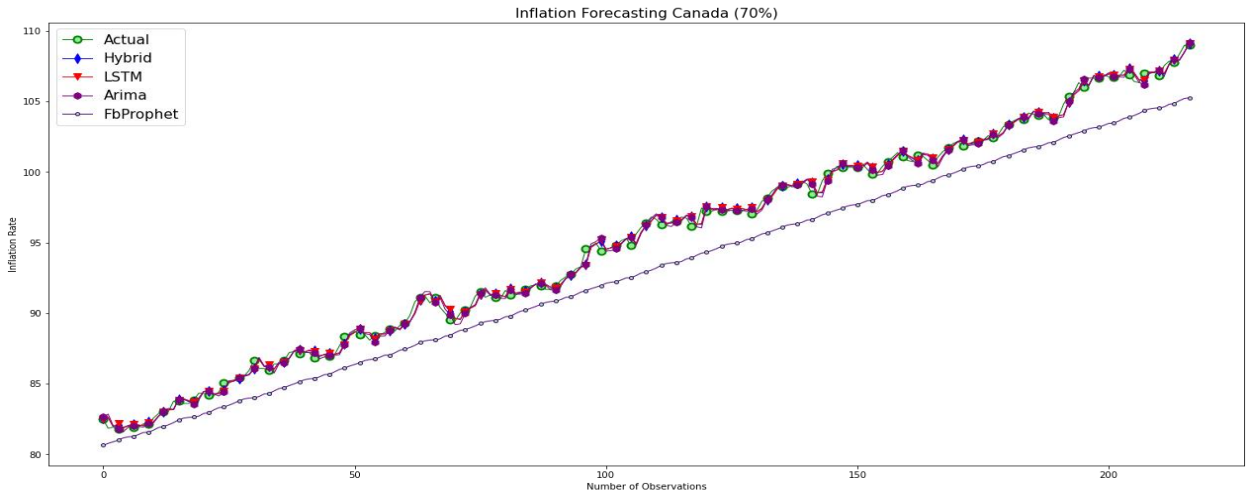

Figure 5 Inflation forecasting of Canada

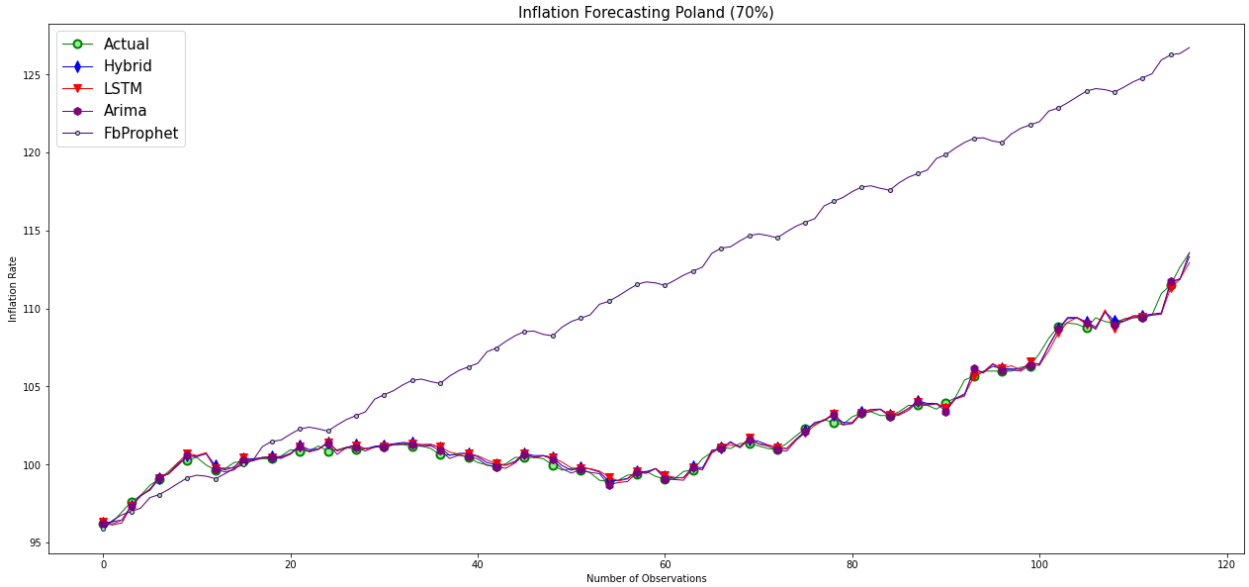

Figure 6 Inflation forecasting of Poland

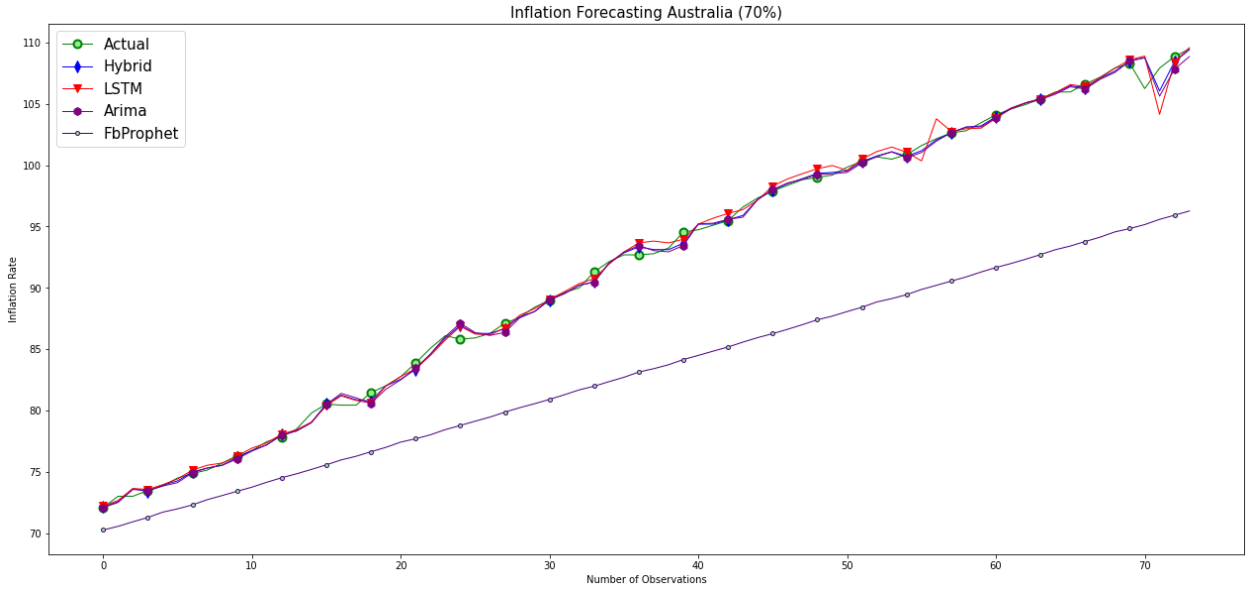

Figure 7 Inflation forecasting of Australia

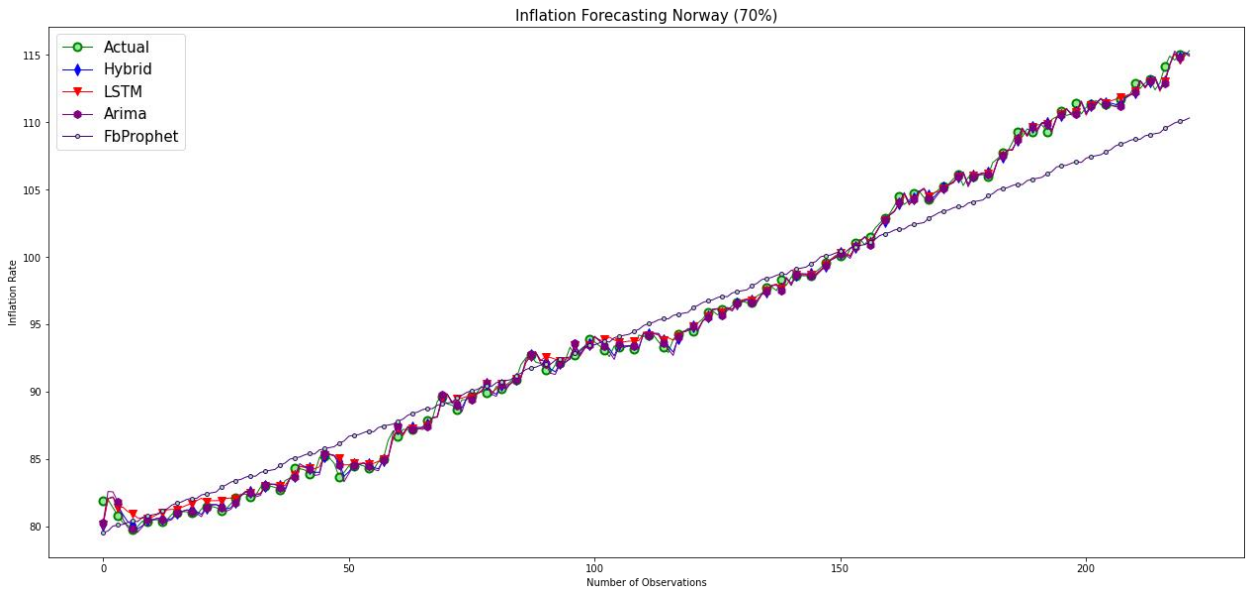

Figure 8 Inflation forecasting of Norway

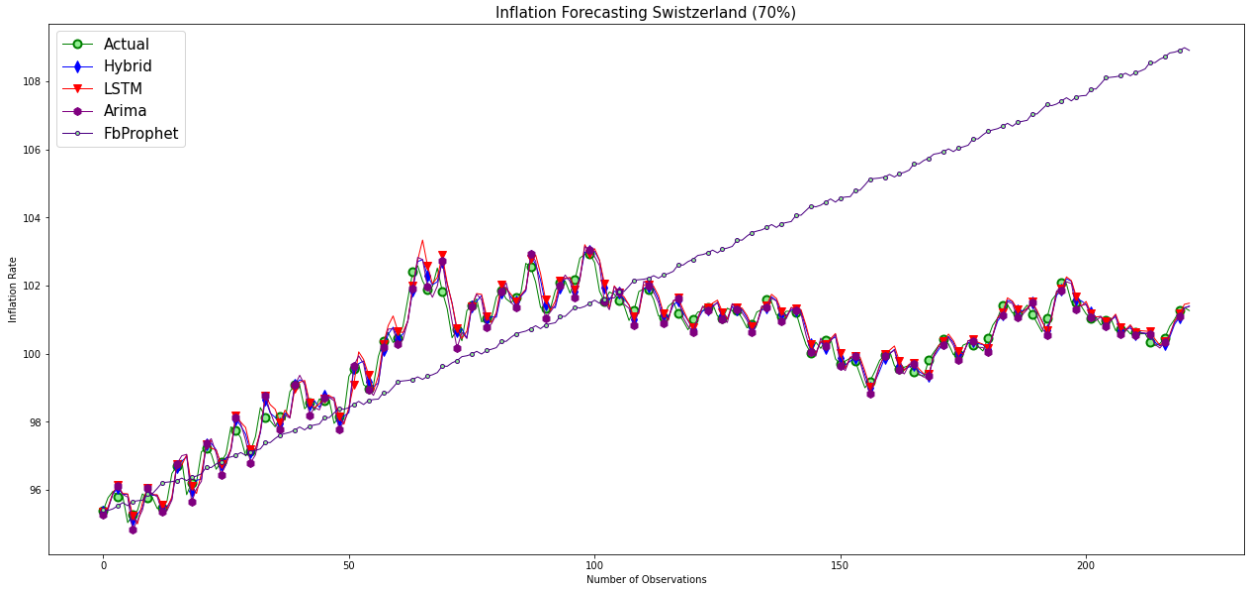

Figure 9 Inflation forecasting of Switzerland

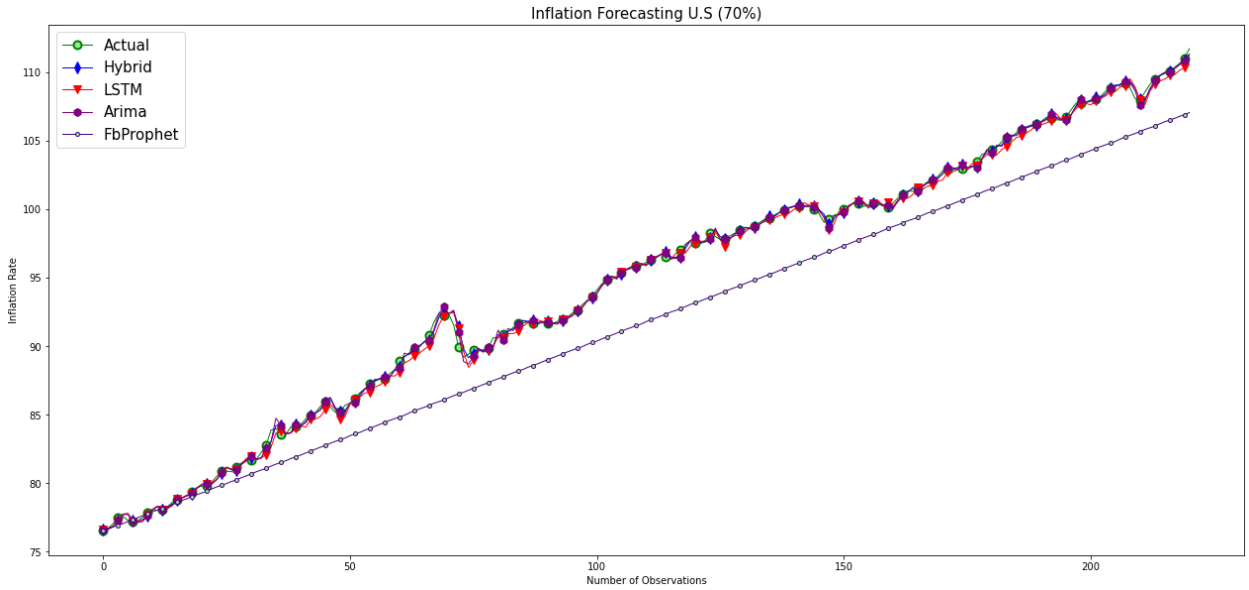

Figure 10 Inflation forecasting of U.S

Evaluation metrics were calculated for all four models used for forecasting of inflation for developed countries as shown in Table 3. Initially the three models were tested separately and from results it shows that ARIMA and LSTM are performing better than PROPHET, which gave us an idea of implementing the HYBRID model (ARIMA+LSTM) to improve the performance. As shown in the Table 1, performance of HYBRID model outperforms every other model in terms of

R^2, MAE, MAPE and RMSE which makes it reliable to use for monthly inflation rate forecasting problem. Whereas, PROPHET model no doubt is good algorithm but for inflation (CPI) forecasting problem using walk forward validation method, it doesn't perform well. From the results shown in Table 1 it can be seen that R^2 of HYBRID, ARIMA and LSTM models are quite similar though there is slight betterment in HYBRID model as compared to ARIMA and LSTM individual performance but other evaluations metrics MAE, MAPE and RMSE values are best for HYBRID model. In case of developed countries, results indicate that inflation (CPI) forecast of all developing countries is best by the HYBRID model. Out of all the developed countries, the forecast for Switzerland is best predicted with the least errors (MAE 0.1759, MAPE 0.0017, RMSE 0.2378).

Table 4 Evaluation metrics for developed countries

Country	**Algorithm**	**R^2**	**MAE**	**MAPE**	**RMSE**
Canada	HYBRID	**0.9980**	**0.2587**	**0.0027**	**0.3398**
	ARIMA	0.9976	0.2739	0.0028	0.3693
	LSTM	0.9966	0.3232	0.0034	0.4381
	PROPHET	0.9133	2.1129	0.0219	2.2380
Poland	HYBRID	**0.9927**	**0.2351**	**0.0022**	**0.3107**
	ARIMA	0.9916	0.2378	0.0023	0.3327
	LSTM	0.9912	0.2498	0.0024	0.3419
	PROPHET	-7.8799	9.2317	0.0890	10.8678
Australia	HYBRID	**0.9979**	**0.3218**	**0.0034**	**0.5143**
	ARIMA	0.9973	0.3833	0.0041	0.5862
	LSTM	0.9959	0.4452	0.0047	0.7224
	PROPHET	0.3140	8.5782	0.0896	9.3703
Norway	HYBRID	**0.9982**	**0.3341**	**0.0035**	**0.4349**
	ARIMA	0.9979	0.3556	0.0037	0.4721

	LSTM	0.9977	0.3833	0.0041	0.4942
	PROPHET	0.9640	1.5433	0.0155	1.9782
Switzerland	HYBRID	**0.8973**	**0.1759**	**0.0017**	**0.2308**
	ARIMA	0.8957	0.1804	0.0017	0.2326
	LSTM	0.8793	0.1966	0.0019	0.2503
	PROPHET	-28.1523	3.8385	0.03819	3.8907
U.S.	HYBRID	**0.9992**	**0.17726**	**0.0018**	**0.2595**
	ARIMA	0.9992	0.1891	0.0020	0.2682
	LSTM	0.9984	0.2906	0.0030	0.3806
	PROPHET	0.8884	2.9056	0.0300	3.1951

Inflation forecasting of developing countries Brazil, India, Colombia, Indonesia, Mexico and South Africa are shown in Figures 11, 12, 13, 14, 15 and 16 respectively. Legends show that different models' forecasted inflation is shown in the figures with different plot symbols and colors. From the figures it can be seen that inflation forecast using ARIMA, LSTM and HYBRID models are quite similar but again for developing countries also PROPHET didn't capture the inflation rate. In case of developing countries, results depict that inflation (CPI) of Colombia was forecasted one step ahead well with R^2 as 0.9997, MAE as 0.1759, and RMSE as 0.2308. While LSTM and HYBRID models provided similar performance in terms of MAPE metric.

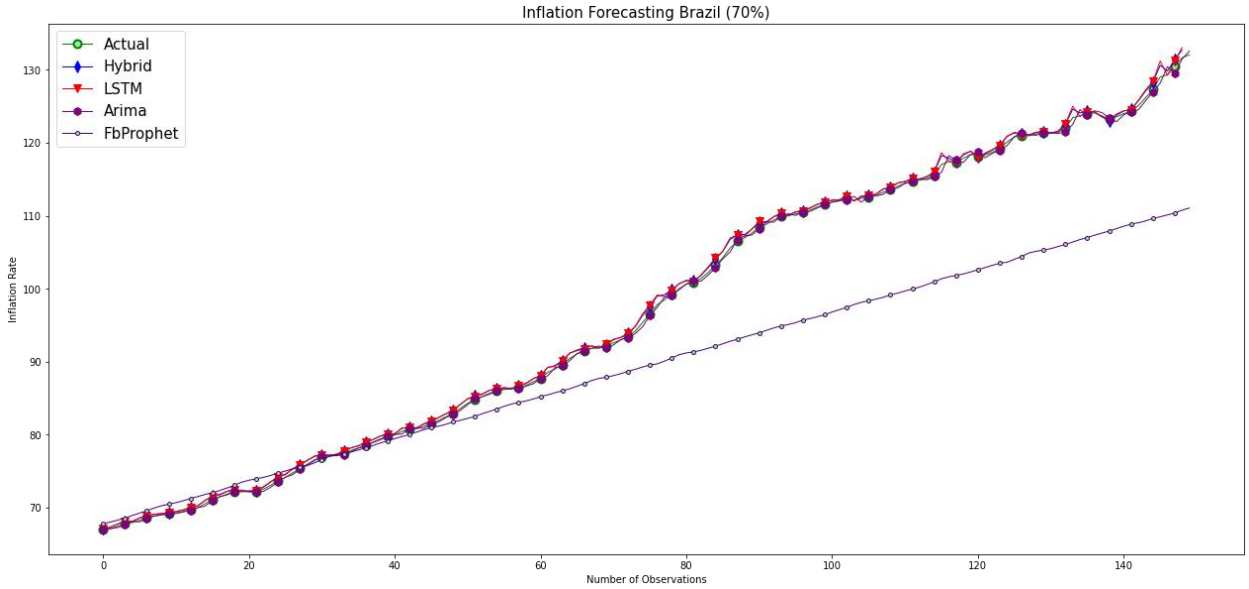

Figure 11 Inflation forecasting of Brazil

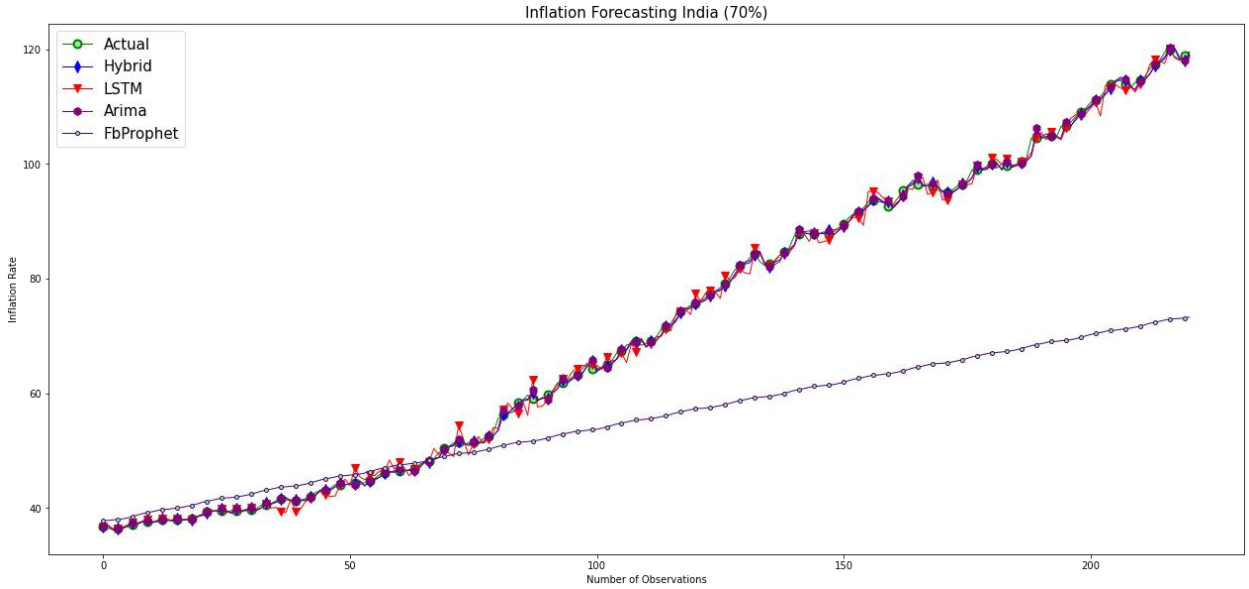

Figure 12 Inflation forecasting of India

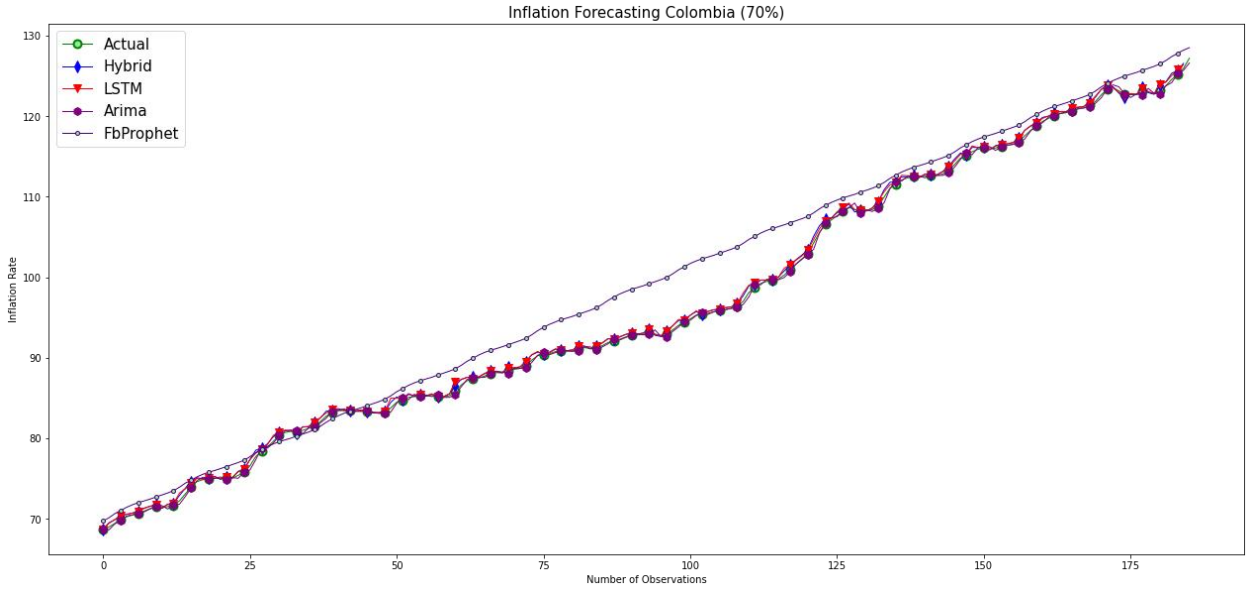

Figure 13 Inflation forecasting of Colombia

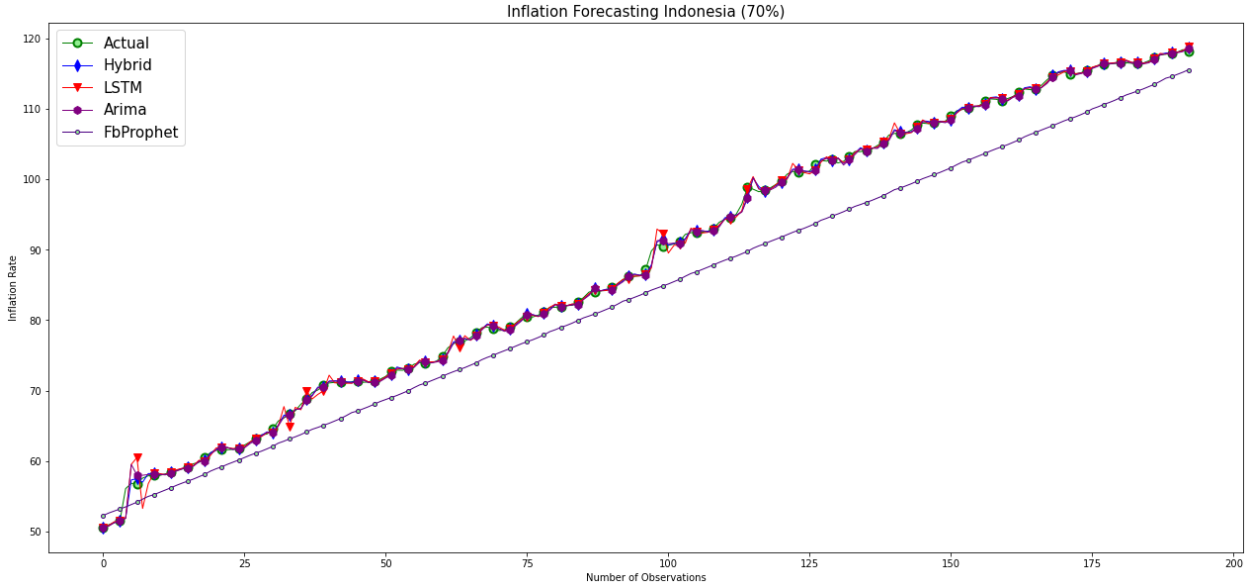

Figure 14 Inflation forecasting of Indonesia

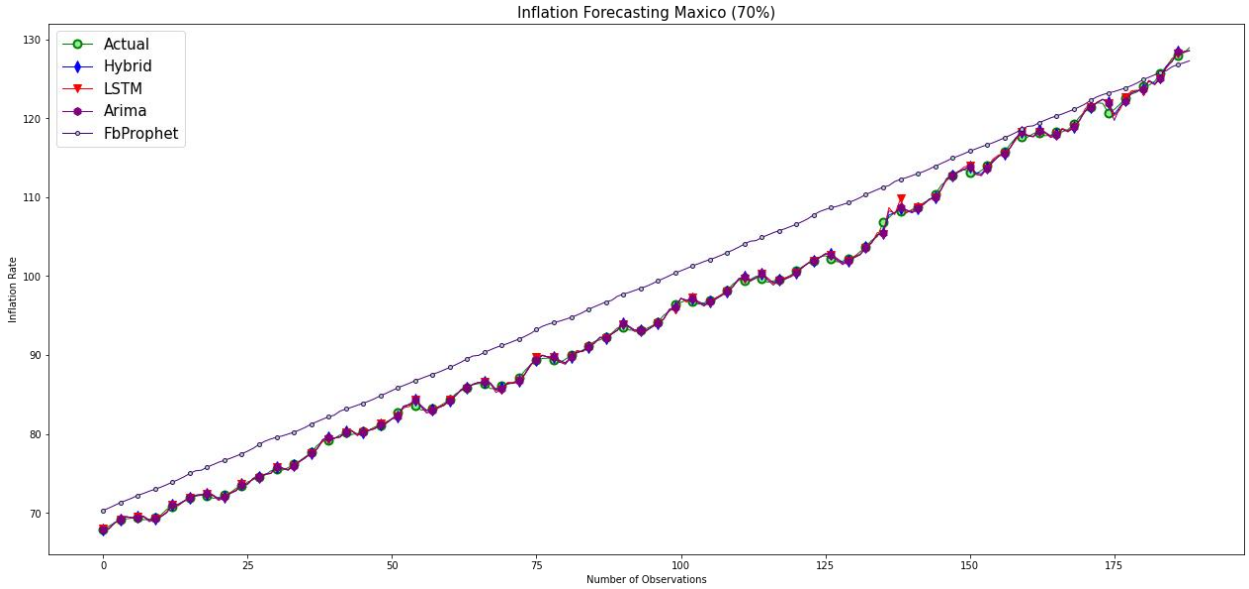

Figure 15 Inflation forecasting of Mexico

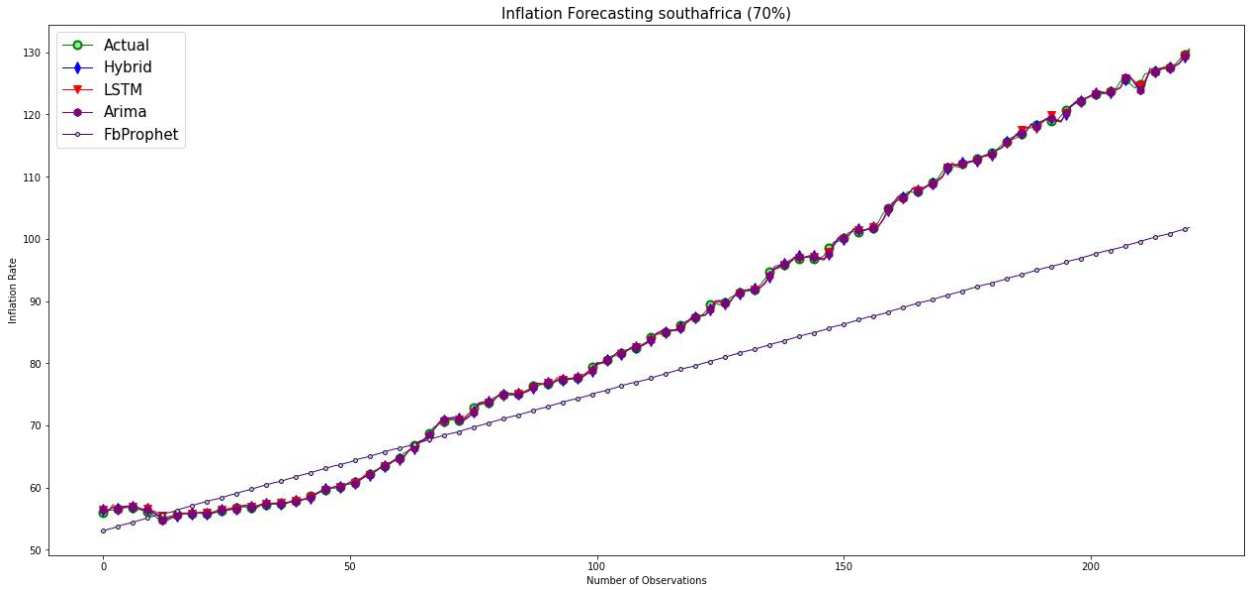

Figure 16 Inflation forecasting of South Africa

Evaluation metrics of all the models for developing countries are shown in Table4. It is clear that the results of HYBRID model outperformed the obtained results from other models. Overall, the proposed models' average results of evaluation metrics MAE as 1.384244, MAPE as 0.013983 and RMSE as 1.60495 with 30% ratio of testing data sets for all developed countries inflation

(CPI) outperformed all four models' performance for all developing countries inflation rate with an average of MAE as 2.193188, MAPE as 0.034412 and RMSE as 2.824421.

Table 5 Evaluation metrics for developing countries

Country	**Algorithm**	**R^2**	**MAE**	**MAPE**	**RMSE**
Brazil	HYBRID	**0.9997**	**0.2235**	**0.0021**	**0.3117**
	ARIMA	0.9997	0.2287	0.0022	0.3142
	LSTM	0.9996	0.2395	0.0022	0.3630
	PROPHET	0.7047	8.2378	0.0738	10.7296
India	HYBRID	**0.9995**	**0.4155**	**0.0058**	**0.5875**
	ARIMA	0.9994	0.4367	0.0061	0.6069
	LSTM	0.9982	0.8277	0.01238	1.1198
	PROPHET	0.2443	17.3693	0.1943	22.9550
Colombia	HYBRID	**0.9997**	**0.1826**	**0.0019**	**0.2339**
	ARIMA	0.9997	0.1909	0.0020	0.2476
	LSTM	0.9997	0.1888	0.0019	0.2488
	PROPHET	0.9584	2.7043	0.0283	3.3845
Indonesia	HYBRID	**0.9994**	**0.2929**	**0.0035**	**0.4827**
	ARIMA	0.9992	0.3271	0.0040	0.5434
	LSTM	0.9985	0.4057	0.0052	0.7552
	PROPHET	0.9305	4.8182	0.0530	5.2470
Mexico	HYBRID	**0.9996**	**0.2481**	**0.0025**	**0.3211**
	ARIMA	0.9995	0.2710	0.2710	0.3504
	LSTM	0.9995	0.2764	0.0028	0.3708
	PROPHET	0.9451	3.7072	0.0409	4.0079
South Africa	HYBRID	**0.9997**	**0.2602**	**0.0030**	**0.3487**
	ARIMA	0.9997	0.2773	0.0032	0.3702
	LSTM	0.9997	0.2799	0.0032	0.3708
	PROPHET	0.6792	10.2272	0.1006	13.5154

4.2 Training-to-testing ratio 80:20

Inflation (CPI) forecasting of developed countries Canada, Poland, Australia, Norway, Switzerland and U.S are shown in Figure 17, 18, 19, 20, 21 and 22.

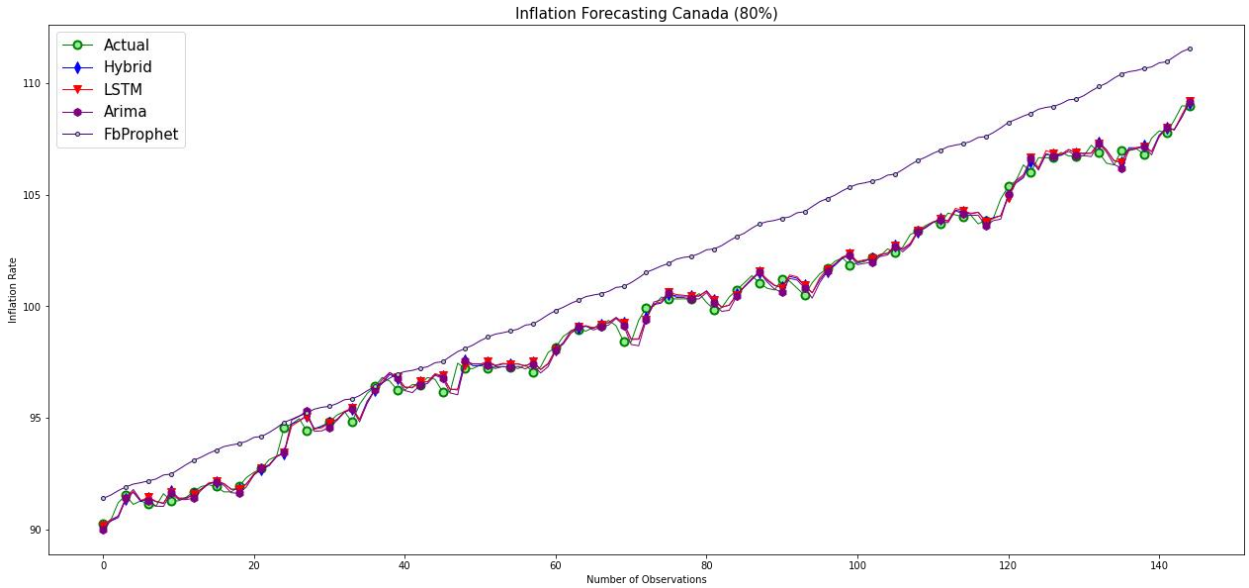

Figure 17 Inflation forecasting of Canada

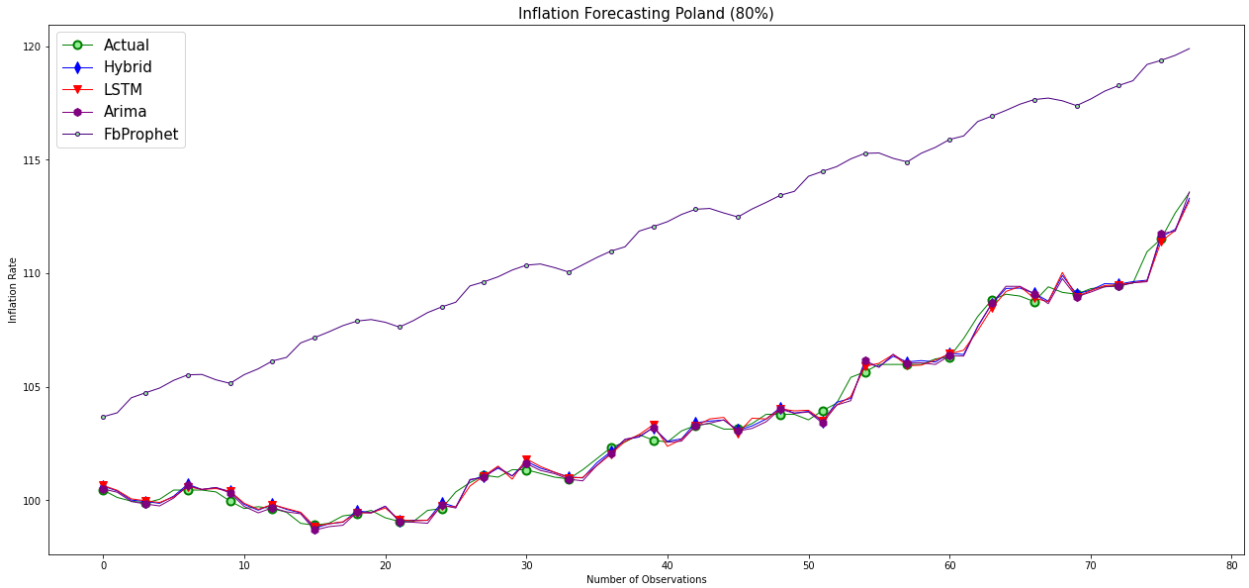

Figure 18 Inflation forecasting of Poland

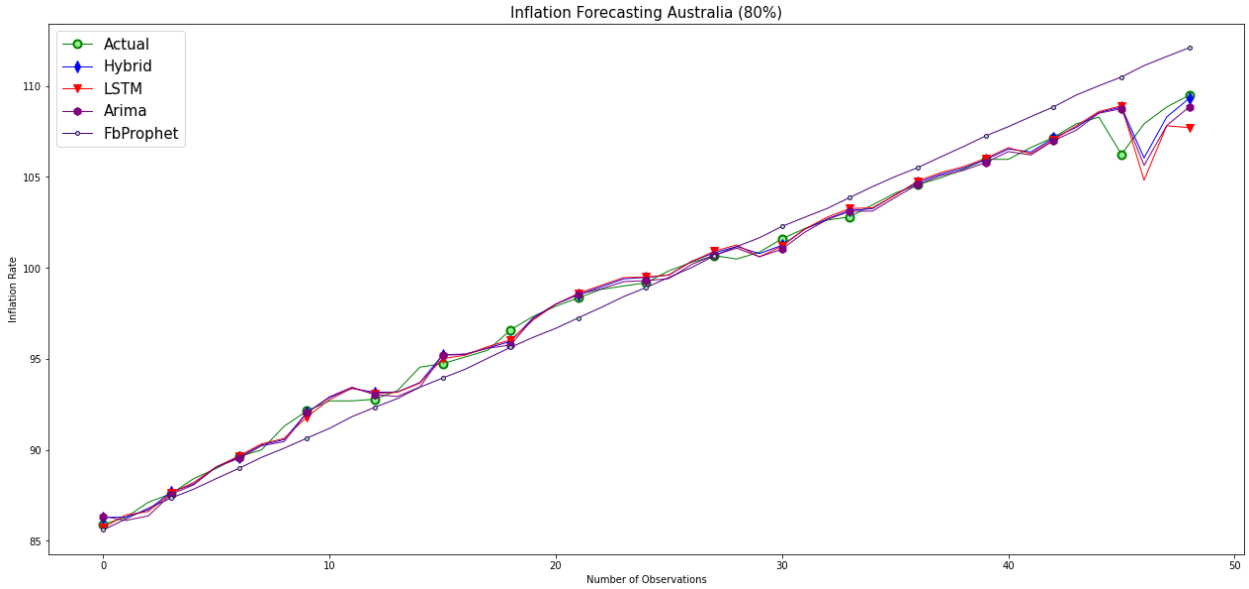

Figure 19 Inflation forecasting of Australia

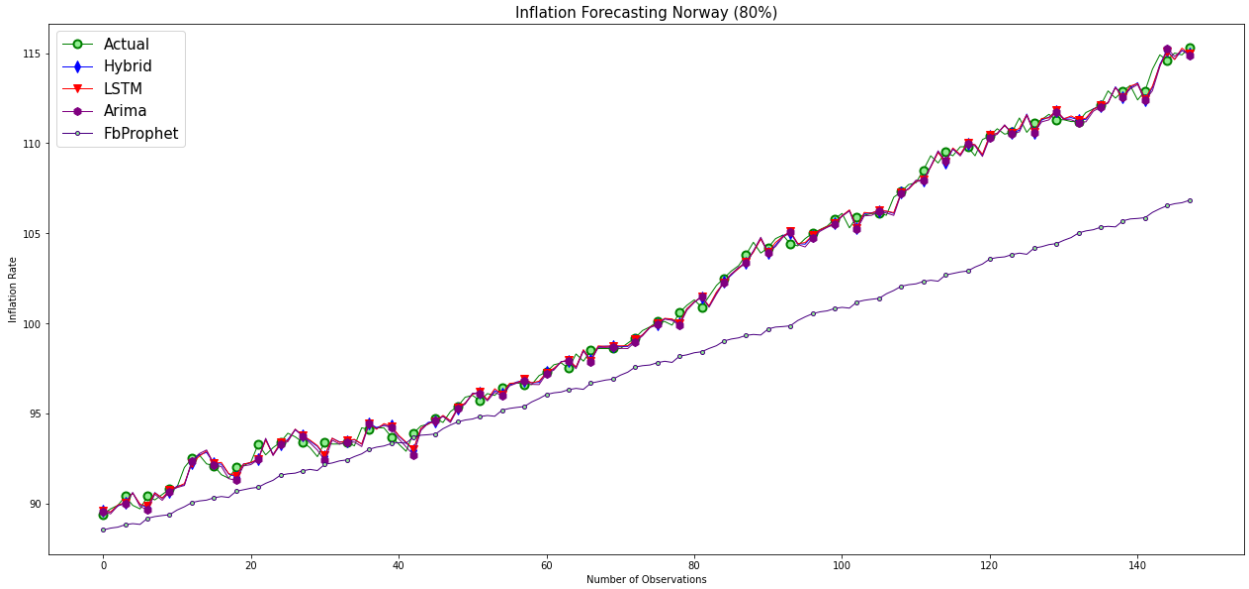

Figure 20 Inflation forecasting of Norway

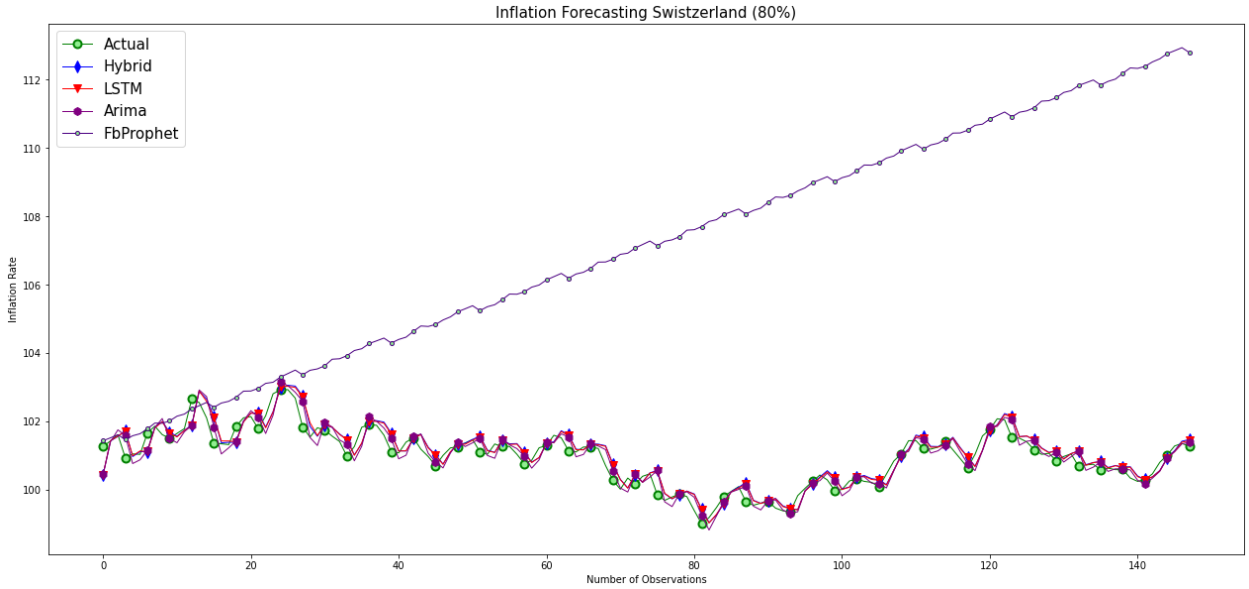

Figure 21 Inflation forecasting of Switzerland

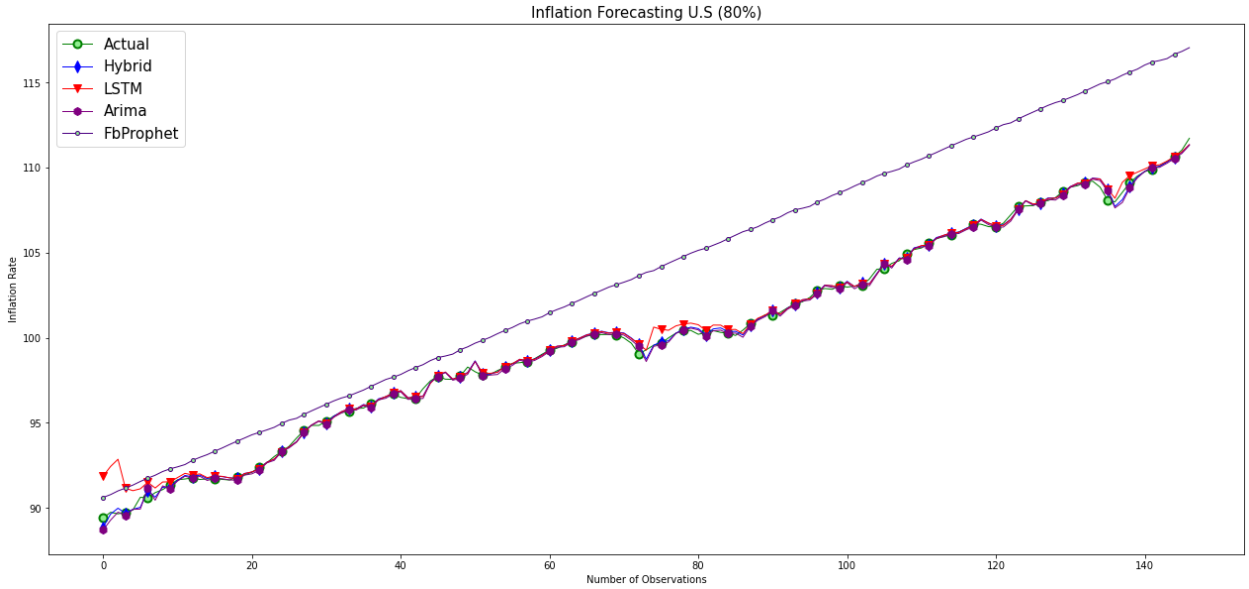

Figure 22 Inflation forecasting of U.S

As our empirical findings show that with ratio of training and testing 70:30, Switzerland performed better in case of developed countries. Evaluation metrics of all the models on 80% training and 20% testing data for developed countries are shown in Table5. In case of developed countries, results indicate that inflation (CPI) of U.S was forecasted the best with highest R^2 as 0.9987, and

least errors in MAE as 0.1536, MAPE as 0.0015 and RMSE as 0.2090 in the HYBRID model. Overall, the Hybrid model gave the best forecasting results. In case of Switzerland, both ARIMA and LSTM give the best results. Whereas, PROPHET model performance was lowest among all models.

Table 6 Evaluation metrics for developed countries

Country	**Algorithm**	**R2**	**MAE**	**MAPE**	**RMSE**
Canada	HYBRID	**0.9954**	**0.2575**	**0.0025**	**0.3409**
	ARIMA	0.9945	0.2709	0.0027	0.3712
	LSTM	0.9952	0.2596	0.0026	0.3455
	PROPHET	0.7945	2.0293	0.0200	2.2834
Poland	HYBRID	**0.9922**	**0.2579**	**0.0024**	**0.3430**
	ARIMA	0.9911	0.2665	0.0025	0.3669
	LSTM	0.9915	0.2663	0.0025	0.3585
	PROPHET	-3.6256	8.2143	0.0793	8.3755
Australia	HYBRID	**0.9931**	**0.3336**	**0.0033**	**0.5600**
	ARIMA	0.9912	0.4007	0.0040	0.6325
	LSTM	0.9883	0.4261	0.0042	0.7323
	PROPHET	0.9619	1.0489	0.01035	1.3216
Norway	HYBRID	0.9968	0.3406	**0.0033**	0.4288
	ARIMA	0.9964	0.3559	0.0035	0.4568
	LSTM	**0.9969**	**0.3401**	**0.0033**	**0.4261**
	PROPHET	0.6942	3.4408	0.0324	4.2484
Switzerland	HYBRID	0.8604	0.2271	**0.0022**	0.2993
	ARIMA	**0.8707**	0.2260	**0.0022**	**0.2881**
	LSTM	0.8668	**0.2224**	**0.0022**	0.2923
	PROPHET	-80.21	6.1567	0.0611	7.222
U.S.	HYBRID	**0.9987**	**0.1536**	**0.0015**	**0.2090**
	ARIMA	0.9984	0.1665	0.0016	0.2296
	LSTM	0.9927	0.2558	0.0026	0.4995

	PROPHET	0.5082	3.5966	0.03498	4.1184

Figures 23 to 28 shows the inflation (CPI) forecasting using different models used for comparative analysis in this research. It can be seen that from the plot representations the all algorithms performed well except PROPHET algorithm.

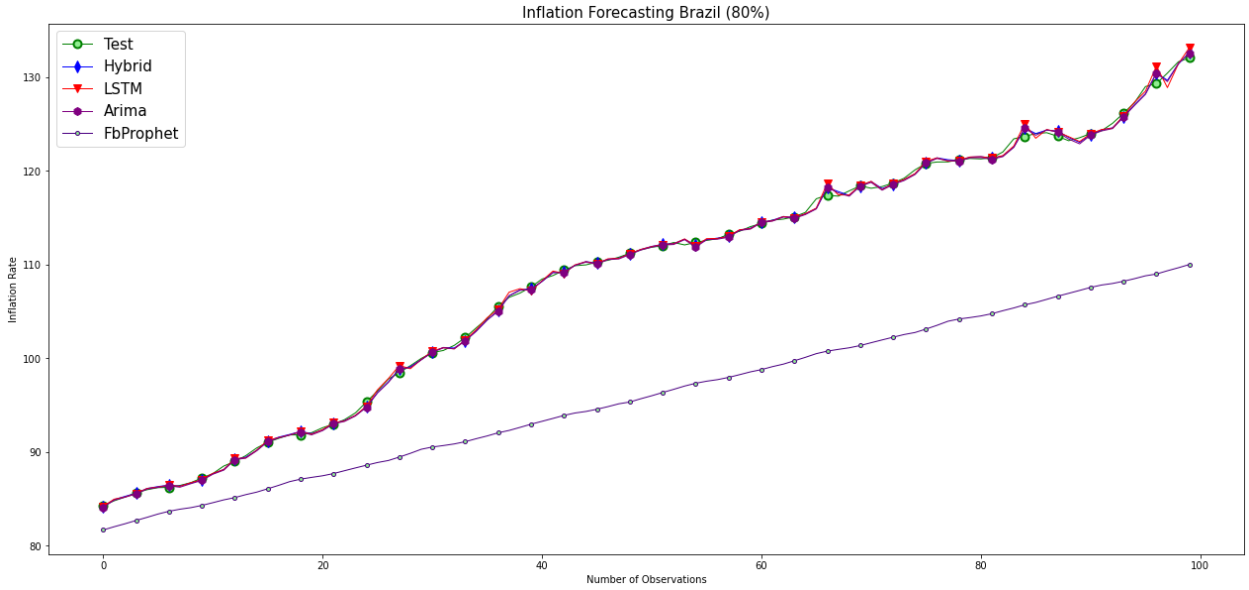

Figure 23 Inflation forecasting of Brazil

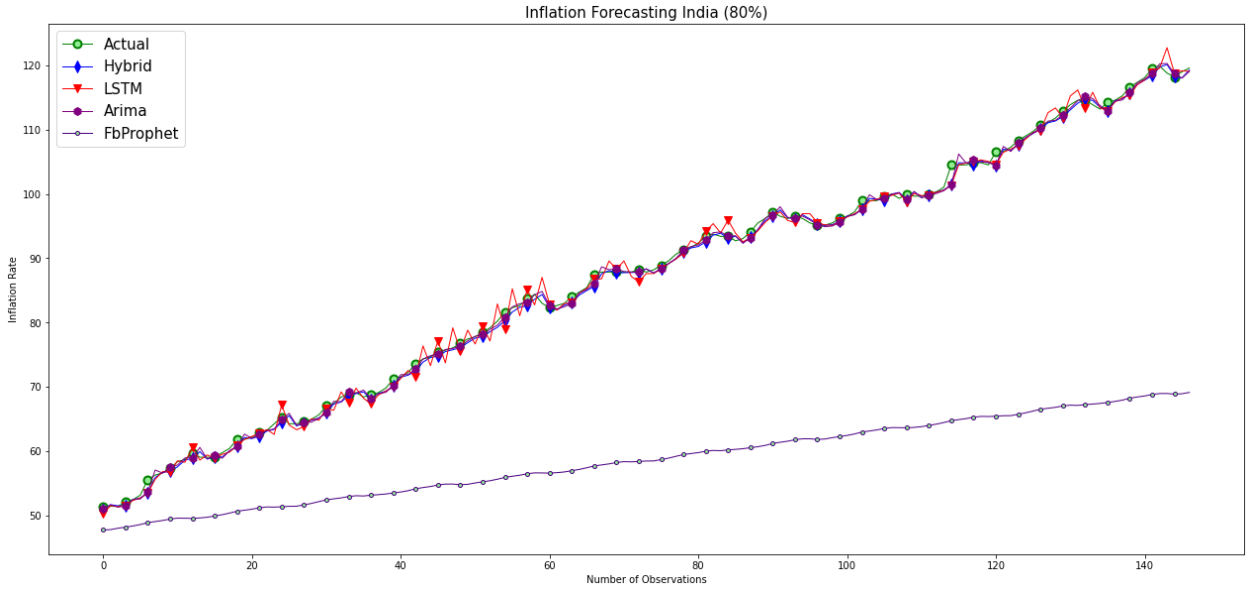

Figure 24 Inflation forecasting of India

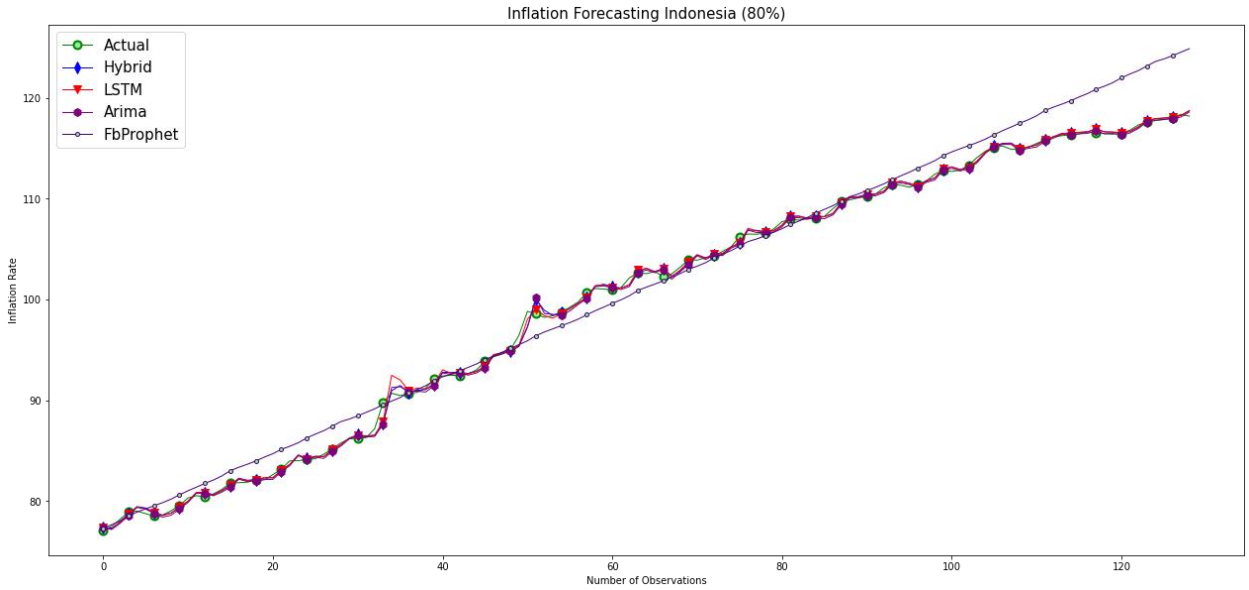

Figure 25 Inflation forecasting of Indonesia

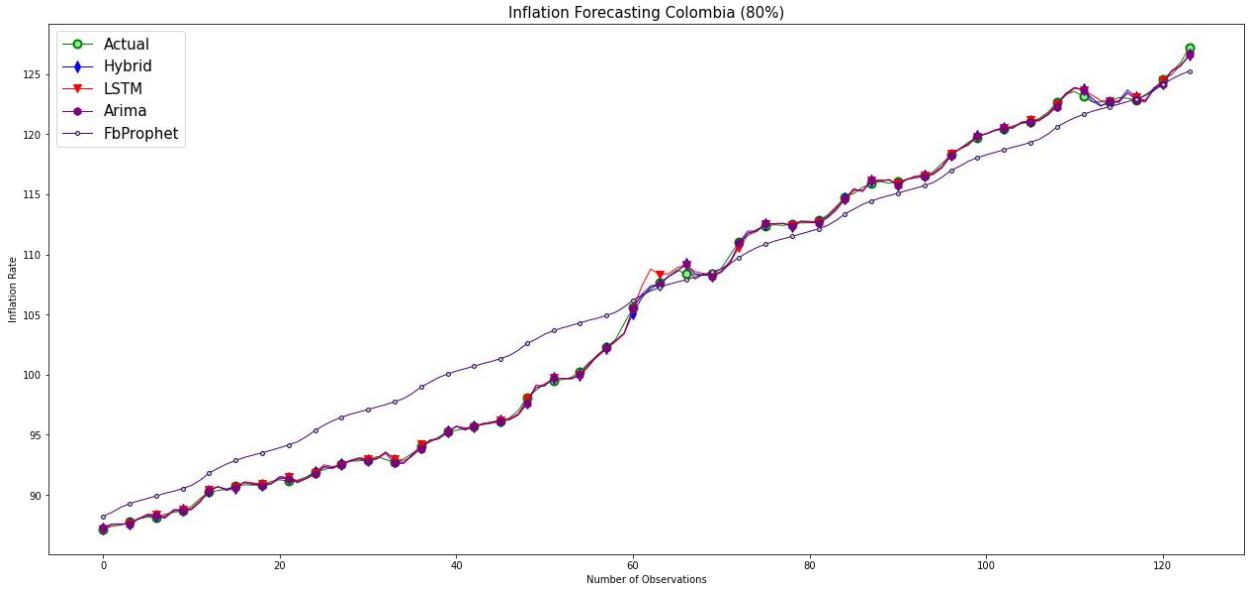

Figure 26 Inflation forecasting of Colombia

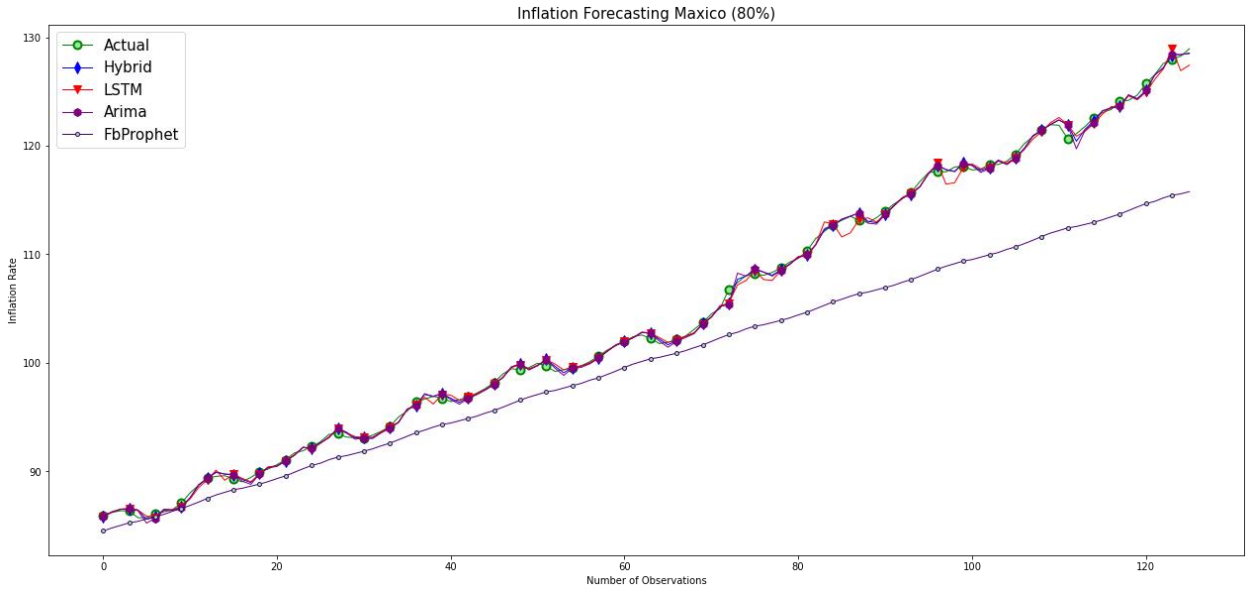

Figure 27 Inflation forecasting of Mexico

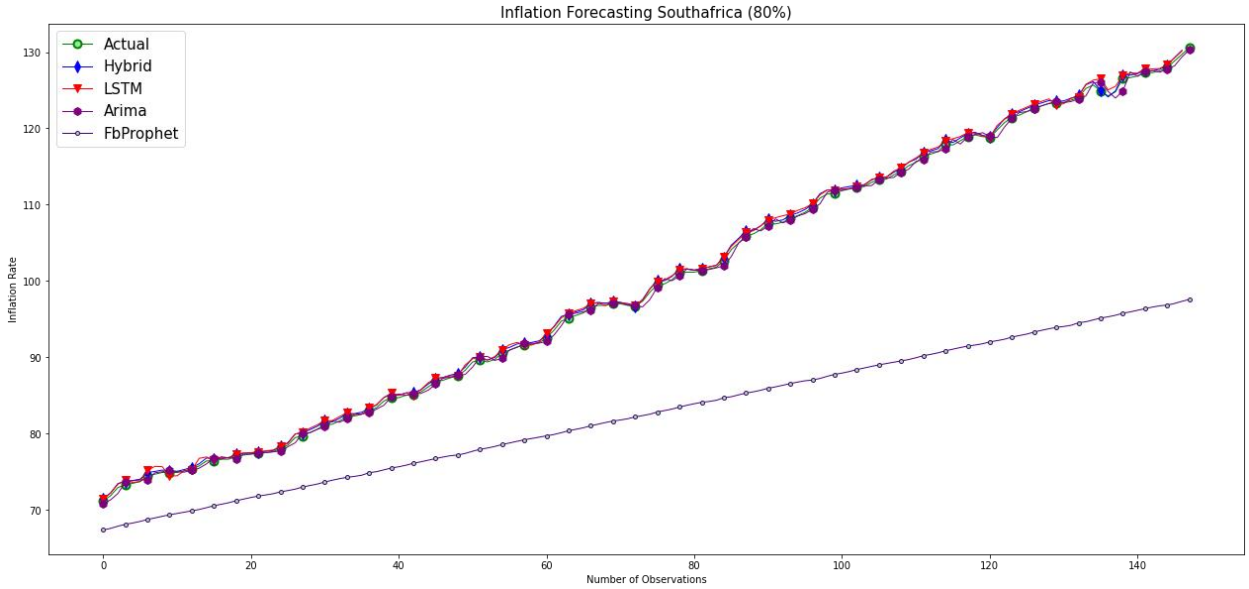

Figure 28 Inflation forecasting of South Africa

As from the figures of forecasting for developing countries it can be analyzed that other than PROPHET all algorithms performed well, which is further verified by using evaluation metrics used for calculating performance of the models. Other 3 models performed well but the proposed HYBRID model evaluation metrics outperformed all of them which makes it the best model for inflation forecasting. According to results of developing countries' inflation forecasting shown in Table6, the inflation (CPI) of Colombia was forecasted one step ahead better with R^2 as 0.9996, MAE as 0.1847, MAPE as 0.0017 and RMSE as 0.2436 via HYBRID model. Overall, Hybrid model performs the best. For Indonesia, LSTM performs the best.

Table 7 Evaluation metrics for developing countries

Country	**Algorithm**	**R^2**	**MAE**	**MAPE**	**RMSE**
Brazil	HYBRID	**0.9993**	**0.2663**	**0.0023**	**0.3537**
	ARIMA	0.9992	0.2819	0.0025	0.3688
	LSTM	0.9989	0.3031	0.0026	0.4426
	PROPHET	-0.0458	12.7107	0.1120	13.9005
India	HYBRID	**0.9986**	0.5429	0.0065	**0.7080**
	ARIMA	**0.9986**	**0.5393**	**0.0064**	0.7157

	LSTM	0.9962	0.8712	0.0103	1.1749
	PROPHET	-1.6111	28.2293	0.3053	31.0981
Colombia	HYBRID	**0.9996**	**0.1847**	**0.0017**	**0.2436**
	ARIMA	0.9995	0.1965	0.0018	0.2573
	LSTM	0.9994	0.2067	0.0019	0.2965
	PROPHET	0.9550	2.1682	0.0218	2.6667
Indonesia	HYBRID	0.9989	0.2923	0.0030	0.4138
	ARIMA	0.9988	0.3150	0.0032	0.4423
	LSTM	**0.9990**	**0.2882**	**0.0029**	**0.4097**
	PROPHET	0.9705	1.6300	0.0157	2.2457
Mexico	HYBRID	**0.9992**	**0.2625**	**0.0024**	**0.3430**
	ARIMA	0.9990	0.2992	0.0028	0.3867
	LSTM	0.9984	0.3564	0.0033	0.4920
	PROPHET	0.7874	4.5228	0.0400	5.7572
South Africa	HYBRID	**0.9994**	**0.2965**	**0.0029**	**0.3952**
	ARIMA	0.9994	0.3135	0.0031	0.4177
	LSTM	0.9993	0.3376	0.0034	0.4524
	PROPHET	-0.1931	17.1550	0.1611	19.3904

The proposed models' average results of evaluation metrics MAE as 1.229738, MAPE as 0.011968 and RMSE as 1.4479 with 20% ratio of testing data sets for all developed countries inflation (CPI) outperformed all the developing countries results with average of MAE as 3.023742, MAPE as 0.029954 and RMSE as 3.473854.

4.3 Training-to-testing ratio 90:10

Figures from 29 to 34 shows the forecasted data using the models for analysis of this research

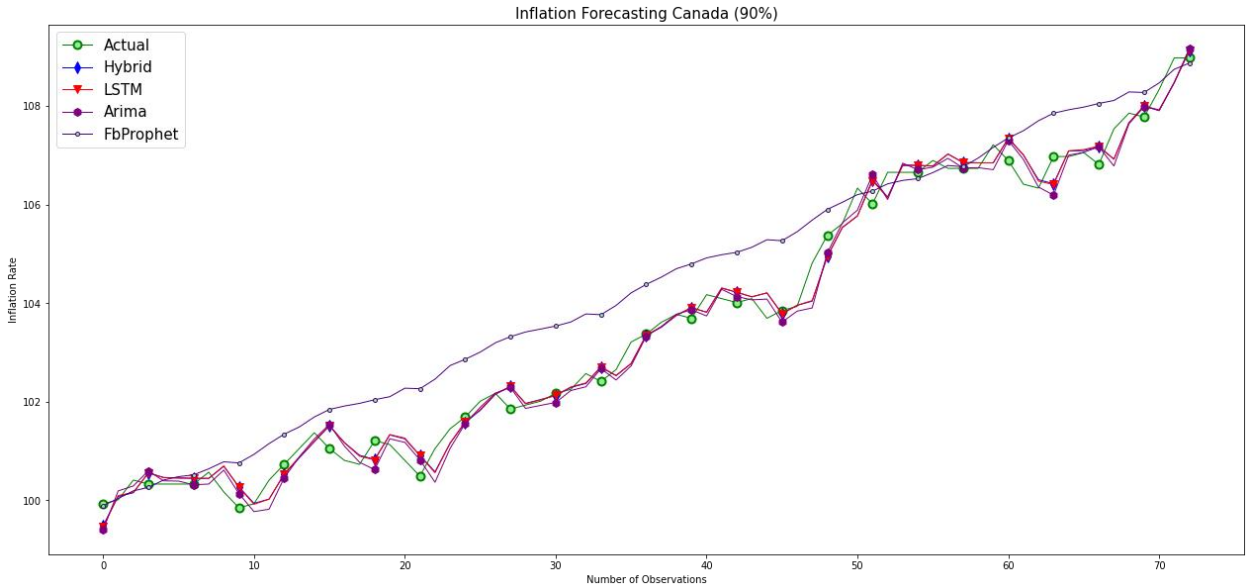

Figure 29 Inflation forecasting of Canada

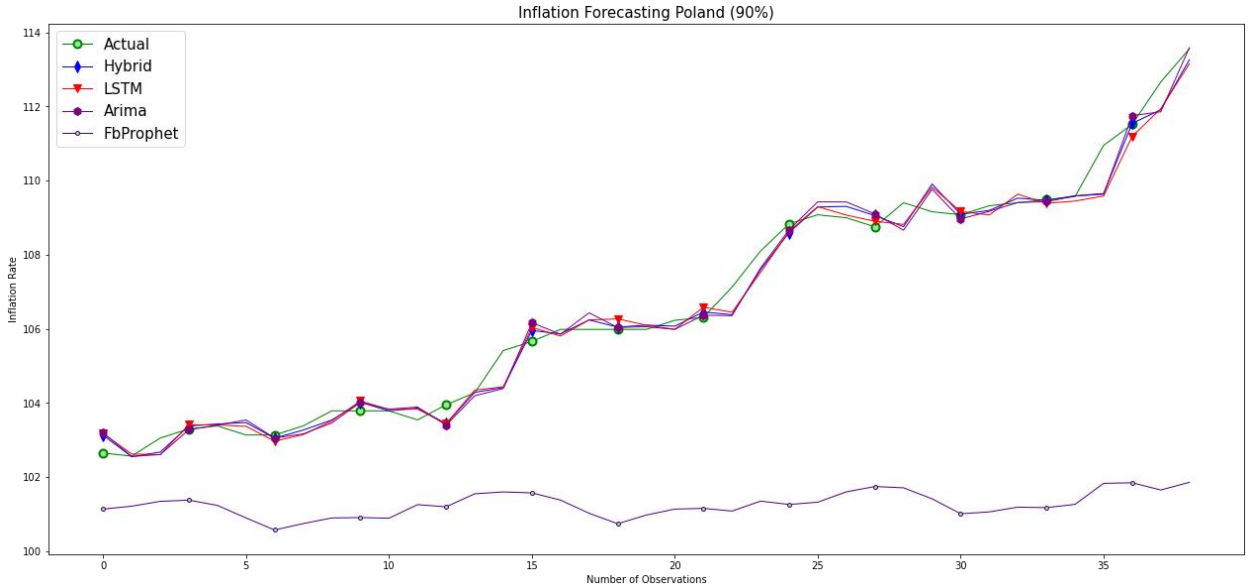

Figure 30 Inflation forecasting of Poland

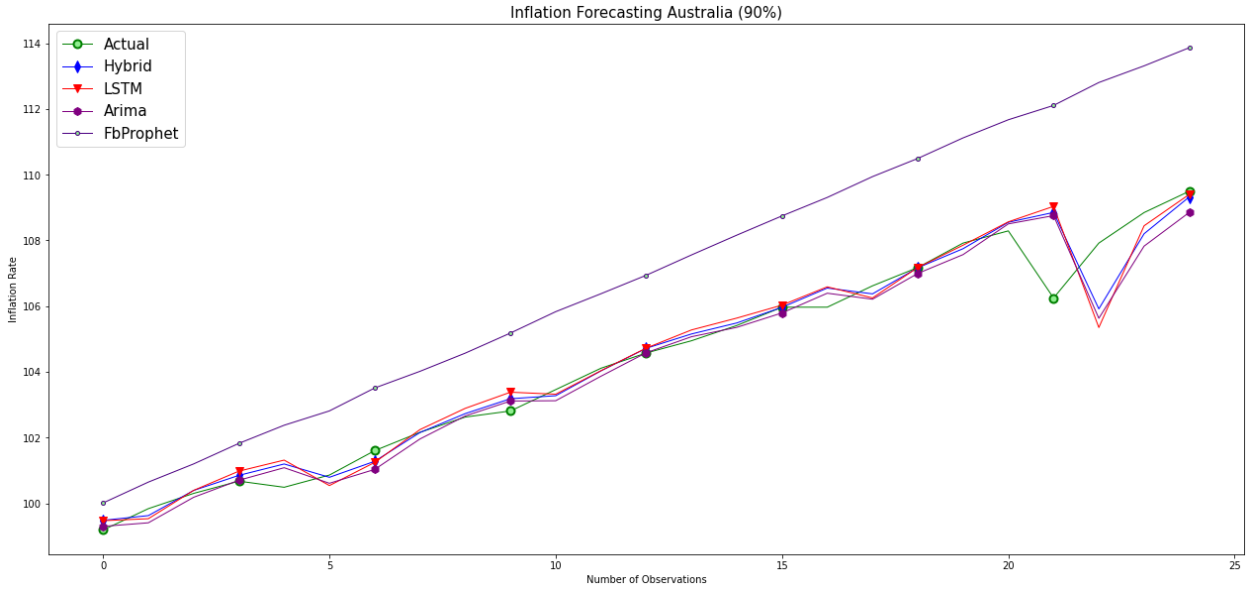

Figure 31 Inflation forecasting of Australia

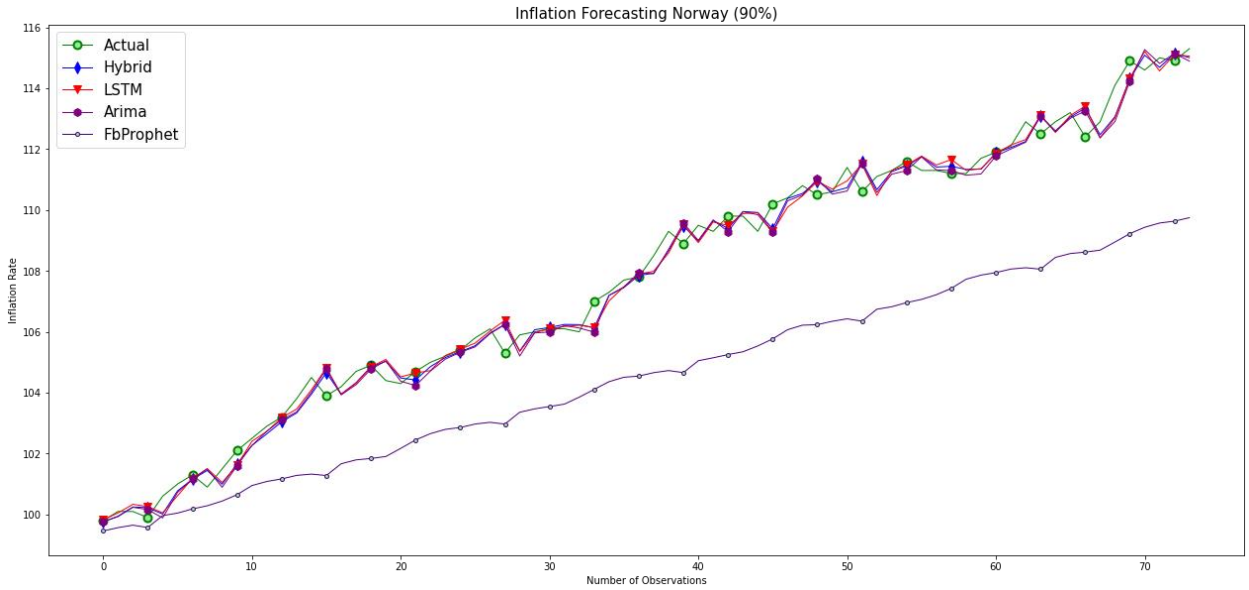

Figure 32 Inflation forecasting of Norway

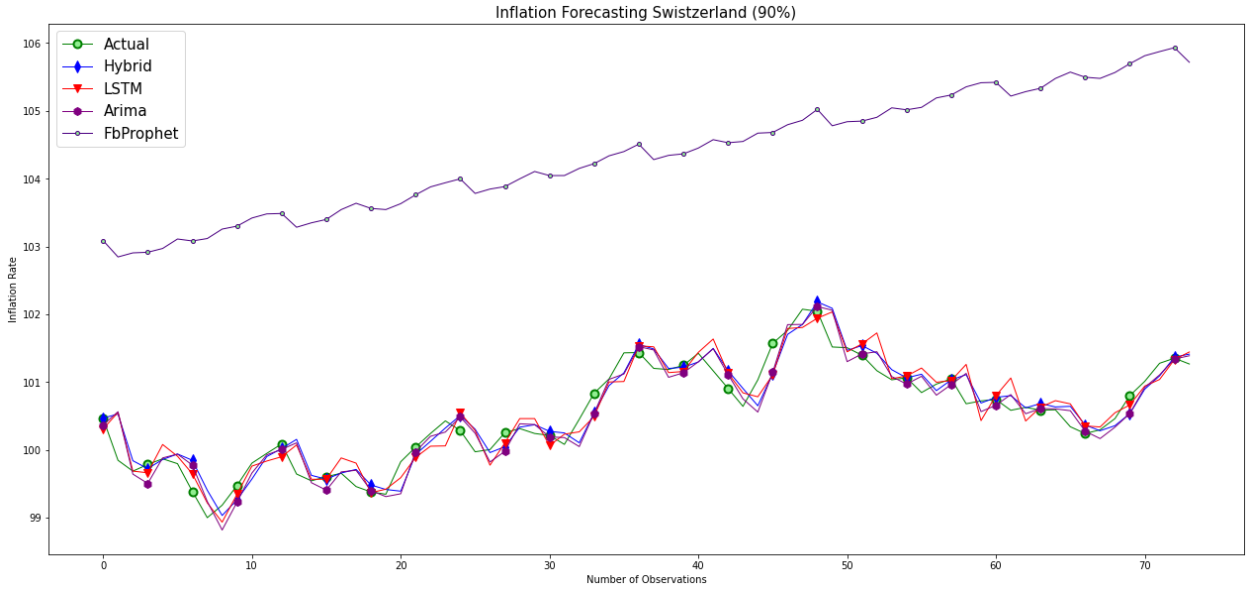

Figure 33 Inflation forecasting of Switzerland

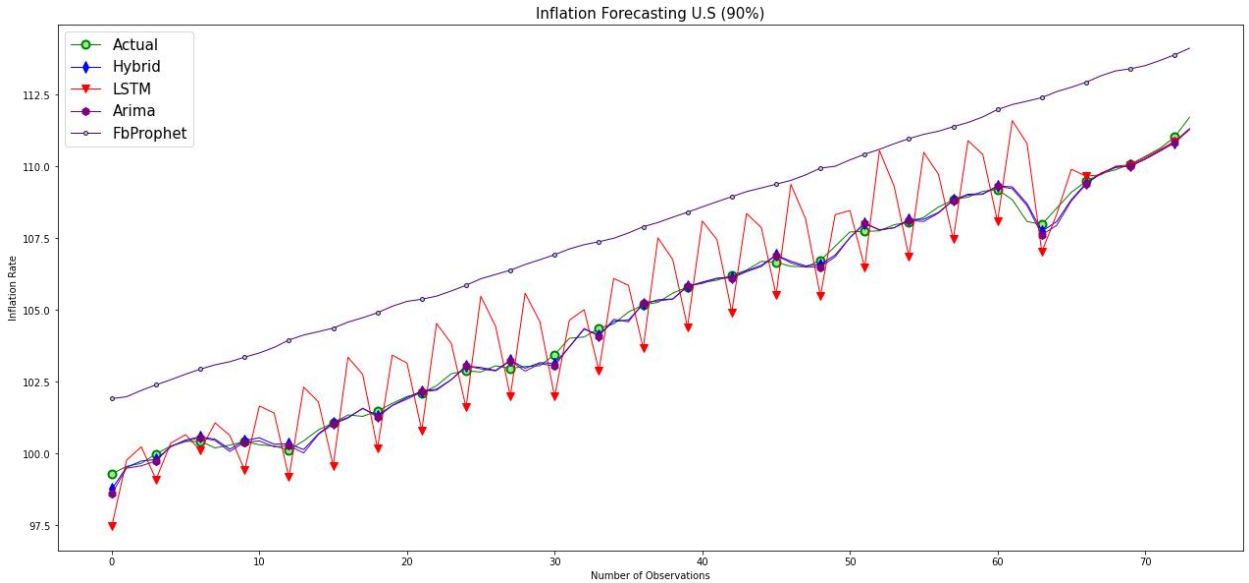

Figure 34 Inflation forecasting of U.S

Evaluation metrics are calculated on 90% training and 10% test data which is shown in Table7, the performance of proposed HYBRID model for this ratio of training and testing data is quite good as compared to other experimented ratios. According to results of developed countries' inflation forecasting shown in Table7, the inflation (CPI) of U.S. was forecasted one step ahead

better with R^2 as 0.9966, MAE as 0.1597, MAPE as 0.0015 and RMSE as 0.2045 in the HYBRID model. Overall, the HYBRID model gives the least error for all the countries.

Table 8 Evaluation metrics for developed countries

Country	**Algorithm**	**R^2**	**MAE**	**MAPE**	**RMSE**
Canada	HYBRID	**0.9867**	**0.2597**	**0.0025**	**0.3170**
	ARIMA	0.9847	0.2641	0.0025	0.3396
	LSTM	0.9863	0.2617	0.0025	0.3212
	PROPHET	0.8893	0.7662	0.0074	0.9144
Poland	HYBRID	**0.9812**	**0.2919**	**0.0027**	**0.4131**
	ARIMA	0.9786	0.3194	0.0029	0.4404
	LSTM	0.9801	0.3256	0.0030	0.4252
	PROPHET	-3.1097	5.4127	0.0500	6.1131
Australia	HYBRID	**0.9453**	**0.3897**	**0.0036**	**0.7147**
	ARIMA	0.9364	0.4650	0.0044	0.7704
	LSTM	0.9274	0.4630	0.0044	0.8234
	PROPHET	0.06770	2.6748	0.02536	2.9518
Norway	HYBRID	**0.9897**	**0.3534**	**0.0032**	**0.4393**
	ARIMA	0.9879	0.3854	0.0035	0.4771
	LSTM	0.9889	0.3605	0.0033	0.4570
	PROPHET	0.3325	3.2579	0.0297	3.5445
Switzerland	HYBRID	**0.9638**	**0.2628**	**0.0026**	**0.3545**
	ARIMA	0.9636	0.2786	0.0027	0.3554
	LSTM	0.9572	0.2924	0.0029	0.3853
	PROPHET	-3.274	2.8812	0.0286	3.8531
U.S.	HYBRID	**0.9966**	**0.1597**	**0.0015**	**0.2045**
	ARIMA	0.9959	0.1752	0.0016	0.2254
	LSTM	0.8379	1.2281	0.0117	1.4247
	PROPHET	0.2458	3.0421	0.0290	3.0738

For developing countries, all models with same split ratio of 90:10 training and testing of total data was used for forecasting the inflation (CPI). The output of all the models is shown in Figures 35 to 40.

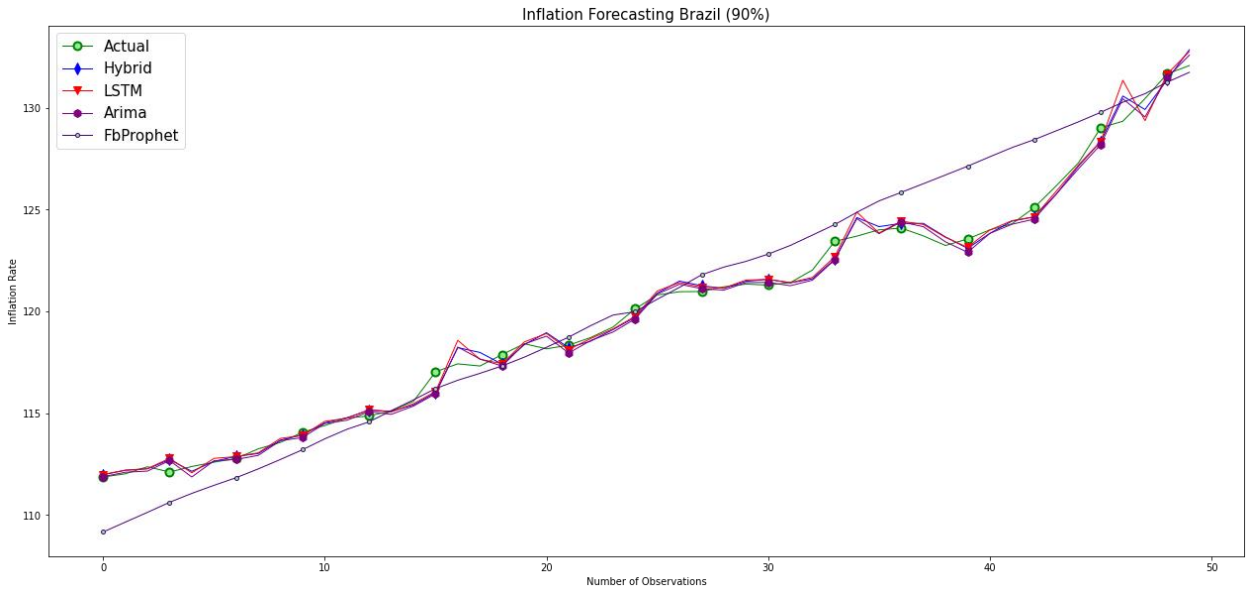

Figure 35 Inflation forecasting of Brazil

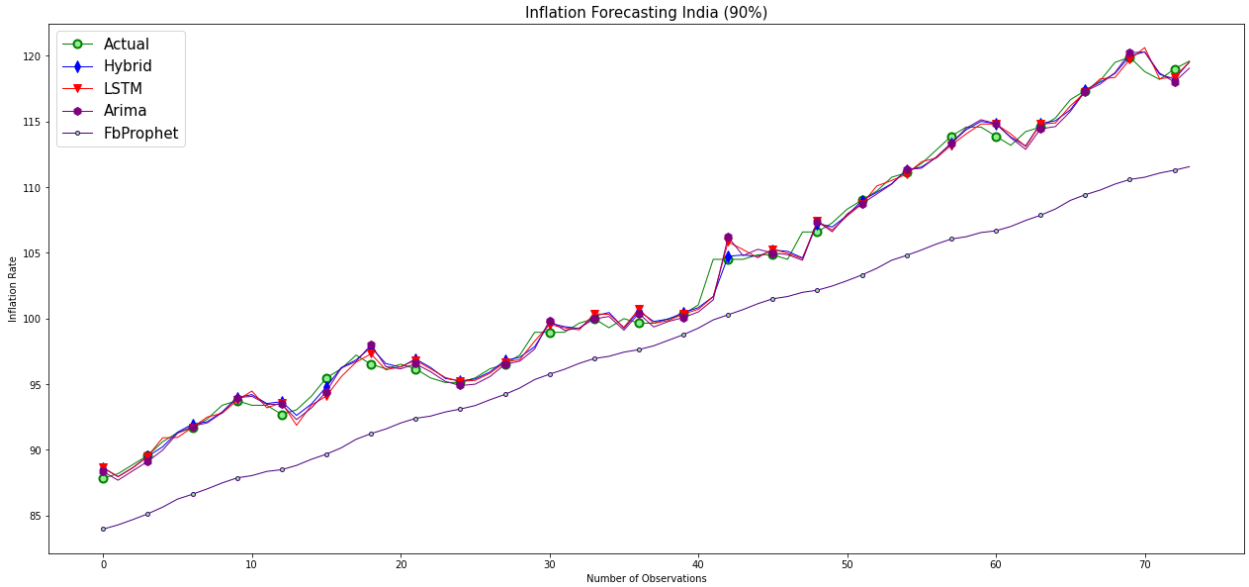

Figure 36 Inflation forecasting of India

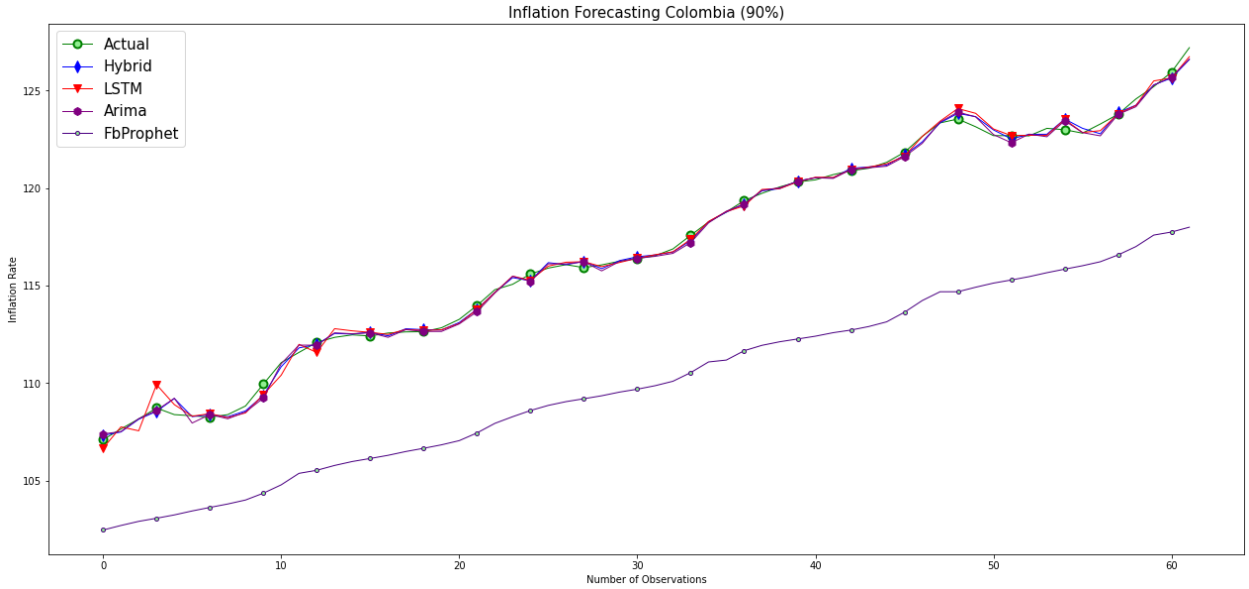

Figure 37 Inflation forecasting of Colombia

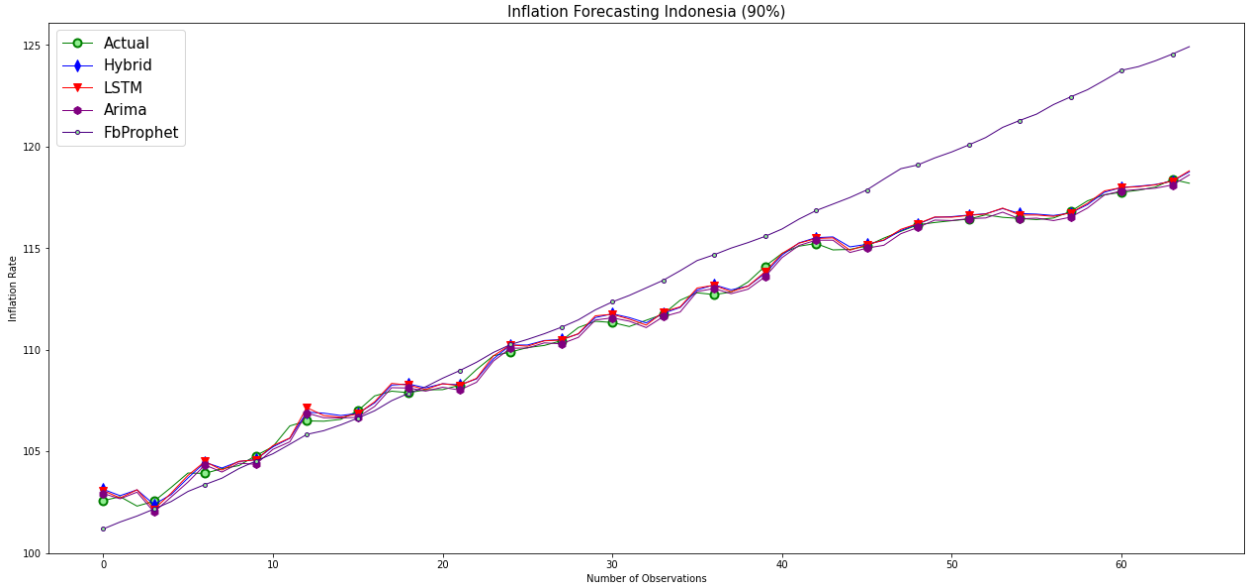

Figure 38 Inflation forecasting of Indonesia

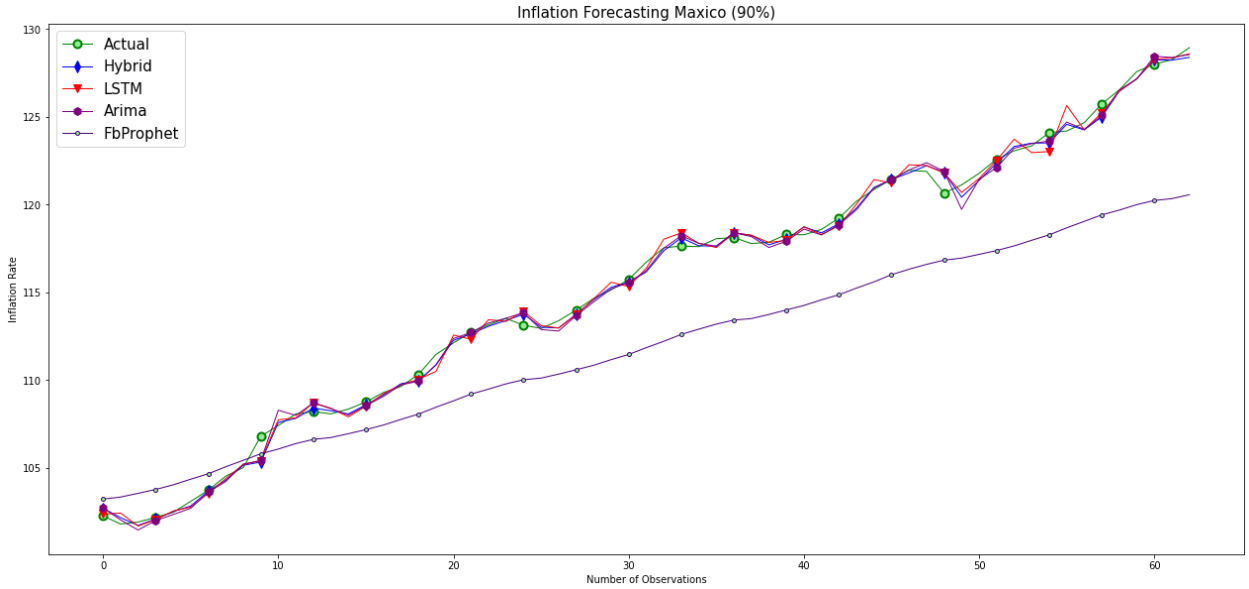

Figure 39 Inflation forecasting of Mexico

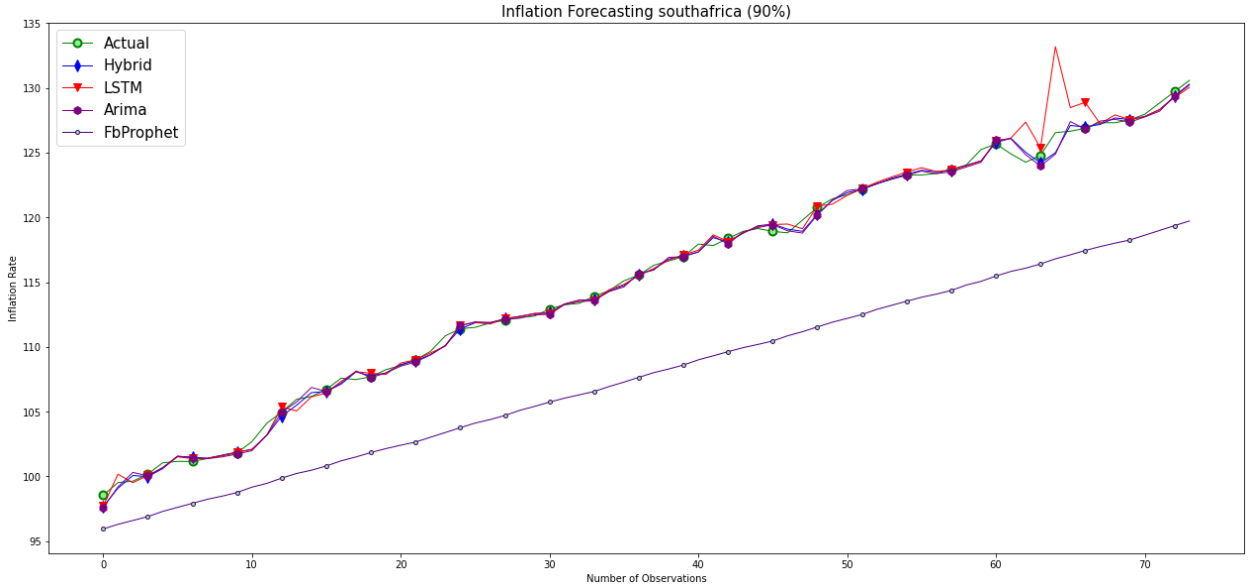

Figure 40 Inflation forecasting of South Africa

Evaluation metrics are shown in Table 8 for the developing countries. This confirms that in this case the proposed HYBRID model performs the best as compared to other 3 models, for inflation forecasting of developed and developing countries. The HYBRID model gives the least error for the forecast of inflation (CPI) for all the countries. However, for Indonesia, LSTM gives the least error. The inflation (CPI) forecast of Colombia gives the maximum R^2 as 0.9978, and least errors

of MAE as 0.2003, MAPE as 0.0017 and RMSE as 0.2574 in HYBRID model. Whereas, PROPHET models ’performance was lowest among all models.

Table 9 Evaluation metrics for developing countries

Country	**Algorithm**	**R^2**	**MAE**	**MAPE**	**RMSE**
Brazil	HYBRID	**0.9931**	**0.3489**	**0.0028**	**0.4561**
	ARIMA	0.9930	0.3561	0.0029	0.4597
	LSTM	0.9908	0.3676	0.0030	0.5291
	PROPHET	0.9137	1.2525	0.0104	1.6211
India	HYBRID	**0.9947**	**0.4907**	**0.0047**	**0.6763**
	ARIMA	0.9933	0.5769	0.0055	0.7660
	LSTM	0.9938	0.5455	0.0052	0.7355
	PROPHET	0.6747	4.9374	0.0471	5.3427
Colombia	HYBRID	**0.9978**	**0.2003**	**0.0017**	**0.2574**
	ARIMA	0.9973	0.2195	0.0018	0.2864
	LSTM	0.9965	0.2407	0.0020	0.3267
	PROPHET	-0.5878	6.8919	0.0586	6.9802
Indonesia	HYBRID	0.9962	0.2439	0.0022	0.2994
	ARIMA	0.9961	0.2415	0.0022	0.3033
	LSTM	**0.9963**	**0.2350**	**0.0021**	**0.2972**
	PROPHET	0.6613	2.0713	0.01802	2.8517
Mexico	HYBRID	**0.9972**	**0.3030**	**0.0026**	**0.3968**
	ARIMA	0.9963	0.3536	0.0030	0.4580
	LSTM	0.9958	0.3875	0.0033	0.4890
	PROPHET	0.6803	3.8033	0.0320	4.2751
South Africa	HYBRID	**0.9976**	**0.3235**	**0.0028**	**0.4389**
	ARIMA	0.9972	0.3434	0.0029	0.4735
	LSTM	0.9878	0.4829	0.0040	0.9956
	PROPHET	0.2601	7.4545	0.0635	7.7792

As mentioned earlier, the experiments were performed to find the best model for inflation forecasting by splitting the data into three different training-to-testing ratios of 90:10, 80:20 and 70:30. Evaluation metrics used for calculating performance for all models on different split ratios of total data sets are mentioned in Table 2-Table 8. ARIMA and LSTM model performed averagely on every case of data splitting, whereas PROPHET didn't perform well because in inflation forecasting there wasn't any seasonality or holidays effects as PROPHET works best on that type of data which have strong seasonal effects in historical data. We included this model because it is one of the popular models' for forecasting according to attempted research on financial time series but after empirical confirmation we conclude that it is not suitable for the inflation (CPI) forecasting applications. ARIMA is robust tool to capture seasonal peaks while LSTM better matches the stable part of the series. This leads us to consider switching to a HYBRID model that would only retain the virtues of the two models. On individual basis these models were performing well but evaluation metrics were not excellent and this led us to design HYBRID model which outperformed all other models' performances and all evaluation metrics were up to the mark. Overall, the proposed models' average results of evaluation metrics MAE as 1.023796, MAPE as 0.009648 and RMSE as 1.222454 with 10% of testing data for all developed countries inflation (CPI) outperformed all other models' performance as well as for all developing countries inflation (CPI) with an average of MAE as 1.361308, MAPE as 0.011847 and RMSE as 1.562288.

CHAPTER 5

Conclusions and Future Work

5.1 Conclusions

The basic idea of the study is to find the best model to forecast inflation (CPI) in the scenario of the economic situation of developed and developing counties. Machine Learning approaches were used for the obtained data to find the best model i.e. among ARIMA, PROPHET, LSTM and HYBRID. Overall, we have seen that ARIMA and LSTM are good models for inflation forecasting, whereas PROPHET doesn't perform well in this application because in our case we don't have seasonal trend in historical data and this requires seasonality in the data set. Performance of ARIMA and LSTM lead us to the idea of making hybrid model with ARIMA+LSTM, which outperformed every other model for forecasting inflation (CPI) of developed and developing countries. Evaluation metrics used for performance measurement are R^2, MAE, MAPE, and RMSE. These metrics of HYBRID model were better than all models in developed and developing countries. Noticeably, 90% training data for available historical record performed well which shows that large amount of data for training would usually provide more robust output as compared to keeping 80% and 70% training data for forecasting inflation (CPI) of a country. Also, it was investigated in our research whether models perform differently while the data is from different economies of developed and developing countries and figured out that HYBRID, ARIMA and LSTM models performed better on data of developed countries as compared to data of developing countries while PROPHET model couldn't perform well either on developed or developing countries' financial time series data. It was also noticed that HYBRID model provided least errors on CPI data of U.S as well as for Colombia for all proposed split ratios

of training and testing evaluation along with walk forward validation in forecasting as time progress.

5.2 Future Work

For further research, predictive powers can be maximized by using different learning algorithms with different type of data, for instance bivariate and multivariate time series data. Including other macroeconomic variables for research will provide a clear picture of models learning ability. Optimization of parameters is no doubt expensive as well as time taking task which is minimizing the chances to obtain 100% performances of a model; it limits the experiments with adjusting parameters of models. For further research work, the parameters can be optimized in the proposed models by changing the order of ARIMA p, d, q, and number of epochs, batch sizes and neurons in LSTM model and interval width, change point prior scale, seasonality, holiday's effects in PROPHET model. In our work, we combined the classical and deep learning models to improve forecasting. There is still room for further research as investigation for improving forecasting can be made via connecting ARIMA model with PROPHET model and LSTM model with PROPHET model. HYBRID can provide more robust results as compared to individual use of model for forecasting challenging time series data according to our study and previous literature. According to this study, we suggest for implementing the modern approaches to expand the complexity of machine learning. Inflation forecasting is very challenging, especially when it is utilized for making monetary policy for central banks because end users wellbeing is dependent on accurate CPI based inflation forecasting. Therefore, modern approaches need more attention in field of time series data. Single-step forecasting is already tested in our study but multi-step forecasting can be studied to obtain the performance.

References

[1] M. Pasaogullari and B. H. Meyer, “Simple Ways to Forecast Inflation: What Works Best?,” EC (FRB Cleveland), pp. 1–6, Dec. 2010, doi: 10.26509/frbc-ec-201017.

[2] Ludwig Maximilians University and I. Baybuza, “Inflation Forecasting Using Machine Learning Methods,” RJMF, pp. 42–59, Dec. 2018, doi: 10.31477/rjmf.201804.42.

[3] M. C. Medeiros, G. F. R. Vasconcelos, Á. Veiga, and E. Zilberman, “Forecasting Inflation in a Data-Rich Environment: The Benefits of Machine Learning Methods,” Journal of Business & Economic Statistics, vol. 39, no. 1, pp. 98–119, Jan. 2021, doi: 10.1080/07350015.2019.1637745.

[4] J. Mohamed, “Time Series Modeling and Forecasting of Somaliland Consumer Price Index: A Comparison of ARIMA and Regression with ARIMA Errors,” AJTAS, vol. 9, no. 4, p. 143, 2020, doi: 10.11648/j.ajtas.20200904.18.

[5] S. S. Namin and A. S. Namin, “1. Graduate Research Assistant and Ph.D. Student, Department of Agricultural and Applied Economics,” p. 19.

[6] M. J. Kane, N. Price, M. Scotch, and P. Rabinowitz, “Comparison of ARIMA and Random Forest time series models for prediction of avian influenza H5N1 outbreaks,” BMC Bioinformatics, vol. 15, no. 1, p. 276, Dec. 2014, doi: 10.1186/1471-2105-15-276.

[7] S. R. Tattikota, “Integration of Econometric Models and Machine Learning- Study on US Inflation and Unemployment,” p. 40.

[8] K. Szafranek, “Bagged neural networks for forecasting Polish (low) inflation,” International Journal of Forecasting, vol. 35, no. 3, pp. 1042–1059, Jul. 2019, doi: 10.1016/j.ijforecast.2019.04.007.

[9] J. Yoon, “Forecasting of Real GDP Growth Using Machine Learning Models: Gradient Boosting and Random Forest Approach,” Comput Econ, vol. 57, no. 1, pp. 247–265, Jan. 2021, doi: 10.1007/s10614-020-10054-w.

[10] E. Gjika Dhamo, L. Puka, and O. Zaçaj, “FORECASTING CONSUMER PRICE INDEX (CPI) USING TIME SERIES MODELS AND MULTI REGRESSION MODELS (ALBANIA CASE STUDY),” presented at the Business and Management 2018, Vilnius Gediminas Technical University, Lithuania, Sep. 2018. doi: 10.3846/bm.2018.51.

[11] J. Contreras, R. Espinola, F. J. Nogales, and A. J. Conejo, “ARIMA models to predict next-day electricity prices,” IEEE Trans. Power Syst., vol. 18, no. 3, pp. 1014–1020, Aug. 2003, doi: 10.1109/TPWRS.2002.804943.

[12] K. Maehashi and M. Shintani, “Macroeconomic forecasting using factor models and machine learning: an application to Japan,” Journal of the Japanese and International Economies, vol. 58, p. 101104, Dec. 2020, doi: 10.1016/j.jjie.2020.101104.

[13] A. Rodríguez-Vargas, “Forecasting Costa Rican inflation with machine learning methods,” Latin American Journal of Central Banking, vol. 1, no. 1–4, p. 100012, 2020, doi: 10.1016/j.latcb.2020.100012.

[14] Macroeconomic factors influence on forecasting with the Machine Learning techniques , it is efficient in decision making for inflation – Available from: https://en.wikipedia.org/wiki/Macroeconomics [accessed August 20, 2021].

[15] M. Lawnik and A. Banasik, “Delphi Method Supported by Forecasting Software,” Information, vol. 11, no. 2, p. 65, Jan. 2020, doi: 10.3390/info11020065.

[16] M. Ahmmed, Md. N. Uddin, Md. R. I. Rafiq, and M. J. Uddin, “INFLATION AND ECONOMIC GROWTH LINK – MULTI-COUNTRY SCENARIO,” IJEFI, vol. 10, no. 4, pp. 47–53, Jul. 2020, doi: 10.32479/ijefi.9942.

[17] Economic indicators based on CPI and CPI parameters –Available from: https://www.investopedia.com/terms/c/consumerpriceindex.asp [accessed septemeber 10, 2021].

[18] Monthly data of different stock exchanges to forecast i.e. NASDAQ, Nikkei 225 Index, Hang seng Index (HIS), S&P commodity Price Index (GSPC), Dow Jones industrial average index (JS) from 1985 to 2018 –Available from: https://finance.yahoo.com/.

[19] D. Sen, K. M. M. Tunç, and M. E. Günay, “Forecasting electricity consumption of OECD countries: A global machine learning modeling approach,” Utilities Policy, vol. 70, p. 101222, Jun. 2021, doi: 10.1016/j.jup.2021.101222.

[20] O. Barkan, J. Benchimol, I. Caspi, A. Hammer, and N. Koenigstein, “Forecasting CPI Inflation Components with Hierarchical Recurrent Neural Networks,” p. 29.

[21] Inflation effects on developed and developing countries and suggesting mitigation measure to curb its influence on economy –Available from: www.clevelandfed.org [accessed September 5, 2021].

[22] Developed countries recession was noticed during the year 2008 and 2011 due to oil crisis in given fiscal years of different countries such as Japan, Canada, USA and Germany –Available from: www.ukessays.com [accessed August 24, 2021].

[23] B. M. A. Abdulrahman, A. Y. A. Ahmed, and A. E. Yahia, “Forecasting of Sudan Inflation Rates using ARIMA Model,” vol. 8, no. 3, p. 7, 2018.

[24] G. Milunovich, “Forecasting Australian Real House Price Index: A Comparison of Time Series and Machine Learning Methods,” SSRN Journal, 2019, doi: 10.2139/ssrn.3417527.

[25] A. Richardson, T. van Florenstein Mulder, and T. Vehbi, “Nowcasting GDP using machine-learning algorithms: A real-time assessment,” International Journal of Forecasting, vol. 37, no. 2, pp. 941–948, Apr. 2021, doi: 10.1016/j.ijforecast.2020.10.005.

[26] M. A. Acosta, “Machine learning core inflation,” Economics Letters, vol. 169, pp. 47–50, Aug. 2018, doi: 10.1016/j.econlet.2018.05.001.

[27] S. Sokolov-Mladenović, M. Milovančević, I. Mladenović, and M. Alizamir, “Economic growth forecasting by artificial neural network with extreme learning machine based on trade, import and export parameters,” Computers in Human Behavior, vol. 65, pp. 43–45, Dec. 2016, doi: 10.1016/j.chb.2016.08.014.

[28] L. Wang, H. Zou, J. Su, L. Li, and S. Chaudhry, “An ARIMA-ANN Hybrid Model for Time Series Forecasting: An ARIMA-ANN Hybrid Model,” Syst. Res., vol. 30, no. 3, pp. 244–259, May 2013, doi: 10.1002/sres.2179.

[29] B. Al-hnaity and M. Abbod, “Predicting Financial Time Series Data Using Hybrid Model,” in Intelligent Systems and Applications, vol. 650, Y. Bi, S. Kapoor, and R. Bhatia, Eds. Cham: Springer International Publishing, 2016, pp. 19–41. doi: 10.1007/978-3-319-33386-1_2.

[30] A. Vishwakarma, A. Singh, A. Mahadik, and R. Pradhan, “Stock Price Prediction Using Sarima and Prophet Machine Learning Model,” Communication and Technology, vol. 9, no. 1, p. 6, 2020.

[31] E. Žunić, K. Korjenić, K. Hodžić, and D. Đonko, “Application of Facebook’s Prophet Algorithm for Successful Sales Forecasting Based on Real-world Data,” IJCSIT, vol. 12, no. 2, pp. 23–36, Apr. 2020, doi: 10.5121/ijcsit.2020.12203.

[32] Ozan Kozan, “Bitcoin Forecasting Using ARIMA and PROHET” IEEE (UBMK’18) 3rd International conference on Computer Science and Engineering, pp. 621-624, 2018.

[33] T. Fu, “A review on time series data mining,” Engineering Applications of Artificial Intelligence, vol. 24, no. 1, pp. 164–181, Feb. 2011, doi: 10.1016/j.engappai.2010.09.007.

[34] P. Misra and Siddharth, “Machine learning and time series: Real world applications,” in 2017 International Conference on Computing, Communication and Automation (ICCCA), Greater Noida, May 2017, pp. 389–394. doi: 10.1109/CCAA.2017.8229832.

[35] A. Isakova, “Modeling and Forecasting Inflation in Developing Countries: The Case of Economies in Central Asia,” p. 31.

[36] Department of CSE, School of Engineering and Technology, CHRIST Deemed to be University, Mysore Road, Bengaluru, 560074, India, R. J. Chadalavada, S. Raghavendra, Department of CSE, School of Engineering and Technology, CHRIST Deemed to be University, Mysore Road, Bengaluru, 560074, India., V. Rekha, and Department of CSE, School of Engineering and Technology, CHRIST Deemed to be University, Mysore Road, Bengaluru, 560074, India, “Electricity requirement prediction using time series and Facebooks PROPHET,” IJST, vol. 13, no. 47, pp. 4631–4645, Dec. 2020, doi: 10.17485/IJST/v13i47.1847.

[37] Countries list according International Monetary Fund based on various factors, Six developing countries, Brazil, Colombia, Indonesia, South Africa, Mexico and India, figures available on Wikipedia: https://en.wikipedia.org/wiki/Developing_country.

[38] Countries list according International Monetary Fund based on various factors, Six developed countries, Canada, United States, Norway, Australia, Switzerland and Poland, figures - Available on: https://en.wikipedia.org/wiki/Developed_country.

[39] Secondary Data source is used for the study and data is collected ranges 1960 to 2021 from the FRED database of the Federal Reserve Bank of St.Louise –Available from: https://fred.stlouisfed.org/series/CPIAUCSL [accessed May 21, 2021].

[40] LSTM is the network with loops in them, allowing information to persist. It is essential to these successes is the use of “LSTMs,” Figure LSTM loops of Recurrent Neural Network – Available from: https://colah.github.io/posts/2015-08-Understanding-LSTMs/ [accessed july 8, 2021].

[41] G. P. Zhang, “Time series forecasting using a hybrid ARIMA and neural network model,” Neurocomputing, vol. 50, pp. 159–175, Jan. 2003, doi: 10.1016/S0925-2312(01)00702-0.