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Inflation prediction in emerging economies: Machine learning and FX reserves integration for enhanced forecasting

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ABSTRACT

The present study makes two significant contributions to the extended body of literature in the context of International Finance. First, it forecasts the inflation in an emerging economy by employing a combination of traditional forecasting and *Machine Learning* models to test whether machine learning models outperform traditional forecasting models. Second, it explicitly includes an often-neglected variable i.e. foreign exchange reserves into the forecasting models to ascertain whether its inclusion enhances predictive accuracy. The outcomes of the study revealed interesting findings. It is observed that machine learning models consistently outperform traditional models, with Random Forest and Gradient Boosting are the top performers across different sets of determinants. Moreover, the study unveils that the inclusion of foreign exchange reserves into the models as a determinant has a positive impact on the predictive effectiveness of both traditional and machine learning-based inflation forecasting models.

1. Introduction

In the realm of international finance, the accurate forecasting of macroeconomic variables, especially inflation, holds significant importance for policymakers and economic and financial analysts. It enables financial markets and institutions to make informed decisions regarding spending, investment, and financial planning (Faust & Wright, 2013; Katona, 1972). Moreover, it is crucial for formulating monetary policy decisions (Bernanke, 2007). Central banks, which are often responsible for maintaining price stability, rely on accurate inflation forecasts to devise and implement effective monetary policy measures. For instance, by forecasting future inflation trends, central banks can adjust interest rates, manage money supply, and employ other policy tools to achieve inflation targets (Batini & Haldane, 1999; Dunbar & Owusu-Amoako, 2023).

Traditional econometric models such as multiple regression, auto regressive moving average (ARMA), autoregressive integrated moving averages (ARIMA) and vector autoregression (VAR) models have widespread attention in macroeconomic forecasting for several decades. However, these models suffer from certain limitations due to their reliance on linear relationships, which may fail to capture economic systems' inherent nonlinearity and complexity. Additionally, these models often make assumptions about the data's distributional properties, which may lead to biased estimates. (S. Chen & Ranciere, 2019; Dai, Zhang, & Liang, 2024; Liang, Wang, & Duong, 2024).

Given these limitations, researchers have recognized the need for more suitable economic and financial forecasting models. As a result, machine learning (ML) and artificial intelligence (AI) techniques have gained growing popularity (Masini, Medeiros, & Mendes, 2023). ML and AI techniques offer various advantages over traditional econometric models, including the effective handling of large and high-dimensional datasets, capturing nonlinear relationships, providing greater flexibility, and facilitating data-driven modeling, which in its turn enhance the accuracy and effectiveness of economic forecasts (Liang, Huynh, & Li, 2023; Liang, Luo, Li, & Huynh, 2023; Wasserbacher & Spindler, 2022).

Recently, an increasing number of studies have utilized a diverse range of ML and AI techniques, such as support vector machines, random forests, decision trees, and neural networks to forecast macroeconomic and financial indicators such as GDP growth (Kurihara &

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Fukushima, 2019; Maccarrone, Morelli, & Spadaccini, 2021), economic recession (Cicceri, Inserra, & Limosani, 2020), unemployment rates (Gogas, Papadimitriou, & Sofianos, 2022; Yamacli & Yamacli, 2023), uncertainty (Rizvi & Naqvi, 2010; Rizvi, Naqvi, Bordes, & Mirza, 2014), and energy prices (Alshater, Kampouris, Marashdeh, Atayah, & Banna, 2022; Tschora, Pierre, Plantevit, & Robardet, 2022; Yang, Sun, Hao, & Wang, 2022). However, despite the growing popularity of ML and AI techniques across various domains, their application in inflation forecasting remains relatively limited. Existing researchers predominantly rely on traditional models, such as the Augmented Phillips Curve (PC), to forecast inflation, which may result in biased forecasts due to their limited ability to capture the complexities of inflation dynamics (Ülke, Sahin, & Subasi, 2018).

Another limitation in the existing literature on inflation forecasting is the insufficient attention given by researchers to the inclusion of *"foreign exchange reserves (FXReserves)"* within ML and AI models. FXReserves, representing a nation's holdings of foreign currencies, are a critical determinant of inflation. The significance of FXReserves cannot be over stated, given their fundamental contributions in effectively managing exchange rate stability and controlling inflation (Aizenman & Lee, 2007; Aizenman & Marion, 2003; Aizenman & Riera-Crichton, 2008). Higher levels of reserves act as a buffer against external shocks, reduce exchange rate volatility, and enhance a country's credibility and capacity to maintain price stability (Obstfeld & Rogoff, 1996). The omission of FXReserves from the inflation forecasting models can result in oversimplified models that fail to capture the complexities of the economic landscape. However, the inclusion of FXReserves holds transformative potential to enhance the precision and reliability of forecasting models. Integrating FXReserves into the modeling framework allows researchers to adeptly capture the intricate impact of exchange rate dynamics and external shocks (Ariyasinghe & Cooray, 2021). By doing so, researchers can unlock a more comprehensive understanding of the multifaceted dynamics influencing inflation, ultimately contributing to the advancement of robust and accurate forecasting methodologies in the field.

Furthermore, besides forecasting inflation in the presence of FXReserves, it is also important to test the accuracy of inflation forecasts. The literature suggests various measures to test the inflation forecast accuracy of ML and AI models, such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). However, each method has its limitations. Therefore, when evaluating the forecast accuracy, multiple indicators should be considered to gain a comprehensive understanding of the model's performance (Talagala, Hyndman, & Athanasopoulos, 2018).

Contextualizing the above debate, the present study contributes to the growing knowledge of inflation forecasting in the following three ways: First, the study employs a combination of traditional and ML models to forecast inflation. Second, the study explicitly focuses on the inclusion of FXReserves in forecasting models. Third, the study evaluates the accuracy of inflation forecasts by considering multiple indicators to ensure unbiased and reliable forecasts. The outcomes of our study will advance the field of inflation forecasting by employing innovative methodologies, shedding light on previously unexplored factors, and establishing a robust framework for evaluating forecast accuracy. These contributions collectively aim to empower decision-makers with more informed and precise tools for navigating the complex landscape of economic forecasting.

The rest of the paper is structured as follows. Section 2 provides an overview of the recent literature on the determinants of inflation, the influence of foreign reserves on inflation dynamics and the power of ML and AI in forecasting. Section 3 explains our methodology and data. Section 4 discusses results and Section 5 concludes and offers policy recommendations.

2. Literature review

2.1. Determinants of inflation

The determinants of inflation have been the subject of constant research activity in the field of economics. The existing body of literature concerning this topic can be broadly classified into five primary domains, encompassing monetary factors, demand-pull factors, cost-push factors, exchange rate dynamics, and the significance of exchange rate reserves. Within this section, our focus will revolve around examining the influence exerted by these factors in managing inflation, with particular emphasis placed on the role of foreign exchange reserves.

Monetary Factors: Monetary factors, such as money supply and monetary policy, are widely recognized as key determinants of inflation. According to the quantity theory of money, an increase in the money supply without corresponding increases in real output leads to inflation (Friedman, 1968). Empirical studies consistently support the positive relationship between money supply growth and inflation (Cecchetti, 1994; Papadamou, Kyriazis, & Tzeremes, 2019). The stance and effectiveness of monetary policy in managing inflation expectations and aggregate demand also play a crucial role (Taylor, 2000).

Demand-Pull Factors: Demand-pull factors arise from excessive aggregate demand, characterized by increased consumer spending and investment. Strong economic growth, low unemployment, and increased consumer and business confidence can stimulate demand-pull inflation. Research shows that higher levels of economic activity, as measured by variables such as GDP growth and consumer spending, are associated with higher inflation (Blanchard, 2000). Furthermore, inflation expectations can amplify demand-pull inflationary pressures (Mankiw, 2006).

Cost-Push Factors: Cost-push factors encompass the upward pressure on prices resulting from increased production costs. These factors include changes in wages, energy prices, and raw material costs. Rising wages, driven by labor market dynamics and bargaining power, can contribute to inflation by inflating firms' production costs (Galí, 2015). Similarly, fluctuations in energy prices and commodity markets can transmit cost shocks throughout the economy, leading to higher inflation (Kilian, 2009).

Exchange Rate Dynamics: Exchange rate dynamics play a crucial role in influencing domestic inflation through various channels. Depreciation of the domestic currency can elevate the cost of imported goods and services, thereby contributing to higher inflation (Rizvi, Naqvi, & Mirza, 2014; Rizvi, Naqvi, Mirza, & Bordes, 2017). Conversely, currency appreciation may result in imported deflationary pressure (Baharumshah, Sirag, & Mohamed Nor, 2017; Mirza, Naqvi, Rizvi, & Boubaker, 2023). Furthermore, exchange rate volatility can impact inflation expectations and price-setting behavior, thereby influencing future inflationary trends (Mirza et al., 2023).

Foreign Exchange Reserves (FXReserves): Foreign exchange reserves, comprising foreign currency assets held by central banks, play a critical role in managing exchange rate stability and controlling inflation. Adequate levels of reserves act as a buffer against external shocks, reduce exchange rate volatility, and enhance a country's credibility and ability to maintain price stability (Obstfeld & Rogoff, 1996). Empirical studies have demonstrated that sufficient foreign exchange reserves can contribute to lower inflation rates (Edison & Pauls, 1993).

The role of FXReserves in controlling inflation has been extensively examined by (Aizenman & Riera-Crichton, 2008). Their research highlights the significance of reserves as a vital tool for managing inflationary pressures and upholding price stability (Aizenman & Hutchison, 2012). The maintenance of adequate reserves enables nations to intervene in the foreign exchange market during currency depreciation, thereby stabilizing the exchange rate and mitigating inflationary pressures. Moreover, foreign exchange reserves enhance a country's credibility and signal a firm commitment to maintaining price stability. Sufficient reserves instill confidence in investors, signaling the nation's capacity to safeguard its currency and ensure macroeconomic stability. This improved credibility contributes to a reduction in inflation expectations and influences price-setting behavior, consequently leading to a decrease in inflation (Aizenman, Edwards, & Riera-Crichton, 2012). Lastly, foreign exchange reserves facilitate the implementation of an independent monetary policy. With substantial reserves as a cushion, central banks have greater flexibility to pursue policies prioritizing price stability, as they are less constrained by external pressures and speculative attacks. This independence empowers central banks to effectively respond to inflationary pressures through interest rate adjustments or the implementation of alternative monetary measures (Aizenman, 2019).

2.2. Foreign exchange reserves and inflation forecasting efficiency

To enhance the accuracy of inflation forecasting, it is crucial to consider important determinants as predictors. One such determinant that has received significant attention is FXReserves, which can capture the impact of exchange rate dynamics and external shocks. Several studies have investigated the relationship between foreign exchange reserves and inflation forecasting, providing insights into the effectiveness of incorporating reserve variables in these models. For instance, (Ariyasinghe & Cooray, 2021) examined the forecasting performance of inflation models that included foreign exchange reserves as a predictor variable. They found that incorporating reserves significantly improved the accuracy of inflation forecasts, suggesting that reserve variables capture important information related to exchange rate dynamics and external shocks. (Özdemir, 2019) investigated the forecasting accuracy of inflation models that incorporated foreign exchange reserves. The results of their study revealed that the inclusion of reserve variables led to improved forecasting performance. This indicates that foreign exchange reserves contain information that is relevant to understanding inflation dynamics in the context of South Korea. (Aizenman & Hutchison, 2012) conducted a panel analysis of emerging economies to examine the role of foreign exchange reserves in inflation forecasting. Their findings indicated that the incorporation of reserve variables significantly enhanced the accuracy of inflation forecasts. This suggests that foreign exchange reserves provide valuable information about exchange rate dynamics, capital flows, and external shocks that have an impact on inflation in these economies. (Ariyasinghe & Cooray, 2021) conducted their research within the context of Sri Lanka and found that FXReserves bears significant importance in enhancing the predictive accuracy of forecasting models. (Mirza et al., 2023) performed there in the context of 21 inflation targeting economies and found that FXReserves is an important determinant of inflation which help to reduce the exchange rate variations that translates into the domestic prices. (Chitu, Gomes, & Pauli, 2019) also emphasized on the importance of FXReserves and showed that FXReserves are an important factor that helps in inflation management. (Dąbrowski, 2021) found that FXReserves is a crucial factor that contributes to improving the predictive efficiency of inflation dynamics.

The importance of FXReserves can be justified through several theoretical channels. One such channel is exchange rate pass through (ERPT) channel. The ERPT channel is based on the idea that fluctuations in exchange rates influence the prices of imported goods and services in domestic markets (Krugman & Obstfeld, 2009). When a country's currency depreciates, the cost of imported goods rises, potentially leading to higher domestic prices. However, having adequate FXReserves emerges as a mitigating factor in this channel, enabling countries to intervene in the foreign exchange market and stabilize their currency. This intervention, in turn, curtails the pass-through of currency depreciation to domestic prices, ultimately preventing or moderating inflationary pressures associated with volatile exchange rates (Aizenman & Riera-Crichton, 2008).

Another theoretical channel supporting the importance of FXReserves is the Speculative Attack Deterrence channel. According to this channel, operating as a deterrent against speculative attacks on a nation's currency, FXReserves can daunt the activities that could induce sharp depreciations, and eventually contributes to averting the exacerbation of inflationary trends (Blanco & Garber, 1986). Notably, the possession of substantial FXReserves serves as a communicative signal to the market, affirming the country's capacity to safeguard its currency (D. Kim & Moneta, 2021). This, in turn, dissuades speculative endeavors and acts as a preventive measure against the looming risks of inflation (He, Wang, & Yu, 2023).

Debt servicing and fiscal stability is another important channel which signifies the importance of FXReserves in controlling inflation. This channel postulates that FXReserves can be utilized to service external debt, contributing to fiscal stability. Given that countries often hold external debt denominated in foreign currencies, the costs of servicing such debt may surge during times of currency depreciation, which poses a significant threat to fiscal stability due to exchange rate movements and eventually raises inflation (Nguyen, Nguyen, & Hang Hoang, 2019). However, the maintenance of sufficient FXReserves allows a nation to strategically utilize these reserves for servicing external debt, effectively reducing the risk of fiscal imbalances and disruptions in debt servicing due to adverse exchange rate movements. This strategic use of reserves ultimately contributes to controlling inflation by promoting fiscal stability (Qian, 2017; Steiner, 2017).

Summarizing the above disclosure, it becomes evident that FXReserves serve as a significant factor influencing inflation dynamics. Therefore, incorporating FXReserves into forecasting models is crucial to avoid biased estimates. However, it is important to note that studies incorporating FXReserves into their forecasting models are not very rich, and have mainly relied upon traditional econometric models, such as ARIMA, VAR, and APC. These models are limited in their ability to capture the inherent non-linearity and complexities in inflation dynamics and may produce biased forecasts (S. Chen & Ranciere, 2019). Given these limitations, ML and AI methodologies have gained popularity as alternative approaches that outperforms traditional forecasting model, as these techniques have potential to capture nonlinear relationships, complex patterns, and high-dimensional data structures more effectively.

2.3. Machine learning (ML)/artificial intelligence (AI) and macroeconomic forecasting

Machine learning (ML) and artificial intelligence (AI) models have gained considerable attention in recent years due to their potential to improve the accuracy of economic and financial forecasting. The literature has witnessed the utilization of various ML and AI models in economic forecasting. Regression models, decision trees, random forests, support vector machines, and neural networks are among the ML techniques widely employed in the prediction of various economic variables. These models have been successfully utilized to forecast macroeconomic indicators such as GDP growth (Kurihara & Fukushima, 2019; Maccarrone et al., 2021), economic recession (Cicceri et al., 2020), unemployment rates (Gogas et al., 2022; Yamacli & Yamacli, 2023), uncertainty (Gupta, Pierdzioch, & Salisu, 2022), and energy prices (Alshater et al., 2022; Tschora et al., 2022; Yang et al., 2022).

ML and AI models have also been extensively applied to predict financial variables. For example, researchers have utilized various ML models, including deep learning architectures such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, to forecast stock prices (Kumbure, Lohrmann, Luukka, & Porras, 2022; Tsantekidis et al., 2017), exchange rates (W. Chen, Xu, Jia, & Gao, 2021; Plakandaras, Papadimitriou, & Gogas, 2015), bond yields (Gogas, Papadimitriou, Matthaiou, & Chrysanthidou, 2015; J. M. Kim, Kim, & Jung, 2021) and credit risk (Khandani, Kim, & Lo, 2010; Y. Li, 2019; Zhu, Zhou, Xie, Wang, & Nguyen, 2019).

Not only this, researchers are also exploring hybrid approaches for macroeconomic and financial forecasting (Bhanja & Das, 2022;

Polamuri, Srinivas, & Krishna Mohan, 2022). These hybrid approaches integrate economic theory and domain knowledge with the ability of ML models to capture complex patterns. Examples include combining autoregressive integrated moving average (ARIMA) models with ML algorithms as error correction models (De Gooijer & Hyndman, 2006) and incorporating dynamic factor models with deep learning architectures (Heaton, Polson, & Witte, 2017).

Surprisingly, despite the wide range of applications of ML models, only a few researchers have focused on the utilization of ML techniques to predict inflation. For instance, (Aras & Lisboa, 2022) employed random forecast and tree-based assembled ML models to forecast inflation in Turkey and observed that these models provide better accuracy and explainable predictions for inflation forecasting in a data-rich environment.

(Ülke et al., 2018) compared the effectiveness of time series models and ML models for inflation forecasting. By analyzing empirical data from the United States spanning the period between 1984 and 2014, the study found that ML models outperform time series models. (Özgür & Akkoç, 2022) did the similar research in the context of Turkey and confirmed that ML models are more effective in forecasting inflation. (Araujo & Gaglianone, 2023) examined the efficacy of ML methodologies in enhancing inflation forecasting in the Brazilian context and found that ML models often outperform traditional econometric models in terms of mean-squared error. (Medeiros, Vasconcelos, Veiga, & Zilberman, 2021) used random forecast methodology to forecast U.S. inflation and disclosed that ML models consistently outperform other models in terms of forecasting accuracy. (Rodríguez-Vargas, 2020) conducted an empirical investigation to assess the forecasting efficacy of several ML techniques, namely k-nearest neighbors, random forests, extreme gradient boosting, and a long short-term memory (LSTM) network, in predicting inflation in Costa Rica. The findings of the study revealed that the LSTM model demonstrated the highest performance among the considered forecasting models. Moreover, the study observed that combining forecasts yielded superior results compared to individual forecasts.

After reviewing the available body of knowledge, it is reasonable to propose that none of the researchers have explicitly focused on the inclusion of the FXReserves into ML and AI models while forecasting inflation, which is a notable research gap and highlights the need for further exploration in this area. Addressing this gap has the potential to advance the field of inflation forecasting and contribute to the development of more robust and reliable economic analyses. Accordingly, the present study proposes following hypotheses:

H1. "*Machine learning models demonstrate superior accuracy in predicting inflation as compared to traditional models*".

H2. "*The inclusion of foreign exchange reserves positively influences the predictive accuracy of the forecasting models*".

3. Methodology

3.1. Overview of machine learning methodologies

The use of ML and AI techniques in forecasting macroeconomic variables has gained traction in recent years. This section presents an overview of some commonly utilized ML methodologies in the field of macroeconomic and financial forecasting.

3.1.1. Machine learning models

Support Vector Machines (SVM): Support Vector Machines (SVM) is a popular supervised learning algorithm that has been widely used for economic forecasting tasks such as predicting inflation and exchange rates. SVM aims to find the optimal hyperplane that separates data points of different classes or predicts a continuous variable. It is particularly effective in capturing nonlinear relationships and handling high-dimensional data (Kurani, Doshi, Vakharia, & Shah, 2023). One strength of SVM is its ability to handle complex data patterns and generalize well to unseen data. However, SVM may struggle with large datasets due to high computational requirements (Chhajer, Shah, & Kshirsagar, 2022).

Random Forests (RF): Random Forests is an ensemble learning method that combines multiple decision trees to make predictions. It has been extensively applied to economic forecasting, offering advantages such as handling high-dimensional data, capturing nonlinear relationships, and providing robust predictions. Random Forests excel at handling noisy and missing data, and they are less prone to overfitting compared to individual decision trees (Fan, Zhang, Yu, Hong, & Dong, 2022). However, one limitation of Random Forests is that they may lack interpretability due to the ensemble nature of the model (Aria, Cuccurullo, & Gnasso, 2021).

Artificial Neural Networks (ANN): Artificial Neural Networks (ANNs) are deep learning models inspired by the neural structure of the human brain. ANNs have gained popularity in economic forecasting, including inflation and exchange rate prediction, due to their ability to capture complex nonlinear relationships and adapt to changing patterns in the data. ANNs are flexible and can handle large and diverse datasets, making them suitable for capturing intricate economic dynamics (Yoon, 2021). However, a key weakness of ANNs is their lack of interpretability, as they operate as complex "black box" models that make it challenging to understand the underlying decision-making process (Buhrmester, Münch, & Arens, 2021; Linardatos, Papastefanopoulos, & Kotsiantis, 2020).

Long Short-Term Memory (LSTM) Networks: Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) designed to capture sequential dependencies in data. LSTMs have shown promise in forecasting macroeconomic variables with temporal patterns, such as GDP growth, inflation, and exchange rates. Their key strength lies in effectively modeling dynamic patterns and capturing both short-term fluctuations and long-term trends (Egan, Fedorko, Lister, Pearkes, & Gay, 2017). LSTMs are particularly useful when dealing with time series data that exhibit long-term dependencies. However, LSTMs may suffer from difficulties in training due to the vanishing/exploding gradient problem and can be computationally intensive (Rezaeianjouybari & Shang, 2020).

Gradient Boosting Machines (GBM): Gradient Boosting Machines (GBM) is an ensemble learning method that sequentially trains weak learners, typically decision trees, to create a strong predictive model. GBM has been successfully employed in economic forecasting due to its ability to handle complex relationships, nonlinearity, and high-dimensional data. GBM is known for producing accurate and robust predictions, often outperforming other models (Natekin & Knoll, 2013) However, GBM can be computationally expensive and may require careful hyperparameter tuning to prevent overfitting (Konstantinov & Utkin, 2021).

However, it is important to note that each of these ML and AI models has its own strengths and weaknesses, making them suitable for different forecasting scenarios. The choice of model should consider factors such as data characteristics, interpretability requirements, computational resources, and the specific forecasting task at hand. Therefore, the evaluation of forecast accuracy is of utmost importance to assess the performance of ML and AI models.

3.2. Overview of forecasting accuracy metrices

Researchers employ various metrics such as mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and directional accuracy to compare the forecasted values against the actual outcomes (Bontempi, Ben Taieb, & Le Borgne, 2013). Statistical tests, such as the Diebold-Mariano test, are also utilized to compare the forecast accuracy of ML models against traditional econometric models (Makridakis, Spiliotis, & Assimakopoulos, 2020).

The Mean Absolute Error (MAE): MAE measures the average magnitude of errors between predicted and actual values, providing an assessment of average forecasting accuracy (Hyndman & Koehler, 2006).

The Root Mean Squared Error (RMSE): RMSE calculates the square root of the average of squared errors, penalizing larger errors more heavily than MAE (Talagala et al., 2018).

The Mean Absolute Percentage Error (MAPE): MAPE evaluates the average percentage difference between predicted and actual values, offering a relative measure of forecast accuracy (Armstrong & Collopy, 1992). However, MAPE can be sensitive to zero values and may produce infinite values when the actual value is zero (Makridakis, 1993).

Theil's U Statistic: Theil's U Statistic is a measure that compares the forecasted values of a model with a benchmark model, such as a naïve or random walk forecast, providing a relative performance evaluation (Mizrach, 1992). A value less than one indicates that the model performs better than the benchmark.

Directional Accuracy (DA): DA assesses whether the model's predictions correctly indicate the direction of change in the forecasted variable, making it suitable for binary or directional forecasts (De Gooijer & Hyndman, 2006). It measures the percentage of correct directional predictions.

R-squared (R^2): R^2 measures the proportion of the variance in the actual values that is explained by the forecasted values, providing an indication of the model's ability to capture the underlying variability (Hyndman & Koehler, 2006). Higher R-squared values suggest a better fit between the forecasted and actual values.

The Diebold-Mariano: The Diebold-Mariano test is a statistical test used to compare the forecast accuracy of two competing models (Diebold & Mariano, 2012). It assesses whether the difference in forecast errors between the models is statistically significant, providing insights into the relative performance of the models.

However, each metric has its own strengths and weaknesses. Therefore, when evaluating forecast accuracy, it is recommended to consider multiple indicators to gain a comprehensive understanding of the model's performance (Hyndman & Koehler, 2006; Talagala et al., 2018). By doing so, researchers can rigorously assess the forecast accuracy of AI and ML models and make informed decisions regarding their suitability for economic forecasting tasks.

3.3. Econometric methodology

The present study employs a combination of traditional forecasting and machine learning models to achieve the dual objective of the study.

3.3.1. Multiple regression

Multiple regression analysis is a traditional econometric technique that has been broadly employed to predict or analyze various economic and financial indicators (Gjika Dhamo, Puka, & Zaçaj, 2018).

The standard form of multiple regression is presented in Eq. (1).

$$Y_t = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots \beta_n X_n + \epsilon_t \tag{1}$$

Referring to Eq. (1), INF is inflation, β_s are the slope coefficients associated with each independent variable, and ε represents the error term (the difference between the predicted and actual inflation values).

A significant drawback of this methodology is that it tends to generate biased estimates when the data exhibit the problems of stationarity, serial correlation, heteroscedasticity, and normality (Inoue & Kilian, 2008).

3.3.2. Autoregressive moving average (ARMA)

The ARMA model is another popular technique used to analyze the time-series data. This model combines two components, autoregressive (AR) and moving average (MA) to forecast the stationary series. The AR component encompasses the lagged values of the variables being forecasted (p), while MA model incorporates the lagged values of forecast errors (q). (Zhang, 2018).

Eq. (2) shows the standard form of ARMA (p, q) model:

$$\begin{aligned} INF_t = & \beta_0 + \beta_1 INF_{t-1} + \beta_1 INF_{t-2} + \dots + \beta_p INF_{t-p} \\ & + \alpha_1 \epsilon_{t-1} + \alpha_2 \epsilon_{t-2} + \dots + \alpha_q \epsilon_{t-q} + \in_t \end{aligned} \tag{2}$$

Referring to the above equation, $\beta_1 \dots \beta_p$ are AR coefficients, while $\alpha_1 \dots \alpha_1$ are MA coefficients.

One major drawback of this model is that it only takes into account a fixed number of previous observations and forecast errors. This makes the model less effective for long-term forecasting. Another limitation of this model is that it often yields to biased estimates if the mean, variance, and covariance does not hold constant aptitude over time (S. Chen & Ranciere, 2019).

3.3.3. Autoregressive integrated moving average (ARIMA)

The ARIMA model is an extension of the ARMA model which provides accurate forecasting even in the case of non-stationary series (Ang, Bekaert, & Wei, 2007). In addition to AR and MA, this model also has an integrated component (I), which involves differencing to handle the non-stationarity in time-series data. The ARIMA model is widely employed my numerous researchers to forecast and analyze various macroeconomic indicators (De Gooijer & Hyndman, 2006; Jarrett & Kyper, 2011). However, this model is sensitive to any outlier in model, and often limited in their ability to capture the inherent nonlinearity and complexity of economic systems due to their reliance on linear relationships (S. Chen & Ranciere, 2019).

The general form of the ARIMA (p, d, q) model is presented in Eq. (3).

$$\begin{aligned} \Delta^d INF_t = & \beta_0 + \beta_1 \Delta^d INF_{t-1} + \beta_2 \Delta^d INF_{t-2} + \dots + \beta_p \Delta^d INF_{t-p} \\ & + \alpha_1 \epsilon_{t-1} + \alpha_2 \epsilon_{t-2} + \dots + \alpha_q \epsilon_{t-q} + \in_t \end{aligned} \tag{3}$$

Referring to Eq. (3), Δ^d is the differencing operator applied d times to the series to make it stationary. Differencing is applied only if the data is non-stationary.

3.3.4. Random Forest (RF)

A Random Forest (RF) is a machine learning technique introduced by (Breiman, 2001). It is a very powerful tool that harnesses the strength of *"multiple"* decision trees working together to enhance predictive accuracy of high dimensional data. Individual regression trees overfit training sets, and produce high predictive variance which may yield biased forecasting (Araujo & Gaglianone, 2023). RF effectively addressed this concern through a process termed *"bootstrap aggregation (bagging)."* In this method, the same decision tree is repeatedly trained on distinct bootstrapped versions of the training data. These individual tree outputs are then averaged, leading to improved model performance. This practice helps to reduce the forecast variance without leading to potential biases.

Random Forest technique seamlessly integrates its machine learning decision tree algorithms with the principles of time-series modeling while forecasting the macroeconomic indicators. This integration enables the RF to provide nuanced and insightful predictions for critical macroeconomic metrics, even in the case of high-dimensional data.

3.3.5. Support vector regression (SVR)

Support vector regression (SVR) is another machine learning technique that has become exceedingly popular to forecast the macroeconomic and financial variables. This technique harnesses the principles of Support Vector Machines (SVM) to address regression tasks. Its unique methodology, focusing on maximizing the margin of error around predictions, sets SVR apart from conventional regression methods. By introducing kernel functions, SVR excels at capturing nonlinear and complex relationships, making it particularly variable in the domains like inflation forecasting, where the data exhibit non-linear trends. Many researchers have used this methodology to forecast the GDP growth, unemployment, and inflation rates (Plakandaras et al., 2015; Priliani, Putra, & Muslim, 2018; Ülke et al., 2018). SVR's ability to discern non-linear correlations aligns well with the multifaceted nature of economic systems, strengthening its significance in enhancing the precision of macroeconomic forecasting models.

3.3.6. K Neighbourhood (K−NN)

The K Neighbourhood (K-NN) algorithm stands as a prominent non-parametric supervised machine learning approach that offers a distinct perspective on forecasting. Unlike traditional methods, K-NN does not fit a model by formulating complex set of equations, rather the prediction of this model hinges on the proximity of a new data point to its closest neighbor 'k' within the training dataset (Ülke et al., 2018). For instance, K-NN algorithms looks at its 'k' closest companions within the training data sets while predicting a dependent variable for a new data point. The proximity of the new point to its neighbors, then, determines the weight of their influence on the final prediction. It is important to note that the overall predictive accuracy of the K-NN model is dependent on 'k'. Opting for a small 'k' values steer predictions that closely mimic the idiosyncrasies of the training data, potentially leading to overfitting, where the model captures noise instead of signal. While a larger 'k' value promotes smoother predictions.

A number of researchers have employed this technique in the forecasting of various financial and economic indicators due to its inherent capability to capture the non-linear and complex relationships (Maccarrone et al., 2021). By relying on historical patterns and local relationships within data, K-NN can swiftly respond to economic fluctuations. Moreover, its ability to handle sparse data and provide data-driven insights allows economists to uncover hidden relationships among variables and gain a better understanding of intricate economic dynamics.

3.3.7. Gradient boosting

Gradient Boosting is a powerful machine learning technique that has gained growing popularity due to its exceptional predictive performance across various disciplines. It operates as an ensemble learning method that combines the strengths of multiple weak learners, often decision trees, to create a robust and accurate predictive model. Gradient Boosting involves sequentially training a series of weak learners, where each subsequent learner corrects the errors made by its predecessors. This iterative process minimizes the residual errors between the predicted and actual values (Yoon, 2021). It is important to note that when we talk about "gradient" in Gradient boosting, we're referring to an optimal way to tweak the model's setting. This tweak minimizes errors by adjusting the model's parameters in a smart direction, which enhances the model's predictive accuracy. The most exciting feature of Gradient Boosting is its ability to handle complex relationships in high dimensional data. It automatically detects non-linear patterns and interactions between variables, and make it well-suited for the forecasting of economic variables where data exhibits intricate behavior (Aras & Lisboa, 2022).

3.3.8. Extreme gradient boosting – XGBoost

Extreme Gradient Boosting (XGBoost) is also an advanced and highly efficient machine learning algorithm that falls under the Gradient Boosting framework. It has gained widespread recognition and dominance due to its ability to handle missing values and high dimensional complex datasets (T. Chen, He, & Benesty, 2018). Numerous researchers utilized this technique to forecast the macro-economic and financial variables (Y. S. Li, Pai, & Lin, 2023; Rodríguez-Vargas, 2020). It is worthwhile to mention that XGBoost incorporates several algorithmic optimizations to the basic principles of Gradient Boosting that significantly enhance its speed, accuracy, and generalization capabilities. Its algorithmic enhancements include parallel tree construction, regularization techniques, and a custom loss function, which makes it more superior and versatile technique (Araujo & Gaglianone, 2023).

3.4. Model structure

The following equations broadly explain the structure of our empirical models, which will be estimated using a combination of traditional and ML forecasting approaches to achieve the proposed study objective.

$$Inflation = f\ (IntRate, M2, Export, Import, IP) \quad \text{(Model 1)}$$

$$Inflation = f\ (IntRate, M2, Export, Import, IP, XR) \quad \text{(Model 2)}$$

$$Inflation = f\ (IntRate, M2, Export, Import, IR, XR, FXReserves) \quad \text{(Model 3)}$$

where: IntRate is interest rate, M2 is money supply, IP is industrial production, XR is exchange rate, FXReserves is foreign exchange reserves.

Model 1 is the initial model of the study. Building upon the foundations established by the initial model, we extend our analytical framework by incorporating XR in model 2, and FXReserves in model 3.

3.5. Data sources

We utilized a dataset comprising monthly observations spanning 20 years to empirically estimate the econometric relationship among the modeled variables, specifically focusing on the case of Pakistan. The data has been retrieved from the Refinitiv database, covering the period from June 1, 2003, to June 1, 2023.

4. Empirical results

4.1. Correlation matrix

Fig. 1 shows the output of correlation matrix which signifies the importance of incorporating FX-reserves into the forecasting model. The coefficient of correlation between inflation and FXReserves is −0.41, which holds substantial weight and sufficient enough to justify the explanatory role of FXReserves in determining inflation. Accordingly, it is reasonable to conclude that including FXReserves as a predictor in the inflation forecasting models has the potential to improve their predictive accuracy.

4.2. Graphical representation of actual vs predictive inflation rates

Fig. 2 shows the graphical representation of actual vs predicted inflation rates. These graphs have been constructed by applying a diverse range of proposed traditional and ML forecasting methodologies to our baseline model (Model 1). The objective is to evaluate the potential superiority of ML techniques over traditional forecasting models. It is evident with the discernible upward trend of graphs in the Random Forest and Gradient Boosting approaches that ML methodologies stands out with relatively higher predictive accuracy when compared to the traditional forecasting methodologies. However, if we compare the output of the traditional models only, it becomes evident that ARMA model is comparatively superior to other traditional models.

4.3. Forecasting accuracy

While graphical representation serves as a convenient method for assessing forecasting accuracy, sometimes it yields to deceptive outcomes. That's why we have undergone a more thorough examination through numerical analysis. We employe RMSE, MSE, and MAPE as robust metrics to evaluate the forecasting accuracy of proposed models (model 1 to model 3) vis-à-vis the predictive efficacy of both traditional and ML approaches. The results are reported in Table 1 and Fig. 3.

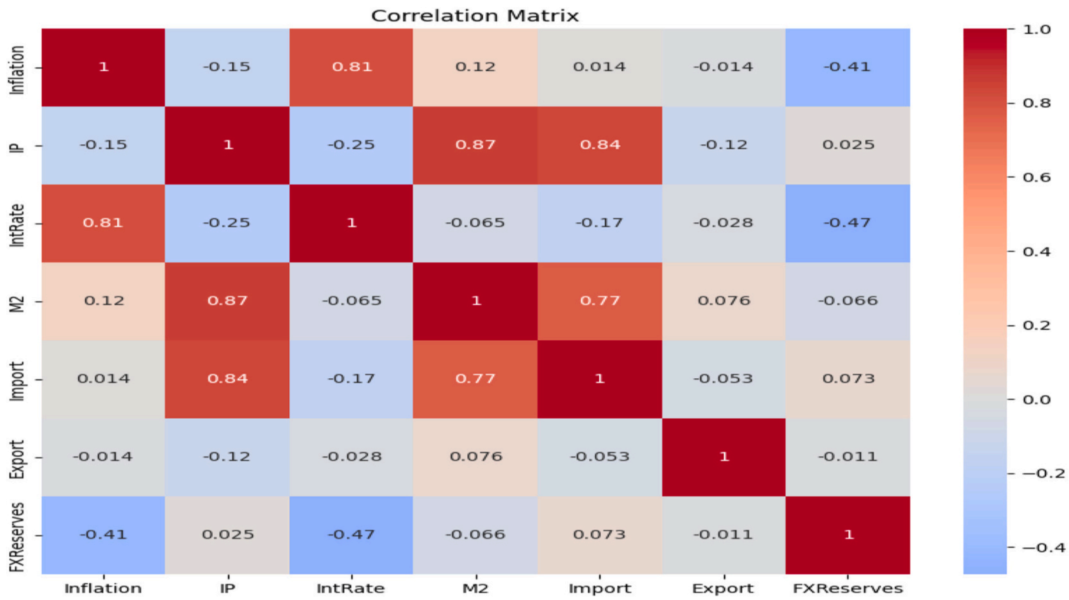

Fig. 1. Correlation matrix.

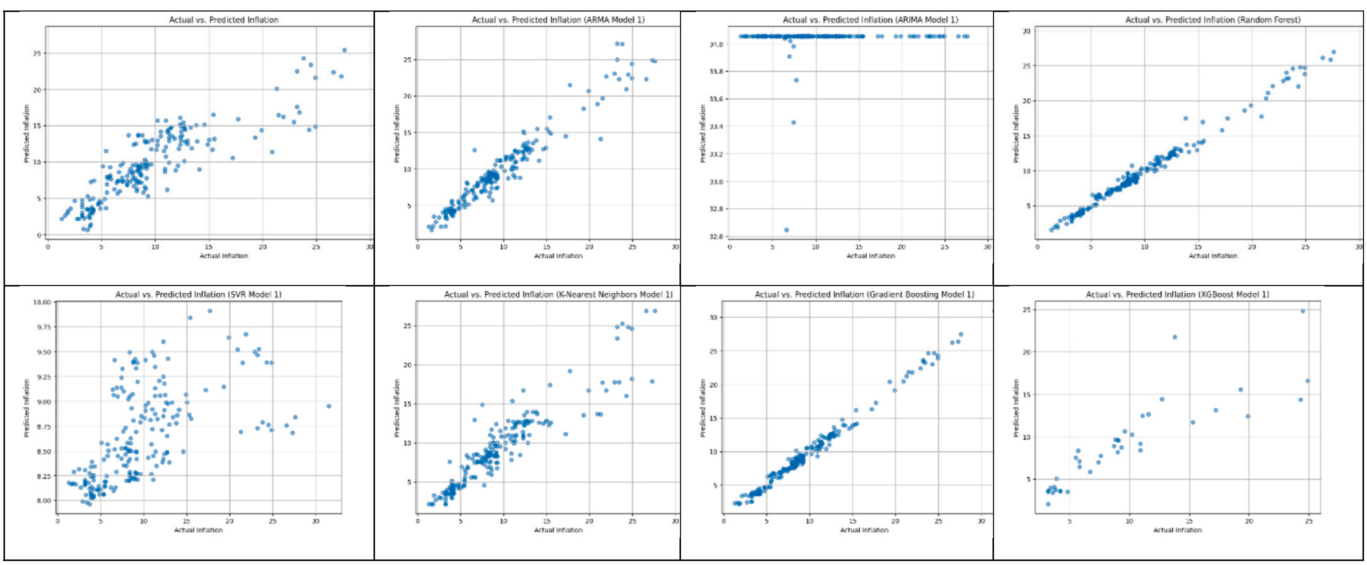

Fig. 2. Graphical representation of actual vs predictive inflation rates.

4.3.1. Overall model performance- traditional vs machine learning model

When considering the overall performance of traditional forecasting versus ML Models in the context of inflation forecasting, it's evident that ML models tend to outperform traditional models. Random Forest and Gradient Boosting stand out as top performers across all the three models, as shown by their lower RMSE, MSE, and MAPE values. Hence, we confidently accept our 1st hypothesis that *"machine learning models demonstrate superior accuracy in predicting inflation as compared to traditional models"*. The outcomes of the study are aligned with several researchers that have highlighted the importance of ML models in improving the predictive accuracy of economic forecasts (Alshater et al., 2022; Tschora et al., 2022; Wasserbacher & Spindler, 2022).

4.3.2. Does the inclusion of FXReserves make any difference?

When examining the predictive accuracy of traditional models between Model 1 and Model 3, it becomes evident that the inclusion of FXReserves into the model leads to positive impact on the predictive efficiency of the forecasting models. Looking at the evaluation metrices, we observe that the values in Model 3 are often lower than those in Model 1. The slight improvements in RMSE, MSE, and MAPE values suggest that FXReserves contributes positively to refining the predictive accuracy of traditional models. Likewise, in the context of ML models, the inclusion of FXReserves in model 3 consistently results in improved predictive accuracy as compared to model 1. The modest improvement in the values of RMSE, MSE, and MAPE in Model 3 signifies that the incorporation of FXReserves enhances the machine learning models' ability to make more accurate inflation forecasts. Hence, we confidently accept our 2nd hypothesis that *"the inclusion of FXReserves positively influences the predictive accuracy of the forecasting models"*. The outcomes of the study are aligned with (Aizenman & Lee, 2007; Aizenman & Marion, 2003; Ariyasinghe & Cooray, 2021; Özdemir, 2019).

4.4. Feature importance

Moving forward, we have employed a feature importance test for the output of Random Forest and Gradient Boosting algorithms that stand

Table 1
Forecasting accuracy.

Panel A: Model 1			
	RMSE	MSE	MAPE
Multiple Regression	2.7785	7.7200	0.2405
ARMA	1.4370	2.0648	0.1220
ARIMA	24.9467	622.3387	3.9848
Random Forest	0.6918	0.4786	0.0547
SVR	5.6494	31.9159	0.5267
K Neighbourhood	2.1846	4.7724	0.1529
Gradient Boosting	0.5840	0.3411	0.0663
Extreme Gradient Boosting - XGBoost	3.0756	9.4590	0.1728
Panel B: Model 2			
	RMSE	**MSE**	MAPE
Multiple Regression	2.7753	7.7024	0.2386
ARMA	1.4397	2.0726	0.1246
ARIMA	24.9467	622.3387	3.9848
Random Forest	0.6875	0.4727	0.0524
SVR	4.6320	21.4553	0.4210
K Neighbourhood	1.4897	2.2192	0.1205
Gradient Boosting	0.5693	0.3241	0.0636
Extreme Gradient Boosting - XGBoost	2.9112	8.4748	0.1635
Panel C: Model 3			
	RMSE	MSE	MAPE
Multiple Regression	2.7513	7.5697	0.2414
ARMA	1.4699	2.1606	0.1231
ARIMA	24.9467	622.3387	3.9848
Random Forest	0.7261	0.5272	0.0566
SVR	4.6545	21.6639	0.4230
K Neighbourhood	1.2948	1.6765	0.1144
Gradient Boosting	0.4863	0.2365	0.0568
Extreme Gradient Boosting - XGBoost	3.0691	9.4192	0.1648

out as top performers across all the models. Feature importance test reveals the significance and impact of individual variables in a predictive model. It also helps to understand which variable contributes the most to the model's performance in making accurate predictions. The outcome of random forest reveals that, closely following the interest rate, FXReserves emerges as the second most crucial determinant of inflation which holds a significant explanatory power in predicting inflation (see Fig. 4). Interestingly, the results of Gradient Boosting show that FXReserves takes on the role of the fourth most influential determinant of inflation (see Fig. 5). It is noteworthy that both models emphasized the importance of inclusion of FXReserves into the model.

5. Conclusion and policy implications

This research underscores the critical importance of accurate inflation forecasting for economic analysts and policymakers alike. Recognizing the limitations inherent in traditional econometric models, which rely on linear relationships and may overlook the intricate nonlinearity and complexity of economic systems, researchers are increasingly turning to more adept forecasting approaches rooted in machine learning models. While ML techniques have found widespread application in predicting various macroeconomic indicators, their adaptation to the realm of inflation forecasting remains relatively novel. To the extent of author's best knowledge, none of the researchers have incorporated FXReserves, which is an important determinant of inflation, into the ML models.

It is important to note that consideration of all the important determinants of inflation is crucial for accurate forecasting, and their exclusion can yield potential biases. On this note, the present study makes two significant contributions to the extend body of knowledge. First, it employs a combination of tractional and ML approaches to test *"whether machine learning models outperform traditional ones in predicting*

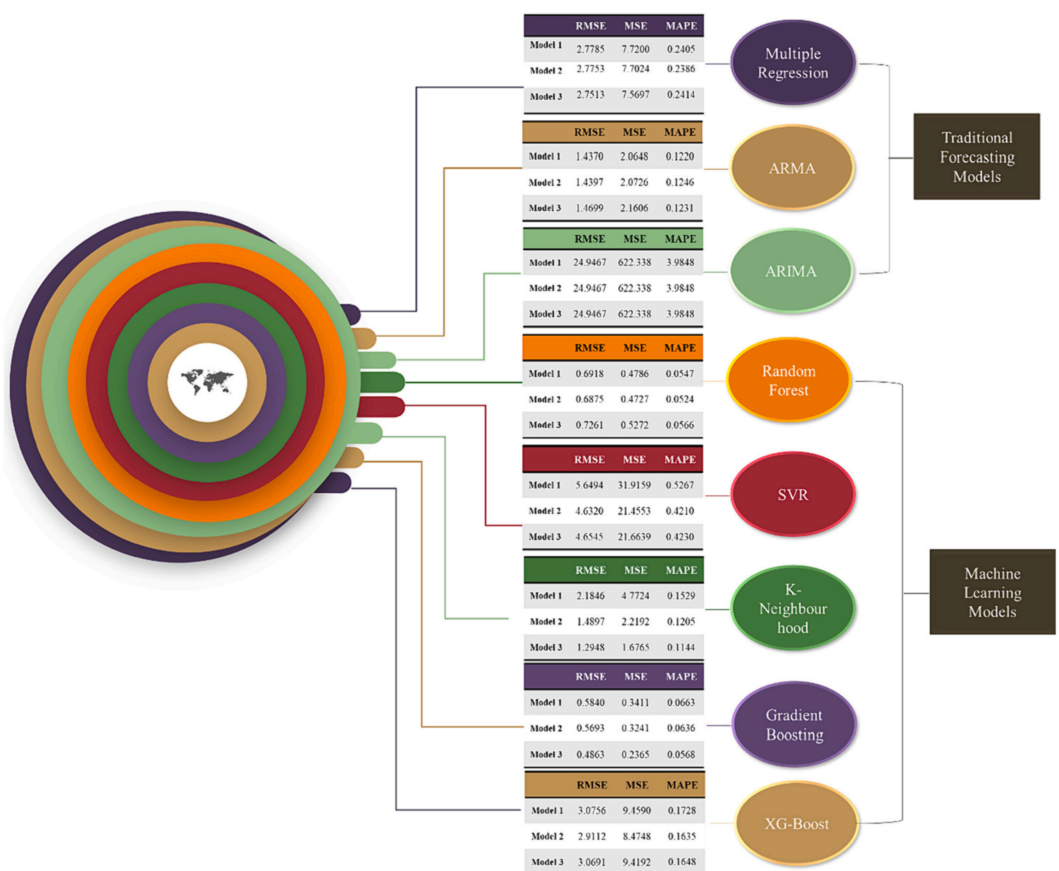

Fig. 3. Visual representation of results.

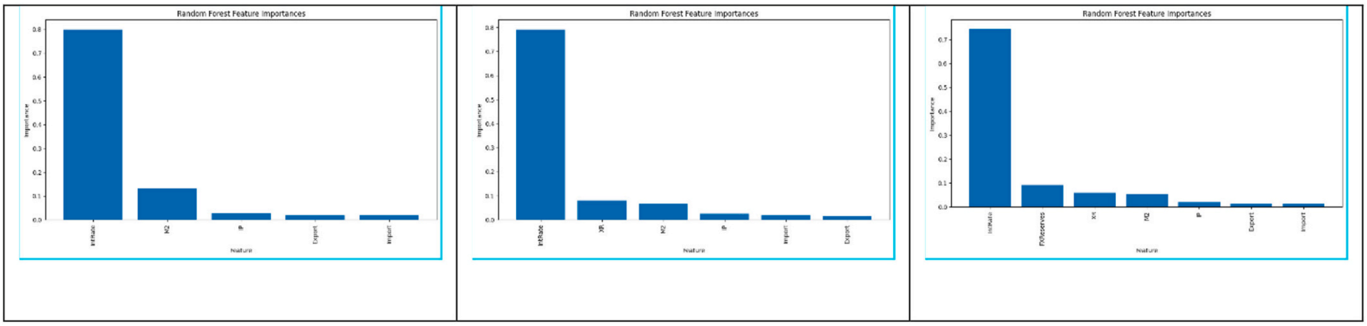

Fig. 4. Random forest (feature importance).

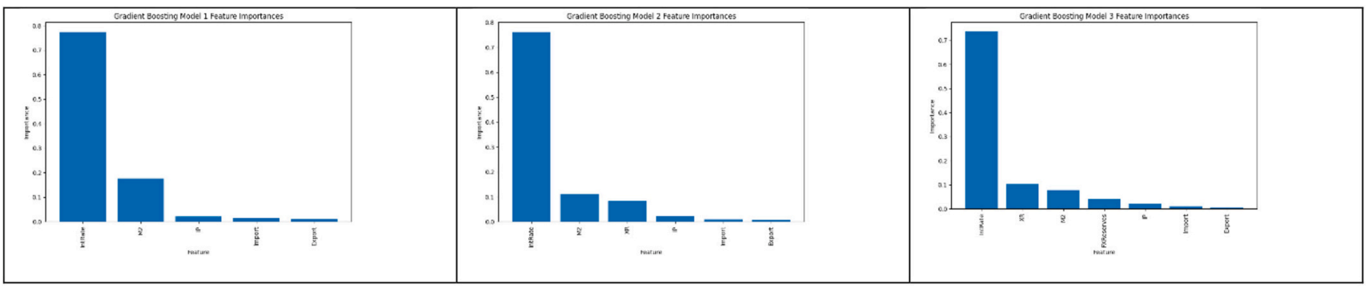

Fig. 5. Gradient boosting (features importance).

inflation accuracy?". Second, it explicitly includes the FXReserves into the forecasting models to ascertain *"whether their inclusion enhances predictive accuracy?"*

Results demonstrate that in the context of inflation forecasting, ML models consistently outperform traditional models. Notably, Random Forest and Gradient Boosting are the top performers across all three models. Moreover, the study unveils that the integration of FXReserves into the models has a positive impact on the predictive effectiveness of both traditional and machine learning-based forecasting models. The findings of the study provide dual insights. Firstly, our results demonstrate the superiority of machine learning models over traditional econometric approaches in predicting inflation. Simultaneously, our study underscores the critical importance of accounting for all the relevant factors by incorporating FXReserves into forecasting models.

These results have profound implications for shaping economic strategies and policy decisions, especially in the context of emerging economies such as Pakistan. Firstly, the demonstrated superiority of ML models over traditional econometric approaches provides policymakers with a solid foundation for informed decision-making. Accurate inflation forecasts enable a proactive approach in policy formulation, allowing for tailored interventions to address specific inflationary pressures. This targeted policymaking is crucial for avoiding generic solutions and ensures interventions align with the nuanced dynamics of the economy. Secondly, the improved accuracy of inflation predictions contributes to enhanced economic stability in emerging economies. With a better understanding of inflationary pressures, policymakers can implement preemptive measures to mitigate potential risks. This proactive stance helps prevent the escalation of inflationary trends, fostering a more stable economic environment. Increased economic stability instills confidence in businesses and consumers, promoting a positive economic landscape Moreover, the ability of machine learning models to capture complex patterns and relationships in economic data allows for a more comprehensive assessment of the factors influencing inflation. Policymakers can identify the primary drivers of inflation and craft policies that directly target those factors. This targeted approach ensures that interventions are not only timely but also focused on addressing the root causes of inflation, thereby increasing the effectiveness of policy measures. Additionally, the incorporation of machine learning models in policymaking facilitates real-time analysis of economic indicators. This capability enables policymakers to respond swiftly to emerging trends, adapt policies to changing economic conditions, and stay ahead of potential challenges. Real-time analysis ensures that policies remain relevant and effective in dynamic environments, contributing to the overall resilience of the economy.

However, in addition to the above, the integration of all relevant factors, particularly key variables like foreign exchange reserves, into ML models also holds undeniable significance in shaping economic policies. Neglecting foreign exchange reserves can result in incomplete assessments of potential risks and vulnerabilities and consequently policymakers may overlook crucial signals that could indicate impending challenges. This oversight may leave the economy vulnerable to unforeseen disruptions, as the absence of comprehensive information hampers the ability to formulate proactive and effective policies. On the other hand, the integration of foreign exchange reserves into forecasting models provides policymakers with a more comprehensive understanding of how fluctuations in these reserves impact inflation and overall economic stability. This nuanced insight allows for the formulation of policies that consider the broader economic context, ensuring a more holistic approach to economic management. Since, these reserves serve as a buffer against external shocks and financial crises, including them into forecasting models enables policymakers to assess the resilience of the economy to global economic uncertainties. Moreover, the ability to predict how changes in foreign exchange reserves may affect inflation and other economic indicators empowers decision-makers to proactively implement measures to safeguard against potential disruptions. Last but not least, the integration of foreign exchange reserves into ML models contributes to the development of more adaptive and responsive economic policies. As global economic conditions evolve, the models can dynamically adjust predictions based on changes in reserves, allowing for timely modifications to policy strategies. This adaptability is crucial for policymakers to navigate the dynamic and interconnected nature of the global economy effectively.

CRediT authorship contribution statement

Nawazish Mirza: Conceptualization, Methodology, Project administration, Writing – review & editing. **Syed Kumail Abbas Rizvi:** Conceptualization, Data curation, Software, Formal analysis, Writing – review & editing. **Bushra Naqvi:** Conceptualization, Methodology, Project administration, Writing – review & editing. **Muhammad Umar:** Conceptualization, Supervision, Visualization, Writing – original draft.

Data availability

Data will be made available on request.

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