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AN INTELLIGENT MACHINE LEARNING BASED INFLATION FORECASTING

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Abstract
This research study delves into the intricate dynamics of inflation forecasting, emphasizing the significance of machine learning techniques in contrast to traditional econometric approaches. It investigates the interplay between inflation and various economic variables such as interest rates, money supply, gold prices, and exchange rate across six diverse countries with different economic landscapes. By examining data spanning from January 1999 to December 2022, encompassing historical trends and economic shifts, this research explores the predictive capabilities of machine learning models in comparison to the traditional econometric models. Key findings reveal that no single model consistently outperforms others across all countries, underscoring the complexity and context-dependence of economic forecasting. The implications for model selection in inflation forecasting emphasize the importance of context-specific approaches, balancing complexity and interpretability, and continuous evaluation to adapt to evolving economic conditions. The study contributes to the ongoing discourse on hybrid methods for economic forecasting, suggesting a synthesis of machine learning and econometric models for enhanced accuracy and flexibility. Overall, this research offers valuable insights into the evolving landscape of inflation

forecasting, providing policymakers, economists, and financial institutions with nuanced perspectives and methodologies for informed decision-making in an ever-changing global economic environment.

Keywords: Inflation Prediction, Macroeconomic Variables, Machine Learning, Traditional Models

Introduction

In the contemporary landscape of economics, the ability to accurately predict and anticipate fluctuations in inflation rates stands as a fundamental cornerstone for economic policy formulation, financial decision-making, and market stability. Inflation has always been a major contributing factor in economic phenomenon. It remains a focal point for governments, financial institutions, and businesses (Faust & Wright, 2013). Accurate inflation prediction can aid in policymaking, pricing stability, avert economic crises, and stimulate economic growth. The inflation rate plays a vital role in the stability and policymaking of an economy. The dynamics of inflation, with its cascading effects on purchasing power, investment patterns, and overall economic equilibrium demands comprehensive and precise forecasting models. Envisioning accurate and timely forecasting of inflation via machine learning techniques could eradicate the flaws of conventional methodologies. This forecast could aid the governments, financial institutions, and businesses to make informed choices, avert economic crises, and stimulate economic growth (Dunbar & Owusu-Amoako, 2023).

While significant research has been conducted on inflation forecasting across various international contexts, there remains a notable research deficit, particularly concerning groups of countries. A thorough cross examination of the complex factors influencing inflation in developed, emerging, and fast-growing is scarce in the literature. Additionally, much of the existing research adopts a univariate approach, focusing on the impact of individual components on inflation, rather than considering the intricate interactions among multiple

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variables. Furthermore, there is a need for more recent evaluations that reflect recent economic trends and events, especially in the post-covid period, as the dynamics and reactions of many variables have evolved. Developed countries, alongside developing and emerging ones, have been significantly affected by the pandemic. To address this research gap, the proposed study aims to conduct a thorough, comparative investigation of inflation forecasting in six countries from different categories, i.e., United Kingdom, United States, Pakistan, Sri Lanka, China and India. The study considered the unique economic features of each nation and incorporates a wide range of variables. By comparing the countries, the study aims to assess the role of exogenous factors and the economic landscape in inflation forecasting in each context. Furthermore, the cross-country comparative analysis seeks to enhance understanding of how well these variables predict inflation across different economic situations and geographical locations.

Drawing from the study of Svensson (1997) that advocated the significance of inflation forecasting in monetary policymaking, this study offered valuable insights into inflation forecasting and laid the foundation for forthcoming studies. With the changing dynamics of an economy, finding out the effectiveness of inflation predictors on the inflation index is highly essential. This research attempts to address the usage of machine learning in the economic framework of inflation in all distinct countries, which is a divergence from conventional techniques. Moreover, with such a massive contributor to the rate of inflation in play, multiple variables are encompassed resulting in a more comprehensive and adaptable framework for inflation prediction. This study dwells around the use of machine learning in inflation forecasting. As Paruchuri (2021) concluded, machine learning is a promising approach for economic forecasting, offering potential benefits in terms of speed and reliability. In this research, we aim to create a more holistic framework for inflation forecasting, capable of accommodating the complex dynamics that emerge in a globalized world.

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This study has the potential to enhance precision in inflation prediction while incorporating the economic effects of an ever-evolving world. Comparative analysis amongst countries would greatly contribute to the existing body of economic literature. Policymakers in these countries, especially the developing countries, could benefit from the analysis and comparison, effectively targeting the right economic variable. This research is important because it can help us better understand how an economy responds to inflationary pressures. The study contributes in the existing knowledge by, (1) leveraging the power of machine learning and economic variables around different countries to improve the accuracy and timeliness of inflation predictions, (2) incorporating a wide array of variables including interest rate, money supply (M2), gold pricing, and exchange rate to envision the intricate dynamics of a globalized economy, (3) accurately predicting inflation and highlighting the important variables that play a role in affecting inflation. The study utilizes machine learning techniques to enhance the accuracy and timeliness of inflation forecasting and uniquely conducts a comparative analysis across developed, emerging, and developing countries. Incorporating a wide array of economic variables provides a comprehensive framework for inflation prediction. The study is expected to provide valuable insights for policymakers, particularly in developing countries, to target effective economic variables for inflation control.

Literature Review

The literature review covers two distinct areas, one scrutinizes the efficacy of traditional econometric models for inflation forecasting while the other delving into the application of machine learning techniques in the same context. Svensson (1997) helps us understand what's important and hard about using inflation targeting. They pointed out that it's very key to using targets for inflation in money policies. Supporting openness, trustworthiness, and responsibility in money policies could be crucial. Looking at the practical use of inflation targeting, Svensson used stories from real-life examples. The research

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focused on how leaders make choices by looking ahead. It examined projections of the output gap and inflation expectations for future decisions. It checked how well different rules and predictions work, stressing the importance of being flexible in dealing with unexpected money problems. In addition, the study discussed accountability, openness, and communication tactics in relation to inflation forecast targeting. Groen, Paap, and Ravazzolo (2013) explained changes happening all over the world by using simple signs of possible predictions which use past numbers for inflation, real activity data and surveys other than term structure and just monetary information. The research used the Bayesian method to mix different types of regressions chosen from possible predictors. Looking at inflation forecasts, it showed that putting many variables together into a model allows changes in the variations. This leads to very good accuracy and wider forecasting aspects.

In Pakistan, Hanif and Malik (2015) assessed the forecasting performance of various inflation models. The analysis encompassed different forecast horizons and varying inflation regimes. Three popular testing measures-random walk, ARIMA and AR (1) were used to check performance. The study showed that ARDL and special mix of point predictions remained better than random walk model, also they beat structural VAR and Bayesian VAR models at predicting inflation in Pakistan. The research focused on the change-based performance of predicting results in a country where inflation changes too frequently. The need for a careful approach in making policies based on the success of forecasting models for each area was suggested. In Nigeria, Tule, Salisu, and Chiemeke (2020) discussed getting better at predicting inflation by knowing how oil costs change. The study showed that predicting correctly can be very important to understand future changes in prices and the role this plays. The results show how important it is to consider oil costs and useful numbers in forecasting for Nigeria's inflation. The researchers collected lots of old records about oil prices and Nigeria's high cost living over a long time and used different types of econometric models to study the connection between inflation and oil prices. The research looked at different methods, including VAR, ARIMA and machine learning techniques. The study also looked at how some outside factors might affect the link between higher prices and oil costs, like world economic changes or political events. The study's findings showed the best way to improve inflation predictions in Nigeria by considering how internal economy parts and changes in world oil prices interact with each other. The results have big effects on research domains and real life uses in areas of finance and policy making for Nigeria economy. They also helped to make business prediction models and policy-making processes better.

McKnight, Mihailov, and Rumler (2020) used the new Keynesians Phillips Curve framework to refine the inflation forecasting methods by incorporating time varying trends. The methodology highlighted the relationship between inflation, output gap and the time varying trend while capturing the evolving dynamics of inflation over changing economic conditions. It described how theory implied projections are generated for the trend and cyclical components of inflation, which are then merged to create a forecast for inflation. The study carefully analyzed the suggested forecasting process against popular time series models using quarterly data for the Euro area and the US spanning nearly fifty years. The outcomes demonstrated that theory-based forecasts' higher performance, even outperforming benchmarks that were thought to be difficult to exceed in earlier research. The study indicated that theory should still be a major source of information for policymakers. Eroglu and Yeter (2023) studied how inflation and the growth of money supply change together in Turkish economy. The study suggested a concept called time-changing cause and effect where the connection between these factors can be different during certain economic times. The results provided insightful information that could help decision makers implement more sophisticated and flexible methods of economic management. In Albania, Konomi and Zani (2023) forecasted inflation using ARIMA econometrics model, which was based on qualitative and quantitative data of 2009-2022. The

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Albanian economy often has issues from the effects of money growth or rising prices (inflation). At the same time, inflation in Albania has made a round pattern and a big trend. Because of these circumstances, the basic models like ARMA or ARIMA to predict future inflation could be used. The researchers emphasized the need to think about using the ARIMA model when making rules.

In parallel to the traditional econometric model, the researchers also applied certain modern models to predict the inflation rate. Haider and Hanif (2009) investigated how artificial neural networks (ANNs) can be used to anticipate monthly inflation in Pakistan. Researchers used Artificial Neural Networks (ANNs) in monetary topics like economics and finance. This research talked about old time-series models like AR (1) and ARIMA compared with the prediction skill of an ANN model. The researchers used a simple feed forward ANN model with 12 hidden layers. The study found that the ANN forecasts did a better job than the AR (1) and ARIMA models. The study showed that the ANN models give good and correct forecast results outside sample. This means they are effective in predicting inflation trends in Pakistan. The results, like earlier studies in the US and OECD countries, show that using ANN methods is being more supported for forecasting economic items. In Brazil, Garcia, Medeiros, and Vasconcelos (2017) discussed the effectiveness of high dimensional econometric models, such as shrinkage and complete subset regression, in capturing the short-term volatility of inflation in a data rich setting. The study focused real time inflation forecasting in Brazil. The analysis covered the period from January 2003 to December 2015 and took advantage of the circumstances of a rising economy that targets inflation. Using a direct forecast approach, the study modeled inflation as a function of predictors assessed at the current moment, with different horizons. Macroeconomic variables, lag inflation, and data derived factors were all included in the collection of predictors. The models that were taken into consideration span both linear and nonlinear options, ranging from shrinkage models such as LASSO to full subset regression. The study's conclusions provide important new

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information to the body of knowledge on real time inflation forecasting, especially as it relates to Brazil.

Extending the literature, Sestanovi (2019) investigated how the Jordan Neural Network (JNN) might be used to anticipate inflation, highlighting the network's ability to handle nonlinearities and non-normally distributed macroeconomic data. The study made use of labor markets, financial, external, and lag inflation indicators to cover the countries of the Euro area from January 1999 to January 2017. The research found an ideal model that balances low mean squared error in both in the sample and out of sample circumstances by analyzing 250 JNN configurations. Notably, the study added to the JNN literature by analyzing model parameters, identifying important variables for precise forecasts, and addressing the underutilized application of JNNs in macroeconomic time series prediction. The study advanced the knowledge of efficient inflation forecasting through using cutting-edge neural network techniques. Momo, Riajuliislam, and Hafiz (2021) explored how crucial it is to forecast changes in the inflation rate to control economic expansion and maintain stable political and financial environments. The study used a variety of machine learning algorithms, including support vector regression, random forest regressor, decision tree, AdaBoost, gradient boosting, and XGBoost, since it acknowledged the nonlinear and complicated nature of inflation. These algorithms were selected based on their capacity to represent the complex dynamics of inflation, a variable that is affected by a multitude of causes. The models show impressive accuracy, especially when considering factors like food, non-food, clothing footwear, transportation, and consumer price index. Of them, AdaBoost was the most effective at predicting inflation rates, producing the best results.

Akbulut (2021) further elaborated the phenomenon by comparing machine learning and time series model techniques, emphasizing the machine learning models as a reliable complementary method for estimation of inflation in emerging economies, especially as the amount of data and computational

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power increases. Similarly, Rosni and Othman (2022) proposed that machine learning has been highly effective in the time series modelling used to analyze statistics and support potential evaluations of future food prices for decision making and effective management in data poor food price situations. In Turkey, Nakorji and Aminu (2022) suggested training of machine learning models, like Linear Regression, Bayesian Ridge Regression, Kernel Ridge Regression, Random Forests Regression, and Support Vector Machines, to forecast consumer price inflation. The results show that machine learning algorithms outperform the official forecasts of the Central Bank of Turkey. The study concluded that machine learning algorithms, by treating inflation forecasting as an estimation problem and using summary statistics of surveys of expectations data as features, can produce more accurate forecasts. Further delving into the Turkish economy, Ozgur and Akkoc (2022) compared the predictive power of machine learning algorithms for inflation rate forecasting with industry standards like ARIMA and VAR models. The paper highlighted the importance of variable selection in inflation forecasting and suggested that shrinkage methods, specifically LASSO and elastic net algorithms, outperform conventional econometric methods in the case of Turkish inflation.

While there has been a lot of research on inflation forecasting in different international contexts, there's still a significant gap, especially when it comes to comparing groups of countries. We don't have enough studies that look at the complex factors affecting inflation across multiple countries, even though we've seen separate studies on developed, emerging, and fast-growing economies. Comparative analyses that cover all three groups are rare. Additionally, most existing research focuses on individual factors impacting inflation rather than exploring the intricate interactions among multiple variables. Moreover, there's a need for more recent evaluations that consider the latest economic trends and events, especially in post-covid period, as many variables have changed. Both developed and developing countries have been significantly impacted by the pandemic. To fill this research gap, our study involved a thorough and

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comparative investigation of inflation forecasting in six countries, considering each nation's unique economic features and a wide range of variables. By comparing the developing, defaulted, emerging, and developed economies, we aim to understand how different factors and economic landscapes influence inflation forecasting in each context.

Data and Methodology

The research utilized diverse datasets from United Kingdom, United States, Pakistan, Sri Lanka, China, and India spanning from January 1999 to December 2022. Data sources include World Bank, Central Banks, and Federal Reserve Economic Data (FRED), covering variables of inflation rate, interest rates, money supply (M2), gold pricing and exchange rate. The selection of these countries allows for a comprehensive comparison of machine learning and conventional techniques to forecast inflation across divergent economies, shedding light on unique economic dynamics and challenges. The entire methodological framework is explained in below given flow diagram.

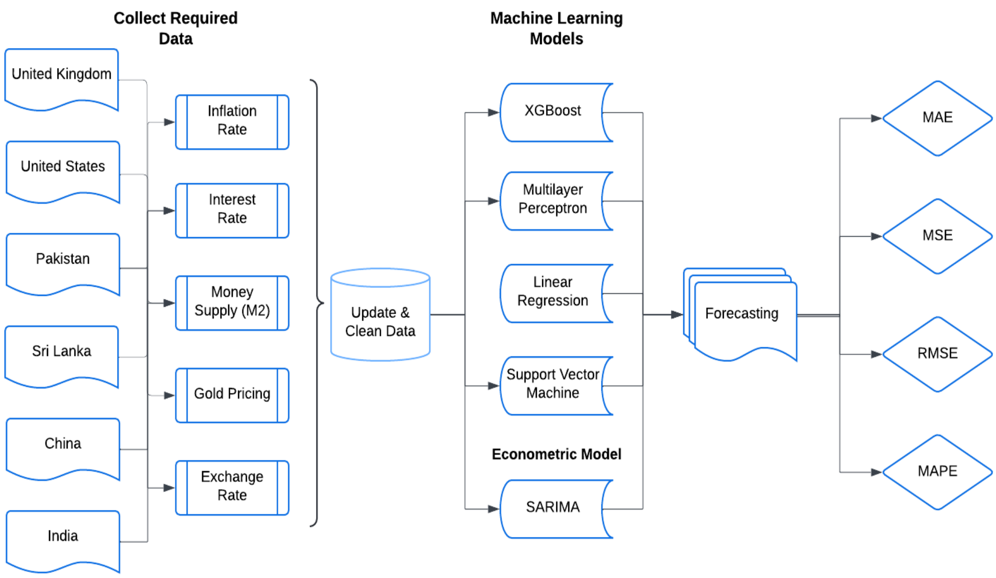

Figure 1. Flow Diagram

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The flow diagram illustrates a comprehensive methodology for forecasting inflation using a combination of machine learning and econometric models. The process began with the collection of essential economic data from six countries. Data of the key variables including inflation rate, interest rate, money supply (M2), gold pricing, exchange rate were gathered for each country. This data were then meticulously updated and cleaned to ensure accuracy and consistency. The final data were put into various machine learning models including XGBoost, Multilayer Perceptron, Linear Regression, and Support Vector Machine, alongside an econometric model SARIMA. These models were employed to generate inflation forecasts. The accuracy and reliability of these forecasts were evaluated using several performance metrics, i.e. Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). This multi-faceted approach ensures a robust analysis, leveraging diverse models and metrics to enhance the precision and timeliness of inflation predictions. The machine learning and econometric techniques used in the study are explained below.

XGBoost

XGBoost, also known as Extreme Gradient Boosting, is a popular and potent machine learning technique that excels at processing structured data. It falls under the group of ensemble learning, which combines several weak models, usually decision trees, to produce a more potent prediction model. To get the final output, XGBoost iteratively constructs decision trees, optimizes them to minimize a predetermined loss function, and then aggregates their predictions. XGBoost can accurately represent intricate correlations between inflation and many predictor factors, including money supply, interest rates, exchange rates, gold price, and previous variations in inflation. Because of its ability to manage non-linear correlations and interactions between various variables, it can effectively capture the subtleties inherent in economic dynamics. This mathematical expression of the model takes following form.

$$Objective\ Function = \sum i = 1nLoss\ (yi, y\hat{\ }i) + \sum k = 1\ K\Omega(fk) \quad (1)$$

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Multi-Layer Perceptron

A fundamental architecture within the realm of artificial neural networks (ANNs) is the Multi-Layer Perceptron. Well known for their adaptability and efficacy across various machine learning tasks, MLPs are structured with layers consisting of interconnected nodes, or neurons. These neurons process input data through weighted connections and activation functions, facilitating the network's ability to capture complex nonlinear relationships within datasets. With an input layer, one or more hidden layers, and an output layer, MLPs excel at tasks like regression, classification, and time series forecasting. Their capability to discern intricate patterns from vast datasets, coupled with advancements in optimization algorithms such as backpropagation, has solidified MLPs as a cornerstone in modern deep learning frameworks. From image recognition to financial forecasting, MLPs continue to drive innovation across diverse domains, offering a potent solution for addressing multifaceted real-world challenges. The model is expressed as.

$$f(L)(x) = a(w(L)0 + \sum UL - 1i = 1w(L)\, if\ (L-1)\ i(x)) \qquad (2)$$

Linear Regression

Linear Regression is a basic technique widely used in machine learning. In economic planning, regression analysis is still important because it gives a clear and easy way to understand the links between different factors that affect outcomes. Regression models help us to see how economic factors affect inflation rates in predicting future prices. They use multiple linear regression and take in possible items that can predict, like real money exchange rates, gold prices, money supply and interest rates. It is easy to use regression models, but they are simpler than machine learning algorithms. It's important not just for academia but also real-world decisions as well. Below model shows how linear regression shows the relationship between independent and dependent variable.

$$y = \beta 0 + \beta 1 \cdot X1 + \beta 2 \cdot X2 + \ldots + \beta n \cdot Xn + \epsilon \qquad (3)$$

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Support Vector Machine (SVM)

SVM is a powerful way of learning that helps knowing what is right and wrong in information. By choosing the best kind of seed, such as circle function or line kernels, one can quickly find complex patterns in large businesses. Historical data is used to train the SVM model with money supply, interest rate, exchange rate, gold pricing and inflation price changes. The first step in the process is picking out important economic factors. After that, SVM looks for the best hyperplane to separate classes with more space and match the training set as well. The SVM's power comes from adjusting settings, which means making the best choices for hyper-settings by testing different ways. Common measures such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) are used to judge the final model. They show how accurate it is in making predictions. These numbers give a way to measure how well the model can predict inflation rates. RMSE is very helpful because it gives a complete check of how good the model's predictions are by calculating the average size of mistakes between what was forecasted and what is actual. This model is mathematically written as follows.

$$f(\mathbf{x}) = \sum i = 1N\alpha iyiK(\boldsymbol{x}i, \boldsymbol{x}) + b \tag{4}$$

Seasonal Autoregressive Integrated Moving Average

Seasonal Autoregressive Integrated Moving Average (SARIMA) model is one of most important tools for predicting economy. It is especially good at catching complexity of time series data that show seasonal changes. This model builds on ARIMA framework by adding seasonal features. The ARIMA time forecasting model is often used in economics because it can correctly get patterns of changes over time from data. Autoregressive (AR), moving average (MA) and difference (I) are three important pieces of the ARIMA model. By adding seasonality in the data, to make it specifically well suited for capturing recurring patterns and trends over time is the concept of SARIMA. This method works best with data from different time points, so it can be used for economic variables that change over time like inflation rates. Overall, SARIMA models

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offer a robust framework for inflation forecasting by incorporating both temporal dynamics and seasonal patterns, providing valuable insights for economic analysis and decision-making. The mathematical expression of SARIMA model is in equation 5.

$$Yt = c + \phi 1Yt - 1 + \phi 2Yt - 2 + \cdots + \phi pYt - p + \theta 1\epsilon t - 1 \cdots + \theta q\epsilon t - q + \epsilon t \qquad (5)$$

Results and Discussion

In this section, we scrutinize the efficacy of four distinct machine learning models. We applied XG Boost, MLP, Linear Regression, and SVM alongside the traditional econometric model SARIMA, in their ability to forecast inflation rates across six diverse economies of United Kingdom, United States, Pakistan, Sri Lanka, China, and India. This segment unveils not just the predictive capabilities of these models but also sheds light on the intricate nuances of inflation dynamics within each country's economic landscape. The results first explain how inflation rates are spread out in six different countries. This is explained in Figure 2.

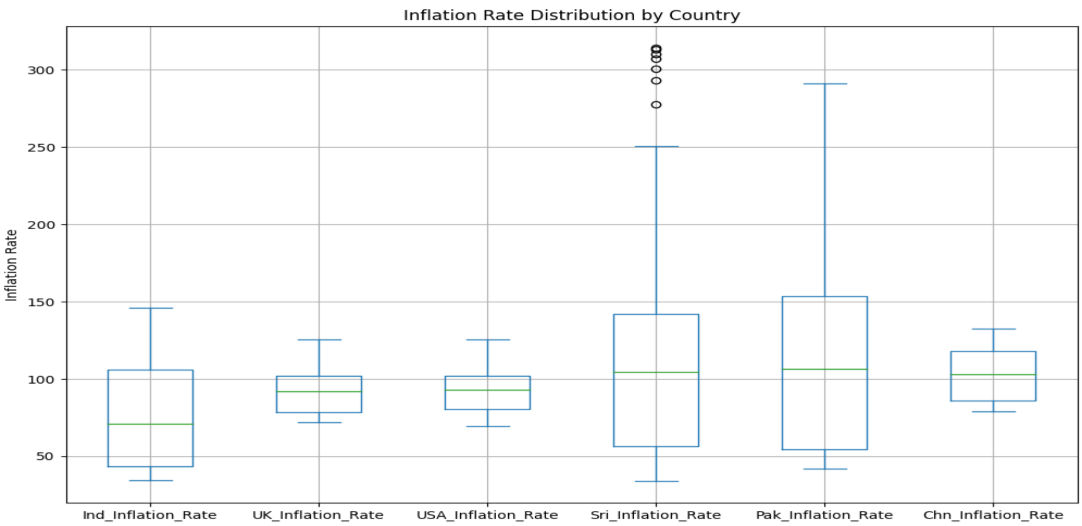

Figure 2. Comparison of Inflation Rate among Different Countries

Figure 2 shows India and Pakistan have bigger ranges with number of outliers that show times when inflation was very high. US and China have more compact ranges, which means their inflation rates are likely to be more stable. Sri Lanka has a wide range, which means that inflation changes but not as much

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as in India or Pakistan. The median inflation rate seems highest in Sri Lanka and lowest in China. The study further proceeded to forecast inflation by using linear regression and machine learning models. The results are given in table 1.

Table 1. Performance Metrics across Countries

Country	Model	MAE	MSE	RMSE	MAPE
United Kingdom	XG Boost	0.459	0.343	0.585	0.523
	MLP	67.670	4738.500	68.800	73.959
	Linear Regression	0.802	1.355	1.164	0.847
	SVM	0.361	0.289	0.537	0.395
United States	XG Boost	0.597	0.795	0.891	0.682
	MLP	73.722	5560.700	74.570	79.890
	Linear Regression	1.399	3.543	1.882	1.604
	SVM	0.595	0.799	0.894	0.670
Pakistan	XG Boost	1.697	11.548	3.398	1.423
	MLP	91.016	10740.842	103.638	80.039
	Linear Regression	3.369	27.096	5.205	3.731
	SVM	1.565	6.025	2.455	1.343
Sri Lanka	XG Boost	2.900	35.010	5.910	2.670
	MLP	80.164	8102.347	90.103	74.909
	Linear Regression	12.783	278.828	16.698	18.257
	SVM	3.924	50.067	7.075	6.439
China	XG Boost	0.680	0.698	0.836	0.695
	MLP	80.724	6711.260	81.920	78.694
	Linear Regression	1.429	4.543	2.131	1.384
	SVM	0.947	1.250	1.117	0.976
India	XG Boost	1.240	2.350	1.530	1.770
	MLP	55.410	3945.110	62.810	69.150
	Linear Regression	2.495	8.227	2.868	4.995
	SVM	0.583	0.550	0.742	1.046

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The table shows an evaluation of models based on performance metrics across the selected countries. In India, SVM model emerged as the top performer, excelling in both training and test results. Its adeptness in handling non-linearities and variations underscored its effectiveness. Meanwhile, in the United Kingdom, the XG Boost model demonstrated exceptional training capabilities, indicating its proficiency in learning intricate patterns. However, when faced with unseen data, SVM exhibited remarkable performance, particularly on the test set, showcasing its ability to capture economic patterns without succumbing to overfitting. In United States, the close performance between XG Boost and SVM on the test set suggested the efficacy of both models. Yet, XG Boost's superiority in discerning complex relationships within training data hinted at its potential for economic measures with intricate interconnections. Despite XG Boost occasionally showing superior training results in Pakistan, its high error rates on validation and test sets necessitated a more conservative approach, highlighting the suitability of SVM for comprehending economic trends in a broader context. Similarly, in Sri Lanka and China, XG Boost emerged as the preferred model for its robust performance on the test set, emphasizing its effectiveness in capturing underlying economic trends despite its complexity. Notably, the SVM model's versatility across various datasets and countries renders it a commendable choice for economic predictions. The utilization of the SARIMA model as a benchmark underscores the importance of simplicity combined with domain knowledge in economic forecasting. Each model's efficacy is contingent upon the economic context, elucidating the nuanced nature of economic data across different regions. The graphical representation of inflation forecasting with each model is in figure 3.

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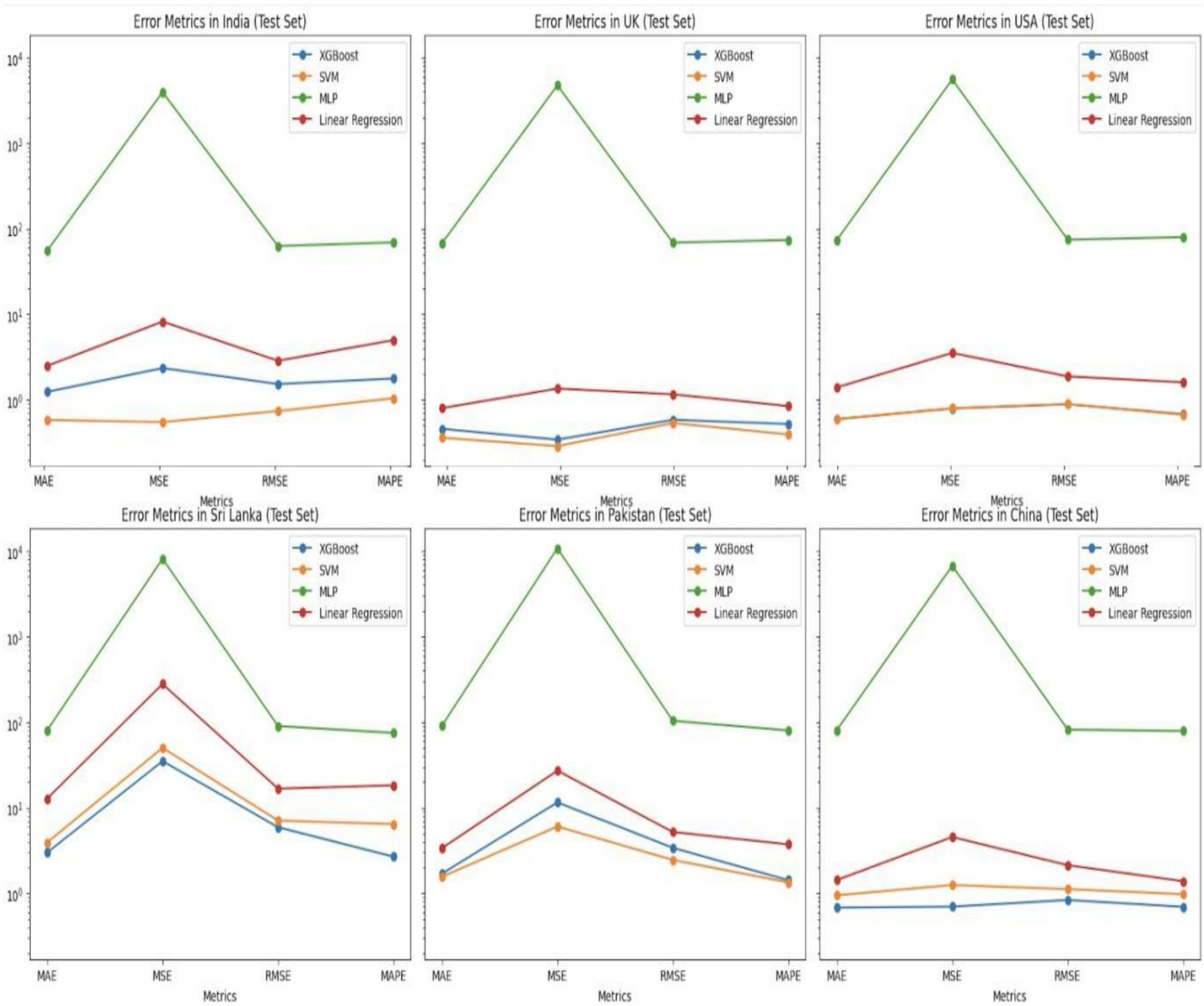

Figure 3. Error Metrics Test Data

Figure 3 confirms the better predicting power of SVM and XG Boost in most cases. Further delving into the importance and effect of each variable in an economy, Table 2 shows the weightage and coefficient estimation of each variable in a country using XGBoost and Linear Regression.

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Table 2. Weightage of Each Economic Variable

Country	Model	Interest Rate	Money Supply	Gold Pricing	Exchange Rate
United Kingdom	XG Boost	0.290	0.250	0.240	0.220
	Linear Regression	0.020	0.020	0.001	0.060
United States	XG Boost	0.350	0.270	0.180	0.210
	Linear Regression	-0.042	-0.004	0.061	0.041
Pakistan	XG Boost	0.205	0.315	0.197	0.280
	Linear Regression	-0.190	0.018	0.173	0.173
Sri Lanka	XG Boost	0.301	0.350	0.207	0.139
	Linear Regression	-0.176	-0.026	0.278	-0.023
China	XG Boost	0.158	0.280	0.338	0.220
	Linear Regression	0.052	-0.070	0.148	-0.060
India	XG Boost	0.210	0.320	0.250	0.220
	Linear Regression	0.030	-0.060	-0.080	0.090

Examining the importance of factors in inflation forecasting reveals interesting trends between nations, which are visible in both XGBoost weightage and linear regression coefficients. The weightage across different variables affecting inflation rate forecasting varies across countries, reflecting diverse economic contexts and policy priorities. In United States and United Kingdom, interest rates hold the highest weightage at 0.350 and 0.290 respectively, indicating their critical role in shaping inflation expectations and monetary policy decisions. Meanwhile, in Sri Lanka, India and Pakistan, money

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supply (M2) carries the greatest influence, underscoring the significance of liquidity conditions in driving inflation trends. In China, the gold rate is relatively more impactful with a weightage of 0.338, possibly reflecting cultural and economic factors influencing gold demand and its inflationary implications. These weights illustrate how different variables are perceived and prioritized within each country's economic forecasting frameworks, guiding policymakers in crafting targeted strategies to manage inflation effectively. Overall, these results confirm the crucial role that money supply plays in influencing inflation dynamics in a variety of economies, which will be helpful to economists and policymakers who are attempting to understand intricate economic relationships.

The analysis further evaluates the performance of four different machine learning models, XG Boost, MLP, Linear Regression, and SVM in predicting inflation rates across six countries. Using scatter plots shown in figure 4, we compared the actual inflation rates with the predicted values from each model. The plot includes a dashed line that indicates perfect prediction, where the predicted values exactly match the actual rates. This visual assessment, coupled with statistical performance data, enables a comprehensive understanding of each model's effectiveness. The best performance model for the inflation rate in each country is explained in figure 4 below.

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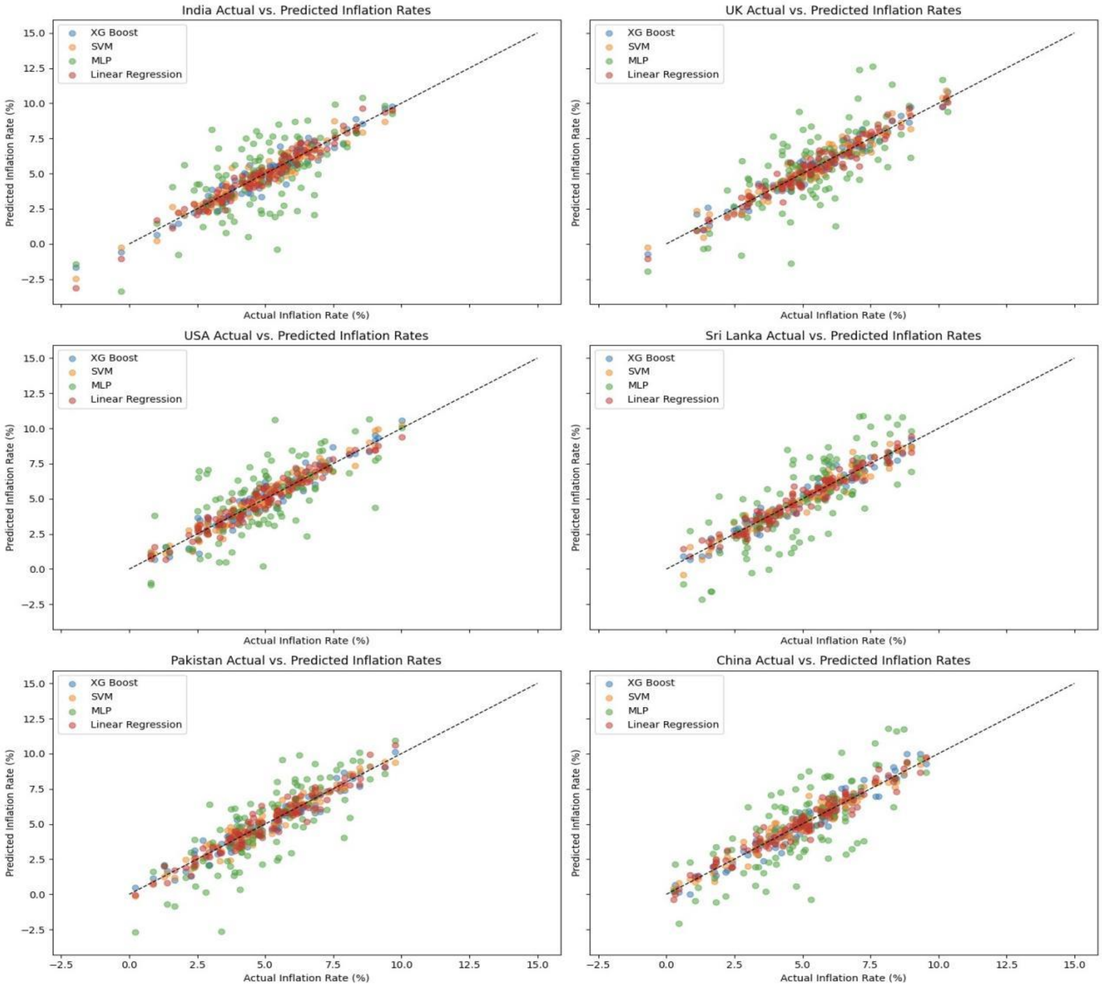

Figure 4. Best Model Performance.

The overall results indicate that SVM and XGBoost are the most effective models for inflation forecasting across different economic contexts. SVM excels in India, United Kingdom, and Pakistan, while XGBoost leads in the United States, Sri Lanka, and China. This underscores the importance of selecting the appropriate model based on the specific economic environment to achieve the most accurate and reliable inflation forecasts.

Conclusion

To forecast inflation rates, a crucial economic indicator with broad ramifications for economic stability and policymaking, we compared sophisticated machine learning models with conventional econometric

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techniques in this study. By examining six different countries, we have been able to learn more about the efficacy of predictive models and economic patterns. Our analysis illuminated the intricacies of economic forecasting by revealing differences in model performance among the countries. Machine learning models, like XG Boost, showed promise in terms of prediction, but they also had drawbacks, like overfitting and trouble generalizing to new data. Remarkably, despite its ease of use, Linear Regression demonstrated efficacy in identifying economic patterns, especially in China. Furthermore, conventional econometric models such as SARIMA showed strong performance in situations when cyclical tendencies were evident.

Our findings have ramifications for economic policymaking and provide policymakers with insightful information. Proactive policy interventions are made possible by machine learning algorithms, which let policymakers predict inflationary patterns and adjust their policies accordingly. Picking the best model, however, depends on how well it predicts the future and how well it can be tailored to different economic situations. Transparent and easily understood models, like SARIMA and linear regression, let stakeholders comprehend policy decisions more clearly, which promotes responsibility and confidence. Every country has different economic possibilities and difficulties, requiring different policy solutions. For example, the flexibility of SVM models demonstrates their capacity to handle intricate economic dynamics in Pakistan and India. On the other hand, the success of XG Boost in the US highlights how crucial sophisticated modeling methods are for capturing complex economic linkages. It is recommended that policymakers include machine learning predictions in their decision-making procedures, utilizing the advantages of every model to successfully tackle distinct economic issues.

In conclusion, this study contributes to the evolving landscape of economic forecasting by highlighting the potential of machine learning models alongside traditional econometric methods. By harnessing the strengths of both approaches and addressing inherent challenges, policymakers can leverage

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advanced predictive analytics to navigate the complexities of modern economies and make informed decisions for sustainable growth and stability. Despite the comprehensive nature of this study, several limitations must be acknowledged. These include challenges related to data availability and quality, model complexity, economic and political changes, interdisciplinary collaboration, methodological constraints, generalizability across economies, scope of economic indicators, and future-readiness of models. Addressing these limitations is essential for enhancing the reliability and applicability of economic forecasting models. Hence, future research endeavors should focus on diversifying data sources, incorporating real-time data analysis, fostering interdisciplinary collaboration, exploring advanced machine learning techniques, conducting comparative studies across a wider range of countries, considering the impact of fiscal policy changes, investigating hybrid modeling approaches, monitoring model performance over time, enhancing transparency and interpretability, and addressing ethical considerations in economic forecasting.

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