A Data-Driven Approach to Inflation Forecasting in Pakistan: Comparative Analysis of ARIMA, SVM, Tree-Based Models, and Regularized Regression(1989-2024)

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Abstract

This research elaborates on the use of machine learning models and how they compare to traditional models in predicting Inflation, a complex economic phenomena that guides monetary policymaking. The results showed that the Lasso Model was the closest in forecasting annual Inflation rate. ARIMA struggled to give accurate predictions especially for the spike in inflation after COVID-19.

Keywords: Machine Learning, Inflation, Regression Models

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1 Introduction

1.1 Background

Inflation, defined as a persistent rise in the overall price level of goods and services in an economy, is a key macroeconomic variable with long-term consequences for economic prosperity, growth, and welfare. In developing economies like Pakistan that have experienced macroeconomic uncertainty and vulnerability to domestic and external shocks, proper forecasting of inflation is of utmost concern. Persistent high inflation can destroy purchasing power, mislead investment choices, widen inequality in income, and destabilize economic confidence overall [1]. The success of monetary and fiscal policy actions depends on the capacity to foresee future paths of inflation so that early intervention can be undertaken to counteract their negative influences.

Since the last three and a half decades, the economy of Pakistan has experienced volatile inflation rates fueled by a complex combination of domestic determinants like monetary policy stances, fiscal imbalances, supply-side shocks, and structural determinants, and external determinants like fluctuations in international commodity prices and exchange rate movements [2]. Determining the causes of inflation in Pakistan and developing plausible forecast models is a significant area of research for policymakers and economists.

Traditional statistical methods, like the AutoRegressive Integrated Moving Average (ARIMA) model, have been commonly used for inflation forecasting. The economic environment has, however, grown more nonlinear and complex. In such a scenario, traditional regression methods like Lasso, Ridge, and Elastic Net offer a compelling choice. These models incorporate penalty terms that manage bias and variance, and they are well-suited to multicollinearity and feature selection—goals that usually evade traditional time series models.

1.2 Why Forecasting Inflation in Pakistan Matters

Accurate inflation forecasts are of critical importance in the Pakistani economy for a number of compelling reasons. Firstly, they are important inputs to the State Bank of Pakistan (SBP) in designing and implementing effective monetary policy. Having the capacity to forecast future inflationary pressures, the SBP can make policy decisions in advance, e.g., the benchmark interest rate and reserve requirements, to ensure price stability, an intrinsic goal statutorily mandated. The use of accurate forecasts enables the SBP to employ a forward-looking policy strategy, thus minimizing implementation lags and maximizing the efficacy of monetary interventions [3].

Secondly, good inflation forecasts are crucial for making good fiscal policy choices. Such inflation forecasts are used by the government to develop the budget, project revenues, and determine spending on social welfare. Surprise increases in inflation would reduce the government's real purchasing power, and fiscal policy intervention might be needed. Good forecasts allow for effective coordination between the monetary and fiscal authorities, leading to overall macroeconomic stability.

1.3 Significance of Forecasting Inflation

The ability to produce sound inflation forecasting has far-reaching implications. To the central bank, it is the basis for monetary policymaking. To business corporations, it affects pricing, wage negotiations, and investment. To the citizen, it affects the purchasing power of income and assets. In a country like Pakistan which experiences supply-side inflation and instability, sound means of forecasting can stabilize expectations and enhance institutional credibility.

With the passage of time, the developing economies have largely used hybrid or data-centric approaches to increase predictive power. Pakistan, nonetheless, still relies on traditional tools, at times falling behind the application of machine learning or regularization methods in macroeconomic projections. This research aims to fill this gap.

1.4 Objectives of the Study

The aim of this report is to compare and evaluate the capacity of both non-regularized and regularized time series models to predict inflation in Pakistan for the period 1989-2024. The specific objectives are as follows:

1. To create and apply an ARIMA model based on past data on inflation.

2. Applying Ridge, Lasso, and Elastic Net regression techniques that use appropriate macroeconomic markers as variables.

3. In order to compare relative predictive power of models like these with error measures like RMSE, MAE, and MAPE.

4. To find out whether regularized regression techniques—i.e., Elastic Net—provide a more accurate model for forecasting inflation in Pakistan.

2 Literature Review

ARIMA models, originally developed by Box and Jenkins [4], have been the gold standard for forecasting inflation for a long time. The models are well adapted to macroeconomic time series data because they can handle both non-stationarity and autocorrelation—two of the most prevalent features of such data.

A series of empirical research works have proven the effectiveness of ARIMA models in forecasting inflation in the specific context of Pakistan. For example, Khan et al. [5] attempted different ARIMA settings to forecast CPI inflation and concluded that appropriately calibrated models possessed strong short-run predictive power. Similarly, Ali and Hussain [6] compared ARIMA forecasts with and without seasonality and structural break corrections in the context of food inflation, hinting at the need for data preprocessing. In addition, Narayan and Sharma [7], in their Fiji's context-focused work, noted the stability of the ARIMA model even after undergoing economic shocks. However, the effectiveness of this model largely depends on appropriate lag structure identification and the inclusion of structural breaks [8].

Although ARIMA remains a traditional one, machine learning techniques—regularized regression models, specifically—have gained greater popularity in economic forecasting due to their greater flexibility and ability to handle multicollinearity among predictors. Ridge regression [9], with an L2 penalty in the OLS objective that reduces the magnitude of coefficients, Lasso regression [10] with an L1 penalty that sets some coefficients to zero, effectively performing variable selection, and Elastic Net [11], a mix of L1 and L2 penalties, are particularly well-suited for high-dimensional problems with highly correlated predictors.

Despite their limited application to the case of inflation in Pakistan so far, international evidence supports their efficacy. Medeiros et al. [12] demonstrated the superior prediction capability of Ridge and Lasso regression compared to conventional models in the United States, while Solente et al. [**?**] demonstrated the superiority of Elastic Net over ARIMA in certain European countries, particularly in cases of economic uncertainty.

In inflation measurement in Pakistan, one has to adjust for the important macroeconomic factors. Total reserves stabilize exchange rates and lower the effects of import price shocks [13]. The rate of unemployment, even though controversial, has an effect on inflation through wage behavior [14]. Real interest rates have a substantial effect on aggregate demand and saving behavior. Trade indicators, particularly imports, exports, and exchange rate volatility, have a considerable effect on inflationary pressures [2, 15]. Externally high debt also increases inflationary pressures [16]. Oil rents also have an effect on inflation through their effect on energy prices [17].

Industrial production affects inflation by triggering demand and supply constraints. Money supply, i.e., broad money as a ratio of GDP, is also a major determinant [18, 19]. Currency misalignment and trade distortions are reflected by the price level ratio [20], and cost-push inflation occurs due to wage rises without productivity [21]. The Consumer Price Index (CPI) still remains the primary indicator for monitoring and modeling inflation.

The macroeconomic and methodological results outlined here provide a solid basis for Pakistan's inflation modeling on which the merits of traditional statistical techniques are emphasized as well as the potential of new machine learning methods in high-density data-based prediction.

3 Data and Methodology

3.1 Data Description and Variables

The annual macroeconomic time series of Pakistan are utilized in this study. The data is sourced from the World Bank's World Development Indicators (WDI) website. The data spans from 1989 to 2024, which is a period of 35 years. The data from 2020 to 2024 is taken as testing data. The data from 1989 to 2019 is used as training data for the prediction models. The data include key economic variables that are effective for model inflation. All the data are of annual frequency, consistent with the variable of interest. The data utilized in this study can be made available on request. The dependent variable is the Consumer Price Index (CPI) as proxy for inflation. The independent variables are the following macroeconomic variables: total reserves excluding gold, unemployment rate as a percentage of the total labor force, real interest rate, imports and exports of goods and services as a percentage of GDP, official exchange rate (LCU per USD), external debt stocks as a percentage of GNI, oil rents as a percentage of GDP, industry (including construction) as a percentage of GDP, broad money as a percentage of GDP, ratio of the price level of the PPP conversion factor over the market exchange rate, and percentage of wage and salaried employees in total employment. Each of these variables were selected on the basis of theoretical importance and empirical convention in inflation modeling. Missing observations are addressed by using time-series interpolation techniques. Model training is done in the time period 1989 to 2019, while the time period 2020 to 2024 is reserved for out-of-sample prediction.

3.2 Model Estimation

Inflation is predicted and modeled using four methodologies: the ARIMA model, Ridge Regression, Lasso Regression, and Elastic Net Regression. Each of these methodologies has varying strengths with respect to their ability to handle time-series behavior, multicollinearity issues, and high-dimensional predictor spaces.

3.2.1 Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model represents the autoregressive and moving average sections of the inflation time series. But it does not incorporate exogenous predictors. It is suitable for univariate forecasting. It relies solely on the past values and lagged forecast errors of the CPI series.

The general form of the ARIMA(p, d, q) model is:

$$\Phi_p(L)(1-L)^d y_t = \Theta_q(L)\varepsilon_t, \tag{1}$$

where y_t represents the CPI, L is the lag operator, $\Phi_p(L)$ and $\Theta_q(L)$ are polynomials of order p and q respectively, and ε_t is a white noise error term. The stationarity of the series is verified using the Augmented Dickey-Fuller (ADF) test, and the optimal lag orders are chosen based on the Akaike Information Criterion (AIC).

3.2.2 Ridge Regression

Ridge regression introduces L_2 which regularizes the ordinary least squares method to address multicollinearity and prevent overfitting. The minimization objective is expressed as:

$$\min_{\beta}\left\{\sum_{i=1}^{n}\left(y_i-\beta_0-\sum_{j=1}^{p}\beta_j x_{ij}\right)^2+\lambda\sum_{j=1}^{p}\beta_j^2\right\}, \tag{2}$$

where λ is a regularization parameter that controls the strength of the penalty. Ridge regression shrinks the coefficients towards zero but does not set any of them exactly to zero.Hence, it preserves all predictors in the model.

3.2.3 Lasso Regression

Lasso regression incorporates L_1 regularization, but it choses specific variables by shrinking some variables' coefficients to zero. The objective function is defined as:

$$\min_{\beta} \left\{ \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\}. \tag{3}$$

This formula is particularly useful when only a subset of predictors are strongly related with the dependent variable.

3.2.4 Elastic Net Regression

Elastic Net combines the penalties of both Ridge and Lasso regression to balance the benefits of coefficient shrinkage and variable selection. Its objective function is:

$$\min_{\beta} \left\{ \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda_1 \sum_{j=1}^{p} |\beta_j| + \lambda_2 \sum_{j=1}^{p} \beta_j^2 \right\}. \tag{4}$$

Alternatively, it can be expressed in the α-parameterized form as:

$$\text{Penalty} = \lambda \left[\alpha \sum_{j=1}^{p} |\beta_j| + (1 - \alpha) \sum_{j=1}^{p} \beta_j^2 \right], \tag{5}$$

where $\alpha \in [0, 1]$ determines the balance between Lasso ($\alpha = 1$) and Ridge ($\alpha = 0$) penalties. Optimal values of λ and α are determined through cross-validation.

3.2.5 Random Forest Regression

Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the average prediction for regression tasks. It reduces overfitting by combining the predictions of many de-correlated trees, each trained on a bootstrap sample of the data and a random subset of features. The model's prediction for a new input is given by:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^{T} h_t(x), \tag{6}$$

where T is the number of trees and $h_t(x)$ is the prediction of the t-th decision tree.

Random Forest handles non-linear relationships and feature interactions naturally. It is robust to overfitting due to averaging, tolerant to missing data, and resistant to noise and multicollinearity. However, it sacrifices some interpretability and may require careful tuning of hyperparameters such as the number of trees, maximum depth, and the minimum number of samples required to split a node.

3.2.6 Support Vector Machine (SVM) Regression

Support Vector Machine (SVM) for regression, also known as Support Vector Regression (SVR), is a machine learning method that finds a function to predict continuous values by maximizing the margin around the regression line while allowing some errors within a specified threshold, controlled by the parameter ε. It uses a kernel function (e.g., linear, polynomial, or radial basis function) to transform the data into a higher-dimensional space, capturing non-linear relationships, and the prediction for a new input is given by: The prediction for a new input in Support Vector Regression (SVR) is given by:

$$\hat{y} = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) K(x_i, x) + b, \tag{7}$$

where N is the number of support vectors, α_i, α_i^* are Lagrange multipliers, $K(x_i, x)$ is the kernel function, and b is the bias term.SVR is robust to outliers due to its margin-based approach, effective in high-dimensional spaces, and capable of modeling complex relationships, but it can be sensitive to the choice of kernel and hyperparameters like C (regularization) and ε, requiring careful tuning for optimal performance.

All models are estimated using the training subset (1989–2019), and forecasts are generated for the evaluation period (2020–2024). This structure allows for a comparative analysis of traditional time series and modern regularized regression approaches in forecasting inflation in Pakistan, to evaluate which model gives the closest and most accurate predictions.

4 Results

The main aim of this research was to forecast the inflation pattern in Pakistan, using a large macroeconomic dataset for 35 years (1989–2024). The dataset includes 14 well-selected predictor variables that cover a wide range of economic activities, namely imports, exports, broad money, interest rate, and total reserves. The dependent variable of the research was the rate of inflation for a year. Data utilized in the research were taken from the World Development Indicators (WDI) database [22] and provide the consistency and international comparability of the data. To ensure temporal consistency and to mimic real forecasting situations, the data was split into training data from the years 1989–2019 and testing data from the years 2020–2024. This was to avoid look-ahead bias and to allow for an actual out-of-sample evaluation. Moreover, preprocessing was carried out with extreme care prior to modeling. Particular care was taken in the integrity of the analysis. All Non-numeric placeholders were replaced with NA values. Following that, two-stage imputation was applied: initially with forward fill algorithm method (Last Observation Carried Forward) so as to keep the continuity of local temporal patterns intact [23], followed by mean imputation for the rest. Z-normalization was performed on the parameters estimated using the training set, avoiding hence data leakage as well as the feature comparability [24]. The unscaled as well as scaled dataset were preserved so that sensitivity of the model can be checked considering the effect of feature scaling.

4.1 Descriptive Statistics

The Exploratory data analysis performed pointed out variable distributions and relationships. A box and whisket plot provided above shows that (Figure 1) heteroskedasticity was detected. Furthermore, several significant outliers across several economic indicators were found. This suggests macroeconomic instability cases.

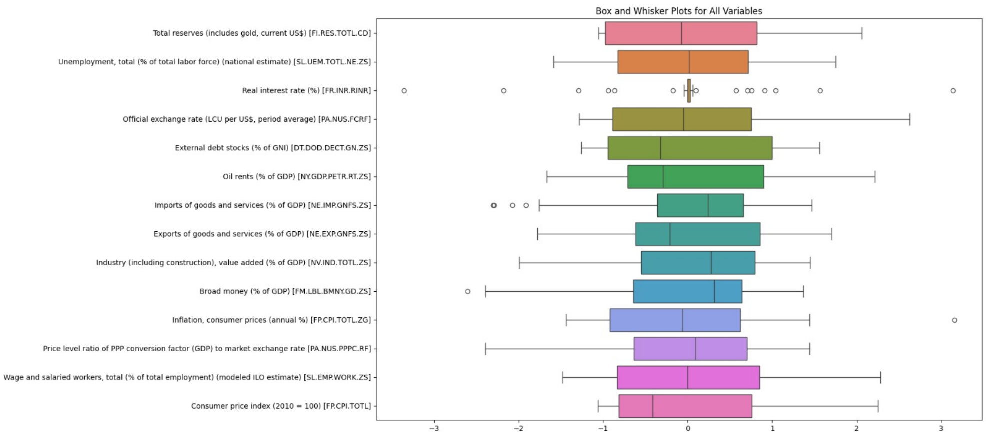

Fig. 1 Box and Whisker Plot

To analyze annual inflation rates in Pakistan from 1989-2024 a line graph is shown below in Figure 2.

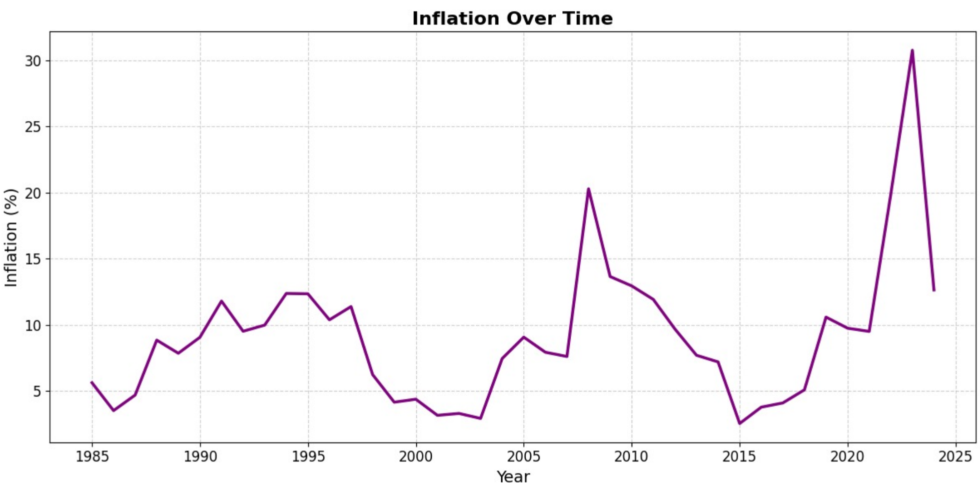

Fig. 2 Annual Inflation Rates over Time

This graph shows how inflation in Pakistan has gone up and down from 1985 to 2024. It stayed moderate for many years but spiked sharply around 2008 and again in 2023, reaching over 30

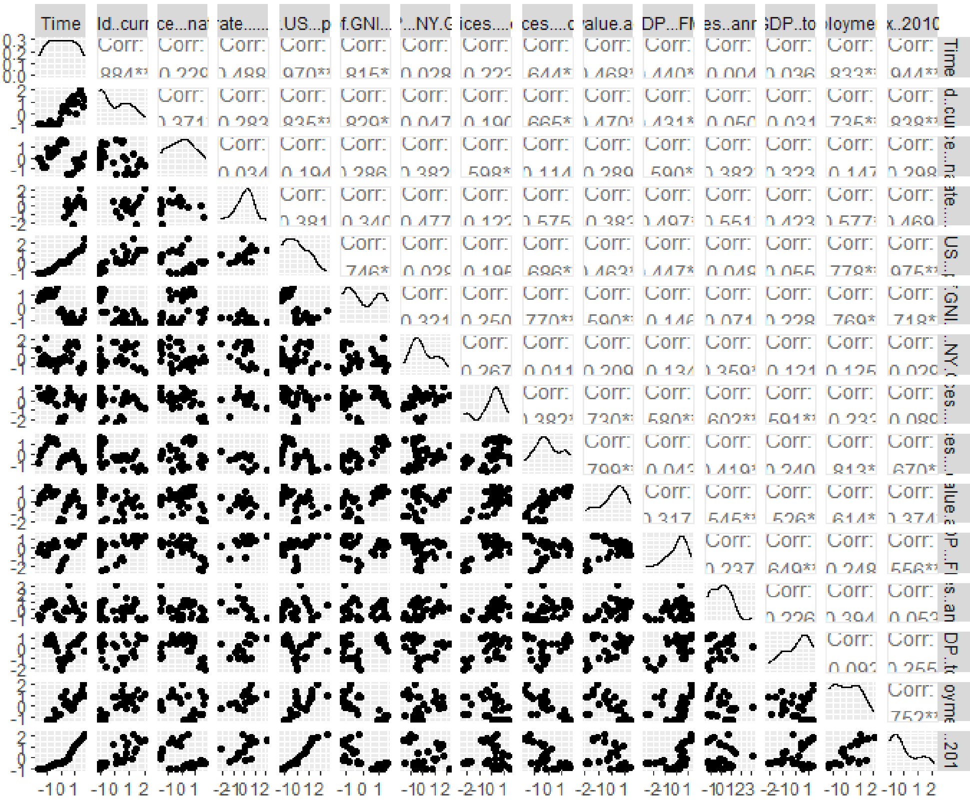

Fig. 3 Scatter Plot

Moreover, a corresponding scatterplot shown below (Figure 3) shows high linear correlations between some predictors, suggesting the potential for multicollinearity, a widely documented issue that can overstate standard errors and compromise coefficient estimates in linear regression models [25].

A heatmap was plotted to visualize the corelation between all variables.

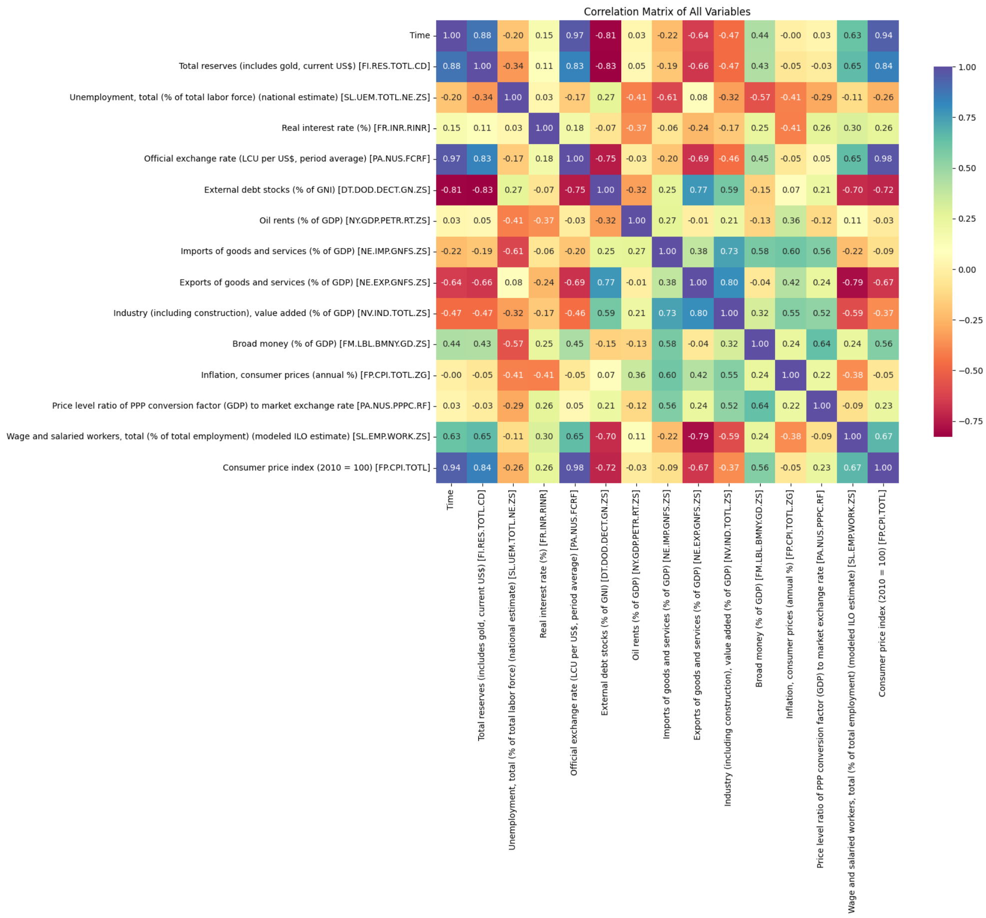

Fig. 4 Heatmap of All Variables

The correlation matrix highlights strong relationships between key economic indicators. Consumer Price Index (CPI) shows a high positive correlation with Time (r = 0.94), indicating a consistent rise in inflation over the years. Similarly, Total Reserves also increased steadily (r = 0.88 with Time).

A near-perfect correlation between Inflation (consumer prices) and CPI (r = 0.99) confirms CPI as a reliable inflation indicator. The Official Exchange Rate also strongly correlates with CPI (r = 0.98), suggesting exchange rate movements significantly affect price levels.

Negative correlations were observed between Exports and Inflation, and between Unemployment and Time, hinting at declining export performance and minor improvements in employment over time. Wage and salaried workers showed a moderate positive link with Time (r = 0.63) but a slight negative relation with inflation.

A historgram was also plotted for all the numerical columns of the data.

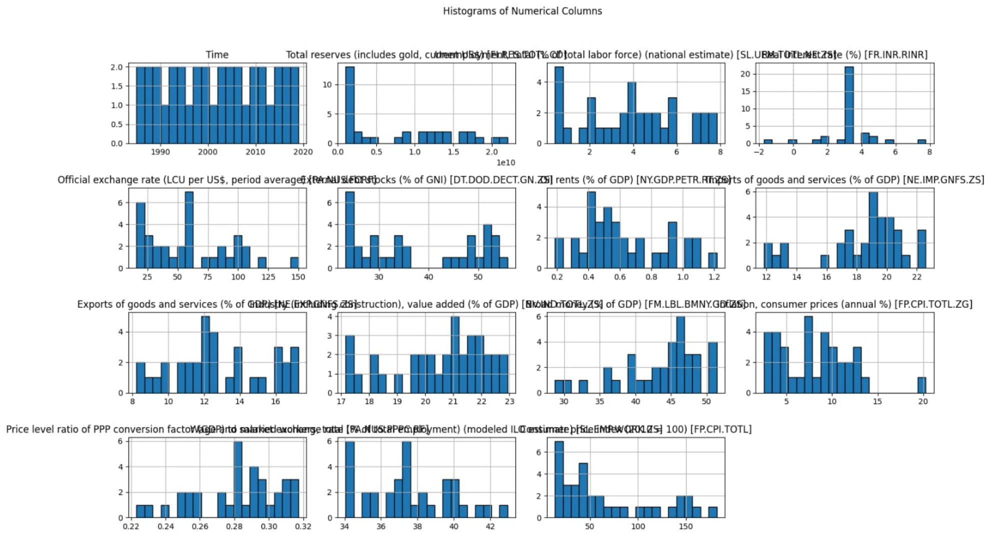

Fig. 5 Histogram for all columns

4.2 ARIMA Model Results

The baseline ARIMA (Auto Regressive Integrated Moving Average) model, primarily applied for forecasting univariate time series [26], was used to predict inflation. The ARIMA model was used as a reference to compare Machine Learning Models to. Before predictions differencing was performed to make the inflation data stationary. The Augmented Dickey-Fuller (ADF) test [27] confirmed stationarity after three rounds of differencing (p = 0.01). The differenced inflation data is shown in the Figure below.

Optimal ARIMA configuration was achieved by utilizing the auto.arima() function with the help of AIC minimizing techniques. Still the model, was inadequate in capturing the complex dynamics of inflation, and therefore, the model generated a trend that greatly underestimated the spectacular inflation spike of 2023. As can be seen in Figure 3 below, the ARIMA model predictions were always trailing the actual inflation that was realized in the economy, indicating the weakness of the model in capturing the external macroeconomic forces—a basic flaw of univariate models [28].

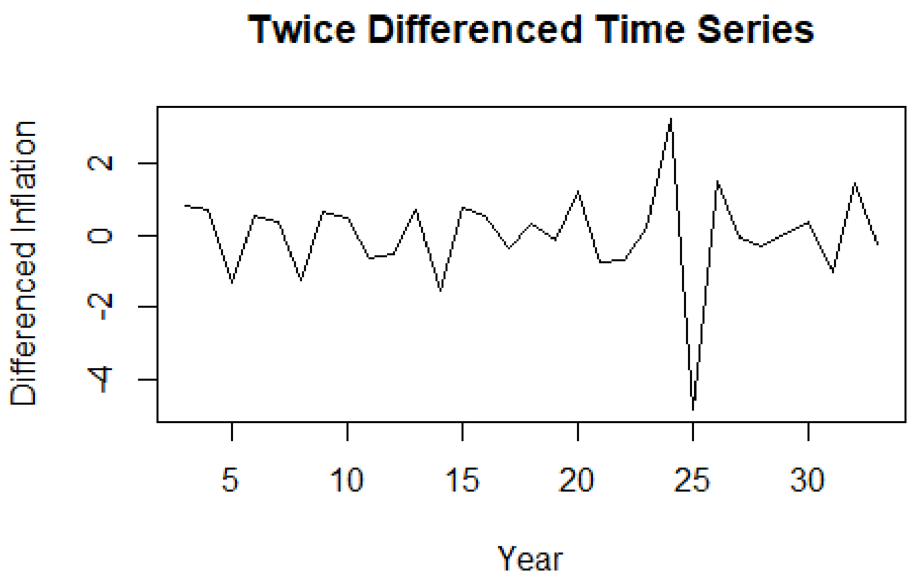

Fig. 6 Annual Inflation Rate After Differencing is applied

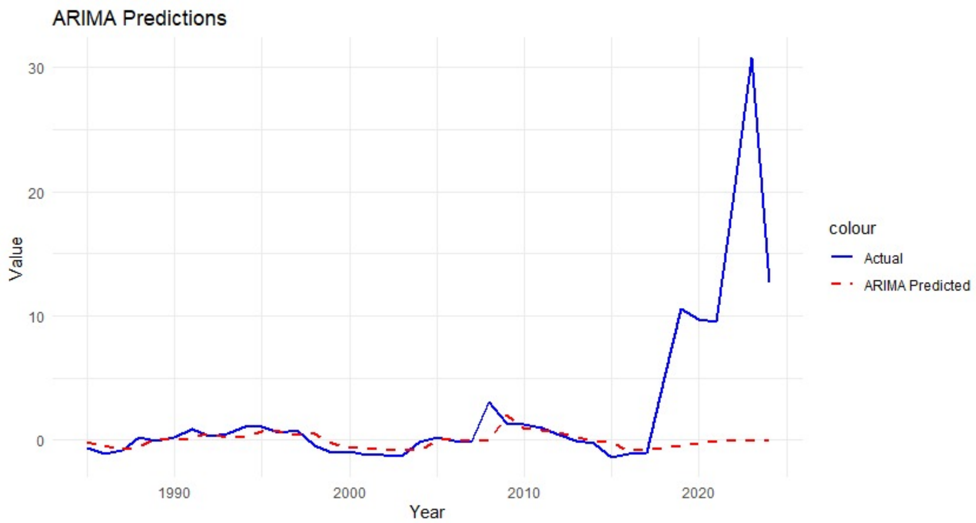

Fig. 7 ARIMA Model Predictions compared to Actual Inflation Rate from 1985 to 2024

4.3 Comparison of all models

Figure 7 below shows model predictions against real inflation rates. Lasso works best, followed by ElasticNet and Ridge. ARIMA, however, exhibited flat trajectories and weak correlation during crisis periods. This plot explains RMSE-based ordering and verifies the real-world limitation of ARIMA, especially in multivariate economic contexts. Table 2 below shows the exact predictions made by all models compared to the actual annual inflation rate.

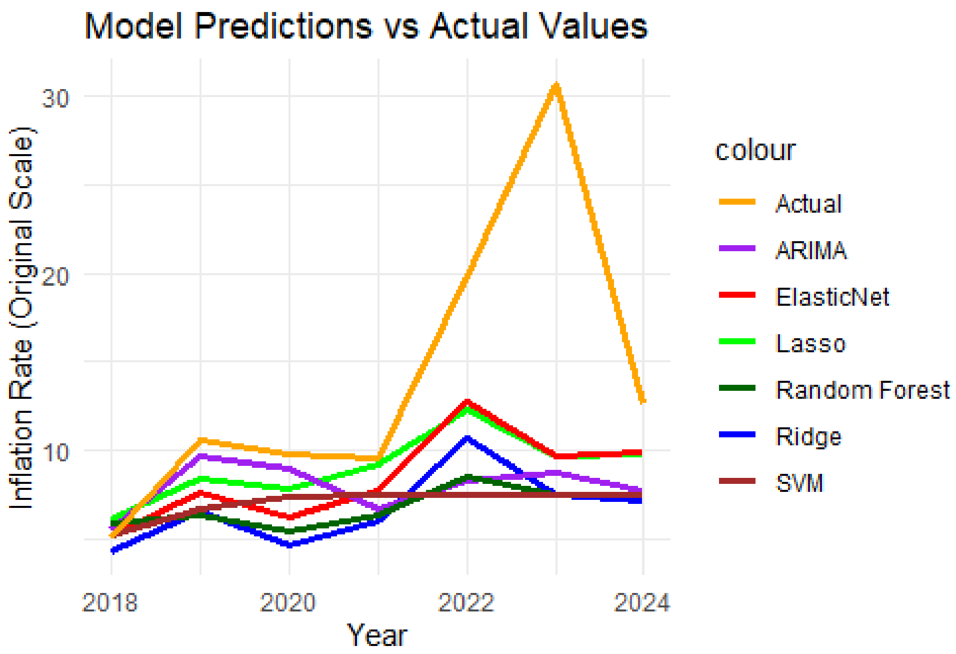

Fig. 8 All Model Predictions compared to Actual Inflation Rate from 2018 to 2024

All output from the models was generated in normalized form and inverse-transformed afterward to be more easy to interpret. It is noteworthy that the training set R^2 was very high overall (0.9986), which implies that the chosen predictors explained more than 99.8% of all variance in terms of inflation in the past. Such high R^2s are, however, deceptive when put into context of multicollinearity—a situation that is corroborated by inflated standard errors and the fact that some predictors were unable to remain statistically significant in a related multiple linear regression analysis [29].

Table 1 RMSE of Models

Ridge	Lasso	ElasticNet	ARIMA	Random Forest	SVM
2.469251	2.075649	2.197697	2.887993	2.59087	2.603218

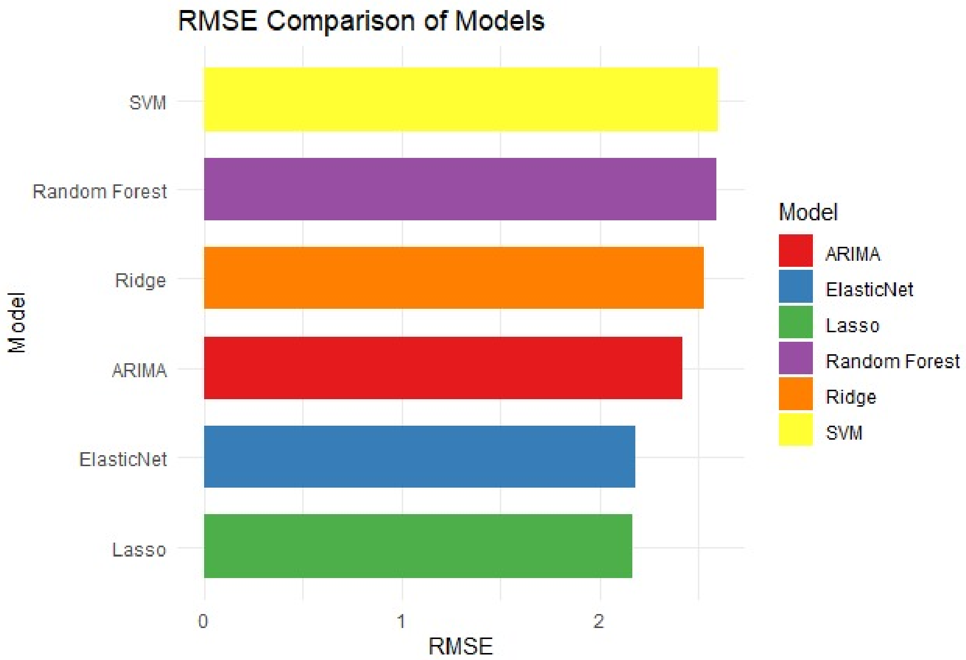

Fig. 9 RMSE Comparison of Models

By performance metrics, RMSE indicated a robust ordering: Lasso has the smallest RMSE then ElasticNet then Ridge and then finally ARIMA. Refer to table 1 above for the exact values The reason for this is most likely the enhanced performance of the Lasso model in separating driving forces of inflation from false signals. The inability of ARIMA to capture contemporaneous macroeconomic variables rendered it unable to respond to structural shocks, policy moves, or geopolitical events that defined the 2023 inflation surge. The findings indicate the substantial benefits of using multivariate machine learning techniques compared to standard univariate time series models for macroeconomic forecasting. In particular, regularized regression models and Lasso, in turn, showed higher prediction power, interpretability, and robustness in the presence of multicollinearity. The findings indicate the vital role of systematic preprocessing, model choice, and accounting for exogenous macroeconomic variables in successful inflation modeling for developing countries such as Pakistan.

Lastly,to evaluate the performance of our predictive models, we analyzed the absolute percentage error over the years 2018 to 2024, as shown in the "Absolute Error by Year" plot below. This visualization highlights how each model's accuracy varies over time, providing insights into their reliability for inflation forecasting.

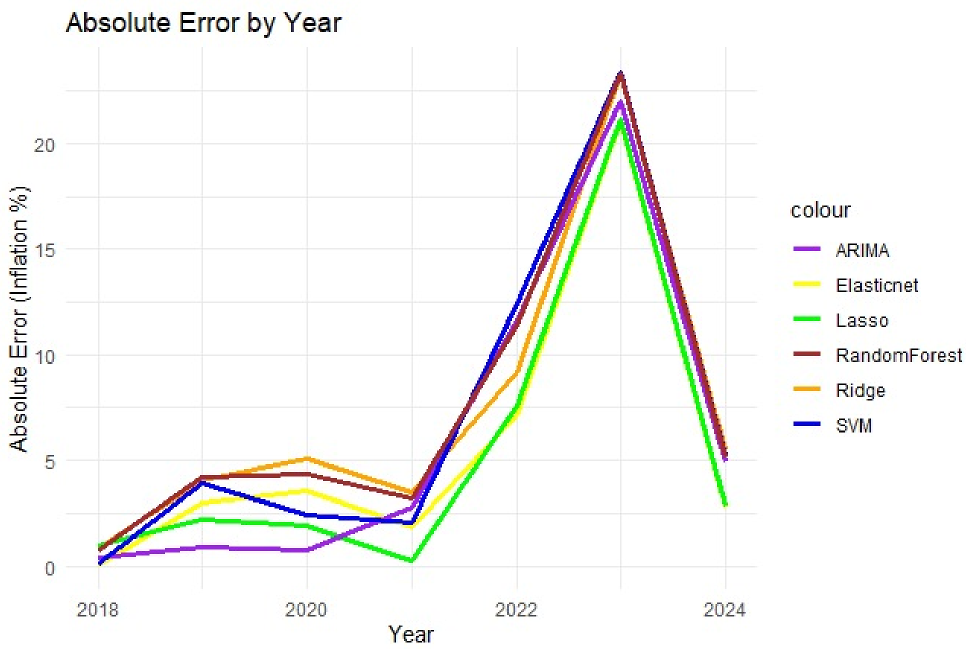

Fig. 10 Absolute Error by Year

The "Absolute Error by Year" plot illustrates the percentage error in inflation predictions across various models (ARIMA, Elasticnet, Lasso, RandomForest, Ridge, SVM) from 2018 to 2024, with each model represented by a distinct color. The ARIMA model (purple) exhibits the highest error, peaking sharply around 2022-2023 at over 20 percent, indicating significant predictive challenges during this period, while SVM (blue) and Lasso (green) maintain relatively lower and more stable errors. RandomForest (brown) and Ridge (orange) show moderate errors with a noticeable increase around 2022, suggesting these models struggle with recent data trends, whereas the overall trend indicates improving accuracy by 2024 across most models.

5 Discussion

The comparison of four different forecasting models, ARIMA, Ridge Regression, Lasso Regression, and ElasticNet, provided strong evidence for the superiority of regularized machine learning models over conventional univariate time series forecasting in the case of macroeconomic inflation forecasting. Out of the four models, Lasso Regression

Table 2 Model Predictions vs. Actual Inflation Rates (2020–2024)

Year	Ridge	Lasso	ElasticNet	Random Forest	SVM	ARIMA	Actual
2018	4.22	6.08	5.14	5.85	5.18	5.47	5.08
2019	6.53	8.36	7.57	6.34	6.66	9.65	10.58
2020	4.65	7.82	6.18	5.36	7.32	8.99	9.74
2021	6.02	9.20	7.66	6.31	7.42	6.71	9.50
2022	10.70	12.24	12.70	8.48	7.44	8.27	19.87
2023	7.49	9.63	9.68	7.50	7.42	8.78	30.77
2024	7.12	9.75	9.85	7.50	7.42	7.69	12.63

performed the best. Hence, it proved to be the most reliable model in our study. It was the most notable for its superior capability to realize inflation magnitude and directional volatility, particularly in high variance settings such as were experienced in the years after 2019, during and after the pandemic. The model has an inherent feature selection ability where penalties are paid by less informative predictors by adding an L1 regularization term. This most likely gave it a superior generalization ability and lower variance due to noise [10]. This fact was backed up by the model having the lowest Root Mean Square Error (RMSE). Most importantly, Lasso Regression model had the closest estimations of actual inflation values during the testing period.

ElasticNet, by leveraging the strengths of both Lasso and Ridge through the addition of a penalty function, worked exceedingly well. It illustrated a better ability to cope with bias-variance trade-offs, especially when faced with multicollinearity—a common situation with macroeconomic data where many predictors have large linear correlations [11]. Ridge Regression, though with increased stability and less sensitivity to overfitting due to its L2 regularization, failed to capture the inflation peak in 2023 adequately, illustrating its inability to respond to nonlinear or drastic economic changes. On the other hand, the ARIMA model, which was constructed using only historical inflation patterns, consistently exhibited worse performance on all metrics taken into account. The values were made stationary twice. Although effective differencing and parameter estimation were readily achieved using the auto.arima() function [30], the model exhibited a large lag in its reaction to inflationary shocks. Its forecasts were much more subdued and failed to capture the steep increase in inflation that occurred in Pakistan after the COVID-19 Pandemic. This poor performance shows the intrinsic limitations and unreliability of univariate time series models when capturing the complex macroeconomic phenomena. ARIMA performs better when values are completely stationary, but this is rarely the case in real world scenarios, especially in a dynamic economy like Pakistan where there are frequent policy shifts and external shocks governing the inflation rate [31].

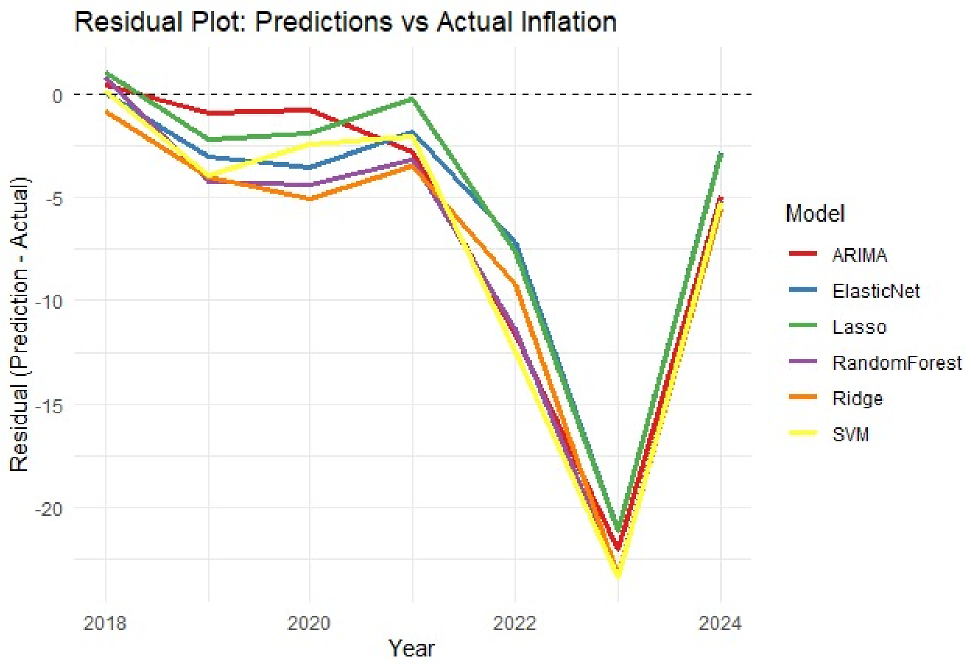

Fig. 11 Residual Plot for model predictions vs actual inflation

5.1 Limitations

Although the results of this study are strong and useful, there are some limitations to be noted. Firstly, the data set included only 35 yearly observations (1989–2024), which could be too few to safely train high-complexity models without risk of overfitting. Although cross-validation and regularization techniques were used to minimize the risk, the very high R-squared value, indicates a risk of overfitting, particularly in the context of multicollinearity of predictors.

Secondly, the data were averaged on an annual basis, constraining the short-run fluctuations and lagged effects between the variables. Monthly or quarterly data could increase temporal granularity. Hence, it could enable better predictions of inflation rates in Pakistan. Moreover, the models lacked higher-order polynomials, which are typical features of real macroeconomic systems [32]. The lack of these may have constrained the models from capturing more complex dynamics.

Third, while the choice of the 14 macroeconomic variables was taken with care in light of the literature and the availability of reliable data, key external variables such as geopolitical risk measures were excluded due to the lack of data availability. This omission has likely decreased the model sensitivity to external shocks that have been found to be affecting inflation in developing economies.

5.2 Implications for Policy and Implementation

The superior performance of the Lasso and ElasticNet classifiers has significant policy implications for the control of macroeconomic conditions and the design of policy. These results emphasize the importance of incorporating a broad set of macroeconomic variables in models designed to forecast inflation, in place of utilizing merely previous inflation levels. Machine learning algorithms, especially those that allow automatic feature selection and regularization, provide a realistic approach for financial institutions or banks to attempt to improve the accuracy of inflationary trend forecasting.

The ineffectiveness of ARIMA indicates that standard statistical techniques, though they had a monopoly in the past, can be less than ideal under circumstances of unstable economic conditions with extreme structural shifts and non-linear dynamics. Therefore, policymakers would do well to employ multivariate and data-driven techniques to gain a greater understanding of inflation dynamics and to inform monetary and fiscal policy decisions with greater foresight.

5.3 Future Research Directions

Future research projects may build upon this initial effort in several directions. One natural extension would involve the use of more granular data—e.g., inflation rates reported monthly or quarterly so that short-run dynamics may be identified and lag structures typical of macroeconomic models may be imposed. In addition, use of real-time or high-frequency data sources (e.g., news sentiment, commodity price volatility, or global economic indicators) may make the model more sensitive to sudden shocks. Investigation of alternative modeling methods, such as ensemble methods, gradient boosting machines (e.g., XGBoost), and deep learning structures (e.g., Long Short-Term Memory networks), may substantially improve predictive accuracy, especially as access to larger datasets becomes more practical. In addition, hybrid models that combine time series components with machine learning forecasting methods (e.g., ARIMA-LSTM or VAR-Ridge combinations) may provide an optimal balance between gains, maintaining both temporal and multivariate relationships. Finally, future research must also address the incorporation of structural break estimation methods (e.g., Bai-Perron tests[33]) with regime-switching models (e.g., Markov Switching Regression[34]) to capture better macroeconomic policy or economic regime shifts. Such improvements may make it possible to create models that are both more accurate and interpretable for policy evaluation purposes.

6 Conclusion

This research aimed to explain the subtle forces driving inflation in Pakistan with a data-driven, multimodel framework. It uncovered the strength of contemporary machine learning methods to reflect economic reality where conventional methods fail. Although ARIMA provided a conservative benchmark, it was Lasso Regression that shone, as it predicted the inflation spike after 2020 with the most clarity. The path through data cleaning, model tuning, and predictive analysis shed light on a deep reality that inflation is the beat of an economy, influenced by a complex interlinked variables. As Pakistan navigates increasingly uncertain fiscal and geopolitical landscapes, smarter forecasting methods such as these will be indispensable to chart the path toward stability and resilience.

Supplementary information.

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