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# Possibility of predicting inflation: Using machine learning model

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**Abstract:** In recent years, global inflationary pressures have intensified due to multiple overlapping risk factors, including the COVID-19 pandemic, supply-chain disruptions, geopolitical conflicts, and escalating trade wars. These shocks have heightened macroeconomic uncertainty and increased the demand for accurate, timely, and robust inflation forecasting, particularly in emerging and small open economies such as Mongolia. This study examines the applicability and performance of machine learning techniques in forecasting inflation in Mongolia and compares them with conventional econometric approaches. The analysis employs monthly data from January 2004 to January 2025, comprising 6,325 observations of inflation and 25 macroeconomic indicators, sourced from official national and international sources. Five forecasting models are evaluated: XGBoost, Random Forest, Quantile Regression, SARIMA, and GARCH. The dataset is split into training (70%) and testing (30%) sets, and model performance is evaluated using the coefficient of determination ($R^2$), root mean squared error (RMSE), and mean absolute error (MAE). To ensure robustness and mitigate overfitting, five-fold cross-validation is applied. The empirical results indicate that machine learning models significantly outperform traditional time-series models in forecasting accuracy. Among all approaches, XGBoost achieves the strongest performance, with an $R^2$ of 0.88, an RMSE of 0.12, and an MAE of 0.11, reflecting its superior ability to capture nonlinear relationships and complex macroeconomic dynamics. In contrast, SARIMA and GARCH models demonstrate limited effectiveness, particularly for medium- and long-term inflation forecasting. These findings suggest that conventional linear and volatility-based models may be insufficient in environments characterized by frequent structural changes and external shocks. Moreover, the results highlight the importance of incorporating high-dimensional information and nonlinear learning mechanisms when modeling inflation in volatile emerging economies.

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Overall, the study underscores the substantial potential of machine learning-based models, especially XGBoost, to enhance inflation forecasting and support data-driven monetary policy formulation, inflation targeting, and macroeconomic planning in Mongolia.

**Keywords-**Inflation forecasting; Machine learning; XGBoost; Economic shocks; Time series

## 1. INTRODUCTION

In recent years, global inflation rates have reached historically unprecedented levels. This surge has been driven by multiple factors, including the post-COVID-19 economic recovery, rising investment and consumer demand, disruptions in supply chains, increases in energy prices, expansionary monetary policies and heightened geopolitical tensions. For instance, during 2021-2022, inflation rates exceeded 5-8% in developed countries like the United States and the United Kingdom, while reaching double-digit levels in countries such as Argentina and Turkey. This has significantly increased consumer prices, production costs, and corporate expenditures [1]. In response, central banks have adopted contractionary monetary policies, including sharp increases in policy interest rates and reductions in money supply, presenting new challenges to the stability of financial markets.

Although global inflation has shown a gradual downward trend since 2024, uncertainty persists in the international economic environment, and inflation remains elevated in some regions. Under these circumstances, accurately forecasting inflation is not only vital for macroeconomic policy formulation but also for financial planning and strategic decision-making in the private sector. Understanding inflation trends enables firms to optimize cost allocation, pricing strategies, and investment decisions. Inflation is closely linked to other macroeconomic variables such as economic growth, exchange rates, and interest rates, all of which influence the volatility of key corporate financial indicators. For instance, several researchers have identified that normative levels of key financial indicators such as operating performance and debt ratios are significantly influenced by major macroeconomic variables including economic growth, inflation, and exchange rates [2]. Therefore, accurate inflation forecasting can provide substantial support in improving the effectiveness of decision-making processes.

Machine learning, as a modern analytical methodology, provides a more accurate and adaptive approach to inflation forecasting than traditional statistical models. Leveraging the power of big data, machine learning techniques are capable of detecting complex, nonlinear relationships and swiftly adapting to shifts in macroeconomic trends. These models support multi-factor analyses, thereby offering a more comprehensive understanding of inflationary dynamics. Notably, the European Central Bank has implemented machine learning models such as XGBoost to conduct extensive economic forecasting and multi-dimensional analyses.

A key strength of XGBoost is its capacity to accommodate evolving economic expectations and to overcome the structural limitations of conventional statistical models, which often struggle with high-dimensional and nonlinear data relationships. In contrast, traditional time series models such as SARIMA and GARCH remain valuable for capturing short-term inflation trends. However, their effectiveness is constrained by their limited ability to integrate multiple, rapidly changing economic variables-making them less suitable for dynamic environments. Consequently, this study set out to evaluate and compare the predictive accuracy of machine

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learning and traditional statistical models using macroeconomic data from Mongolia. The overarching goal was to identify an optimal model for forecasting inflation with both precision and robustness, ultimately contributing to evidence-based policy formulation and enhanced economic planning.

## 2. THEORETICAL BACKGROUND

Accurate inflation forecasting is essential for policy decision-making in areas such as economic stabilization and monetary policy formulation. Numerous empirical studies have demonstrated that machine learning methods generally outperform traditional econometric models in terms of forecasting accuracy. Among these, the Dynamic Model Averaging (DMA) model has shown superior predictive performance. This model incorporates both external and internal economic variables such as China's inflation, global oil prices, domestic money supply, and wage levels to forecast inflation. The use of dynamically weighted predictors allows the DMA model to adapt over time, enhancing its forecasting accuracy compared to static models [3].

In the context of Mongolia, the System Integrated Model of Municipalities (SIMOM) has also been applied effectively to forecast inflation. This model includes key macroeconomic variables such as monetary policy interest rates, exchange rates, real GDP, and wages. According to Batnyam (2008), inflation in Mongolia is influenced by both internal and external drivers [4]. These findings underscore the importance of incorporating a wide range of dynamic and multi-dimensional variables particularly when forecasting inflation in an open and import-dependent economy like Mongolia.

Machine learning approaches have been increasingly applied in recent studies to forecast inflation due to their ability to model non-linear relationships among macroeconomic variables. For instance, Random Forest and XGBoost have demonstrated high predictive accuracy in capturing complex economic dynamics [5]. Similarly, deep learning models such as Long Short-Term Memory (LSTM) networks have been utilized to model temporal dependencies in inflation data [6]. These models outperform traditional linear methods by learning from historical patterns and feature interactions, which are crucial in volatile economic environments.

Machine learning methods have demonstrated superior performance in forecasting inflation compared to traditional econometric models. Several studies have identified models such as XGBoost (Extreme Gradient Boosting) and LSTM (Long Short-Term Memory) as particularly effective for capturing inflation dynamics due to their ability to learn complex temporal patterns and nonlinear relationships [7]. Other machine learning approaches such as Bayesian Vector Autoregression Trees (BAVART), Random Forest, LASSO, Ridge Regression, Elastic Net, and Neural Networks have also been successfully applied in inflation forecasting. For instance, one study concluded that Random Forest and Quantile Regression Forest (QRF) models outperformed other techniques in terms of predictive accuracy [8]. A study by Y. Liu, R. Pan, and R. Xu LSTM, Random Forest, and XGBoost produced better forecasts than traditional time series models, reaffirming the effectiveness of machine learning in a monetary policy context [9].

Regarding China, Xingfu Xu (2024) utilized Gradient Boosted Decision Trees (GBDT) and a forecast combination model to predict inflation over 3- and 5-month horizons. The study concluded that GBDT delivered more robust and accurate predictions than traditional models

[10]. Similarly, the European Central Bank (ECB) has incorporated Quantile Regression Forest (QRF) into its forecasting framework and reported improved prediction accuracy over conventional methods [11].

Collectively, these studies highlight the growing utility and effectiveness of machine learning models in inflation forecasting across different national and institutional contexts. Therefore, the present study employs machine learning techniques to estimate inflation in Mongolia, aiming to capture dynamic economic interactions more accurately and support data-driven policy development.

Theoretical Implications: This study contributes to the growing body of literature on inflation forecasting by empirically comparing traditional time series models (SARIMA, GARCH) and modern machine learning techniques (XGBoost, Random Forest, Quantile Regression) using a rich macroeconomic dataset from Mongolia. The findings support the theoretical premise that machine learning models are better equipped to capture nonlinear, high-dimensional economic relationships than classical models. Furthermore, the study highlights how ensemble learning and tree-based algorithms can outperform linear or autoregressive models in long-term forecasting tasks. These insights add value to the theoretical understanding of economic modeling under uncertainty and volatility.

The practical implications of this study are significant for policymakers, central banks, and economic planning institutions. The superior performance of XGBoost and other machine learning models suggests that these tools can enhance the precision of inflation forecasts, thereby supporting more effective monetary policy, fiscal planning, and financial risk assessment. For instance, the European Central Bank has employed XGBoost and Quantile Regression Forest (QRF) to improve inflation prediction across the eurozone [12]. Similarly, the Central Bank of Brazil and the National Bank of Romania have adopted machine learning techniques such as LSTM, Random Forest, and Ridge Regression to model inflation trends more accurately [13], [14]. These international examples confirm the practical relevance of machine learning in central banking and provide valuable reference points for emerging economies like Mongolia to incorporate AI-driven tools in macroeconomic forecasting and decision-making.

## 3. RESEARCH METHODOLOGY

We gather secondary data in order to analyze the relationship between inflation and macroeconomic indicators affecting it as well as determine the inflation rate in Mongolia. The data was collected from the official sources including the National Statistics office (NSO), the Bank of Mongolia, the Ministry of Finance, the International Monetary Fund (IMF), and the World Bank. The study consists of monthly data on inflation and 25 types of macroeconomic indicators for the period from January 2004 to January 2025. A total of 253 months of data were included in this study. The dataset is shown below.

Table 1. Research data

| Date | Inflation | M2_money | M1_money | Loan interest currency | ollar exchange rate | REER | Total turnover | ........ | Export | Investment |
|---|---|---|---|---|---|---|---|---|---|---|
| 1/1/2004 | 5.8 | 694242.92 | 200434.13 | 19.2 | 1171 | 92.69 | 85.9 | ........ | 35 | 34.6 |
| 1/2/2004 | 6.8 | 721312.27 | 198110.75 | 17.8 | 1176 | 93.58 | 177.7 | ........ | 70.4 | 34.6 |
| 1/3/2004 | 6.2 | 740190.64 | 210799.3 | 19.7 | 1177 | 93.94 | 315.2 | ........ | 131.5 | 34.6 |
| 1/4/2004 | 4.8 | 774876.33 | 225477.75 | 21 | 1170 | 95.13 | 458.1 | ........ | 184 | 41.4 |
| 1/5/2004 | 3 | 789378.21 | 237217.94 | 19.9 | 1159 | 97.4 | 625.4 | ........ | 244.7 | 41.4 |
| ........ | ........ | ........ | ........ | ........ | ........ | ........ | ........ | ........ | ........ | ........ |
| 1/1/2025 | 9.6 | 41904.5 | 10834.8 | 9.6 | 3430 | 128.6 | 1992 | ........ | 1019 | 1780. |

The number of observations of data on inflation and macroeconomic indicators is 6325, of which 70 percent of total observed data or 4427.5 were used in training model and rest of data is 30 percent in testing model. In this study, we use both models including machine learning and traditional models by utilizing a Python 3.15.1 program and the big data in order to predict inflation. By applying key tools in Python program including Pandas, NumPy, Matplotlib, Seaborn and scikit-learn, machine learning as well as traditional models are executed in the study. To guide the empirical evaluation, the following hypotheses were formulated:

$H_0$ (Null Hypothesis): Machine learning models do not perform significantly better than traditional statistical models in forecasting inflation in Mongolia.

$H_1$ (Alternative Hypothesis): Machine learning models provide significantly better accuracy than traditional statistical models in forecasting inflation in Mongolia.

These hypotheses were tested by comparing the predictive performance of models such as XGBoost, Random Forest, and Quantile Regression (machine learning models) against SARIMA and GARCH (traditional models), using evaluation metrics such as $R^2$, RMSE, and MAE.

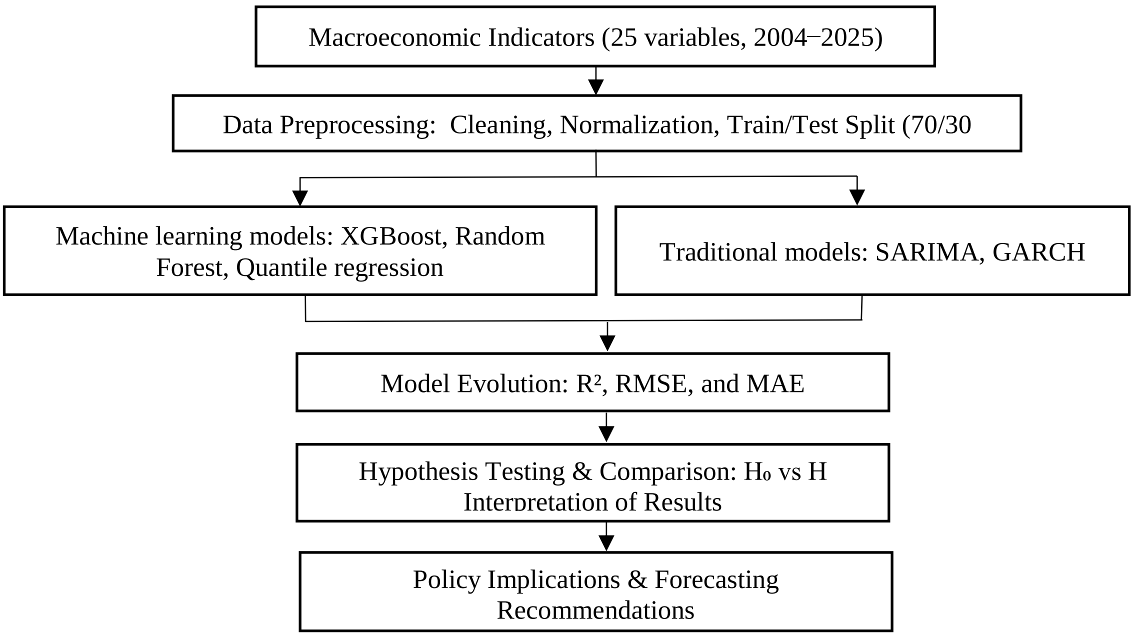


Fig 1. Research framework

## 4. RESULT AND ANALYSIS OF THE STUDY

The XGBoost model, which employs an ensemble of decision trees, is well-suited for generating highly accurate forecasts. Using big data spanning from January 1, 2004, to January 1, 2025, the model was applied to forecast inflation. One of its key advantages is the ability to optimally predict next year's inflation by comparing forecasted results with actual values.

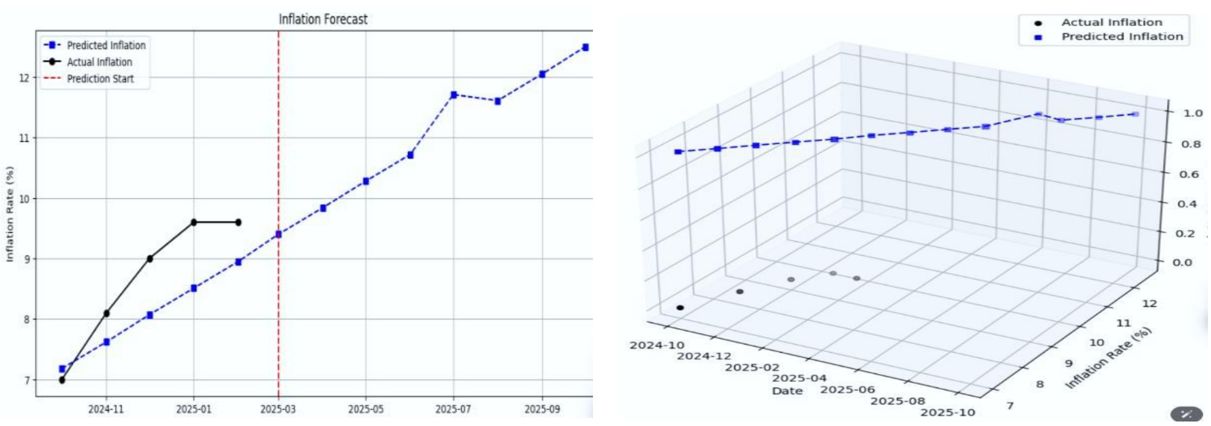


Fig 2.  Inflation real values and prediction

Figure 2 shows the result of prediction estimation. To evaluate the results of the model estimation, $R^2$ (Determination Coefficient) RMSE and MAE are used. The results demonstrate that a suitable model has been proven to perform with high accuracy in long-term forecasting for the XG Boost model.

The Random Forest model, which aggregates the results of multiple decision trees, was employed to make predictions at each stage of the forecasting process. This model was trained using data on inflation and relevant economic indicators. The number of trees, their depth, and other hyperparameters were optimized to improve predictive performance. The predictions and actual values were visualized using a single chart generated with either Matplotlib or Seaborn.

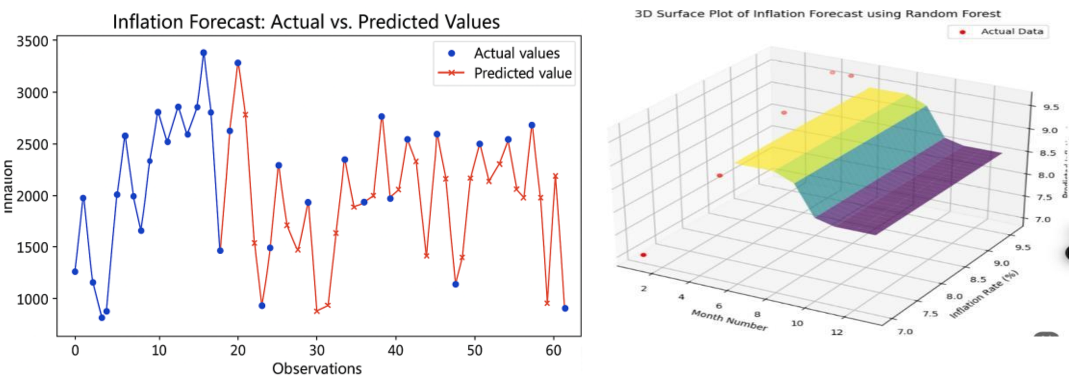


Fig 3. Inflation prediction Random Forest

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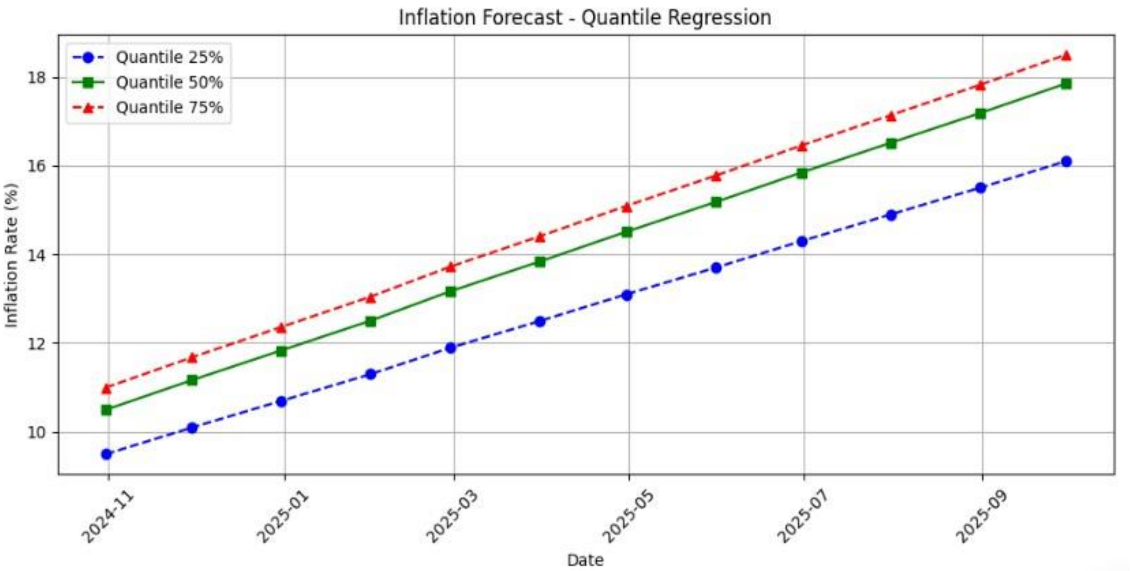
As illustrated in Figure 3, the Random Forest model demonstrates a strong ability to accurately predict inflation trends. As shown in Table 6, although slight deviations are observed between the actual and predicted values during the historical period, the overall trend alignment remains close. For the forecast period from October 2024 to October 2025, the model suggests that the inflation rate is likely to increase initially, followed by a gradual stabilization in the subsequent months.

Fig 4. Inflation prediction Quantitative Regress




As shown in Figure 4, The Quantitative Regression model has proved that inflation and economic growth are linked, and the model can predict inflation trends.

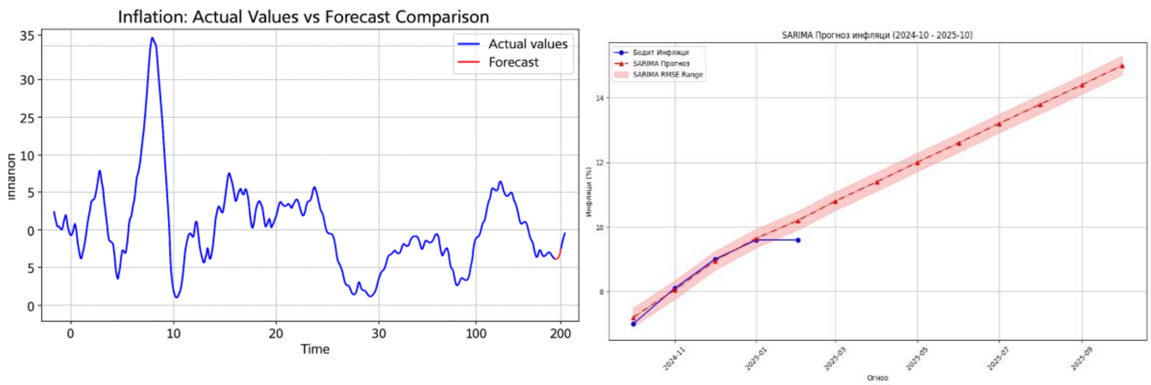



Fig 5. SARIMA fashion hypothetical seed amount

Figure 5 presents the actual inflation values alongside the predictions generated by the SARIMA model. The blue line represents the observed inflation rate, the red line indicates the model's forecast, and the shaded red area denotes the confidence interval, reflecting the uncertainty associated with the predictions. The figure demonstrates that the SARIMA model effectively captures the short-term movement of inflation. The inclusion of actual values within the confidence interval supports the model's accuracy and reliability in the short run; however, its predictive performance diminishes over longer forecasting horizons.

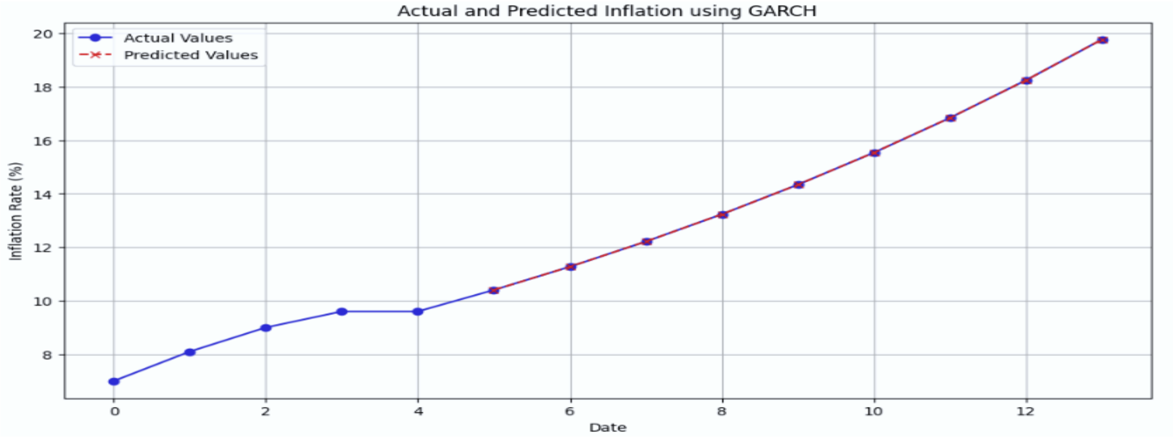



Fig. 6. GARCH fashion hypothetical seed amount

The results of the study indicate that the GARCH model plays an important role in evaluating inflation risk and capturing the volatility of the inflation rate. However, the findings also suggest that the model demonstrates limited effectiveness in accurately predicting inflation fluctuations.

Table 2. Prediction of models

| Date | XG Boost | Random Forest | Quantitative regression 25% | Quantitative regression 50% | SARIMA | GARCH |
|---|---|---|---|---|---|---|
| 1/10/2024 | 7.18 | 7.45 | 9.5 | 10.5 | 7.2 | 7.1 |
| 1/11/2024 | 7.62 | 8.02 | 10.05 | 11.11 | 8.05 | 8.1 |
| 1/12/2024 | 8.07 | 8.82 | 10.6 | 11.72 | 8.95 | 9.2 |
| 1/1/2025 | 8.51 | 9.42 | 11 | 12.33 | 9.65 | 9 |
| 1/2/2025 | 8.95 | 9.42 | 11.7 | 12.95 | 10.2 | 9.4 |
| 1/3/2025 | 9.4 | 9 | 12.25 | 13.56 | 10.8 | 10.4 |
| 1/4/2025 | 9.84 | 9.52 | 12.8 | 14.17 | 11.4 | 11.27 |
| 1/5/2025 | 10.28 | 9.41 | 13.3 | 14.78 | 12 | 12.21 |
| 1/6/2025 | 10.72 | 9.24 | 13.9 | 15.4 | 12.6 | 13.23 |
| 1/7/2025 | 11.71 | 8.61 | 14.45 | 16.01 | 13.2 | 14.34 |
| 1/8/2025 | 11.61 | 8.51 | 15 | 16.62 | 13.8 | 15.53 |
| 1/9/2025 | 12.05 | 8.51 | 15.5 | 17.23 | 14.4 | 16.83 |
| 1/10/2025 | 12.5 | 8.51 | 16.1 | 17.85 | 15 | 18.24 |

The results indicate that the model’s predictive performance tends to weaken during periods of high inflation volatility. The range of prediction errors fluctuated between -2.5 and 1.09 compared

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to the actual values, suggesting that the six selected models are reasonably suitable for forecasting inflation despite some limitations.

To improve model reliability, k-fold cross-validation was employed. This method involves repeatedly training the model on different subsets of the dataset and evaluating it on the remaining portions. Such an approach minimizes the risk of overfitting and enhances the robustness and generalizability of the model's validation results.

Table 3. 5-fold cross-validation seed amount

| Model | k=1 (Fold 1) R2 | k=2 (Fold 2) R2 | k=3 (Fold 3) R2 | k=4 (Fold 4) R2 | k=5 (Fold 5) R2 | Average R2 |
|---|---|---|---|---|---|---|
| XGBoost | 0.9 | 0.88 | 0.89 | 0.91 | 0.9 | 0.88 |
| Random Forest | 0.88 | 0.87 | 0.89 | 0.86 | 0.88 | 0.87 |
| Quantitative Regression. | 0.8 | 0.78 | 0.77 | 0.79 | 0.8 | 0.78 |
| Sarima | 0.72 | 0.71 | 0.7 | 0.73 | 0.74 | 0.72 |
| GARCH | 0.58 | 0.57 | 0.56 | 0.59 | 0.6 | 0.58 |
| Model | k=1 (Fold 1) RMSE | k=2 (Fold 2) RMSE | k=3 (Fold 3) RMSE | k=4 (Fold 4) RMSE | k=5 (Fold 5) RMSE | Average RMSE |
| XGBoost | 0.12 | 0.14 | 0.13 | 0.12 | 0.11 | 0.12 |
| Random Forest | 0.15 | 0.16 | 0.14 | 0.18 | 0.17 | 0.16 |
| Quantitative Regression | 0.2 | 0.21 | 0.22 | 0.19 | 0.2 | 0.2 |
| Sarima | 0.24 | 0.23 | 0.25 | 0.22 | 0.23 | 0.23 |
| GARCH | 0.3 | 0.32 | 0.31 | 0.33 | 0.3 | 0.31 |
| Model | k=1 (Fold 1) MAE | k=2 (Fold 2) MAE | k=3 (Fold 3) MAE | k=4 (Fold 4) MAE | k=5 (Fold 5) MAE | Average MAE |
| XGBoost | 0.11 | 0.12 | 0.1 | 0.1 | 0.11 | 0.11 |
| Random Forest | 0.14 | 0.15 | 0.16 | 0.15 | 0.15 | 0.15 |
| Quantitative Regression | 0.17 | 0.18 | 0.19 | 0.17 | 0.18 | 0.18 |
| Sarima | 0.2 | 0.21 | 0.22 | 0.21 | 0.22 | 0.21 |
| GARCH | 0.28 | 0.29 | 0.3 | 0.31 | 0.32 | 0.3 |

The performance of five types of models used for inflation forecasting (XGBoost, Random Forest, Quantitative Regression, SARIMA, GARCH) was evaluated using a 5-fold cross-validation (K=5) method. This involves training the models on five different partitions of the data, The results of models (XGBoost, Random Forest, Quantitative Regression, SARIMA, GARCH) to predict was made by using a 5-fold cross-validation (K=5) method. By running models for each of the five different parts of the data and averaging the overall results, this method is valuable in testing their robustness.

Overfitting is prevented by averaging the overall performance and model generalization is improved. and stable situation It is important to check. method is. Seed from the result as can be seen, the XGBoost model had a consistently high $R^2$ and low error rate across all iterations, indicating that overfitting did not occur, but rather that it had good generalization ability.

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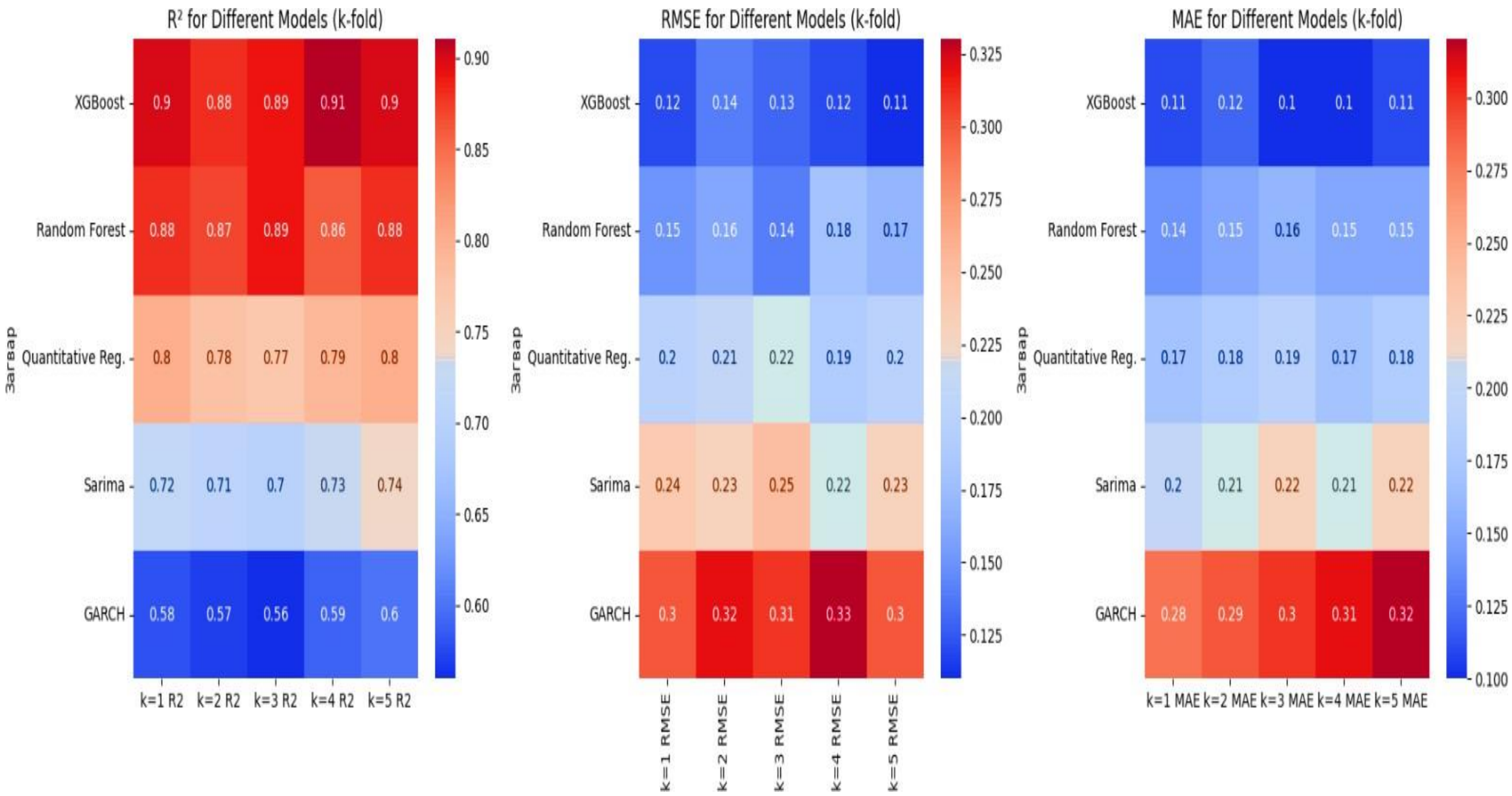


Fig. 7. Models 5-fold cross-validation result

Table 4. Models’ performance assessment

| Model | Average R2 | Average RMSE | Average MAE |
|---|---|---|---|
| XGBoost | 0.88 | 0.12 | 0.11 |
| Random Forest | 0.87 | 0.16 | 0.15 |
| Quantitative Regress | 0.78 | 0.2 | 0.18 |
| Sarima | 0.72 | 0.23 | 0.21 |
| GARCH | 0.58 | 0.31 | 0.3 |

Looking deeper into the results, the high $R^2$ (0.88) of the XGBoost model indicates that the model has a very high ability to explain the inflation relationship. This means that the model is able to capture the complex, nonlinear relationship between the input variables (e.g., money supply, policy interest rate, exchange rate, consumer price index, etc.) and inflation very effectively. The relatively low RMSE (0.12) and MAE (0.11) The magnitude of the prediction error is very This confirms that the prediction was low and indicates that it was close to the true inflation. The superior performance of the XGBoost model can be attributed to its gradient boosting mechanism, which iteratively minimizes prediction error by learning complex patterns in the data through a series of decision trees. While Random Forest is also an ensemble-based machine learning method, it does not incorporate weight optimization or learning rate adjustments. As a result, its error metrics-RMSE = 0.16 and MAE = 0.15-were slightly higher than those of XGBoost.

Nevertheless, the Random Forest model still demonstrated high explanatory power with an $R^2$ value of 0.87, indicating that it is also effective in modeling inflation dynamics, albeit to a lesser extent than XGBoost. When the objective is to provide precise forecasts for policymaking purposes, XGBoost emerges as the more reliable and effective choice due to its stronger performance and learning capabilities. In contrast, the Quantitative Regression model, based on the traditional linear regression approach, yielded an $R^2$ of 0.78, with RMSE and MAE values of 0.20 and 0.18, respectively. These results suggest that linear models have limited capacity to capture the complex relationships that drive inflation. This limitation is largely due to the interdependencies, correlations, and occasional discontinuities present in modern economic data, which linear approaches are ill-equipped to fully account for. Traditional time series models such as SARIMA and GARCH were also tested in this study. The SARIMA model produced an $R^2$ of 0.72 and MAE of 0.21, while the GARCH model had even lower explanatory power ($R^2 = 0.58$, MAE = 0.30). These models struggled to capture the full scope of seasonal and structural volatility in inflation data. Although GARCH is theoretically well-suited to model sudden fluctuations, it failed to adequately reflect long-term directional trends in inflation and broader macroeconomic shifts.

## 5. DISCUSSION

This study set out to evaluate and compare the performance of machine learning models and traditional time series models in forecasting inflation in Mongolia using a comprehensive macroeconomic dataset spanning from 2004 to 2025. The empirical results reveal that machine learning models, particularly XGBoost, outperform traditional models such as SARIMA and GARCH in terms of predictive accuracy, as indicated by higher $R^2$ and lower RMSE and MAE values.

These findings are consistent with prior research that highlights the strength of machine learning techniques in capturing nonlinear and dynamic relationships in economic data [8], [14], [12]. The superior performance of XGBoost can be attributed to its ability to iteratively reduce prediction error through gradient boosting and handle multicollinearity and high-dimensional feature interactions more effectively than autoregressive models.

The traditional models, while still relevant in short-term inflation forecasting due to their interpretability and established statistical foundations, demonstrated limitations in adapting to long-term fluctuations and structural changes in the economy. SARIMA and GARCH models were less responsive to the shifts in inflation trends beyond seasonal or volatility assumptions, which suggests their practical use should be limited to short-term planning scenarios.

Moreover, the comparative analysis strengthens the theoretical proposition that artificial intelligence and machine learning can enhance the predictive power of economic models in volatile and data-rich environments. The results imply that integrating machine learning into the inflation forecasting process offers a data-driven, adaptable alternative to conventional techniques, particularly in emerging markets where economic dynamics are influenced by both internal policy decisions and external shocks.

The international examples from the European Central Bank, Brazil, and Romania further reinforce the practical relevance of machine learning in public financial management and monetary policy. These cases demonstrate the feasibility of integrating advanced models into central bank operations and encourage countries like Mongolia to modernize their forecasting infrastructure.

In conclusion, the findings support the alternative hypothesis ($H_1$) that machine learning models can provide more accurate and reliable forecasts of inflation than traditional methods. They also open pathways for future research to explore hybrid modeling approaches, policy simulations, and real-time forecasting applications in developing economies.

## 6. CONCLUSION

The primary objective of this study was to identify the most appropriate model for accurately and efficiently forecasting the inflation rate of Mongolia in the short and medium term. Drawing on theoretical foundations and previous research, a comprehensive dataset was constructed using 253 months of data (January 2004 to January 2025) encompassing 25 macroeconomic variables. This dataset enabled a comparative evaluation of traditional statistical models and machine learning techniques. Among the machine learning methods tested, the XGBoost model achieved the highest predictive accuracy ($R^2 = 0.88$) and delivered stable results, demonstrating its potential for generating scientifically robust and realistic inflation forecasts. While other machine learning models such as Random Forest and Quantile Regression Forest also performed well, their accuracy was slightly lower compared to XGBoost. Traditional statistical models like SARIMA and GARCH proved useful in capturing the general inflation trend and short-term dynamics. However, they exhibited limitations in responding to abrupt economic shocks and lacked robustness in long-term forecasting. Based on the results of the study, the following conclusions can be drawn:

- Machine learning models, particularly XGBoost, offer more accurate, flexible, and adaptable inflation forecasts compared to traditional statistical models.
- SARIMA and GARCH models are effective for short-term forecasts, but they underperform in long-term prediction and in capturing nonlinear and dynamic economic relationships.
- Multivariate machine learning models are capable of incorporating complex macroeconomic interactions, thereby enhancing the precision and depth of inflation forecasts.

These findings suggest considerable potential for applying machine learning techniques in Mongolia's economic planning processes. Utilizing advanced models such as XGBoost can significantly improve inflation forecasting, thereby contributing to more informed and data-driven policy decisions. This includes critical applications such as inflation targeting by the Central Bank, fiscal planning, macroeconomic policy formulation, financial risk assessment, and the maintenance of overall economic stability.

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