# An Innovative Approach to Short term Inflation Forecasting in Rwanda

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**Abstract**

There is broad consensus that accurate *forecasting of inflation is critical for effective economic planning and* policy formulation. This study seeks to enhance the short-term forecasting capabilities of the National Bank of Rwanda (NBR) by applying a range of machine learning models to predict key components of the inflation index: Core, Food, and Energy inflation. The study assessed several machine learning algorithms, including Decision Tree, Random Forest, Gradient Boosting, K-Nearest Neighbors (KNN), Support Vector Regression (SVR), Elastic Net, and XGBoost. A comparative analysis revealed that Elastic Net regression consistently outperformed the other models in forecasting inflation components. Furthermore, when compared with the existing Near Term Forecasting (NTF) system used by NBR for short-term forecasts, Elastic Net regression showed superior performance. Based on these findings, the study recommends that the National Bank of Rwanda adopt a hybrid model to significantly enhance the accuracy of short-term inflation projections. The study recommends to the National Bank of Rwanda to explore these advanced modeling techniques to improve the Bank's economic projections and decision-making processes

**Keywords:** Machine learning, Inflation, Forecasting, Rwanda.

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# 1 Introduction

The primary goal of central banks is the maintenance of price stability. Central banks usually base their monetary policy decisions on the short- to medium-term inflation projections rather than its observed values because of the operation lag, also known as the effect lag, of monetary measures. Thus, monetary authorities' ability to forecast inflation accurately is essential to implementing effective and efficient policy actions Narmandakh (2022).

For a long time, econometric models have served as the foundation of inflation forecasting. These models typically depend on economic theory and historical data to identify relationships between various economic variables and inflation. Some of the most widely used traditional econometric models for inflation forecasting include Phillips curve models, based on the idea that unemployment and inflation are inversely related Phillips (1958); Autoregressive Integrated Moving Average (ARIMA) Models, which capture the autocorrelation in inflation data Box & Jenkins (1976); Vector Autoregression (VAR) Models, which allow for the simultaneous analysis of multiple economic variables (Sims, 1980a); and Dynamic Stochastic General Equilibrium (DSGE) Models, which incorporate microeconomic foundations and rational expectations Smets & Wouters (2007a).

In Rwanda, the National Bank of Rwanda (NBR) uses traditional econometric models in inflation forecasting. For example, it uses short term models such as multivariate NTF system models for its near-term forecasts, while Bayesian Vector Auto Regressive (BVAR) and Quarter Projection Models (QPM) are used to forecast medium-term inflation Mwenese & Kwizera (2018).
Although splitting up forecast horizons explicitly is difficult, it is logically obvious that predicting inflation for one quarter (near term) and for eight quarters (medium term) are two distinct tasks. Although, using the concept of money's neutrality may be adequate to anticipate inflation in the long term, it is particularly challenging for the short term Romer (2012).

Inflation forecasting using macroeconomic variables faces two main challenges: the large number of potential predictors and the limited length of available time series data. This situation causes the "curse of dimensionality," as described by Stock & Watson (2012). The complexity of inflation dynamics, affected by various macroeconomic factors, creates significant difficulties in building accurate forecasting models. These limitations can result in an "overfitting problem," where the model becomes too closely tailored to the particular patterns in the training data as opposed to identifying general patterns. While such models may perform well with the training data, they often produce inaccurate forecasts when applied to new, out-of-sample data. For that reason, multivariate models, despite their theoretical appeal, often underperform simpler univariate models in practice Hyndman & Athanasopoulos (2021).

One method to deal with the overfitting issue is to pre-select explanatory variables based on economic theory, such as focusing on measures of real economic activity. However, this method has its own drawbacks. Variables' predictive potential might fluctuate with time and according to the forecast horizon. Variables that are good predictors in the short term may perform poorly for longer forecast horizons, and vice versa. Additionally, the risk of overfitting to a particular data sample remains, even with theoretically grounded variable selection. This problem of overfitting has been a long-standing focus in the computer science discipline of machine learning (ML), which has developed various techniques to tackle this problem Baybuza (2018).

Therefore, this study aims to Examine how machine learning techniques can be used for forecasting short term inflation rates in Rwanda. By leveraging advanced ML techniques such as Gradient boosting, extreme gradient boosting, K nearest neighbour, Decision tree, random forests, and support vector machines, the study seeks to develop a stronger and more precise forecasting model tailored to Rwanda's economic context. This innovative approach not only has the potential to enhance the precision of inflation projections but also to provide policymakers with a more nuanced understanding of the factors driving inflationary pressures in the country.

The study's specific objectives were:

- To evaluate the performance of several machine learning models in forecasting short term inflation in Rwanda.
- To determine the best machine learning model in predicting short term inflation in Rwanda.
- To compare the Machine leaning models with traditional model (Near term forecasts system )in pre-

dicting short term inflation in Rwanda.

The study's significance is in its potential to contribute to the fast-growing body of literature in finding the right inflation forecasting techniques in the context of Rwanda which could lead to a more effective monetary policy formulation.

Given the curse of dimensionality and the subsequent overfitting problem discussed previously, traditional models used by the National Bank of Rwanda may lack the flexibility to capture the complexities of inflation dynamics in a rapidly evolving economy like Rwanda's, potentially leading to forecast errors and suboptimal policy responses. This research aims to assess how well machine learning models perform as potential "satellite" models, designed to complement the existing classical models and improve forecast accuracy. By introducing and rigorously testing machine learning techniques, we aim to determine whether these models offer enhanced precision and reliability, thereby supporting the National Bank of Rwanda in achieving more accurate and actionable inflation forecast.

The rest of the paper is structured as follows: In Section 2, the focus is on a review of the relevant literature, with the current state of research in the field highlighted. Section 3 focuses on the methodology employed in the study, such as details about the data collection process, data pre-processing and the analytical techniques utilized. In Section 4, we present the results of the study, highlighting key findings and implications as well as providing insights and interpretations. Finally, Section 5 concludes the paper with a summary of findings and policy recommendations.

## 2 Related Literature

This section discusses the theoretical underpinnings of machine learning models commonly used in forecasting. This includes a detailed exploration of regression models, neural networks, support vector machines, ensemble methods, and hybrid models.

By synthesizing these empirical and theoretical perspectives, this literature review aims to offer a holistic view of the landscape of forecasting with machine learning. It identifies the key trends, highlight the gaps in current research, and propose directions for future studies to enhance the accuracy and reliability of forecasts in various fields.

## 2.1 Theoretical review

Inflation forecasting has been a critical area of research in economics and finance for decades. The ability to accurately predict future inflation rates is crucial for central banks, policymakers, and financial institutions to make informed decisions. Traditionally, econometric models have been the cornerstone of inflation forecasting. These models are grounded in economic theory and typically rely on historical data to make predictions about future inflation rates.

One of the most widely used econometric models for inflation forecasting is the Phillips Curve. Developed by William Phillips in 1958, this model asserts that unemployment rates and inflation are inversely related.

The basic premise of the Phillips Curve is that as unemployment decreases, inflation tends to increase, and vice versa Mitchell (1999). Over the years, various economists have proposed modifications and extensions to the Phillips Curve. Phelps (1967) and M. Friedman (1968) introduced the concept of inflation expectations, emphasizing the role of adaptive and rational expectations in determining inflation dynamics. In the 1970s, supply-side economists highlighted the impact of supply shocks, such as oil price increases, which resulted in the development of the New Keynesian Phillips Curve that incorporates forward-looking expectations and real rigidities.

More recently, researchers have noted a flattening of the Phillips Curve, suggesting that the relationship between unemployment and inflation has weakened in many advanced economies. This phenomenon is attributed to factors such as globalization, central banks' improved credibility in anchoring inflation expectations, and changes in labor market dynamics Blanchard (2016). Nonlinear versions of the Phillips Curve have also emerged, accounting for asymmetric behavior under different economic conditions, where inflation is less responsive during periods of high unemployment but more sensitive when labor markets are tight Del Negro et al. (2020). Furthermore, additional variables such as global supply chains, technological advancements, and demographic trends have been integrated to better capture the complexities of inflation dynamics in the modern economy Bianchi & Melosi (2017)and Borio & Filardo (2007). These developments reflect the ongoing evolution of the Phillips Curve as economists adapt it to contemporary challenges.

Time series models represent another traditional approach to inflation forecasting . Methods such as Autoregressive Integrated Moving Average (ARIMA) models, developed by Box and Jenkins in the 1970s, have been widely used to predict inflation by analyzing historical data trends and patterns . These models assume that past behavior and trends in data can be used to predict future values, making them valuable tools for policymakers and economists.

In the 1980s, Christopher Sims introduced the Vector Autoregression (VAR) model, which revolutionized the way economists analyze dynamic relationships among several time series variables Sims (1980) . VAR models allow for the examination of how economic variables interact with each other over time, providing a flexible and data-driven method for forecasting and policy analysis without the need for substantial theoretical presumptions about the underlying data-generating process.

Dynamic Stochastic General Equilibrium (DSGE) models represent a more recent and sophisticated approach to macroeconomic modeling and forecasting. DSGE models incorporate micro-economic foundations and explicitly account for the stochastic nature of economic shocks and the dynamic interactions between economic agents. These models have been widely used by central banks and policymakers for forecasting and policy analysis due to their theoretical rigor and ability to incorporate various structural features of the economy, , while seminal work by Smets and Wouters demonstrated the efficacy of DSGE models in forecasting macroeconomic variables, including inflation, by estimating a DSGE model for the euro area and showing its superior predictive performance compared to traditional models Smets & Wouters (2007b).

These models have been widely used by central banks and financial institutions globally Stock & Watson (2012). However, their limitations in capturing non-linear relationships and handling large datasets have become increasingly apparent, especially in the context of developing economies with volatile economic conditions Mandalinci (2017).

In recent years, the advent of machine learning has transformed inflation forecasting. Techniques such as neural networks, support vector machines, and ensemble methods utilize vast amounts of data and sophisticated algorithms to detect relationships and patterns that conventional models may overlook. These advanced methods excel in managing non-linear relationships and high-dimensional data, delivering more precise and reliable forecasts. A recent study by Zhang et al. (2018) highlights the effectiveness of neural networks in outperforming traditional linear models for forecasting financial time series, showing improved accuracy in capturing complex dynamics.

Support Vector Machines (SVM) are another effective machine learning technique. They function by determining the best hyperplane in a high-dimensional space to divide various data types, making them useful for both classification and regression tasks. SVMs can handle non-linear data using kernel functions, allowing them to capture complex inflation dynamics effectively C.-K. Huang et al. (2005).

## 2.2 Empirical review

Empirical studies on inflation forecasting have explored the effectiveness of various methodologies across different economic contexts and time periods. Traditional econometric models such as the Phillips Curve and ARIMA have been extensively tested and benchmarked against newer machine learning techniques, providing insights into their comparative performance.

In a study by Stock & Watson (2007), the authors evaluated the forecasting accuracy of different models, including VAR, DSGE, and traditional time series models, across several macroeconomic variables, including inflation in the United States. Their research highlighted the strengths of structural models in capturing long-term relationships and policy implications but also noted the challenges in accurately modeling economic shocks and structural changes .

Machine learning methods, particularly ensemble techniques like Random Forests and Gradient Boosting Machines (GBM), have shown promising results in enhancing inflation forecasting accuracy. Li & Sheng (2020) investigated the application of random forests for forecasting inflation in the United States over the period 1995-2018. Their study compared the performance of random forests with traditional ARIMA models. They found that random forests significantly outperformed ARIMA models in terms of forecast accuracy, particularly during periods of economic instability. The model's capacity to manage high-dimensional data and nonlinear relationships was a key advantage, making it more efficient in conveying the complexities of inflation dynamics.

Another study by Liu (2019) focused on using Support Vector Machines (SVMs) to forecast inflation rates in China from 2000 to 2015. The authors compared the performance of SVMs with that of traditional econometric models like the Phillips Curve. Their findings revealed that SVMs showed superior performance, especially in capturing complex, nonlinear patterns in the data. The study highlighted SVM's robustness in high-dimensional feature spaces, making it a powerful tool for inflation forecasting.

McNelis (2021) applied Long Short-Term Memory (LSTM) networks to forecast inflation in several European countries over the period 1990-2020. The study compared the results of LSTM networks with traditional VAR models. McNelis found that LSTM networks outperformed VAR models, particularly in terms of long-term forecasts. The ability of LSTMs to capture temporal dependencies and complex sequential patterns was crucial in improving forecast accuracy, demonstrating the potential of deep learning approaches in economic forecasting.

Chen & Guestrin (2016) implemented XGBoost, a popular Gradient Boosting Machine (GBM), to predict inflation rates in various G20 countries from 2000 to 2016. Their study demonstrated that XGBoost provided high accuracy and robustness compared to traditional models. The incremental learning approach of GBM allowed the model to correct previous errors, enhancing overall prediction performance. This highlights the effectiveness of boosting techniques in handling complex forecasting tasks.

W. Huang et al. (2020) explored hybrid models that combine ML techniques with traditional econometric methods for forecasting inflation in Japan over the period 2005-2019. Their research indicated that hybrid models provided a balanced approach, leveraging the strengths of both ML and traditional methods. The results showed improved accuracy and interpretability, making the forecasts more reliable for policymakers. This study emphasizes the potential of integrating machine learning with traditional approaches to enhance forecast reliability and usability.

Chakraborty & Joseph (2017) provide a thorough summary of several ML algorithms and their applications in economics and finance. Their study highlights the potential of ML methods to handle complex, non-linear relationships and large datasets, making them especially appropriate for economic forecasting tasks.

In their study, Malhotra & Maloo (2017) focused on the period from 2001 to 2015 to analyze food inflation in India using gradient boosted regression trees (BRT). They considered various predictor factors, finding that minimum support prices (MSP) and farm wages had the most significant impact, while international food prices were less relevant for explaining domestic food price variations.

In developing countries, Alaru (2023) using a period from 2000 to 2020 for his analysis explored the application of machine learning algorithms to analyze factors affecting inflation rates in Ghana. He used Random Forest regression and support vector regression models and found that Random Forest was the best model for predicting Ghana's inflation rates.

While ML applications in economic forecasting are growing globally, research specific to Rwanda remains limited. Hakizimana (2022) applied machine learning techniques of Random forest, Ridge Regression, LASSO Regression and K Nearest Neighbor (KNN) in inflation forecasting and did a comparison between these techniques and the traditional forecasting models. He found that Random forest model had the smallest mean squared error (MSE) and works best in forecasting inflation followed by standard models ARMA model and VAR model.

Rutayisire (2015) provides a comprehensive analysis of inflation dynamics in Rwanda using traditional econometric methods, highlighting the need for more advanced techniques to capture the complex factors influencing inflation in the country.

To conclude Musekera (2024) forecasted fresh food inflation in Rwanda using six different Machine learning models and Auto regressive moving average model(ARMA), he found that decision tree and gradient boosting models outperform other models in predicting food inflation in Rwanda .

Despite the growing body of research on inflation forecasting, there remains a significant gap in the application of advanced machine learning techniques within the context of Rwanda's economy. Traditional models, such as ARIMA and VAR, have been extensively used, but their limitations in capturing complex, non-linear patterns in inflation data are well-documented. Current literature primarily focuses on developed economies, where data availability and economic structures differ significantly from those in Rwanda. Consequently, there is limited empirical studies that leverage machine learning models tailored to the unique economic environment of Rwanda. Hakizimana (2022) forecasted the overall Consumer Price Index (CPI) in his study, while this research focuses on forecasting the headline components ( Core, Food, and Energy inflation) . These specific components provide deeper insights into inflation dynamics and may offer more granular information essential for a thorough analysis of inflation trends. This distinction highlights a significant gap in the literature, underscoring the importance of innovative approaches that incorporate machine learning techniques. By improving the accuracy and reliability of inflation forecasts, such methods can offer more robust and actionable tools for policymakers and economic stakeholders in Rwanda. Such advancements are crucial for fostering informed decision-making and shaping effective economic policies.

# 3 Data and Methodology

This section highlights, the data preprocessing and model used to forecast inflation components

## 3.1 Data preprocessing

### 3.1.1 Used data and selection of variables

The study uses secondary data obtained from the National Bank of Rwanda whereas Python programming language was used as a tool to predict in sample inflation for Rwanda, on monthly data spanning 2012 February to 2024 June. The quarterly indices were leveraged from monthly forecasts before computation of year on year and quarter on quarter changes. To predict Core inflation, the study has employed its one lag, exchange rate, and Real Composite Index of Economic Activity (CIEA). For food inflation, its one lag, exchange rate of Rwandan francs against US dollar, international food prices and CIEA were employed. Lastly, the exchange rate, international oil prices and its own lag were used to predict energy inflation.

### 3.1.2 The Models Used

In this study, numerous machine learning models were used to predict indices for monthly data for Core , food , and energy , before being weighted to compute the headline inflation. Each model brings distinct advantages for time series forecasting, which are briefly described below.

1. **Decision Tree Regressor**

The Decision Tree Regressor (DTR) is a non-linear model that creates a tree-like structure by dividing the data into subsets according to feature values. Every leaf node in the training data reflects a predicted value derived from the majority outcome.This model has been used due to its several advantages in forecasting such as handling non-linear relationships between features and target variables as well as interpret-ability as it provides a visual representation of decision paths Quinlan (1993).

**2. Random Forest Regressor**

The Random Forest Regressor (RFR) is a technique for ensemble learning that builds several decision trees during training and outputs the average forecast of each one.This helps in improving predictive accuracy and controlling overfitting Breiman (2001). It has many advantages including the reduction of overfitting compared to individual decision trees. It also handles large datasets and high-dimensional data well.
The prediction for a Random Forest model is given by this equation :

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

where $T$ is the number of trees, and $f_t(x)$ is the prediction from the $t$-th tree.

**3. Gradient Boosting Regressor**

Gradient Boosting Regressor (GBR) constructs models sequentially, where each new model aims to correct the errors of the previous models. This boosting method helps in reducing bias and variance. It provides many advantages including being effective for large datasets with complex patterns as well as achievement of higher accuracy compared to other methods J. H. Friedman (2001). The prediction for Gradient Boosting is given by the following equation:

$$\hat{y} = \sum_{m=1}^{M} \lambda_m h_m(x) \tag{2}$$

where $M$ is the number of boosting rounds, $\lambda_m$ is the weight of the $m$-th model, and $h_m(x)$ is the prediction of the $m$-th model.

**4. K-Nearest Neighbors Regressor**

The K-Nearest Neighbors Regressor (KNN) forecasts the desired value by calculating the mean of the values of its $k$ closest neighbors in the feature space, and provides a simple and intuitive model and adaption on complex and non-linear relationships Cover & Hart (1967).

Its equation is formulated as :

$$\hat{y} = \frac{1}{k}\sum_{i=1}^{k} y_i \tag{3}$$

where $k$ is the number of neighbors, and $y_i$ are the target values of the nearest neighbors.

**5. Support Vector Regressor**

The Support Vector Regressor (SVR) seeks to identify a function that differs from the actual target values by at most a specified margin and is as flat as possible. It is effective in high-dimensional spaces Vapnik & Cortes (1995). It is also robust to overfitting, especially in high-dimensional space.
The SVR model is defined as:

$$\hat{y} = \sum_{i=1}^{N} \alpha_i K(x_i, x) + b \tag{4}$$

where $\alpha_i$ are the Lagrange multipliers, $K(x_i, x)$ is the kernel function, and $b$ is the bias term.

**6. Elastic Net Regression**

Elastic Net Regression combines the penalties of Lasso (L1) and Ridge (L2) regression, which helps in feature selection and regularization. It handles multi-collinearity and selects a subset of features Zou & Hastie (2005) and provides a balance between Lasso and Ridge penalties. The Elastic Net objective function is:

$$\text{Loss} = \frac{1}{2}\|y - X\beta\|_2^2 + \alpha\left(\frac{1-\rho}{2}\|\beta\|_2^2 + \rho\|\beta\|_1\right) \tag{5}$$

L1 regularization encourages sparsity by adding a penalty based on the absolute value of coefficients, effectively reducing less relevant features to zero and simplifying the model. L2 regularization, on the other hand, adds a penalty based on the squared value of coefficients, helping to prevent multicollinearity and reducing the impact of less significant predictors. Elastic Net balances these techniques with a key parameter $\alpha$ where $\alpha = 1$ results in a purely Lasso model and alpha $= 0$ results in a purely Ridge model, providing flexibility to handle different types of data and model complexity

**7. XGBoost Regressor**

XGBoost (Extreme Gradient Boosting) is an optimized gradient boosting algorithm that is efficient and scalable. It enhances performance by handling missing values, regularizing, and parallelizing the computation. It is a high predictive performance with effective handling of various data types Chen & Guestrin (2016) The prediction for XGBoost is given by:

$$\hat{y} = \sum_{k=1}^{K} \lambda_k \cdot f_k(x) \tag{6}$$

where $K$ is the number of trees, $\lambda_k$ are the leaf scores, and $f_k(x)$ is the prediction from the $k$-th tree.

Each model's choice is motivated by its ability in managing different types of data patterns and relationships, ensuring robust and accurate forecasting of inflation components.

**8. Hybrid model**

The hybrid approach combines the Elastic Net Regression model with the NTF multivariate system currently used by the National Bank of Rwanda. The NTF multivariate system is specifically designed to project inflation components by analyzing their interactions and historical trends. In this hybrid framework, the Elastic Net model enhances the forecasting process by leveraging its predictive power and flexibility, while the NTF system ensures the consistency and structure of multivariate projections. By integrating these two methods, the study aimed to capitalize on their respective strengths, producing more accurate and robust forecasts for short-term inflation dynamics across core, food, and energy components.

## 3.2 Evaluation Metrics

To assess the performance of the machine learning models used for inflation forecasting, numerous metrics for evaluation were used. These metrics offer a thorough understanding of these models' accuracy and reliability.

**3. Mean Absolute Error (MAE)**

MAE calculates the average size of a series of predictions' errors without taking into account their direction. It is the mean of the absolute differences between the actual observation and the forecast over the test sample, with each individual difference being given equal weight.

It is calculated as :

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{7}$$

where $y_i$ is the actual value and $\hat{y}_i$ is the predicted value.

**2. Root Mean Squared Error (RMSE)**

RMSE is a widely used metric that assesses the average magnitude of the errors between predicted and actual values. It gives a relatively high weight to large errors, making it beneficial for evaluating models in which significant errors are especially undesirable. It is calculated as :

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{8}$$

where $y_i$ is the actual value and $\hat{y}_i$ is the predicted value.

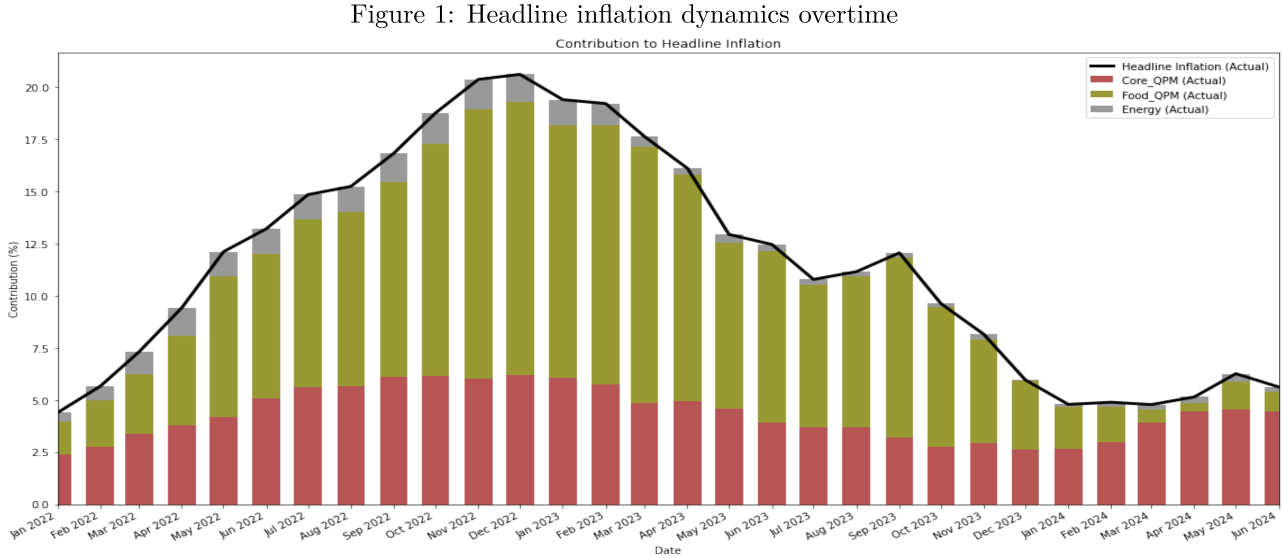
# 4 Discussion of Findings

## 4.1 Developments in Headline Inflation

To analyze the dynamics of inflation, three main components were considered: Core, Food, and Energy inflation. These components help policymakers to understand fluctuations within headline inflation. As indicated in figure 1, inflation in Rwanda has been marked by volatility, sometimes exceeding the National Bank of Rwanda's (NBR) target range of 2-8 percent and external shocks and weather-related challenges have significantly influenced these deviations.

Core inflation, which constitutes 61 percent of the overall headline inflation, consists of non-volatile components such as clothing and footwear, housing, furnishings, health, transport, communication, recreation and culture, education, restaurants and hotels, as well as miscellaneous goods and services. Food inflation, comprising food and all beverages, accounts for 32 percent of the overall headline inflation, while energy inflation , which has a weight of 6.7 percent, includes solid and liquid fuels, water, electricity, and gas.

Figure 1: Headline inflation dynamics overtime

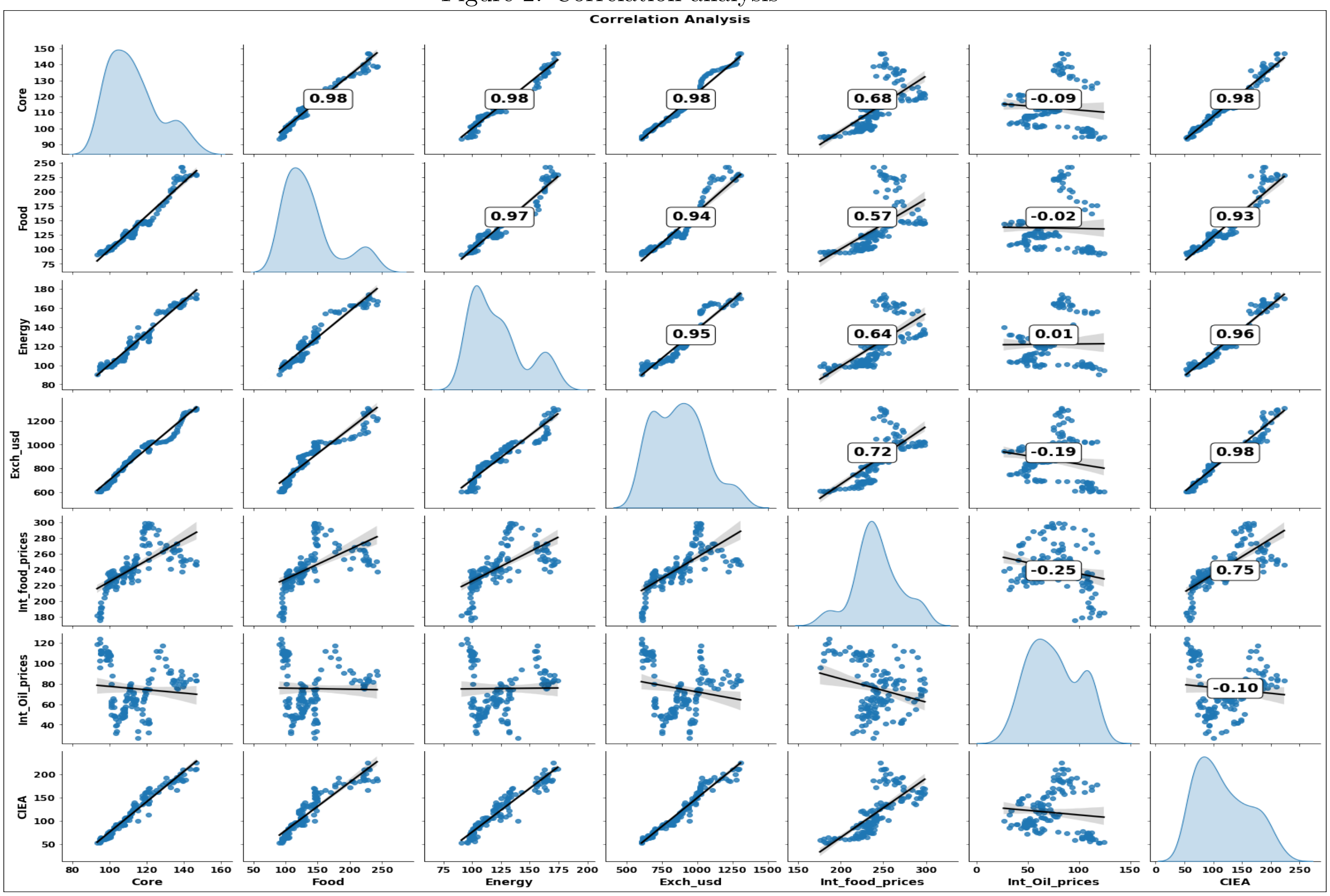



Source: Authors' computation

#### 4.1.1 Correlation Analysis

The correlation analysis reveals a very strong positive relationship between the variables under consideration. As per figure 2 , the correlation coefficients for all pairs of variables are strong , except for international oil prices. The existence of strong correlation can indicate the significance of each variable in influencing the targeted variables .

Figure 2: Correlation analysis




Source: Authors' computation

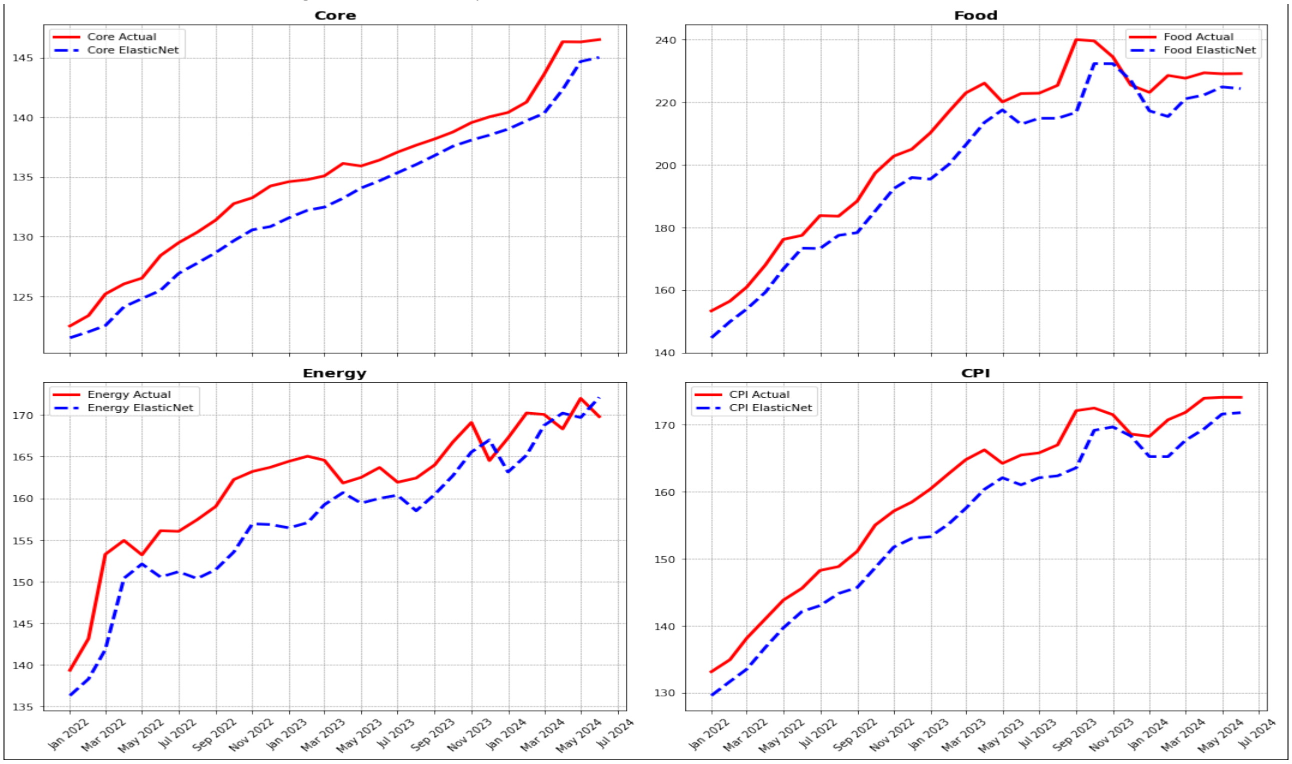
## 4.2 Forecasting Inflation Components

This subsection focuses on forecasting year-on-year core, food and energy inflation using different Machine learning models.

### 4.2.1 Monthly Consumer price Index Forecasting

The forecasts was conducted by means of seven machine learning models namely : Decision Tree Regressor Random Forest Regressor, Gradient Boosting Regressor, The K-Nearest Neighbors Regressor , Support Vector Regressor, Elastic Net Regression, and Extreme Gradient Boosting. As per figure 3, over the forecasted period, the Elastic Net regression model demonstrates a close alignment between its inflation forecasts and actual outcomes for all targeted variables. In contrast, other models show significant deviations from the actual values. This alignment, observable in both the index values month-on-month as per figure 5 and year on year changes as indicated by figure 6 , highlights the Elastic Net model's effectiveness in handling variables with linear relationships. For all models the headline index forecasts was computed through weighted average of core , food and energy consumer price indices .

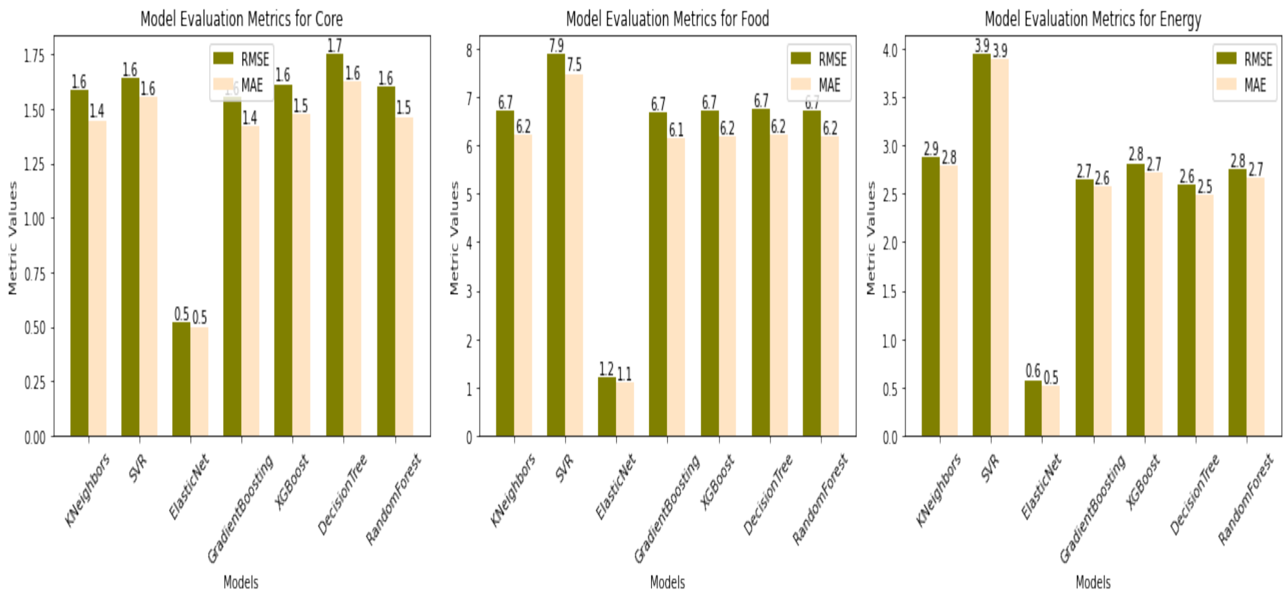
Figure 3: Monthly Consumer price Indices forecast vs actual




Source: Authors' computation

The superiority of the elastic net regression model over the other models in predicting headline components as per figure 4, is strengthened by root mean square of errors (RMSE) and mean absolute errors (MAE) as evaluation metrics where this model has the lowest metrics compared to other models.

Figure 4: Forecast evaluation metrics




Source: Authors' computation

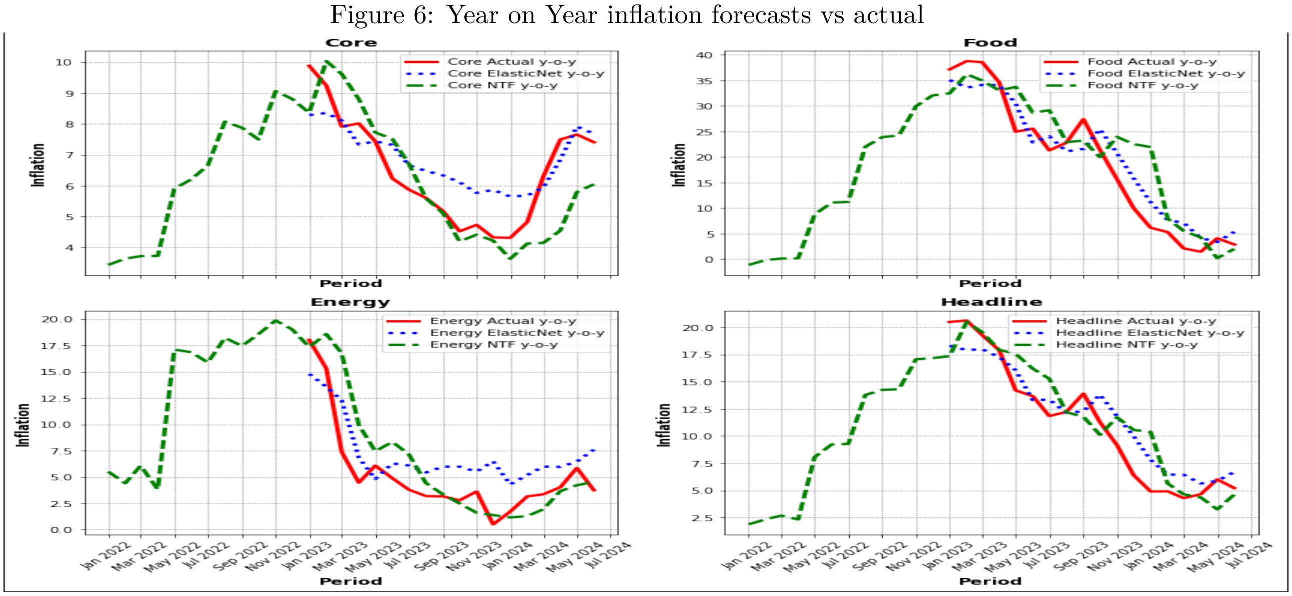
#### 4.2.2 Month on month and year on year changes (forecasts against actual values)

Month on month and year on year inflation were computed using indices as indicated in figure 5 and 6 respectively. The forecasts for elastic net regression and existing Near Term Forecasting (NTF) system which is currently used by NBR for short term forecasts were compared with actual inflation. It was found that the forecasts aligned with the actual outcomes despite the observed slight deviations for both NTF and elastic net regression. As per figure 7 in the appendix the elastic net outperforms the NTF multivariate model. To conclude the hybrid model (combination of elastic net regression and NTF multivariate system as per figure 8 and 9 was employed and marked a significant improvement in short term forecasts accuracy

Figure 5: Month on Month inflation forecast vs actual


Source: Authors' computation

Figure 6: Year on Year inflation forecasts vs actual




Source: Authors' computation

# 5 Conclusion and Suggestions.

This study forecasted key inflation components core, food, and energy using various machine learning models. Among the models tested, the Elastic Net Regression model demonstrated superior performance compared to other machine learning models and the current multivariate model known as Near-Term Forecasting System employed by the NBR for short-term inflation forecasting. These findings underscore the potential of machine learning techniques to significantly enhance the accuracy of inflation forecasts.

Currently, the NBR relies on the NTF system for near-term forecasting. While this traditional model has been instrumental, integrating machine learning techniques presents a promising opportunity for improvement. The study recommends that the hybrid model can be employed to improve forecasts accuracy.

In light of these insights, several key suggestions are proposed:

National bank of Rwanda should actively encourage and support the adoption of these new forecasting models. This could involve creating frameworks for model validation and integration, as well as fostering collaboration between NBR and research institutions to continuously refine and update forecasting techniques.

Investing in training programs for NBR staff on machine learning techniques is vital. By equipping analysts with the skills needed to develop, implement, and interpret machine learning models, NBR can enhance its analytical capabilities and ensure effective use of advanced forecasting tools.

Establishing a rigorous framework for evaluating the performance of machine learning models against traditional models will also be essential. This framework should include criteria for assessing accuracy, reliability, and relevance to specific forecasting needs.

Ongoing research on applying hybrid models and machine learning techniques in general to economic forecasting should be integrated into mainstream forecasting practices at the NBR. This includes staying abreast of technological advancements, exploring new algorithms, and adapting to changes in economic conditions that may affect forecasting accuracy.

By implementing these suggestions, policymakers and NBR can build a more accurate and reliable forecasting system, ultimately contributing to more informed economic decisions and better management of inflationary pressures in Rwanda.

## References

Alaru, A. F. N. (2023). Navigating inflation in Ghana: How can machine learning enhance economic stability and growth strategies. *Journal of Economic Analysis*, *45*(3), 231-248.

Baybuza, I. (2018). Inflation forecasting using machine learning methods. *Russian Journal of Money and Finance*, *77*(4), 42–59.

Bianchi, F., & Melosi, L. (2017). Escaping the great recession. *American Economic Review*, *107*(4), 1030–1058.

Blanchard, O. (2016). The us phillips curve: Back to the 60s? *Peterson Institute for International Economics Policy Brief*, *16*(1).

Borio, C., & Filardo, A. (2007). Globalization and inflation: New cross-country evidence on the global determinants of domestic inflation. *BIS Working Papers*(227).

Box, G. E. P., & Jenkins, G. M. (1976). *Time series analysis: Forecasting and control* (Revised ed.). San Francisco: Holden-Day.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5-32.

Chakraborty, C., & Joseph, A. (2017). Machine learning at central banks.

Chen, T., & Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining* (p. 785-794). ACM.

Cover, T., & Hart, P. (1967). Nearest neighbor pattern classification. *IEEE Transactions on Information Theory*, *13*(1), 21-27.

Del Negro, M., Lenza, M., Primiceri, G., & Tambalotti, A. (2020). What's up with the phillips curve? *Brookings Papers on Economic Activity*.

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *The Annals of Statistics*, *29*(5), 1189-1232.

Friedman, M. (1968). The role of monetary policy. *American Economic Review*, *58*(1), 1–17.

Hakizimana, C. (2022). Forecasting inflation of Rwanda using macroeconomics variables (2006q1-2019q4). *University of Rwanda.*

Huang, C.-K., Nakamori, Y., & Wang, S.-Y. (2005). Forecasting stock market movements with artificial neural networks. *Computers Operations Research*, *32*(10), 2513-2526.

Huang, W., Lou, Y., & Yuan, Z. (2020). Forecasting with deep neural networks: An empirical study of financial time series. *International Journal of Forecasting*, *36*(4), 1126-1140.

Hyndman, R. J., & Athanasopoulos, G. (2021). *Forecasting: Principles and practice* (3rd ed.). OTexts. (Available at `https://otexts.com/fpp3/`)

Li, Y., & Sheng, X. (2020). Forecasting the financial market with machine learning: A study of predictive performance. *Quantitative Finance*, *20*(12), 2021-2039.

Liu, W., H. (2019). Inflation forecasting using support vector machines. *Computational Economics*, 1031-1045.

Malhotra, A., & Maloo, M. (2017). Understanding food inflation in India: A Machine Learning approach. *arXiv preprint arXiv:1701.08789*.

Mandalinci, S. (2017). Forecasting economic variables with machine learning: An empirical study. *Journal of Economic Dynamics and Control*, *80*, 1-19.

McNelis, P. D. (2021). *Forecasting with machine learning.* Cambridge: Cambridge University Press.

Mitchell, W. F. (1999). The origins of the phillips curve. *Center of Full Employment and Equity, Working Paper*, 99–02.

Musekera, J. (2024). Agriculture performance and inflation dynamics in rwanda: Application of machine learning. *Journal of Economic Studies*, *21*(1), 41-70.

Mwenese, B., & Kwizera, A. (2018). Modelling and forecasting inflation dynamics in Rwanda. *BNR Economic Review*, *13*, 45–71.

Narmandakh, B. (2022). Inflation forecasting with machine learning methods: A case of mongolia. *Tokyo, Japan: The University Of Tokyo.*

Phelps, E. S. (1967). Phillips curves, expectations of inflation and optimal unemployment over time. *Economica*, *34* (135), 254–281.

Phillips, A. W. (1958). The relation between unemployment and the rate of change of money wage rates in the united kingdom, 1861-1957. *Economica*, *25* (100), 283-299.

Quinlan, J. R. (1993). *C4.5: Programs for machine learning.* San Mateo, CA: Morgan Kaufmann Publishers.

Romer, D. (2012). What have we learned about fiscal policy from the crisis?

Rutayisire, M. J. (2015). *Threshold effects in the relationship between inflation and economic growth: Evidence from Rwanda.* African Economic Research consortium.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica*, *48* (1), 1-48.

Smets, F., & Wouters, R. (2007a). Shocks and frictions in us business cycles: A bayesian dsge approach. *American Economic Review*, *97* (3), 586-606.

Smets, F., & Wouters, R. (2007b). Shocks and frictions in us business cycles: A bayesian dsge approach. *American Economic Review*, *97* (3), 586-606.

Stock, J. H., & Watson, M. W. (2007). Why hasn't inflation been more settled? *Brookings Papers on Economic Activity*, *2007* (1), 149-215.

Stock, J. H., & Watson, M. W. (2012). *Disentangling the channels of the 2007-2009 recession* (Tech. Rep.). National Bureau of Economic Research.

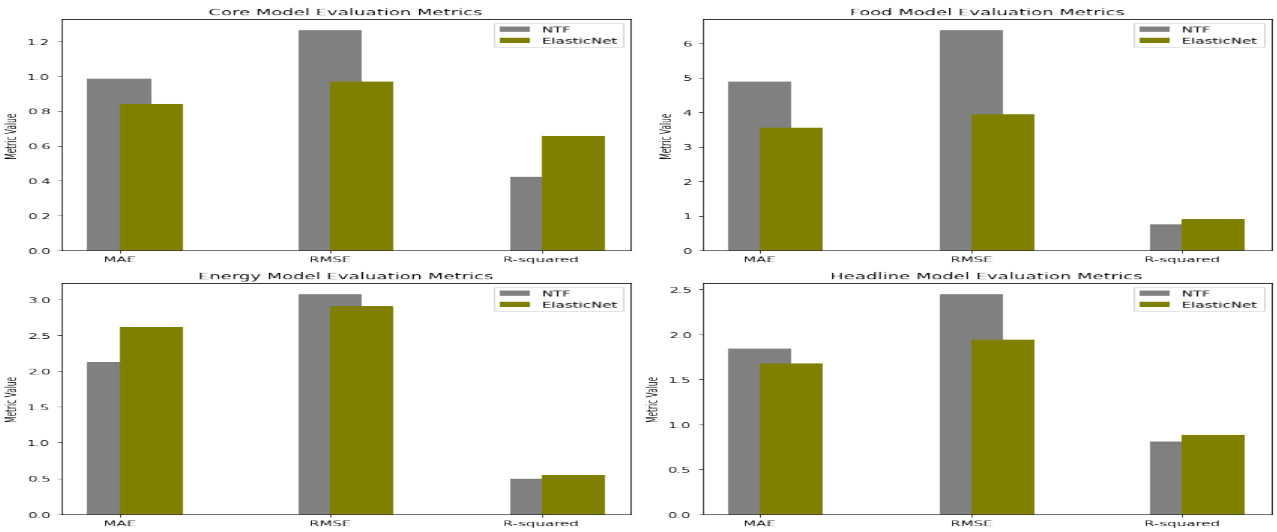
Vapnik, V., & Cortes, C. (1995). Support-vector networks. *Machine Learning*, *20* (3), 273-297.

Zhang, G., Patuwo, B. E., & Hu, M. Y. (2018). Forecasting financial time series with neural networks: A review and practical implementation. *Computational Statistics  Data Analysis*, *129* , 173–186.

Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *67* (2), 301-320.

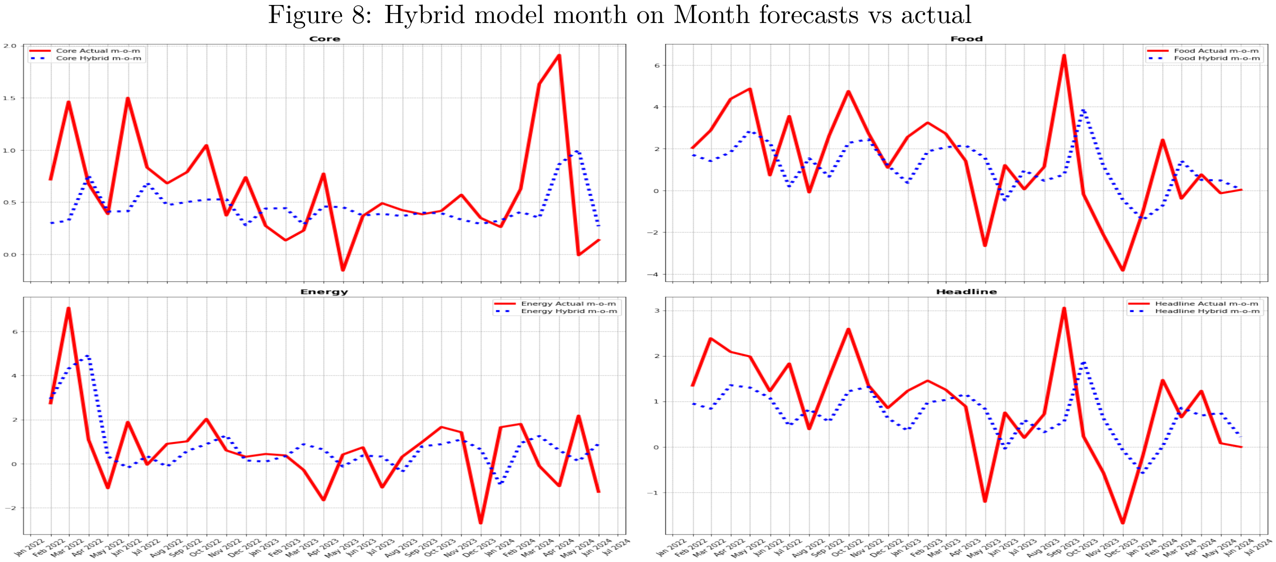
**Appendix**

Figure 7: NTF vs Machine learning evaluation metrics



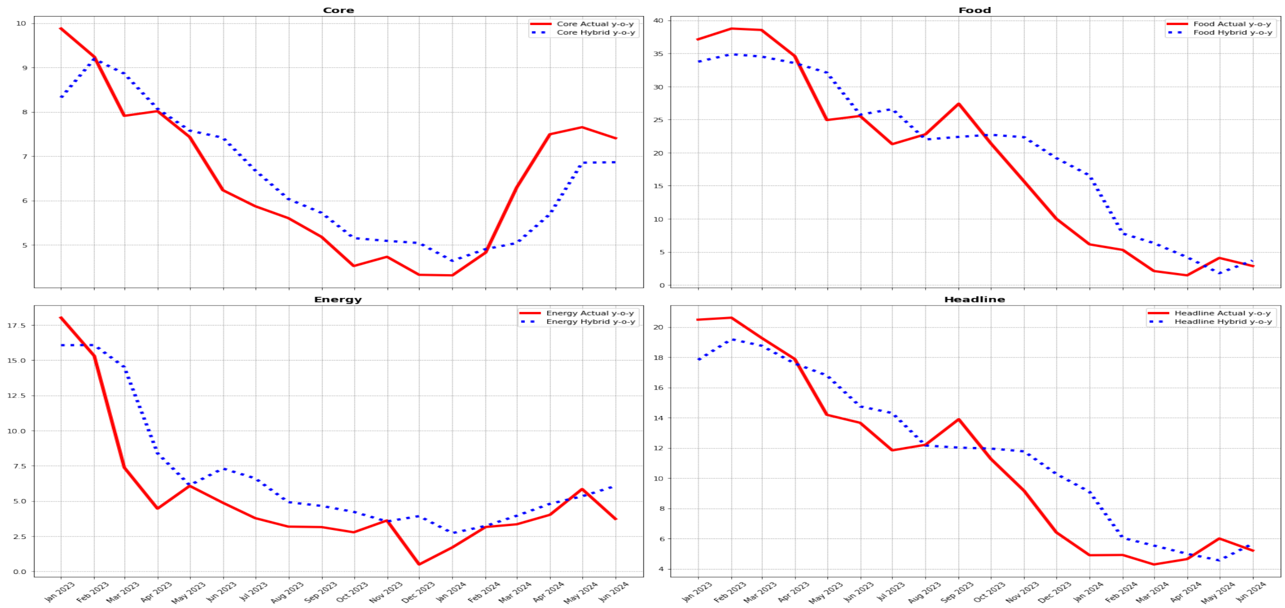

Source: Authors' computation

Figure 8: Hybrid model month on Month forecasts vs actual




Source: Authors' computation

Figure 9: Hybrid model y-o-y forecasts vs actual




Source: Authors' computation