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FORECASTING THE INFLATION FOR BUDGET FORECASTERS: AN ANALYSIS OF ANN MODEL PERFORMANCE IN TÜRKİYE

Bütçe Tahmincileri için Enflasyon Tahmini: Türkiye'de YSA Modeli Performansının İncelenmesi

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Keywords:
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Abstract

The reliability of budget revenue and expenditure forecasts depends on the accuracy of inflation forecasts. Without realistic inflation forecasts, it is not possible to produce sound budget forecasts. This study aims to guide budget forecasters in Türkiye by providing accurate inflation forecasts. The analysis utilizes data from the 2005–2023 period. The basket exchange rate (USD and Euro), unemployment, imports, exports, budget revenues and expenditures, interest rates, industrial production index, money supply, general price index, and minimum wage are forecasted using Holt-Winters, ARIMA, SARIMA, Prophet, LSTM, and Hybrid models. These forecasts are then used as inputs in ANN, SVR, RF, and GBM models to forecast monthly inflation. The results indicate that the forecasts generated with ANN are significantly more realistic than those presented in Türkiye's budget law and the Medium-Term Program. The study demonstrates that ANN can be an effective tool for budget forecasters in accurately forecasting inflation and, consequently, improving budget forecasts. The findings are further evaluated through a comparative analysis with forecasts from institutions such as the IMF, OECD, Central Bank, and the European Union. To support future academic research, inflation forecasts for 2025, along with forecasts for independent variables, are also included in the study.

Anahtar Kelimeler:
Bütçe Tahmini
Enflasyon Tahmini
Yapay Sinir Ağları

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Öz

Bütçe gelir ve harcama tahminlerinin güvenilirliği, enflasyon tahminlerinin doğruluğuna bağlıdır. Gerçekçi enflasyon tahminleri olmadan sağlıklı bir bütçe tahmini yapmak mümkün değildir. Bu çalışma, Türkiye'de bütçe tahmincilerine enflasyon tahminleri konusunda rehberlik etmek amacıyla hazırlanmıştır. Çalışmada, 2005-2023 dönemine ait veriler kullanılmıştır. Döviz kuru sepeti (Dolar ve Euro), işsizlik, ithalat, ihracat, bütçe gelir ve harcamaları, faiz oranı, sanayi üretim endeksi, para arzı, genel fiyat endeksi ve asgari ücret, Holt-Winters, ARIMA, SARIMA, Prophet, LSTM ve Hibrit yöntemleriyle tahmin edilmiştir. Daha sonra bu tahminler kullanılarak YSA, SVR, RF ve GBM yöntemiyle aylık enflasyon tahminleri üretilmiştir. Sonuçlar, çalışmada YSA ile edilen tahminlerin, Türkiye'nin bütçe kanunu ve orta vadeli programda yer alan enflasyon tahminlerinden daha gerçekçi olduğunu göstermektedir. Çalışma, YSA yönteminin bütçe tahmincileri tarafından enflasyonu doğru tahmin etmek için etkili bir araç olarak kullanılabileceğini ortaya koymaktadır. Bulgular, IMF, OECD, Merkez Bankası ve Avrupa Birliği tahminleriyle karşılaştırmalı analiz yoluyla değerlendirilmiştir. Gelecek akademik araştırmaları desteklemek amacıyla, 2025 yılına ilişkin bağımsız değişkenler ve enflasyon tahminleri de çalışmaya dahil edilmiştir.

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1. Introduction

Inflation is a critical element for sound fiscal policy and economic stability. Accurate inflation forecasting plays a crucial role in the formulation of reliable budget forecasts. To allocate resources, manage public debt, and configure fiscal policy, governments use budget forecasts as their primary tool. Misforecasting inflation can lead to high discrepancies between the planned and actual public expenditures and revenue collection, thereby reducing the effectiveness of fiscal policy. For instance, unforeseen inflationary shocks can significantly distort budget forecasts, especially for government expenditure on wages, pensions, tax revenue, and entitlement programs (Bretschneider and Gorr, 1992). Governments will tend to overspend budgeted amounts when inflation is under-forecasted, thereby generating fiscal deficits. Excess inflation forecasting results in over-contracting of the budget, which is most likely to injure economic growth (Allan, 1965).

Inflation forecasting has been extensively studied in the literature since it is of great significance for monetary and fiscal policy. The conventional econometric models such as Autoregressive Integrated Moving Average (ARIMA), Vector Autoregressive (VAR), and Phillips Curve-Based (PC) approaches have conventionally formed the basis of inflation forecasting (Stock and Watson, 1999, 2003). However, these models are prone to fail in describing the dynamic and complex character of inflation, particularly in periods of economic crises and structural adjustment. More recently, Machine Learning (ML) techniques, particularly Artificial Neural Networks (ANN), have gained prominence due to their ability to model nonlinear relationships and detect advanced patterns in massive data sets (Moshiri and Cameron, 2000; Nakamura, 2005). Some comparative studies have established the superior predictive performance of ANN models in inflation forecasting relative to traditional statistical methods (Choudhary and Haider, 2012; Medeiros et al., 2021).

Despite such advancements, there is controversy surrounding the effectiveness and validity of other methods of inflation forecasting. Some literature captures the failure of econometric models to uncover dynamic economic relations (Atkeson and Ohanian, 2001; McKnight et al., 2020). Others point out that while ML methods such as ANN, Long Short-Term Memory (LSTM), and hybrid models improve accuracy, their use in policymaking is limited by data availability and computational expense (He et al., 2012; Garcia et al., 2017). Considering these controversies, this study aims to investigate the performance of ANN models in inflation forecasting specifically for budget forecasters, who require timely and realistic models for fiscal planning.

The purpose of this study is to constitute a comprehensive analysis of the performance of ANN regarding its forecasting purposes concerning inflation in Türkiye and whether it as a tool could be reasonably used by budget forecasters. In the literature, this study fills a gap by extending the applications of ANN in fiscal planning through inflation forecasting. Unlike previous studies that concentrate on short-term inflation forecasting or central bank decision-making, this study corresponds with the needs of budget planners relating to inflation forecasting based on leading macroeconomic indicators available at the time of preparing the budget. In this regard, a more realistic assessment of the application of ANN for actual fiscal practice can be portrayed.

Türkiye provides a particularly good example of inflation forecasting due to its history of chronic inflation and macroeconomic turmoil. Since the second half of the 20th century, Türkiye has had repeated episodes of high inflation, currency devaluations, and foreign debt crises that have posed gigantic challenges to fiscal planning (Kara, 2024a). The latest inflationary pressures, fueled by exchange rate instability and global commodity price shocks, have served to reinforce the imperative of accurate inflation forecasting. Unusually high inflation rate volatility has often led to substantial disparities between forecast and actual budget outcomes, with a need for a quest for better forecasting tools.

The most elementary issue addressed in this study is the uncertainty for budget planners in inflation forecasting. The budgeting process in Türkiye is extremely complicated due to the very high volatility of the economic variables. Fluctuations in primary macroeconomic determinants such as exchange rates, unemployment, imports, exports, interest rates, and money supply directly affect inflation forecasts. Thus, the use of models that generalize traditional methods and are better able to capture complex economic relationships is central to improving forecast accuracy. The approach employed in this study presents a new solution, in that it not only adheres to the process employed by budget forecasters but also produces more plausible forecasts.

The methodology of the research applied here is a two-stage process for enhancing the accuracy of inflation forecasting. In the first stage, various forecasting methods were applied to independent variables, and the models yielding the most accurate results were selected. Specifically, the Holt-Winters, ARIMA, Seasonal ARIMA (SARIMA), Prophet, LSTM, and Hybrid models were evaluated, and the most reliable forecasting techniques were identified. In the second stage, these forecasts were used as inputs for an ANN model to forecast inflation. Also, ANN’s performance was compared with some other ML techniques.

In Türkiye, budget forecasters typically rely on the most recent macroeconomic data available when preparing budget forecasts for the following year. This study replicates that process by utilizing data up to September 2023 to generate inflation forecasts through December 2024. By simulating the workflow of budget forecasters, the study establishes a realistic forecasting framework.

This paper is structured as follows: Section 2 reviews the relevant literature on inflation forecasting, discussing both traditional and ML-based methodologies. Section 3 presents the dataset and methodology, detailing the forecasting models used for independent variables and inflation. Section 4 discusses the results, comparing ANN-based forecasts with government and other institutional forecasts. Section 5 outlines policy recommendations based on the findings, emphasizing the integration of ANN models into budget forecasting frameworks. Finally, Section 6 concludes with a discussion of the study's implications for future research and policymaking in inflation forecasting for budgetary applications.

2. Literature Review

Advanced methodologies have been developed and tested in inflation forecasting, and performance has varied according to the broader economic environment, horizon, and coverage of available data. Traditional econometric techniques like ARIMA, VAR, and PCs have long constituted the foundation with an extremely stable base for describing inflationary processes. However, with more complex economic systems and the availability of large datasets, more advanced techniques like ML algorithms and hybrid models have evolved. These techniques have been unearthing new channels for modeling inflation dynamics and, as such, offer possible enhancements in forecasting accuracy during times of economic turbulence or structural change periods.

While most of the traditional models usually take their basis on a group of pre-specified economic relations, ML algorithms like ANN, Random Forests (RF), and Least Absolute Shrinkage and Selection Operator (LASSO) are flexible in that the model can learn from the changes in the economic environment through the fact that they focus more on pattern identification in big data. Meanwhile, hybrid approaches have also been applied, which integrate elements from both traditional econometrics and modern ML to siphon the strengths of each method. Hence, much of the recent literature has concentrated on investigating the relative performance of these methodologies, thus highlighting their strengths, weaknesses, and the most appropriate areas of economic application.

The contributions of Stock and Watson are particularly significant. Their studies of the predictive performance of different models, particularly their (2003) and (2004) works, present evidence that many models feature higher out-of-sample forecasting errors than a simple Autoregressive (AR) model of inflation for the United States (U.S.). In a follow-up study, Stock and Watson (2007) provided further empirical evidence reinforcing the earlier finding that univariate models often outperform multivariate approaches in the U.S. context. Their earlier work (1999) highlighted the effective use of PC analysis for inflation forecasting, where strong predictive performance was demonstrated. However, in their subsequent research (2008), they revisited this approach and noted that the efficacy of PC models is not consistent over time, identifying the episodic nature of its forecasting success.

The examination of PC has been expanded in numerous studies. Atkeson and Ohanian (2001) demonstrated that in the U.S., forecasts relying on simple averages of past inflation outperformed those produced by PC models. However, McKnight et al. (2020) presented an alternative model rooted in the New Keynesian PC, applied to both the U.S. and the Eurozone, which surpassed the accuracy of traditional Random Walk (RW) approaches. In a similar vein, Kapur (2013) employed an augmented version of the PC to forecast inflation in India, yielding highly accurate results.

ANN has emerged even more into focus in forecasting inflation during recent years, especially with a high degree of noticeability in many comparative analyses. For instance, Choudhary and Haider (2012), amongst others, have tested the performance of ANN and AR in terms of forecasting in 28 OECD countries. According to them, ANN outperformed AR in almost half of the cases, while the AR forecast was superior in almost a quarter of the cases. Similarly, Haider and Hanif (2008) applied ANN in inflation forecasting in Pakistan. They showed that ANN outperformed both AR and ARIMA with a significant difference in accuracy. Nakamura (2005) expanded upon such findings by showing that ANN improved upon univariate autoregressive models for the U.S. While such cases of success pervade, higher performance by ANN is not absolute or categorical. He et al. (2012) tested within their paper the forecasting of U.S. inflation and discovered that while ANN held much potential, results were most effectively obtained by ARIMA-GARCH.

This followed other concepts of the subsequent ANN models. Moshiri and Cameron (2000) applied their research in Canadian inflation where they compared the results of using the Back-Propagation Artificial Neural Networks (BPN) with ARIMA, VAR, and Bayesian VAR (BVAR). The researchers found that the BPN has made equivalent forecasts to the traditional models and, at times, outpaced traditional models, especially where economic variables experienced instability. Almosova and Andresen (2023) forecasted the U.S. inflation with LSTM Recurrent Neural Networks and compared it with AR, ANN, SARIMA, and Markov-Switching. Their findings determined that while LSTM outperformed AR, ANN, and Markov-Switching, it did not differ from SARIMA, which evidences that though there are obvious advantages to ANNs, they cannot claim to be superior to all statistical methods in general. Following up, Barkan et al. (2023) tested the Hierarchical Recurrent Neural Network (HRNN) model against other models such as the PC, VAR, and RW. The results indicated that the proposed model of HRNN outperformed all the other methods significantly.

ML techniques have also become popular and are among the most preferred and utilized inflation forecasting techniques. They are great since they are capable of handling huge amounts of data, and simulate complex dependencies, and because of these, they are among the best economic forecasting techniques. For example, Araujo and Gaglianone (2023) used ML for inflation forecasting in Brazil, comparing it with traditional techniques such as RW, Autoregressive Moving Average (ARMA), VAR, and PC against the emerging ones such as RF and ANN. The findings indicated that ML models, especially RF, outperformed the other traditional techniques. Likewise, Medeiros et al. (2021) conducted an extensive study for the U.S. based on heterogeneous models like RF, LASSO, Ridge Regression (RR), Principal Component Factors, and even advanced techniques like Boosted Factors and Complete Subset Regressions. The analysis also validated that RF always provided the best forecasts.

In a similar vein, the study by Ülke et al. (2018) considered a comparison between ML methods comprising K-nearest Neighbors (k-NN), ANN, and Support Vector Machine (SVM) against traditional models comprising AR, Auto Regressive Distributed Lag (ARDL), VAR, and Naive in forecasting U.S. inflation. The results of the study indicated that the best performer in the forecasting of core personal consumption expenditure inflation was the model that used SVM, while core consumer price index inflation was performed better by ARDL.

Beyond these advanced models, many studies have compared classical models, ARIMA, VAR, AR, SARIMA, SVM, LASSO, and Bayesian approaches to understand their relative strengths and weaknesses. For example, Bos et al. (2002) compared the performance of the Autoregressive Fractionally Integrated Moving Average (ARFIMA) and ARIMA in U.S. inflation forecasting. Their results showed that ARIMA outperformed in point forecast accuracy, although ARFIMA generated more sound multi-step forecast intervals. This stresses that one has to trade off for both short-run accuracy and long-run predictability. Moser et al. (2007) examined forecasting methods for Austria using factor models, VAR, and ARIMA. They concluded that the factor models resulted in better forecasts among these models. Furthermore, they stress that combining factor models with VAR yielded even better forecast quality.

In a study conducted by Doguwa and Alade (2013) in Nigeria, it was found that in comparison to SARIMA with Exogenous Variables (SARIMAX), better forecast accuracy was produced by the SARIMA model. Also, a multi-scope study on the US data by Gil-Alana et al. (2012) suggests that Survey-Based Expectations models outperform the conventional models of AR, VAR, ARMA, and ARFIMA.

A similar evaluation of models including RW, ARIMA, AR, ARDL, VAR, and BVAR in Pakistan by Hanif and Malik (2015) established that the most plausible forecast was provided by the ARDL model. Likewise, in a study carried out on inflation forecasting in Pakistan by Bokil and Schimmelpfennig (2005), the results showed that the Leading Indicators Model forecasts were more accurate than the forecasts made by VAR and ARIMA models.

For the U.S., Groen et al. (2013) forecasted inflation using the Bayesian Regression model, contrasting it with RW, AR, RR, and PC models. Their results indicated that the Bayesian model resulted in more accurate short-term forecasts. Wright (2009) also investigated inflation forecasting in the U.S., evaluating a Bayesian model with counterparts such as AR, ARMA, RW, and those from the Survey of Professional Forecasters and Blue Chip. Once more, the Bayesian model proved to be the most reliable option.

Garcia et al. (2017) examined inflation forecasting in Brazil using various methods, including RW, Complete Subset Regression (CSR), AR, LASSO, FOCUS, and RF. They found that LASSO and FOCUS excelled in the short term, while Adaptive LASSO performed best in the long term. Cumulatively, CSR proved to be the most successful, and the average of all models yielded even better results.

Inoue and Kilian (2008) introduced bagging predictors for inflation forecasting in the U.S. Their results showed that bagging predictors outperformed equally weighted forecasts, median forecasts, Adaptive Regression by Mixing, and Bayesian forecast averages. However, they found performance parity between bagging and other advanced models like Bayesian shrinkage, RR, and iterated LASSO. Tang and Zhou (2015) applied SVM-based models (Fixed-SVM, PSO-SVM, GA-SVM) and BPNN to inflation forecasting in China. Among these, the PSO-SVM model emerged as the most accurate.

In addition to the commonly used methods, several studies have employed more unconventional approaches to inflation forecasting, demonstrating the versatility and innovation in this field. For instance, Sbrana et al. (2017) utilized the Moments Estimation Through Aggregation method to forecast inflation in the Eurozone, demonstrating that this novel approach produced highly accurate forecasts. Hauzenberger et al. (2023) examined inflation forecasting for the U.S. using sophisticated dimension reduction methods, revealing that these approaches were competitive with traditional linear models based on principal components. Notably, the Autoencoder and squared principal components emerged as the most successful in generating accurate forecasts.

Faust and Wright (2013) conducted an extensive survey on inflation forecasting methods in the U.S. They discovered that a simple glide path forecasting from the current inflation rate performed as well as, if not better than, model-based forecasts for long-term inflation rates, particularly in the long run. Theoharidis et al. (2023) applied a Variational Autoencoders and Convolutional LSTM Networks (VAE-ConvLSTM) model to inflation forecasting in the U.S. Their results, compared with models like RR, LASSO, RF, Bayesian Methods, Vector Error Correction Model (VECM), and Multilayer Perceptron, revealed that the VAE-ConvLSTM approach produced more accurate forecasts.

While the current literature is mostly focused on inflation forecasting in various countries, the body of research for Türkiye has also contributed significantly to the explanation of inflation processes, both with traditional econometric models and newer ML approaches. To this end, efforts have been made to forecast inflation in Türkiye with a range of approaches, each yielding some insight into the performance of competing forecasting techniques in the country's specific economic context.

One of the earlier studies, Meçik and Karabacak (2011) forecasted inflation using the ARIMA method and the results were consistent with the actual rates of inflation. Erilli et al. (2012) studied the forecasting of inflation in periods of crisis using Fuzzy Regression in Türkiye, noting that this technique gave very high forecasting accuracy. A more thorough assessment was carried out by Öğünç et al. (2013), who applied numerous models comprising univariate models, decomposition cases, time-varying parameter models based on PC, as well as VAR and BVAR models. Their analysis showed that the model allowing the use of more economic data has better predictive capabilities than the RW model and also found improvement in forecast accuracy by using multiple forecasts.

Bayramoğlu and Öztürk (2017) compared ARIMA with the Grey System model. The result indicated that ARIMA was more convenient in the forecast of the Producer Price Index, while the Grey System model had more appropriate forecasts in the Consumer Price Index. Similarly, another study by Kızılkaya (2017), using the ARIMA model, showed that it outperformed official forecasts. More recently, Özgür and Akkoç (2022) compared ML techniques (RR, LASSO, ADALASSO, and Elastic Net) with traditional models like VAR and ARIMA. The results indicated that Elastic Net produced the best forecasts. More recently, Nas et al. (2024) investigated the performance of several ML models and found the decision tree model to outperform both the RF and multilayer sensor models.

The extensive body of research on inflation forecasting demonstrates that the literature in this field is both vast and methodologically diverse. Studies aimed at identifying the determinants of inflation are equally comprehensive and traced back even further in economic research. However, given the breadth of this literature, it is not feasible to discuss all contributions in detail. Nonetheless, it is essential to highlight some of the most notable recent studies. For instance, Lim and Sek (2015) identify GDP growth, money supply, government spending, and imports as key determinants of inflation across 28 countries. Similarly, Deniz et al. (2016) find that while the specific drivers of inflation vary across industrialized and emerging economies, exchange rates, output gaps, money supply, budget balances, real wages, and GDP growth play significant roles. Čaklovica and Efendic (2020) further emphasize the importance of economic openness, unemployment, real wages, institutional factors, and external variables, such as food and oil prices, in shaping short-term inflationary dynamics within EU28 countries. More recently, Jakšić (2022) identified exchange rates, commodity prices, interest rates, and wage levels as being major inflation drivers for economies situated in Central, Eastern, and Southeastern Europe. For Türkiye, Kara (2024b) finds that inflation is greatly affected by government expenditures, while government revenues have little or no effect on inflation. Fiscal policy effects are also noted by Kinlaw et al. (2023), who identify public spending as the key inflation driver in the U.S. Lastly, Martins and Verona (2023) show that both supply shocks and inflation expectations provide significant contributions to U.S. inflation, whereas unemployment makes only a small contribution. These contributions reinforce the multifactor character of inflation dynamics as well as the necessity for incorporation in inflation forecast equations of an elaborate set of macroeconomic variables.

3. Data Set

The data set includes the most important macroeconomic variables in the budget forecasting process in Türkiye (Table 1). The variables are chosen carefully to represent the actual conditions and limitations budget forecasters have in Türkiye. The methodology of the study included utilizing data up to September of the current year to generate forecasts up to December of the subsequent year. This procedure is consistent with the time frame utilized by budget planners in Türkiye. By repeating this same process, the aim was to improve the accuracy of inflation forecasts, which has always been one of the most challenging issues for budget forecasters.

Table 1. Data Definitions

Variable	Explanation	Acronyms	Source	Period
Exchange Rate	Monthly Dollar & Euro Basket Exchange Rate Average	BSK	Central Bank of the Republic of Türkiye	January 2005 – September 2023
Interest Rate	Central Bank's Overnight Interest Rate's Monthly Average	INT		
Money Supply	M3 Money Supply on A Monthly Basis	MSP		
Industrial Production Index	Monthly Industrial Production Index	IPI		
General Price Index	General Price Index on A Monthly Basis	GPI	Istanbul Chamber of Commerce	
Unemployment	Monthly Unemployment Rate	UNP	Turkish Statistical Institute	
Export	Monthly export amount (USD)	EXP		
Import	Monthly Import amount (USD)	IMP		
Wage Growth	Net Minimum Wage on A Monthly Basis	WGH		
Government Budget Expenditure	Monthly Government Budget Expenditure	EXT	Ministry of Treasury and Finance of the Republic of Türkiye	
Government Budget Revenue	Monthly Government Budget Revenue	REV		

The selection of the variables in this study is guided by both economic theory and usefulness to budget forecasters. Inflation forecasting models tend to be founded on a combination of monetary policy indicators, labor market conditions, and real economic activity. To this degree, key macroeconomic determinants of inflation are included in the dataset to provide theoretical consistency and empirical robustness. The selection of these specific variables is not arbitrary but follows from both their demonstrated applicability to inflation dynamics and availability in the budget forecasting procedure. Because budget forecasters operate under time pressure and only utilize officially published data, the indicators selected represent the most relevant and realistically obtainable set of variables for inflation forecasts.

By incorporating key monetary, fiscal, and real sector variables, the study not only aims to maximize the realism of inflation forecasts but also to enable methodological comparability with economic theory. The choice of variables is consistent with conventional models of inflation, such as the Quantity Theory of Money, the Phillips Curve, and cost-push models of inflation, thereby complementing the empirical and theoretical foundations of the study. Moreover, this advanced technique guarantees that the forecasting model remains applicable in a policy context, where institutional constraints and availability justify the use of economic forecasts.

This structural framework of forecasting enables budget forecasters to generate higher-accuracy forecasts from theoretically sound and empirically accessible variables. Therefore, the study enhances the accuracy and reliability of inflation forecasts, making them stronger in fiscal planning and decision-making in the economy.

4. Methodology

In the analysis, four forecasts of independent variables were made using the following methods: Holt-Winters, Prophet, ARIMA, SARIMA, and LSTM. Also, a mean of these methods was computed in order to create a forecast which is called the Hybrid model. All these forecasts were then incorporated for forecasting inflation in an ANN. To evaluate the robustness of the ANN model, its performance was compared with other ML techniques, including RF, SVR, and Gradient Boosting Machines. Various error indicators were applied to assess the accuracy of all models. The following sections provide a detailed explanation of these methods.

4.1. Holt-Winters

The Holt-Winters Method was developed by Holt (1957) and Winters (1960) to model trend and seasonal components in time series. In this method, separate smoothing coefficients are used for level, trend, and seasonality to generate forecasts. This method can be applied in two different model structures: additive and multiplicative. The multiplicative model is suitable for situations where seasonal fluctuations vary in proportion to the series' average level. Initial values are determined through regression analysis or decomposition techniques, while the optimal values of the α (level), β (trend), and γ (seasonality) coefficients are optimized to minimize the Mean Square Error (Erişoğlu and Erişoğlu, 2022).

4.2. Prophet

The Prophet method, developed by Facebook's Data Science Team, is an open-source ML model used for time-series forecasting. Unlike traditional time-series methods, Prophet performs well even with missing and outlier data. One of its key advantages is the curve-fitting technique that allows users to make forecasts with the help of Bayesian-based intuitive parameters (Kayran and Uzun Araz, 2023). The general equation of the Prophet is:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon(t) \qquad (1)$$

The core equation of the Prophet model comprises a trend function g(t), a seasonal component s(t), a holiday effect h(t), and an error term ε(t). Prophet's intuitive and user-friendly approach makes time-series analysis more accessible, enabling even users with limited statistical knowledge to perform effective forecasting (Taylor and Letham, 2018).

4.3. ARIMA

ARIMA model, introduced by Box and Jenkins (1976), is a widely used statistical method for time-series forecasting. ARIMA captures both AR and MA components while incorporating differencing (I) to make a non-stationary series stationary. The model is denoted as ARIMA (p, d, q), where p represents the number of lagged observations in the AR component, d indicates the number of differencing operations applied to achieve stationarity, and q refers to the number of lagged forecast errors in the MA component. The general mathematical representation of an ARIMA model is:

$$\Phi_p(B)(1-B)^d y_t = \theta_q(B)\varepsilon_t \tag{2}$$

In equation B is the backshift operator, $\Phi_p(B)$ represents the AR polynomial, $\theta_q(B)$ denotes the MA polynomial, and ε_t is a white noise error term (Box and Jenkins, 1976). The optimal values for p, d, and q are typically selected using criteria such as the Akaike Information Criterion (AIC) to minimize forecast errors and improve model accuracy.

4.4. SARIMA

The SARIMA model is an advanced statistical model used for forecasting time-series data that exhibit seasonality. The SARIMA model, which is an extension of the ARIMA model developed by Box and Jenkins (1976), consists of seven parameters: The first three (p, d, q) represent the non-seasonal component of the trend, while the remaining four parameters (P, D, Q, s) define the seasonal component. Here, p represents the degree of AR term, d represents the degree of differencing, and q represents the degree of MA. Among the seasonal parameters, P represents the degree of seasonal AR, D represents the degree of seasonal differencing, Q represents the degree of seasonal MA, and s represents the number of steps in a seasonal cycle (Malki et al., 2022). The mathematical formula of the SARIMA model is:

$$f(B)\Phi(B^S)(1-B)^d(1-B^S)^D y_t = c + q(B)\Theta(B^S)\varepsilon_t \tag{3}$$

In the equation, $\Phi(B^S)$ represents the seasonal AR parameter, while $\Theta(B^S)$ denotes the seasonal MA parameter. For the model to be applied, the non-seasonal parameters p, d, q and the seasonal parameters P, D, Q along with the seasonal period s, must be specified. The most used metric for selecting the optimal SARIMA model is the AIC, which assesses the model's forecasting accuracy. The model with the lowest AIC value is considered to provide the best fit. The formula for AIC is as follows:

$$AIC = -2\log(L) + 2k \tag{4}$$

In the equation, k represents the total number of parameters estimated in the SARIMA model. L indicates the maximum likelihood function for the model. This criterion is an important measure used to increase the accuracy of the SARIMA model (Malki et al., 2022).

4.5. LSTM

LSTM is a type of Recurrent Neural Network (RNN) widely used in time-series forecasting. LSTM was developed to address the vanishing gradient problem commonly encountered by traditional RNNs, which can cause the model's learning process to slow down or even halt. By learning long-term dependencies, LSTMs overcome this challenge (Yadav et al., 2020). LSTM consists of three main gates. Input Gate: Determines whether the new input will be stored in memory; Forget Gate: Functions to discard irrelevant information and Output Gate:

Selects which information will be presented as output (Siami-Naimi et al., 2019). The fundamental computational formula of LSTM is as follows.

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (5)$$

The output of the input gate is represented by i_t, and similarly, the input value is calculated using weights W_i and bias b_i. This gate determines which new information should be added to the cell state.

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f \quad (6)$$

Here, f_t is the output of the forget gate; W_f is the weight matrix; h_{t-1} is the previous cell state; x_t is the current input; and b_f is the bias value of the gate. This gate determines the extent to which previous information should be forgotten.

$$\widetilde{C_t} = \tanh(W_C.[h_{t-1}, x_t] + b_C \quad (7)$$

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t} \quad (8)$$

The updated cell state C_t is determined by the effects of the outputs from the forget and input gates:

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o \quad (9)$$

The output gate controls which information from the cell state will be provided as output:

$$h_t = o_t * \tanh(C_t) \quad (10)$$

Here, h_t is found by multiplying o_t, the output of the output gate, with the value obtained from applying the hyperbolic tangent function to the cell state C_t. This value represents the current output of the LSTM cell and ranges between (-1) and (1). This multiplication reflects the cell state information in the output, allowing the model to capture long-term dependencies in temporal data for time-series forecasting (Song et al., 2020).

4.6. Hybrid

Research presented in scientific writings suggests that combining multiple models and taking their averages usually improves the overall forecasts made. Hansen et al. (2011) argued that according to the Model Confidence Set Technique, average forecasting values obtained from various models are likely to be more accurate than those of the best-performing model alone. Moreover, it has been shown that even in the case of short-term forecasting, the use of the simple average of the models in the confidence set results in a more accurate forecast. Heretofore, accuracy in forecasting can also be enriched through model dressing hence the combination of models yields different benefits (Garcia et al., 2017).

In this study, the average of the four methods mentioned above was computed, and this approach was named the hybrid model. The hybrid model combines the forecasts from Holt-Winters, Prophet, ARIMA, SARIMA, and LSTM models to get an overall forecast, thereby trying to take advantage of the strengths of each single method. It is based on the idea that combining many models results in more reliable outcomes than relying on a single model, especially in cases where complex patterns occur in data.

4.7. Artificial Neural Networks (ANN)

ANNs are models inspired by the information processing structure of the human brain, capable of extracting meaning from complex and nonlinear data. ANNs consist of artificial neurons and the connections between them, performing operations such as learning, classification, and clustering, based on the structure of nerve cells in the human brain (Zakaria et al., 2014). Each neuron calculates a net input using incoming data and weights. This net input is then processed through a linear or nonlinear activation function to produce an output. The weighting of the inputs determines the level of importance the neuron assigns to the data, while a bias value allows the network to learn even when the data is zero. The most common activation function, the sigmoid, transforms the input into a nonlinear output, enhancing the network's learning capacity (Haykin, 1998). In addition to the sigmoid function, other activation functions, such as linear, step, sine, threshold, and hyperbolic tangent, are also commonly used (Öztemel, 2006, 51). The formulas for net input and the sigmoid function are shown below.

$$NET = \sum_{i}^{n}(X_i W_i) \tag{11}$$

$$F(Net) = \frac{1}{1 + e^{-Net}} \tag{12}$$

The structure of an ANN consists of input, output, and hidden layers. The input layer receives raw data and passes it on to the hidden layer, which processes the data and transmits it to the output layer. In this structure, connections between neurons may be either feedforward or feedback. In feedforward networks, data flows unidirectionally from the input layer to the output layer, while in feedback networks, data can also be transmitted backward between layers. This characteristic makes feedback networks dynamic in nature (Jain et al., 1996).

ANNs can be classified based on their learning structure into supervised, unsupervised, and reinforcement learning models (Krenker et al., 2011). From the perspective of learning time, they are divided into online and offline learning. In online learning, the network continues the learning process during usage, whereas in offline learning, the network becomes ready for use after a training process. When new information is needed, the network must be retrained offline. The training of an ANN begins with determining the weight values, which are updated until the best result is achieved, allowing the network to generalize based on the examples presented to it. Various learning rules, such as Hebb, Hopfield, and Delta, aim to minimize the difference between the network's outputs and the expected outputs (Öztemel, 2003).

4.8. Random Forest (RF)

RF is a supervised learning algorithm based on an ensemble of multiple decision trees. The model constructs several independent decision trees by randomly sampling subsets of the data and features. For regression tasks, the final forecast is obtained by averaging the outputs of all individual trees, while in classification problems, the majority vote determines the final decision. RF is particularly effective in handling high-dimensional and complex datasets, reducing the risk of overfitting by aggregating multiple forecasts. Additionally, it can model nonlinear relationships between variables, making it a robust method for economic and time-series forecasting. The general mathematical formulation of the RF model is as follows (Breiman, 2001):

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} f_t(x) \tag{13}$$

In the equation $\hat{y}$ represents the forecasted value, *T* is the total number of decision trees, and $f_t(x)$ denotes the forecast from each individual tree *t*. By leveraging multiple trees, RF improves forecasting accuracy and stability, making it a valuable tool for forecasting inflation.

4.9. Gradient Boosting Machines (GBM)

GBM is a powerful ensemble learning algorithm that builds a sequence of decision trees, where each tree corrects the errors of the previous one. Unlike RF, which constructs trees independently, GBM builds trees sequentially, optimizing for residual errors using gradient descent. This iterative approach enhances predictive accuracy while maintaining flexibility in capturing nonlinear relationships.

GBM is widely used in economic and financial forecasting due to its ability to handle complex data structures and improve forecasting accuracy. By assigning higher weights to misclassified observations, it effectively reduces bias and variance, making it suitable for time-series forecasting and macroeconomic modeling. The general mathematical formulation of the GBM regression model is as follows (Friedman, 2001):

$$\hat{y} = \sum_{t=1}^{T} \lambda f_t(x) \tag{14}$$

In the equation $\hat{y}$ represents the forecasted value, *T* is the total number of decision trees, and $f_t(x)$ denotes the forecast from each individual tree *t*, and λ is the learning rate, which controls the contribution of each tree. By sequentially minimizing forecasting errors, GBM offers superior forecasting accuracy, making it a valuable tool for inflation forecasting.

4.10. Support Vector Regression (SVR)

SVR is an ML algorithm based on SVMs, designed for regression tasks. Unlike traditional regression models, SVR aims to find a function that approximates the data within a given margin of tolerance, rather than minimizing the absolute error. This allows SVR to effectively handle high-dimensional and nonlinear relationships by mapping input data into a higher-dimensional space using kernel functions.

SVR is particularly useful for economic and financial forecasting due to its robustness in dealing with outliers and its ability to generalize well with unseen data. The model is trained by minimizing a loss function that ignores small deviations from the true values while penalizing larger errors. The mathematical formulation of SVR is as follows (Drucker, 1997):

$$\min_{w,b,\xi,\xi^*} \frac{1}{2}\left|\left|w\right|\right|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{15}$$

$$\begin{aligned} \text{Subject to: } & y_i - (w \cdot \phi(x_i) + b) \leq \epsilon + \xi_i \\ & (w \cdot \phi(x_i) + b) - y_i \leq \epsilon + \xi_i^* \\ & \xi_i, \xi_i^* \geq 0 \end{aligned} \tag{16}$$

In the equation w is the weight vector, b is the bias term, $\phi(x_i)$ is the kernel function mapping inputs into a higher-dimensional space, ϵ defines the margin of tolerance, ξ_i and ξ_i^* are slack variables allowing some observations to fall outside the margin, and C is a regularization parameter controlling the trade-off between model complexity and tolerance to deviations. By leveraging kernel functions and margin-based optimization, SVR provides accurate and stable forecasts, making it a valuable tool for inflation forecasting.

4.11. Error Indicators

In the study, various error indicators have been used to comparatively measure the accuracy of the forecasts. The equations for these indicators are presented in the table below.

$$MSE = \left(\frac{1}{n}\right) * \Sigma(y_i - \hat{y}_i)^2 \tag{17}$$

$$RMSE = \sqrt{\left[\left(\frac{1}{n}\right) * \Sigma(y_i - \hat{y}_i)^2\right]} \tag{18}$$

$$MAE = \left(\frac{1}{n}\right) * \Sigma|y_i - \hat{y}_i| \tag{19}$$

$$MPE = \left(\frac{1}{n}\right) * \Sigma\left[\frac{(y_i - \hat{y}_i)}{y_i}\right] * 100 \tag{20}$$

$$MAPE = \left(\frac{1}{n}\right) * \Sigma\left|\left[\frac{(y_i - \hat{y}_i)}{y_i}\right] * 100\right| \tag{21}$$

The Mean Squared Error (MSE) measures the average of the squared differences between the forecasted and actual values. This metric penalizes larger errors more significantly, as the differences are squared. A smaller MSE indicates better model accuracy, while a larger MSE suggests substantial forecasting errors. Despite its usefulness, MSE is sensitive to outliers due to the squaring of errors, which can disproportionately influence the overall error measurement.

The Root Mean Squared Error (RMSE) is the square root of the MSE and provides a more interpretable measure of error by returning the value to the same unit as the original data. RMSE gives a clear indication of the magnitude of the errors, making it easier to interpret the model's forecasting performance. Like MSE, RMSE is also sensitive to large errors. However, because the interpretation of the RMSE is in original units, it is more practical for model evaluation.

The Mean Absolute Error (MAE) designates the mean absolute deviation between forecasted and actual values. Unlike MSE, it does not overemphasize large errors but treats all differences equivalently. Hence, MAE is considered a more robust central tendency measure when data may include some outliers or if extreme fluctuations are to be granted less impact on the outcome.

The Mean Percentage Error (MPE) finds the average percentage error between forecasted and actual values. It's especially helpful for comparing model performance across datasets of varying scales. MPE gives a sense of the model's relative accuracy, but it has a drawback. When actual values are near zero, even small differences can cause unusually large percentage errors, which may lead to misleading results.

The Mean Absolute Percentage Error (MAPE) simply gives the average of absolute percentage errors. It's a common metric for evaluating the accuracy of forecasting models. MAPE is especially useful for comparisons across datasets. It standardizes errors, making it easier to compare across different scales. However, like MPE, it can be distorted by small actual values, leading to unusually high percentage errors.

5. Results

The work was carried out in four major stages. Each of the stages was carefully organized so that it would divide the research into smaller convenient sections. This allowed for a thorough investigation at every stage and deliberation and analysis of every component that was worth including in the end output. Dividing the study into stages is also aimed at enhancing clarity and coherence, supporting the transparency and reproducibility of the methodology. The process began with the first stage, focusing on forecasting the independent variables.

5.1. First Stage: Forecasting the Independent Variables

To achieve the primary objective of this study, producing the most accurate and realistic inflation forecasts using an ANN, it was first necessary to forecast the independent variables for the target period. In budget planning, forecasters forecast inflation before forecasting budget items for the upcoming year. However, since the inflation figure used in budget calculations is itself a forecast, there is inherent uncertainty in the process. To simulate this uncertainty and replicate the real-world approach of budget forecasters, this study first generated forecasts for key macroeconomic indicators using multiple methods. Specifically, four forecasting techniques, along with a hybrid model, were applied to forecast independent variables from October 2023 to December 2024. The accuracy of these forecasts was then assessed by comparing them with actual values, and the MAPE was reported in the Table 2. The most accurate forecasts, as determined by this evaluation, were subsequently used as inputs for the ANN, RF, SVR, and GBM models to forecast inflation over the same period. Detailed forecasts for all independent variables can be found in Appendix A (A1–A11), while the Table 2 presents a summary of their forecasting performance.

Table 2. Forecasting Results for Independent Variables (MAPEs)

Variable	Method					
	Holt-Winters	**LSTM**	**Prophet**	**ARIMA***	**SARIMA***	**Hybrid**
BSK	3,3629	49,6784	21,4465	**2,3292**	*	7,4363
UNP	8,9241	19,3377	33,0774	*	**5,5779**	15,5206
EXP	4,5372	6,3505	4,3334	*	**4,0806**	4,1576
IMP	**5,3338**	25,2906	6,3197	*	6,1771	6,9652
EXT	10,7095	11,9165	48,3201	*	**10,5830**	19,1495
REV	19,7634	22,8691	42,7335	*	**12,8751**	14,5103
INT	**4,5518**	65,4885	63,7742	*	8,1831	34,8151
IPI	4,0219	**1,9769**	8,1346	*	2,0298	3,3276
MSP	10,1985	6,7530	7,7572	7,3089	*	**2,0854**
GPI	4,9450	4,9190	10,7046	3,4645	*	**2,4949**
WGH	16,1155	17,6804	46,1207	**12,9457**	*	22,6539

Note: Bold values indicate the best MAPEs for each independent variable.
*The SARIMA model was used for seasonal, and the ARIMA model was used for non-seasonal data.

The outcomes shown in Table 2 prove to be insightful in assessing the independent variable capability for forecasting by different models. From the models critiqued, SARIMA came out best, as shown by the lowest MAPE values recorded on UNP, EXP, EXT, and REV, which suggests a superior ability to learn the latent trend alongside capturing short-term fluctuations of those significant macroeconomic indicators. Therefore, it can be said that SARIMA is indeed a very trustworthy forecasting tool based economic variables that follow the patterns of seasonality and cyclical behaviors of inflation modeling as well.

For this research, SARIMA's improved performance is particularly critical as the reliability of inflation forecasts largely depends on forecasting the independent variables with precision. Because UNP, EXP, EXT, and REV are among the determinants of inflation dynamics, accurate forecasts of these variables enhance the general efficiency of the process of forecasting inflation. By delivering improved input data, SARIMA indirectly helps ANN perform better by ensuring inflation forecasting is done based on more accurate macroeconomic forecasting, thus strengthening the validity of this research study.

In comparison, Prophet performs worst among the models in question, and it does not produce the best forecast for any of the variables. Prophet is highly flexible and can handle non-standard time series. et, its relatively larger error rates point to a lack of suitability in identifying the structural patterns of macroeconomic variables, which tend to be erratic due to policy interventions and external shocks. This result indicates that Prophet may not be appropriate for forecasting extremely volatile and policy-sensitive indicators.

Further, this result serves to highlight a key methodological point: despite the flexibility afforded by more recent ML methods like LSTM and Prophet, older statistical models like SARIMA may prove superior in particular macroeconomic contexts. That SARIMA performs so well in this analysis serves to illustrate the value of choosing the most suitable methodology based on the particular features of the data available as opposed to preferring newer or more complex methods. By doing so, this emphasizes the value of a hybrid approach, where classical econometric models can complement ML algorithms in achieving optimum forecasting performance.

Among the variables, IPI and MSP are forecast with the least errors. This implies that these variables have relatively stable and consistent patterns that can be easily modeled using statistical techniques. IPI is driven to a great extent by manufacturing cycles and economic activity, which have recognizable trends, and MSP is influenced by monetary policy decisions, which follow a systematic framework, thus being predictable.

Conversely, EXT, REV, and WGH are associated with the largest forecasting errors. The finding reflects the inherent uncertainty and complexity of fiscal policy and labor market variables which are subject to discretionary policy changes, political shocks, and political influences. Unlike monetary variables, which tend to follow a more structured adjustment process, government budget items and the labor market can experience sudden shifts due to policy interventions, collective bargaining agreements, or unexpected fiscal adjustments. These factors make them more challenging to forecast accurately, highlighting the need for specialized modeling approaches when dealing with such volatile economic indicators.

5.2. Second Stage: Forecasting Inflation

In this foundational stage of the study, which reflects the primary objective, monthly inflation forecasts were generated using the most accurate independent variable forecasts identified in Table 2. Specifically, the models that produced the lowest MAPE for each independent variable were selected, and their forecasts were used as inputs for the ANN model.

This study employs normalized values for all input variables, as required by the ANN model to ensure optimal performance and numerical stability. Given that ANN operates more effectively when input data are scaled within a consistent range, normalization was applied to prevent any variable from disproportionately influencing the forecasting process. To maintain comparability and consistency across models, the same normalization procedure was extended to the SVR, GBM, and RF models, ensuring that differences in forecasting accuracy stem from the models' inherent predictive capabilities rather than disparities in data scaling. Additionally, all error metrics presented in Table 3 were computed using normalized values to preserve the validity and integrity of model comparisons.

Based on both actual (January 2005 – September 2023) and forecasted independent variables (October 2023 – December 2024), the ANN model produced inflation forecasts for October 2023 – December 2024. The resulting inflation forecasts, along with some key error statistics, are presented in the Table 3.

Table 3. Forecasting Results for Inflation

Period	ANN	RF	GBM	SVR	Actual
October 2023	4,16	3,93	2,42	5,10	3,43
November 2023	3,94	3,99	2,47	5,20	3,28
December 2023	3,73	4,26	2,42	4,68	2,93
January 2024	3,31	4,30	2,44	4,71	6,70
February 2024	3,17	4,05	2,23	4,23	4,53
March 2024	3,30	5,30	4,15	4,01	3,16
April 2024	3,07	5,17	2,47	3,83	3,18
May 2024	2,73	5,31	2,48	4,11	3,37
June 2024	2,83	5,29	2,47	3,46	1,64
July 2024	2,84	4,40	2,48	3,77	3,23
August 2024	2,52	3,99	2,48	3,58	2,47
September 2024	2,48	4,08	2,48	3,31	2,97
October 2024	2,34	3,97	2,49	3,19	2,88
November 2024	2,67	3,91	2,49	3,17	2,24
December 2024	2,68	3,75	2,14	3,04	1,03
MSE	0,39	0,95	0,58	0,48	-
MAE	4,46	8,68	5,43	6,01	-
MAPE	12,74	27,2	14,61	18,47	-
RMSE	6,21	9,77	7,61	6,91	-
MPE	-1,44	-23,2	6,34	-15,31	-

Table 3 presents a comparative analysis that indicates that ANN possesses the lowest error rates in all the most important performance metrics, demonstrating its superior ability to forecast inflation with greater accuracy. As a model that can learn complex and nonlinear relationships, ANN significantly outperforms traditional ML methods in generating accurate monthly inflation forecasts. With a MAPE of 12.74%, ANN makes the most precise forecasts, significantly reducing forecasting errors that have a tendency to hinder budget planning. This improved performance is due to ANN's ability to accurately represent complicated interdependencies between macroeconomic variables, allowing it to react to variations in economic conditions more effectively compared to conventional statistical techniques.

The high variation between ANN and other models is an indicator of its reliability in capturing inflationary dynamics with the least errors in forecasting. The short-term horizon of monthly inflation forecasting renders traditional models inadequate in responding to rapid movements caused by exchange rate fluctuations, changes in fiscal policy, or price shocks from individual industries. ANN's much lower rates of error indicate that it accurately integrates these volatile variables into its predictive model, making forecasts that more accurately depict actual inflation trends. The results in Table 3 suggest that ANN not only excels in overall precision but also is more stable over different time periods, minimizing extreme outliers present in other models. This stability is particularly valuable to budget forecasters, as even tiny variations in monthly inflation forecasts can compound over time to create astronomical fiscal mistakes.

The significantly higher error rates in the remaining models are an indication that the traditional ML methods have minimal efficacy when applied to inflation forecasting. On a notable note, the highest error rates are obtained from the RF model, with the highest MAPE and MSE of 27.2% and 0.95, respectively, which are extreme deviations from the truth. Likewise, SVR and GBM models are indicative of greater error compared to ANN, a pointer to the susceptibility of orthodox models to movements in multiple macroeconomic dimensions. These findings make the argument even stronger than traditional statistical as well as ML models in their failure to incorporate inflation determinant complexity as the explanation for their weaker forecasts.

On determinants of the inflation gap, the published error margins in Table 3 indicate that precision in forecasting inflation is highly sensitive to a combination of macroeconomic variables. Among the most prominent drivers of differences between forecasted and realized inflation are exchange rate volatility, public expenditure volatility, wage growth trends, and external trade deficits. In import-dependent economies, such as Türkiye, exchange rate volatility has a direct impact on inflation via import prices, widening the inflation gap. Similarly, surprise fiscal expansions or revenue shortfalls can exert upward pressure on inflation, reducing the forecasting accuracy of models.

Labor market conditions, namely employment and wage dynamics, also have a strong impact on the inflation gap. Growth in wages not accompanied by productivity growth can fuel cost-push inflation, generating forecast errors. ANN's lower rates of error mean that it is better able to capture the nonlinear relationship between these economic variables and hence it is a more reliable instrument for budget forecasters requiring accurate inflation forecasting.

Last, the findings in Table 3 highlight ANN's superior performance in forecasting inflation and its ability to more accurately model the determinants of the inflation gap. Accurate inflation forecasts are particularly crucial for budget forecasters, as inflation errors can undermine the credibility of public expenditure and revenue forecasts. The significantly lower error rates achieved by ANN suggest that its use in budget planning can lead to more informed and efficient fiscal decision-making.

5.3. Third Stage: Comparison of Forecasts

To measure how close the forecasts are, these must be compared to what is forecasted by the government and other institutions, typically on a year-to-year basis. For such a significant comparison, monthly forecasts from January to December 2024 obtained with the assistance of ANN added up to an annual forecast of inflation (39,75), thereby making them comparable to official statistics. This forecast was then compared to Türkiye's central government budget, Medium-Term Plan (MTP), Central Bank target, Central Bank Market Participant's Survey (MPS), IMF World Economic Outlook (WEO), OECD Economic Outlook (EO), and EU Economic Forecasts (EF).

Table 4. Comparison of Inflation Forecasts

Source	Forecast	Source	Forecast
2024 Budget	33	MTP 2023	13,8
Central Bank's Target	5	MPS September 2023	38,59
IMF WEO October 2023	62,50	OECD EO September 2023	39,20
EU EF November 2023	53,60	ANN Forecast	39,75
RF Forecast	68,79	GBM Forecast	35,49
SVR Forecast	54,61	Actual	44,38

Annual inflation forecasts in Table 4 are derived from the cumulative monthly forecasts of each model rather than simply adding the twelve monthly values. Using a cumulative method means that the annual forecast reflects the compounding aspect of inflation over time and provides a more accurate approximation of year-end inflation rates. By incorporating the interplay between adjacent months, such a method follows standard inflation forecasting practices used by financial institutions and policymakers. The forecasted inflation rates for the yearly periods hence offer a better benchmark against institutional and official forecasts.

A comparison of forecasts shows the ANN providing a 2024 inflation forecast of 39.75%, nearest to the OECD EO (39.20%) and the MPS (38.59%), although much higher than the government budget (33%) and the MTP (13.8%) forecast. The Central Bank target inflation (5%), as a longer-run policy objective than forecast over the near term, stands significantly lower than all other forecasts, indicating a divergence between policy goals and market forecasts.

Among the ML models, the ANN forecast is far closer to institutional forecasts compared to RF, GBM, and SVR. The RF model anticipates a 68.79% per annum inflation rate, which severely over-forecast actual inflationary trends, indicating its tendency to overfit short-term volatility. The GBM model (35.49%), on the other hand, under-forecast inflation compared to ANN but is still closer to market-based forecasts compared to RF. The SVR model (54.61%), while smaller than RF, still suggests a considerable deviation from actual inflation dynamics, demonstrating its limited potential in following long-run inflationary trends. Such divergences emphasize the superiority of ANN in making inflation forecasts that not only achieve greater accuracy but also follow more closely expert forecasts used in policy and budget planning.

The actual inflation rate of 44.38% for 2024 also confirms ANN's satisfactory performance because it remains within a correct margin of error from its forecast. Over-forecasting of RF's and SVR's and under-forecasting of GBM contrast with the issue of gaining sensitivity to economic shocks at the cost of long-run trend stability. ANN's ability to mimic inflation patterns with minimal errors relative to real inflation reasserts its reliability as a forecasting instrument, particularly for budget forecasters who require forecasts grounded on macroeconomic reality rather than statistical or policy assumptions.

5.4. Fourth Stage: Forecasting 2025

The study was not solely designed for retrospective analysis but also to serve as a foundation for future academic research. To facilitate long-term comparisons and enable forecasting beyond realized data, forecasts for 2025 were generated. Once actual data becomes available, these forecasts can be evaluated for accuracy, providing a valuable reference for subsequent studies. As in the previous period, both independent variable and inflation forecasts were produced. The forecasts for independent variables are presented in Appendix B, while the primary focus, inflation forecasts, is detailed in the Table 5.

Table 5. 2025 Inflation Forecasts

Period	ANN Forecast	Period	ANN Forecast
January 2025	2,39	July 2025	4,04
February 2025	1,89	August 2025	1,47
March 2025	3,66	September 2025	1,77
April 2025	2,44	October 2025	1,83
May 2025	4,96	November 2025	1,36
June 2025	1,21	December 2025	0,87
2025 Cumulative Annual ANN Forecast		31,63	

Based on the ANN model, monthly inflation in 2025 was forecasted to fluctuate between 0,87 and 4,04 percent, with an annual rate of 19,74 percent. This forecast aligns with expectations, particularly considering the tight policy measures currently in place in Türkiye, which may lead to such an outcome in 2025. The differing inflation forecasts for 2025, recently mentioned by the Ministry of Treasury and Finance, the Central Bank Governor, and the President, highlight the prevailing uncertainty surrounding economic conditions. In this context, the approach may be somewhat challenging. However, while the primary aim is to provide a realistic inflation forecast for 2024, the 2025 forecast serves as a reference point for future studies. By analyzing potential deviations, researchers can further explore factors contributing to forecast errors and enhance the budget forecasting process for policymakers in Türkiye.

6. Discussion

This study was motivated by a practical need; providing a workable inflation forecast to budget forecasters. Unlike micro-economists who may pursue highly technical inflation forecasts, the objective was to equip fiscal planners with a realistic inflation forecast that aligns with the budget preparation period. Thus, the approach was tailored not for theoretical accuracy but for applicability within the constraints faced by budget planners.

The empirical findings of this study align with prior research that identifies ANNs as a highly effective model for inflation forecasting, particularly in capturing complex, nonlinear relationships and adapting to macroeconomic volatility better than traditional econometric approaches (Choudhary and Haider, 2012; Haider and Hanif, 2008; Nakamura, 2005; Moshiri and Cameron, 2000; Barkan et al., 2023). ANN's ability to learn from data patterns without requiring strong parametric assumptions has been found to be one of its greatest strengths, enabling it to outperform conventional statistical models in the majority of economic applications. The improved forecasting ability of ANN in this study confirms these findings, particularly in the case of Türkiye, where inflation is highly sensitive to currency fluctuations, fiscal policy changes, and global economic conditions. By using these variables in its predictive model, ANN has proven to be a viable option as a more precise tool for inflation forecasting than other ML methods.

However, not all studies have named ANN the most precise forecasting method, as its performance could vary with the economic environment, data structure, and forecasting horizon. Sometimes econometric models have performed better with traditional econometric models that accurately captured time-dependent inflationary patterns, while others have worked better than ANN in terms of accuracy and stability (He et al., 2012; Almosova and Andresen, 2023; Araujo and Gaglianone, 2023; Ülke et al., 2018). These findings show that while ANN can offer considerable gains, its superior predictive abilities are not absolute, and its utilization needs to be properly assessed in light of some macroeconomic parameters as well as structures of data.

This study is superior to that in the literature which made fairly accurate forecasts using actual, observable independent variables. The technique used to construct the inflation forecast was grounded in all of the forecasted values of these independent variables. Thus, creating data that would realistically be available to those engaged in budgetary planning. This guarantees that the results are useful and designed for a particular purpose, which is budgetary planning, rather than achieving a perfect backward simulation based on past records. In developing a forecast based on expected values rather than measured outcomes, the study sought to replicate the inherent level of uncertainty that in reality, is always experienced by fiscal analysts.

In addition, the forecasts for 2025 were made by forecasting the independent variables as of that year and then forecasting inflation based on those variables. The purpose of this is that in the course of time, the model shall be evaluated using the forecast as well as its assessed performance as the basis of comparison and such advances will in turn help in improving the art of forecasting.

In the context of the wider literature, the findings contribute to the ongoing discussion on the efficacy of various forecasting methods for inflation and their subsequent impact on fiscal planning accuracy. While other studies have achieved high levels of accuracy through advanced ML techniques, their results often rely on realized data that would not yet be available during the budget preparation period. By contrast, this study’s approach, based on anticipated independent variables, highlights the trade-offs between forecasting accuracy and applicability, particularly in the context of the unpredictable economic climate in Türkiye.

The dataset and staged methodology further reinforce the study’s pragmatic design. By focusing on essential macroeconomic indicators, including the exchange rates, unemployment, exports, imports, expenditure, revenue, interest rate, wage growth, and production indexes, the study intentionally targeted variables that consistently appear in the preparation documents used by budget analysts in Türkiye. Each stage of the methodology was crafted to align with the real-world forecasting challenges faced by budget offices, bridging the gap between theoretical accuracy and practical utility. The comparative analysis revealed that the ANN model outperformed the government forecasts. The model produced results that are very close to real-world inflation values. This outcome confirms the ANN model's utility for budget planning under realistic data limitations.

Even though the findings of this study reconfirm the greater predictive ability of ANN, there is a need to acknowledge its strengths and weaknesses. The most important strength of ANN lies in its ability to capture complex, nonlinear relationships unhindered by pre-economic assumptions. This flexibility makes it possible for it to track inflationary patterns that would otherwise not be captured by traditional statistical models, and thus it proves to be particularly useful for economies that undergo frequent structural changes. Additionally, ANN is demonstrating greater flexibility to short-term economic shifts, allowing for more precise monthly inflation forecasts, which are critical for budget planning. Compared to the other ML models examined, ANN is more robust across different time horizons, with reduced susceptibility to extreme forecast errors.

That being noted, ANN also has its weaknesses. One of these is the fact that ANN is dependent upon large datasets and high computation, something that can be a burden for policymakers with limited access to high-frequency macroeconomic datasets. Another possible downpoint is ANN's low interpretability; while it performs well in making short-term foresight, it cannot be easily reverse-engineered or interpreted since every tweak in the weights and secret layers can turn out to be inscrutable. In contrast, traditional econometric models, while less accurate, are clearer and more theoretically coherent, and this might be desirable in certain policy contexts. Future research would need to explore the merging of ANN with hybrid approaches, accessing its predictive power while improving its explainability for practical policymaking applications.

7. Policy Recommendations

The research reveals the profound challenges the increasing inflation in Türkiye poses to fiscal planning as it derails revenue, tax, and expenditure forecasts among others. In the view of Kara (2024a), compounding the inflationary forecast errors in Türkiye, inflation affects the quality of budget forecasts. Empirical findings such as this demonstrate the necessity for the enhancements of inflation forecasting techniques as a safeguard for the viability of the budgetary process. To mitigate such challenges, it becomes imperative to identify and evaluate policy options that would improve forecasting and provide a buffer for fiscal planning against inflation risks. This part discusses risks posed by an inflationary environment on the fiscal planning process and suggests possible improvements in the forecasting processes to reduce such risks.

Practical Inflation Forecasts to Improve Budget Forecasting Precision: In forecasting inflation, the most important aspect is the forecasts that fund managers can realistically utilize within their budgeting timelines. Straightforward but credible forecasts of future inflation trends, such as the one generated by the ANN model, should take precedence over complex but sophisticated techniques. In this way, by constricting inflation forecasts to the relevant budget execution periods for budget analysts, fiscal institutions enhance the planning of revenue and expenditure.

Integrate Predictive Methods into Budget Forecasts to Reflect Real-World Constraints: Given that budget officers typically work with macro-level data rather than detailed microdata and often face a lag in the release of updated economic indicators, the use of forecasted values for inflation determinants should be institutionalized. This approach provides budget analysts with a model of inflation that aligns more closely with the aggregated data available during the preparation process. Implementing such practices will promote forecasts that not only meet academic standards but also address the practical needs of policy formulation.

Regularly Update and Improve the Core Data Set for Inflation Forecasting: To enhance the robustness of inflation forecasts, policymakers should prioritize the consistent collection of macroeconomic data that most influence inflation, such as exchange rates, unemployment, exports, imports, expenditure, revenue, interest rate, wage growth, production indexes. Ensuring that this core data set remains up-to-date and accessible is essential for effective inflation forecasting.

Emphasizing Mid-Term Forecasting Accuracy for Greater Budget Credibility: Mid-term forecasts are very important for economic stability and fiscal planning. Therefore, budget institutions should prioritize models like ANN, which evidenced greater accuracy throughout multiple forecasting periods. Greater mid-term forecasting accuracy will ensure that the general public and investors will show confidence in fiscal policies, especially in tumultuous economic conditions.

Encourage the Use of Real-Time Data to Enhance the Development and Training of the Forecasting Models: To complement the intrinsic uncertainties in budget planning, fiscal authorities should accept models with effective results over forecasted values rather than relying on actual data only. This adaptation would result in forecasts reflecting real-time uncertainties; hence, more practicable in budget planning under changed economic conditions.

Encourage the Union of Economists with Budgetary Policy Analysts for New Methodology Development: Policymakers should facilitate partnerships between economists specializing in advanced forecasting techniques and budget analysts. This collaboration can give rise to innovation in developing inflation forecasts specifically for fiscal planning. The emergence of hybrid models which would be a balance between practical application and methodological rigor could also emanate from such partnerships.

Establish Criteria for Fiscal Forecasting Models: With the introduction of an evaluation criterion that evaluates forecasting methods in relation to their usefulness in the process of budget development, and the degree of the current country's uncertainties, the fiscal policymakers will be able to appreciate the merits and demerits of any given model. This will also help the policymakers with added refinements in making their forecasts, resulting in better fiscal policies and cushioning budgets against shocks.

Improvement in the Integration of Multinational and Market-Based Inflation Forecasts into Budgetary Processes: Given the accuracy that has so far been established in inflation forecasts provided by multinational organizations like the OECD and those market-based, such as MPS, enhancing their integration into budgetary processes could raise the standard of inflation forecasts within fiscal policy. External forecasts often use more complex econometric techniques and the most detailed real-time data available and, in many cases, may provide better information than internal forecasts. By using these reliable external forecasts as benchmarks or supplements, budget analysts can leverage their predictive accuracy and achieve a more neutral view when budgetary assumptions are developed. With such high-caliber forecasts of inflation embedded consistently, budget offices should be able to enhance their forecasting frameworks and thus have more accurate budgetary anticipations, de facto tracking global economic patterns and market influences.

Embrace Uncertainty Projection for Budgetary Policy: Given the study's focus on the significance of forecasting with the pregnancy of some degree of uncertainty about the future, it is apparent that the intention is to act as a proxy of a real-life fiscal problem. In this context, fiscal institutions are suggested to incorporate predictive uncertainty as a form of strategy, and as a way to test the robustness of their budgets as well as prepare for any eventual fiscal slippage.

The recommendations hereinafter are aimed at helping fiscal policymakers and budget analysts to produce inflation forecasts that meet both the technical requirements and those specific demands imposed by the very process of practical budget preparation. In closer associating inflation forecasting methods with the needs of budget preparation, Türkiye can further enhance its fiscal frameworks and increase coherence in economic policy.

8. Conclusion

The critical role of inflation forecasting accuracy in attaining realistic budget revenue and expenditure forecasts was emphasized in this study. Government budgets play an indispensable role in ensuring economic stability and the sustainability of public spending, together with fiscal balance. Errors in inflation forecasts can undermine these objectives directly. A mis-forecasting of inflation certainly results in less reliable budget forecasts, which affect the efficiency of public expenditure, the accuracy of revenue forecasts, and the attainment of fiscal targets. In other words, proper inflation forecasting is of the essence in the budgetary planning process of the public sector.

In this context, an ANN model has been developed with the purpose of obtaining more realistic inflation forecasts. To begin with, eleven independent variables that underpin the inflation forecasts were forecasted. This was followed by the forecasting of inflation itself with the ANN, SVR, GBM, and RF models based on those variables. The forecasts are then compared with the forecasts made by the government and international organizations. Results showed that the ANN model's forecasts were better than the other forecasts.

These results are very useful to guide public institutions and budget preparers. They assist those seeking more realistic inflation forecasts in budget forecasting. The proposed methodology offers an alternative to improve forecast accuracy. It also serves as a useful reference for academic studies examining inflation's impact on public budgets. In high-inflation contexts like Türkiye, this approach could help achieve more reliable forecasts.

In conclusion, this study highlights the central role of inflation in budget forecasting. It demonstrates that ANN can achieve greater forecasting accuracy than traditional methods. This approach could help develop more realistic inflation forecasts. Such improvements would benefit both public budget planning and academic research.

Despite the strong empirical findings, this study has certain limitations that should be acknowledged. Initially, while the ANN model reveals better forecasting performance, its effectiveness relies on input data availability and quality. Errors or biases in the forecasted independent variables have the potential of spilling over into the terminal inflation forecasts with the possibility of affecting reliability. Second, even while the study has a severe approach, reliance upon historical macro relationships is grounded upon the hypothesis of continuity in existing trends, and this may not always be present in the context of unanticipated economic crises or structural adjustments. Third, the black-box nature of ANN models represents a limitation on interpretation and, therefore, limits their immediate direct applicability for policy arguments, compared to classical econometric ones that give a clearer theoretical conceptualization.

Future research needs to explore hybrid approaches that blend ANN with more explainable models for the purpose of enhancing transparency and usability in policymaking environments. Furthermore, the incorporation of real-time macroeconomic and high-frequency financial data could make forecasting more effective by enabling models to better adapt to shifting economic patterns in real-time. Broadening the analysis to various countries with disparate inflation patterns would also provide significant insights into how ANN's forecast capability can be applied.

Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate Statement
The authors declare that they have contributed equally to the article.

Declaration of Researcher's Conflict of Interest
There are no potential conflicts of interest in this study.

References

Allan, C.M. (1965). Fiscal marksmanship, 1951-1963. *Oxford Economic Papers*, 17(2), 317-327. https://doi.org/10.1093/oxfordjournals.oep.a040992

Almosova, A. and Andresen, N. (2023). Nonlinear inflation forecasting with recurrent neural networks. *Journal of Forecasting*, 44(2), 240-259. doi:10.1002/for.2901

Araujo, G.S. and Gaglianone, W.P. (2023). Machine learning methods for inflation forecasting in Brazil: New contenders versus classical models. *Latin American Journal of Central Banking*, 4(2), 100087. doi:10.1016/j.latcb.2023.100087

Atkeson, A. and Ohanian, L. (2001). Are Phillips Curves useful for forecasting inflation? *Federal Reserve Bank of Minneapolis Quarterly Review*, 25(1), 2–11. Retrieved from https://citeseerx.ist.psu.edu/

Barkan, O., Benchimol, J., Caspi, I., Cohen, E., Hammer, A. and Koenigstein, N. (2023). Forecasting CPI inflation components with hierarchical recurrent neural networks. *International Journal of Forecasting*, 39(3), 145-1162. doi:10.1016/j.ijforecast.2022.04.009

Bayramoğlu, A.T. and Öztürk, Z. (2017). ARIMA ve Gri sistem modelleri ile enflasyon tahmini. *İnsan ve Toplum Bilimleri Araştırmaları Dergisi*, 6(2), 760-776. doi:10.15869/itobiad.300059

Bokil, M. and Schimmelpfennig, A. (2005). *Three attempts at inflation forecasting in Pakistan* (IMF Working Paper No. 05/105). Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=887974

Bos, C.S., Franses, P.H. and Ooms, M. (2002). Inflation, forecast interval,s and long memory regression models. *International Journal of Forecasting*, 18(2), 243-264. doi:10.1016/S0169-2070(01)00156-X

Breiman, L. (2001) Random forests. *Machine Learning*, 45, 5–32. https://doi.org/10.1023/A:1010933404324

Bretschneider, S. and Gorr, W.L. (1992). Economic, organizational, and political influences on biases in forecasting state sales tax receipts. *International Journal of Forecasting*, 7(4), 457-466. doi:10.1016/0169-2070(92)90029-9

Čaklovica, L. and Efendic, A. (2020). Determinants of inflation in Europe – A dynamic panel analysis. *Financial Internet Quarterly*, 16(3), 51-79. doi:10.2478/fiqf-2020-0018

Choudhary, M.A. and Haider, A. (2012). Neural network models for inflation forecasting: An appraisal. *Applied Economics*, 44(20), 2631–2635. doi:10.1080/00036846.2011.566190

Deniz, P., Tekce, M. and Yilmaz, A. (2016). Investigating the determinants of inflation: A panel data analysis. *International Journal of Financial Research*, 7(2), 233-246. doi:10.5430/ijfr.v7n2p233

Doguwa, S.I. and Alade, S. (2013). Short-term inflation forecasting models for Nigeria. *CBN Journal of Applied Statistics*, 4(3), 1-29. Retrieved from https://www.econstor.eu/

Drucker, H., Burges, C.J., Kaufman, L., Smola, A. and Vapnik, V. (1997). Support vector regression machines. In M.C. Mozer, M. Jordan and T. Petsche (Eds.), *Advances in neural information processing systems 9* (pp. 155-161). Paper presented at the NIPS 1996. Retrieved from https://papers.nips.cc/paper_files/paper/1996

Erilli, N.A., Körez, M., Öner, Y. and Alakuş, K. (2012). Kritik kriz dönem enflasyon hesaplamalarında bulanık regresyon tahminlemesi. *Doğuş Üniversitesi Dergisi*, 13(2), 239-253. Retrieved from https://dergipark.org.tr/tr/pub/doujournal/

Erişoğlu, Ü. and Erişoğlu, M. (2022). Holt-Winters üstel düzleştirme yöntemi ile finansal gelişmişlik endeksinin tahmini. A. Akpınar and A. Güler (Eds.), *Fen ve matematik bilimlerinde güncel yaklaşımlar* içinde (s. 107-123). Lyon: Livre de Lyon.

Faust, J. and Wright, J. (2013). Forecasting inflation. In G. Elliott, and A. Timmermann (Eds.), *Handbook of economic forecasting* (pp. 2-56). Amsterdam: Elsevier.

Friedman, J.H. (2001). Greedy function approximation: A gradient boosting machine. *The Annals of Statistics*, 29(5), 1189–1232. doi:10.1214/aos/1013203451

Garcia, M.G., Medeiros, M. and Vasconcelos, G. (2017). Real-time inflation forecasting with high-dimensional models: The case of Brazil. *International Journal of Forecasting*, 33(3), 679-693. doi:10.1016/j.ijforecast.2017.02.002

Gil-Alana, L., Moreno, A. and de Gracia, F.P. (2012). Exploring survey-based inflation forecasts. *Journal of Forecasting*, 31(6), 524-539. doi:10.1002/for.1235

Groen, J.J., Paap, R. and Ravazzolo, F. (2013). Real-time inflation forecasting in a changing world. *Journal of Business & Economic Statistics*, 31(1), 29-44. doi:10.1080/07350015.2012.727718

Haider, A. and Hanif, M.N. (2008). Inflation forecasting in Pakistan using artificial neural networks. *Pakistan Economic and Social Review*, 47(1), 123-138. Retrieved from https://www.jstor.org/

Hanif, M.N. and Malik, J.M. (2015). Evaluating the performance of inflation forecasting models of Pakistan. SBP Research Bulletin, 11(1), 43-78. Retrieved from https://www.sbp.org.pk/

Hansen, P., Lunde, A. and Nason, J. (2011). The model confidence set. *Econometrica*, 79(2), 453-497. https://doi.org/10.3982/ECTA5771

Hauzenberger, N., Huber, F. and Klieber, K. (2023). Real-time inflation forecasting using non-linear dimension reduction techniques. *International Journal of Forecasting*, 39(2), 901-921. doi:10.1016/j.ijforecast.2022.03.002

Haykin, S. (1998). *Neural networks: A comprehensive foundation*. New Jersey: Prentice Hall PTR.

He, Q., Shen, H. and Tong, Z. (2012). Investigation of Inflation Forecasting. *Applied Mathematics & Information Sciences*, 6(3), 649-655. Retrieved from https://digitalcommons.aaru.edu.jo/

Holt, C.C. (2004). Forecasting seasonals and trends by exponentially weighted moving averages. *International Journal of Forecasting*, 20(1), 5-10. doi:10.1016/j.ijforecast.2003.09.015

Inoue, A. and Kilian, L. (2008). How useful is bagging in forecasting economic time series? A case study of U.S. consumer price inflation. *Journal of the American Statistical Association*, 103(482), 511-522. doi:10.1198/016214507000000473

Jain, A.K., Mao, J. and Mohiuddin, K.M. (1996). Artificial neural networks: A tutorial. *Computer*, 29(3), 31-44. Retrieved from https://ieeexplore.ieee.org/

Jakšić, S. (202Modelingling determinants of inflation in CESEE countries: Global vector autoregressive approach. *Review of Economic Perspectives*, 22(2), 137-169. doi:10.2478/revecp-2022-0007

Jenkins, G. and Box, G. (1976). *Time series analysis: Forecasting and control*. San Francisco: Holden Hay.

Kapur, M. (2013). Revisiting the Phillips Curve for India and inflation forecasting. J*ournal of Asian Economics*, 25, 17-27. doi:10.1016/j.asieco.2012.12.002

Kara, B. (2024a). *Türkiye'de kamu bütçesi tahminlerinin gerçekliği*. Ankara: Gazi Kitabevi.

Kara, B. (2024b). The impact of budget revenue and expenditure forecasting errors on inflation in Turkey: An analysis of the 1975-2021 period. *İstatistik ve Uygulamalı Bilimler Dergisi,* 9, 19-28. doi:10.52693/jsas.1417919

Kayran, G. and Uzun Araz, Ö. (2023). Toplu taşıma yolcu talebinin SARIMA ve Prophet yöntemleri ile tahmini. *Journal of Industrial Engineering (Turkish Chamber of Mechanical Engineers)*, 34(3), 334-356. doi:10.46465/endustrimuhendisligi.1281645

Kızılkaya, O. (2017). Türkiye'nin enflasyon ve işsizlik oranının yapay sinir ağları ve Box-Jenkins yöntemiyle tahmini. *Social Sciences Studies Journal*, 3(12), 2197-2207. doi:10.26449/sssj.299

Kinlaw, W., Kritzman, M., Metcalfe, M. and Turkington, D. (2023). The determinants of inflation. *Journal of Investment Management*, 21(3), 29-41. doi:10.2139/ssrn.4137861

Krenker, A., Bešter, J. and Kos, A. (2011). Introduction to the artificial neural networks. In K. Suzuki (Ed.), *Artificial neural networks-methodological advances and biomedical applications* (pp. 1-18). India: InTech.

Lim, Y.C. and Sek, S.K. (2015). An examination on the determinants of inflation. *Journal of Economics, Business and Management*, 3(7), 678-682. doi:10.7763/JOEBM.2015.V3.265

Malki, A., Atlam, E.-S., Hassanien, A., Ewis, A., Dagnew, G. and Gad, I. (2022). SARIMA model-based forecasting required number of COVID-19 vaccines globally and empirical analysis of peoples' view towards the vaccines. *Alexandria Engineering Journal*, 61(12), 12091-12110. https://doi.org/10.1016/j.aej.2022.05.051

Martins, M.M. and Verona, F. (2023). Inflation dynamics in the frequency domain. *Economics Letters*, 231, 111304. doi:10.1016/j.econlet.2023.111304

McKnight, S., Mihailov, A. and Rumler, F. (2020). Inflation forecasting using the New Keynesian Phillips Curve with a time-varying trend. *Economic Modelling*, 87, 383-393. doi:10.1016/j.econmod.2019.08.011

Meçik, O. and Karabacak, M. (2011). ARIMA modelleri ile enflasyon tahminlemesi: Türkiye uygulaması. *Sosyal Ekonomik Araştırmalar Dergisi*, 11(22), 177-198. Retrieved from https://dergipark.org.tr/en/pub/susead/

Medeiros, M.C., Vasconcelos, G.F., Veiga, Á. and Zilberman, E. (2021). Forecasting inflation in a data-rich environment: The benefits of machine learning methods. *Journal of Business & Economic Statistics,* 39(1), 98-119. doi:10.1080/07350015.2019.1637745

Moser, G., Rumler, F. and Scharler, J. (2007). Forecasting Austrian inflation. *Economic Modelling*, 24(3), 470–480. doi:10.1016/j.econmod.2006.10.003

Moshiri, S. and Cameron, N. (2000). Neural network versus econometric Models in forecasting inflation. *Journal of Forecasting*, 19(3), 201-217. https://doi.org/10.1002/(SICI)1099-131X(200004)19:3<201::AID-FOR753>3.0.CO;2-4

Nakamura, E. (2005). Inflation forecasting using a neural network. *Economics Letters*, 86(3), 373 – 378. doi:10.1016/j.econlet.2004.09.003

Nas, S., Akboz Caner, A. and Ergin Ünal, A. (2024). Türkiye'de enflasyon oranlarının makine öğrenme yöntemi ile tahmini. *Gaziantep University Journal of Social Sciences*, 23(3), 1029-1045. doi:10.21547/jss.1371005

Öğünç, F., Akdoğan, K., Başer, S., Gülenay Chadwick, M., Ertuğ, D., Hülagü, T., . . . Tekatlı, N. (2013). Short-term inflation forecasting models for Turkey and a forecast combination analysis. *Economic Modelling*, 33, 312-325. doi:10.1016/j.econmod.2013.04.001

Özgür, Ö. and Akkoç, U. (2022). Inflation forecasting in an emerging economy: Selecting variables with machine learning algorithms. *International Journal of Emerging Markets*, 17(8), 1889-1908. doi:10.1108/IJOEM-05-2020-0577

Öztemel, E. (2003). *Yapay sinir ağları*. İstanbul: Papatya Yayıncılık.

Sbrana, G., Silvestrini, A. and Venditti, F. (2017). Short-term inflation forecasting: The M.E.T.A. approach. *International Journal of Forecasting*, 33(4), 1065-1081. doi:10.1016/j.ijforecast.2017.06.007

Siami-Naimi, S., Tavakoli, N. and Namin, A. (2019). *The performance of LSTM and BiLSTM in forecasting time series*. Papers presented at the 2019 IEEE International Conference on Big Data. Retrieved from https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9005997

Song, X., Liu, Y., Xue, L., Wang, J., Zhang, J., Wang, J., . . . Cheng, Z. (2020). Time-series well performance prediction based on long short-term memory (LSTM) neural network model. *Journal of Petroleum Science and Engineering*, 186, 106682. https://doi.org/10.1016/j.petrol.2019.106682

Stock, J.H. and Watson, M.W. (1999). Forecasting inflation. *Journal of Monetary Economics*, 44(2), 293-335. doi:10.1016/S0304-3932(99)00027-6

Stock, J.H. and Watson, M.W. (2003). Forecasting output and inflation: The role of asset prices. *Journal of Economic Literature*, 41(3), 788–829. doi:10.1257/002205103322436197

Stock, J.H. and Watson, M.W. (2004). Combination forecasts of output growth in a seven country dataset. *Journal of Forecasting*, 23(6), 405-430. doi:10.1002/for.928

Stock, J.H. and Watson, M.W. (2007). Why has U.S. inflation become harder to forecast? *Journal of Money, Credit and Banking*, 39, 3-33. https://doi.org/10.1111/j.1538-4616.2007.00014.x

Stock, J.H. and Watson, M.W. (2008). *Phillips Curve inflation forecasts* (Working Paper No. 14322). Retrieved from https://www.nber.org/system/files/working_papers/w14322/w14322.pdf

Tang, Y. and Zhou, J. (2015). *The Performance of PSO-SVM in Inflation Forecasting*. Papers presented at the 12th International Conference on Service Systems and Service Management. Retrieved from https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=7170251

Taylor, S.J. and Letham, B. (2018). Forecasting at scale. *The American Statistician*, 72(1), 37-45. https://doi.org/10.1080/00031305.2017.1380080

Theoharidis, A.F., Guillén, D.A. and Lopes, H. (2023). Deep learning models for inflation forecasting. *Applied Stochastic Models in Business and Industry*, 39(3), 447-470. doi:10.1002/asmb.2757

Ülke, V., Sahin, A. and Subasi, A. (2018). A comparison of time series and machine learning models for inflation forecasting: Empirical evidence from the USA. *Neural Computing and Applications*, 30, 1519–1527. doi:10.1007/s00521-016-2766-x

Winters, P.R. (1960). Forecasting Sales by Exponentially Weighted Moving Averages. *Management Science*, 6(3), 324–342. https://doi.org/10.1002/for.1088

Wright, J.H. (2009). Forecasting US inflation by Bayesian model averaging. *Journal of Forecasting*, 28(2), 131-144. doi:10.1002/for.1088

Yadav, A., Jha, C. and Sharan, A. (2020). Optimizing LSTM for time series prediction in Indian stock market. *Procedia Computer Science*, 167, 2091-2100. https://doi.org/10.1016/j.procs.2020.03.257

Zakaria, M., Al-Shebany, M. and Sarhan, S. (2014). Artificial neural network: A brief overview. *Journal of Engineering Research and Applications*, 4(2), 7-12. Retrieved from www.ijera.com

Appendix A: October 2023 – December 2024 Forecasts for Independent Variables

Table A.1. Forecasts for Unemployment

	Holt-Winters	LSTM	Prophet	SARIMA	Hybrid	Actual
October 2023	9,1	9,3	11,3	8,9	9,6	8,2
November 2023	9,1	9,6	11,9	8,9	9,9	8,8
December 2023	9,7	9,9	12,8	9,4	10,4	8,9
January 2024	10,4	10,1	12,6	9,9	10,8	9
February 2024	10,6	10,3	12,0	9,9	10,7	8,7
March 2024	10,0	10,4	11,2	9,3	10,2	8,6
April 2024	9,3	10,5	10,4	8,8	9,7	8,6
May 2024	8,6	10,5	10,5	8,1	9,4	8,5
June 2024	8,6	10,5	11,2	8,0	9,6	9,2
July 2024	9,5	10,6	11,0	9,0	10,0	8,8
August 2024	9,0	10,6	11,2	8,5	9,8	8,6
September 2024	9,0	10,7	11,3	8,3	9,8	8,6
October 2024	9,1	10,8	11,3	8,3	9,9	8,7
November 2024	9,1	10,9	12,0	8,3	10,0	8,6
December 2024	9,7	10,9	12,8	8,8	10,6	8,5

Table A.2. Forecasts for Exchange Rate Basket

	Holt-Winters	LSTM	Prophet	ARIMA	Hybrid	Actual
October 2023	28,71	35,24	22,63	28,42	28,75	28,62
November 2023	29,50	37,14	23,77	29,08	29,87	29,76
December 2023	30,28	39,32	24,67	29,72	31,00	30,39
January 2024	31,06	41,66	25,21	30,36	32,07	31,45
February 2024	31,85	44,07	24,80	31,00	32,93	32,00
March 2024	32,63	46,49	25,02	31,64	33,95	33,41
April 2024	33,41	48,87	25,28	32,29	34,96	33,52
May 2024	34,20	51,16	26,13	32,93	36,10	33,54
June 2024	34,98	53,31	26,95	33,57	37,20	33,80
July 2024	35,76	55,29	27,42	34,21	38,17	34,27
August 2024	36,55	57,10	27,74	34,86	39,06	35,27
September 2024	37,33	58,71	27,06	35,50	39,65	35,87
October 2024	38,11	60,14	27,64	36,14	40,51	35,79
November 2024	38,90	61,39	28,43	36,78	41,38	35,50
December 2024	39,68	62,48	29,04	37,43	42,16	35,77

Table A.3. Forecasts for Export

	Holt-Winters	LSTM	Prophet	SARIMA	Hybrid	Actual
October 2023	21986	21813	22246	22073	22029	22367
November 2023	21882	22498	22146	22135	22165	22437
December 2023	21833	23505	22162	22366	22466	22614
January 2024	19656	20932	20493	20250	20333	20001
February 2024	20539	20673	21212	20747	20793	21091
March 2024	22498	24565	22966	23003	23258	22651
April 2024	21012	21217	21779	21340	21337	19295
May 2024	21030	22984	21932	21587	21883	24173
June 2024	21652	22229	22873	21777	22133	19016
July 2024	21110	21637	22183	21231	21540	22479
August 2024	21389	23246	21914	21499	22012	22007
September 2024	22479	23826	23089	22521	22979	21974
October 2024	22742	23962	23408	22982	23273	23485
November 2024	22638	24833	23583	22992	23511	22289
December 2024	22589	25918	23785	23097	23847	23463

Table A.4. Forecasts for Import

	Holt-Winters	LSTM	Prophet	SARIMA	Hybrid	Actual
October 2023	26320	24168	28307	26014	26202	27292
November 2023	27660	23341	28630	26185	26454	26849
December 2023	28897	22381	30104	27799	27295	27260
January 2024	26762	21531	28082	26414	25697	26187
February 2024	25699	20851	27873	25782	25051	27857
March 2024	27859	20440	30501	27638	26609	29952
April 2024	26269	20294	29426	26117	25527	29185
May 2024	28196	20247	30280	27951	26668	30649
June 2024	27359	20336	30973	26166	26209	24905
July 2024	29160	20354	30661	27787	26991	29783
August 2024	28622	20465	30377	26811	26568	27007
September 2024	29078	20453	30955	26487	26743	27116
October 2024	28443	20417	30386	26298	26386	29410
November 2024	29783	20389	31215	26800	27047	29748
December 2024	31020	20333	32499	28133	27996	32287

Table A.5. Forecasts for Government Budget Expenditure

	Holt-Winters	LSTM	Prophet	ARIMA	Hybrid	Actual
Oct. 2023	534435100	570482438	64749301	580072200	437434760	569210857
Nov. 2023	561878400	599218084	477133412	596213000	558610724	671182985
Dec. 2023	838667000	626707811	563404490	653732300	670627900	1392476506
Jan. 2024	648463100	663708335	617969071	632991400	640782977	767968295
Feb. 2024	711633700	684223762	355219372	699671100	612686983	689904673
Mar. 2024	722908300	712641677	394781158	693861800	631048234	692807231
Apr. 2024	757312800	733913904	416844138	747737900	663952186	773642510
May 2024	742003600	763071641	470540833	749309400	681231368	787727639
June 2024	759930900	785513766	407512613	808779500	690434195	866498264
July 2024	886065600	806153865	663823811	807877000	790980069	827705758
Aug. 2024	893324000	822347206	653074403	871478700	810056077	820314488
Sep. 2024	936636400	843946003	254487394	874076800	727286649	932067951
Oct. 2024	867425300	855964029	227838976	938301000	722382326	955478385
Nov. 2024	894687400	879433158	572928043	944659800	822927100	956105370
Dec. 2024	1312056000	901274246	542843451	1011528000	941925424	1706788225

Table A.6. Forecasts for Government Budget Revenue

	Holt-Winters	LSTM	Prophet	ARIMA	Hybrid	Actual
Oct. 2023	430261215	450089931	301063800	557930486	434836358	473750122
Nov. 2023	588076812	459091729	339884200	624104913	502789414	746809887
Dec. 2023	576142358	468273564	245357700	560344524	462529537	549944707
Jan. 2024	546288126	477639035	352157000	633809184	502473336	617249000
Feb. 2024	612941091	487191816	359189000	625179246	521125288	536107000
Mar. 2024	621409688	496935652	333700400	637573722	522404865	483842000
Apr. 2024	696980716	506874365	328230100	649321381	545351641	595813000
May 2024	883136833	517011853	576645400	823383160	700044311	1007136000
June 2024	777925665	527352090	348008400	675429806	582178990	591218000
July 2024	797975080	537899132	490253900	804554408	657670630	730930000
Aug. 2024	1113640519	548657114	634712500	901351261	799590349	690720000
Sep. 2024	799036092	559630256	450536900	806450065	653913328	831603497
Oct. 2024	868545629	570822862	378897200	877472089	673934445	769207199
Nov. 2024	1187119654	582239319	419241300	961009752	787402506	939459855
Dec. 2024	1163028201	593884105	298970400	917385410	743317029	877577463

Table A.7. Forecasts for Overnight Interest Rate

	Holt-Winters	LSTM	Prophet	SARIMA	Hybrid	Actual
October 2023	35,3	20,5	16,8	34,3	26,7	36,5
November 2023	38,8	22,1	16,3	37,1	28,6	41,5
December 2023	41,7	22,4	18	39,4	30,4	44
January 2024	44,1	22	17,5	41,5	31,3	46,5
February 2024	45,8	21,2	17,2	42,9	31,8	46,5
March 2024	47,2	20	17,9	44,3	32,4	53
April 2024	48,3	18,5	17,2	45,4	32,3	53
May 2024	49,2	17	16,3	46,3	32,2	53
June 2024	50,8	15,5	18,4	48,4	33,3	53
July 2024	51,6	14	18,4	49,3	33,3	53
August 2024	52,4	12,7	18,3	50,6	33,5	53
September 2024	53,1	11,5	18,4	51,8	33,7	53
October 2024	53,3	10,7	18,5	52,1	33,6	53
November 2024	53,6	10	18,9	52,7	33,8	53
December 2024	53,8	9,4	17,8	53,3	33,6	49

Table A.8. Forecasts for Industrial Production Index

	Holt-Winters	LSTM	Prophet	SARIMA	Hybrid	Actual
October 2023	108,11	105,44	112,81	107,30	108,41	106,90
November 2023	108,74	105,71	114,25	106,68	108,84	105,07
December 2023	109,28	105,94	113,64	106,68	108,88	107,28
January 2024	109,45	106,06	109,66	107,13	108,07	107,82
February 2024	109,72	106,07	111,56	105,96	108,33	110,45
March 2024	110,06	106,37	115,39	106,78	109,65	110,10
April 2024	108,47	106,34	114,79	106,60	109,05	104,63
May 2024	109,82	106,30	114,17	106,55	109,21	106,78
June 2024	111,09	106,20	115,16	106,22	109,67	104,28
July 2024	111,04	106,01	115,88	107,42	110,09	104,75
August 2024	112,36	105,86	116,24	106,66	110,28	103,11
September 2024	112,40	105,76	117,50	107,10	110,69	104,83
October 2024	112,93	105,68	118,45	106,52	110,89	103,98
November 2024	113,60	105,69	119,42	106,58	111,32	106,98
December 2024	114,15	105,68	119,38	106,36	111,39	112,34

Table A.9. Forecasts for Money Supply

	Holt-Winters	LSTM	Prophet	ARIMA	Hybrid	Actual
Oct. 2023	13187068605	12660259840	11315669401	13150388790	12578346659	13097974238
Nov. 2023	13733000074	13093295104	11752794069	13658437178	13059381606	13388504649
Dec. 2023	14302542507	13485339648	12532681133	14185019335	13626395656	14032110771
Jan. 2024	14896759050	13862022144	12807871693	14730769333	14074355555	14170572337
Feb. 2024	15516762547	14206865408	13319003640	15296341404	14584743250	14588406812
Mar. 2024	16163717947	14545294336	13721976445	15882410529	15078349814	14983979333
Apr. 2024	16838844827	14867467264	14260292507	16489673047	15614069411	15258074085
May 2024	17543420052	15149976576	14803532627	17118847268	16153944131	15763121325
June 2024	18278780552	15395716096	15335644304	17770674117	16695203767	16325989816
July 2024	19046326257	15667662848	15839022591	18445917779	17249732369	16989587529
Aug. 2024	19847523165	15799282688	16230129872	19145366374	17755575525	17675451244
Sep. 2024	20683906572	15895826432	16786991028	19869832642	18309139168	18037952952
Oct. 2024	21557084464	15980609536	17463790136	20620154649	18905409696	18490024940
Nov. 2024	22468741079	16324576256	17935801533	21397196508	19531578844	18871576626
Dec. 2024	23420640653	16643947520	19105243273	22201849123	20342920142	19499570053

Table A.10. Forecasts for General Price Index

	Holt-Winters	LSTM	Prophet	ARIMA	Hybrid	Actual
Oct. 2023	806680606	799744495	694266928	804296275	776247076	796787500
Nov. 2023	842670963	831018342	719826072	838382514	807974473	820206931
Dec. 2023	878661321	863515146	745456284	872468754	840025376	839128458
Jan. 2024	914651678	897282731	772899942	906554993	872847336	878460269
Feb. 2024	950642036	932370790	801353927	940641233	906251996	919256515
Mar. 2024	986632393	968830961	828919755	974727472	939777646	953993097
Apr. 2024	1022622751	1006716899	859436086	1008813712	974397362	1000407747
May 2024	1058613108	1046084360	890037269	1042899951	1009408672	1026356315
June 2024	1094603466	1086991277	922803615	1076986191	1045346137	1065901125
July 2024	1130593823	1129497851	955661070	1111072430	1081706294	1076998143
Aug. 2024	1166584181	1173666635	990843328	1145158670	1119063204	1087528686
Sep. 2024	1202574539	1219562631	1027320806	1179244910	1157175721	1138266482
Oct. 2024	1238564896	1267253381	1063899713	1213331149	1195762285	1139987269
Nov. 2024	1274555254	1316809068	1103066731	1247417389	1235462110	1170582455
Dec. 2024	1310545611	1368302620	1142342656	1281503628	1275673629	1180170768

Table A.11. Forecasts for Wage Growth

	Holt-Winters	LSTM	Prophet	ARIMA	Hybrid	Actual
October 2023	12016	10997,77	7452,96	11429,12	10473,96	11402,32
November 2023	12016	10997,77	7452,96	11429,12	10473,96	11402,32
December 2023	12016	10997,77	7452,96	11429,12	10473,96	11402,32
January 2024	13805,91	13395,36	8672,48	14260,80	12533,64	17002,12
February 2024	13805,91	13395,36	8672,48	14260,80	12533,64	17002,12
March 2024	13805,91	13395,36	8672,48	14260,80	12533,64	17002,12
April 2024	13805,91	13395,36	8672,48	14260,80	12533,64	17002,12
May 2024	13805,91	13395,36	8672,48	14260,80	12533,64	17002,12
June 2024	13805,91	13395,36	8672,48	14260,80	12533,64	17002,12
July 2024	13805,91	13395,36	8672,48	14260,80	12533,64	17002,12
August 2024	13805,91	13395,36	8672,48	14260,80	12533,64	17002,12
September 2024	13805,91	13395,36	8672,48	14260,80	12533,64	17002,12
October 2024	13805,91	13395,36	8672,48	14260,80	12533,64	17002,12
November 2024	13805,91	13395,36	8672,48	14260,80	12533,64	17002,12
December 2024	13805,91	13395,36	8672,48	14260,80	12533,64	17002,12

Appendix B: 2025 Forecasts for Independent Variables

Table B1. 2025 Forecasts for Independent Variables

	UNP	BSK	INT	GPI	IPI	WGH
Jan.	9,3	38,27	51,92	1190841385	103,24	21513,4
Feb.	9,4	38,90	51,33	1215440467	102,94	21513,4
Mar.	8,9	39,53	51,21	1244128209	102,60	21513,4
Apr.	8,4	40,15	50,70	1270991487	102,30	21513,4
May	8,0	40,78	50,26	1296710793	102,11	21513,4
June	8,1	41,41	50,66	1322696126	101,88	21513,4
July	8,5	42,04	50,53	1350042999	101,69	21513,4
Aug.	8,4	42,67	50,46	1376146855	101,49	21513,4
Sep.	8,2	43,30	50,44	1404879998	101,32	21513,4
Oct.	7,8	43,93	50,08	1428539693	101,11	21513,4
Nov.	8,1	44,56	49,89	1455637937	100,93	21513,4
Dec.	8,5	45,19	49,57	1483565084	100,75	21513,4

	EXP	IMP	EXT	REV	M3
Jan.	22049	27793	1162263618	868378087	20410235000
Feb.	23194	27121	1199726070	758235606	21131872500
Mar.	23772	29006	1235464261	923917646	21662997500
Apr.	21866	27438	1270269315	786268879	22499997500
May	23049	29171	1304517737	945020033	23311782500
June	21808	27549	1338463127	829378090	24240452500
July	23683	30275	1372242096	979055404	25127970000
Aug.	22298	29293	1405927471	854813494	26028495000
Sep.	24057	29483	1439560873	1015620656	26975942500
Oct.	25951	29554	1473165468	890088679	28108967500
Nov.	25447	30524	1506754023	1044503636	29173515000
Dec.	25030	31754	1540333657	923743754	30407545000