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Forecasting inflation in Turkey: A comparison of time-series and machine learning models

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Abstract

Purpose — This paper aims to analyze inflation in Turkey. For this purpose, the accuracy of some Machine Learning (ML) models in forecasting inflation have been tested a new and complementary approach has been tried to be given to time series models.

Methods — This paper forecasts inflation in Turkey by using time-series and machine learning (ML) models**.** The data spans from the period 2006:M1 to 2020:M12.

Findings —According to the root mean squared error and R-square evaluation criteria, the forecasts obtained from the ML algorithms were less accurate than the forecasts obtained from the VAR model. However, it has been observed that the findings obtained from the MLP algorithm, which takes into account nonlinear relationships, give more accurate results compared to the forecasts obtained from linear-based Lasso and Ridge models. From this point of view, it is suggested that nonlinear ML should be evaluated as a complementary method for inflation forecasting.

Implication — According to the study's findings, the nonlinear ML algorithms can be thought of as a complementary method to forecast inflation in emerging economies with volatile inflation rates. Central banks and policymakers can benefit from computational power and big data for inflation forecasting.

Originality — We evaluate the forecasting performance of ML models against each other and a time series model and investigate possible improvements upon the naive model. So, this is the first study in the field that uses both linear and nonlinear ML methods to compare the time series inflation forecasts for Turkey.

Keywords — inflation forecasting, time series models, machine learning models, emerging economies

Introduction

Inflation is one of the most crucial indicators that reflects the status of the Economy. Contracts are usually set in nominal terms, so the level of inflation significantly impacts the behaviour of the economic agents such as households, firms, and investors. Furthermore, policymakers direct the Economy using monetary policy, which needs a reliable inflation forecast. In case of failure in inflation forecasting, large welfare losses occur (Barkan et al., 2021). Lastly, since the debt and interest payment levels are being affected by the level of inflation, governments need accurate forecasts for choosing appropriate fiscal policies. This fact is especially crucial in emerging

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economies such as Turkey, with high public debt levels. (According to the Central Government Budget, Turkey has nearly 7,597 billion TL foreign debt stock in the first quarter of 2021 (MTFRT, 2021) (Republic of Turkey Ministry of Treasury and Finance)).

Turkey has experienced high and persistent inflation rates since the 1970s. Especially after the 1994 crisis, the inflation rates have gone through the ceiling and exceeded 120%. Although a series of stabilization programs supported by the IMF have been implemented in recent years, inflation remains a crucial problem for the Turkish Economy. To reduce inflation, CBRT started to adopt an explicit inflation-targeting regime in 2006. Adapting this regime and ongoing high inflation has made forecasting inflation in Turkey more important for CBRT (The CPI inflation in Turkey is 20.3%, 11.84%, and 14.6% in 2018, 2019, and 2020 respectively.)

Despite its needfulness, forecasting inflation is a challenging task. Today, even Central Banks sometimes make projections that do not systematically fit the actual values. Recently, even European Central Bank has overestimated the inflation values (Medeiros et al., 2021). The CBRT likewise, has underestimated most of the level of inflation in the recent 10 years. From this point of view, researchers began to look for a new and applicable methodology to forecast inflation more accurately. Due to improvements in computational power and size of the datasets, ML models have recently come to be seen as the solution to tackle difficult forecasting tasks. As big data accumulated in the field of economics, ML algorithms became used in forecasting inflation, too. However, studies using machine learning methods to estimate inflation are noteworthy that studies are generally conducted in developed countries. Studies based on machine learning algorithms have remained limited in developing countries such as Turkey, as the data volume is newly developing, and researchers have turned to conventional methods.

To fill this gap, Özgür and Akkoç (2021), for the first time, performed a comparative analysis using ML and time-series algorithms simultaneously to predict inflation in Turkey. As an ML algorithm, they used Ridge, Lasso and derivatives of Lasso and elastic net algorithms. The ML findings were compared to the results of the random walk, ARIMA, and multivariate VAR models. The study filled an important gap in the literature in that it uses machine learning algorithms that do not require assumptions about the relationships of independent variables with a large data set and compare the findings with the results obtained from time series models (Özgür & Akkoç, 2021). Their ML methodologies were also able to choose the most appropriate measures of inflation. However, only linear models were used in the study. However, there may be nonlinear relationships between inflation and other economic variables. This situation is critical in developing economies such as Turkey, where uncertainty is relatively high.

This paper aims to make an empirical and methodological contribution to the literature by using a nonlinear ML algorithm while comparing ML and time series models in forecasting inflation in Turkey. For that purpose, the predictions obtained from neural network algorithm (multilayer perceptron model) with different tuning parameters have been used in addition to shrinkage models. The results have been compared with the findings from the time series model, namely the VAR model. This study is the first study in the field that uses both linear and nonlinear ML methods to compare Turkey's time series inflation forecasts

There is a vast literature on inflation forecasting. Preliminary empirical studies that predict inflation are based on three main models: the mark-up models (e.g. Brouwer & Ericsson, 1998; Banerjee et al., 2001; Christopher & Jansen, 2004; Bennouna, 2015), the monetary models (e.g. Callen & Chang, 1999; Altimari, 2001; Jonsson, 2001), and the Phillips curve (e.g. Coe & McDermott, 1997; Önder, 2004; J. H. Stock & Watson, 2013; Chen, 2019; Ball & Mazumder, 2019, 2020). However, as the available data and computational power increase, machine learning algorithms have started to be a preferred method in inflation forecasting. ML algorithms have been used in forecasting different economic variables, but this study does not attempt to present all of them. Instead, focus on studies that apply ML algorithms to inflation forecasting. In this section, the studies with the ML approach are mentioned, and studies based on conventional econometric techniques are excluded.

Firstly, it is noteworthy that most of the studies dealing with the ML algorithm in inflation forecasting focus on the US. Stock and Watson (1999) is one of the pioneer studies that handle forecasting inflation in the US using neural network approaches. They compare the forecasts at the one, six, and twelve-month horizons for monthly US economic time series. The results indicate that most nonlinear methods, including the ANN method, produce worse forecasts than the linear AR methods (J. Stock & Watson, 1999). Nakamura (2005), in a later study, forecast a new US inflation by using a neural network approach. The author uses the GDP deflator as the indicator of inflation. The neural networks outperform univariate autoregressive models such as AR models with different baselines (Nakamura, 2005).

Ülke, Sahin, and Subasi (2018) use different indicators such as CPI for all items, core-CPI, the personal consumption expenditure deflator (PCE), and the core-PCE, for inflation forecasting in the US. They use AR, random walk, ARDL, VAR models as benchmark models and the SVR as the ML approach. The results indicate the outperformance of the SVR model in forecasting core-PCE inflation, and the ARDL model provides the best results in forecasting core-CPI inflation (Ulke, Sahin, & Subasi, 2018). Almosova & Andresen (2019) show that the artificial neural network gives better results than the linear AR and random walk models. Medeiros et al. (2021) similarly note the outperformance of the ML models against univariate benchmarks for inflation forecasting in the US, such as random walk and AR (Medeiros et al., 2021). They find that the performance of using ML methods can be as better as 30% in terms of mean squared errors. They also pay special attention to the nonlinear random forest model, which gives more accurate results than the other ML algorithms such as Lasso, adaptive Lasso, and Ridge regression. Barkan et al. (2021) improve the forecasts of the US by using the disaggregated indexes that comprise CPI. They use AR and VAR models as time series benchmarks and test the performance of ML models such as KNN and neural network approaches. The results demonstrate the superiority of the neural network model, especially in low levels of CPI hierarchy (Barkan et al., 2021).

Some other studies handle inflation in different countries. For example, Medeiros, Vasconcelos, and De Freitas (2016) use LASSO regression to forecast inflation in Brazil. They also use linear autoregressive and factor models based on principal components as the benchmark specifications. Their results indicate that the LASSO results are more accurate than the benchmark specifications in short-horizon forecasts. However, the results differ in long-horizon forecasts. Another important finding of the study is the relevance of the variables. The most important variables selected by the LASSO regression are related to government debt and money instead of unemployment and production (Medeiros et al., 2016). So, the authors' findings do not support the Phillips curve mechanism. In a later study, Garcia, Medeiros, and Vasconcelos (2017) re-estimate the inflation rates in Brazil by using ML algorithms. They employ linear shrinkage models such as the Lasso and the adaptive Lasso, including random forest as an alternative nonlinear ML model. They compare their results with the AR and the random walk model. The results differ according to the period considered (Garcia et al., 2017).

Chakraborty and Joseph (2017) forecast CPI inflation in the UK on a medium-term horizon of two years by using various modelling approaches, such as artificial neural networks, tree-based models, support vector machines, recommender systems, and different clustering techniques. The results indicate the high performance of the ML models (Chakraborty & Joseph, 2017). Similar findings are being obtained by Baybuza (2018) for Russian inflation forecasts, too. The author compares the Russian inflation forecasts of different time series methods to the results of ML algorithms such as Lasso and Ridge regressions, elastic net model, and random forest model. Rodríguez-Vargas (2020) compares the performance of ML models in forecasting inflation in Costa Rica. The results point out the extended short-term memory network, univariate KNN, and random forests as the best-performing models (Rodríguez-Vargas, 2020). In conclusion, ML methods can improve the quality of forecasting Russian inflation compared to univariate time series models (Baybuza, 2018).

To the best of our knowledge, the paper of Özgür and Akkoç (2021) is the first and unique study that tries to forecast inflation in Turkey using ML techniques and compares the results with some time series benchmark models. The algorithms they employ are Ridge regression, Lasso regression, and elastic net algorithms. They state that shrinkage methods such as Lasso and elastic net algorithms outperform conventional econometric methods (Özgür & Akkoç, 2021).

On the other side, this study aims to enrich the literature by adding the nonlinear predictions from the neural network algorithm. That way, this study is the first to forecast the inflation in Turkey, a developing country, with linear ML models such as Lasso and Ridge regression and nonlinear ML models such as multilayer perceptron algorithm, and to compare the results with the findings of time series model. The second contribution of the study is methodological, which evaluates ML models' forecasting performance against each other and a time series model and thereby investigates possible improvements upon the naive model. The third contribution of the model is about data. This study makes use of the current data set covering the period 2006:M1-2020:M12. We also eliminate the variables with missing data since it can cause bias in the model.

Methods

This section will forecast the inflation rates using both time series regression and different ML algorithms. This study uses the multivariate VAR methodology for the benchmark time series analysis and benefits from different supervised ML algorithms with a labelled dataset. These algorithms consist of linear shrinkage models such as Ridge regression, Lasso regression, and a neural network algorithm.

The data spans from the period 2006:M1 to 2020:M12 based on the availability of the data. We use the conventional 75%-25% division for the train/test splitting of the data. So, each model is being trained over the period 2006:M1 to 2017:M3. The rest of the dataset covering the period 2017:M4 to 2020:M12 is being used as the test dataset to measure the accuracy of the predictions. The root means squared error (RMSE) and the square of correlation coefficient (R^2) values are being used as the evaluation metrics. We benefit from the Python software as the development environment.

In the benchmark VAR model, the CPI variable shows the consumer price index based on 2003. The CBRT also uses the annual change in CPI for inflation targeting. Based on monetary models (e.g. Altimari, 2001; Callen & Chang, 1999; Jonsson, 2001), the exchange rate (EXC), the stock market index (BIST), and the money supply (M2) series have been used as the explanatory variables. EXC is the sale price of the US dollar. BIST is the 2003 based stock market index of Borsa Istanbul. And M2 is the money supply that includes term deposits.

All of the VAR model datasets have been obtained from the Central Bank of Turkey (CBRT, 2021). The definitions and the sources of the variables are given in Table 1.

Table 1. Variable Definitions and Data Sources

Name	Description	Source
CPI	consumer price index (2003=100)	CB of Turkey
EXC	US dollar (sale price)	CB of Turkey
BIST	Stock market index (January 1986=100) (according to closing price)	CB of Turkey
M2	M2 money supply (level)	CB of Turkey

On the other hand, the ML algorithm is a method that learns from data, and it creates its own algorithm from a large number of variables. For this reason, 28 different features thought to affect inflation were considered, and the choice of the model to be used was left to the method itself. Following Özgür and Akkoç (2021), these data include groups of features such as production indicators, the quantity of money supply, gold prices, exchange rates, interest rates, government budget indicators, and so on. However, it eliminated the variables with missing values. The CPI is used as the indicator of the output. The definitions and the sources of the variables are given in the table in Appendix 1. The complete data set has been obtained from the CBRT database. The program codes and data set are available upon request from the authors.

Benchmark Model

We used the VAR model, developed by Sims (1980), as the benchmark model to evaluate the accuracy of the forecasts of the ML algorithms. The VAR is a widely used model in forecasting variables when two or more time series are expected to influence each other. One of the advantages of the VAR model is that it does not require the endogenous and exogenous distinction between the variables (Wojciech & Derek, 1992). In addition, since only the lagged values of the variables are included in the analysis, the success of the future forecasts increases (Kumar et al., 1995).

In the VAR model, the variables are modelled as a weighted combination of their own past values and the past values of other signals in the model plus an error term (Chang et al., 2012). Therefore, the VAR model can be specified as:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + C x_t + \varepsilon_t \tag{1}$$

where $y_t = (y_{1t}, y_{2t}, \dots, y_{kt})'$ is a k*1 vector of endogenous variables, $x_t = (x_1, x_{2t}, \dots, y_{dt})'$ is a d*1 vector of exogenous variables, $A_1, \dots, A_p$ are k*k matrices of lag coefficients, C is a matrix of exogenous variable coefficients and ε_t is the k*1 vector of error terms which are considered white noise.

Since all the variables in the VAR system must be stationary, it is necessary to test the stationarity of the data in the first stage and make the necessary transformation for non-stationary series. The augmented Dickey-Fuller test developed by Dickey and Fuller (1979) is a widely used statistical procedure that tests whether a time series contains a unit root.

For an equation of a time series (Y_t) as follows:

$$Y_t = \rho Y_{t-1} + u_t \tag{2}$$

where u_t is a white noise error term, the stationarity can be tested with the following hypothesis:

$$\begin{aligned} &H_0: \rho \geq 1 \\ &H_1: \rho < 1 \end{aligned} \tag{3}$$

If the t-stat is less than the critical values, then the null hypothesis is rejected, and the time series are accepted to be stationary (Dickey & Fuller, 1979). If the variables are not stationary, the analysis is repeated by taking the differences. This process continues until there is no nonstationary variable left.

The next step in the VAR estimation process is determining the lag length. At this stage, benefiting from information criteria such as Akaike (AIC), Bayesian (BIC), and Hannan-Quinn (HQIC) is very common. AIC focuses on finding the lag length that minimizes the means squares of error. On the other hand, BIC and HQIC focus on finding a consistent model. The criteria are calculated as follows:

$$\begin{aligned} &AIC = \left(\frac{2n}{f - m - 1}\right) m - 2ln[L_{max}] \\ &BIC = ln[f]m - 2ln[L_{max}] \\ &HQIC = 2ln\big[ln[f]\big]m - 2ln[L_{max}] \end{aligned} \tag{4}$$

where *f* is the number of observations, *m* is the number of parameters to be estimated and L_{max} is the maximized value of the log-likelihood for the estimated model. The coefficients of m show the degree to which the number of model parameters is being penalized. So, BIC and HQIC are more stringent than AIC in penalizing the loss of degrees of freedom.

Among the alternative models, the one with the minimum information criteria provides a good balance between fit and complexity. Finally, the selected model can be tested in terms of autocorrelation. Although many tests are used to test the presence of autocorrelation, the Durbin-Watson (DW) test is the most used. Where σ is the autocorrelation coefficient, the null and alternative hypotheses for the DW test are as follows:

$$\begin{aligned} &H_0: \sigma = 0 \\ &H_1: \sigma \neq 0 \end{aligned} \tag{5}$$

The DW test statistic is calculated as follows:

$$DW = \frac{\sum_{t=2}^{t=n}(\hat{u}_t - \hat{u}_{t-1})^2}{\sum_{t=1}^{t=n}(\hat{u}_t)^2}$$

or as;

$$DW = 2(1 - \sigma) \quad (6)$$

If σ=-1, DW will be equal to 4, and there is negative autocorrelation. If σ=0, DW will be equal to 2, and there is no autocorrelation. If σ=1, then DW will be equal to 0, and there is positive autocorrelation. After calculating the value of the DW test statistic (*d*), it is compared with the lower bound (*d_l*) and upper bound (*d_u*) critical values to determine whether there is an autocorrelation problem. The decision mechanism is as follows:

If 0$< d < d_l$, then the null hypothesis is rejected.
If $d_l \leq d \leq d_u$, then the test is inconclusive.
If $4 - d_l < d < 4$, then the null hypothesis is rejected.
If $4 - d_u \leq d \leq 4 - d_l$, then the test is inconclusive.
If $d_u \leq d \leq 4 - d_u$, then the null hypothesis cannot be rejected.

If there is no autocorrelation problem, the model indicated by the information criteria will be preferred.

Machine Learning Models

Econometric methods are frequently being used in the estimation of economic variables. However, these methods are generally estimated with models being created in line with economic theories. As mentioned in the literature review section, different economic theories have been developed for the estimation of inflation. However, there is no consensus on the determinants of inflation. At this point, the existence of a method that creates its own algorithm from a large data set containing different variables is important. In addition, as the data volume increases in the future, the accuracy of the forecasts will increase.

The ML algorithms are generally sensitive to the scaling of the data. Therefore, standard normalization that gives data with zero mean and unit variance has been used. Then the forecasts were made with both linear and nonlinear models.

Linear models

Shrinkage methods are being widely used to estimate the parameters in high-dimensional datasets. Among these algorithms, Lasso (Least Absolute Shrinkage and Selection Operator), proposed by Tibshirani (2016), and the Ridge regression proposed by Hoerl & Kennard (1970), have received particular attention.

Lasso regression algorithm is an ML algorithm that uses linear models but also satisfies an additional constraint. It uses l1 regularization, which minimizes the sum of the coefficients' absolute values and shrinks coefficients for some features that have a low contribution to the prediction task. Thus, some coefficients become exactly zero.

The solution to a minimization problem defines the Lasso estimator:

$$\hat{\beta} = \arg\underbrace{min}_{\hat{\beta}} \sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{k} x_{ij}\beta_j\right)^2,$$

$$\text{subject to } \sum_{j=1}^{k}|\beta_j| \leq t \quad (7)$$

where β's are the estimated coefficients.

The Ridge regression algorithm is again a widely used linear model, but it uses l2 penalty, which minimizes the square of the magnitude (Euclidean length) of the coefficients (min $\sum(\beta_i)^2$)

to shrink coefficients. Therefore, the magnitudes of the coefficients are restricted to be small as possible. However, none of them become exactly zero.

The solution to a minimization problem defines the Ridge estimator:

$$\hat{\beta} = \arg\underbrace{min}_{\hat{\beta}} \sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{k} x_{ij}\beta_j\right)^2,$$

subject to $\sum_{j=1}^{k} \beta_j{}^2 \leq t$ (8)

where β's are the estimated coefficients.

Evaluation metrics

In order the examine the performance of the models, this study benefits from two different evaluation metrics: root mean squared error (RMSE) and the square of correlation coefficient (R^2) value (or the test set accuracy) RMSE is given by:

$$\text{RMSE}= \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t - \hat{x}_t)^2} \qquad (9)$$

where x_t indicates the monthly change in time t, and $\hat{x}_t$ indicates the relevant prediction.

The R^2 value lies between 0 and 1, where higher values indicate a better data performance to fit the model.

$$R^2 = \frac{\hat{\beta}_1^2(\sum \hat{Y}_i^2)}{\sum Y_i^2 - (\sum Y_i)/n} = \frac{\sum(Y_i - \hat{Y}_i)^2 - \sum(\hat{\varepsilon}_i)^2}{\sum(Y_i - \hat{Y}_i)^2} \qquad (10)$$

Neural Networks

In this paper, a relatively simple multilayer perceptron's (MLP) method for regression can be seen as a generalization of linear models that perform multiple stages with hidden layers. The perceptron model was developed by an American psychologist Rosenblatt (1958), who is acknowledged as a pioneer in the training of neural networks. In this algorithm, the input features are weighted by the learned coefficients, and computing the weighted sums is repeated by multiple times (Muller & Guido, 2017).

The first layer includes input features for each predictor variable, the second layer is the hidden layer, and there is one output layer. Each feature is weighted by the learned coefficients and connected to nodes in the hidden layer. Each node in the hidden layer is also multiplied by a weight, and the weighted values are added together to produce the output.

In addition to the computation of the weighted coefficients by multiple times, the MLP algorithm also uses a nonlinear function such as rectifying nonlinearity (relu) and the hyperbolic tangent (tanh), thereby giving more powerful results than a linear model.

Results and Discussion

In the first step, the VAR model is employed to forecast inflation. As the series affect each other, it is modelled by the system of equations with one equation for each variable:

$$\begin{aligned}CPI_t = \alpha_1 &+ \beta_{11,1}CPI_{t-1} + \cdots + \beta_{p1,1}CPI_{t-p} + \beta_{12,1}EXC_{t-1} + \cdots + \beta_{p2,1}EXC_{t-p} + \\ &\beta_{13,1}BIST_{t-1} + \cdots + \beta_{p3,1}BIST_{t-p} + \beta_{14,1}M2_{t-1} + \cdots + \beta_{p4,1}M2_{t-p} + \varepsilon_{1t}\end{aligned}$$

$$\begin{aligned}EXC_t = \alpha_2 &+ \beta_{11,2}CPI_{t-1} + \cdots + \beta_{p1,2}CPI_{t-p} + \beta_{12,2}EXC_{t-1} + \cdots + \beta_{p2,2}EXC_{t-p} + \\ &\beta_{13,2}BIST_{t-1} + \cdots + \beta_{p3,2}BIST_{t-p} + \beta_{14,2}M2_{t-1} + \cdots + \beta_{p4,2}M2_{t-p} + \varepsilon_{2t}\end{aligned}$$

$$\begin{aligned}BIST_t = \alpha_1 &+ \beta_{11,3}CPI_{t-1} + \cdots + \beta_{p1,3}CPI_{t-p} + \beta_{12,3}EXC_{t-1} + \cdots + \beta_{p2,3}EXC_{t-p} + \\ &\beta_{13,3}BIST_{t-1} + \cdots + \beta_{p3,3}BIST_{t-p} + \beta_{14,3}M2_{t-1} + \cdots + \beta_{p4,3}M2_{t-p} + \varepsilon_{3t}\end{aligned}$$

$$M2_t = \alpha_1 + \beta_{11,4}CPI_{t-1} + \cdots + \beta_{p1,4}CPI_{t-p} + \beta_{12,4}EXC_{t-1} + \cdots + \beta_{p2,4}EXC_{t-p} + \beta_{13,4}BIST_{t-1} + \cdots + \beta_{p3,4}BIST_{t-p} + \beta_{14,4}M2_{t-1} + \cdots + \beta_{p4,4}M2_{t-p} + \varepsilon_{4t} \quad (11)$$

In the first step, the series have been tested for stationarity by using Augmented Dickey-Fuller (ADF) test. The null hypothesis of the test states that the data has a unit root. The results are given in Table 2.

Table 2. Augmented Dickey-Fuller Test on Variables

Variable Name	BIST	EXC	M2	CPI
Test stat	0.471	3.237	6.250	4.536
No. lags chosen*	14	5	0	5
Critical value 1%	-3.471	-3.469	-3.467	-3.469
Critical value 5%	-2.879	-2.878	-2.878	-2.878
Critical value 10%	-2.576	-2.576	-2.575	-2.576
p-value	0.984	1.000	1.000	1.000

*The optimal lag length has been chosen according to the Akaike Information Criteria.

According to the ADF test, the t-stats of all variables are greater than all of the critical values. Therefore, the null hypothesis cannot be rejected. So, none of the series is stationary at level. Therefore, take the variable into the first differences of all series and test the stationarity of the new series. The results are shown in Table 3.

Table 3. Augmented Dickey-Fuller Test on the First Differenced Variables

Variable Name	BIST	EXC	M2	CPI
Test stat	-3.431	-6.773	-0.6221	-3.168
No. lags chosen*	14	2	11	4
Critical value 1%	-3.471	-3.468	-3.471	-3.469
Critical value 5%	-2.879	-2.878	-2.879	-2.878
Critical value 10%	-2.576	-2.576	-2.576	-2.576
p-value	0.010	0.000	0.866	0.022

*The optimal lag length has been chosen according to the Akaike Information Criteria.

In the following result of the ADF test in the first differences variables in table 3, all of the series except the first difference of M2 are stationary at a 5% level of significance (t-stat of M2 (-0.6221)>t-critical (-2.879)). However, all of the series in the MVAR model should have the same number of observations. Therefore, the second difference of all series is used and re-run the ADF test.

According to Table 4, the t-stats of all variables are greater than the critical values. Therefore, all of the variables are stationary in their second differences. So, the analysis continues with the second differenced series. In the next step, split the dataset into training data for the period of 2006:M1 to 2017:M3 and the last forty-five observations as the test data. The forecasts obtained from test data will be compared against the actual values of CPI.

Table 4. Augmented Dickey-Fuller Test on the Second Differenced Variables

Variable Name	BIST	EXC	M2	CPI
Test stat	-4.997	-7.223	-5.375	-7.439
No. lags chosen*	13	9	14	10
Critical value 1%	-3.471	-3.471	-3.471	-3.471
Critical value 5%	-2.879	-2.879	-2.879	-2.879
Critical value 10%	-2.576	-2.576	-2.576	-2.576
p-value	0.000	0.000	0.000	0.000

*The optimal lag length has been chosen according to the Akaike Information Criteria.

Determining lag length (p) before estimating a VAR model is very important. Benefiting from information criteria such as Akaike (AIC), Bayesian (BIC), and Hannan-Quinn (HQIC) is very common. The three methods are used to determine the lag length. Table 5 shows the results.

Table 5. The Lag Length Selection

p	AIC	BIC	HQIC
0	42.10	42.18	1.927e+18
1	40.11	40.47	2.619e+17
2	39.52	40.17*	1.455e+17
3	39.33	40.27	1.207e+17
4	38.95*	40.18	8.233e+16*

*highlights the minimums.

According to Table 5, AIC and HQIC reach their minimum level at a lag order of 4. Therefore, lag 4 chooses as the lag length and trains our model of p=4. Table 6 shows the results of the VAR model for the equation CPI.

Autocorrelation problems were checked by using Durbin-Watson test statistics. The test statistic is 2.15, and the autocorrelation coefficient is found to be -0.075. As the autocorrelation coefficient is greater than d_u and is less than 4-d_u, the null hypothesis cannot be rejected, there is no serial correlation, and the VAR(4) model can be used in forecasting.

Table 6. The VAR model results for equation CPI

	Coefficient	Standard Error	T-Statistic	Probability
Constant	0.040	0.142	0.282	0.778
L1.BIST*	0.002	0.004	0.686	0.492
L1.EXC*	-0.655	3.335	-0.196	0.844
L1.M2*	0.000	0.000	1.711	0.087
L1.CPI*	-0.388	0.090	-4.293	0.000
L2.BIST*	0.003	0.005	0.532	0.595
L2.EXC*	5.956	4.074	1.462	0.144
L2.M2*	0.000	0.000	0.517	0.605
L2.CPI*	-0.605	0.097	-6.254	0.000
L3.BIST*	0.006	0.005	1.243	0.214
L3.EXC*	1.262	4.078	0.309	0.757
L3.M2*	0.000	0.000	-0.480	0.632
L3.CPI*	-0.163	0.098	-1.671	0.095
L4.BIST*	-0.002	0.004	-0.465	0.642
L4.EXC*	4.914	2.859	1.719	0.086
L4.M2*	-0.000	0.000	-0.393	0.694
L4.CPI*	-0.437	0.090	-4.858	0.000

Note: * indicates that the second difference of the variable is taken.

As shown in Table 6, the CPI variable is being affected by its own one and two-term lags at a 5% level of significance. It is also being affected by its own three-term lag at a 10% significance level. In addition, it is affected by one term lag of M2 and four terms lag of EXC at a 10% level of significance. This finding is consistent with the Monetarist and Keynesian views about inflation. According to these views, the increase in money supply will increase aggregate demand, production will rise above the natural level in the short run, and then the aggregate supply will decrease due to rising wages arising from unemployment falling below the natural level. Although the natural output is restored, this process ends with a price increase. If the money supply increases, the increase in the price level will also continue. Thus, the main inflation factor is seen as rapid monetary expansion (Mishkin, 2000). The finding is also consistent with studies advocating the importance of monetary variables in determining inflation (e.g. Altimari, 2001; Callen & Chang, 1999; Jonsson, 2001).

In the next step, by use the last four observations to forecast the following 45 observations, which also consist of our test dataset. The results can be seen in Figure 1.

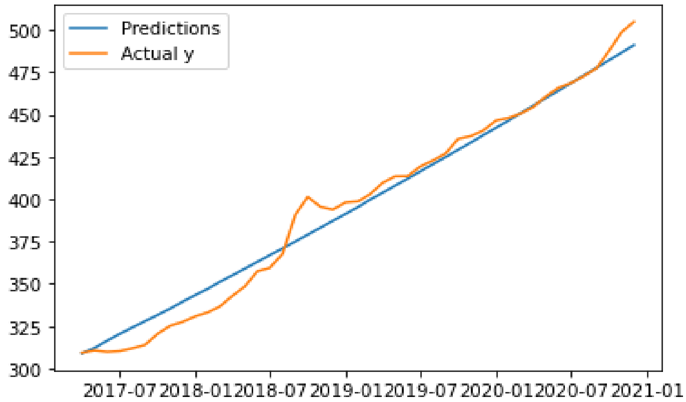

Figure 1. Forecasted and Actual Values for CPI (2019:M7-2020:M12)

In Figure 1, the orange line shows the actual values of the CPI during 2017:M4-2020:M2. On the other hand, the straight blue line shows the forecast results of the VAR(4) model for that period. Although the forecasts of the VAR model deviate from the actual values in periods when inflation is volatile, it can be argued that it provides accurate forecasts in general.

In the second step, make inflation forecasts using ML algorithms. First, the forecast used standard normalization that gives data with zero mean and unit variance for that purpose. Table 7 shows the magnitudes of the coefficients obtained from the Lasso and Ridge models. By looking at the magnitudes of the coefficients, the most important features are selected by the algorithm.

Table 7. Coefficients of Lasso and Ridge Regression

Feature	Lasso regression	Ridge regression
ind	0.00e+00	0.149
int	0.00e+00	-1.655
dur	0.00e+00	0.354
nondur	0.00e+00	1.427
enr	-1.82e-01	0.580
cap	0.00e+00	-0.076
ltech	0.00e+00	-0.717
mltech	-1.02e-02	0.603
mhtech	0.00e+00	2.080
htech	0.00e+00	-1.214
min	-6.39e-01	-0.471
man	0.00e+00	0.125
mes	1.17e+00	2.304
eftrans	8.57e-01	3.823
cbtrans	-5.34e+00	-6.409
cumh	0.00e+00	9.903
bist	0.00e+00	0.644
usds	0.00e+00	3.097
usdb	0.00e+00	3.068
r1	0.00e+00	-0.180
r2	0.00e+00	-1.763
dep	4.59e+01	27.449
cred	2.74e+01	17.996
M2	2.27e+01	18.558
asset	0.00e+00	6.174
budrev	5.15e-01	5.915
budexp	0.00e+00	5.606
build	0.00e+00	-0.377

We can also plot the coefficients of the different models to see the most important features. Figure 2 shows the coefficient magnitudes for Lasso and Ridge regression.

As shown in Table 7 and Figure 2, only ten coefficients are different from zero in Lasso regression. Therefore, the Lasso model uses only ten of the features. Among these automatically selected features, the most important ones are dep (deposit account (TRY)), cred (Total credits (TRY)), and M2 (M2 money supply (TRY)). It is noteworthy that monetary variables are found to be relatively important. Furthermore, this finding confirms monetarist and Keynesian views about inflation.

The finding is again consistent with studies advocating the importance of monetary variables in determining inflation (e.g. Altimari, 2001; Callen & Chang, 1999; Jonsson, 2001). Additionally, the finding is consistent with Medeiros et al. (2016). By addressing the Brazilian Economy, they drew attention to the relative importance of monetary variables such as money supply and public debt instead of unemployment and production in determining inflation in emerging economies. Some studies draw attention to the importance of monetary variables in determining inflation in the Turkish Economy (e.g. Bulut, 2016; Gungor & Berk, 2006; Lim & Papi, 1997).

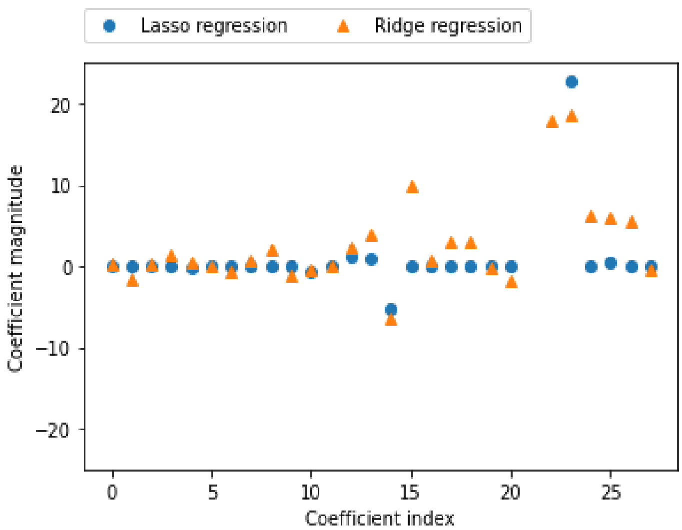

Figure 2. Comparing Coefficient Magnitudes for Ridge and Lasso Regression

The forecasting results obtained from the Lasso and Ridge regression can be visualized as shown in Figure 3.

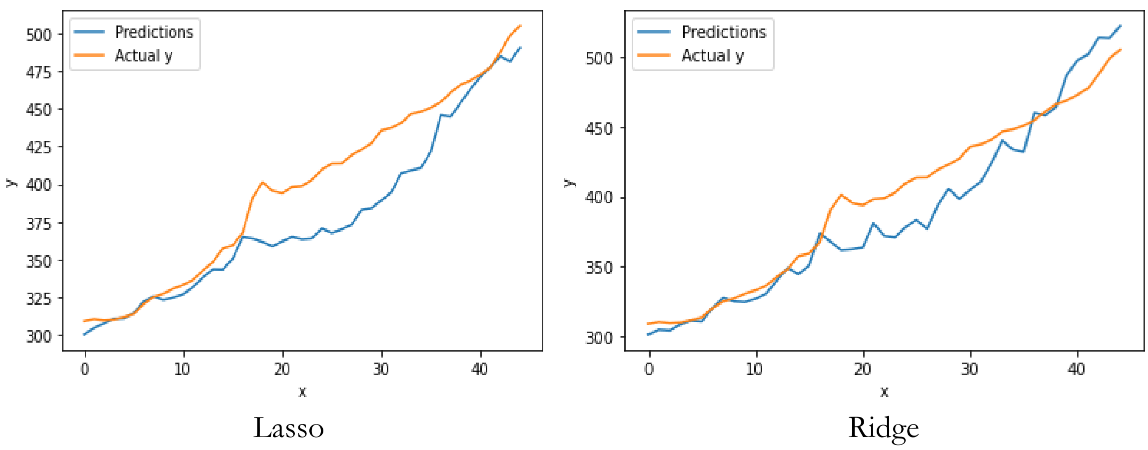

Figure 3. Lasso and Ridge Regression Forecasts and Actual Values for CPI (2017:M4-2020:M12)

In Figure 3, the orange curves show the actual values of the CPI during 2017:M4-2020:M2. On the other hand, blue curves show the forecasts obtained from Lasso and Ridge models, respectively. Visually, both algorithms perform worse than the VAR model, especially in periods of high inflation. This finding is consistent with Medeiros et al. (2016) and Ülke et al. (2018). While Medeiros et al. (2016) argued that the time series model outperforms the LASSO model in forecasting inflation for Brazil, Ülke et al. (2018) found the forecasts of the time series model for the US to be more accurate than the forecasts of support vector regression.

Comparing this result with the findings of the Ozgur and Akkoc (2021) study, which is the only similar study for Turkey, some differences can be discussed. Namely, Ridge regression gives more accurate forecasts than the VAR model in the related study, while Lasso regression produces less accurate predictions. It is thought that this difference is due to the fact that the variables with missing values were not included in the data set in our study. It should be noted that there may be a nonlinear relationship between inflation and other economic variables. The existence of uncertainty may also stimulate nonlinearities. Therefore, in the next step to enhance the forecasts, the benefit from a nonlinear ML model is employed.

A multilayer perceptron algorithm employed the nonlinear ML method and benefited from two hidden layers and the "relu" as the activation function. The analysis used 15 nodes for the first hidden layer and 3 nodes for the second one. The complexity of the neural network has been regulated by using an l2 penalty that shrinks the weights towards zero as well. Figure 4 gives the MLP results for different alpha values.

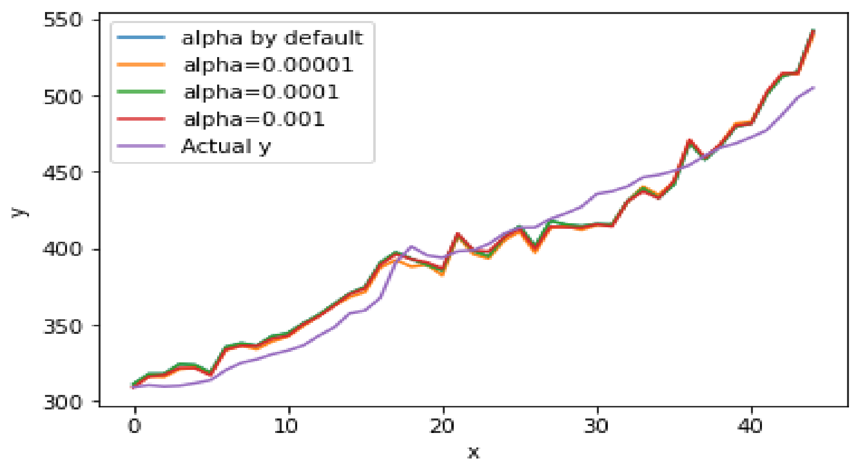

Figure 4. MLP Forecasts and Actual Values of CPI (2017:M4-2020:M12)

In Figure 4, the purple curve shows the actual values of the CPI during 2017:M4-2020:M2. The curves in other colours show the forecasts obtained from MLP algorithm with different alpha values. Visually, the forecasting results obtained from MLP seem to be more accurate than the linear ML algorithms in general.

The MLP model seems to be more successful in approximating actual values during periods of sudden ups and downs in inflation. This finding is particularly important for developing countries with volatile inflation rates. The relative success of the MLP model also supports the existence of nonlinear relationships between inflation and other economic variables. It is thought that the MLP algorithm can be an important useful method since it will be difficult to forecast inflation with linear models in periods of increased uncertainty. Lastly, tuning the parameter alpha seems to have no radical effect on the results. This result is consistent with the findings of Gungor and Berk (2006), who found the prediction power of the MLP model to be reasonably good. It is also in line with the findings of the study by Medeiros et al. (2021), which indicate that the nonlinear model outperforms the Lasso and Ridge models.

Consequently, comparing the results in the ML algorithms that observe the forecasting performance of the MLP algorithm is more accurate than the linear-based Lasso and Ridge regression algorithms. On the other hand, by only looking at Figures 3 and 4, it is hard to compare the results of the MLP algorithm and the VAR model. Therefore, we benefited from some evaluation metrics.

Table 8. Performance Metrics of Different Models

Algorithm	Test Set Accuracy	RMSE
Time Series Model		
VAR (4)	0.993	8.61
ML Models		
Ridge Regression	0.890	13.39
Lasso regression	0.810	25.79
MLP(alpha by default)	0.948	13.45
MLP(alpha=0.00001)	0.951	13.05
MLP(alpha=0.0001)	0.948	13.45
MLP(alpha=0.001)	0.949	13.28

Table 8 shows the evaluation metrics for different algorithms. The table shows that the time series model provides more significant performance than the ML models. The test set accuracy (0.9927) is higher in VAR(4) model than in the ML models. This means that the output estimations of the VAR model are more accurate in the data set that is not used for training purposes. Similarly, the RMSE value (8.61) is lower in VAR(4) model than in the ML models. Accordingly, the forecasts obtained from the VAR model were found to be closer to the actual values. These findings are consistent with Medeiros et al. (2016) and Ülke et al. (2018), which handle Brazil and the US, respectively.

On the other hand, using nonlinear ML algorithms seems to improve the forecasting performance compared to linear ML models. Namely, the MLP model reaches nearly 95% accuracy, which seems quite good. Additionally, MLP forecasts were more successful in approximating actual values during periods of volatile inflation. Since inflation is more volatile in developing countries, it is relatively important to use algorithms that take into account nonlinear relationships in estimating inflation in such countries. This finding confirms the results of Gungor and Berk (2006) and Medeiros et al. (2021).

The relative success of the MLP model also supports the existence of nonlinear relationships between inflation and other economic variables. As the linear relationships are damaged with increasing uncertainty, it is thought that the MLP algorithm can be an important useful method for forecasting inflation. Lastly, it is good to be reminded that the performance of the ML algorithms may increase with the progress in the computational power and the data size. So, the performance of the MLP may increase in the future. We also believe that considering other explanatory variables, increasing the volume of the data and also tuning parameters in different ways may be helpful to increase the accuracy even more.

Conclusion

Inflation forecasts have crucial effects on the behaviour of economic agents. Policymakers also need accurate inflation forecasts in steering the Economy by using fiscal and monetary policies. However, forecasting inflation is challenging, and there is no consensus on the best methodology. We, in this paper, have included assessments of different ML methods, compared the results with time-series forecasts, and contributed to the debate by providing an enlightening guide for forecasting inflation in a more accurate way. The results can be summarized as follows.

Firstly, it was observed that the forecasts obtained with the monetary model-based VAR model showed a high performance in forecasting the real inflation level for the 2017:M4-2020:M12 period. Secondly, according to the results of Lasso and Ridge regression, dep (deposit account (TRY)), cred (Total credits (TRY)), and M2 (M2 money supply (TRY)) variables were found to have the highest coefficients. Therefore, the monetary variables were found to be more effective on the level of inflation. Furthermore, this finding is consistent with the monetary models of inflation. On the other hand, the forecasts obtained from linear-based Lasso and Ridge regression were found to be less accurate than the results of the VAR model. Thirdly, although the performance of the MLP model in forecasting inflation was found to be less than the VAR model, it was found to be higher than the linear-based Lasso and Ridge regression. This result was interpreted as taking into account that the nonlinear relationships between the variables positively affected performance.

In sum, in a pseudo-out-of-sample forecasting experiment using recent Turkish data, the performance of the VAR model is found to be better than the ML algorithms. However, although the Lasso and Ridge regression algorithms use variable selection mechanisms, the MLP model seems to outperform due to potential nonlinearities. As uncertainty is thought to induce nonlinearities, the performance of the nonlinear ML models is expected to be better, especially in periods of high uncertainty. Since inflation is more volatile and uncertain in developing economies, the MLP algorithm is thought to be an important useful method for forecasting inflation. The performance of the method will increase further in the future, depending on the progress in the computational power and data volume.

From this point of view, it can be said that policymakers can benefit from ML algorithms that take nonlinear relationships into account in forecasting inflation. In the cases such as the inability to create a data set suitable for time series analysis and the inability to determine explanatory variables that will affect the output, the MLP method will solve the problem by deriving its own algorithm. In this context, it is suggested that nonlinear ML models should be considered as an alternative method for estimating inflation.

While a nonlinear machine learning algorithm is found to approach the performance of time series estimations, several caveats for future research remain. Firstly, the results are sensitive to train and test split. We used the conventional 75%-25% division for the train/test splitting of the data. But the researchers may re-forecast the inflation rates for the short and medium-term by choosing a shorter period for test data.

Another limitation of the study is the dataset size that benefits from the dataset over the period 2006:M1-2020:M12. However, the performance of the empirical methods increases with the size of the data. Especially in the ML methodology, many variables are being used, and it can be argued that as the data size increases, the forecasting performance and accuracy will increase.

As Baybuza (2018) states, the most significant disadvantage of ML models is the loss of interpretability in the classical sense (Baybuza, 2018). However, forecasts obtained from the ML algorithms would be beneficial to both academics and practitioners aiming at a specific inflation target level. The results of this study will be expected to be useful as a guide for central banks and policymakers in developing countries with volatile inflation rates.

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Appendix 1. Variable Definitions and Data Sources

Name	Description	Source
ind	Industry production index-Total industry	CB of Turkey
int	Industry production index -intermediate goods	CB of Turkey
dur	Industry production index-durable consumer product	CB of Turkey
nondur	Industry production index-nondurable consumer product	CB of Turkey
enr	Industry production index-energy	CB of Turkey
cap	Industry production index-capital good	CB of Turkey
ltech	Industry production index- low technology	CB of Turkey
mltech	Industry production index- medium-low technology	CB of Turkey
mhtech	Industry production index-medium high technology	CB of Turkey
htech	Industry production index-high technology	CB of Turkey
min	Industry production index-mining and quarrying	CB of Turkey
man	Industry production index-manufacturing industry	CB of Turkey
mes	Eft transactions- the quantity of payment messages (number)	CB of Turkey
eftrans	Eft transactions- total payment (TRY)	CB of Turkey
cbtrans	Eft transactions-total outflow from CB (number)	CB of Turkey
cumh	Cumhuriyet gold(coin) sale price (TRY)	CB of Turkey
bist	BIST-100 index according to closing price (January, 1986=0.01)	CB of Turkey
usds	USD dollar sale price (TRY)	CB of Turkey
usdb	USD dollar buying price(TRY)	CB of Turkey
r1	interest rate up to 1 year (TRY deposits) (%)	CB of Turkey
r2	interest rate for 1 year and more (TRY deposits) (%)	CB of Turkey
dep	deposit account (TRY)	CB of Turkey
cred	Total credits (TRY)	CB of Turkey
M2	M2 money supply (TRY)	CB of Turkey
asset	CB balance sheet-assets (TRY)	CB of Turkey
budrev	Central government-budget revenues (TRY)	CB of Turkey
budexp	Central government-budget expenditures (TRY)	CB of Turkey
build	Construction- building with 2 or more apartments (number)	CB of Turkey
CPI	Consumer price index (2003=100)	CB of Turkey