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FORECASTING CONSUMER PRICE INDEX USING MACROECONOMIC VARIABLES: A COMPARATIVE ANALYSIS OF MACHINE LEARNING AND DEEP LEARNING APPROACHES

Ahmed İhsan ŞİMŞEK[1]

ABSTRACT

The Turkish economy has faced many economic difficulties throughout it's history. At this point, predicting inflation accurately is very important for policy makers, businesses, investors and consumers. This study aims to estimate the Turkish Consumer Price Index. Producer price index, M1 money supply, gold price, dollar price, natural gas price and interest rate variables were used to estimate the CPI for Turkey. The variables used in the research were obtained through EVDS, the Central Bank's Electronic Data Management System. Monthly data from January 2003 to August 2023 was used in the study. The obtained data were estimated using DDPG, XGBoost, SVR, KNN and CNN-BiLSTM methods. Model performances were compared using RMSE, MSE, MAE, MAPE and R2 statistical coefficients. When model performances were evaluated, the best CPI prediction for Turkey was obtained by the SVR method.

Keywords: CIP Prediction, SVR, Time Series, Decision Support System, Machine Learning, Deep Learning

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MAKROEKONOMİK DEĞİŞKENLER KULLANARAK TÜKETİCİ FİYAT ENDEKSİNİN TAHMİN EDİLMESİ: MAKİNE ÖĞRENMESİ VE DERİN ÖĞRENME YAKLAŞIMLARININ KARŞILAŞTIRMALI BİR ANALİZİ

Ahmed İhsan ŞİMŞEK[1]

ÖZ

Türkiye ekonomisi tarih boyunca birçok ekonomik zorlukla karşılaşmıştır. Bu noktada enflasyonun doğru bir şekilde tahmin edilmesi politika yapıcıları, işletmeler, yatırımcılar ve tüketiciler açısından oldukça önemlidir. Bu çalışmanın amacı Türkiye Tüketici Fiyat Endeksi'nin tahmin edilmesidir. Türkiye için TÜFE'nin tahmin edilmesinde üretici fiyat endeksi, M1 para arzı, altın fiyatı, dolar fiyatı, doğalgaz fiyatı ve faiz oranı değişkenleri kullanılmıştır. Araştırmada kullanılan değişkenler Merkez Bankasının Elektronik Veri Yönetim Sistemi olan EVDS üzerinden elde edilmiştir. Çalışmada Ocak 2003'ten Ağustos 2023'e kadar olan aylık veriler kullanılmıştır. Elde edilen veriler DDPG, XGBoost, SVR, KNN ve CNN-BiLSTM yöntemleri kullanılarak tahmin edilmiştir. Model performansları RMSE, MSE, MAE, MAPE ve R2 istatistik katsayıları kullanılarak karşılaştırılmıştır. Model performansları değerlendirildiğinde Türkiye için en iyi TÜFE tahmini SVR yöntemi tarafından elde edilmiştir.

Anahtar Kelimeler: TÜFE Tahmini, SVR, Zaman Serisi, Karar Destek Sistemleri, Makine Öğrenmesi, Derin Öğrenme

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1. INTRODUCTION

Throughout its history, the Turkish economy has encountered several economic challenges. One of the most prominent issues among these is inflation. The conventional interpretation of inflation is to a persistent rise in the costs of commodities and services as time progresses. Nevertheless, the process of assessing inflation necessitates the examination of diverse aspects of price fluctuations, resulting in the identification of many classifications of price inflation. The CPI and the PPI are both monitored by the U.S. Bureau of Labor Statistics. The CPI is used to gauge fluctuations in the costs of goods and services commonly bought by households, while the PPI is employed to assess price variations at the production stage (Ayestaran et al., 2023). The rise in the cost of products and services will lead to a decline in individuals' purchasing power, thereby causing a fall in the demand for things that are no longer being offered. As a consequence of this, manufacturers will reduce their investment. A fall in producers' investment will result in a corresponding decrease in national revenue, so representing a decline in economic growth (Ridwan, 2022). Figure 1 shows Turkey's monthly CPI change in the last 20 years.

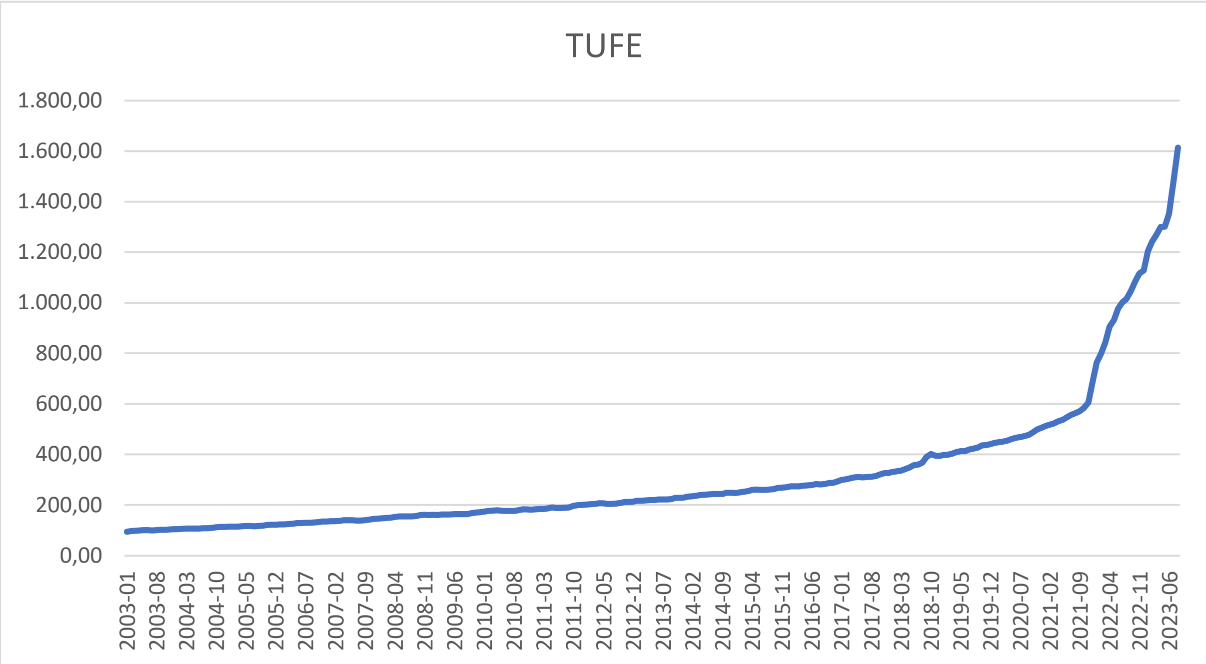

Figure 1. Consumer price index of Türkiye

The CPI is a significant metric that has a profound impact on the rate of inflation, the buying power of individuals, investment decisions, and government economic policies. It serves as an indicator of the dynamic nature of these factors. The CPI is a statistical measure that quantifies the overall magnitude of consumer prices within a given nation. It is widely regarded as one of the primary indicators used to assess the presence and extent of inflation. Nevertheless, this particular metric is susceptible to variations that arise from the intricate interplay of several causes. The task of forecasting Turkey's CPI necessitates a comprehension of the complex relationship of many components and the ability to anticipate forthcoming patterns.

Upon examination of the literature, a variety of variables influencing inflation can be identified. Inflation is influenced by a variety of macroeconomic factors. Some of these factors are stated in the literature as money supply (Doan Van, 2020; Tursoy & Muhammad, 2020; Summarminingsih et al., 2021; Biswas, 2023), exchange rate (Sean et al., 2019; Romdhane et al., 2019; Peer&Baig, 2021; Philips et al., 2022; Gürkaynak et al., 2023), gold price (Tufail & Batool, 2013; Batten et al., 2014; Lucey et al., 2017; Anandasayanan et al., 2019; Duong, 2023), interest rate (Ayub et al., 2014; Amaefula, 2016; Khumalo et al., 2017; Dogan et al., 2020; Galindo & Steiner, 2022; Ramadhan & Ermawati, 2023), producer price index (Gang et al., 2009; Li et al., 2019; Lima, 2019; Woo et al., 2019; Wei & Xie, 2022; Sun et al., 2023), oil price (Sek et al., 2015; Choi et al., 2018; Lacheheb & Sirag, 2019; Mukhtarov et al., 2019; Balcilar et al., 2019; Sultan & Alkhateeb, 2020; Zakaria et al., 2021; Köse &Ünal, 2021; Kilian & Zhou, 2022; Li & Guo; 2022; Aharon et al., 2023; Ding et al., 2023; Lee et al., 2023), and natural gas price (Shah et al., 2014; Jalaee et al., 2021; Krompas, 2022; Boeck et al., 2023).

In their study, Nguyen et al. (2023) conducted an estimation of the CPI in the United States. The researchers utilized many variables, including CPI, Oil Price, Gold Price, and Fund Rate, to carry out their analysis. This work aimed to examine the prediction performances achieved by the utilization of MARS, MLR, SVR, and ARDL methodologies. The study utilized a dataset spanning a period of 62 months, from 2017 to 2022. Nevertheless, there are additional macroeconomic variables that exert an influence on the CPI. Including more macroeconomic factors in the analysis at this juncture would yield more precise prognostic outcomes. Furthermore, the utilization of a broader variety of data will enhance the accuracy of the outcomes achieved during both the training and testing stages, bringing them into closer alignment with the actual values. At present, alongside the factors employed in this research, the inclusion of Money Supply (M1), natural gas prices, which exert a significant impact on inflation as a consequence of recent global events, and the PPI variables will enable a more precise estimation of consumer inflation. In their work, Nguyen et al. (2023) exclusively utilized the Support Vector Regression (SVR) approach among the many machine learning techniques. In contrast to the aforementioned study, the present investigation incorporated additional factors, including money supply, natural gas price, and producer price index. Furthermore, the forecasting of consumer inflation was conducted utilizing several machine learning techniques, including SVR, XGBoost, KNN, a hybrid approach CNN-BiLSTM and Deep DDPG, a reinforcement learning method that has gained prominence in recent price prediction studies. Inflation projections often rely on the utilization of machine and deep learning techniques. Nevertheless, this study aims to address the aforementioned research gap by comprehensively examining a multitude of macroeconomic factors that influence inflation. Additionally, it seeks to provide inflation forecasts by employing diverse machine learning, deep learning, and hybrid algorithms that integrate both approaches.

The objective of this paper is to offer an academic viewpoint on the forecasting of the CPI in Turkey. This study intends to examine the significance, determinants, and consequences of the CPI in order to establish a foundation for comprehending and forecasting inflation patterns in Turkey. In this study, the CPI for Turkey was predicted using a range of economic indicators, including the producer price index, M1, gold price, dollar price, natural gas price, and interest rate. The variables included in the study were obtained from the electronic data management system known as "EVDS," which is operated by the Central Bank of the Republic of Turkey. The analysis employed a dataset consisting of 248 months of data, including the time period from January 2003 to August 2023. In the subsequent phase of the investigation, initial emphasis is placed on the examination of research employing machine and deep learning techniques for the purpose of inflation forecasting. Subsequently, the data and methodologies to be employed are presented. Following that, the study examined the prediction performances achieved by the strategies utilized. Ultimately, the findings were assessed and an attempt was made to establish a roadmap for future research endeavors.

2. LITERATURE REVIEW

The CPI is an important metric that significantly impacts inflation rates, individual buying power, investment decisions, and government economic policies. It serves as an indicator of the dynamic nature of these components. Numerous academic studies have been undertaken in the realm of research, wherein machine learning and deep learning methodologies have been employed to forecast the CPI. CPI is a crucial metric for assessing inflation. Machine learning and deep learning techniques have the potential to effectively estimate this variable with a high level of accuracy. Table 1 shows the studies conducted on the consumer price index.

Table 1. *Literature Review*

Author(s)	Year	Analysed Country	Data	Variables	Model	Metrics	Results
Alvarez-Diaz&Gupta	2016	USA	01.1980-12.2013	CPI	Random Walk, SARIMA, ANN, Genetic Programming	MAPE	SARIMA, Random Walk
Huong et al.	2016	AU, Spain, OECD	01.1960-01.-2005	CPI	Time Series, ANN, Multi-Objective Optimization	MSE	Multi-Objective Optimization
Milunovich	2016	Australia	Q3.1972-Q3-2017	Housing Index, Real GDI, CPI, Unemployment Rate, Mortgage Rate, Exchange Rate	SVR, RBF, MLP, ARMA, VAR, KRR, XGBoost	MSE	SVR
Ambukege et al.	2017	Tanzania	01.2000-12.2015	CPI	Neuro Fuzzy	RMSE, MAPE	Gaussian
Budiastuti et al.	2017	Indonesia	01.2012-12.2016	28 Commodity Prices	SVR, SVR-Poly, SVR-RBF, RF	MSE, R^2	SVR-RBF

Ao et al.	2020	USA	01.2000-07.2019	CPI	ARIMA, LSTM	RMSE, MAE	LSTM
Riofrio et al.	2020	Ecuador	01.2005-06.2019	CPI	SVR, LSTM, SARIMA, Exponential Smoothing, Facebook Prophet	MAPE, AIC	SVR
Sarveswararao&Ravi	2020	India	01.2013-05.2021	CPI	RF, MLP, SVM, XHBoost, KNN, LSTM, GRNN, GMDH	SMAPE	GRNN
Zahara	2020	Indonesia	01.2014-12.2018 daily	28 food price	MLP, LSTM	RMSE	MLP
Yang&Guo	2021	China	04.2005-06.2021	Shenzen300, interest rate, exchange rate, wheat future price, CPI	ARMA, BVAR, BP, GRU-RNN	MSE, MAPE, SMAPE	GRU-RNN
Ali&Mohamed	2022	Somalia	07.2017-02.2021	CPI	ARIMAX, STL Decomposition, ROBETS, SES, ANN	RMSE, MAE, MAPE, MASE	ANN
Aras&Lisboa	2022	Turkey	01.2007-08.2021	Economic Confidence Index, interest rate, excjamge rate, production index, CPO	SVM, ANN, RF, Adaboost, Ext.Rand.Trees, GBDT, XGBoost	RMSE, MAE	RF
Sarangi et al.	2022	India	01.2013-05.2021	CPI	ANN, ANN-PSO,	MSE, MAE, ,MAPE	ANN-PSO
Nguyen et al.	2023	USA	01.2017-02.2022	Crude Oil, Gold, FED Fund Rate, CPI	MLR, SVR, ARDL, MARS	MAPE, MAE, RMSE, R^2	MARS
Barkan et al.	2023	USA	01.1994-03.2019	CPI	HRNN-GRU	RMSE	HRNN
Adnan et al.	2023	India	01.1960-05.2022	CPI	LSTM, BiLSTM, ANN-LSTM-Adaboost Hybrid	R^2	ANN-LSTM-Adaboost Hybrid
Sibai et al.	2023	Saudi Arabia	11.2013-11.2020	CPI	Decision Tree, KNN, Linear Regression, ANN, RF, SVM	MAE, MSE, RMSE, R^2	ANN, KNN
Xu et al.	2023	China	10.2006-12.2020	CPI, Stock Price Index, M2, Exchange Rate, Oil Price, Interest Rate	DL-MIDAS, ANN-MIDAS, LSTM, MIDAS, LSTM-low	RMSE	DL-MIDAS
Liu et al.	2023	USA	01.1950-08.2021	CPI	ARIMA, LSTM, Elman, NAR	MAE, RMSE, R^2	NAR

(Álvarez-Díaz & Gupta, 2016) estimated the USA's CPI estimates with Random Walk, SARIMA, ANN and Genetic Programming approaches, using monthly CPI data between 1980-2013. According to the study results, the best MAPE error coefficients were obtained with SARIMA and Random Walk approaches. (Riofrío et al., 2020) used SVR, LSTM, SARIMA, Exponential Smoothing and Facebook Prophet methods to estimate Ecuador's CPI. According to the MAPE and AIC values obtained from monthly data between 2005 and 2019, it was determined that the method that gave the best performance was SVR. Some studies compared time series analysis and machine learning methods (Ali & Mohamed, 2022; Ao et al., 2020; Huong et al., 2016; Liu et al., 2023; Milunovich, 2020; Sibai et al., 2023; Yang & Guo, 2021). Huong et al. (2016) used time series, ANN and multi-objective optimization to estimate the CPI of AU, Spain and OECD countries. According to the MSE values obtained from monthly CPI data between 1960-2005, it was seen that the best prediction performance was obtained with the Multi-Objective optimization model. Ao et al. (2020) compared the prediction performance of ARIMA and LSTM methods using CPI data between 2000 and 2019 to estimate USA CPI values. According to the results obtained, it was observed that the RMSE and MAE values of the LSTM model were lower and had better prediction performance. Yang and Guo (2021) used Shenzen300, interest rate, Exchange rate and wheat future price variables to estimate China CPI and solved the data for the years 2005-2021 with ARMA, BVAR, BP and hybrid GRU-RNN model. According to MSE, MAPE and SMAPE values, it has been shown that the best prediction performance is obtained with the GRU-RNN model. Ali and Mohamed (2022) compared various time series and machine learning methods for Somalia's CPI prediction and revealed that machine learning methods gave better prediction performance. Liu et al. (2023) estimated the USA CPI using CPI data between 1950 and 2021. The data was solved with ARIMA, LSTM, Elman and NAR models and it was determined that the best prediction performance was obtained by the NAR model. Sibai et al. (2023) used 8-year CPI data in their CPI estimation for Saudi Arabia. According to the results of Decision Tree, KNN, Linear Regression, ANN, RF and SVM methods, it was revealed that the best prediction performance was obtained with ANN and KNN methods. (Ambukege et al., 2017) used the NeuroFuzzy method to estimate Tanzania's CPI. Sarveswararao and Ravi (2020) used 8 different machine and deep learning methods for India's CPI prediction and found that the best prediction performance was achieved by the GRNN model according to the SMAPE statistical coefficients obtained from the models. When the literature is examined, it is seen that machine learning and deep learning methods show better performances than traditional methods. In the literature, there are studies comparing machine learning and deep learning methods. Zahara et al. (2020) used 28 daily food prices between 2014 and 2019 to estimate Indonesia's CPI and solved this data with MLP and LSTM. According to RMSE values, the MLP method gave better results than LSTM. In the literature, CPI values are generally used alone (Barkan et al., 2023; Mohammed Adnan et al., 2023; Sarangi et al., 2022; Sibai et al., 2023). Sarangi et al. (2022) compared ANN and ANN-PSO methods for India CPI prediction and revealed that the ANN-PSO method obtained more reliable predictions. Barkan et al. (2023) compared the HRNN and GRU methods for USA CPI estimation and found that the RMSE values of the HRNN method they proposed were lower and gave better results than the GRU method. Mohammed Adnan et al. (2023) compared LSTM, BiLSTM and the ANN-LSTM-Adaboost method, which is a hybrid model, in its CPI estimation for India. It was determined that the hybrid model achieved higher R2 values. Although CPI data is generally used alone in CPI estimations, there are also studies in the literature that use other variables that affect CPI (Aras & Lisboa, 2022; Budiastuti et al., 2017; Milunovich, 2020; Nguyen et al., 2023; Xu et al., 2023). Budiastuti et al. (2017) compared the performances of SVR, SVR-RBF and RF methods for Indonesia's CPI estimation in their study using 28 commodity price data between 2012 and 2016. According to the MSE and R2 values obtained by the methods, the best prediction performance was obtained with the SVR-RBF method (Milunovich, 2020). Using real price housing index, GDI, CPI, unemployment rate, mortgage rate and Exchange rate variables to estimate Australia's CPI, these data were estimated with SVR, RBF, MLP, ARMA, VAR, KRR and XGBoost methods. According to the MSE values produced by the models, it was determined that the best prediction performance was obtained with the SVR method. Aras and Lisboa (2022) compared economic confidence index, interest rate, Exchange rate, production index data between 2007 and 2021 with 7 different methods to estimate CPI for Turkey. According to the RMSE and MAE coefficients obtained, it was revealed that the best prediction performance was obtained with the RF model. Xu et al. (2023) 15 years of data on Stock Price Index, M2 money supply, Exchange rate, Oil price and interest rate variables were used in estimating China CPI. When the RMSE values of the models were compared, it was observed that good prediction performance was achieved with the DL-MIDAS method. Nguyen et al. (2023) compared MLR, SVR, ARDL and MARS methods for USA CPI estimation. In this study, Crude oil, Gold Price, FED Fund Rate variables were used and the performances of the models were compared with MAPE, MAE, RMSE and R2 values. According to the results obtained, it was revealed that the best prediction performance was obtained with the MARS method.

There are many studies in the literature for CPI estimation. In these studies, machine learning and deep learning methods were used in addition to traditional time series analysis methods. When we look at the literature in general, it is observed that CPI data is generally used alone. At this point, adding other variables affecting CPI to the model will provide more accurate predictions. In our study, in addition to Turkey's CPI data, it is aimed to improve CPI prediction performances by adding variables that directly affect CPI, such as Gold Price, Exchange rate, interest rate, producer price index, M1 money supply, oil and natural gas price, to the model. Again, the number of hybrid models in which machine learning and deep learning methods are used together is quite low in the literature. There are studies in the literature that hybrid methods give better prediction results than machine or deep learning methods used alone (Budiastuti et al., 2017; Mohammed Adnan et al., 2023; Yang & Guo, 2021). In this study, in addition to DDPG, XGBoost, SVR, KNN methods, the CNN-BiLSTM hybrid model was used to estimate Turkey's CPI. At this point, it can be compared whether hybrid models will give better results based on the prediction performances obtained.

3. METHODOLOGY

In this study, 248 months of data from January 2003 to August 2023 were used. Gold price, dollar/TL Exchange rate, interest rate, PPI, M1 money supply, oil price and natural gas price variables were used to estimate Turkey's CPI. Data for the variables used in the study were obtained from EVDS, the electronic data system of the Central Bank of the Republic of Turkey. In the study, predictions were made using 5 different methods. The methods used in this study are DDPG, XGBoost, SVR, KNN and CNN-BiLSTM. Prediction performances of the methods used are RMSE, MSE; MAE, MAPE and R2 were compared using statistical coefficients. Mathematical expressions for these coefficients are shown in Equations 1-5.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i-\hat{y}_i)}{N}} \quad (1)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i-\hat{y}_i)^2 \quad (2)$$

$$MAE = \frac{\sum_{i=1}^{n}|y_i-x_i|}{n} \quad (3)$$

$$MAPE = \frac{\sum_{t=1}^{n}\frac{u_t}{Y_t}}{n}*100 \quad (4)$$

$$R^2 = 1-\frac{\sum_i(y_i-\hat{y}_i)^2}{\sum_i(y_i-\mu)^2} \quad (5)$$

3.1. DDPG Algorithm

The conventional DQN method, along with additional algorithms derived from it, which are based on the state-action value function, have demonstrated significant advancements in addressing the control problem associated with discrete actions (Dong & Zou, 2020). Deep Reinforcement Learning (DRL) is a subfield within the broader domain of machine learning that integrates the principles of deep learning with reinforcement learning. DDPG, as an algorithm within the domain of deep reinforcement learning, exhibits a notable capacity for effectively and reliably addressing challenges associated with continuous action spaces (Mnih et al., 2015). When comparing the discrete action space with the continuous action space of the DDPG algorithm, it can be observed that the latter exhibits improved effectiveness and higher precision in achieving economic efficiency (Liu et al., 2021). The DDPG method is derived from the Actor-Critic architecture and utilizes a set of four neural networks. Both the Actor and Critic components consist of a primary network and a target network. The primary function of the target network is to enhance the stability of the algorithm's training process (Li et al., 2023).

The analysis of the gradient-based policy μ(s_t) will be expanded within the context of the actor-based deep neural network (DNN) methodology. The Bellman equation is a mathematical expression that defines the optimal-value function $Q^{\mu}(s_t, a_t)$) as shown in Equation 6.

$$Q^{\mu}(s_t, a_t) = E\left[r(s_t, a_t) + \gamma \max Q^{\mu}(s_{t+1}, a_{t+1})\right] \quad (6)$$

The individual starts the procedure by generating an approximation to the optimal value function Q^μ (s_t, a_t) via the utilization of the provided recursive equation. The critic network, referred to as the Q network, obtains updates by computing the loss function, designated as the mean-squared Bellman error (MSBE), as presented in Equation 7 and Equation 8.

$$L = \frac{1}{T}\sum_t[y_t - Q(s_t, a_t|\emptyset^Q)]^2 \quad (7)$$

where:

$$y_t = r(s_t, a_t) + \gamma Q'(s_{t+1}, \mu'(s_{t+1}|\emptyset^{\mu'})|\emptyset^{Q'}) \quad (8)$$

The policy network, also known as the actor network, observes a state from the environment and performs a continuous action at each time step t. Similar to other algorithms within the realm of reinforcement learning (RL), the fundamental objective of the agent is to choose the strategy that achieves the highest degree of optimal performance. The DDPG algorithm utilizes a policy gradient approach to determine the policy that maximizes optimality. The policy undergoes updates through the involvement of the actor network, with support from the critic network. The equation representing the gradient for updating the policy is given by Equation 9.

$$\nabla_{\emptyset^{\mu}} J \approx E_{s_t}\left[\nabla_{\emptyset^{\mu}} Q(s, \alpha|\emptyset^{Q}) \mid s = s_t, \alpha = \mu(s|\emptyset^{\mu})\right] \tag{9}$$
$$= E_{s_t}\left[\nabla_{\alpha} Q(s, \alpha|\emptyset^{Q})|_{s=s_t, \alpha=\mu(s|\emptyset^{\mu})} \nabla_{\emptyset^{\mu}} \mu(s|\emptyset^{\mu}) \mid_{s=s_t}\right]$$

Mendiola-Rodriguez and Ricardez-Sandoval (2022) provide a succinct description of the phases involved in the DDPG learning process each episode. The starting circumstances of the states in the model are captured and recorded from the outset. The policy network is responsible for accepting the state as an input and generating an action as an output. Before reintegrating the action into the environment, it is usual to include a form of Gaussian process known as Ornstein-Uhlenbeck (OU) noise. The existence of noise may be construed as indicative of a discrepancy between the factual performance of a corporation and the projected results derived from accounting models. Following the completion of a certain task, the environment is provided with a reward denoted as r_t and then generates the next state, s_{t+1}. The components of the Markov Decision Process (MDP), represented as $(s_t, \alpha_t, r_t, s_{t+1})$, are stored in the buffer memory. Subsequently, a random sample is extracted from the buffer memory, including a minibatch of T transitions $(s_t, \alpha_t, r_t, s_{t+1})$. In the subsequent stage, the critic network is presented with the state s_t, and action α_t. The target value y_t, is determined by the critic network, and the critic is updated by the minimization of the loss function L. This loss function is computed using the TD error. In order to update the actor-network, it is necessary to compute the derivative of the policy. The last stage is the process of upgrading the target networks.

The learning process appears to have concluded when the user has successfully finished a predefined quantity of episodes or when they have fulfilled a certain condition for completion, as determined by the user. This criteria may encompass the lack of progress in rewards throughout a significant number of instances.

3.2. XGBoost Algorithm

XGBoost is widely recognized as a prominent technique for boosting trees in the context of gradient boosting machine (GBM) (Dong et al., 2020). XGBoost, a prominent model within the Boosting Tree family, exhibits robust growth and adaptability. The approach combines numerous tree models in order to construct a more robust learner model. In addition, XGBoost has the capability to leverage CPU multitasking for parallel computation, resulting in enhanced computational efficiency (Li et al., 2019).

The methods employed for solving the XGBoost algorithm is presented in Equations 10-18. Within the framework of this research, Equation 10 represents the assemblage of regression trees, denoted by the symbol F. The variable f_k denotes the quantity of weak learners, with K being the overall count of weak learners. The equation representing the objective function is shown as Equation 11. The parameter $l(y_i, \hat{y}_i^{(t)})$ in Equation 11 includes a range of loss functions that are employed to address specific problems. Equation 11 is a commonly utilized approach for measuring the disparity between the observed value (y_i) and the predicted value $(\hat{y}_i^{(t)})$, as well as the overall intricacy of the model, denoted by $\sum_{k=1}^{t} \Omega(f_k)$. The process of evaluating the objective function entails substituting the predicted value $(\hat{y}_i^{(t)})$ for the i-th sample in the t-th iteration. The computation is performed by utilizing the second-order approximation of the Taylor expansion at the expected value of y from the previous iteration, represented as $(\hat{y}_i^{(t-1)})$, as seen in Equation 10. In the given context of Equation 14-15, the variables g_i and h_i represent the first and second derivatives of the loss function $l(y_i, \hat{y}_i^{(t)})$ correspondingly. Based on the above discussion, we may now proceed with the computation of the derivative by substituting the corresponding formulas, denoted as Equations 13, 14, and 15, into Equation 12. Equations 16 and 17 can be employed to formulate solutions for a given problem. The variable obj* is employed to represent the numerical value of the score for the loss function. A lower score indicates that the analyzed tree structure is more nearer to the optimal. The variable w_j^* denotes the optimal solution for the weights in the specific situation under evaluation.

$$\hat{y}_i = \emptyset(x_i) = \sum_{k=1}^{K} f_k(y_i), f_k \in \mathcal{F} \tag{10}$$

$$min\, L^{(t)}(y_i, \hat{y}_i^{(t)}) = min\left(\sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t)}) + \sum_{k=1}^{t} \Omega(f_k)\right) \tag{11}$$

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda w^2 \tag{12}$$

$$min\, L^{(t)} = min\left(\sum_{i=1}^{n}\left[g_i f_t(x_i) + \frac{1}{2} h_i f_t(x_i)\right] + \Omega(f_t)\right) \tag{13}$$

$$g_i = \partial_{\hat{y}_i^{(t-1)}} l(y_i, y_i^{t-1}) \tag{14}$$

$$h_i = \partial^2_{y_i^{t-1}}\, l(y_i, y_i^{t-1}) \tag{15}$$

$$w_j^* = -\frac{\sum g_i}{\sum h_i + \lambda} \tag{16}$$

$$obj^* = -\frac{1}{2}\sum_{j=1}^{T}\frac{(\sum g_i)^2}{\sum h_i+\lambda} + \gamma.T \tag{17}$$

3.3. SVR Algorithm

Support Vector Machine SVM models have gained significant traction and seen extensive advancements within academic spheres since its first proposal. SVM models may be categorized into two types based on the data format: SVR models for regression and SVC models for classification. In contrast to other learning approaches, SVM rely on the principle of structural risk reduction, which endows them with robust generalization capabilities. Additionally, SVMs possess the desirable property of converging to the global optimal solution by locating the local optimum point (Zheng et al., 2021). SVR is an extension of SVM that addresses regression problems. The objective of SVR is to ensure that all sample points closely match the regression hyperplane, while minimizing the overall divergence between the sample points and the hyperplane (Xu et al., 2010; Chen et al., 2017).

Gao et al. (2023) state that the primary aim of SVR is to ascertain a linear regression function, represented as f(x), inside a space characterized by a high number of dimensions.

$$f\ (x) = \ \omega\ \Phi\ (x) + b \tag{18}$$

Let x be a member of the set of real numbers, representing the sample vector. The function Φ has non-linear characteristics in its mapping. The use of a linear insensitivity loss function, represented as L(f (x), y, ε), contributes to enhancing the robustness of the optimization problem. The mathematical representation of this loss function is as outlined below:

$$\mathrm{L}(f\ (\mathrm{x}), \mathrm{y}, \varepsilon) = f(x) = \begin{cases} 0 & |\mathrm{y} - f\ (\mathrm{x})| \leq \varepsilon \\ |\ y - f\ (\mathrm{x})| - \varepsilon & |\mathrm{y} - f\ (\mathrm{x})| > \varepsilon \end{cases} \tag{19}$$

In order to identify the estimation of ω and b, it is important to solve the subsequent optimization problem:

$$\begin{cases} Min. \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}\xi_i \\ sub.t. \begin{cases} y_i - \omega\Phi(x_i) - b \leq \varepsilon + \xi_i \\ -y_i + \omega\Phi(x_i) + b \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \end{cases} \tag{20}$$

Let x_i be an input vector in the d-dimensional real space, denoted as $x_i \in R^d$. Similarly, let y_i be the corresponding output value, represented as $y_i \in$ R, with i being the serial number. In this context, the variable d symbolizes the cardinality of the input vector. The variable n denotes the number of training samples. The symbol ε is used to denote the measure of regression precision. The variable C represents a penalty factor that serves to quantify the extent of penalty applied to a data sample in cases when its mistake surpasses the threshold value ε. The variables ξ_i and ξ_i^* are utilized as slack variables to apply penalties on the complexity of the fitting parameters.

The optimization problem can be effectively addressed by the utilization of a Lagrange function, which provides a mathematical expression for the resultant solution.

$$\omega^* = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\ \Phi(x_i) \tag{21}$$

$$b^* = \frac{1}{N_{nsv}}\left\{\sum_{0<\alpha_i<C}\left[y_i - \sum_{x_i \in SV}(\alpha_i - \alpha_i^*)K(x_i, x_j) - \varepsilon\right] + \sum_{0<\alpha_i<C}\left[y_i - \sum_{x_j \in SV}(\alpha_j - \alpha_j^*)K(x_i, x_j) + \varepsilon\right]\right\} \tag{22}$$

The variable N_{nsv} denotes the number of support vectors that have been ascertained. The Lagrange multipliers, represented as α_i and α_i^* are constrained to be non-negative. The utilization of the kernel function, represented as $K(x_i, x_j)$,is observed in this particular circumstance. The Gaussian kernel function, known for its exceptional generalization capacity, is selected.

$$K(x_i, x_j) = \exp\left(-\frac{\|x - x_i\|^2}{2\sigma^2}\right) \tag{23}$$

The ultimate regression function can be represented as shown in Equation (24).

$$f(x) = \ \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)K(x_i, x) + b^* \tag{24}$$

3.3. KNN Algorithm

The K-nearest neighbor approach is a machine learning algorithm that is often regarded as easy to apply (Aha et al., 1991). The fundamental principle of the KNN algorithm is to assign an unknown data point to a specific category based on its similarity to other data points with known categories. The technique calculates the closest neighbor based on a specified k-value, which sets the number of nearest neighbors to be taken into account. This k-value is used to assign a class to a given sample data point. The utilization of multiple closest neighbors is a determining factor in ascertaining the class to which a particular data point belongs. This is the underlying rationale behind the name KNN. The approach is classified as a memory-based technique due to the requirement of having data points stored in memory during execution (Phyu, 2009; Amra & Maghari, 2017). The KNN approach is commonly utilized as a classification and regression tool in the domain of machine learning. The core principle is on the procedures of training and prediction within a specified model. Through the training phase, the model acquires knowledge about the input data and corresponding labels of the training sample instances. Subsequently, every occurrence is assigned a distinct coordinate inside an n-dimensional spatial framework, contingent upon its distinctive characteristics. During the prediction phase, the model determines the k closest points to the mapping values in the prediction sample. The labels of the prediction sample are thereafter forecasted by taking into account the labels of the selected points. It is necessary to carefully evaluate the selection of k, the choice of distance measure, and the criteria for classification decisions throughout the algorithm. The KNN approach exhibits several significant advantages, including its fundamental architecture and ease of usage, expedient training duration, and resilience to outliers. Therefore, it is commonly utilized for the automated categorization of category domains that exhibit large sample sizes and extensive overlap or intersection across these various domains (Huang, 2022; Kantardzic, 2011).

According to Jadhav and Channe (2016), the KNN method possesses both advantages and downsides. The KNN algorithm possesses several advantages in the context of machine learning. These advantages encompass its simplicity in terms of comprehension and application, its efficient training process, its ability to handle noisy training data without compromising performance, and its efficiency in scenarios where the dataset consists of several class labels. Nevertheless, this approach exhibits significant drawbacks, including a tendency towards passive learning, a susceptibility to the specific structure of the data, a substantial memory need, and a sluggish execution speed resulting from its inherent character as a supervised lazy learning method.

3.4. CNN-BiLSTM Algorithm

By combining the Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) models, accurate predictions of multivariate time-series signals may be achieved with a high level of performance (Kim et al., 2023). The CNN-BiSLSTM model is a hybrid architecture that integrates the CNN and LSTM models. The BiSLSTM model is an improvement upon the BiLSTM model as it integrates a $1 - \tanh()$ function into the output gate. The adjustment leads to the output gate possessing a value range of around (0.24, 1). Therefore, it is evident that BiSLSTM exhibits enhanced model fitting performance during the course of training, while also possessing comparable strong learning capabilities to BiLSTM. Therefore, BiSLSTM exhibits appropriateness in the examination of temporal data linkages (Wang et al., 2021).

The sequential steps of the CNN-BiLSTM model are presented in equations 24-29.

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{24}$$

In Equation 24, the variable i_t is employed as the input gate to assess the appropriateness of retaining the current input data using a mathematical process.

$$\tilde{c}_t = tanh(W_c.[h_{t-1}, x_t] + b_c), \tag{25}$$

The variable $\tilde{c}_t$ is employed in the calculation of data that requires updating using Equation 25.

$$f_t = \sigma\left(W_f.[h_{t-1}, x_t] + b_f\right), \tag{26}$$

The symbol f_t is frequently utilized in scholarly literature to denote the forgetting gate. Equation 26 demonstrates the utilization of the sigmoid function in assessing the relevance of prior memory for the present memory state.

$$C_t = f_t * C_{t-1} + i_t * \tilde{c}_t, \tag{27}$$

The variable i_t is utilized as a mechanism to calculate the requirement of an update. Furthermore, the variable $\tilde{c}_t$ is employed to calculate if the current state necessitates an update, as defined by Equation 27.

$$o_t = 1 - \tanh\left(\sigma(W_o.[h_{t-1}, x_t] + b_0)\right), \tag{28}$$

After the acquisition of the latest state, the calculation of the output gate value o_t is performed using Equation 28. In contrast to BiSLSTM, the incorporation of the $1 - \tanh(x)$ function is observed at this particular level. The updated memory cell has the ability to calculate the present hidden state by utilizing Equation 29.

$$h_t = o_t * \tanh(C_t). \tag{29}$$

4.RESULTS AND DISCUSSION

The performance metrics of the suggested DDPG, SVR, KNN, XGBoost, and CNN-BiLSTM models are presented in Table 2. This research utilized a set of five statistical indicators. The evaluation of the disparity between anticipated values and actual values is commonly conducted using a statistical metric known as RMSE. A decrease in score indicates a stronger alignment between the model's predictions and actual outcomes. The MSE is calculated as the average of the squared discrepancies between the predicted values and the actual values. The model's predictions exhibit more accuracy as the MSE decreases. The MAPE is a metric that calculates the average % difference between expected and actual values. It is used to assess the accuracy of predictions in terms of percentage. The MAE is a metric that quantifies the average absolute difference between the predicted and actual values. A low MAE indicates that the model's predictions tend to be precise, hence reducing the influence of notable outliers. The R2 metric quantifies the proportion of variation in the data that can be explained by a model. When the coefficient of determination R2 value approaches 1, it indicates that a substantial proportion of the variability in the data can be accounted for by the model.

Table 2. *Performance Metrics of the Suggested Models*

	DDPG	XGBoost	SVR	KNN	CNN-BiLSTM
RMSE	29.1182	25.6341	12.2356	104.4851	15.8967
MSE	847.8680	657.1057	149.7106	10917.1461	252.7036
MAE	26.1516	11.3021	9.1678	91.9482	10.4170
MAPE	93.5539	0.0218	0.0317	0.5671	0.0445
R^2	0.9888	0.9948	0.9984	0.9133	0.9952

Based on the findings shown in Table 2, it can be observed that the DDPG algorithm exhibits a comparatively elevated RMSE and MAE, suggesting a moderate level of prediction inaccuracy. Nevertheless, a substantial R-squared value of 0.9888 signifies the model's capacity to elucidate a considerable proportion of the variability observed in the data. XGBoost has strong performance in terms of low MAE and MAPE values, which suggest precise predictions with minimum deviation. A substantial R2 coefficient 0.9948 signifies a robust capacity to elucidate the variability observed in the data. The SVR model has exceptional performance, as seen by its notably low RMSE, Mean Square Error MSE, MAE, and MAPE values. The R2 score of 0.9984 demonstrates a remarkably strong capacity to elucidate the extent of variability present in the data. The KNN algorithm has a higher root RMSE in comparison to other models, therefore suggesting a greater magnitude of prediction discrepancy when compared to such models. Nevertheless, the R2 coefficient of determination, with a value of 0.9133, suggests a substantial level of explanatory capability. The CNN-BiLSTM model has strong performance, with minimal values across all error measures. A substantial R2 coefficient of 0.9952 signifies a robust capacity to elucidate the extent of variability observed within the dataset.

Upon analyzing the performance indicators employed for evaluating the model with superior performance, it becomes evident that the SVR model has exceptional characteristics. The SVR model has the lowest RMSE in comparison to alternative models. This suggests that there is a low level of discrepancy between the actual values of the model and its corresponding predictions. A low RMSE value is indicative of forecasts that can be considered dependable. The MSE value exhibits a reduced magnitude in comparison to other models. A low MSE, which represents the average squared difference between the model's predicted values and the actual values, suggests that the model's predictions are often accurate. The MAE value of the SVR model is comparatively lower than those of other models. This suggests that the model has a lower average error rate and demonstrates a higher degree of proximity between its predictions and the actual data. The SVR model exhibits a significantly low MAPE score, suggesting that the model's percentage error rate is consistently low and its predictions are typically precise. The coefficient of determination R2 for the SVR model exhibits a significantly elevated level. This exemplifies the model's capacity to explain a significant portion of the variance observed in the data. A high R2 value signifies a strong concordance between the model and the actual data, indicating that the model effectively accounts for the majority of the observed variability. Consequently, it can be observed that the SVR model exhibits superior performance in comparison to other models, as indicated by its low error metrics and high R-squared value. This model exhibits a high level of predictive accuracy by effectively collecting and representing patterns within the dataset.

When the literature is examined, many methods have been proposed for CPI estimation. Similar to our study, it was determined that the SVR method gave better prediction performance in the CPI predictions made by (Milunovich, 2020) for Australia and (Riofrío et al., 2020) for Ecuador. However, the CNN-BiLSTM hybrid method used in this study showed worse prediction performance than the SVR method. It is generally stated in the literature that more accurate results are obtained in studies where more than one method is used together rather than using models alone (Budiastuti et al., 2017; Mohammed Adnan et al., 2023; Yang & Guo, 2021). At this point, the CNN-BiLSTM method used in our study showed a worse performance than the SVR method. This result shows results contrary to the general opinion in the literature. There are many factors that affect CPI. In addition to the variables used in this study for CPI prediction, adding different variables in future studies may provide more accurate prediction results. Additionally, there are many different machine learning and deep learning methods to be used in CPI estimation. This study can be repeated with methods such as RF and GRU. In addition, contrary to what is stated in the literature, the CNN-BiLSTM method, which is a hybrid method, did not give the best results. This can be investigated again using different hybrid models such as XGBoost-LSTM and SVR-LSTM.

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ÇALIŞMANIN ETİK İZNİ

Yapılan bu çalışmada "Yükseköğretim Kurumları Bilimsel Araştırma ve Yayın Etiği Yönergesi" kapsamında uyulması belirtilen tüm kurallara uyulmuştur. Yönergenin ikinci bölümü olan "Bilimsel Araştırma ve Yayın Etiğine Aykırı Eylemler" başlığı altında belirtilen eylemlerden hiçbiri gerçekleştirilmemiştir.

Etik kurul izin bilgileri

Çalışmada ikincil veriler kullanıldığından herhangi bir etik kurul izni alınmamıştır.

ARAŞTIRMACILARIN KATKI ORANI

1.yazarın araştırmaya katkı oranı %100

Yazar 1: Özet, verilerin toplanması, literatür taraması, uygulama, tartışma ve sonuç.

ÇATIŞMA BEYANI

Araştırmada herhangi bir kişi ya da kurum ile finansal ya da kişisel yönden bağlantı bulunmamaktadır. Araştırmada herhangi bir çıkar çatışması bulunmamaktadır.