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Forecasting Vietnam Inflation Using Machine Learning Approaches: A Comprehensive Analysis

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Abstract

Purpose: This study investigates the predictive ability of selected machine learning methods for inflation prediction in Vietnam.

Design/methodology/approach: This study computes forecasts using autoregressive integrated moving average, extreme gradient boosting, linear regression, random forest, K-nearest neighbour, four variants of the recurrent neural network, and causal convolutional neural network. This research assesses their properties according to criteria from the optimal forecast literature. Then, their performance is compared with the predictions of the International Monetary Fund and Asian Development Bank used by the State Bank of Vietnam as a policy benchmark tool.

Findings: Although there is no single best model to predict inflation for various horizons, the findings suggest that the K-nearest neighbour (KNN) model provides better forecasts than others for the 12-month horizon. These forecasts are relatively in line with the projections of well-known international organisations under several conditions. The KNN forecast even outperformed those when considering the COVID-19 crisis.

Research implications: The results suggest that the machine learning models selected in this study could be used as an additional benchmark tool for policy decision-making under uncertainty, offering a data-driven approach to supplement traditional economic judgment.

Originality/value: This study is the first attempt to employ different advanced machine learning methods to predict inflation in Vietnam. More importantly, these results are then compared with other conventional ones and benchmark forecasts for robustness checks.

Keywords: Inflation, forecasting, machine learning, deep learning, COVID-19 crisis, Vietnam

JEL Classifications: E31, C45, C49, C53

1. Introduction

According to the global survey of IPSOS (2022), 40% of the surveyed participants agreed that inflation is one of the biggest concerns in the post-COVID-19 pandemic. More specifically, the survey also indicated that the level of concern about rising prices has escalated for 14 consecutive months. Hence, better inflation control reflects the effective implementation of monetary policy and the credibility of a central bank, especially in emerging markets and developing economies (Kose et al., 2019).

It is acknowledged that because money policy is inherently imposed with a lag, policy decisions consider the expected trajectory of inflation and other macroeconomic factors during the policy horizon. For the inflation targeting scheme, acquiring better and more accurate predictions for inflation itself and key economic variables is essential to implement adequate policy decisions. It is seen that the inflation forecasts from central banks are often proprietary. Thus, market participants tend to utilise the inflation predictions from international organisations such as the International Monetary Fund (IMF), the World Bank, the Asian Development Bank (ADB), and the Organisation for Economic Cooperation and Development (OECD). Unfortunately, the accuracy of macroeconomic forecasts published by these organisations is still questionable (Artis & Marcellino, 2001; Eicher & Rollinson, 2023). Therefore, developing better models for inflation prediction has attracted more attention from policymakers, investors, practitioners, and academic researchers.

Many studies have been devoted to forecasting inflation using various methods. The literature on utilising conventional approaches shows confounding results in developed markets. For example, early studies argued the disadvantages of Phillips-curve-based inflation modelling against simple univariate forecasting models (Faust & Wright, 2013; Stock & Watson, 2010). However, other studies have shown opposite findings (Bańbura & Bobeica, 2023). Additionally, several studies have suggested that other conventional approaches outperformed others across different forecasting periods. For instance, Bayesian model averaging yields better forecasting results than other models (e.g., random walk, ridge regression) for the current quarter and the quarter one year beyond the current quarter (Groen et al., 2013). However, neural networks provide more accurate inflation forecasting than different autoregressive model specifications for short horizons (e.g., one and two quarters) (Nakamura, 2005). Furthermore, recent studies have focused more on leveraging machine learning (ML) models to predict inflation, yielding similar conclusions that there is no best predicting model. For example, one of the best models for inflation forecasts is random forest (Aras & Lisboa, 2022), gradient boosting (Naghi et al., 2024), long short-term memory (Almosova & Andresen, 2023), a gated recurrent unit (Yang & Guo, 2021), and an autoencoder (Hauzenberger et al., 2023). Nonetheless, the confounding results using ML models vary based on inflation measures and forecast horizons (Ülke et al., 2018). Due to disagreement on inflation forecasts across various machine learning models and country settings, the present study revisits this issue using the comprehensive analysis of ML models frequently utilised in the literature for the case of Vietnam. This study, therefore, aims to address the following research questions:

Research question 1: Is there one machine learning model that outperforms others across different horizons?

Research question 2: Are forecasting results derived from machine learning models more accurate than those projections reported by prestigious international organisations?

Vietnam achieved remarkable economic growth (Le et al., 2024) and is considered one of the next dragons in Asia. Maintaining this achievement requires appropriate monetary policies to control inflation. Implementing these policies to support the economy often lags or is under political pressure rather than evidence-based (Lastunen & Richiardi, 2023). For the inflation targeting scheme, more accurate predictions for inflation are vital, especially in Vietnam, where the data is limited (Boubaker et al., 2025; Nguyen et al., 2022).

This study contributes to the existing literature in several ways. First, a bulk of studies on inflation forecasting are devoted to analysing whether the predicted values derived from different machine learning models are similar to actual values and more accurate than forecast values obtained from other ML algorithms and conventional methods (Aras & Lisboa, 2022; Araujo & Gaglianone, 2023; Li et al., 2023; Medeiros et al., 2021; Özgür & Akkoç, 2022; Rodríguez-Vargas, 2020; Ülke et al., 2018). Inflation prediction would be helpful when it could be used as a benchmark for authorities adjusting policy tools and regulating the monetary market, and market participants adjusting their business strategies and operations. Besides the report of inflation forecasts published by national government bodies that are often proprietary, the macroeconomic forecasts reported in the World Economic Outlook (WEO) issued by the International Monetary Fund and Asian Development Outlook (ADO) introduced by the Asian Development Bank are often utilised by the public without any costs despite of disagreement on the accuracy of international institutions' forecasts (Artis, 1996; Barrionuevo, 1992; Eicher & Rollinson, 2023; Tsuchiya, 2023). Therefore, this study aims to validate whether obtainable results from advanced ML models are superior to those from conventional ones and the WEO and ADO forecasts.

Second, the consequences of the unprecedented COVID-19 pandemic on the global economy are still unpredictable, especially from an inflation perspective. Pham, Le and Nguyen (2022) showed that the presence of the bias of some predictive points may correspond to financial shocks. Boaretto and Medeiros (2023) reemphasised the advantages of using ML models for inflation forecasting, mainly during volatile periods like the COVID-19 turmoil. Therefore, it is essential to account for the impact of the recent health crisis to forecast inflation. Therefore, this study may be one of the attempts to forecast inflation before, during, and after the COVID-19 turmoil to assess the accuracy and reliability of ML models.

Third, Article 3 of the Vietnamese Banking Act No. 46/2010/QH12 stipulates that one of the primary objectives of the national monetary policy is to stabilise and maintain a low level of inflation under the decision of the National Assembly of Vietnam (The National Assembly of Vietnam, 2010). So far, no official documentation on inflation forecasts has been published by the State Bank of Vietnam. A limited number of studies have attempted to predict inflation using different methods, such as dynamic model averaging (Thu & Leon-Gonzalez, 2021), Grey systems modelling and Discrete Grey Models (Nguyen & Tran, 2015), and the feedforward artificial neural network (ANN) with backpropagation as a variant of ML (Nguyen et al., 2022; Pham, Le, & Nguyen, 2022). However, there is a lack of comparison between advanced ML methods and other conventional ones, as well as benchmark forecasts such as WEO and ADO reports for robustness checks. Thus, the advantages of ML in inflation prediction in Vietnam over other methods are inclusive. The present study attempts to address this gap. Therefore, this study may provide a timely and complementary reference for Vietnam inflation forecasts that would be useful for policy decision-making amid uncertainty, delivering a data-driven method to complement conventional economic judgment.

Last, prior studies show mixed findings on important features in inflation forecasts (Malladi, 2024). This raises the question of whether these features are relevant to the context of Vietnam due to substantial differences in institutional quality and national background. The findings, therefore, attempt to provide critical features that the Vietnamese authorities should focus on to strengthen the accuracy of their forecasting models. These features may also be relevant to other countries with similar structures.

The remainder of this study is organised as follows. Section 2 introduces a brief overview of the literature on inflation prediction, while Section 3 discusses data and various machine learning models used to predict inflation in this study. Section 4 presents empirical results, while Section 5 concludes.

2. Literature review

2.1 Inflation forecasting models

The literature on inflation forecasting can be divided into two main parts. The first strand uses conventional methods, revealing mixed findings in developed countries (e.g., the US and Europe) where extensive data facilitate econometric models (Stock & Watson, 2009). Stock and Watson (2010) found that Phillips-curve-based inflation modelling suffers from measurement problems and unstable results. More specifically, it is an overwhelming effort to systematically enhance simple univariate forecasting models such as the random walk (Atkeson & Ohanian, 2001) or the time-varying unobserved component models (Stock & Watson, 2007). Faust and Wright (2013) and Orphanides and van Norden (2005) also provided a similar conclusion. Bańbura and Bobeica (2023), however, exhibited some Phillips specifications that outperform a univariate model. Furthermore, Wright (2009) found that Bayesian model averaging (BMA) beat AR inflation prediction out of the sample. For further validation, Groen et al. (2013) showed that the results of their BMA specifications are more accurate than those of other models (e.g., simple AR, random walk, ridge regression, and unobserved components model with stochastic volatility) for the current quarter and the quarter one year beyond the current quarter. Additionally, Binner et al. (2010) suggested that nonlinear autoregressive models based on the kernel approach outperform naïve random walk models and recurrent neural networks. Nakamura (2005) pointed out that inflation forecasting derived from neural networks is better than that of univariate autoregressive (AR) models for short horizons of one and two quarters. Nonetheless, prior studies demonstrate the difficulties of forecasting inflation, especially when accounting for the recessions in the forecasting procedure (Stock & Watson, 2010), and often ignore the recent machine learning (ML) approaches with the increasing availability of big data in economics and computing power (Medeiros et al., 2021).

In the second strand, ML methods, as useful forecasting tools, have gained much attention from scholars. ML is often used in classification issues where the predicted variable is discrete and the data are cross-sectional. This method is also well-suited and useful for forecasting continuous time-series data (e.g., inflation or other macroeconomic variables) (Coulombe et al., 2022; Rodríguez-Vargas, 2020). Similarly, Medeiros et al. (2021) further demonstrated that the superiority of the ML approach holds even in real-time. The literature on ML in forecasting inflation, however, shows mixed results. Several studies using a hundred potential predictors suggest that one of the best ML models for inflation forecasts is random forest (RF) (Aras & Lisboa, 2022; Das & Das, 2024; Medeiros et al., 2021) or gradient boosting (Kanaparthi, 2024; Mirza et al., 2024). Although Naghi et al. (2024) replicated the findings of Medeiros et al. (2021) for forecasting inflation in Canada and the UK until the COVID-19 outbreak, a stochastic volatility model and gradient boosting methods yielded more accurate forecasts during the health crisis periods. However, Rodríguez-Vargas (2020) revealed that the best-performing models for inflation prediction in Costa Rica are long short-term memory (LSTM), univariate k-nearest neighbors, and followed by RF. LSTM is also considered highly efficient for US inflation forecasts (Almosova & Andresen, 2023). Moreover, Özgür and Akkoç (2022) found that among shrinkage methods, Lasso and Elastic net algorithms offer better forecasting results than other shrinkage methods and benchmark specifications (e.g., autoregressive integrated moving average (ARIMA) and multivariate vector autoregression models (VAR)). A similar conclusion is drawn from a study by Huang et al. (2024) in China. However, Ülke et al. (2018) argued that the confounding results in inflation forecasts depend on inflation measures and prediction horizons. For instance, multivariate models (e.g., VAR and the autoregressive distributed lag (ARDL)) provide the most accurate outcomes in all horizons for CPI inflation forecasting. Significantly, the ARDL is the best-fitting model for predicting the core CPI and PCE. Nonetheless, SVR is the best model for forecasting the core-PCE compared to k-NN, ANN, two univariate (AR and Naïve), and two multivariate models. In addition, other studies show that a more effective ML model for inflation forecasts is a gated recurrent unit (Yang & Guo, 2021), an autoencoder as a particular form of deep neural network (Hauzenberger et al., 2023), and the convolutional long short-term memory combined with variational autoencoders (Theoharidis et al., 2023). Pinto and Marçal (2020) asserted that none of the machine learning models is superior to the others in forecasting inflation in American countries, except for the extreme learning method.

Nonetheless, ML models are not always better than conventional ones. Plakandaras et al. (2017) argued that autoregressive and structural models yield homogeneous predicting performance, and linear models should be recommended over the more complicated nonlinear ones. Joseph et al. (2024) reinforced the early findings that the AR benchmark is hard to beat across different settings. Shrinkage methods such as Ridge regression, Elastic net, and Lasso are better candidates for inflation forecasts in the UK with longer horizons of 6 and 12 months.

In sum, the literature shows that no best forecasting model can fit all horizons across countries (Wolpert, 1996). Given the necessity of predicting inflation precisely, improving forecasting models is challenging. The present study attempts to reconsider this issue by applying the comprehensive analysis of ML models frequently utilised in the literature for predicting inflation in Vietnam, considering the uncertainty caused by the COVID-19 turmoil.

2.2 Feature selection for inflation forecasting

The literature suggests various features that can be used for inflation forecasting. They can be categorised into several primary groups, as follows.

Monetarist theory states that money supply inevitably affects prices and inflation (Frisch, 1983). One of the crucial theories explaining this relationship is the quantity theory of money (QTM) (McCallum & Nelson, 2010). More specifically, the quantity of money in the economy is crucial to determining the overall price level. Several theoretical studies argue that a sudden increase in money supply causes a proportional rise in inflation (Friedman, 1989; Friedman & Schwartz, 1963). Other studies, however, challenge the statement of QTM (Cogley & Sbordone, 2008; Del Negro et al., 2015). Mishkin (2009) asserts that expansionary monetary policy effectively controls inflation risks during the global financial crisis. Additionally, systematic evidence demonstrates a link between monetary policy, interest rates, and inflation. Several studies consider different perspectives of monetary policy when examining the factors affecting inflation or forecasting inflation, such as various measures of money supply (Nguyen, 2024; Ooft et al., 2024), nominal and real interest rates (Stock & Watson, 1999), and interest rate policies (Alvarez et al., 2001). In this sense, the features related to monetary policy rates are crucial for inflation prediction.

Furthermore, greater levels of financial sector development enable central banks to utilise interest rates more efficiently for managing inflation and its volatility (Ouyang & Rajan, 2019). Mehrotra and Yetman (2015) also highlight that financial development increases access to finance, which in turn permits improved consumption smoothing. As a consequence, central banks can prioritise inflation management over output stabilisation, thereby contributing to reduced and more stable inflation rates. Therefore, features associated with stock market development are essential for forecasting inflation (Yang & Guo, 2021).

Furthermore, the cost-push theory of inflation posits that prices for goods and services are driven by increasing production costs (Schwarzer, 2018). Therefore, commodity prices, as critical inputs for various industries, have received considerable attention from academics and policymakers when studying inflation (Devaguptapu & Dash, 2021; Gerlach & Stuart, 2024). Thus, features associated with commodity prices are necessary for predicting inflation (Ciner, 2011; Nguyen & Tran, 2015). In addition, global uncertainty (e.g., geopolitical events) can disrupt crucial supply chains and commodity markets. Uncertainty is a critical factor contributing to the changes in inflation. For this reason, features related to the uncertainty are utilised to predict inflation (Adeosun et al., 2023; Araujo & Gaglianone, 2023).

Additionally, a substantial body of research examining the co-movement of international inflation rates suggests that global phenomena predominantly drive country-specific inflation rates, implying that a single country often experiences inflationary pressures transmitted from the broader international context (Hall et al., 2023). Bäurle et al. (2021) find that foreign inflationary shocks explain 50% of the Swiss price changes. Moreover, Hall et al. (2023) indicate that inflationary shocks in the US are transmitted strongly and consistently to the euro region and the UK. Their findings also highlight that the euro region transmits inflation to other areas, but to a lesser extent, while the UK inflation marginally impacts the other two areas. Nonetheless, these studies suggest the need to use the inflation spillover feature to forecast inflation (Araujo & Gaglianone, 2023).

All in all, this study employs various features (e.g., monetary policy rates, financial development, commodity prices, global uncertainty, and international inflation spillovers) to predict inflation in Vietnam.

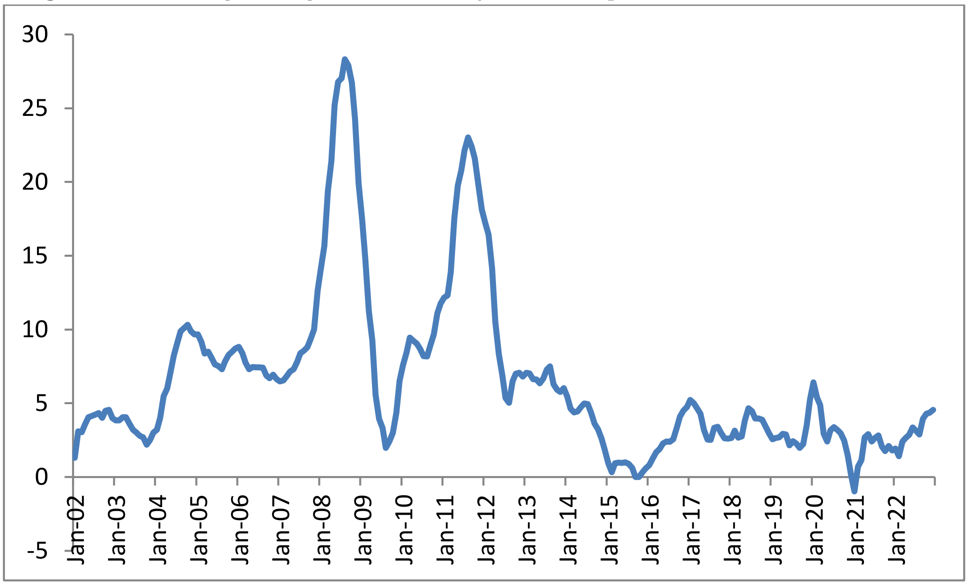
3. Data and Methodology

3.1. Data

This study concentrates on the analysis of the inflation rate, which is the consumer price index (CPI) measured by the Vietnamese General Statistics Office (GSO), used to estimate the official inflation measure and as a benchmark for the target of monetary policy in Vietnam. The predicted variable is the monthly percentage change in the consumer price index (CPI) in YoY. The literature suggests that the forecast horizon (h) may vary from one to 18 months (Araujo & Gaglianone, 2023). In the context of Vietnam, several studies use the h values of 12 months (Nguyen & Tran, 2015; Pham, Le, & Nguyen,

2022) or various predicted horizons ($h = 1,3,6$) (Thu & Leon-Gonzalez, 2021). To compare our predicted values with multiple benchmarks, $h = 12$ was selected. This is also because of a financial year (12 months), so SBV could easily use the forecasting results. The use of a 12-month horizon is comparable with other studies in different markets, such as in Costa Rica (Rodríguez-Vargas, 2020) and Brazil (Araujo & Gaglianone, 2023). The result of this horizon objectively compares to the projection values of inflation from the International Monetary Fund and the Asian Development Bank. However, the current analysis still presents validation checks for various horizons to check which model is the most suitable for forecasting Vietnamese inflation.

Figure 1. Percentage change in the monthly consumer price index (%YoY) in Vietnam



The sample period spans over 21 years of data, from January 2002 to December 2022 ($T = 252$ observations). **Figure 1** presents the evolution of the inflation rate in our sample period, which slightly increased from 2002 to 2007 and reached a peak of 28.32% in September 2008. The inflation rose because of the substantial increase in manufacturing costs under the high inflation of the globe, an increase in food prices, and the implementation of loosening fiscal and monetary policies with relaxed management to promote economic growth. Then, the inflation declined in the subsequent years before reaching a new peak of 23.02% in August 2011, mainly due to the increased manufacturing input price, high appreciation of USD over VND, and the adjustment of the interbank rate (GSO, 2011). Since then, the Vietnamese government has gradually stuck to an inflation-targeting regime while implementing strict but flexible monetary policies. More specifically, inflation generally declined during the period of the COVID-19 pandemic, especially when the Vietnamese economy experienced a negative inflation rate for the first time. The inflation slightly increased in a later year, but was still lower than the target inflation. Therefore, this would be a challenge for the accuracy of the forecasting model.

One of the primary determinants of the inflation dynamics in emerging economies is inertia or the degree of persistence (Araujo & Gaglianone, 2023). Gaglianone et al. (2018) suggested that time-varying persistence is considerably relevant to constructing more accurate forecasting models. The literature also suggests that various predictors of inflation can be divided into five main groups. The first vector of variables is related to financial development. The relationship between financial development and inflation has been extensively explored in prior studies (Bittencourt, 2011; Kim & Lin, 2010). Fama (1981) demonstrates that a negative relationship between stock return and inflation is expressed as a stagflation phenomenon. This view is consistent with the rational expectation hypothesis that stock prices and inflation depend on the anticipation of future actual activity (Eldomiaty et al., 2020). Therefore, stock market development is used to forecast inflation. Following Thu and Leon-Gonzalez (2021) in Vietnam, this study considers the growth rate of two existing stock exchanges, namely the Ho Chi Minh Stock Exchange and the Hanoi Stock Exchange, as a measure of the stock market's development.

The second vector of variables is related to monetary policy according to the monetarist theory (Frisch, 1983; Lim, 1987). An increase in the money supply due to production growth and employment causes increasing inflation. Díez et al. (2024) demonstrate that the refinancing and discount rates are two primary policy rates in Vietnam. Therefore, this study accounts for refinancing and discount rates as a measure of monetary policy to forecast Vietnamese inflation (Forni et al., 2003; Pham, Le, & Nguyen, 2022). This choice is also necessary because of the unavailable data on the monthly amount of money supply in Vietnam for such a study period.

The third vector of variables is associated with commodity prices. The literature suggests that rising commodity prices lead to increasing inflation, but it can have different implications depending on whether a nation is an importer or exporter of commodities (De Gregorio, 2012). Following Groen et al. (2013), this study considers various variables relating to Vietnam’s import and export (e.g., agriculture, metal, coal, coffee, cotton, crude oil, olive, swine, poultry, rice, rubber, and fuel).

The fourth vector of variables pertained to global uncertainty (Adeosun et al., 2023). Uncertainty can negatively impact economic activity via the demand and supply sides. On the demand side, uncertainty may delay enterprises’ investment and hiring, thus eliminating households’ confidence and hampering financial conditions. On the supply side, uncertainty threatens physical and human capital savings, erodes efficient resource allocation, reduces investment attractiveness, and disrupts global supply chains. Therefore, the shock dynamics of both sides have an impact on inflation (Caldara et al., 2026). Following Araujo and Gaglianone (2023), this study only considers the economic policy uncertainty of major economies that are also Vietnam’s trading partners, including Australia, Germany, Hong Kong, India, Japan, Korea, Russia, China, Singapore, the UK, and the US.

The fifth vector of variables is about international inflation spillover. The literature has comprehensively analysed how international price changes spill over to country-specific inflation (Auer et al., 2019; de Sá Farias et al., 2024; Hall et al., 2023). In the view of SBV (2008), observing the inflation rates of major trading partners with Vietnam is necessary when managing Vietnamese inflation. In this sense, this study utilizes consumer price indices from several countries, including India, Hong Kong, Japan, China, the US, and Germany.

More importantly, recent studies demonstrate that ML methods coupled with hundreds of predictors enhance the prediction accuracy of stock returns (Gu et al., 2020) and inflation (Araujo & Gaglianone, 2023). Therefore, this study initially considered 45 predictors in forecasting inflation.

Appendix A1 displays the correlation matrix among the variables used for the inflation forecast. Accordingly, multiple regressors have high correlations. For conventional regression models, high correlations may result in multicollinearity issues. However, ensemble models are designed to address multicollinearity problems using decision trees, while other ML models may reduce their performance when the number of features is too high. Therefore, feature reduction is necessary to maximise prediction accuracy (Sandri & Zuccolotto, 2008). If the Pearson correlation score of each feature pair is more significant than 0.8, one feature in the pair was removed from the input features for the forecasting process (Midi et al., 2010). As a result, the database used in this analysis includes 37 contemporaneous monthly variables, as presented in **Table 1**.

Table 1. Variables used in the forecast model for inflation

Variables	Definition	Unit	Obs	mean	STD	Min	Max	Sources
CPIVIETNAM	Percentage change in the monthly consumer price index	% YOY	252	6.57	5.75	-0.97	28.32	EIKON
HNX	Growth rate of the Hanoi Stock Exchange	%	210	145.81	96.00	51.05	473.99	EIKON
HOSE	Growth rate of HCM Stock Exchange	%	252	624.93	337.83	136.21	1498.28	EIKON
CPI INDIA	India Consumer Price Index	% YOY	242	117.42	44.57	57.4	198.8	EIKON
CPI HONGKONG	Hong Kong Consumer Price Index	% YOY	242	110.3	17.47	87.7	139.4	EIKON
CPIJ	Japan Consumer Price Index	%YOY	252	0.27	1.11	-2.50	4.00	EIKON
CPIC	China Consumer Price Index	%YOY	252	2.33	1.93	-1.80	8.70	EIKON
CPIUS	US Consumer Price Index	%YOY	252	104.39	13.25	81.2	136.7	EIKON
CPIG	Germany Consumer Price Index	%YOY	252	1.73	1.47	-0.6	8.82	EIKON
DRATE	Discount rate	%	252	5.10	2.55	2.50	13.00	SBV
RRATE	Refinancing rate	%	252	6.93	2.58	4	15	SBV
EPUA	Australia Economic Policy Uncertainty Index	Index	252	109.32	61.41	25.66	337.04	EPU
EPUG	Germany Economic Policy Uncertainty Index	Index	252	181.98	142.05	28.43	844.85	EPU
EPUHK	Hong Kong Economic Policy Uncertainty Index	Index	252	141.77	72.17	23.01	425.36	EPU
EPUI	India Economic Policy Uncertainty Index	Index	240	90.90	48.57	23.35	283.69	EPU
EPUJ	Japan Economic Policy Uncertainty Index	Index	252	106.90	32.33	47.60	237.68	EPU
EPUK	Korea Economic Policy Uncertainty Index	Index	252	150.33	73.00	37.31	538.18	EPU
EPUR	Russia Economic Policy Uncertainty Index	Index	252	190.78	154.76	13.27	964.14	EPU
EPUC	China Economic Policy Uncertainty Index	Index	252	272.82	249.88	26.14	970.83	EPU
EPUS	Singapore Economic Policy Uncertainty Index	Index	240	152.18	80.29	50.5	414.99	EPU
EPUUK	UK Economic Policy Uncertainty Index	Index	252	132.27	72.31	24.04	558.22	EPU
EPUUS	US Economic Policy Uncertainty Index	Index	252	140.56	66.91	44.78	503.96	EPU
PAGRI	Agriculture Price Index[1]	Index	252	101.12	20.61	57.90	155.10	IMF
PMETA	Base Metals Price Index[1]	Index	252	133.67	48.93	40.11	238.78	IMF
PPMETA	Precious Metals Price Index[1]	Index	252	92.26	39.22	24.83	160.43	IMF
PCOAL	Coal Price Index[1]	Index	252	132.91	93.74	33.62	577.58	IMF
PCOFFROB	Coffee, Robusta cash price	US¢[2]	252	79.57	24.44	22.82	121.98	IMF
PCOTTIND	Cotton price	US¢[2]	252	81.16	28.72	39.89	229.67	IMF
POILDUB	Crude Oil, Dubai Fateh	US$[3]	252	66.58	27.49	18.35	130.08	IMF
POLVOIL	Olive Oil price	US$[4]	252	3936.33	832.65	1313.41	5853.98	IMF
PPORK	Swine price	US¢[2]	252	71.16	17.17	36.66	128.67	IMF
PPOULT	Poultry/whole bird spot price	US¢[2]	252	100.17	30.31	61.49	227.96	IMF
PNRG	Fuel (Energy) Index[1]	Index	252	159.47	64.05	49.45	376.41	IMF
PNGAS	Natural Gas Price Index[1]	Index	252	179.35	105.09	43.93	893.10	IMF

PCOFFOTM	Coffee, Other Mild Arabicas price	US¢[2]	252	132.91	93.74	33.62	577.58	IMF
PRICENPQ	Rice price	US$[4]	252	416.88	137.69	185.27	1015.21	IMF
PRUBB	Rubber price	US¢[2]	252	95.35	44.23	25.73	280.79	IMF

Notes: [1]Year base 2016 = 100; [2]US cents per pound; [3]US$ per barrel; [4] US$ per metric ton. CPIVIETNAM, percentage change in the monthly consumer price index of Vietnam; HNX, the growth rate of monthly Hanoi Stock Exchange index; HOSE, the growth rate of monthly Ho Chi Minh Stock Exchange index; CPIINDIA, percentage change in the monthly consumer price index of India; CPIHONGKONG, percentage change in the monthly consumer price index of Hong Kong; CPIJ, percentage change in the monthly consumer price index of Japan; CPIC, percentage change in the monthly consumer price index of China; CPIUS, percentage change in the monthly consumer price index of the US; CPIG, percentage change in the monthly consumer price index of Germany; DRATE, the monthly interest rate at which commercial banks can sell valuable papers to the State Bank of Vietnam to obtain liquidity; RRATE, the monthly interest rate set by the State Bank of Vietnam for lending funds to commercial banks; EPUA, the value of monthly Economic Policy Uncertainty Index of Australia; EPUG, the value of monthly Economic Policy Uncertainty Index of Germany; EPUHK, the value of monthly Economic Policy Uncertainty Index of Hong Kong; EPUJ, the value of monthly Economic Policy Uncertainty Index of Japan; EPUK, the value of monthly Economic Policy Uncertainty Index of Korea; EPUR, the value of monthly Economic Policy Uncertainty Index of Russia; EPUC, the value of monthly Economic Policy Uncertainty Index of China; EPUS, the value of monthly Economic Policy Uncertainty Index of Singapore; EPUUK, the value of monthly Economic Policy Uncertainty Index of the UK; EPUUS, the value of monthly Economic Policy Uncertainty Index of the US; PAGRI, Agriculture Price Index, 2016 = 100, includes Food and Beverages and Agriculture Raw Materials Price Indices; PMETA; Base Metals Price Index, 2016 = 100, includes Aluminium, Cobalt, Copper, Iron Ore, Lead, Molybdenum, Nickel, Tin, Uranium and Zinc Price Indices; PPMETA; Precious Metals Price Index, 2016 = 100, includes Gold, Silver, Palladium and Platinum Price Indices; PCOAL; Coal Price Index, 2016 = 100, includes Australian and South African Coal; PCOFFROB; Coffee, Robusta, International Coffee Organization New York cash price, ex-dock New York; PCOTTIND; Cotton, Cotton Outlook 'A Index', Middling 1-3/32-inch staple, CIF Liverpool; POILDUB; Crude Oil (petroleum), Dubai Fateh; POLVOIL; Olive Oil, extra virgin less than 1% free fatty acid, ex-tanker price UK; PPORK; Swine (pork), 51-52% lean Hogs, U.S. price; PPOULT; Poultry (chicken), Whole bird spot price, Ready-to-cook, whole, iced, Georgia docks; PNRG, Fuel (Energy) Index, 2016 = 100, includes Crude oil (petroleum), Natural Gas, Coal Price and Propane Indices; PNGAS; Natural Gas Price Index, 2016 = 100, includes European, Japanese, and American Natural Gas Price Indices; PCOFFOTM; Coffee, Other Mild Arabicas, International Coffee Organization New York cash price, ex-dock New York; PRICENPQ; Rice price (5 percent broken milled white rice, Thailand nominal price quote); PRUBB, Rubber price (Singapore Commodity Exchange). All variables are at a monthly frequency. EIKON denotes the Refinitiv Eikon dataset; SBV represents the State Bank of Vietnam; EPU denotes the Economic Policy Uncertainty database (please see https://www.policyuncertainty.com/); IMF represents the IMF Primary Commodity Prices (please see https://www.imf.org/en/research/commodity-prices)

Data were collected from various sources. For ease of data collection, the data on consumer price indices of countries and the growth rate of stock exchanges were primarily gathered from the Refinitiv Eikon dataset (EIKON) deposited at the London Stock Exchange Group. The information on refinancing and discounted rates was obtained from the State Bank of Vietnam (SBV) website. Economic Policy Uncertainty Indexes were collected from the EPU database (EPU) constructed by Baker et al. (2016), while information about various commodities relating to Vietnam's imports and exports was extracted from the IMF Primary Commodity Prices (IMF).

The Augmented Dickey-Fuller and Phillips-Perron unit root tests are performed to check the stationarity of all series. Unit root tests of the level and transformed series are reported in **Appendix A2**.

3.2. Methodology

For comparison purposes, this study selected the best-performing machine learning models for forecasting inflation from the literature, as comprehensively discussed in the previous section. Note that Binner et al. (2010) suggested that the development of neural networks should be used in future studies in forecasting inflation. This study considers four variants of recurrent neural networks: long short-term memory, residual long short-term memory, gated recurrent units, and bidirectional gated recurrent units. These methods will be discussed in turn. It is essential to note that this research does not provide too detailed descriptions of the machine learning methods to save space. Instead, the present study focused more on discussing the data and critical features of the prediction models and assessment practices. For comprehensive discussions, please see Athey and Imbens (2019), Shalev-Shwartz and Ben-David (2014), Hastie et al. (2009), and others. Because hyperparameters determine a model's learning process and thereby significantly influence its forecasting performance on out-of-sample data (Arnold et al., 2024), hyperparameter tuning was applied to selected models in this study. Hyperparameter tuning is an experimental method that systematically tests different hyperparameter combinations to identify the optimal set that enhances model performance. This iterative approach seeks to balance the model's complexity with its ability to generalize from the training data. Such a tuning process is crucial for improving the model's predictive accuracy. Therefore, hyperparameters and their tuning, as treated with care, will be discussed in turn.

3.2.1. Autoregressive integrated moving average

Following Das and Das (2024), this study uses the autoregressive integrated moving average (ARIMA) as one of the benchmark models for comparison with other ML models. ARIMA is commonly considered one of the 'hard to beat' models (Öğünç et al., 2013). This method is also often employed by several studies in Vietnamese inflation prediction (Nguyen & Tran, 2015). The conventional ARIMA model combines the moving-average and autoregressive terms. Following Özgür and Akkoç (2022), the conventional $ARIMA\ (p, d, q)$ model can be expressed as:

$$y_t' = c + \sum_{i=1}^{p} \emptyset_i y_{t-i}' + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \epsilon_t, \tag{1}$$

where y_t' is the differenced and stationary series of the predicted variable (monthly inflation), $\emptyset_i$ is the coefficient of the d-order difference observations, θ_j is the coefficient for errors, ε_t is the error term, ϵ_t denotes the white noise error term, d is the degree of the first differencing component, p represents the order of the autoregressive component, and q denotes the degree of the moving average component. The choice of these parameters is determined by evaluating the partial autocorrelation function and comparing the information criteria of the models.

3.2.2. Linear regression

Following Plakandaras et al. (2017) and Malladi (2024), linear regression is used as a benchmark for comparison purposes. Linear regression (LR) is a straightforward machine learning algorithm that includes multiple features for analysis. This technique attempts to fit the forecast function of the monthly inflation by utilising potential predictor variables (x_i). The general form is expressed as:

$$y_t = f(x_{it}) + \varepsilon_t = \beta_0 + \sum_{i=1}^{n} \beta_i x_{it} + \varepsilon_t, \tag{2}$$

where y_t is the predicted variable (monthly inflation), f is some fixed but unknown function of $x_{1t}, x_{2t}, \dots, x_{nt}$, and ε_t is a random error term. In this equation, f is the forecast function that provides accurate information about x explaining y. The conventional ordinary least squares model attempts to minimise the least square errors:

$$\widehat{\beta_x} = argmin_{\widehat{\beta_x}} \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j\, x_{i,j} \right)^2. \tag{3}$$

3.2.3. K-nearest neighbour

K-nearest neighbour (KNN) learning by analogy is relatively useful for solving regression and classification problems (Wu et al., 2008). KNN is often used for time series forecasting (Martínez et al., 2019) because time series may contain repetitive patterns.

Let $t_i, i \in \{1,2,\dots,T\}$ denotes t_i^{th} number of months in a particular year over the examined period and $Y = \{y_t\}_{t \in R^t}$ is the time series of a predicted variable (monthly inflation). Let $Y^d = \{y_t - y_{t-d}\}_{d,t \in R^t}$ be the d^{th} order difference between consecutive time series observations of the monthly inflation. $X_n = \{X_{n,t}\}, n \in \{1,2,3,\dots,N\}$ represents the time series of a generic set of n covariates.

The i^{th} data point (target) can be expressed as a vector of n covariates $(x_1^i, x_2^i, \dots, x_N^i)$ that are the lagged values of the target y_i^1. Consider a new observation, for instance, the next period $y_{i+1}^1$to be forecasted, whose covariates are identified and represented as $(\overline{x_1}, \overline{x_2}, \dots, \overline{x_n})$, and there is an association between the available information and the covariates of the new observations to be predicted. The last targets are utilised as covariates of the new observation. Note that the minimum lag cannot be less than the number of prediction periods. The KNN algorithm utilises the covariates of the new observation to identify the k most similar training observations, based on a specified distance metric. The forecast is performed by aggregating the values over the periods during which the k-nearest neighbours are assigned, often using an average, either simple or weighted by distance.

When performing the forecasts in Python, the number of nearest neighbours (k), the number of lags of monthly inflation (n), and the method for estimating multi-horizon predictions were selected to minimise the average SSR in the prediction sample. Forecasts were estimated using k nearest neighbours, with k tuned to produce the best result. This study used $n = 24$ lags for all variables, given that m features were selected. A multiple-input multiple-output (MIMO) strategy is employed. Specifically, the input is a vector of $24 * m$ values, and the output is expected to be a vector of h values, where h is the number of next-month inflation (horizon). The neighbours are also a vector of $24 * m$ values, and their corresponding labels are a vector of their h next-month inflation. The forecast is computed by finding k neighbours of the input using the Euclidean distance, and the output is the mean of the k corresponding labels, with weights optimised via hyperparameter tuning

3.2.4. Random forests

Medeiros et al. (2021), using big data in economics to predict U.S. inflation, found that the random forest (RF) model yielded the most accurate results among other machine learning models. A similar finding is observed in forecasting Brazilian inflation, especially during the COVID-19 pandemic (Boaretto & Medeiros, 2023). Therefore, RF was selected for this study.

The RF model, as proposed by Breiman (2001), is relatively analogous to boosting models. Dietterich (2000) emphasised that RF is among the most common ensemble models in ML. Similar to gradient boosting, the RF model utilises regression trees. However, the regression trees in the RF model are trained separately, and their outputs are averaged to yield forecasts. The RF procedure can be undertaken in two steps (Boubaker et al., 2025; Yoon, 2021).

Step 1: For $m = 1$ to M iterations:

(i) From the training data (N), a bootstrapped sample set (Z) of size N is generated.

(ii) Once the bootstrapped data is created, a random forest tree (T_m) is developed by replicating the following steps for each terminal node of the trees until the minimum size (n_{min}) is obtained.

- Choose x predictor variables randomly from the X variables,
- Identify the most appropriate variable, and split the point among the x variables, and
- The node is divided into two child nodes, and the split can be estimated in the same way that the mean squared error (MSE) is minimised as:

$$F_0(x) = \frac{1}{n}\sum_{i=1}^{n}(y_i - y)^2 , \tag{4}$$

where y_i and y are observed and forecast values of monthly inflation, respectively. At each node, extra randomness is added by randomly allocating a subset of variables to split the nodes. This process may significantly decrease the dependence on single trees and enhance flexibility against a possible overfitting issue. An overfitting issue may arise once a completely established tree fits the model perfectly. Alternatively, a perfectly fitting tree model may yield inaccurate forecasts when new data is present. Therefore, the RF model may trim trees or reduce the number of nodes at the expense of the in-sample fit.

Step 2: Output of the ensemble trees $(\{T_m\}_{m=1}^{M})$:

$$\widehat{F_{rf}^{M}}(x) = \frac{1}{M}\sum_{m=1}^{M} T_m\,(x), \tag{5}$$

where $\widehat{F_{rf}^{M}}(x)$ is the final output as computed by averaging the outputs of all the trees (T_m). Averaging multiple predictions can reduce variance and smooth the forecast performance of the trees.

For the forecasting exercise, the following hyperparameters were utilized:

- Number of trees
- Maximum depth of the tree
- Minimum samples required to split a node
- Minimum samples required at a leaf node
- Number of features considered when looking for the best split
- Whether bootstrap samples are used when building trees
- Criterion used to measure the quality of a split
- Maximum number of leaf nodes

These hyperparameters were optimized using Bayesian search to achieve the best forecasting performance.

3.2.5. Extreme gradient boosting

Several studies have used gradient boosting algorithms to predict inflation (Medeiros et al., 2021). Thus, this study utilises extreme gradient boosting (XGB), a gradient-boosting decision tree, which is a boosting learning technique that can handle regression and classification tasks (Li & Zhang, 2020; Nobre & Neves, 2019). In brief, boosting is an ensemble learning technique that can turn a weak classifier into a simple tree model by incorporating it into a stronger model that mitigates signal interference. XGB learns via a series of decision trees to categorise the labelled training data. By adding and training new trees to reduce errors from the previous iteration, each subsequent tree mitigates errors introduced by the previous tree and learns to improve model precision. Additionally, XGB can perform classification or regression duties with generalisation and efficient capabilities via the regularisation term and parallel computation.

A tree model used to forecast monthly inflation is expressed as:

$$\widehat{y_i} = \sum_{nl=1}^{NL} f_{nl}(x_i), f_{nl} \in SP, \tag{6}$$

where $\widehat{y_i}$ is the predicted value of monthly inflation, f_{nl} is a regression tree, SP is the space of regression trees, NL is the total number of trees, and $f_{nl}(x_i)$ represents the leaf weight that the i^{th} sample includes in the nl^{th} tree. This model is built on a dataset $DS = \{x_i, y_i\}$ with p samples and q featues, and $\{x_i \in R^q, R^q \rightarrow L, y_i \in R, i = 1 \dots p\}$ where R^q is a dataset with the number of features q, $x_i \in R^q$ is the i^{th} training sample x, L is the number of leaves in the tree, $y_i \in R$ is the i^{th} training sample y.

The forecast value of the i^{th} iteration can be formed as:

$$\widehat{y_i^t} = \widehat{y_i^{t-1}} + f_t(x_i). \tag{7}$$

The objective function (OBJ) of XGB consists of a loss function (LF) and a complexity function (CF) terms. A loss function is expressed as:

$$LF_{(t)} = \sum_{i=1}^{p} (y_i - \widehat{y_i})^2, \tag{8}$$

where y_i is the actual monthly inflation, and $\widehat{y_i}$ is derived from Equation 6.

A complexity function is expressed as:

$$CF_{(f_{nl})} = \varphi L + \frac{1}{2}\tau \sum_{j=1}^{L} \omega_j^2, \tag{9}$$

where φL penalises the number of leaves in the tree, φ represents a minimum loss reduction, τ denotes L2 regulation on leaf weights, and ω is the vector of scores on leaves.
Therefore, the general form of the objective function is written as:

$$OBJ_{(t)} = LF\left(y_i, \widehat{y_i^{t-1}} + f_t(x_i)\right) + CF(f_t). \tag{10}$$

It is crucial to note that the loss function term can be approximated using a second-order Taylor expansion to enable fast pruning. Equation 10 is rewritten as:

$$OBJ\ (t) \cong \sum_{i=1}^{p}[LF(y_i, \widehat{y_i^{t-1}}) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + CF(f_t), \tag{11}$$

where g_i is the first-order derivative and expressed as $g_i = \partial_{\hat{y}^{(t-1)}} LF(y_i, \hat{y}^{(t-1)})$, and h_i is the second-order derivative, is defined as $h_i = \partial^2_{\hat{y}^{(t-1)}} LF(y_i, \hat{y}^{(t-1)})$.

Therefore, Equation 11 can be simplified as:

$$\widetilde{OBJ\ (t)} \cong \sum_{i=1}^{p}[\, g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \varphi L + \frac{1}{2} \tau \sum_{j=1}^{L} \omega_j^2. \tag{12}$$

Equally, Equation 12 can be rewritten as:

$$\widetilde{OBJ\ (t)}\ \cong \sum_{j=1}^{L}[\, \omega_j \sum_{i \in I_j} g_i + \frac{1}{2} \omega_j^2 (\sum_{i \in I_j} h_i + \tau)] + \varphi L, \tag{13}$$

where I_j is the instance set of leaf j.

In the end, the optional ω and the optimal objection reduction are estimated as follows:

$$\omega_j^* = -\frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \tau}, \tag{14}$$

$$\widehat{OBJ_{(t)}} = -\frac{1}{2} \sum_{j=1}^{L} \frac{\left(\sum_{i \in I_j} g_i\right)^2}{\sum_{i \in I_j} h_i + \tau} + \tau L. \tag{15}$$

The following key hyperparameters of the XGB model were incorporated into the specification and were tuned to obtain the optimized forecasting performance:

- Number of boosting rounds
- Maximum tree depth
- Minimum loss function required to make a further split
- Minimum sum of instance weights required in a child node
- Learning rate

3.2.6. Long short-term memory

This study considers long short-term memory (LSTM) in the current analysis, as Rodríguez-Vargas (2020) found that this algorithm is among the best-performing models for inflation prediction. LTSM, introduced by Hochreiter and Schmidhuber (1997), has been shown to achieve higher accuracy than other neural network models (Almosova & Andresen, 2023). Unlike traditional neural networks, an LTSM is a recurrent neural network that maintains a feedback loop between the current output and past decisions. Therefore, this model allows us to address the vanishing gradient issue during updating. Alternatively, the longer-run dependencies can be solved. In general, an LSTM unit can memorise or forget information via a particular memory cell state, which is deliberately controlled by three gates: an input gate, an output gate, and a forget gate.

Following Barkan et al. (2023), an LSTM unit is determined by a set of equations:

$$\begin{gathered}
i = \sigma\left(x_t u^i + s_{t-1} w^i + b^i\right), \\
f = \sigma(x_t u^f + s_{t-1} w^f + b^f), \\
o = \sigma(x_t u^o + s_{t-1} w^o + b^o), \\
\tilde{c} = \tanh(x_t u^c + s_{t-1} w^c + b^c)\,, \\
c_t = f * c_{t-1} + i * \tilde{c}, \\
s_t = o * \tanh(c_t)\,,
\end{gathered} \tag{16}$$

where i, f, and o are input, forget, and output gates, respectively, x_t is the current input, $\sigma(x) = \frac{1}{1+e^{-x}}$ is the sigmoid or logistic activation function, (u^i, w^i, b^i) are the learned parameters that regulate the input gate i, (u^f, w^f, b^f) is the learned parameters that regulate the forget gate f, (u^o, w^o, b^o) are the learned parameters that regulate the output gate o, σ is the sigmoid activation function, $\tilde{c}$ denotes the new candidate activation for the cell state estimated by u^c, w^c, and b^c, $tanh$ is the hyperbolic tangent function, $*$ represents element-wise multiplication, c_t is the cell state that is automatically revised by the linear combination $f * c_{t-1} + 1 * \tilde{c}$ where c_{t-1} is the past value of the cell state, and s_t is the hidden state. The input gate decides which parts of $\tilde{c}$ should be employed to adjust the memory cell state, while the forget gate identifies which parts of c_{t-1} should be dropped. Because the updated cell state c_t is distorted via a nonlinear hyperbolic tangent, the output gate defines which parts of c_t should be indicated in the output. For a more detailed process of inflation forecast, please see (Yang & Guo, 2021).

Given that a total of 252 sample observations are used in this study, this is comparable with prior studies in inflation prediction, which apply LSTM for small sample sizes ranging from 60 observations (Zahara & Ilmiddaviq, 2020), 192 observations (Rodríguez-Vargas, 2020), and 212 observations (Araujo & Gaglianone, 2023). For predicting Vietnam inflation, the current analysis computed a simple one-layer model using all features described in **Table 1**, with their 24 lags. Before training, the data were scaled using the z-distribution technique, with a mean of 0 and a standard deviation of 1. After training and prediction, the scaling was reverted to obtain predictions at the desired level.

When training the model, this study used the Adam optimiser by Kingma and Ba (2015) with the hyperbolic tangent activation function. The model's hyperparameters were tuned to find the optimal configuration. The values tested included:

- Batch Size: 32, 64, 128. The batch size was chosen to ensure the applied algorithm was stochastic gradient descent and to maintain temporal dependencies in the training sample.
- Learning Rate: 0.1, 0.05, 0.001.
- Number of LSTM Units: 16, 32, 64, 128.
- Number of LSTM Layers: 1, 2.

All experiments maintained a learning rate decay of 0. The input is a matrix of $24 * m$, where m is the number of features and lag number of 24, while the output is a vector of *h* next-month inflation.

3.2.7. Residual long short-term memory

Residual long short-term memory (ResLSTM) introduced by Wu et al. (2016) includes residual connections among the LSTM layers in a stack. This model significantly enhances gradient flow in the backward pass, enabling the encoder and decoder networks to be trained.

Given $LSTM_i$ and $LSTM_{i+1}$ are the i^{th} and $(i+1)^{th}$ LSTM layers in a stack with their corresponding parameters W^i and W^{i+1}. Without residual connections, the stacked LSTM at the t^{th} time step is formed as follows:

$$c_t^i, s_t^i = LSTM_i(c_{t-1}^i, s_{t-1,}^i x_t^{i-1}; W^i),$$

$$x_t^i = s_t^i,$$

$$c_t^{i+1}, s_t^{i+1} = LSTM_{i+1}(c_{t-1}^{i+1}, s_{t-1,}^{i+1} x_t^i; W^{i+1}), \tag{17}$$

where x_t^i, the input to $LSTM_i$ at the time step t; c_t^i and s_t^i are the memory and hidden states of $LSTM_i$ at the time step t, respectively.

When residual connections between them are considered, Equation 17 is rewritten as follows:

$$c_t^i, s_t^i = LSTM_i(c_{t-1}^i, s_{t-1,}^i x_t^{i-1}; W^i),$$

$$x_t^i = s_t^i + x_t^{i-1},$$

$$c_t^{i+1}, s_t^{i+1} = LSTM_{i+1}(c_{t-1}^{i+1}, s_{t-1,}^{i+1} x_t^i; W^{i+1}). \tag{18}$$

Similar to other studies using a recurrent neural network for a small sample size (e.g., 192 observations when forecasting Brazil inflation (Araujo & Gaglianone, 2023) or 464 observations when predicting the agricultural price index (Ji et al., 2022), the total sample of 252 observations utilised in the present study is sufficient. This study employs a ResLSTM architecture with residual connections between layers. To identify the optimal configuration when forecasting Vietnam inflation, a hyperparameter tuning procedure was conducted with the following specifications:

- Hidden dimension: 16, 32, 64, 128
- Learning rate: 0.1, 0.05, 0.001
- Batch size: 32, 64, 128
- Number of LSTM layers: 1, 2
- Residual connections: Input + output of the first LSTM layer; output of previous layer + output of subsequent LSTM layer when applicable

The input is a matrix of shape (lag, n) where n is the number of features and lag equals 24, while the output is a vector of h next-month inflation predictions. A Bayesian search was performed over all parameter combinations, and the best-performing model configuration was selected based on validation set performance.

3.2.8. Gated recurrent units

Several studies have argued that a gated recurrent unit may outperform an LSTM, as it eliminates the cell state (c_t) and results in a simpler unit that requires fewer learnable parameters (Dey & Salem, 2017). Because it uses two gates (e.g., an update gate (z) and a reset gate (r)), GRU is considered faster and more efficient in terms of computer resources. Yang and Guo (2021) reported that GRU outperforms other models in forecasting Chinese inflation. However, others have shown that GRU performs better than LSTM only sometimes (Pham, Le, Dang, et al., 2022). Similarly, the GRU's training time is perhaps much lower than that of the LSTM, yet their performance is the same (Wang et al., 2020).

The general form of a GRU unit is as follows:

$$z = \sigma(x_t u^z + s_{t-1} w^z + b^z),$$

$$r = \sigma(x_t u^r + s_{t-1} w^r + b^r),$$

$$v = \tanh(x_t u^v + (s_{t-1} * r) w^v + b^v),$$

$$s_t = z * v + (1 - z) s_{t-1}, \tag{19}$$

where (u^z, w^z, and b^z) are the learned parameters that regulate the update gate z, (u^r, w^r, and b^r) are the learned parameters that regulate the reset gate r, v is the candidate activation that is the function of the input x_t and the past hidden output s_{t-1} and is regulated by the learned parameters (u^r, w^r, and b^r), σ and $tanh$ denote the sigmoid and the hyperbolic tangent functions, respectively, and s_t is the hidden output includes the candidate activation v and the past state s_{t-1} regulated by the update gate z. For a more comprehensive discussion, please see Barkan et al. (2023).

Given that a total of 252 sample observations are employed in this research, this is comparable to other studies, such as Yang and Guo (2021), which use a sample of 195 observations to predict China's inflation. To identify the optimal configuration within a GRU architecture for forecasting Vietnam inflation, a hyperparameter tuning procedure was conducted with the following specifications:

- Hidden dimension: 16, 32, 64, 128
- Learning rate: 0.1, 0.05, 0.001
- Batch size: 32, 64, 128
- Number of GRU layers: 1, 2

The input is a matrix of shape (lag, n) where n is the number of features and lag equals 24, while the output is a vector of h next-month inflation predictions. A Bayesian search was performed over all parameter combinations, and the best-performing model configuration was selected based on validation set performance.

3.2.9. Bidirectional Gated Recurrent Units

A bidirectional gated recurrent model (BiGRU) is a bidirectional model that combines the forward and backward directions using the GRU framework. It involves two parallel GRU layers that process the input sequence in both directions.

The general model of BiGRU is constructed as:

$$s_t^f = z_t^f * c_t^f + \left(1 - z_t^f\right) s_{t-1}^f,$$

$$s_t^b = z_t^b * c_t^b + \left(1 - z_t^b\right) s_{t+1}^b,$$

$$s_t = \left[s_t^f, s_t^b\right], \tag{20}$$

where z_t^f is the update gate z for the forward GRU, z_t^b is the update gate z for the backward GRU, s_{t-1}^f is the past hidden state in the forward direction, s_{t+1}^b represents the next hidden state in the backward direction, s_t is the final hidden state that seizes the combined past and future information, and s_t^f and s_t^b represent the candidate hidden states estimated by using the reset gate r and the current input x_t as mentioned above.

In the BiGRU architecture for inflation forecasting, the model uses the Adam optimizer as suggested by Kingma and Ba (2015) with a default learning rate decay of 0 and a hyperbolic tangent activation function. To identify the optimal configuration, a hyperparameter tuning procedure was conducted with the following specifications:

- Hidden dimension: 16, 32, 64, 128
- Learning rate: 0.1, 0.05, 0.001
- Batch size: 32, 64, 128
- Number of BiGRU layers: 1, 2

The input is a matrix of shape (lag, n) where n is the number of features and lag equals 24, while the output is a vector of h next-month inflation predictions. A Bayesian search was conducted across all parameter combinations, and the best-performing model configuration was selected based on validation set performance.

3.2.10. Causal Convolutional Neural Network

Convolutional neural networks (CNNs) have been used for macroeconomic forecasting, including energy (Kim & Cho, 2019), agricultural commodities (Murugesan et al., 2022), and financial variables (Wu et al., 2023). However, they are less often used for inflation prediction (Staffini, 2023). CNN places weight on high correlations with nearby data. A local connection can convert features more efficiently. CNN (so-called convolutional filtering) is a form of weight sharing, meaning that convolutional kernels share similar weights. The operands are mitigated in the neural network via filtering and weight sharing, thereby reducing overfitting. The CNN model is expressed as:

$$f * g(i) = \sum_{j=0}^{n-1} f(j)g(i-j), \tag{21}$$

where f is the learnable weights in a CNN (or so-called the filter or kernel) as considered as a sequence $[f(o), f(1), \dots f(n-1)]$, g is the input signal being filtered, $*$ is the sign of the convolution operand, $f * g(i)$ is the convolution's output value at position i, j is the loop variable corresponding to which kernel weight $f(j)$ is utilised, n represents the kernel length, and $g(i-j)$ is the input value at position $i-j$. The three CNN dimensions are length, width, and height. Causal CNN is an advanced technique that enables converting a traditional CNN for use with one-dimensional time-series data (Wang et al., 2019).

Following Wang et al. (2019), the causal form of hidden layers is generally expressed as:

$$a(i,j) = \left(w_j^l * f^{l-1}\right)(i), \tag{22}$$

where $a(i, j)$ is the outputs of the layer according to filter operands, w_j^l is the convolution-filter weights between two layers, f^{l-1} is a set of inputs to the layer, and l is the number of hidden layers.

Note that time-series data restricts forecasts from including future information. In this study, ensuring the model stays within the time-series rule is crucial. In each prediction round, only instantaneous data is considered, and future features are not allowed. Therefore, the predictions $y(x_{t+1}|x_1, x_2, \dots, x_t)$ are independent of input vector $x_{t+1}, x_{t+2}, \dots, x_T$. Given that a total of 252 sample observations are utilised in this analysis, this is comparable with prior studies using CNN to predict macroeconomic indicators (e.g., 208 observations (Cook & Hall, 2017), 240 observations (Murugesan et al., 2022), and 492 observations (Theoharidis et al., 2023)) or stock price (e.g., 365 observations (Wu et al., 2023). Regarding a Causal CNN architecture for forecasting Vietnam inflation, the CNN configuration utilizes the same number of input and output channels as the number of selected features, with a stride of 1 and a dilation of 1. The padding is adjusted according to the kernel size to ensure causality. The CNN output is averaged along the channel axis, then passes through a fully connected layer to produce h next-month inflation predictions. The model uses the Adam optimizer with a default learning rate decay of 0. To identify the optimal configuration, a hyperparameter tuning procedure was conducted with the following specifications:

- Hidden dimension of the fully connected layer: 16, 32, 64, 128
- Learning rate: 0.1, 0.05, 0.001
- Batch size: 32, 64, 128
- Kernel size: 3, 5, 7, 9 (with padding adjusted accordingly)

The input is a matrix of shape (lag, n) where n is the number of features and lag equals 24, while the output is a vector of h next-month inflation predictions. A Bayesian search was conducted across all parameter combinations, and the best-performing model configuration was selected based on validation set performance.

3.2.11. Model validation

Rodríguez-Vargas (2020) emphasised two aspects to consider when performing cross-validation with time series: the autocorrelation among variables and the preservation of the ordering of observations. In other words, conventional cross-validation techniques (e.g., k-fold or leave-one-out) are inappropriate because they require a random sample partition. A random partition cannot be applied for two reasons: (1) the training sample may finish up with observations that arise later than the validation sample (so-called data leakage), and (2) the validation sample may wind up with greater autocorrelation that could violate a fundamental principle of the evaluation. For time series, this study therefore follows prior studies and performs a rolling-origin validation (Tashman, 2000) or a rolling-origin-recalibration validation (Bergmeir & Benítez, 2012). More specifically, a series of individual observation test sets is formed, with each test set containing only information available before it. As described by Hyndman and Athanasopoulos (2018), the procedure can be done as follows.

Given that k is the minimum number of observations for a training set, h is the predicted horizon, and T is the total number of observations, observation $t = k + i$ is chosen as the test set, observations $1,2, \dots k + i - h$ are employed to compute the model, and the predicted error is estimated for $t = k + i$. This procedure will be rerun for $i = 0,1, \dots, T - k$. A precision measure is calculated over all errors.

Following prior studies such as Hubrich (2005), Bos et al. (2002), Mishkin (1991), and others, root-mean-square-error (RMSE), mean absolute percent error (MAPE), and mean absolute error (MAE) are primarily used to assess forecasting performance at each forecast horizon. These tests are computed as follows:

$$RMSE = \sqrt{\frac{1}{h}\sum\nolimits_{i=1}^{h}\left(Y_i - \widehat{Y}_i\right)^2}, \tag{23}$$

$$MAPE = \frac{100}{h}\sum_{i=1}^{h}\left|\frac{Y_i - \widehat{Y}_i}{Y_i}\right|, \tag{24}$$

$$MAE = \frac{1}{h}\left|Y_i - \widehat{Y}_i\right|, \tag{25}$$

where Y is observed, and $\widehat{Y}$ is the predicted value for the h horizon. The procedure for validating the models' overall performance is as follows. First, after training the models to predict 12 out-of-sample forecasts for each year, this study would not immediately measure the metrics; instead, it would add the predictions and ground truths to 2 separate lists. Upon completing four years of model training, this procedure provides the final prediction list and the final ground truth list. This study then used these lists as input for 3 metrics: RMSE, MAPE, and MAE. The resulting calculations were utilised to assess the final overall performance of each model. This process was repeated for various horizons ($h = 1, 3, 6, 9, 12$).

3.2.12. Forecasting procedure

The general forecasting procedure is as follows. In experimental settings, the objective of the present study is to test whether ML's forecasting results outperformed those from conventional methods and from the IMF and ADB, accounting for the impact of the unprecedented COVID-19 turmoil. In this sense, this study provides forecast results for before the COVID-19 pandemic (year 2019), during the crisis (years 2020-2021), and post-health crisis (year 2022). To do that, this study did not fix the length of the training set. This study first used a set of samples from January 2002 to December 2018 to train models. After training, this research used the models to produce the first set of 12 out-of-sample forecasts for January 2019 to December 2019. Following this, to predict the second set of 12 out-of-sample forecasts from January 2020 to December 2020, a training set was used comprising samples from January 2002 to December 2019. In other words, each year this analysis retrained the models to forecast the next 12 months of the following year. This process was repeated until the final year. Hence, this procedure allows inflation to be forecast more accurately by using rolling information to predict the subsequent 12 months of inflation.

This study also tested various horizons. For $h = 12$, the forecasting procedure was relatively uncomplicated when predicting 12-month samples of the testing year simultaneously. For $h = 1, 3, 6, 9$ at the beginning, this study used the models to predict the next h-month samples. For example, models used in this study received input from 24 previous months (January 2017 to December 2018) to produce predictions for January 2019 to March 2019 ($h = 3$). Afterwards, this analysis extended the one-month input window, which spanned February 2017 to January 2019, to produce 3-month forecasts ($h = 3$) from February 2019 to April 2019. This process was repeated until December of the testing year. These series were included in the evaluation. The properties of the forecasts were evaluated using the actual 12-month inflation values each year.

More importantly, this study used a two-step procedure to enhance the reliability of the empirical results.

Step 1 (Pre-processing):

- This study performed unit root tests on the level and transformed series to ensure that all series are stationary, as shown in Appendix A2. The results initially show that the original features are stationary, including DRATE, EPUA, EPUHK, EPUI, EPUJ, EPUK, EPUUK, EPUUS, CPIC, PCOTTIND, and PPORK. Then, this study applied first differences to the remaining features to ensure they were stationary, as indicated in the transformed part of Appendix A2.
- This study computed the correlation matrix between stationary features (e.g., first differences and the original stationary features). As discussed in Section 3.1, eight (08) features (e.g., those that have high correlations with other features were removed.
- This study performed the Johansen cointegration test on first-differenced variables (Johansen, 1988). The procedure of the Johansen Cointegration test is as follows:
  (1) Take the first difference of all variables. This satisfies the necessary condition for applying the Johansen cointegration procedure.
  (2) Remove variables that have a high correlation.
  (3) Standardise the data.
  (4) Determine the optimal lag selection using the VAR model with the AIC criterion. The optimal lag result is 2.
  (5) Perform Johansen Trace test with no deterministic trend and 1% significance level. Table 2 indicates no cointegration.

Table 2. The result of the Johansen cointegration test

Null Hypothesis	Trace Statistic	Critical Value (1%)	Decision
$r \leq 0$	128.80	135.98	Fail to reject
$r \leq 1$	80.05	104.96	Fail to reject
$r \leq 2$	51.37	77.82	Fail to reject
$r \leq 3$	32.16	54.68	Fail to reject
$r \leq 4$	16.13	35.46	Fail to reject
$r \leq 5$	7.60	19.93	Fail to reject
$r \leq 6$	0.46	6.63	Fail to reject

In sum, the pre-processing steps ensure that all variables used in this analysis are stationary, thereby reducing the classical spurious regression problem associated with non-stationary data as discussed by several studies in the literature (Cheng et al., 2021, 2022; Wong & Pham, 2025). However, regression of stationary series per se does not guarantee the absence of spurious-like relationships. Therefore, additional diagnostic tests are required to assess model validity.

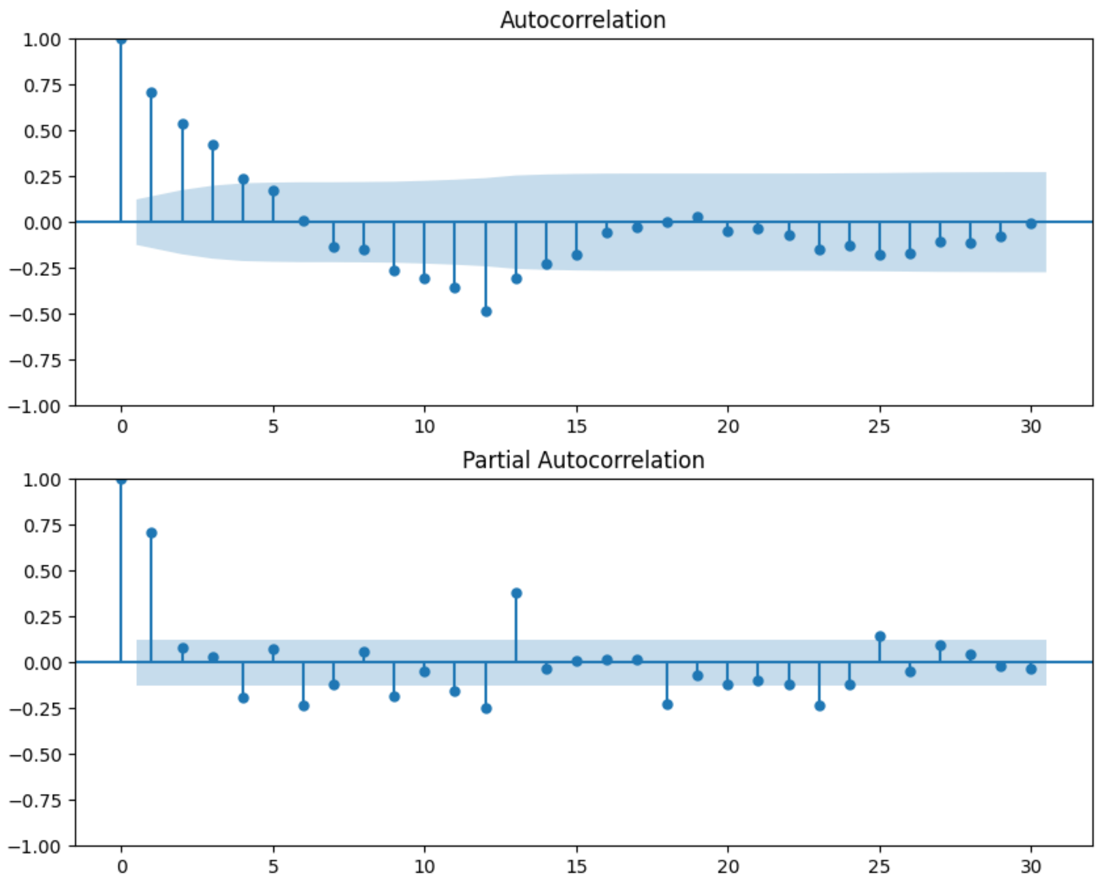
Step 2 (Diagnostic tests)

- To validate the forecasting results of ML models, this study conducted several diagnostic tests, including the unit root test (e.g., Augmented Dickey-Fuller (ADF) test), the normality test (e.g., the Jarque-Bera test), the autocorrelation test (e.g., Ljung-Box test), and the nonlinearity test (e.g., McLeod-Li). It is worth noting that this study employed the McLeod-Li test for nonlinearity as widely used in the literature (de Lima, 1997; Lee et al., 1993). However, Hui et al. (2017) recently showed that their proposed model (HWBZ test) is a fast and efficient test for the nonlinearity feature. We leave this task for future studies to confirm our findings. The results of diagnostic tests are discussed in a later section.

It is noted that determining the parameters $p, d,$ and q for the ARIMA model is crucial. In **Appendix A2**, the p-value of the ADF of the original CPIVietnam is greater than 0.05. Therefore, the null hypothesis cannot be rejected. When performing a differencing test, the p-value of ADF is less than 0.05. Thus, the null hypothesis is rejected. Hence, the parameter $d = 1$ is selected. Next, this study used the autocorrelation function (ACF) and the partial autocorrelation function (PACF) to estimate the parameters p and q. **Figure 2** shows that (1) the point 12 is the last position of a significant spike, so $q = 12$ is selected; (2) the point 23 is the last position of a significant spike, so $p = 23$ is chosen. Therefore, ARIMA (23,1,12) is used for the training set. The same procedure was applied to determine ARIMA parameters for the remaining years.

In addition, this study utilised the *Python* programming language to estimate all the ML models and feature selection techniques. LTSM, GRU, BiGRU, ResLSTM, and CNN were obtained from the *PyTorch* package, while the other models and techniques were estimated using the scikit-learn library in *Python*.

Figure 2. ACF and PACF tests



3.2.13 Hyperparameter tuning for selected models

This study follows the suggestions Araujo and Gaglianone (2023) and Aras and Lisboa (2022) to perform hyperparameter tuning for machine-learning models as mentioned above. Hyperparameter tuning is a vital strategy for optimizing the predictive accuracy of complex machine learning architectures by tailoring parameters to specific data characteristics. Utilising Bayesian Optimization within a rolling-origin validation framework, this approach ensures efficient parameter search while maintaining temporal order to prevent data leakage. Ultimately, this dynamic calibration enables models to adapt to structural economic shifts, as evidenced by varying optimal configurations during the COVID-19 pandemic, thereby enhancing forecasting robustness. Nonetheless, this approach is widely used in the literature (Hanifi et al., 2024; Ozden & Guleryuz, 2022; Quan, 2024; Schratz et al., 2019).

The hyperparameter tuning procedure is as follows:

Step 1 (Data preparation): The dataset is split into training and test sets based on the forecast year and horizon, with appropriate scaling and differencing applied.

Step 2 (Cross-validation strategy)**:** A TimeSeriesSplit with five (05) folds is employed to preserve temporal ordering during validation. Unlike standard k-fold cross-validation, which randomly splits the data, TimeSeriesSplit preserves the chronological order of time series data by using expanding windows. In each fold, the model is trained on all past observations up to a certain point and validated on the subsequent time period, ensuring that future data is never used to predict the past. This approach prevents data leakage and provides a realistic evaluation of the model's forecasting performance.

Step 3 (Search method)**:** Bayesian Optimization is employed for efficient hyperparameter exploration. In contrast to grid search, which exhaustively tests all parameter combinations, or random search, which samples randomly, Bayesian Optimization uses a probabilistic model to guide the search process intelligently. It builds a surrogate model of the objective function (validation performance). It uses this model to select the most promising hyperparameter combinations for evaluation next, balancing the exploration of new regions with the exploitation of known good regions. This study conducts 10 iterations of Bayesian Optimization, which provides a good balance between thoroughness of search and computational efficiency.

Step 4 (Hyperparameter space): Each model has its own specific hyperparameter search space, as shown in **Appendix A3.**

Step 5 **(**Model selection)**:** The configuration that achieves the best performance on the validation set is selected as the optimal model.

Step 6 (Evaluation)**:** The optimized model is evaluated on the test set using RMSE, MAPE, and MAE to assess forecasting performance.

The optimal hyperparameters for each model are reported in **Appendix A4**. Due to the length restriction, this study reports only optimal hyperparameters for $h = 12$. The results of other horizons are available upon request.

4. Results

This study compares the predictive performance of widely used time-series models with various ML models for Vietnamese inflation prediction across different horizons. Thereafter, the present study examines simulated out-of-sample forecasting performance (testing) data for the years 2019-2022. For validation, this study compares the predicted values from proposed models with the projections published by the IMF and ADB. For practical implications, this research further compares the predicted and actual values for 2023. This analysis uses 10 models (KNN, LR, RF, XGB, ARIMA, LSTM, GRU, BiGRU, ResLSTM, and CauCNN) to forecast inflation over 5 horizons (1 month, 3 months, 6 months, 9 months, and 12 months). In total, this study evaluated 50 different results.

Table 3. Pseudo out-of-sample forecasting model validation results

Horizon	**Methods**	**LSTM**	**ARIMA**	**XGB**	**LR**	**RF**	**KNN**	**GRU**	**BiGRU**	**ResLSTM**	**CauCNN**
h = 1	MAE	0.63	0.47*	0.54	0.77	*0.51*	0.67	0.71	0.89	0.74	0.83
	MAPE	0.45	0.24*	0.37	0.48	*0.32*	0.48	0.54	0.63	1.70	0.52
	RMSE	0.84	0.64*	0.73	0.94	*0.70*	0.87	0.95	1.19	1.02	1.02
h = 3	MAE	0.91	0.90	0.76*	1.22	*0.81*	0.97	1.22	1.13	1.01	5.80
	MAPE	0.57	0.41*	*0.42*	0.67	0.43	0.59	0.70	0.61	0.64	3.14
	RMSE	1.34	1.32	1.07*	1.67	*1.14*	1.32	1.80	1.62	1.55	8.21
h = 6	MAE	2.24	1.41	0.99*	1.87	*1.13*	1.22	1.61	1.53	1.30	6.26
	MAPE	1.06	0.62	0.47*	0.84	*0.50*	0.62	0.78	0.70	0.58	2.67
	RMSE	3.00	2.01	1.34*	2.51	*1.48*	1.64	2.26	2.04	1.61	7.70
h = 9	MAE	2.47	1.83	1.49*	2.69	1.60	*1.58*	2.30	1.81	3.17	6.51
	MAPE	1.31	0.72*	*0.73*	1.22	0.74	0.80	1.10	0.82	1.59	2.49
	RMSE	3.15	2.57	1.83*	3.39	*1.96*	2.09	2.69	2.20	3.97	9.17
h = 12	MAE	2.83	2.49	*1.53*	2.63	1.61	1.28*	3.35	3.82	2.48	13.52
	MAPE	2.10	1.72	*1.13*	1.94	1.16	1.09*	2.00	2.45	1.69	7.35
	RMSE	3.63	3.35	*1.88*	3.58	1.96	1.84*	4.02	4.87	3.00	19.01

Notes: * denotes the most accurate forecast results; *italics* represent the second-best forecast results.

Table 3 shows the validation results for all models with $h = 1, 3, 6, 9, 12$. It is essential to note that the lowest values indicate the most accurate forecast. For the shorter forecast horizon ($h = 1$), the ARIMA model seemingly beat others. This somewhat supports the early findings of Junttila (2001) that ARIMA models are seemingly better than others in forecasting inflation using time series. Kontopoulou et al. (2023) argued that the ARIMA may exhibit superior performance than ML models for small datasets for short-term forecasting. It may be true in the case of the current analysis, where the number of observations is relatively small. However, ARIMA is only appropriate for short forecasts (Baciu, 2015). In addition, XGB yields better-performing predictions for increased horizons $h = 3, 6,\ 9$. This finding is comparable to that of Li et al. (2023), who suggest that the extreme gradient boosting model outperformed other ML models in forecasting Taiwanese inflation for $h = 3, 6$. More importantly, KNN is the most suitable model for an increased horizon $h = 12$. Similarly, other studies have suggested that KNN is one of the best-performing forecasts for Costa Rican inflation (Rodríguez-Vargas, 2020). De La Vega et al. (2014) and Iaousse et al. (2023) proved that KNN is more reliable and effective than ARIMA and other ML models for longer prediction horizons. There are several advantages of KNN over others. KNN is reasonably easy to apply, making it more accessible to a substantial range of users. KNN is tolerant and resistant to noise. Therefore, KNN is considered more effective for smaller datasets (Bansal et al., 2022).

As mentioned above, this study focused on forecasting results for $h = 12$, reflecting a financial year (12 months), thereby providing relevant implications for the State Bank of Vietnam and other Vietnamese government departments to inform their policy adjustments and decisions. For this reason, several diagnostic checks for $h = 12$ were performed, as presented in **Table 4**.

Table 4. The results of diagnostic tests, $\boldsymbol{h = 12}$

Tests (p-value)	**LSTM**	**ARIMA**	**XGB**	**LR**	**RF**	**KNN**	**GRU**	**BiGRU**	**ResLSTM**	**CauCNN**
ADF[1]	0.00	0.02	0.00	0.00	0.09	0.00	0.03	0.00	0.00	0.02
Jarque-Bera[2]	0.26	0.8	0.39	0.5	0.38	0.02	0.38	0.96	0.47	0.07
Ljung-Box[3]	0.82	0.41	0.58	0.99	0.73	0.63	0.53	0.81	0.78	0.92
McLeod-Li[4]	0.97	0.98	0.88	0.11	0.88	0.95	0.92	0.95	0.96	0.96

Notes: [1] The null hypothesis is that the time series has a unit root.[2] The null hypothesis that the data is normally distributed.[3] The null hypothesis that the time series has no autocorrelation up to lag 3. [4] The null hypothesis that the squared residuals have no autocorrelation (e.g., no ARCH effects).

As shown in **Table 4**, most ML models (except KNN and CauCNN) used in this study exhibit a stationary, normal distribution, no autocorrelation, and stable conditional variance. Although the KNN and CauCNN results (with p-values from the Jarque-Bera test of 0.05 and 0.1, respectively) reject the null hypothesis that the data are normally distributed, this does not necessarily mean that the forecasting results derived from KNN and CauCNN are unreliable. The explanation is that KNN is a nonparametric supervised ML technique, so it does not assume normality of the underlying data (Altman, 1992; Kapadnis et al., 2023). Similarly, Szarek et al. (2023) suggested that CauCNN is suitable for data with non-Gaussian distributions. Along with the pre-processing analysis presented above, the results of diagnostic tests indicate that our empirical model does not suffer from the classical spurious regression problem associated with non-stationary data. All variables entering the models are stationary, and residual-based unit root tests indicate that the residuals are stationary.

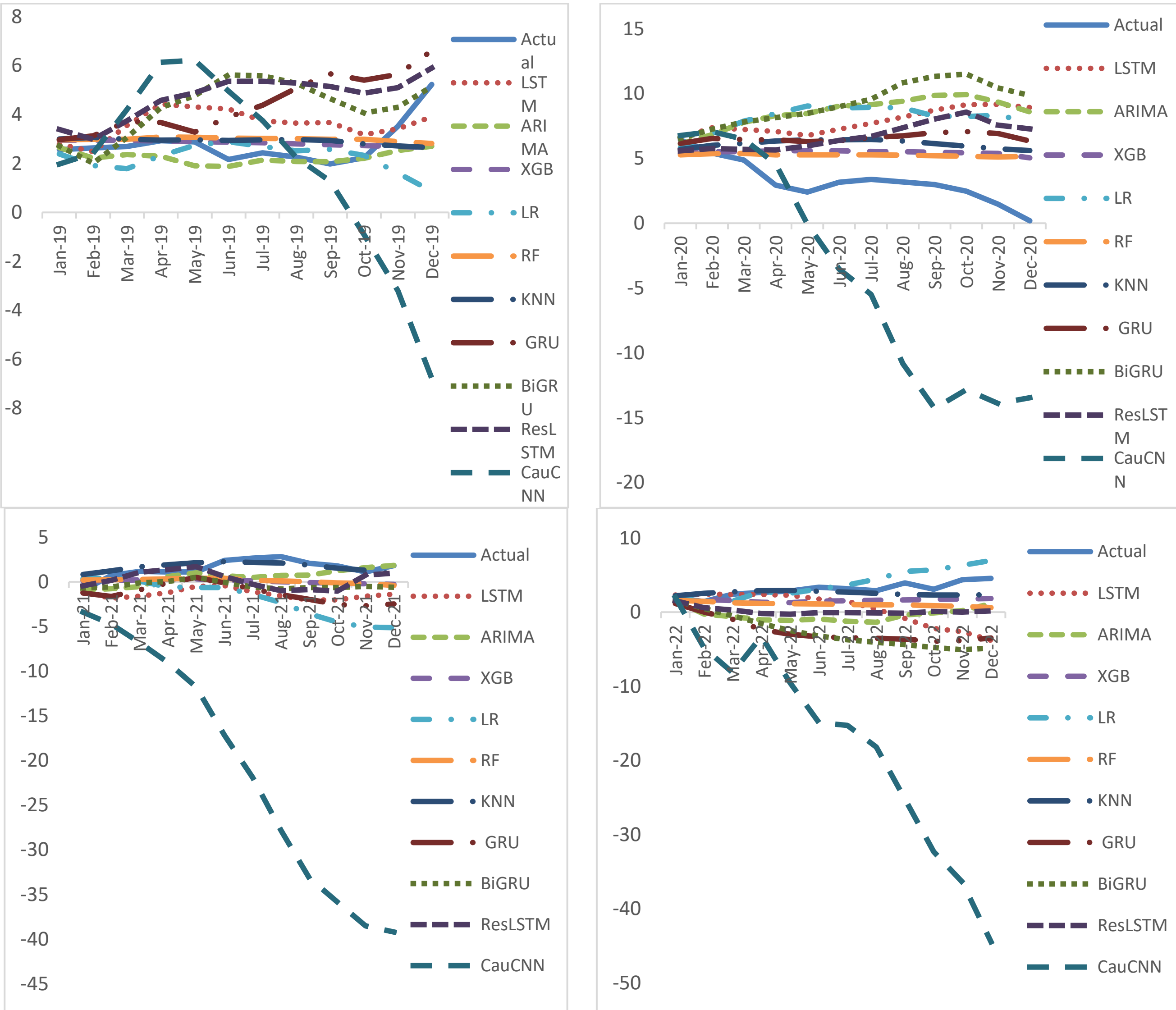
Furthermore, the Ljung–Box and McLeod–Li tests show that residuals are serially uncorrelated and free from ARCH-type non-linear dependence in the conditional variance. In contrast, the Jarque-Bera test suggests that residual distributions are generally well behaved. Collectively, these diagnostic results provide evidence that the ML models are statistically well specified and that predictive performance is not driven by residual autocorrelation, volatility clustering, or non-stationary behavior. Nevertheless, several studies have argued that stationarity and satisfactory diagnostic results do not entirely preclude spurious-like relationships (Cheng et al., 2021; Wong et al., 2024), particularly in forecasting and machine-learning contexts. Accordingly, diagnostic evidence supports the adequacy and reliability of the empirical models, but the results should be interpreted as predictive associations rather than definitive economic causality.

Figure 3 and **Appendix A5** indicate the forecasting results of inflation for the 12-month horizon ($h = 12$) across all ML models between 2019 and 2023. The forecasting performance of KNN is the most accurate for this horizon. This finding is comparable with those of Rodríguez-Vargas (2020) in the Costa Rican inflation or Priambodo et al. (2019) and Maccarrone et al. (2021) in GDP forecasts. Nonetheless, these findings again confirm the conclusion of Ülke et al. (2018) that there is no single best model to predict inflation.

Since the study was conducted at the beginning of 2023, and inflation information is published annually in the first quarter of the following year, this study computed the inflation forecast for 2023 for further validation and practical implementation purposes, as presented in **Figure 3**. Additionally, **Figure 4** compares inflation forecast results derived from this study with those of different prestigious organisations (e.g., the IMF and ADB), along with the inflation target approved by the Vietnamese government (VG target). Note that the two projection figures, collected from the IMF report in April and the updated ones in October each year, are reported. Additionally, this study focuses solely on the results from the outperformed models, as mentioned above, for the sake of clarity. These are KNN, XGB, ARIMA, LSTM, and ResLSTM.

Furthermore, **Figures 4** and **Table 5** show that the forecasting results derived from KNN models for the years 2019-2023 slightly differ from those reported by the IMF and ADB. More specifically, KNN results are superior to IMF and ADB projections for inflation forecasts during the COVID-19 pandemic (e.g., year 2021) and the subsequent recovery phase from the health crisis (e.g., 2023). This study's predictions and international organisation projections were lower than the actual inflation rates for 2019 and 2022. For 2020, the predictions and projections were higher than the actual inflation rate.

Figure 3. The results of predicted values and actual values, $\boldsymbol{h} = \mathbf{12}$



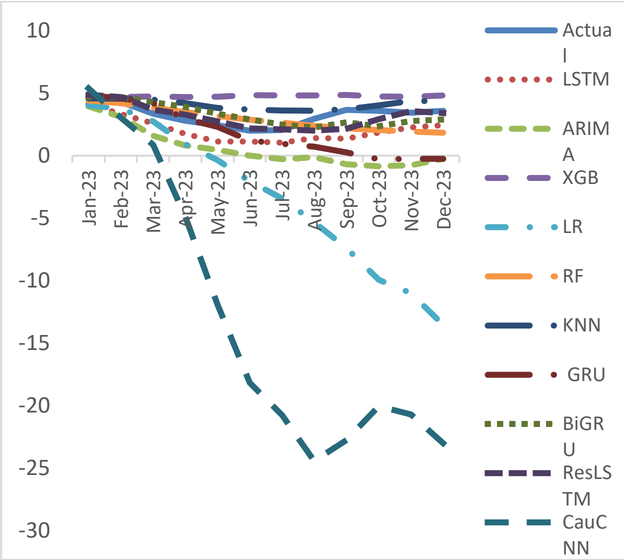


Figure 4. Percentage change in consumer price (%YoY) in Vietnam in the 12-month horizon, end of period.

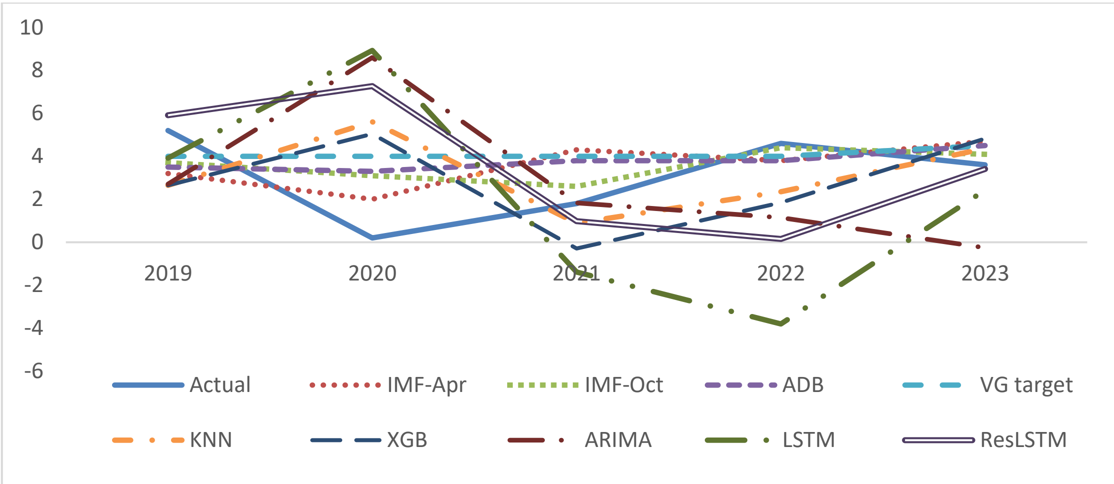


Table 5. Comparison results of forecast methods vs. actual inflation rate, 2019-2023.

Method	2019	2020	2021	2022	2023
Actual	5.23	0.19	1.81	4.55	3.58
IMF-Apr	3.20	2.00	4.30	3.80	4.70
IMF-Oct	3.70	3.10	2.60	4.40	4.10
ADB	3.5	3.3	3.8	3.8	4.5
VG target	4.00	4.00	4.00	4.00	4.5
KNN	2.65	5.61	0.89	2.35	4.37
XGB	2.65	5.04	-0.29	1.84	4.83
ARIMA	2.71	8.60	1.84	1.15	-0.26
LSTM	3.91	8.93	-1.39	-3.80	2.43
ResLSTM	5.90	7.27	0.99	0.15	3.41

Notes: This table compares end-of-year inflation forecasts from various models and organisations against the actual year-on-year inflation rate. Forecasts from the IMF are presented for both their April and October reports. VF target is the inflation target approved by the Vietnamese government.

Additionally, this study also reports the importance of the feature based on KNN results, as shown in **Appendices A6-A9**. For the ease of exposition, this study focuses on analysing the top ten most important features. **Appendix A6** suggests that the most crucial features in explaining the Vietnamese inflation forecast before the health crisis include economic policy uncertainty (EPU) indices (e.g., the US, Japan, Singapore, Russia, Korea, and UK), followed by the historical partner countries' inflation rates (e.g., Germany and Japan), and commodity price indices (e.g., PNRG, PPMETA). **Appendix A7** demonstrates that commodity price indices (e.g., PCOFFOTM, PCOFFROB, PCOAL, PNGAS, POILDUB, PNRG, PMETA, and PRUBB) may play a more significant role in predicting Vietnamese inflation during the first year of the COVID-19 pandemic. **Appendix A8** reveals that the EPU indices and monetary policy (e.g., discounting and refinancing rates) are the most critical features during the second year of the global health crisis. Furthermore, **Appendix A9** reemphasises that the essential features are EPU indices, commodity price indices, and the inflation rates of partner countries. These results somewhat support the early studies that have emphasised the critical role of EPU in predicting inflation (Balcilar et al., 2017; Ghosh et al., 2021, 2022), and especially the spillover effect of the Ukraine–Russia war on the global economy (Maurya et al., 2023).

5. Conclusions

This study evaluated conventional and advanced methods using machine learning in forecasting inflation in Vietnam before, during, and after the COVID-19 pandemic. The empirical results highlight several important points as follows.

Empirical findings demonstrate that some ML algorithms consistently outperform the conventional models regarding RMSE, MAPE, and MAE. However, the superior performance depends on the forecast horizon. The findings align with the view of Wolpert (1996) that no universal best model exists for various horizons. For example, the K-nearest neighbour algorithm was considered the best model for forecasting inflation for the 12-month horizon in Vietnam. Furthermore, the results are slightly different from the projections of the IMF and ADB in predicting Vietnamese inflation. More specifically, the findings provided a better prediction in some years. Thus, the Vietnamese authorities could utilise this study’s forecasts in a timely manner to determine the appropriate monetary policies. Alternatively, the Vietnamese authorities and the State Bank of Vietnam (SBV) could use the selected ML models and feature techniques in this study as an additional tool to forecast inflation. Moreover, the findings also offer alternative models for other government departments to use for various forecasting purposes. For instance, the ARIMA model is more suitable for short-term forecast horizon (e.g., $h = 1$), and XGB is better suited for medium-term forecast horizons (e.g., $h = 3, 6, 9$). Additionally, the forecast outcomes in this research can be used by Vietnamese businesses and foreign investors to identify and adjust their strategies in advance, rather than relying on periodic reports issued by the IMF or ADB, which are sometimes delayed.

Additionally, this study highlights several key features, including economic policy uncertainty and inflation rates of Vietnam's trading partners, commodity prices, and monetary policy (e.g., discount and refinancing rates). The findings suggest that the Vietnamese authorities should pay more attention to these features to manage and control inflation. Also, these features should be incorporated into the forecasting models that the SBV currently uses to improve their accuracy. Nonetheless, the use of machine learning methods for predicting inflation is a promising endeavour for policy decision-making under uncertainty, offering a data-driven approach to supplement traditional economic judgment.

This paper may suffer from several limitations. Due to data unavailability, the current analysis only considers several monthly features that reflect the unique characteristics of the Vietnamese economy. As money policy is one of the critical factors in explaining inflation (Friedman, 1995), future direction may consider some features in forecasting inflation, such as money supply, foreign exchange reserves, and domestic credit if their monthly data are available. Furthermore, this study is limited to ten selected models. Future studies may consider more advanced models relevant to forecasting, such as transformers (Chan & Yeo, 2024; Tong et al., 2023). Additionally, the present study highlights several new and crucial features in forecasting inflation, rather than what is historically known in the literature. Future studies may also incorporate these features into ML models used in this study, as well as in other emerging markets, over a more extended period to validate the above findings. Lastly, this current analysis employed ten selected models for the small sample size ($N = 252$ observations), which is a limitation for deep learning models. Future studies could employ these models to higher frequency data (e.g., daily/weekly) if available.

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Appendices

Appendix A1. Correlation matrix among variables used in this study

	CPI Vietnam	HNX	HOSE	CPI INDIA	CPI HONGKONG	RRATE	DRATE	CPIUS	EPUA	EPUG	EPUHK	EPUI	EPUJ	EPUK	EPUR
CPI Vietnam	1.00	-0.21	-0.21	0.03	-0.00	0.41	-0.14	0.29	-0.18	0.04	-0.05	-0.26	-0.17	-0.09	-0.02
HNX	-0.21	1.00	0.78	0.04	0.02	-0.02	-0.07	-0.03	-0.16	0.03	-0.17	-0.09	-0.13	-0.09	-0.08
HOSE	-0.21	0.78	1.00	0.06	0.00	-0.03	-0.07	-0.00	-0.19	-0.06	-0.14	-0.10	-0.16	-0.10	-0.17
CPI INDIA	0.03	0.04	0.06	1.00	-0.07	-0.06	0.13	-0.02	0.15	0.02	-0.07	0.17	0.13	-0.03	-0.09
CPI HONGKONG	-0.00	0.02	0.00	-0.07	1.00	0.07	0.06	-0.06	-0.08	-0.06	0.01	0.04	-0.02	-0.01	-0.09
RRATE	0.41	-0.02	-0.03	-0.06	0.07	1.00	0.10	0.20	-0.04	0.04	0.05	-0.02	-0.09	-0.01	0.02
DRATE	-0.14	-0.07	-0.07	0.13	0.06	0.10	1.00	-0.21	0.39	-0.00	0.19	0.68	0.39	0.02	0.00
CPIUS	0.29	-0.03	-0.00	-0.02	-0.06	0.20	-0.21	1.00	-0.13	0.07	-0.01	-0.15	-0.18	-0.01	-0.05
EPUA	-0.18	-0.16	-0.19	0.15	-0.08	-0.04	0.39	-0.13	1.00	0.13	0.44	0.61	0.74	0.55	0.04
EPUG	0.04	0.03	-0.06	0.02	-0.06	0.04	-0.00	0.07	0.13	1.00	0.05	0.04	0.10	0.15	0.07
EPUHK	-0.05	-0.17	-0.14	-0.07	0.01	0.05	0.19	-0.01	0.44	0.05	1.00	0.39	0.45	0.55	-0.02
EPUI	-0.26	-0.09	-0.10	0.17	0.04	-0.02	0.68	-0.15	0.61	0.04	0.39	1.00	0.54	0.25	0.03
EPUJ	-0.17	-0.13	-0.16	0.13	-0.02	-0.09	0.39	-0.18	0.74	0.10	0.45	0.54	1.00	0.50	0.07
EPUK	-0.09	-0.09	-0.10	-0.03	-0.01	-0.01	0.02	-0.01	0.55	0.15	0.55	0.25	0.50	1.00	0.04
EPUR	-0.02	-0.08	-0.17	-0.09	-0.09	0.02	0.00	-0.05	0.04	0.07	-0.02	0.03	0.07	0.04	1.00
EPUC	0.04	-0.02	-0.09	0.01	0.08	0.06	0.02	-0.04	0.22	0.31	0.09	0.08	0.12	0.21	-0.10
EPUS	0.04	-0.05	-0.12	0.02	-0.05	0.09	0.04	-0.01	0.29	0.61	0.13	0.12	0.22	0.27	0.01
EPUUK	-0.02	-0.10	-0.10	0.04	-0.03	0.00	0.09	-0.12	0.57	0.14	0.40	0.18	0.62	0.55	0.06
EPUUS	-0.15	-0.03	-0.07	0.05	-0.09	-0.09	0.01	-0.07	0.64	0.18	0.43	0.29	0.60	0.64	0.04
CPIG	0.22	-0.01	-0.06	-0.02	0.05	0.07	-0.15	0.34	-0.03	0.19	-0.04	-0.14	-0.13	0.08	-0.08
CPIJ	0.27	-0.11	-0.14	0.01	0.03	0.19	-0.06	0.20	0.02	-0.03	-0.03	-0.07	-0.10	-0.02	0.09
CPIC	0.42	-0.22	-0.25	0.05	0.09	0.27	0.38	0.03	0.15	0.05	0.28	0.28	0.08	-0.02	0.02
PALLFNF	0.23	0.16	0.20	0.04	0.04	0.13	-0.23	0.54	-0.22	0.01	-0.12	-0.16	-0.20	-0.08	-0.14
PNFUEL	0.20	0.08	0.15	-0.05	0.02	0.06	-0.23	0.37	-0.15	-0.08	-0.08	-0.17	-0.13	-0.04	-0.02
PFANDB	0.16	0.05	0.09	-0.08	0.07	0.08	-0.20	0.33	-0.14	-0.03	-0.09	-0.15	-0.13	-0.04	-0.02
PFOOD	0.16	0.05	0.08	-0.08	0.07	0.08	-0.19	0.33	-0.13	-0.03	-0.07	-0.13	-0.12	-0.02	-0.03
PINDU	0.12	0.09	0.16	-0.03	0.00	0.01	-0.21	0.25	-0.18	-0.12	-0.13	-0.16	-0.17	-0.06	0.02
PAGRI	0.17	0.07	0.11	-0.08	0.07	0.09	-0.22	0.35	-0.16	-0.05	-0.09	-0.16	-0.15	-0.05	-0.03
PRAWM	0.16	0.11	0.19	-0.07	0.07	0.09	-0.23	0.27	-0.20	-0.09	-0.09	-0.20	-0.21	-0.06	-0.08
PALLMETA	0.12	0.08	0.15	-0.01	-0.04	0.02	-0.16	0.24	-0.09	-0.09	-0.06	-0.12	-0.06	-0.02	-0.01
PMETA	0.10	0.08	0.15	-0.02	-0.01	-0.00	-0.19	0.23	-0.16	-0.12	-0.13	-0.15	-0.15	-0.05	0.03
PPMETA	0.10	0.04	0.09	0.01	-0.08	0.07	-0.03	0.17	0.10	0.01	0.11	-0.01	0.15	0.05	-0.09
PNRG	0.21	0.16	0.19	0.05	0.04	0.13	-0.20	0.52	-0.21	0.04	-0.13	-0.13	-0.19	-0.08	-0.16
PNGAS	0.03	0.24	0.18	0.05	0.04	-0.00	-0.06	0.05	-0.07	0.19	-0.06	-0.01	-0.01	0.01	-0.07
PCOAL	0.17	0.04	0.05	0.02	0.04	0.11	-0.16	0.36	-0.09	0.05	0.01	-0.09	-0.12	0.05	-0.20
PCOFFOTM	0.05	0.10	0.09	0.03	-0.07	-0.01	-0.21	0.12	-0.13	0.01	-0.10	-0.20	-0.04	-0.13	0.09
PCOFFROB	0.13	0.01	0.03	-0.04	-0.04	0.10	-0.14	0.18	-0.15	-0.06	-0.10	-0.15	-0.13	-0.18	0.01
PCOTTIND	0.22	-0.13	-0.09	0.04	0.10	0.21	0.26	0.29	0.24	0.04	0.27	0.23	0.16	0.24	0.02
POILBRE	0.24	0.02	0.10	0.03	0.01	0.16	-0.19	0.63	-0.22	-0.10	-0.14	-0.15	-0.24	-0.13	-0.15
POILDUB	0.24	0.03	0.12	0.04	0.00	0.16	-0.18	0.62	-0.23	-0.12	-0.14	-0.16	-0.25	-0.14	-0.14
POLVOIL	0.01	-0.02	-0.07	-0.08	0.00	-0.01	-0.11	0.15	-0.02	-0.01	0.01	-0.00	-0.04	0.01	-0.02
PPORK	0.02	-0.06	-0.02	0.23	0.02	0.05	0.17	0.18	0.17	0.07	0.18	0.26	-0.01	0.02	-0.01
PPOULT	0.10	-0.07	-0.04	-0.15	-0.11	0.05	-0.02	0.22	0.03	0.11	-0.03	-0.01	-0.04	0.05	0.05
PRICENPQ	0.17	-0.12	-0.10	0.00	0.01	-0.22	-0.10	0.10	-0.01	-0.10	0.05	-0.02	0.04	-0.02	0.01
PRUBB	0.19	0.11	0.15	-0.06	0.05	0.07	-0.20	0.24	-0.17	-0.14	-0.03	-0.18	-0.16	-0.02	-0.02

	EPUC	EPUS	EPUUK	EPUUS	CPIG	CPIJ	CPIC	PALLFNF	PNFUEL	PFANDB	PFOOD	PINDU	PAGRI	PRAWM	PALLMETA
CPI Vietnam	0.04	0.04	-0.02	-0.15	0.22	0.27	0.42	0.23	0.20	0.16	0.16	0.12	0.17	0.16	0.12
HNX	-0.02	-0.05	-0.10	-0.03	-0.01	-0.11	-0.22	0.16	0.08	0.05	0.05	0.09	0.07	0.11	0.08
HOSE	-0.09	-0.12	-0.10	-0.07	-0.06	-0.14	-0.25	0.20	0.15	0.09	0.08	0.16	0.11	0.19	0.15
CPI INDIA	0.01	0.02	0.04	0.05	-0.02	0.01	0.05	0.04	-0.05	-0.08	-0.08	-0.03	-0.08	-0.07	-0.01
CPI HONGKONG	0.08	-0.05	-0.03	-0.09	0.05	0.03	0.09	0.04	0.02	0.07	0.07	0.00	0.07	0.07	-0.04
RRATE	0.06	0.09	0.00	-0.09	0.07	0.19	0.27	0.13	0.06	0.08	0.08	0.01	0.09	0.09	0.02
DRATE	0.02	0.04	0.09	0.01	-0.15	-0.06	0.38	-0.23	-0.23	-0.20	-0.19	-0.21	-0.22	-0.23	-0.16
CPIUS	-0.04	-0.01	-0.12	-0.07	0.34	0.20	0.03	0.54	0.37	0.33	0.33	0.25	0.35	0.27	0.24
EPUA	0.22	0.29	0.57	0.64	-0.03	0.02	0.15	-0.22	-0.15	-0.14	-0.13	-0.18	-0.16	-0.20	-0.09
EPUG	0.31	0.61	0.14	0.18	0.19	-0.03	0.05	0.01	-0.08	-0.03	-0.03	-0.12	-0.05	-0.09	-0.09
EPUHK	0.09	0.13	0.40	0.43	-0.04	-0.03	0.28	-0.12	-0.08	-0.09	-0.07	-0.13	-0.09	-0.09	-0.06
EPUI	0.08	0.12	0.18	0.29	-0.14	-0.07	0.28	-0.16	-0.17	-0.15	-0.13	-0.16	-0.16	-0.20	-0.12
EPUJ	0.12	0.22	0.62	0.60	-0.13	-0.10	0.08	-0.20	-0.13	-0.13	-0.12	-0.17	-0.15	-0.21	-0.06
EPUK	0.21	0.27	0.55	0.64	0.08	-0.02	-0.02	-0.08	-0.04	-0.04	-0.02	-0.06	-0.05	-0.06	-0.02
EPUR	-0.10	0.01	0.06	0.04	-0.08	0.09	0.02	-0.14	-0.02	-0.02	-0.03	0.02	-0.03	-0.08	-0.01
EPUC	1.00	0.71	0.13	0.13	0.07	-0.06	0.05	-0.03	0.02	0.03	0.04	-0.01	0.03	0.01	-0.00
EPUS	0.71	1.00	0.21	0.27	0.11	-0.03	0.07	-0.10	-0.07	-0.05	-0.04	-0.12	-0.05	-0.05	-0.09
EPUUK	0.13	0.21	1.00	0.54	-0.01	-0.04	0.03	-0.16	-0.03	-0.05	-0.04	-0.03	-0.06	-0.09	0.02
EPUUS	0.13	0.27	0.54	1.00	-0.07	-0.04	-0.02	-0.08	-0.01	-0.04	-0.03	-0.02	-0.05	-0.08	0.04
CPIG	0.07	0.11	-0.01	-0.07	1.00	0.17	0.03	0.29	0.21	0.29	0.29	0.08	0.29	0.18	0.04
CPIJ	-0.06	-0.03	-0.04	-0.04	0.17	1.00	0.12	0.15	0.11	0.11	0.10	0.08	0.11	0.09	0.06
CPIC	0.05	0.07	0.03	-0.02	0.03	0.12	1.00	0.01	-0.04	-0.02	-0.03	-0.15	-0.03	-0.08	-0.10
PALLFNF	-0.03	-0.10	-0.16	-0.08	0.29	0.15	0.01	1.00	0.66	0.55	0.54	0.57	0.58	0.54	0.55
PNFUEL	0.02	-0.07	-0.03	-0.01	0.21	0.11	-0.04	0.66	1.00	0.82	0.82	0.86	0.85	0.67	0.87
PFANDB	0.03	-0.05	-0.05	-0.04	0.29	0.11	-0.02	0.55	0.82	1.00	1.00	0.49	0.99	0.56	0.46
PFOOD	0.04	-0.04	-0.04	-0.03	0.29	0.10	-0.03	0.54	0.82	1.00	1.00	0.49	0.99	0.55	0.46
PINDU	-0.01	-0.12	-0.03	-0.02	0.08	0.08	-0.15	0.57	0.86	0.49	0.49	1.00	0.54	0.64	0.93
PAGRI	0.03	-0.05	-0.06	-0.05	0.29	0.11	-0.03	0.58	0.85	0.99	0.99	0.54	1.00	0.66	0.50
PRAWM	0.01	-0.05	-0.09	-0.08	0.18	0.09	-0.08	0.54	0.67	0.56	0.55	0.64	0.66	1.00	0.51
PALLMETA	-0.00	-0.09	0.02	0.04	0.04	0.06	-0.10	0.55	0.87	0.46	0.46	0.93	0.50	0.51	1.00
PMETA	-0.01	-0.13	-0.01	-0.01	0.06	0.07	-0.15	0.53	0.82	0.44	0.44	0.99	0.48	0.52	0.94
PPMETA	0.02	0.04	0.08	0.14	-0.02	-0.00	0.06	0.34	0.57	0.30	0.29	0.38	0.31	0.25	0.67
PNRG	-0.04	-0.09	-0.19	-0.10	0.28	0.14	0.02	0.96	0.44	0.37	0.36	0.38	0.40	0.41	0.35
PNGAS	-0.00	0.04	-0.14	0.02	0.04	0.01	0.03	0.53	0.01	-0.03	-0.04	0.05	-0.02	0.08	0.05
PCOAL	0.02	0.02	-0.09	-0.03	0.23	0.09	0.02	0.62	0.29	0.24	0.23	0.28	0.27	0.33	0.23
PCOFFOTM	-0.07	-0.09	-0.07	-0.03	0.06	0.08	0.01	0.23	0.32	0.36	0.29	0.19	0.36	0.25	0.21
PCOFFROB	-0.10	-0.10	-0.08	-0.13	0.10	0.13	0.05	0.28	0.28	0.31	0.25	0.19	0.31	0.22	0.20
PCOTTIND	0.03	0.01	0.14	0.18	0.19	0.15	0.34	0.14	0.04	0.07	0.07	-0.04	0.08	0.07	-0.04
POILBRE	-0.06	-0.15	-0.13	-0.14	0.33	0.17	0.02	0.82	0.56	0.49	0.49	0.46	0.52	0.48	0.42
POILDUB	-0.09	-0.18	-0.14	-0.15	0.32	0.18	0.01	0.83	0.56	0.51	0.50	0.46	0.53	0.47	0.42
POLVOIL	-0.02	-0.11	-0.03	0.01	0.07	0.05	-0.10	0.13	0.23	0.14	0.14	0.20	0.14	0.07	0.25
PPORK	0.02	0.03	-0.05	-0.02	0.16	0.18	0.20	-0.03	-0.18	-0.11	-0.12	-0.21	-0.14	-0.23	-0.21
PPOULT	0.13	0.16	0.02	0.04	0.14	0.00	-0.06	0.16	0.28	0.35	0.36	0.19	0.34	0.21	0.13
PRICENPQ	-0.01	-0.04	0.03	-0.01	-0.05	-0.06	0.21	0.13	0.17	0.11	0.11	0.10	0.10	0.04	0.12
PRUBB	-0.02	-0.06	-0.04	-0.05	0.15	0.13	-0.04	0.41	0.58	0.44	0.43	0.59	0.53	0.82	0.48

	PMETA	PPMETA	PNRG	PNGAS	PCOAL	PCOFFOTM	PCOFFROB	PCOTTIND	POILBRE	POILDUB	POLVOIL	PPORK	PPOULT	PRICENPQ	PRUBB
CPI Vietnam	0.10	0.10	0.21	0.03	0.17	0.05	0.13	0.22	0.24	0.24	0.01	0.02	0.10	0.17	0.19
HNX	0.08	0.04	0.16	0.24	0.04	0.10	0.01	-0.13	0.02	0.03	-0.02	-0.06	-0.07	-0.12	0.11
HOSE	0.15	0.09	0.19	0.18	0.05	0.09	0.03	-0.09	0.10	0.12	-0.07	-0.02	-0.04	-0.10	0.15
CPI INDIA	-0.02	0.01	0.05	0.05	0.02	0.03	-0.04	0.04	0.03	0.04	-0.08	0.23	-0.15	0.00	-0.06
CPI HONGKONG	-0.01	-0.08	0.04	0.04	0.04	-0.07	-0.04	0.10	0.01	0.00	0.00	0.02	-0.11	0.01	0.05
RRATE	-0.00	0.07	0.13	-0.00	0.11	-0.01	0.10	0.21	0.16	0.16	-0.01	0.05	0.05	-0.22	0.07
DRATE	-0.19	-0.03	-0.20	-0.06	-0.16	-0.21	-0.14	0.26	-0.19	-0.18	-0.11	0.17	-0.02	-0.10	-0.20
CPIUS	0.23	0.17	0.52	0.05	0.36	0.12	0.18	0.29	0.63	0.62	0.15	0.18	0.22	0.10	0.24
EPUA	-0.16	0.10	-0.21	-0.07	-0.09	-0.13	-0.15	0.24	-0.22	-0.23	-0.02	0.17	0.03	-0.01	-0.17
EPUG	-0.12	0.01	0.04	0.19	0.05	0.01	-0.06	0.04	-0.10	-0.12	-0.01	0.07	0.11	-0.10	-0.14
EPUHK	-0.13	0.11	-0.13	-0.06	0.01	-0.10	-0.10	0.27	-0.14	-0.14	0.01	0.18	-0.03	0.05	-0.03
EPUI	-0.15	-0.01	-0.13	-0.01	-0.09	-0.20	-0.15	0.23	-0.15	-0.16	-0.00	0.26	-0.01	-0.02	-0.18
EPUJ	-0.15	0.15	-0.19	-0.01	-0.12	-0.04	-0.13	0.16	-0.24	-0.25	-0.04	-0.01	-0.04	0.04	-0.16
EPUK	-0.05	0.05	-0.08	0.01	0.05	-0.13	-0.18	0.24	-0.13	-0.14	0.01	0.02	0.05	-0.02	-0.02
EPUR	0.03	-0.09	-0.16	-0.07	-0.20	0.09	0.01	0.02	-0.15	-0.14	-0.02	-0.01	0.05	0.01	-0.02
EPUC	-0.01	0.02	-0.04	-0.00	0.02	-0.07	-0.10	0.03	-0.06	-0.09	-0.02	0.02	0.13	-0.01	-0.02
EPUS	-0.13	0.04	-0.09	0.04	0.02	-0.09	-0.10	0.01	-0.15	-0.18	-0.11	0.03	0.16	-0.04	-0.06
EPUUK	-0.01	0.08	-0.19	-0.14	-0.09	-0.07	-0.08	0.14	-0.13	-0.14	-0.03	-0.05	0.02	0.03	-0.04
EPUUS	-0.01	0.14	-0.10	0.02	-0.03	-0.03	-0.13	0.18	-0.14	-0.15	0.01	-0.02	0.04	-0.01	-0.05
CPIG	0.06	-0.02	0.28	0.04	0.23	0.06	0.10	0.19	0.33	0.32	0.07	0.16	0.14	-0.05	0.15
CPIJ	0.07	-0.00	0.14	0.01	0.09	0.08	0.13	0.15	0.17	0.18	0.05	0.18	0.00	-0.06	0.13
CPIC	-0.15	0.06	0.02	0.03	0.02	0.01	0.05	0.34	0.02	0.01	-0.10	0.20	-0.06	0.21	-0.04
PALLFNF	0.53	0.34	0.96	0.53	0.62	0.23	0.28	0.14	0.82	0.83	0.13	-0.03	0.16	0.13	0.41
PNFUEL	0.82	0.57	0.44	0.01	0.29	0.32	0.28	0.04	0.56	0.56	0.23	-0.18	0.28	0.17	0.58
PFANDB	0.44	0.30	0.37	-0.03	0.24	0.36	0.31	0.07	0.49	0.51	0.14	-0.11	0.35	0.11	0.44
PFOOD	0.44	0.29	0.36	-0.04	0.23	0.29	0.25	0.07	0.49	0.50	0.14	-0.12	0.36	0.11	0.43
PINDU	0.99	0.38	0.38	0.05	0.28	0.19	0.19	-0.04	0.46	0.46	0.20	-0.21	0.19	0.10	0.59
PAGRI	0.48	0.31	0.40	-0.02	0.27	0.36	0.31	0.08	0.52	0.53	0.14	-0.14	0.34	0.10	0.53
PRAWM	0.52	0.25	0.41	0.08	0.33	0.25	0.22	0.07	0.48	0.47	0.07	-0.23	0.21	0.04	0.82
PALLMETA	0.94	0.67	0.35	0.05	0.23	0.21	0.20	-0.04	0.42	0.42	0.25	-0.21	0.13	0.12	0.48
PMETA	1.00	0.38	0.35	0.04	0.25	0.16	0.17	-0.06	0.42	0.42	0.21	-0.19	0.17	0.10	0.50
PPMETA	0.38	1.00	0.20	0.06	0.09	0.23	0.15	0.01	0.22	0.23	0.21	-0.15	-0.01	0.12	0.21
PNRG	0.35	0.20	1.00	0.63	0.63	0.16	0.24	0.15	0.79	0.79	0.08	0.02	0.09	0.10	0.28
PNGAS	0.04	0.06	0.63	1.00	0.42	0.09	0.12	0.08	0.04	0.05	0.02	0.10	-0.07	0.02	-0.02
PCOAL	0.25	0.09	0.63	0.42	1.00	0.12	0.18	0.17	0.40	0.42	0.01	0.10	0.13	0.03	0.19
PCOFFOTM	0.16	0.23	0.16	0.09	0.12	1.00	0.59	0.08	0.12	0.14	-0.01	0.02	-0.05	-0.03	0.22
PCOFFROB	0.17	0.15	0.24	0.12	0.18	0.59	1.00	0.08	0.19	0.22	-0.04	0.03	0.00	-0.00	0.18
PCOTTIND	-0.06	0.01	0.15	0.08	0.17	0.08	0.08	1.00	0.14	0.13	0.01	0.51	0.08	-0.01	-0.00
POILBRE	0.42	0.22	0.79	0.04	0.40	0.12	0.19	0.14	1.00	0.98	0.09	-0.06	0.16	0.12	0.38
POILDUB	0.42	0.23	0.79	0.05	0.42	0.14	0.22	0.13	0.98	1.00	0.09	-0.06	0.16	0.12	0.40
POLVOIL	0.21	0.21	0.08	0.02	0.01	-0.01	-0.04	0.01	0.09	0.09	1.00	0.04	-0.09	0.09	0.03
PPORK	-0.19	-0.15	0.02	0.10	0.10	0.02	0.03	0.51	-0.06	-0.06	0.04	1.00	0.05	-0.12	-0.24
PPOULT	0.17	-0.01	0.09	-0.07	0.13	-0.05	0.00	0.08	0.16	0.16	-0.09	0.05	1.00	-0.03	0.05
PRICENPQ	0.10	0.12	0.10	0.02	0.03	-0.03	-0.00	-0.01	0.12	0.12	0.09	-0.12	-0.03	1.00	0.07
PRUBB	0.50	0.21	0.28	-0.02	0.19	0.22	0.18	-0.00	0.38	0.40	0.03	-0.24	0.05	0.07	1.00

Appendix A2. Unit root tests of level and transformed series

	Level		Transformed	
	A: intercept	**B: intercept with trend**	**A: intercept**	**B: intercept with trend**
	ADF	**ADF**	**ADF**	**ADF**
CPIVIETNAM	0.13	0.13	0.00*	0.00*
HNX	0.41	0.74	0.00*	0.00*
HOSE	0.24	0.01*	0.00*	0.00*
CPI INDIA	0.92	0.33	0.1***	0.44*
CPI HONGKONG	0.91	0.43	0.03**	0.16*
CPIJ	0.12	0.12	0.00*	0.00*
CPIC	0.00*	0.00*	-	-
CPIUS	0.99	0.83	0.05**	0.1***
CPIG	0.66	0.91	0.01*	0.03**
DRATE	0.02**	0.07***	-	-
RRATE	0.08***	0.2	0.00*	0.00*
EPUA	0.00*	0.00*	-	-
EPUG	0.91	0.72	0.00*	0.00*
EPUHK	0.00*	0.00*	-	-
EPUI	0.01*	0.07***	-	-
EPUJ	0.00*	0.01*	-	-
EPUK	0.02**	0.01*	-	-
EPUR	0.77	0.00*	0.00*	0.00*
EPUC	0.71	0.17	0.00*	0.00*
EPUS	0.5	0.00*	0.00*	0.00*
EPUUK	0.02**	0.01*	-	-
EPUUS	0.01*	0.00*	-	-
PAGRI	0.21	0.24	0.00*	0.00*
PMETA	0.21	0.39	0.00*	0.00*
PPMETA	0.68	0.68	0.00*	0.00*
PCOAL	0.49	0.36	0.00*	0.01*
PCOFFROB	0.12	0.38	0.00*	0.00*
PCOTTIND	0.04**	0.07***	-	-
POILDUB	0.04**	0.16	0.00*	0.00*
POLVOIL	0.24	0.55	0.00*	0.00*
PPORK	0.00*	0.00*	-	-
PPOULT	0.82	0.00*	0.00*	0.01*
PNRG	0.16	0.37	0.00*	0.00*
PNGAS	0.06***	0.21	0.00*	0.00*
PCOFFOTM	0.29	0.4	0.00*	0.00*
PRICENPQ	0.17	0.49	0.00*	0.00*
PRUBB	0.08***	0.27	0.00*	0.00*

Notes: *, **, ***Significant at 10, 5, and 1 percent levels, respectively.

Appendix A3. Hyperparameter space

Models	Hyperparameter	Type	Search Space	Meaning
KNN	**N_neighbors**	int	[2, 15]	Number of neighbors to use
	Weights	string	uniform, distance	Weight function used in prediction
LR	**Fit_intercept**	boolean	True, False	Whether to calculate the intercept for this model
	Positive	boolean	True, False	When set to True, forces the coefficients to be positive
RF	**N estimators**	int	100, 200, 300, 500	The number of trees in the forest
	Max depth	int	None, 5, 10, 20	The maximum depth of the tree
	Min samples split	int	[2, 10]	The minimum number of samples required to split an internal node
	Min samples leaf	int	[2, 10]	The minimum number of samples required to be at a leaf node
	Max features	Union[str, float]	'sqrt', 'log2', 0.2, 0.5, 0.8	The number of features to consider when looking for the best split
	Bootstrap	boolean	True, False	Whether bootstrap samples are used when building trees. If False, the whole dataset is used to build each tree.
	Criterion	string	absolute_error, squared_error, friedman_mse	The function to measure the quality of a split
	Max leaf nodes	int	None, 10, 30, 50	Grow trees with max_leaf_nodes in best-first fashion
XGB	**N estimators**	int	60, 80, 100, 120, 140 ,160	The number of boosting rounds or the number of gradient-boosted trees to be built during the training process.
	Max depth	int	[2, 10]	Maximum tree depth
	Gamma	float	0.5, 1, 1.5, 2, 5	Minimum loss reduction required to make a further split
	Min child weight	int	[1, 10]	Minimum sum of instance weights required in a child node
	Learning rate	float	0.03, 0.1, 0.001	Learning rate
ARIMA	**p**	int	23	The number of lag observations (autoregressive terms) included in the model
	d	int	1	First-order differencing
	q	int	12	The number of lagged forecast errors (moving average terms) in the model
LSTM	**Hidden dim**	int	16, 32, 64, 128	Number of LSTM units
	Learning rate	float	0.1, 0.05, 0.001	Learning rate
	Batch size	int	32, 64, 128	Batch size
	No. layers	int	1, 2	Number of LSTM layers
GRU	**Hidden dim**	int	16, 32, 64, 128	Number of GRU units
	Learning rate	float	0.1, 0.05, 0.001	Learning rate
	Batch size	int	32, 64, 128	Batch size
	No. layers	int	1, 2	Number of GRU layers
BiGRU	**Hidden dim**	int	16, 32, 64, 128	Number of single GRU units
	Learning rate	float	0.1, 0.05, 0.001	Learning rate
	Batch size	int	32, 64, 128	Batch size
	No. layers	int	1, 2	Number of BiGRU layers
ResLSTM	**Hidden dim**	int	16, 32, 64, 128	Number of single LSTM units
	Learning rate	float	0.1, 0.05, 0.001	Learning rate
	Batch size	int	32, 64, 128	Batch size
	No. layers	int	1, 2	Number of LSTM layers
CauCNN	**Hidden dim**	int	16, 32, 64, 128	Number of Fully Connected Layer units
	Learning rate	float	0.1, 0.05, 0.001	Learning rate
	Batch size	int	32, 64, 128	Batch size
	Kernel size	int	3, 5, 7, 9	Kernel size of casual convolutional layers

Appendix A4. Optimal hyperparameters for each year, $h = 12$

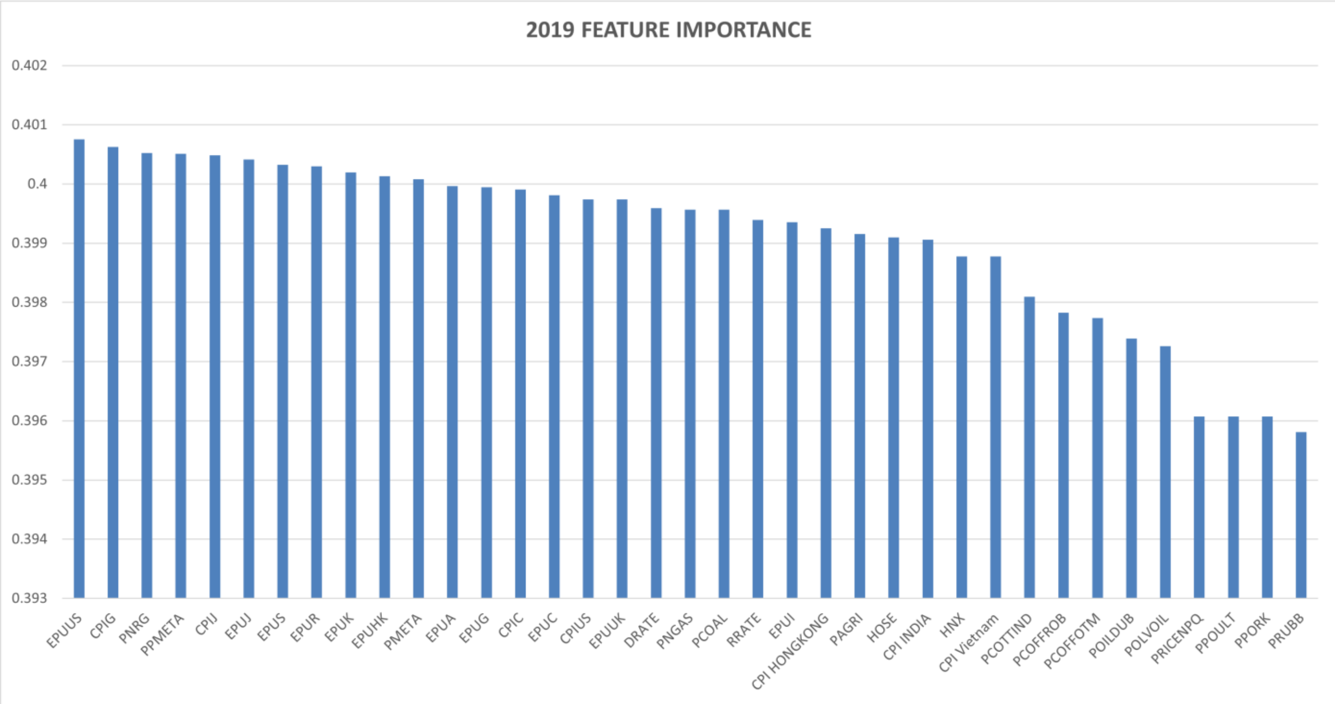
Models	**Hyperparameter settings**	**2019**	**2020**	**2021**	**2022**	**2023**
KNN	**N_neighbors**	14	14	14	14	14
	Weights	Distance	Distance	Distance	Distance	Distance
LR	**Fit_intercept**	False	False	False	False	False
	Positive	False	False	False	False	False
RF	**N estimators**	300	300	300	300	300
	Max depth	20	20	20	20	20
	Min samples split	8	8	8	8	8
	Min samples leaf	5	5	5	5	5
	Max features	log2	log2	log2	log2	log2
	Bootstrap	True	True	True	True	True
	Criterion	friedman_mse	friedman_mse	friedman_mse	friedman_mse	friedman_mse
	Max leaf nodes	30	20	30	30	30
XGB	**N estimators**	80	160	140	140	140
	Max depth	3	4	9	9	9
	Gamma	1.5	5	1.5	1.5	1.5
	Min child weight	5	10	4	4	4
	Learning rate	0.0001	0.0001	0.001	0.001	0.001
LSTM	**Hidden dim**	16	32	64	16	32
	Learning rate	0.05	0.001	0.001	0.05	0.001
	Batch size	32	32	64	32	32
	No. layers	1	2	2	1	2
GRU	**Hidden dim**	64	64	64	32	32
	Learning rate	0.001	0.001	0.001	0.001	0.001
	Batch size	64	64	64	64	32
	No. layers	2	2	2	2	2
BiGRU	**Hidden dim**	32	64	64	16	16
	Learning rate	0.001	0.0001	0.0001	0.01	0.01
	Batch size	32	32	32	32	32
	No. layers	1	1	2	2	2
ResLSTM	**Hidden dim**	128	128	128	32	64
	Learning rate	0.0001	0.0001	0.0001	0.01	0.01
	Batch size	32	32	32	32	32
	No. layers	2	2	2	2	2
CauCNN	**Hidden dim**	32	128	128	16	64
	Learning rate	0.0001	0.001	0.0001	0.01	0.001
	Batch size	32	32	32	32	32
	Kernel size	9	5	3	7	9

Appendix A5. Actual and predicted values for inflation using predictor variables in first difference across all models in 2019-2023, $h = 12$

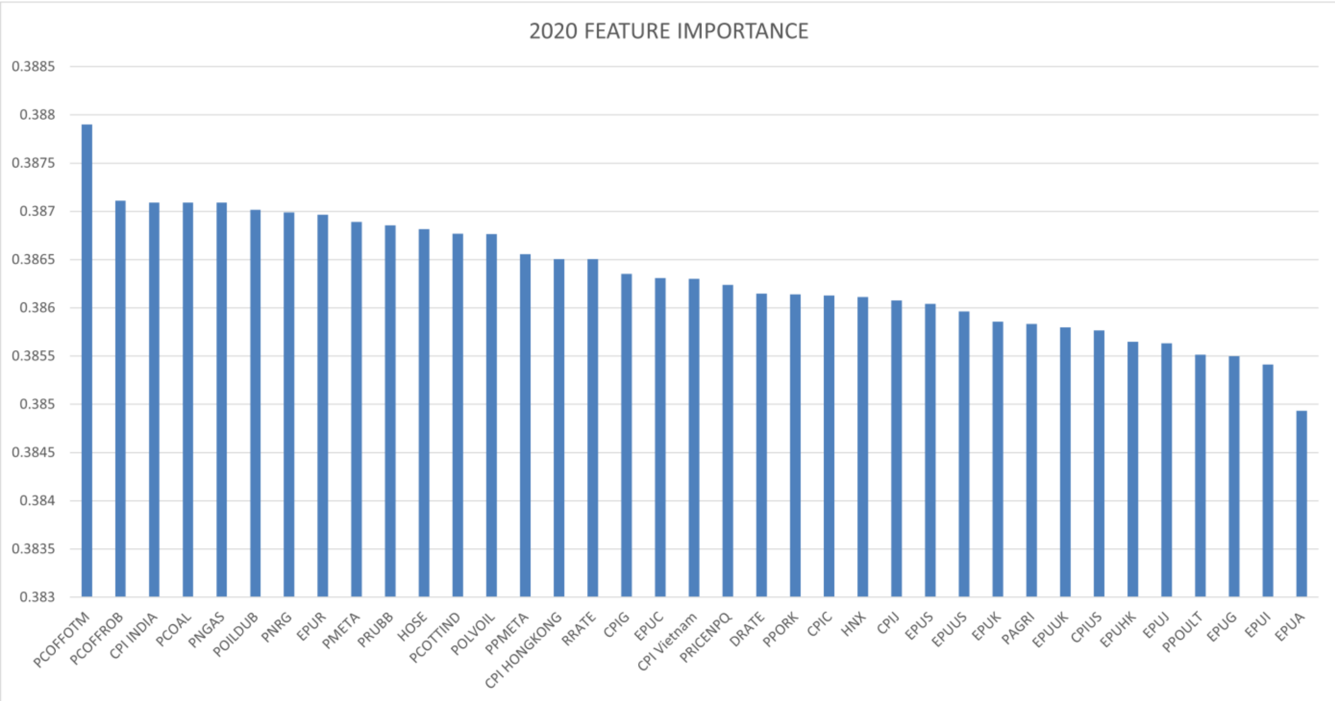
Period	Actual	LSTM	ARIMA	XGB	LR	RF	KNN	GRU	BiGRU	ResLSTM	CauCNN
Jan-19	2.56	2.79	2.64	2.95	2.39	2.96	3.01	2.97	2.72	3.39	1.98
Feb-19	2.64	2.49	2.23	2.96	1.92	2.99	3.06	3.13	2.01	2.99	2.42
Mar-19	2.7	3.56	2.37	2.94	1.79	2.99	2.99	3.71	3.07	3.74	4.20
Apr-19	2.93	4.43	2.30	2.92	2.32	3.08	2.95	3.68	4.29	4.58	6.14
May-19	2.88	4.32	1.91	2.89	2.74	3.08	2.97	3.28	4.78	4.89	6.22
Jun-19	2.16	4.23	1.88	2.87	2.89	3.04	2.94	3.89	5.62	5.36	4.95
Jul-19	2.44	3.75	2.15	2.84	2.70	3.02	2.96	4.38	5.58	5.36	3.76
Aug-19	2.26	3.65	2.08	2.81	2.52	3.01	2.98	5.08	5.28	5.29	2.24
Sep-19	1.98	3.67	2.07	2.77	2.58	2.99	2.94	5.66	4.65	5.15	1.28
Oct-19	2.24	3.18	2.21	2.73	2.33	2.99	2.80	5.40	4.06	4.88	-0.92
Nov-19	3.52	3.41	2.53	2.69	1.62	2.90	2.72	5.65	4.30	5.10	-3.20
Dec-19	5.23	3.91	2.71	2.65	0.87	2.82	2.65	6.61	5.14	5.90	-6.78
Jan-20	6.43	6.58	6.12	5.39	5.81	5.27	5.69	6.16	6.54	5.59	6.77
Feb-20	5.4	7.37	6.83	5.53	6.92	5.36	6.02	6.55	7.26	5.77	7.07
Mar-20	4.87	7.23	7.80	5.52	7.89	5.39	6.16	6.45	7.82	5.70	6.47
Apr-20	2.93	7.07	8.30	5.58	8.45	5.28	6.34	6.42	8.14	5.66	4.59
May-20	2.4	6.76	8.45	5.60	9.04	5.28	6.44	6.31	8.47	5.97	-0.06
Jun-20	3.17	7.26	9.03	5.58	8.87	5.27	6.44	6.37	8.99	6.38	-3.53
Jul-20	3.39	7.71	9.14	5.55	8.94	5.27	6.47	6.62	9.57	6.71	-5.49
Aug-20	3.18	8.18	9.42	5.51	8.89	5.25	6.34	6.75	10.83	7.38	-10.83
Sep-20	2.98	8.73	9.86	5.48	8.26	5.20	6.14	7.00	11.32	8.03	-14.29
Oct-20	2.47	9.14	9.92	5.43	8.23	5.17	5.95	7.07	11.51	8.57	-12.84
Nov-20	1.48	9.17	9.35	5.38	8.33	5.11	5.74	6.93	10.44	7.57	-13.91
Dec-20	0.19	8.93	8.60	5.04	7.84	5.15	5.61	6.35	9.85	7.27	-13.47
Jan-21	-0.97	-1.14	-0.92	0.12	0.37	0.19	0.82	-1.27	-0.66	-0.45	-3.41
Feb-21	0.70	-1.84	-0.76	0.10	0.42	0.22	1.23	-1.65	-0.57	0.16	-4.74
Mar-21	1.16	-1.59	-0.54	0.22	0.05	0.26	1.70	-0.91	-0.14	1.07	-6.80
Apr-21	1.10	-1.22	0.59	0.32	-0.58	0.33	1.90	-0.11	0.03	1.35	-9.05
May-21	1.10	-0.50	1.00	0.32	-0.65	0.39	2.13	0.49	0.51	1.70	-11.77
Jun-21	2.41	-0.43	0.67	0.14	-0.64	0.38	2.25	-0.11	-0.05	0.59	-17.17
Jul-21	2.64	-1.13	0.49	0.09	-1.43	0.16	2.15	-0.81	-0.58	-0.28	-21.94
Aug-21	2.82	-1.58	0.72	0.00	-2.31	0.09	2.09	-1.44	-0.80	-1.00	-27.83
Sep-21	2.06	-2.04	0.75	-0.08	-3.58	0.00	1.88	-1.98	-0.63	-0.87	-33.18
Oct-21	1.77	-2.02	1.25	-0.16	-4.52	-0.12	1.52	-2.54	-0.66	-1.04	-35.84
Nov-21	1.10	-1.60	1.59	-0.22	-5.07	-0.20	1.29	-2.68	-0.52	0.74	-38.53
Dec-21	1.81	-1.39	1.84	-0.29	-5.14	-0.41	0.89	-2.49	-0.60	0.99	-39.21
22-Jan	1.94	2.29	1.54	1.76	2.19	1.58	2.20	1.16	1.55	1.53	1.98
22-Feb	1.42	2.43	-0.27	1.67	1.39	1.44	2.52	0.00	0.48	0.58	-4.83
22-Mar	2.41	2.36	-0.61	1.58	1.49	1.25	2.73	-0.97	-0.49	0.29	-8.18
22-Apr	2.64	2.38	-1.06	1.32	2.73	1.18	2.89	-2.36	-1.56	-0.18	-3.26
22-May	2.86	2.25	-1.13	1.27	2.52	1.14	2.93	-2.98	-2.50	-0.28	-9.53
22-Jun	3.37	1.75	-0.93	1.48	3.12	1.12	2.82	-3.33	-3.24	-0.08	-14.89
22-Jul	3.14	1.46	-1.24	1.53	3.68	1.04	2.71	-3.46	-3.74	-0.06	-15.29

22-Aug	2.89	0.39	-1.37	1.61	4.46	0.99	2.55	-3.51	-4.06	-0.09	-18.18
22-Sep	3.94	-0.86	-0.39	1.65	5.48	0.96	2.40	-3.64	-4.38	-0.17	-25.18
22-Oct	3.1	-2.19	-0.09	1.71	5.67	0.85	2.29	-3.94	-4.76	0.09	-32.32
22-Nov	4.37	-2.65	0.21	1.76	6.30	0.79	2.29	-3.85	-5.07	-0.01	-36.39
22-Dec	4.55	-3.80	1.15	1.84	6.96	0.61	2.35	-3.50	-4.86	0.15	-44.46
23-Jan	4.89	4.14	3.95	4.52	4.03	4.42	4.59	4.84	4.72	4.87	5.39
23-Feb	4.31	3.33	3.11	4.68	3.78	4.20	4.56	4.60	4.68	4.70	3.05
23-Mar	3.35	2.59	1.58	4.75	2.75	3.84	4.50	4.21	4.30	3.70	0.89
23-Apr	2.81	1.74	0.81	4.69	0.92	3.49	4.20	2.95	3.89	3.27	-4.84
23-May	2.43	1.13	0.48	4.72	-0.36	3.18	3.81	2.31	3.35	2.75	-11.91
23-Jun	2.00	1.13	0.01	4.84	-2.04	2.88	3.68	1.21	2.90	2.18	-18.17
23-Jul	2.06	1.04	-0.26	4.81	-3.42	2.65	3.61	0.96	2.50	2.10	-20.78
23-Aug	2.96	1.42	-0.13	4.82	-5.31	2.40	3.60	0.73	2.26	2.01	-24.43
23-Sep	3.66	1.38	-0.70	4.86	-7.39	2.19	3.73	0.26	2.68	2.15	-22.77
23-Oct	3.59	1.86	-0.85	4.73	-9.94	2.05	4.02	-0.28	2.36	2.91	-20.06
23-Nov	3.45	2.25	-0.76	4.71	-11.01	1.93	4.38	-0.26	2.78	3.57	-20.73
23-Dec	3.58	2.43	-0.26	4.83	-13.55	1.84	4.37	-0.25	2.91	3.41	-23.01

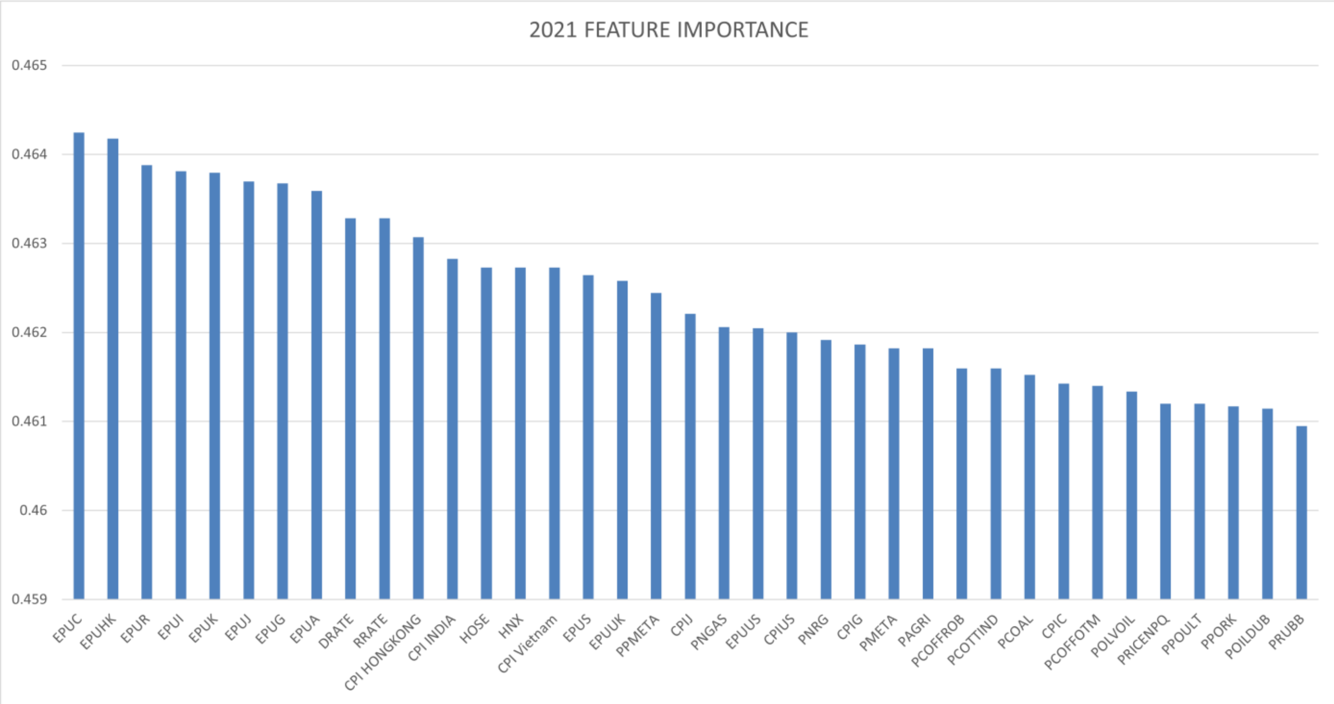
Appendix A6. Feature importance based on KNN results for the year 2019, $h = 12$



Appendix A7. Feature importance based on KNN results for the year 2020, $h = 12$



Appendix A8. Feature importance based on KNN results for the year 2021, $h = 12$



Appendix A9. Feature importance based on KNN results for the year 2022, $h = 12$