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Comparative Analysis of ARIMA and Machine Learning Models for Forecasting Inflation in Cambodia

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ABSTRACT

This research tests the predictive power of selected classical time-series and machine learning models for Cambodia's LNCPI. Monthly observations from January 2008 to April 2026 were split sequentially into an 80% training set and a 20% test set. An automatic seasonal autoregressive integrated moving-average model, ARIMA(3,1,1)(1,0,0)[12] with drift was used as the benchmark and compared to random forest, extreme gradient boosting (XGBoost), and support vector regression (SVR). For forecasts within the test period, we recursively used lagged values of LNCPI and a deterministic time trend, as well as indicators for month to capture any seasonality. Root mean squared error (RMSE), with the raw values characterizing forecast accuracy like mean absolute error (MAE) and mean absolute percentage error (MAPE). The ARIMA model outperformed the others on all three out-of-sample accuracy metrics, producing an RMSE of 0.0170, MAE of 0.0145, MAPE of 0.2726%. Random Forest, XGBoost, and SVR yielded RMSEs of 0.0398, 0.0369 and 0.0474 respectively. Variable-importance results showed that most predictive information rested in the time trend and the first two LNCPI lags, with monthly seasonal indicators contributing little. As the forecast horizon increased, machine-learning forecasts began to flatten out and increasingly under-predict LNCPI. The results show that using a parsimonious seasonal ARIMA specification based on a relatively small univariate dataset has more accurate forecasts than the selected machine-learning models.

Keywords: Cambodia, Consumer Price Index, Inflation Forecasting, ARIMA, Random Forest, XGBoost, Support Vector Regression
JEL Classifications: C22, C45, C53, E31

1. INTRODUCTION

Forecasting CPI accurately is one of the foundation stones in economic planning, monetary policy and investment decision-making. Classical econometric models, including autoregressive integrated moving average (ARIMA), autoregressive (AR) and stochastic volatility models, have been used since a long time ago to model inflation because they are grounded in theory and relatively easy (Atkeson and Ohanian, 2001; Stock and Watson, 2007). However, these methods are mostly unable to properly represent the nonlinear and high-dimensional linkages present in complex economies, specifically in new emerging markets (Mandalinci, 2017; Duncan and Martínez-García, 2019).

In terms of Emerging Market Economies (EMEs), the early studies focused on having powerful but simple forecasting models. Using data from nine EMEs and comparing various econometric specifications, Mandalinci (2017) reported that models containing stochastic volatility and time-varying parameters provided superior forecasts than their fixed-parameter counterparts. Along the same lines, Duncan and Martínez-García (2019) found that simple random walk models frequently outperform complex specifications in contexts with structural breaks or sparse data and should provide a strong benchmark against which new methods can be compared. This reinforces the need to build predictive models for EMEs whilst taking into account both model ease of use as well as the time-varying nature of inflation dynamics.

The introduction of machine learning methods into the field of inflation forecast is in part a response to the limitation of standard econometric models. Alim et al. (2020) and established that when predicting seasonal time series of human brucellosis, XGBoost outperformed the ARIMA model by a substantial margin highlighting the capacity of gradient boosting models while dealing with complex nonlinear patterns thus improving prediction accuracy. Ozgür and Akkoç (2022) extended this by using shrinkage-based ML methods to predict Turkish inflation, for example LASSO or elastic net. The results suggest that in addition to selecting the most relevant predictors, ML approaches outperform ARIMA and vector autoregression (VAR) models in out-of-sample accuracy. The studies indicate ML techniques are more suited for high dimensional datasets and turbulent economic environments.

Hybrid models are frequently used as a precise classifier model to predict complex outcomes. The most popular hybrid models broadens forecasting for the US and other advanced economies showed that adding more details by using MARS, LSTMs or XGBoost to capture both temporal dependencies and nonlinear relationships across different macroeconomic indicators improved CPI prediction significantly (Gur, 2024). Similarly, Nguyen et al. (2023) examined MLR, SVR, ARDL and MARS models for forecasting the US CPI but reported that the MARS model can attain the out-of-sample performance. Such results suggest that hybrid approaches, which combine a building block of ML with econometric insights, outperform other methods in highly complex and multivariate datasets.

Increasing evidence also points toward the value of feature selection and interpretability. Naghi et al. (2024) expanded the ML set of methods to include a broad range of tree based and regularized regression approaches to show that model selection let alone conditional median forecasting were better than unadjusted predictions across Canada and the UK. Coincident with that work, Spelta (2026) proposed a new density-based model averaging procedure based on the optimal transport theorem and applied it to average the forecasts of multiple ML models to enhance accuracy and provide an interpretative measure such as prediction intervals for recent US CPI. This approach shows how model combination strategies can be combined with ML and used successfully to deal with existing uncertainties and structural changes in economic time series.

In emerging economies, ML models have also demonstrated strong potential. Mirza et al. (2024) incorporated foreign exchange reserves into random forest and gradient boosting frameworks for Pakistan, showing that these determinants improve predictive accuracy beyond traditional econometric approaches. Similarly, Ozgür and Akkoç (2022) demonstrated that LASSO and elastic net algorithms outperform ARIMA and VAR models for Turkey's high-inflation periods, emphasizing the benefits of ML in variable selection under volatile conditions.

Subsequent studies revisited the LSTM networks performance relative to several other deep learning (DL) architectures. In the short term context, when analyzing LSTM models, Rygh et al. (2025) identified that these types of models capture long-term dependencies but can sub-optimize compared with more straightforward time series models like for example a LASSO regression or SARIMA models. The studying of different predictive models has also established that hybrid ML or DL approaches improve the performance in terms of accuracy and interpretability comparison with pure ML or DL methods and found hybrid approaches, combining ML or DL with feature selection or sentiment analysis improved interpretability as well as predictive performance in data-rich contexts. The results suggest that traditional econometric models like ARIMA can serve as baseline benchmarks against which advanced ML and hybrid models should by default be evaluated (Nguyen et al. 2023; Simionescu; 2025).

Overall, the literature converges towards a few important insights. Consider ARIMA a still valid baseline model, especially on situations with scarce data or structural challenges (Mandalinci, 2017; Duncan and Martínez-García, 2019). Both ML methods include Random Forest, XGBoost, SVR and MARS exerted better performance than classic counterparts on the high-dimensional nonlinear datasets and also hybridized with DL models or regularized regression methods (Alim et al., 2020; Gur, 2024; Nguyen et al., 2023). Third, the incorporation of macroeconomic, financial and qualitative indicators such as FX reserves or sentiment indices, can lead to significant forecast gains (Mirza et al., 2024; Simionescu, 2025). Finally, approaches like Wasserstein barycenters can be used to combine predictions into interpretable genrealizations that reflect the heavy-tailed multivariate nature of time-series data allowing for robust prediction (Spelta, 2026).

The present study is conducted in this competitive environment, where the objective is to predict CPI using basic ARIMA and advanced models including random forest, XGBoost, and support vector regression each assessed for its forecasting performance via RMSE, MAE and MAPE. These insights help bridge traditional and modern approaches, making the research relevant for model effectiveness in both developed and emerging economies.

2. LITERATURE REVIEW

2.1. ARIMA Model

ARIMA has been extensively used in forecasting consumer price index thanks to its ability to capture historical patterns, trends and stochastic movements within univariate time-series data. Interesting early applications showed that ARIMA was a valid method for forecasting inflation. By demonstrating that ARIMA performs well at taking advantage of the structure present in CPI time-series data volatility. It covered stationarity testing, differencing and autocorrelation analysis to ascertain proper model parameters showing that even as nonlinear models started to appear in the forecasting literature, the model was still a competitive tool (Du et al., 2014).

Subsequent researchers applied ARIMA to various contexts and economic data. Univariate forecasting approaches for CPI inflation forecasting were reviewed by Di Filippo (2015), which suggests that ARIMA models offer good benchmarks, even though forecast performance of single equations may depend on economic conditions and forecast horizons/structural changes. Qureshi et al. (2023) also compared seasonal ARIMA (SARIMA) with machine learning models using data of Pakistan CPI for the interval from 1960 to 2021. Results also revealed that SARIMA models provided decent forecasts, once properly differenced and diagnostic tests for non-seasonal components were executed; however, performance was mostly better with advanced machine learning-type models as they represented complex nonlinear-structured features.

Alomani et al. (2025) compared ARIMA with gradient boosting methods for global inflation forecasting and reported that, while machine learning approaches have an edge in environments that are fast changing, ARIMA does really well at accounting for historical inflation dynamics particularly during validation analysis. Jaworski (2026) expanded this line of inquiry by nesting additional information sets into an ARIMAX framework, converging on the conclusion that traditional ARIMA contours can be improved via outside forecasting features during times of economic uncertainty. Literature shows that ARIMA has stayed as a foundational time-series forecasting tool for CPI prediction due to its statistical robustness, interpretability and ability for time-series modelling. On the other hand, there is some recent evidence that ARIMA can be augmented with nonlinear methods or exogenous variables, thus improving forecasting performance during periods in which CPI dynamics are influenced by structural breaks and external shocks.

2.2. Random Forest

The use of random forest (RF) models for economic forecasting has gained traction because RF can capture nonlinear relationships, handle high-dimensional datasets and address overfitting via ensemble learning. Ceh et al. (2018) showed that RF models were able to predict market prices more accurately than classic regression schemes, suggesting a good predictive performance for complex price prediction issues. The RF derived computations provided an objective assessment of the important predictors and its flexibility can account for non-linearity that are often appreciated by conventional econometric models. Mamedli and Shibitov (2021) applied machine-learning methods to the real-time Russian CPI forecasting and tested RF together with two more models: Gradient boosting and neural networks. The results demonstrated that RF achieved best-in-class forecasting accuracy relative to autoregressive benchmarks, particularly when macroeconomic variables were used. Results showed, in addition to the need for real-time data availability, that parameter optimization and cross-validation were key components for evaluating forecasting performance of machine learning.

Gur (2024) used machine-learning algorithms for forecasting US CPI, and shows that whilst the more linear RF-based methods performed reasonably well, the combination of all economic indicators being considered emerged as the most successful at capturing nonlinear inflation dynamics. McWilliams et al. (2026) further developed a macroeconomic auto-regressive random forest (MARF) framework with RF models augment traditional approaches to forecasting, using macroeconomic information with high-dimensional data and time-varying inflation drivers. Based on the literature RF models proved a strong alternative for forecasting CPI especially in cases where inflation dynamics are impacted by nonlinear factors, structural breaks or a multitude of economic variables. Nevertheless, new evidence also emphasizes the fact that combining RF with standard time-series models can increase prediction robustness.

2.3. XGBoost

While the traditional econometric models failed to recognise complex interactions among economic variables and non-linear relationships, machine learning has gained a widespread acceptance in forecasting inflation and consumer prices. At the beginning, early forecasting methods primarily focus on ARIMA and other similar time-series models that are efficient for processes with stable linear conditions but may not perform well in times when economic structures become more volatile and uncertain (Sun et al., 2025).

The introduction of XGBoost by Chen and Guestrin, (2016) as a scalable and regularized gradient boosting framework that presents limits overfitting risks when handling high-dimensional economic datasets, has opened also new development perspectives. Trang et al. (2021) showed that XGBoost performed well in price prediction by being able to correctly find nonlinear relations, thus achieving good accuracy as compared to other linear regression methods. Similarly, Sharma et al. (2024) found that XGBoost outperformed alternative machine learning models, including random forest and support vector regression, in price prediction through hyperparameter tuning and feature importance analysis.

Sun et al. (2025) presented an extended XGBoost framework integrated with economic uncertainty indicators, and showed that the use of machine learning models improve macroeconomic forecasting through nonlinear effects and uncertainty shocks. Additionally, with the use of consumer price index data, this model was validated and the robustness of predicting macroeconomic indicators by these models were confirmed. Moreover, Ogol et al. (2025) utilized XGBoost as a regression method in food price prediction by incorporating inflation rate, exchange rate, and commodity factors. XGBoost scored higher in terms of predictive accuracy than many standalone models suggests the performance improvement it can bring to price-based forecasting applications. Through either nonlinear capturing of inflation dynamics, mundane economic predictors or by optimization approaches using high dimensions covariates, the current literature could demonstrate that XGBoost may represent a more effective alternative for CPI forecasting.

2.4. Support Vector Regression

CPI forecasting has received significant attention because of its relevance to macroeconomic monitoring through the dynamics and stability of inflation and prices. In-depth studies were based on conventional econometric methods, e.g., multiple regression and ARIMA models to discover the connection between CPI and macroeconomic variables. Cogoljević et al. (2018) applied multiple linear regression to examine several CPI determinants and concluded that lemda values near one showed significant CPI factors for monetary aggregates, exchange rates, discounted interest rates and income variables. However, traditional models are often linear and hence may miss the nonlinear and complex inflation behaviour.

Because of the significant development in machine learning, SVR has been widely used for CPI forecasting because of its ability to model nonlinear relationships by through kernel functions. Applying SVR to build a financial conditions index for CPI forecasting, Wang et al. (2012) was able to show the possibility of machine learning methods helping in better accurate prediction of Inflation output. Subsequently, Qin et al. (2018) combined biological principles and statistical techniques, such as genetic algorithms and support vector machines for more accurate CPI predictions by optimising parameters. Liu et al. (2023) subsequently conducted a review of earlier efforts in forecasting CPI and suggested that SVR-based models have successfully tackled nonlinear features inherent to the CPI series.

Qin et al. (2018) used empirical mode decomposition with SVR to predict China's CPI, while Bolourchi and Gholami (2024) showed that using radial basis function-based SVR could be applied for feature selection and hyperparameter optimisation, which is an effective approach for capturing nonlinear relationships. These results reflect the empirical evidence that SVR provides a reliable alternative for forecasting of CPI in comparison with standard linear models, as SVR is capable of reconstructing complex non-linear relationships along with enhanced prediction precision compared to conventional linear model.

3. METHODOLOGY

This research employs a comparative modelling framework that merges traditional econometric and advanced machine learning techniques to forecast inflation in Cambodia. In particular, this study uses the Autoregressive Integrated Moving Average (ARIMA) model as the reference statistical method and compares it to three standard machine-learning algorithms, random forest (RF), extreme gradient boosting (XGBoost) and support vector regression (SVR). The main objective of this paper is to explore the degree, if any, to which the advanced predictive algorithms of the machine-learning field can produce better and more robust one-step-ahead inflation forecasts than traditional econometric techniques applied within an emerging economy by combining a dynamic time-series modelling with data-driven methods.

3.1. Data

The inflation is measurement through the consumer price index (CPI). Monthly data are employed covering from January 2008 to April 2026; the total observation is 220 months, which extracted from database of the Ministry of Economy and Finance. The data has been classified into the training and test datasets. The training data accounted for 80% of the total sample size, which consists of 176 observations, covering from January 2008 to August 2022, while 20% of the data defines to be a test dataset, consist of 44 observations, covering from September 2022 to April 2026. The test period will be employed to evaluate model forecasting performance accuracy. It is worth to highlight that the CPI is a natural logarithm transformation, denoted as LNCPI. Moreover, the first difference of LNCPI, denoted as DLNCPI, is interpreted as the growth rate of consumer price index or inflation rate. In order to avoid a spurious regression result, prior process with model estimations, the Augmented Dickey-Fuller (ADF) test will be applied LNCPI and DLNCPI.

3.2. ARIMA Model

The conventional ARIMA model, define to be one of the most famous univariate econometric model, which incorporate the autoregressive (AR) terms and moving average (MA). The model specification of ARIMA(p, d, q) model has the following form:

$$LNCPI_t = c + \sum_{i=1}^{p} \beta_i LNCPI_{t-p} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \epsilon_t \tag{1}$$

Where LNCPI is the natural logarithm of consumer price index variable, ε is the error term, and ϵ is the white noise residual term. The optimal lag length of AR, denoted as p, and MA, denoted as q, which can be identified using information criteria such as the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC), also known as Bayesian Information Criteria (BIC). Moreover, to determine the level of d, it is necessary to apply the ADF test of LNCPI. If the series is not stationary at level, it will be transformed into first different, and the ADF test will be applied again (Chakrabarti and Ghosh, 2011; Ozgür and Akkoç, 2022).

3.3. Random Forest Method

The forecast target is a future consumer price index at horizon h so the idea follows the direct forecasting approach used in studies of inflation modeling, with this model trained to predict a future inflation from observations made at time t (Lenza et al., 2025; Xu et al., 2025).

The input variables are lagged inflation values, for example:

$$LNCPI_{t+h} = f(LNCPI_t, LNCPI_{t-1}, \ldots, LNCPI_{t-p}) + \epsilon_t \tag{2}$$

The random forest model makes sense with lots of decision trees trained on each bootstrap samples thus reducing overfitting and improving predictions (Mirza et al., 2024; Xu et al., 2025). The model is estimated using a rolling-window or recursive out-of-sample method (Figure 1). Hyper-parameters include number of trees and max tree depth are then cross validated to get its optimized values (Mirza et al., 2024; Xu et al., 2025).

3.4. XGBoost Method

XGBoost will be used as a univariate forecasting model to forecast LNCPI of Cambodia only using historical values on *LNCPI* itself ($LNCPI_{t-1}, LNCPI_{t-2}, \ldots, LNCPI_{t-p}$), as suggested in Figure 2. Overall, a first step is to convert monthly consumer price index to be in natural logarithm form and then create predictors of future LNCP. Data will be organized chronologically with training, validation and test sets remaining in time order to avoid look-ahead bias. As with contemporary machine-learning studies of inflation, tree-based boosting models are chosen because of their ability to capture nonlinear inflation dynamics and engender better

Figure 1: Random forest algorithm for predicting LNCPI

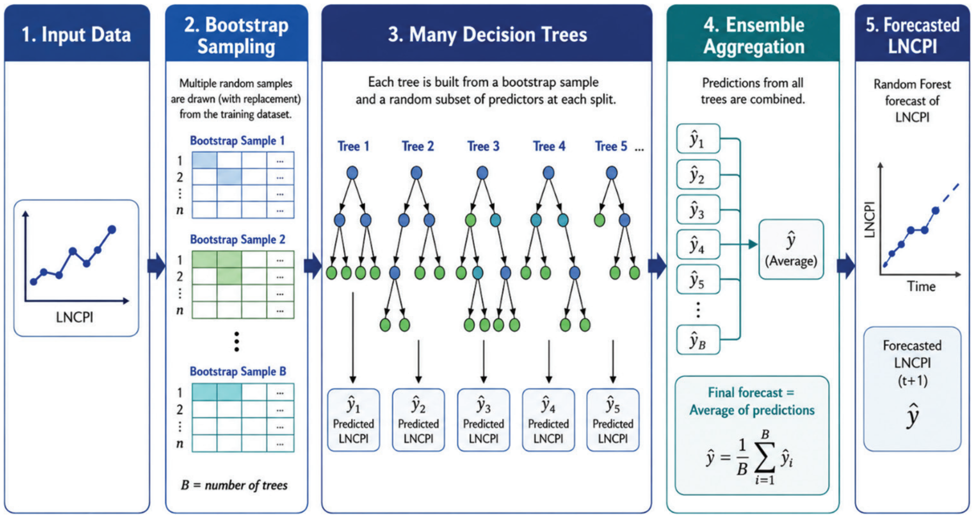
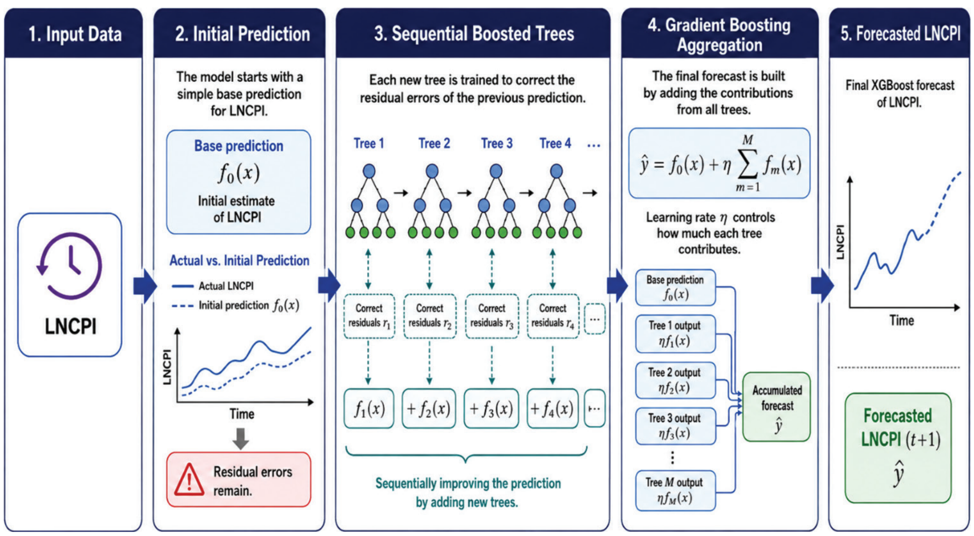


Figure 2: XGBoost learning process for LNCPI prediction



out-of-sample forecasting performance. Hyper-parameters such as learning rate, maximum depth, number of trees, subsample ratio and regularisation terms will be tuned using rolling-window validation (Aras and Lisboa, 2022; Araujo and Gaglianone, 2023; Naghi et al., 2024).

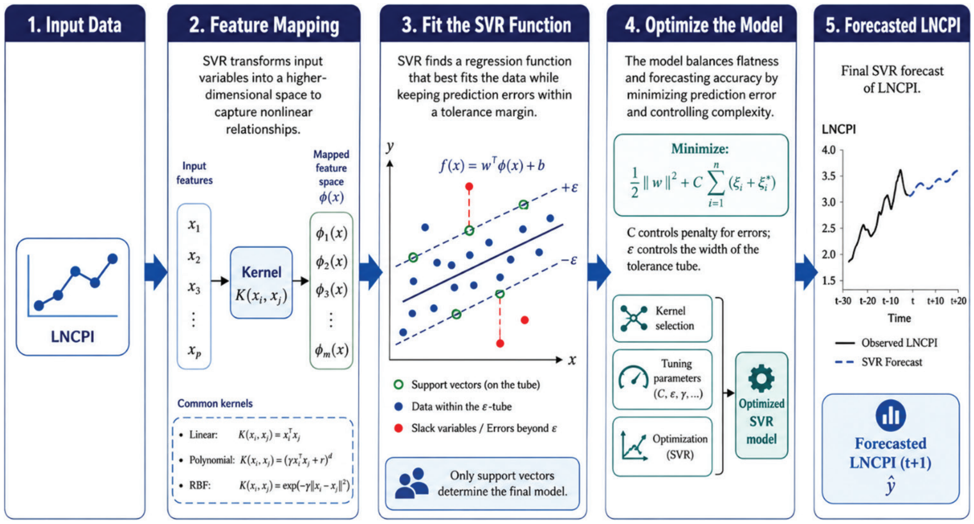
3.5. Support Vector Regression

The SVR will be used as a univariate machine-learning model to predict the inflation rate of Cambodia. The process of the method is to generate the lagged predictors for predicting $LNCPI_{t+1}$ at each time step during a tenor (Nguyen et al., 2023; Xu et al., 2025). For this, it is needed to divide the dataset chronologically into training, validation and test samples to avoid look-ahead bias. SVR will be fitted with linear and radial basis function kernels, where the three main parameters include C, ε and γ, will be selected using rolling-window validation (Figure 3). Following the approach in machine-learning inflation studies from recent years, both tuned and un-tuned SVR specifications can be compared against each other to evaluate the benefit of hyper-parameter optimisation (Naghi et al., 2024).

3.6. Forecasting Accuracy Evaluation

The model performance comparison will be conducted using an out-of-sample based testing framework to test how accurately each model predicts Cambodia's LNCPI. Following Nguyen et al. (2023), the dataset is split in chronological order into train (in sample) and test (out-of-sample), such that no future observation is used to infer the value of the past. The actual test predictions for LNCPI from all models will then be compared with each other. Forecast accuracy will be measured by the root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE); the selection of these three performance metrics based on previous inflation-forecasting studies that suggest each metric captures a different dimension of prediction error (Mirza et al., 2024). RMSE will penalise larger differences between forecast and actual values, MAE measures sum of the absolute difference between LNCPI observed and predicted values, while MAPE captures how far on average the forecasts are from its percentage estimate. Consistent with Alomani et al. (2025), the model with the lowest out-of-sample error will be selected as the best for forecasting inflation in Cambodia.

Figure 3: Support vector regression modeling process for LNCPI prediction



- Root mean squared error

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(LNCPI_t - \widehat{LNCPI}_t\right)^2} \tag{3}$$

Where
$LNCPI_t$: Actual value at time t
$\widehat{LNCPI}_t$: Forecast value at time t
n: Number of forecast observations

- Mean absolute error

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|LNCPI_t - \widehat{LNCPI}_t\right| \tag{4}$$

- Mean absolute percentage error

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{LNCPI_t - \widehat{LNCPI}_t}{LNCPI_t}\right| \tag{5}$$

4. FINDINGS

Descriptive statistics for LNCPI and DLNCPI with 220 observations, covering from January 2008 to April 2026, will be found in Table 1. LNCPI has a mean of 5.12 and median of 5.13, suggesting the distribution is approximately symmetric e.g. a normal distribution. They vary from 4.75 to 5.40 given the low standard deviation of only 0.15 the level of prices diverges little during this sample period. DLNCPI, on the other hand, has a mean of 0.30 and median of 0.32, which suggests that there is little change in average consumer prices. Nevertheless, it is a lot more variable, with standard deviation of 0.94 and minimum-maximum range of values from −4.01 to 7.95. DLNCPI shows a greater range and more dispersion, suggesting that short-term changes in inflation were much more volatile than the overall price level.

The ADF unit root test is used to obtain the model of LNCPI and DLNCPI, this result are show in Table 2. The ADF statistics are −5.08 for LNCPI and −7.89 for DLNCPI, with associated P-values are 0.01 in both tests. Therefore, for both variables the null hypothesis of a unit root is rejected at the 1% significance level. Result shows that LNCPI and DLNCPI are stationary over the sample period. Results show that mean and variance regularly of both series are steady. There is a very low probability for spurious regression of non-stationarity so the variables can therefore be used in subsequent time-series estimation.

Table 3 shows the estimation results and out-of-sample forecasting accuracy of automobile selected ARIMA model. We estimated the ARIMA (3,1,1)(1,0,0)[12] specification with drift using 176 monthly observations from January 2008 to August 2022 and reserved the remaining 44 observations from September 2022 to April 2026 for testing. The specification encompasses short-run autoregressive and moving-average dynamics, along with an annual seasonal autoregressive effect. The drift coefficient is positive of 0.0025 and statistically significant, indicating an upward movement in LNCPI throughout the sample period.

The residual variance 5.383×10^{-5} is small that which indicating less unexplained variation. The log-likelihood is 613.34 and the negative AIC, AICc and BIC values provide support for the chosen specification compared to competing models, but these criteria should be interpreted comparatively rather than in absolute terms of model quality.

The out-of-sample results indicates a very good predictive accuracy for the coefficients with an RMSE of 0.0170, an MAE of 0.0145 and a MAPE of 0.273%. These results further provide a rationale for the still sustainable function of parsimonious univariate models as forecasting benchmarks. ARIMA-type models are similarly identified as difficult benchmarks to beat, especially at longer forecast horizons. However, evidence has emerged additional information can help to forecast inflation better (Aysun and Wright, 2024). Safira et al. (2024) show that including spatial relationships

Table 1: Summary statistics

Variable	n	Mean	Median	Minimum	Maximum	Standard deviation
LNCPI	220	5.12	5.13	4.75	5.40	0.15
DLNCPI	220	0.30	0.32	−4.01	7.95	0.94

Table 2: ADF unit root test

Variable	ADF Statistic	Lag Order	P-value	Decision
LNCPI	−5.08	5	0.01	Reject H_0: Stationary
DLNCPI	−7.89	5	0.01	Reject H_0: Stationary

Table 3: ARIMA model estimation and forecast accuracy

Panel A: Estimated ARIMA coefficients	
Parameter	**Coefficient**
AR (1)	1.3252*** (0.0835)
AR (2)	−0.2674* (0.1539)
AR (3)	−0.2817*** (0.1035)
MA (1)	−0.9648*** (0.0402)
Seasonal AR (1)	0.2552** (0.1222)
Drift	0.0025*** (0.0002)
Panel B: Model fit statistics	
Statistic	**Value**
Residual variance (σ^2)	5.383×10^{-5}
Log-likelihood	613.34
AIC	−1212.69
AICc	−1212.01
BIC	−1190.53
Panel C: Forecast accuracy (test period)	
Metric	**Value**
RMSE	0.017035
MAE	0.014521
MAPE (%)	0.272630

The selected ARIMA (3,1,1)(1,0,0)[12] with drift model was estimated using the training sample. Panel A reports parameter estimates and standard errors (in parenthesis). Panel B presents model selection criteria, while Panel C reports out-of-sample forecast accuracy based on the test sample. Significance levels are denoted by ***P<0.01, **P<0.05 and *P<0.10

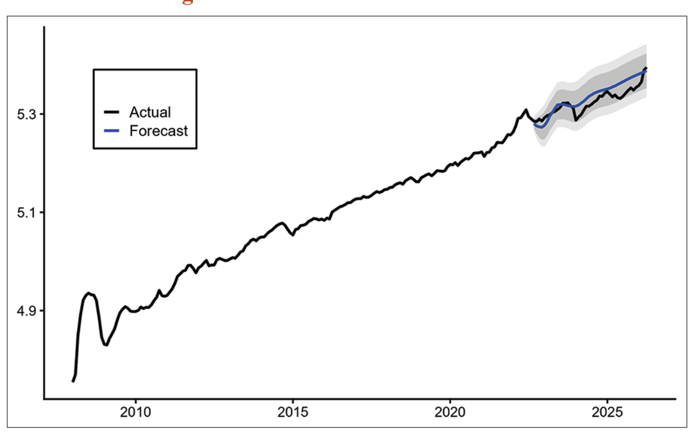
Table 4: Random forest model estimation and forecast accuracy

Panel A. Random forest model information	
Item	**Value**
Model	Random forest regression
Dependent variable	LNCPI
Number of trees	1000
MTRY	3
Minimum node size	5
Training observations used	164
Forecast method	Recursive out-of-sample forecasting
95% Interval method	Approximate 95% interval using quantile random forest
Panel B: Variable importance	
Variable	**Importance**
Trend	0.003937
LNCPI Lag1	0.003750
LNCPI Lag2	0.002731
LNCPI Lag3	0.001763
LNCPI Lag6	0.001410
LNCPI Lag12	0.001141
Month factor	0.000004
Panel C: Forecast accuracy in the test period	
Metric	**Value**
RMSE	0.039785
MAE	0.031776
MAPE (%)	0.594634

decreases prediction errors compared to traditional ARIMA, while Mirza et al. (2024) find that including macroeconomic variables leads to better performance of machine-learning models. Therefore, while the current ARIMA model predicts LNCPI quite well, its performance in estimating the series should be assessed against designs that incorporate relevant exterior, non-linear or spatial information.

The value of LNCPI is compared to the actual and ARIMA predicted values for the test period in Figure 4. It follows the change in the price index closely and shows that it captures this pattern well. Minor deviations of the forecast from the actual series can be observed during periods of short-term fluctuations, but these are small compared to the overall alignment between the forecast and actual series that is maintained through the evaluation period. It is seen that the 80% and 95% prediction intervals are relatively narrow, indicating medium level of forecast

Figure 4: ARIMA Forecast for LNCPI



uncertainty, which increases gradually with forecast horizon. Crucially, the actual observations mostly lie inside the prediction bands indicating that the model generates economically sensible out-of-sample forecasts. The results support the hypothesis that an ARIMA(3,1,1)(1,0,0)[12] model with drift is a suitable choice for

LNCPI and provide reasonably accurate short- to medium-term inflation forecasts.

Table 4 displays the estimated results and out-of-sample forecasting performance of the random forest model. The final model was based on 1,000 trees, with three predictors considered at each split and a minimum terminal-node size of five trained on 164 observations. Recursive forecasts were observed for the test period during 95% prediction intervals approximated using quantile random forest. The feature importance results show that the time trend is by far the strongest predictor, followed closely by LNCPI lag 1 and lag 2. Given the declining significance of the longer lags and that the monthly factor only makes a slight contribution, this suggests that we are capturing mainly long-term trends and local passages in the index rather than seasonal events.

Still, random forest proves to be worse than the baseline ARIMA model. The model has RMSE, MAE and MAPE of 0.0398, 0.0318 and 0.5946% respectively compared to those of ARIMA, which are 0.0170, 0.0145, and 0.2726%. Consequently, random forest errors are about 2.34, 2.19 and 2.18 times those of ARIMA individually. As a side note, this result differs from Mirza et al. (2024), where random forest performed well especially when inflation was modelled with wide range of macroeconomic determinants using foreign–exchange reserves as one of the variable. This also opposes Xu et al. (2025) for predicting Chinese inflation; eight machine-learning models were based on 28 predictors. These discrepancies imply that random forest may need more informative economic data and larger training datasets, to realise its forecasting benefits. Quantile random forest are still useful for measuring uncertainty in forecasts. Lenza et al. (2025) established that quantile regression forests based on a large number of economic predictors provide highly competitive inflation-density forecasts. The more parsimonious of the two ARIMA specifications provided better point forecasts for LNCPI overall in this study.

In Figure 5, the actual value of LNCPI over test period have been compared against random forest forecasted values. The model manages to reproduce the general level of the series near the start of forecast horizon, but then issues forecasts that are again quite flat. Thus, it misses the continued rising trend observed in the actual LNCPI numbers, the growing divergence between the forecast and realised observations over time. At first, the 95% prediction interval encompasses most actual values, but then it widens and its upper line is getting steeper, which indicates that the model underestimates how persistent inflation turns out to be during later periods. This is consistent with the prediction accuracy results in Table 4, which show that the random forest model has relatively larger RMSE, MAE and MAPE values than ARIMA model. In conclusion, the results indicate that organizing a random forest with hyper-parameter tuning does not perform well compared to ARIMA models in predicting the time-series persistence property of LNCPI.

The XGBoost model specification, variable importance and out-of-sample forecasting performance is summarised in Table 5. The model was trained on 80% of the dataset and applied recursively to predict LNCPI over the last 20%. A 0.05 learning rate, three and 300 maximum tree depth and boosting rounds captures a comparative conservative specification that aims to avoid overfitting the non-linear relationship of interest whilst ensuring generalisability. A summary of the variable-importance results shows that first lag of LNCPI is the topmost predictor with respect to total gain of 61.86%, followed by time trend of 25.79%. The

Figure 5: Random forest forecast for LNCPI

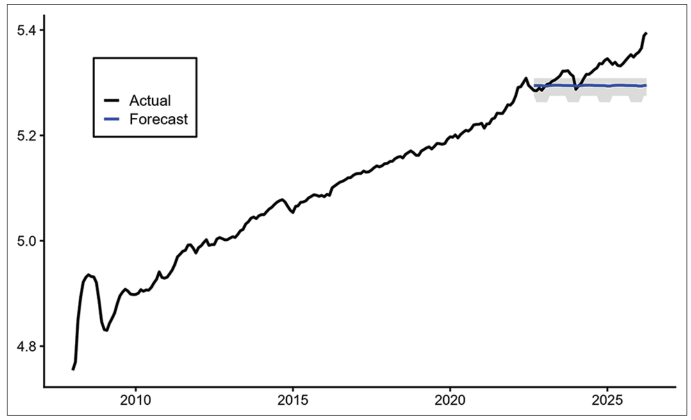


Table 5: XGBoost model estimation and forecast accuracy

Panel A. XGBoost model information			
Item	**Value**		
Model	XGBoost regression		
Dependent variable	LNCPI		
Objective function	Reg: Squared error		
Learning rate eta	0.05		
Maximum tree depth	3		
Subsample	0.8		
Column sample by tree	0.8		
Number of boosting rounds	300		
Training observations used	164		
Forecast method	Recursive out-of-sample forecasting		
95% Interval method	Approximate 95% bootstrap residual interval		
Panel B. Variable importance			
Feature	**Gain**	**Cover**	**Frequency**
LNCPI Lag1	0.618559	0.300529	0.345778
Trend	0.257918	0.091937	0.079265
LNCPI Lag2	0.041234	0.098831	0.120046
LNCPI Lag6	0.037281	0.118850	0.113728
LNCPI Lag12	0.029208	0.130195	0.110856
LNCPI Lag3	0.015684	0.122646	0.111430
Month Factor9	0.000027	0.024572	0.020678
Month Factor12	0.000022	0.024861	0.016657
Month Factor10	0.000018	0.014563	0.013211
Month Factor2	0.000014	0.008409	0.009190
Month Factor11	0.000013	0.024504	0.014360
Month Factor6	0.000009	0.012341	0.014360
Month Factor8	0.000004	0.011524	0.009190
Month Factor7	0.000003	0.000885	0.004595
Month Factor3	0.000002	0.004936	0.006893
Month Factor4	0.000002	0.007354	0.006893
Month Factor1	0.000001	0.002860	0.001723
Month Factor5	0.000000	0.000204	0.001149
Panel C: Forecast accuracy in the test period			
Metric			**Value**
RMSE			0.036903
MAE			0.029062
MAPE (%)			0.543806

other lags contribute much less, and the output from the monthly seasonal factors is little if any useful predictive information. The results suggest that calendar-based seasonality plays little or no role in LNCPI forecasting and that persistence and trend formation are the main driving forces.

However, XGBoost performs worse than the baseline ARIMA model. The RMSE value of 0.0369 in fact constitutes around 116.6% increment over the ARIMA RMSE of 0.0170 and its MAE and MAPE values are twice that of ARIMA standards. This result contrasts with Araujo and Gaglianone (2023), who find that tree-based models, notably XGBoost, regularly figure among the top inflation forecasts when assisted by an extensive information set. Similarly, Mirza et al. (2024) conclude that gradient-boosting models enhance the predictive power of traditional approaches in the presence of multiple macroeconomic determinants including foreign-exchange reserves. Newer evidence from Nigeria suggests that macroeconomic feature selection also improves the performance of complex models, though XGBoost was not the best performing model in that study (Bartholomew et al., 2025).

Consequently, the relatively poor performance into our study may represent a disadvantage of XGBoost driven by the small size of training sample, limited predictors set and recursive forecasting strategy rather than its inherent incapacity. Hence, ARIMA gives more efficient and parsimony forecasts of LNCPI over this dataset.

During the test period, Figure 6 compares each LNCPI actual and predicted value from the XGBoost model. The level of the series is captured well by the model, however, forecasts are rather flat indicating a lack of sensitivity to the trend increase observed in the historical data. The actual versus predicted values diverged further as the forecast horizon increased, implying that the error is accumulated recursively. As a result, the XGBoost model fails to predict the rising trend in LNCPI from the second half of sample period. Such visual results confirm the performance we observed on forecast accuracy indicators in Table 5, where RMSE, MAE and MAPE for XGBoost were fuller than the ARIMA baseline model. In summary, these results indicate that compared to ARIMA, XGBoost is not effective for this application in describing the dynamic behaviour of LNCPI.

Figure 6: XGBoost forecast for LNCPI

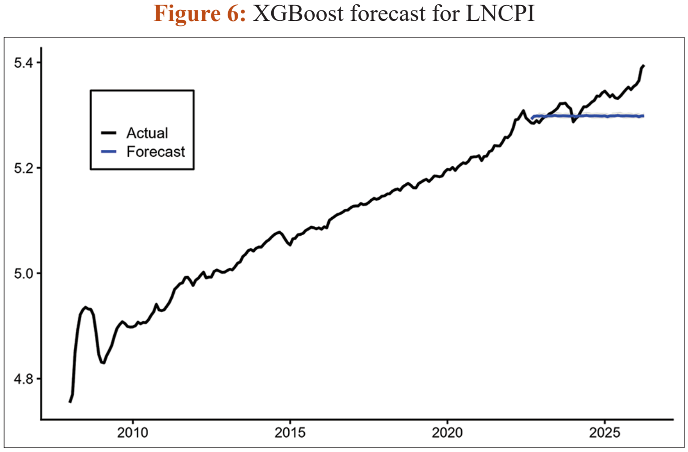


Table 6 contains the specification of all features for SVR model alongside its performance in out-of-sample forecasting. The radial basis function kernel is selected which produced 139 support vectors with cost, gamma and epsilon parameters set to 10, 0.1 and 0.01 respectively. Using a recursive scheme, the model was estimated on the training sample and used to forecast LNCPI in the test period. The relatively large amount of support vectors means that much of the training sample was involved in defining the fitted function.

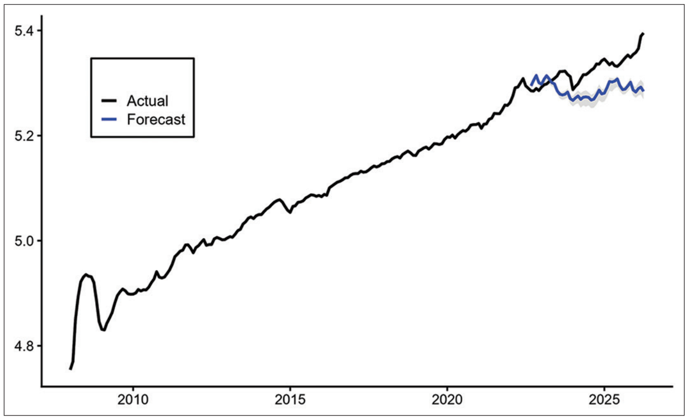
The RMSE, MAE and MAPE values obtained from SVR model are 0.0474, 0.0410 and 0.7681% respectively. The errors are relatively 2.78, 2.82 and 2.82 times higher than that of the baseline ARIMA model respectively. Thus, SVR provides substantially less accurate forecasts in this application. These results contrast with Xu et al. (2025) document that machine-learning methods, including support vector machines, can do better than autoregressive benchmarks estimated using a large information set of 28 predictors of inflation. However, it is compatible with evidence that, depending on sample, forecast period and model specification, the relative performance of machine-learning techniques may vary (Naghi et al., 2024). In summary, limited SVR performance resulted from the predictor reduced set, small training sample and recursive approach. Thus, the ARIMA model was parsimoniously chosen to remain as LNCPI's preferred forecasting specification.

In Figure 7, the true values of LNCPI and predicted LNCPI obtained by using the SVR model during the test period are compared. For the most part, the forecasts track the level of the series during early in the out-of-sample portion of this test, implying that they should do a decent job at capturing inflation's underlying trajectory. However, the predicted values follow a narrower range and do not account for the progressive trend visible in the actual time series. The longer the forecast horizon, the more out of line the actual versus forecast and LNCPI is under-predicted by SVR model respectively. This pattern is a possible indication that the recursive forecasting method cannot properly capture

Table 6: SVR model estimation and forecast accuracy

Panel A: SVR model information	
Item	**Value**
Model	Support vector regression
Dependent variable	LNCPI
Kernel	Radial basis function
Type	EPS-regression
Cost	10
Gamma	0.1
Epsilon	0.01
Number of support vectors	139
Training observations used	164
Forecast method	Recursive out-of-sample forecasting
95% interval method	Approximate 95% bootstrap residual interval
Panel B: Forecast accuracy in the test period	
Metric	**Value**
RMSE	0.047375
MAE	0.041001
MAPE (%)	0.768098

Figure 7: SVR forecast for LNCPI



persistence of inflation. This visual finding is corroborative of the results in Table 6, where RMSE, MAE and MAPE are found to be significantly better in comparison to baseline ARIMA model against all the models mentioned, especially SVR on different values of parameters. In general, ARIMA gives a better forecast about the dynamics of LNCPI over next periods.

5. CONCLUSION AND POLICY IMPLICATION

5.1. Conclusion

The primary objective of this study was to compare the forecasting performance between a traditional statistical model and three machine-learning algorithms for predicting the Cambodian Consumer Price Index. The empirical results show that seasonal ARIMA(3,1,1)(1,0,0)[12] with drift outperformed the random forest, XGBoost and support vector regression models across all forecast evaluation metrics. The ARIMA model generated the smallest RMSE, MAE and MAPE and tracked the observed inflation dynamics over the out-of-sample evaluation phase. Tight prediction intervals and a high percentage of observations lying within them also show that the model is well specified for short to medium-term inflation forecasting.

The machine-learning models were able to capture the main degree of inflation in the early part of the forecast horizon, but their predictive power fell as the length of the horizon extended. Random Forest, XGBoost and SVR forecasts became flat with time, causing a systematic underestimation effect of the LNCPI persistence. Feature importance analysis consistently identified the time trend and recent lagged inflation values as dominant predictors, while seasonal indicators added little explanation. These results indicate that inflation persistence and trend components are the main factors contributing to Cambodia's CPI dynamics over the sample period.

The models based on machine learning clearly performed less well, which can arguably be ascribed to the properties of the used dataset. It was small in terms of observations, with limited predictors and a recursive forecast framework. In contrast to previous studies, which used much more macroeconomic data the empirical analysis here was based primarily on historical inflation data. In such conditions, the parsimonious specification of ARIMA was clearly superior to other alternative non-linear algorithms. Altogether, the results strengthen the argument for coupling forecasting methods to data characteristics while also showing that after other predictor variables, standard time-frequent models perform competitively in inflation forecasting. The machine learning based approaches could further be investigated by including macroeconomic, financial, and spatial or high frequency indicators to ascertain whether the performance of the latter improves.

5.2. Policy Implications

The results have various implications for monetary authorities, government agencies and researchers involved in inflation forecasting. First, the better forecasting performance of the ARIMA model implies that in a low and middle-income country such as Cambodia when only historical price data are available, conventional time-series approaches are still relevant operational tools to forecast inflation in whenever high frequency dynamic information is not used. As such, parsimonious statistical models may remain the best practical benchmarks for routine inflation monitoring and assessment by institutions such as the National Bank of Cambodia and relevant government agencies.

Second, in fact, the machine-learning algorithms do relatively poorly suggesting that additional model complexity does not lead to improved forecasts. More improvements in policy application would come from broadening the information set than adopting more advanced artificial intelligence methods of algorithmic sophistication. Constructing integrated macroeconomic databases with indicators on monetary, fiscal, exchange rate, commodity price, labour market and external sector variables would give more information that can be used to perform out-of-sample forecasting in the future and might improve machine-learning approaches.

Third, inflation persistence and trend variables are sufficiently dominating that they indicate new attention. Recent price movements carry a lot of information about future inflation, so policymakers need to pay close attention. Catching very early anticipations of enduring inflationary pressures will encourage quicker feedback in financial and budget policy, which should minimize the chance of extended inflation run-ups.

The type of design that should be applied to future forecasting systems is one where the new methods complement rather than replace traditional econometric methods i.e., a hybrid modelling strategy. While statistical models offer solid benchmark forecasts, machine-learning models should grow more valuable once greater availability of macroeconomic predictors, bigger datasets and real-time news data become available. In the long-run, a hybrid forecasting framework could reinforce fact-based policy making, financial stability surveillance and macroeconomic planning in Cambodia.

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