Comparison of different Traditional Time Series, Machine Learning, Deep Learning, and Hybrid Approaches for Inflation Forecasting in Sri Lanka.

Hiruni Navodya Kudagama[1[0000-1111-2222-3333]], Sameera Viswakula[2[1111-2222-3333-4444]]

Samantha Mathara Arachchi[3[0000-1111-2222-3333]] and Chamila Siriwardana[4[1111-2222-3-4444]]

[1,2] Faculty of Science, University of Colombo.
[3] University of Colombo, School of Computing.
[4] Central Bank of Sri Lanka.

Abstract. Inflation is one of the most important factor that impacts on economic activities of a country. Inflation forecasting plays a key role in the formulation of monetary policy predictions at central Banks. This study presents a comprehensive investigation into univariate one-step-ahead inflation forecasting using a diverse range of modelling approaches. Traditional time series models (ARIMA, SARIMA) were benchmarked against machine learning models (Random Forest, XGBoost, Support Vector Regression) and deep learning models (Feedforward Neural Networks, LSTM, CNN). Additionally, several hybrid approaches were explored, including simple averaging and weighted averaging of predictions from the best-performing models, with weights based on evaluation metrics. The study utilized monthly Colombo Consumer Price Index(CCPI) headline inflation data from January 2000 to March 2025. RMSE, MSE, MAE, and R-squared were considered as evaluation metrics. Various train-test split ratios (70:30, 80:20, and 90:10) were assessed to identify the optimal splitting ratio. The best performance was observed by taking the splitting ratio as 90:10. While SARIMA captured seasonality better than ARIMA, machine learning and deep learning models demonstrated improvements in accuracy. The MAE-based weighted ensemble model achieved the best performance, with RMSE = 3.1254, MSE = 9.7681, MAE = 2.1775, and an R-squared value of 0.9806.

Keywords: Inflation Forecasting, Time Series, Hybrid Models.

1 Introduction

Inflation is defined as a constant increase in the overall price level of goods and services in an economy over time (John et al., 2023). It reflects the reduction of buying power, influences interest rates, and shapes monetary and fiscal policies aimed at economic stability (Plas, 2023). Accurate inflation forecasting is crucial for effective economic planning, policy formulation, and investment decisions, especially in developing countries like Sri Lanka. It directly impacts the cost of living, wage negotiations, monetary policy decisions, and overall economic stability. Periods of high inflation have often coincided with external shocks, such as oil price volatility, currency devaluations, and global financial crises (Abdulraheem et al., 2025). Sri Lanka, over the past two decades, has experienced several economic shifts, including civil conflict recovery, global market fluctuations, and, more recently, a severe economic crisis in 2022. These events have led to volatile inflation rates, highlighting the need for more reliable and adaptive forecasting tools.

Recent advancements in computational methods have increased the use of machine learning and deep learning techniques for time series forecasting. These models can capture non-linear patterns and adapt to changing data structures. Although several studies have applied these methods to inflation forecasting globally, limited research exists in the Sri Lankan context, especially using updated inflation data up to 2025 and the application of hybrid approaches. This research aims to fill this gap by comparing the effectiveness of traditional time series models (e.g., ARIMA, SARIMA), machine learning methods (e.g., SVR, RF, XGB), deep learning models (e.g., LSTM, CNN, FNN), and novel hybrid approaches in forecasting inflation using historical data.

2 Literature Review.

(K.G. et al., 2023) used ARIMA to forecast Nigeria's inflation (1981–2020), identified ARIMA(0,0,1) as the best model. Model selection relied on AIC and BIC, and stationarity was verified via the ADF test.(Ibrahim Doguwa, 2013) developed SARIMA and SARIMAX, incorporating exogenous variables like PMS prices, government spending, credit data, rainfall, and exchange rates. The study shows that multivariate models outperform univariate ones. Both studies were limited to traditional methods. However, by incorporating machine learning approaches, model performance could be further increased(Abdulraheem et al., 2025).

Machine Learning (ML) methods address key forecasting challenges like nonlinearity, multicollinearity, predictor relevance, and high dimensionality, which limit traditional time series models (TTSM) (Kuhn & Johnson, 2013; Lazzeri, 2021). With advances in computing and data availability, ML is gaining attention as an alternative to traditional approaches. There is also a growing focus on developing more interpretable ML models for macroeconomic forecasting (Doojav & Narmandakh, 2025).(Nkemnole et al., 2024) applied KNN and LSTM models with a Hidden Markov Model (HMM) to predict inflation and transition patterns in Nigeria using GDP per capita data (1960–2022). Data was split 80/20 for training and testing, with preprocessing steps like categorical encoding and min-max scaling. Model performance was evaluated using the Standard error of the mean (SEM), MAPE, and RMSE, showing KNN outperformed LSTM. GDP per capita significantly influenced high inflation. However, the study lacked hyperparameter tuning.

(Doojav & Narmandakh, 2025) assessed ML methods for forecasting inflation in Mongolia using quarterly data from 2007Q3 to 2021Q4 and 120 macroeconomic and financial variables. Models such as Ridge Regression (RR), Lasso, Elastic Net, Random Forest (RF), XGBoost (XGB), Autoregressive (AR), and Factor-Augmented Autoregressive (FAAR) were evaluated using walk-forward cross-validation. RR consistently performed well, while RF and XGB outperformed others for longer-term forecasts. Key predictors varied by horizon: short-term forecasts relied on prices and wages, whereas long-term forecasts were driven by money supply, credit, interest and exchange rates, and fiscal indicators. The study found ML models improved accuracy, especially with larger datasets, but did not consider lagged variables.

(Abdulraheem et al., 2025) evaluated ARIMA, machine learning models (SVR, RF, ANN), and hybrid approaches (ARIMA-SVR, ARIMA-RF, ARIMA-ANN) for forecasting Nigeria's monthly inflation. Following preprocessing steps such as imputation, outlier treatment, standardization, and differencing, models were trained on lagged features and assessed using walk-forward validation across various train-test splits (70:30, 80:20, 90:10). The ARIMA-ANN model with an 80:20 split yielded the best performance based on MSE, RMSE, and MAPE. The study's univariate approach and reliance on grid/random search highlight the potential for future improvements through efficient tuning methods like Optuna (Ülke et al., 2018).

2.1 Previous studies of inflation forecasting done in Sri Lanka.

Previous studies have primarily employed ARIMA models to forecast inflation in Sri Lanka. (Nyoni & Nyoni, 2019) identified ARIMA(1,0,0) as optimal based on AIC using annual data from 1960–2017. However, the analysis excluded key recent events such as the 2019 Easter attacks, the COVID-19 pandemic, and the economic crisis. (Dunuwita Liyanage, 2023) utilized monthly data from 2014–2023, identified ARIMA(1,1,2) and ARIMA(2,1,3) for core and headline inflation, respectively. (Jesmy, 2010.) also applied an ARIMA model to forecast inflation in Sri Lanka using CCPI data from 1953 to 2009, assessing stationarity with the ADF test and selecting models based on AIC and Schwarz Criterion (SC). However, residual diagnostics relied only on visual inspection. The current study enhances this approach by incorporating statistical tests for residual analysis (Ljung-Box, heteroscedasticity, and normality), using both ADF and KPSS for stationarity assessment, and applying the HEGY test to detect seasonal stationarity. Additionally, the above three studies were limited to traditional ARIMA. To overcome these limitations, the present study extends the dataset to March 2025 and explores a wider range of forecasting techniques, ML, DL, and hybrid models (HM).(Raj et al., 2024) examined advanced models such as N-BEATS, Reservoir Computing, Prophet, Neural Prophet, and Bi-LSTM for multi-step inflation forecasting using data from January 2021 to March 2023. However, their analysis relied on visual comparisons, lacked standard evaluation metrics, hyperparameter tuning, and a systematic lag selection method. In contrast, the present study addresses these gaps by using an extended dataset (2000 Jan –2025 March), incorporating quantitative metrics (RMSE, MSE, MAE, R^2), applying hyperparameter optimization, and introducing a structured approach to lag selection. A comprehensive range of forecasting techniques, including TTSM, ML, DL, and HM, are evaluated for inflation prediction in Sri Lanka.

(W. M. S. Bandara & De Mel, 2023) applied ML models (LASSO Regression (LR), Bayesian Ridge Regression (BRR), SVR, RF) to forecast inflation in Sri Lanka, using past inflation lags as inputs. K-fold and Walk Forward Validation were employed, finding WFV superior, with the LR-WFV model performing best based on RMSE and MAPE. However, the study lacked systematic lag selection and relied solely on Grid Search, which may miss the optimal hyperparameters(Optimal Grid Search Techniques for Machine Learning Models, 2025). Additionally, MAPE's considered to be unstable near zero values(Wikipedia contributors, 2024. The present study addresses these limitations by incorporating advanced lag selection methods, using Optuna for hyperparameter tuning, and evaluating models with a broader set of metrics (RMSE, MSE, MAE, MAPE, R^2).(Mustafa, 2019) examined the inverse relationship between inflation and Foreign Direct Investment (FDI) using data from 1978 to 2017, employing simple regression for inflation forecasting. It was identified that Inflation is inversely related to FDI. (R. Bandara, 2011) used a VAR model to study inflation determinants in Sri Lanka from 1993 to 2009, Money Supply(M2), CCPI, Exchange Rate USD, Gross Domestic Product - GDP, Treasury Bill (TB), and unemployment rate (UE) were considered in the study identifying Money Supply (M2), Exchange Rate, and GDP as significant factors. Granger causality tests showed M2 and the exchange rate influenced inflation with long lags (18 months). (Ratnasiri, 2011)used VAR analysis to examine inflation determinants in Sri Lanka from 1980 to 2005, focusing on variables like CCPI, GDP, money supply, exchange rate, rice price, and interest rate. The study found that money supply growth and rice prices are key long-run drivers of inflation, while exchange rate depreciation and the output gap had no significant effects. inflation was shown to be driven by both demand and supply-side factors. However, both studies focused only on identifying significant variables and did not use modern forecasting methods. They also excluded recent economic shocks.

3 Data

This study utilized headline inflation data from the Colombo Consumer Price Index (CCPI), which measures overall inflation by incorporating a diverse variety of products and services. The dataset covers the period from January 2000 to March 2025 and was sourced from the Central Bank of Sri Lanka (CBSL) Data Library (https://www.cbsl.gov.lk/eresearch/).

3.1 Data Preparation & Data Integration

During data preparation, the CCPI series was rebased to a single base year (2021). The data originally published with multiple base years, 1952, 2003, 2006, 2013, and 2021, the series was made consistent using a stepwise splicing process (the process of adjusting index numbers from multiple base periods to a common base). CCPI values were sequentially converted through each base year (1952 → 2003 → 2006 → 2013 → 2021), resulting in a consistent CCPI series rebased to 2021.

Conversion Methodology

A sequential rebasing method was used to convert CCPI values to the 2021 base year. Conversion factors were calculated for overlapping periods where both old and new base year index values were available. For each overlapping month, the factor was derived by dividing the new base year index by the old base year index.

$$\textbf{Conversion Factor}_{\textbf{Month}} = \frac{CCPI_{(2003\ base)}[Month]}{CCPI_{(1952\ base)}[Month]}$$

These monthly factors adjusted the older series to the new base. This process was repeated for each base transition, 1952 to 2003, 2003 to 2006, 2006 to 2013, and 2013 to 2021, resulting in series aligned to the 2021 base year.

Compute Year-on-Year (Y-o-Y) Inflation using CCPI.

The headline CCPI covers various items, capturing both stable and volatile price components. With the index rebased to 2021, year-on-year (YoY) inflation is calculated using the formula.

$$YoY\ Inflation = \frac{(CCPI_t - CCPI_{t-12})}{(CCPI_{t-12})}$$

Selection of Optimal Train-Test Split Ratio

This study evaluated three train-test split ratios, 70:30, 80:20, and 90:10, to identify the most suitable ratio for forecasting inflation. This approach, followed by previous research such as (Jamil, 2021.). Model effectiveness for each split was assessed using evaluation metrics including RMSE, MAE, MSE, and R-squared.

4 Results.

Figure 1 Time Series plot of CCPI

The time series plot of Inflation reveals several notable trends and fluctuations. A major inflation spike occurred between September 2021 and July 2022, followed by a rapid decline until October 2023. Although inflation continued to fall beyond this point, the pace of decline slowed. Another significant inflationary phase was observed from March 2006 to April 2009, with inflation rising steadily from March 2006 to January 2008, then gradually declining until July 2009. These trends are consistent with previous reports. According to (Sri Lanka Inflation Rate: Sri Lanka’s Inflation Surges over 60 per Cent in July - The Economic Times,2022), Sri Lanka's inflation surged to 60.8% in July 2022, reflecting the severity of the economic crisis during that time. Additionally, an International Monetary Fund (IMF) report from 2007 noted that CPI inflation rose from 4% in 2005 to nearly 18% by the end of 2006, driven by strong demand pressures and adjustments in administered prices, particularly in fuel, electricity, and transportation. Inflation continued to climb, reaching 21.75% year-on-year by August 2007.

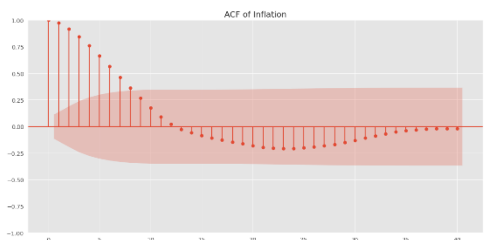

Figure 2 ACF plot of inflation

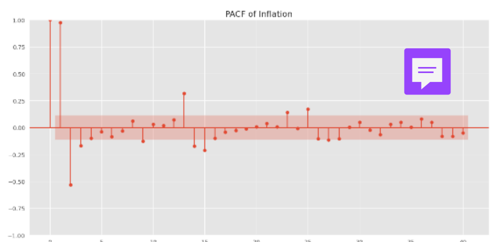

Figure 3 PACF plot of Inflation

The ACF plot indicates significant correlations at higher lags, with up to 9 lags being statistically significant, suggesting strong persistence in the inflation series. In contrast, the PACF plot shows a rapid decay in lag significance

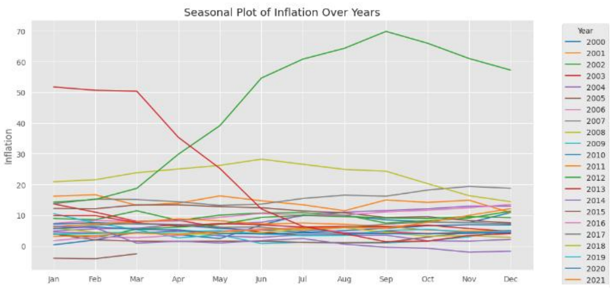

Figure 4 Seasonal Time Plot of Inflation

The seasonal plot of monthly inflation from 2000 to 2025 shows no clear seasonal pattern. However, a period of elevated inflation is evident between March 2022 and May 2023.

4.1 Stationary Tests

To assess the stationarity of the inflation time series, both seasonal and standard unit root tests were conducted.

Seasonal Unit Root Test (HEGY Test)

Table 1 HEGY seasonal stationary test for inflation

	Statistic	P Value
t_1	-3.4047	0.0293
t_2	-4.1975	0.0003
F_3:4	28.2142	0
F_5:6	31.3102	0
F_7:8	28.7489	0
F_9:10	30.8755	0
F_11:12	41.3258	0
F_2:12	1789.0528	0
F_1:12	1644.0634	0

The HEGY test was applied to detect seasonal unit roots. The null hypothesis was rejected across all seasonal frequencies (1 to 12), indicating no seasonal unit roots in the inflation data.

Standard Unit Root Test (HEGY Test)

Table 2 ADF and KPSS test results

	ADF Test		KPSS Test	
	Test statistic.	P Value.	Test statistic.	P Value.
Inflation	-3.8581086	0.0023	0.10219	0.1

Results from the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests confirmed that the inflation series is stationary.

4.2 Univariate Inflation Forecasting.

Univariate time series forecasting involves predicting a variable's future values based only on its past data. Although it is simple and requires limited input, it does not account for external influences.

Univariate Traditional Time Series forecasting.

The ARIMA modeling approach was utilized for univariate time series forecasting under traditional approaches. As discussed previously, three train-test splits were considered.

ARIMA

An Auto-ARIMA model was developed using Python's built-in function. The optimal ARIMA parameters and associated performance metrics (e.g., RMSE, MAE, MSE, R^2) were recorded for each split.

Table 3 ARIMA Model performance under each split

Split Ration	Model	AIC	BIC	MAE	MSE	RMSE	R-squared
70-30	ARIMA(1,1,0)	749.289	755.993	9.5832	350.5513	18.7230	-0.0863
80-20	ARIMA(0,1,1)	832.429	839.399	13.3633	523.1375	22.8722	-0.1720
90-10	ARIMA(3, 0, 1)	1041.00	1062.63	20.8958	728.5570	26.9918	-0.2515

right

ok

The ARIMA model indicated less effectiveness in forecasting, failing to capture key fluctuations. To address this, the SARIMA model was introduced, considering seasonal components to improve performance and better represent the dynamic patterns.

SARIMA

Table 4 SARIMA Model performance under each split

Split Ration	Model	AIC	BIC	MAE	MSE	RMSE	R-squared
70-30	SARIMA(4, 1, 2) (0, 0, 1, 12)	749.289	755.993	9.5544	348.5522	18.6696	-0.0801
80-20	SARIMA(4, 1, 2) (0, 0, 1, 12)	832.429	839.399	13.3162	527.3929	22.9650	-0.1815
90-10	SARIMA(3, 0, 3) (0, 0, 1, 12)	1041.00	1062.63	8.2668	135.1489	11.6254	0.7678

right

ok

The SARIMA(3, 0, 3)(0, 0, 1)[12] model, applied with a 90:10 train-test split, outperformed other traditional univariate models by effectively capturing seasonal and non-seasonal patterns in the data.

However, while it showed better accuracy than the ARIMA model, its performance was still limited in addressing complex and non-linear trends, leaving room for enhancement. As a result, the study progressed to explore machine learning and deep learning models

4.3 Univariate – Machine Learning and Deep Learning Approaches

According to the literature, several machine learning and deep learning models, including RF, XGB, SVR, FNN, LSTM, and CNN, were applied to forecast inflation using univariate CCPI data. to capture non-linear patterns and complex time dependencies. Before fitting the model, a crucial preprocessing step, which involved selecting significant lag terms, was done based on autocorrelation and partial autocorrelation analysis, to ensure relevant historical patterns were effectively captured for accurate forecasting.

Lags Identification for Univariate Machine Learning Models

Since time series data contain temporal dependencies, incorporating past lag values is crucial for accurate forecasting. However, selecting too many or too few lags can result in overfitting or loss of important information (Widodo et al., 2016). To address this, the Auto Correlation Function (ACF) is commonly used to identify significant lags (Schlink & Tetzlaff, 1998; Autocorrelation and Partial Autocorrelation - GeeksforGeeks, 2023). In this study, ACF and Partial ACF (PACF) plots were used to examine the inflation series, revealing that lags from t–1 to t–9 showed significant correlations (Figure 5.2 and 5.3).
Based on these findings, inflation values from the past 1 to 9-time steps were selected as candidate features. Following the method by (Ghorbani et al., 2016), to determine the optimal number of lags for each model, nine configurations were tested using various lag combinations across machine learning and deep learning models. This process was repeated under three train-test splits (70:30, 80:20, 90:10), as the ideal lag structure may differ by model type. Model-specific lag optimization ensured the best forecasting performance for each algorithm.

Univariate Inflation Forecasting Using Machine Learning and Deep Learning.

For univariate one-step-ahead inflation forecasting, the time series data were restructured as a supervised learning problem, using lagged inflation values as inputs (X) and the current value as the target (y). To assess model performance under different data availability scenarios, three sequential train-test splits (70:30, 80:20, 90:10) were applied. Model hyperparameters were optimized using Optuna combined with time series cross-validation (TSCV). Model performance was evaluated using RMSE, MSE, MAE, and R-squared.

Random Forest (RF) Univariate Model Performance

Table 5 RF Model performance under each split

	70%-30% split.	80%-20% split.	90%-10% split.
Optimal Lag	1	1	1
RMSE	11.62832	14.21275	8.028431
MSE	135.2178	202.0023	64.4557
MAE	5.384188	7.606563	5.144962
R-Squared	0.6	0.564506	0.84853

OK OK

Under RF, the 90:10 train-test split delivered the best forecasting performance among the three strategies, outperforming traditional models like ARIMA and SARIMA. However, the Random Forest model still struggled to fully capture the complex patterns in the inflation data.

XGBoost (XGB) Univariate Model Performance

Table 6 XGB Model performance under each split

OK OK

	70%-30% split.	80%-20% split.	90%-10% split.
Optimal Lag	1	1	8
RMSE	11.55442	14.10559072	5.344385
MSE	133.5047	198.9676894	28.56245
MAE	5.532422	7.669324775	3.980255
R-Squared	0.603464	0.5710479758	0.932879

The XGBoost model, when fitted using the 90:10 train-test split configuration, outperformed XGB models fitted in other splits. Additionally, this model outperformed the previously developed RF model.

Support Vector Regression (SVR) Univariate Model Performance

Before model fitting, inflation data were normalized using MinMaxScaler to enhance model convergence and stability. The scaler was fitted only on the training set.

Table 7 SVR Model performance under each split

80-20

9

2.885165476 3.42331508

8.324179823 11.71908614

1.578326818 2.049684819

0.975766579 0.975043396

	70%-30% split.	80%-20% split.	90%-10% split.
Optimal Lag	9	4	9
RMSE	3.247387	3.321302	3.274779
MSE	10.54552	11.03104	10.72418
MAE	2.216485	2.261122	2.25275
R-Squared	0.975218	0.974077	0.974798

NO no

Feed Forward Neural Network (FNN) Univariate Model Performance

Table 8 FNN Model performance under each split

no

70-30

4.0559

16.4507

2.2722

0.9501

LAg 8

	70%-30%split.	80%-20% split.	90%-10% split.
Optimal Lag	2	9	4
RMSE	4.1043	5.4555	3.2623
MSE	16.8455	29.7629	10.6428
MAE	2.2219	2.8735	2.2211
R-Squared	0.9478	0.9097	0.9788

The results indicate that the Feed Forward Neural Network (FNN) model, with a lag of 4, provided the lowest error when evaluated under the 90:10 train-test split.

Long Short-Term Memory (LSTM) Univariate Model Performance.

The LSTM model under the 90:10 train-test split outperformed the LSTM models under the other splitting criteria

Table 9 LSTM Model performance under each split

		70%-30%split.	80%-20% split.	90%-10% split.
	Optimal Lag	7 3	3	3
4.696858476508521	RMSE	4.914466	4.135038	3.367859
22.060479548349946	MSE	24.15198	17.09854	11.34247
2.5104283054811964	MAE	2.856087	2.580182	2.391219
0.9337718279955036	R-Squared	0.930369	0.96314	0.968004

NO

Convolutional Neural Network Model (CNN) Univariate Model Performance.

The CNN model under the 90:10 train-test split outperformed the CNN models trained under the other splitting criteria using Optuna with 3 lags.

Table 10 CNN Model performance under each split

	70%-30%split.	80%-20% split.	90%-10% split.
Optimal Lag	6 4	3	3
RMSE	3.0575 3.0971	3.5986	3.6841
MSE	9.3486 9.5917	12.9498	13.5723
MAE	1.9672 1.7915	2.372	2.7417
R-Squared	0.9719 0.9706	0.9717	0.973

Based on the results of all fitted models so far, majority if the models indicates that the 90:10 train-test split outperformed the other splitting ratios. Therefore, for the further analysis, only the 90:10 split was considered.

NO

4.4 Univariate Inflation Forecasting Using Hybrid Models.

It was observed that SVR, FNN, LSTM, and CNN performed competitively and achieved promising results. After identifying the optimal models, the next step was to develop hybrid models by considering the top 4 models: SVR, LSTM, FNN, and CNN. Three different Hybrid Modelling Approaches were considered,

1) Residual-Based Hybrid Models
2) Simple Averaging Ensemble
3) Error-Based Weighted Ensemble

Residual-Based Hybrid Models

In this approach, SVR was first employed to generate the initial forecasts. The residuals (i.e., prediction errors) from the SVR model were then modeled using CNN, LSTM, and FNN separately. This led to the development of three hybrid models: SVR-FNN, SVR-LSTM, and SVR-CNN, where the final forecast was obtained by summing the SVR prediction with the output of the corresponding residual model. This approach is widely used in previous time series forecasting studies(Jamil, 2022; Zhang, 2003).

Variants of this hybrid architecture have also been successfully applied across various domains. For example, SVR-CNN was considered in (Ghimire et al., 2022) , while SVR-LSTM was considered in (Das et al., 2021; A. Wang & Ren, 2021) . Similarly, SVR-FNN was considered in (Abbasi et al., 2022; Xiang et al., 2018).

Table 11 Residual-Based Hybrid Models' performance

	SVR-CNN	SVR-LSTM	SVR-FNN
RMSE	3.3148	3.2365	3.1925
MSE	10.9877	10.4750	10.1920
MAE	1.9046	1.8635	1.8699
R-squared	0.9781	0.9792	0.9760

Simple Averaging Ensemble

This method involved generating standalone predictions from each of the four base models—SVR, CNN, LSTM, and FNN—and computing the final forecast as the simple arithmetic mean of these individual predictions. This approach assumes that averaging multiple model outputs can reduce individual model biases and improve generalization. (Timmermann, 2006) identified that using simple averages may work as well as more sophisticated approaches.

Table 12 Simple Averaging Ensemble Model performance

	Performance Metrics.- Ensemble Simple Averaging
RMSE	3.259953
MSE	10.627292
MAE	2.132807
R-squared	0.978862

Error-Based Weighted Ensemble

A widely used technique in ensemble methods is the weighted averaging approach, where each model's prediction contributes to the final output based on its performance. In this method, weights are assigned inversely proportional to each model's error metric. The study (Thaker & Höller, 2022) calculates the weights by considering MAE. Predictions are weighted inversely to their MAE (Mean Absolute Error), giving better-performing models higher influence. Models with lower MAE are given higher influence, since they demonstrate better predictive performance. indicating Higher weights.To determine weights, the Inverse MAE (IMAE) is calculated for each model:

$$IMAE_{model} = \frac{1}{MAE_{model}}$$

These IMAE values are then normalized so that the sum of weights equals 1. For example, the weight assigned to the CNN model is calculated as:

$$\omega_{cnn} = \frac{IMAE_{cnn}}{IMAE_{cnn} + IMAE_{lstm} + IMAE_{svr} + IMAE_{fnn}}$$

This process was continued for RMSE and MSE as well.

- **MAE-Based Weighted Ensemble**: Weights assigned according to the inverse of the Mean Absolute Error (MAE) of each model.
- **MSE-Based Weighted Ensemble**: Weights determined using the inverse of the Mean Squared Error (MSE).
- **RMSE-Based Weighted Ensemble**: Weights calculated based on the inverse of the Root Mean Squared Error (RMSE). Weights are as below.

Table 13 Weights under each weighted Ensemble Approach using different Evaluation metrics

Model	Weight		
	Weighted Averaging-MSE	Weighted Averaging-RMSE	Weighted Averaging-MAE
SVR	0.312767	0.284795	0.294548
FNN	0.320702	0.288385	0.282070
LSTM	0.109996	0.168893	0.171302
CNN	0.256535	0.257926	0.252080

Among the fitted standalone models and hybrid approaches, MAE-based weighted ensemble approach provided the lowest errors, indicating the superior performance.

Table 14 Model Evaluation -Ensemble Weighted Averaging Methods

	Performance Metrics. - Ensemble Weighted Averaging		
	MSE	RMSE	MAE
RMSE	3.131564	3.128010	3.125400
MSE	9.806696	9.784445	9.768124
MAE	2.128190	2.179450	2.177506
R-squared	0.980495	0.980539	0.980571

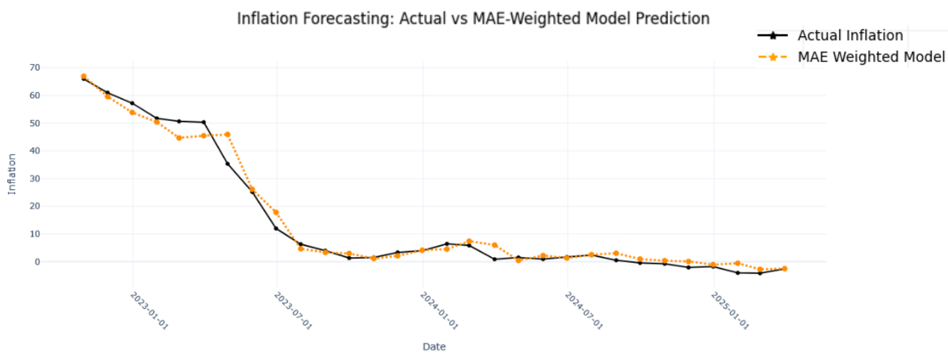

Figure 5 Actual and predicted inflation values under the optimal Model-Weighted Averaging based on MAE values

5 Discussion and Conclusion

Initially, three different train-test split ratios were considered: 70:30, 80:20, and 90:10. This was done to determine the optimal split ratio, as supported by (Abdulraheem et al., 2025). It was found that increasing the size of the training set significantly improved model performance, identifying 90:10 as the optimal split.

The study systematically compared multiple forecasting models for univariate inflation prediction. They are traditional time series models, including ARIMA and SARIMA, Machine learning models including Random Forest(RF), XGBoost(XGB), and Support Vector Regression (SVR), Deep learning models including Feedforward Neural Networks (FNN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) and Hybrid models including Residual-based hybrid models (SVR-CNN, SVR-LSTM, SVR-FNN), simple average ensemble model(average of SVR,CNN,LSTM and FNN, and error-based weighted ensembles (using RMSE, MSE, and MAE as weighting criteria)

Among the traditional models, SARIMA performed better than ARIMA due to its ability to model seasonality. However, both were outperformed by machine learning and deep learning models. SVR, LSTM, CNN, and FNN demonstrated notable accuracy improvements among standalone models.The study further advanced model performance by introducing hybrid modeling approaches. In the residual-based hybrid approach, SVR was used to generate initial forecasts, and its residuals were modeled using FNN, CNN, and LSTM. Additionally, ensemble methods were applied, including a simple average and three weighted averaging techniques based on RMSE, MSE, and MAE.The MAE-weighted ensemble model outperformed all other models, achieving the lowest error metrics of RMSE = 3.125400, MSE = 9.768124, MAE = 2.177506 and the highest R-squared value of 0.980571, indicating excellent predictive performance. When compared with the optimal models in previous studies, such as (Nyoni & Nyoni, 2019), the hybrid models developed in this study provided significantly lower error values, suggesting a superior modeling approach. Moreover, the R-squared value reported in this study exceeds the 0.52 achieved in (Dunuwita Liyanage, 2023), further affirming the efficacy of the proposed models.

Limitations

The models were developed based solely on univariate inflation data, which may not capture all external influences affecting inflation trends. Incorporating multiple macroeconomic indicators (e.g., interest rates, unemployment, GDP) could improve model robustness and accuracy.

Conclusion

This study has indicated the effectiveness of hybrid modeling approaches for improving univariate inflation forecasting. Among all methods evaluated, the MAE-weighted ensemble model achieved the best overall performance by outperforming traditional, machine learning, and deep learning models. Future work incorporating multivariate data and improving model interpretability could further enhance forecasting capabilities and practical relevance.

References

Abbasi, M., Dehban, H., Farokhnia, A., Roozbahani, R., & Bahreinimotlagh, M. (2022). Long-Term Streamflow Prediction Using Hybrid SVR-ANN Based on Bayesian Model Averaging. *Journal of Hydrologic Engineering*, *27*(11), 05022018. https://doi.org/10.1061/(ASCE)HE.1943-5584.0002218

Abdulraheem, A., Muntasir, M., & Shuaibu, N. (2025). *FUDMA Journal of Renewable and Atomic Energy (FJoRAE) Evaluating Time Series and Machine Learning Approaches for Forecasting Inflation in Nigeria*. *2*(1), 42–66. https://doi.org/10.33003/fjorae.2025.0201.04

Aras, S., & Lisboa, P. J. G. (n.d.). *Explainable Inflation Forecasts by Machine Learning Models*. Retrieved April 30, 2025, from http://researchonline.ljmu.ac.uk/

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

Bandara, R. (2011). The determinants of inflation in sri lanka: An application of the vector autoregression model. *South Asia Economic Journal*, *12*(2), 271–286. https://doi.org/10.1177/139156141101200204

Bandara, W. M. S., & De Mel, W. A. R. (2023). Machine learning approaches for forecasting inflation: empirical evidence from Sri Lanka. *Ruhuna Journal of Science*, *14*(1), 29–49. https://doi.org/10.4038/rjs.v14i1.132

Das, H. S., Das, H. S., & Bhattacharjee, S. (2021). Forecasting upper air wind speed using a hybrid SVR-LSTM model. *2nd International Conference on Range Technology, ICORT 2021*. https://doi.org/10.1109/ICORT52730.2021.9581478

Doojav, G. O., & Narmandakh, B. (2025). Forecasting Inflation in Mongolia Using Machine Learning. *International Economic Journal*. https://doi.org/10.1080/10168737.2025.2491386

Dunuwita Liyanage, R. (2023). Inflation Forecasting Using Automatic ARIMA Model in Sri Lanka. *International Journal of Economic Behavior and Organization*. https://doi.org/10.11648/j.ijebo.20231102.13

Ekpeyong, P. (n.d.). *Munich Personal RePEc Archive Analysis of the dynamic of inflation process in Nigeria: An application of GARCH modelling*.

Ghimire, S., Bhandari, B., Casillas-Pérez, D., Deo, R. C., & Salcedo-Sanz, S. (2022). Hybrid deep CNN-SVR algorithm for solar radiation prediction problems in Queensland, Australia. *Engineering Applications of Artificial Intelligence*, *112*. https://doi.org/10.1016/j.engappai.2022.104860

Halim, S., & Bisono, I. N. (2008). Automatic seasonal auto regressive moving average models and unit root test detection *. In *International Journal of Management Science and Engineering Management* (Vol. 3, Issue 4). http://CRAN.R-project.org/.

Huang, L., Zhou, X., Shi, L., & Gong, L. (2024). Time Series Feature Selection Method Based on Mutual Information. *Applied Sciences 2024, Vol. 14, Page 1960*, *14*(5), 1960. https://doi.org/10.3390/APP14051960

Ibrahim Doguwa, S. (n.d.). *Short-term inflation forecasting models for Nigeria*. https://www.researchgate.net/publication/328829101

Jamil, H. (n.d.). *Inflation Forecasting using HYBRID ARIMA-LSTM Model*.

Jamil, H. (2022). *Inflation forecasting using hybrid ARIMA-LSTM model*. https://laurentian.scholaris.ca/handle/10219/3977

Jesmy, M. A. (n.d.). ESTIMATION OF FUTRE INFLATION IN SRI LANKA USING ARIMA MODEL. In *Kalam Journal*.

John, C., Izuchukwu Okoroafor, P., & Chinenye Theresa, A. (n.d.). *Application of Factor Analysis in the Modelling of Inflation Rate in Nigeria*. https://www.researchgate.net/publication/376646546

K.G., E., O.O., P., N.I., P., S.O., E., & C., A. (2023). Modeling and Forecasting Inflation in Nigeria: A Time Series Regression with ARIMA Method. *African Journal of Economics and Sustainable Development*, *6*(3), 42–53. https://doi.org/10.52589/ajesd-hfyc2bnw

Kohlscheen, E. (2021). *What does machine learning say about the drivers of inflation?* https://www.bis.org/publ/work980.htm

MIHALACHE, R.-P., & BODISLAV, D. A. (2023). Forecasting the Romanian inflation rate: An Autoregressive Integrated Moving-Average (ARIMA) approach. *Theoretical and Applied Economics*, *XXX*(1(634), Spring), 67–76. https://ideas.repec.org/a/agr/journl/v1(634)y2023i1(634)p67-76.html

Mustafa, A. M. M. (2019). The Relationship between Foreign Direct Investment and Inflation: Econometric Analysis and Forecasts in the Case of Sri Lanka. *Journal of Politics and Law*, *12*(2), 44. https://doi.org/10.5539/JPL.V12N2P44

Nkemnole, E. B., Wulu, J. T., & Osubu, I. (2024). Application of K-Nearest Neighbours and Long-Short-Term Memory Models using Hidden Markov Model to Predict Inflation Rate and Transition Patterns in Nigeria. *Journal of Applied Sciences and Environmental Management*, *28*(6), 1913–1925. https://doi.org/10.4314/jasem.v28i6.33

Nyoni, & Nyoni, T. (2019). *Predicting inflation in Sri Lanka using ARMA models*.

Optimal Grid Search Techniques for Machine Learning Models. (n.d.). Retrieved April 28, 2025, from https://www.numberanalytics.com/blog/grid-search-techniques-ml

Özmen, M., & Şanli, S. (2015). HEGY SEASONAL UNIT ROOT TEST: AN APPLICATION ON BALANCE OF PAYMENTS IN TURKIS H ECONOMY 1. *Sosyal Bilimler Enstitüsü Dergisi, Cilt*, *24*(2), 159–174.

Plas, J. D. C. van der. (2023). *Dutch Inflation Rate Forecasting Performance of Econometric and Neural Network Models*.

Raj, A. S. A., Kumarasankaralingam, L., Balamurugan, M., Maheswari, B., Gowri, J., & Dutta, A. (2024). Forecasting the Economic Crisis of Sri Lanka: Application of Machine Learning Algorithms for Time Series Data. *Procedia Computer Science*, *235*, 1087–1096. https://doi.org/10.1016/j.procs.2024.04.103

Ratnasiri, H. P. G. S. (n.d.). *Central Bank of Sri lanka The Main Determinants of Inflation in Sri Lanka A VAR based Analysis*.

Schnorrenberger, R., Schmidt, A., & Moura, G. V. (2024). *Harnessing Machine Learning for Real-Time Inflation Nowcasting*.

Thaker, J., & Höller, R. (2022). A Comparative Study of Time Series Forecasting of Solar Energy Based on Irradiance Classification. *Energies 2022, Vol. 15, Page 2837*, *15*(8), 2837. https://doi.org/10.3390/EN15082837

Timmermann, A. (2006). Chapter 4 Forecast Combinations. *Handbook of Economic Forecasting*, *1*, 135–196. https://doi.org/10.1016/S1574-0706(05)01004-9

Ülke, V., Sahin, A., & Subasi, A. (2018). A comparison of time series and machine learning models for inflation forecasting: empirical evidence from the USA. *Neural Computing and Applications*, *30*(5), 1519–1527. https://doi.org/10.1007/S00521-016-2766-X/TABLES/5

Wang, A., & Ren, C. (2021). Prediction of receiving field strength based on SVM-LSTM hybrid model in the coal mine. *2021 IEEE 3rd International Conference on Communications, Information System and Computer Engineering, CISCE 2021*, 813–816. https://doi.org/10.1109/CISCE52179.2021.9445892

Wang, J. J., Wang, J. Z., Zhang, Z. G., & Guo, S. P. (2012). Stock index forecasting based on a hybrid model. *Omega*, *40*(6), 758–766. https://doi.org/10.1016/j.omega.2011.07.008

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

Xiang, Y., Gou, L., He, L., Xia, S., & Wang, W. (2018). A SVR–ANN combined model based on ensemble EMD for rainfall prediction. Applied Soft Computing, 73, 874–883. https://doi.org/10.1016/J.ASOC.2018.09.018

Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. In Neurocomputing (Vol. 50). www.elsevier.com/locate/neucom