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Model Building and Forecasting of Nepal's Total Import Amount Using SARIMA Model

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Abstract

This study aims to analyze and forecast Nepal's monthly total import trends using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. The research employs the Box- Jenkins methodology to develop and evaluate SARIMA models using historical import data from August 2006 to June 2025. A time-series cross-validation (TSCV) approach was used to split the data into training (90%) and testing (10%) sets for model building and evaluation. 240 probable SARIMA models were tested to identify the best-performing model, with the analysis conducted in R software utilizing packages such as forecast, ggplot2, and tseries. The study identified the SARIMA (2,1,1) (1,1,1) [12] model as the most suitable for capturing the seasonal and non-seasonal trends in Nepal's monthly total imports. The model achieved a Mean Absolute Percentage Error (MAPE) of 7.30% on test data, demonstrating high forecasting accuracy. Using the selected model, the study successfully forecasted Nepal's import trends for the next 12 months. This research contributes to the field by providing a rigorous time-series analysis of Nepal's import data using the SARIMA model and time-series cross-validation. The study's application of the SARIMA methodology to Nepal's trade data fills a gap in the literature and offers a robust framework for forecasting trade metrics in similar contexts.

Keywords Box-Jenkins methodology; MAPE; SARIMA; Total Import Amount; TSCV

Introduction

An exchange of money, products, and services between nations that results from a need or desire for certain goods or services is known as international trade (Krueger, 2020). Nepal has been the first among the least developed countries to enter the WTO in 2004. According to Nepal Foreign Trade Statistics, out of ninety-seven chapters of the Harmonized System, the top ten chapters having higher imports represent about 65.05% of Nepal's total imports. Top ten major imported commodities are Diesel, Petrol, LP gas, Gold, Pure Iron, Crude Soya-bean Oil, Other coal, Mobile Telephone, Polythene Granules, Crude Palm Oil. The import of these commodities has contributed NPR 133.95 billion which is 34.28% of total customs revenue collected in FY 2022/23 (Department of Customs, 2023). International trade is a very important constituent of globalization with regard to the drive toward economic interdependence and development (Krugman et al., 2015). The growth of Nepal's economy is dependent on import-export activities on a higher note. Findings indicate imports-led growth in the short term and growth-led imports in the long term, as shown by Panta et al. (2022). Their study provides no evidence of exports-led growth, underscoring Nepal's continued dependence on imports for its economic development. Nepal's trade deficit has long been embedded in its economic structure, and imports have consistently exceeded exports. Joshi et al. (2023) argue that this persistent imbalance has adversely affected the country's foreign exchange reserves and overall macroeconomic stability.

Understanding the trends and patterns of imports is crucial for forecasting and supporting the government in policy making, preparing human resources. Accurate forecasting models would give very important clues to the opportunities and risks in decision making. There are various models available for forecasting import data. With the characteristics of seasonality and trends in imports and exports data, some researchers applied SARIMA to predict imports-exports of paper and paper product (Ersen et al., 2019), imports-exports of Indian wood based panel (Upadhyay, 2013), value of oil and gas exports (Ahmar et al., 2022), hybrid model ARIMA-LSTM for forecasting exports (Dave et al., 2021), ARIMA for forecasting imports-exports of Pakistan (Farooqi, 2014).

Although a substantial body of literature has analyzed Nepal's import and export dynamics, to the best of our knowledge, no study has systematically developed a time series model that captures the underlying trend, rigorously validates its predictive accuracy through time series cross-validation, and subsequently employs it for forecasting purposes. In this study, we are building a SARIMA model for import data from August 2006 to June 2025, validating it with time series cross-validation and forecasting for the next twelve months.

Methods

Datasets: A Longitudinal study was conducted using the total monthly import data of Nepal taken from Nepal Rastra Bank Databases on Nepal Economy ranging from August 2006 to June 2025 for modeling and forecasting using the Box-Jenkins methodology. For data analysis, software R was used.

Box-Jenkins SARIMA Model: The Box–Jenkins methodology, originally proposed by Box and Jenkins in 1970, represents a systematic approach to time series analysis and forecasting (Brockwell & Davis, 2006).

SARIMA Components: SARIMA includes both non-seasonal and seasonal components to capture the basic dynamics of time series data effectively (Box et al., 2015). The model is represented as SARIMA (p, d, q) (P, D, Q) [S], where:

1. p, d, q represents the non-seasonal autoregressive (AR), differencing (I), and moving average (MA) terms, respectively.
2. P, D, Q represent the seasonal counterparts for AR, differencing, and MA.
3. S is the seasonal period.

The general form of SARIMA model is given by equation:

$$\Phi_P(B^S)\phi_p(B)\nabla^d\nabla_S^D X_t = \Theta_Q(B^S)\theta_q(B)\epsilon_t$$

Where: *B*: Backward shift operator, defined as $BX_t=X_{t-1}$

$\nabla=(1-B)$: Non-seasonal differencing operator.

$\nabla_s=(1-B^s)$: Seasonal differencing operator with seasonality *S*.

$\phi_p(B)=1-\phi_1B-\phi_2B^2-....-\phi_pB^p$: Non-seasonal autoregressive (AR) polynomial of order *p*.

$\Phi_p(B^S)=1-\Phi_1B^S-\Phi_2B^{2S}-...-\Phi_pB^{PS}$: Seasonal AR polynomial of order *P*.

$\theta_q(B)=1+\theta_1B+\theta_2B^2+...+\theta_qB^q$: Non-seasonal moving average (MA) polynomial of order *q*.

$\Theta_Q(B^S)=1+\Theta_1B^S+\Theta_2B^{2S}+=...+\Theta_QB^{QS}$: Seasonal MA polynomial of order *Q*.

X_t : Observed time series at time *t*.

ϵt : Error term.

Model Building Process

Generally, four steps, i.e., model identification, estimation, diagnosis, and forecasting, employed in previous research works (Box & Jenkins, 1976). In addition, this study further validates the model using a time series cross-validation method for selecting the best model in terms of the performance of various evaluation metrics. The following are the main 5 steps used.

1. Model identification: Assessing the stationarity of a time series is essential for generating reliable and efficient forecasts. A stationary series is characterized by statistical properties i.e. most notably its mean and variance, that remain constant over time. Checks for stationarity involve application of the ADF- Augmented Dickey Fuller-test (Dickey & Fuller, 1979). In case of a non-stationary series, differencing is applied to make its statistical properties stable. The seasonal differencing (D), is also used when periodic variations are present in the data. The orders of the non-seasonal components (p, d, q), and seasonal components (P, D, Q) are determined by analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. These plots provide insights into the lag dependencies in the time series. Furthermore, the seasonal period (S) is identified based on the frequency of recurring patterns, such as monthly or quarterly cycles.
2. Estimation: Once the model structure is identified, parameter estimation involves determining the numerical values of the coefficients for the AR, MA, seasonal AR, and seasonal MA terms.
3. Validation: The validation of the SARIMA model is done to ensure that it has the strength to predict well on unseen data. The common practice is to divide the data into two, say, 90% for training the model and 10% for testing. For testing, we use Time Series Cross-Validation (TSCV) (Hyndman & Athanasopoulos, 2018).

Time series cross-validation involves splitting data into training and test sets multiple times, with each split expanding the training set by including more past observations. The model is trained on the training set and tested on the subsequent test set in each iteration. Metrics from all iterations are averaged to evaluate the model's performance, ensuring realistic and robust assessment for time-dependent data. The several test metrics computed in this process include the Mean Error, Root Mean Squared Error, Mean Absolute Error, Mean Percentage Error, Mean Absolute Percentage Error, Mean Absolute Scaled Error, and the Autocorrelation Function of the residuals. These metrics help quantify how accurate these forecasts are, and also provide a general idea of the generalization ability of the model. By evaluating these metrics on the test data, one can confirm the model's effectiveness in predicting future values of the time series.

4. Diagnostics: Diagnostics consist of a series of checks that must be performed to ensure that the model adequately captures the pattern of the time series, without overfitting, and leaving no significant variations unexplained. One of the most important aspects of diagnostics consists of residual analysis, which should be uncorrelated and normally distributed; this would confirm that the model has captured the underlying structure in the data. The Ljung-Box Q-test (Ljung & Box, 1978) is used to check whether the residuals are white noise. If the test goes through successfully, this means that no significant autocorrelation in residuals has been found. Furthermore, the ACF plot, histogram, and Q-Q plot of residuals confirm normality, hence a well-fitted model.
5. Forecasting: After the model is validated, the most suitable SARIMA model that was selected for the country's import amount forecast, therefore, was applied on the entire dataset. As such, the model did an import forecast one year ahead, providing useful vision in economic planning and formulating trade policy.

Result

The time series plot of monthly total imports of Nepal from August 2006 to June 2025, which shows an upward pattern along with seasonality (Figure 1).

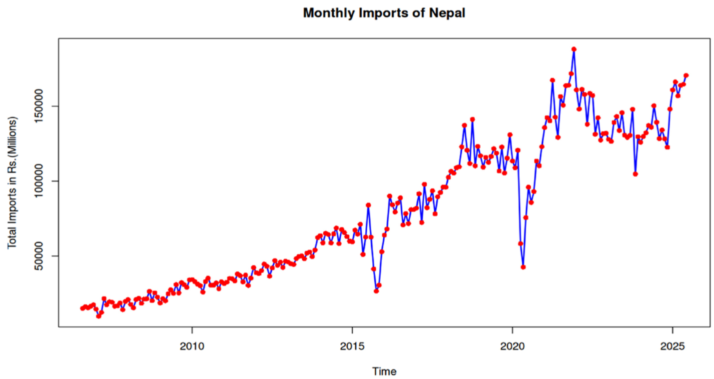

Figure 1. Total imports amount of Nepal from 2006 to 2025

We observe that imports have been trending upward over time and have some sort of seasonality, but in 2015 and 2020 the total imports dropped significantly. The major reason for drop in import amount in 2015 is due to nearly a month of unofficial border blockade by India (Pant, 2018), and the major reason for drop in import amount in 2020 is due to pandemic caused by COVID-19 (Singhal, 2020). Figure 1 also shows that total import series is not stationary which can be confirmed by ADF test(p-value>0.01). Thus, there is a need for differentiation.

We employ a difference of lag of 1 for removing monthly trend and difference of 12 for removing yearly seasonality in order to make the series stationary. Then, again we apply the ADF test for confirming the stationarity of data (p-value<0.01); (Table 1).

Table 1. ADF Unit Root Test of Total Imports and difference of 1 and 12 of Total Imports

	ADF test			
Data	**Dickey Fuller test statistic**	**Lag Order**	**p-value**	**Decision**
Total Imports	--3.5564	6	0.0383	Non-Stationary
diff(diff(imports),12)	-7.1454	5	<0.01	Stationary

Model Identification

Now after making the data stationary, we estimate the order of AR and MA by accessing PACF and ACF plots, respectively (Figure 2 and 3).

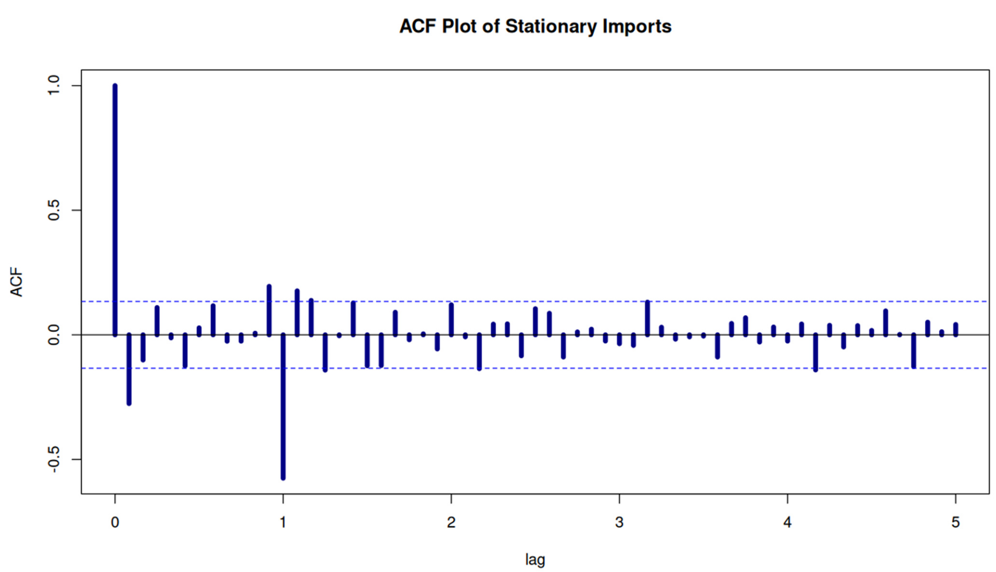

Figure 2. ACF plot of Stationary Imports

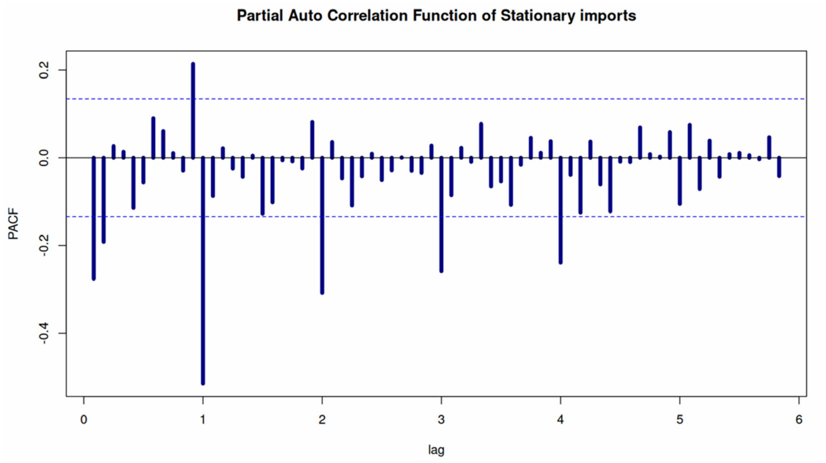

Figure 3. PACF plot of Stationary Imports

The ACF of the stationary series significantly decreases after at lag order 1,2,3 for the non-seasonality part and it significantly decreases after 1,2,3 for seasonality part. This implies that the auto-correlation of the successive pair of observations in time period 1, 2,3 for both non-seasonality and seasonality part. So, the tentative order of moving average process can be 0,1, 2,3 (i.e., q=0,1, 2,3 and Q=0,1,2,3). The PACF of the Stationary imports series significantly decreased after lag order 1,2, and it significantly decreased after lag order 1,2,3,4 for seasonality. So, the tentative order of the auto-regressive process can be 1,2 for non-seasonality and 1,2,3,4 for seasonality (i.e. p=0,1,2 and P=0,1,2,3,4). A total of 240 different possible combinations of models were tested.

Model Estimation and Validation

Even though order selection of models is subjective, there are various model selection criteria proposed by literature (de Gooijer et al., 1985). The goodness-of-fit statistics used were Akaike information criterion (AIC), Standard error and Ljung-Box test. Out of 240 tested models, we select three plausible models having lowest AIC and p-value greater than 0.05 from Ljung-box test which implies that model has no residual auto-correlation left. The top three selected models are displayed in Table 2.

Table 2. Three Plausible SARIMA models

S.N.	Model	AIC	SSE	P-value from Ljung-box test
1	SARIMA (2,1,1) (0,1,2) [12]	4091.843	18553405588	0.3473545
2	SARIMA (2,1,1) (1,1,1) [12]	4091.879	18513560977	0.3639208
3	SARIMA (2,1,1) (1,1,2) [12]	4093.799	18398700330	0.4188671

After selecting the three plausible models we use them to forecast monthly imports. Plotting forecasted values with observed test data shown in Figure 4 depicts monthly forecasted values tend to follow a similar pattern with observed values.

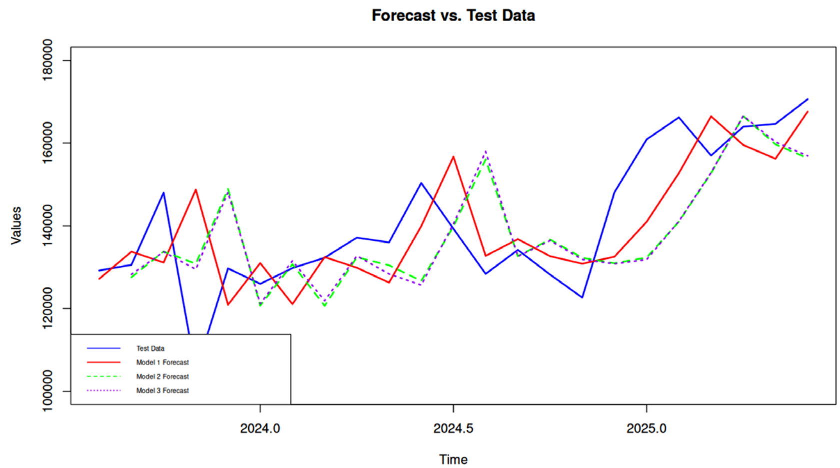

Figure 4. Comparing Monthly Forecasted values of plausible three models with observed values

Table 3 depicts Mean Error (ME), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE), Mean Absolute Scaled Error (MASE), Autocorrelation Function (ACF) of residual.

Table 3. Three plausible SARIMA model performance Comparison on test data

Model	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
SARIMA (2,1,1) (0,1,2) [12]	1298.765	13348.08	9896.097	0.1699323	7.351154	0.9752614	-0.2084387
SARIMA (2,1,1) (1,1,1) [12]	1322.463	13339.6	9822.458	0.1873037	7.298479	0.9680043	-0.2194223
SARIMA (2,1,1) (1,1,2) [12]	1298.973	13430.39	9922.487	0.1768798	7.361862	0.9778621	-0.2172998

Among the three models evaluated, SARIMA (2,1,1) (1,1,1) [12] is the best choice. It has the lowest RMSE of 13339.60, MAE of 9822.46, MAPE of 7.30%, and MASE of 0.968 compared to the other models, indicating better accuracy and performance. Although its ME of 1322.46 shows some bias (not the closest to zero), its overall performance in terms of forecast error is more favorable, making it the most reliable model for forecasting.

Model Diagnosis

Residual plot indicates that residuals resemble white noise structure as they deviate around zero mean and constant variance (Figure 5). Almost all spikes of ACF within significance limits confirm that fitted model has identically independently distributed residuals and no serial autocorrelation among residuals confirmed by Box-Ljung test (p=0.587). Moreover, a bell-shaped histogram (Figure 5) and Q-Q plot of residuals (Figure 6) indicates that residuals are normally distributed.

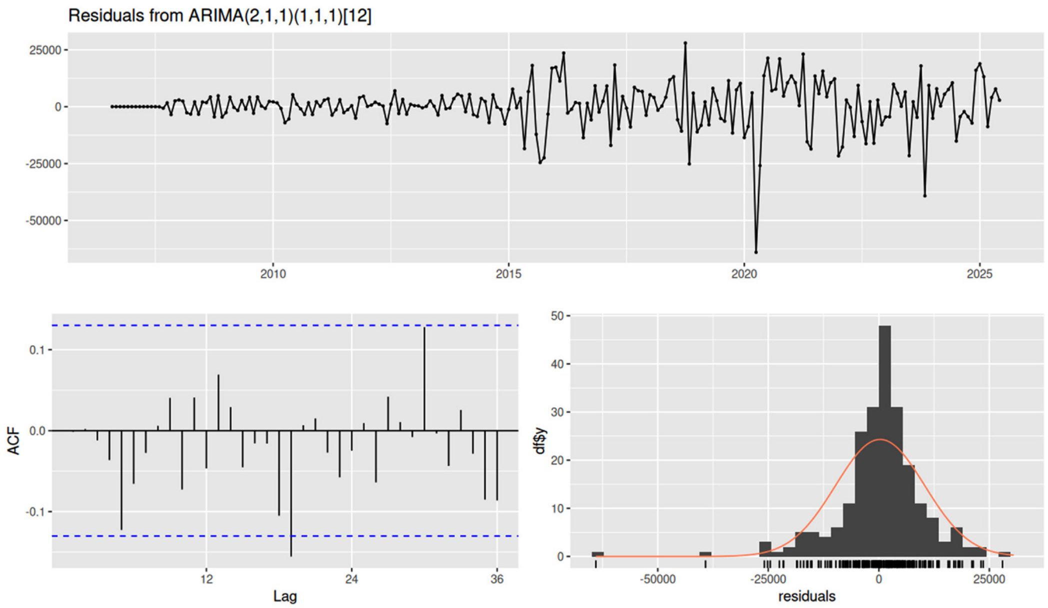

Figure 5. Best model Diagnosis plots

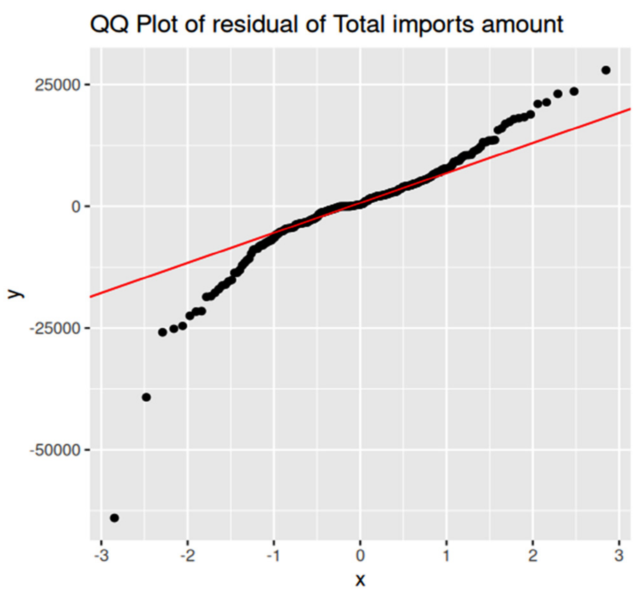

Figure 6. Q-Q plot of residuals of SARIMA Model of Total Import Amount

Forecasting:

Now we fit full data on the SARIMA (2,1,1) (1,1,1) [12] and forecast for the next 12 months from July 2025-June 2026 (Table 4).

Table 4. Forecast for next 1 year (July 2025-June 2026)

Month	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jul 2025	174932.6	161575.4	188289.7	154504.6	195360.5
Aug 2025	166366.5	149717.9	183015	140904.7	191828.3
Sep 2025	170341.9	151696	188987.8	141825.4	198858.4
Oct 2025	170927.3	149919.1	191935.5	138798	203056.6
Nov 2025	167842.7	144775.4	190910	132564.3	203121.1
Dec 2025	176090.4	151213.6	200967.1	138044.7	214136
Jan 2026	173360.9	146758.8	199962.9	132676.5	214045.2
Feb 2026	173132.4	144909	201355.8	129968.5	216296.4
Mar 2026	176613.3	146864.6	206362	131116.6	222110.1
Apr 2026	177399.2	146197.1	208601.3	129679.7	225118.7
May 2026	170020	137428.6	202611.5	120175.7	219864.4
Jun 2026	177411.9	143489.1	211334.6	125531.5	229292.2

Discussion:

Among different time series models, the SARIMA model is used to forecast Nepal's import data. Various studies have proven the potential of SARIMA and ARIMA models in imports and exports forecasting. Among others, Rosyid et al. (2019) applied SARIMA (0,1,3) (0,1,1) [12] for Indonesia's import forecast with a high degree of accuracy, reflected by the MAPE value of 7.21%, and proving helpful in making policies to stabilize the local market. Similarly, (Farooqi, 2014) found that ARIMA (2,2,2) was an appropriate model in the forecasting of Pakistan imports, showing an upward trend over time, and showed how important time-series forecasting is when it comes to economic planning. Li (2024) considered SARIMA (2,1,1) (2,1,1) [12] to be effective in predicting the U.S. import prices from China, capturing seasonality and recent trend slowdowns. Ghauri et al. (2020) presented ARIMA (8,1,5) as a reliable model for forecasting Pakistan's imports. These studies demonstrate how robust the methodologies of SARIMA and ARIMA are in handling seasonality and fluctuations, thus justifying their application to Nepal's import forecasting for strategic economic decisions and trade policy formulation.

Conclusion:

This study aimed to observe patterns of monthly import data from August 2006 to June 2025 and build a model and hence forecast for next twelve months. On the basis of results and discussion, we can conclude that SARIMA (2,1,1) (1,1,1) [12] is the best time series model which captures the total import series of Nepal. This paper makes a valuable contribution to build a time series model in the context of Nepal's import data. The forecasted data showed that the growth and trend of total import amount of Nepal is in increasing order. This study is limited to univariate time series analysis. Despite this limitation this study opens the floor for researchers to develop other models and compare the results.

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