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FORECASTING THE IMPACT OF COVID-19 ON THE HOUSEHOLD FINAL CONSUMPTION EXPENDITURE (HFCE) IN THE PHILIPPINES

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Abstract: The Household Final Consumption Expenditure (HFCE) is a significant component of the Philippine economy. The term "HFCE" refers to families' spending on necessities such as food and drink, clothing, shelter, and health care. The gathered data from this study covers the country's quarterly HFCE from 2001-2021. The study used various forecasting methods, including Triple Exponential Smoothing, Seasonal Autoregressive Integrated Moving Average (SARIMA), and TBATS in modeling time series data to depict the effects of COVID-19 on the country's HFCE Growth Rate. The best model to predict the quarterly HFCE growth rate from 2022 to 2026 was identified using error metrics, particularly RMSE, MSE, and MAE. The SARIMA model had the lowest combined error of the train and test set, marking it as the best model for predicting the HFCE growth rate. Moreover, the HFCE growth rate was also predicted using various machine learning regression algorithms (SVR, XGBoost, and kNN), with a variety of economic indicators as the independent variables, including the inflation rate, unemployment rate, import of goods growth rate, import of services growth rate, export of goods growth rate, and export of services growth rates. The results of error metrics showed that SVR was the best regression algorithm for predicting the Philippines' quarterly HFCE Growth Rate. The findings of this study indicate that as COVID-19 spread over the country, the HFCE growth rate dramatically decreased. Therefore, models used to predict the HFCE growth rate over the next five years are significantly impacted using historical data, including the years when COVID-19 occurred.

Keywords: *COVID-19, Extreme Gradient Boosting (XGBoost), Household Final Consumption Expenditure (HFCE), kNN Regression, Support Vector Regression (SVR), TBATS, Triple Exponential Smoothing.*

1. INTRODUCTION

The COVID-19 pandemic has sparked a global health crisis, requiring several governments to implement stringent preventive measures to stem the virus' spread, including national lockdowns and social distancing measures. The first case of COVID-19 infection in the Philippines was reported in January 2020, and by March, the country was placed under a strict community quarantine that restricted mobility and business activities. While these measures have slowed the community spread of COVID-19, they have significant adverse impacts on family incomes, jobs, education of children, food security, and businesses. A pandemic can disrupt the economy in a variety of ways. Human behavioral changes, such as fear-induced aversion to places of work and public gatherings, were a significant cause of economic damage, besides the impact of mitigation measures (Madhav *et al.*, 2017). The adverse effects of various pandemics on inhabitants' household income have been established in the past literature. The 2020 economic contraction was the highest annual decline ever reported since the National Accounts data series for the Philippines began in 1946. The final consumption of households was mostly the biggest component of the Gross Domestic Product (GDP) among the Association of Southeast Asian Nations (ASEAN) countries on the expenditure side. In the Philippines, Household Final Consumption Expenditure (HFCE) was 73.5 % of the GDP, making it an essential component in demand analysis.

As stated in IHS Markit Philippines Manufacturing PMI (Biswas, 2021), the Household Final Consumption Expenditure (HFCE) went down by 7.9%, while gross capital formation contracted by 34.4%. Drastic declines in output were reported in some sectors of the economy, with the transport and storage industry marking a 30.9% decline, while accommodation and food services output went down by 45.4%. Meanwhile, according to the Philippine Statistics Authority (PSA), during the third quarter of 2020, the unemployment rate increased to 18.9%. Further, World Bank's research said that only 1 in 10 households that operated a business accessed financial services. The incidence of revenue losses among household businesses showed improvement, with the wealthiest households recovering faster than the poorest households. Nearly two out of five households were anxious about not having enough food for the following week. While food security continued to improve overall, concerns among households remained. The share of household heads unable to buy at least one of the food staples remained the same at around 40%, primarily because of food unaffordability. Fewer households reported eating less than usual and worried about not having enough food. Households that needed medical treatment increased to 28% in December from 20% in August 2021. More households cited lack of money as a reason for inadequate access to treatment. However, based on the report of the Statista Research Department, in 2021, the HFCE for health in the Philippines was valued at approximately 627 billion Philippine pesos. Household spending on health has gradually increased over the past five years and was highest in 2021 after the COVID-19 pandemic outbreak. Undeniably, COVID-19 played a massive part in the shift of the economy and household expenditure, and the researchers, being the children of the working class who were greatly affected by the pandemic, saw the need for this study to be conducted.

This study aimed to depict the impact of COVID-19 on the Household Final Consumption Expenditure (HFCE) Growth Rate in the Philippines, wherein different forecasting methods were used to model time series data, particularly Seasonal Autoregressive Integrated Moving Average (SARIMA); Triple Exponential Smoothing; and Trigonometric seasonability, Box-Cox transformation, ARMA errors, Trend components and Seasonal components (TBATS). Further, the best model was identified to forecast the country's HFCE Growth Rate. Moreover, different machine learning regression algorithms such as support vector machine (SVM) regression, extreme gradient boosting (XGBoost), and k-nearest neighbors (kNN) were used to predict the HFCE growth rate, applying various economic indicators as the independent variables, namely: Inflation Rate, Unemployment Rate, Import of Goods Growth Rate, Import of Services Growth Rate, Export of Goods Growth Rate, and Export of Services Growth Rate. Thus, the model with the lowest error metrics – root mean square error (RMSE), mean squared error (MSE), mean absolute error (MAE), and highest R squared were selected as the best machine learning regression algorithms for predicting the HFCE growth rate.

The primary purpose of this study is to forecast the impact of the COVID-19 pandemic on the Philippines' HFCE growth rate from 2022-2026 through time series forecasting models and to identify which model is the best. Moreover, this paper also aims to determine the best machine-learning regression algorithm for predicting the country's HFCE growth rate.

2. METHODOLOGY

2.1 Research Design

This research was conducted using different time series forecasting models, namely SARIMA, Triple Exponential Smoothing, and TBATS in forecasting the quarterly HFCE Growth Rate of the Philippines. In addition, regression algorithm in machine learning was also used in the study and further identified which among them is the best for predicting the country's quarterly HFCE Growth Rate. To supplement the statistical analysis performed in this study, the researchers relied on several sets of secondary data relating to the HFCE Growth Rate, Inflation Rate, Unemployment Rate, Import of Goods Growth Rate, Import of Services Growth Rate, Export of Goods Growth Rate and Export of Services Growth Rate. All the data came from the Time Series Data of the Philippine Statistics Authority (PSA). PSA serves as the central statistical authority of the Philippine government on primary data collection.

2.1 Statistical Data Analysis Procedures

2.1.1 Statistical Tool

The researchers used the software RStudio and Orange to clean, organize, analyze, predict, and present the data. RStudio software was used to forecast future HFCE Growth Rate values by operating SARIMA, Triple Exponential Smoothing, and TBATS. In addition, this software was used to identify the models' accuracy. RStudio was a free software environment commonly used by statisticians to convey statistical computation and graphics. Furthermore, Orange was used in determining which among the machine learning regression algorithms had the lowest values of error metrics, particularly Extreme Gradient Boosting (XGBoost), k-nearest neighbors (kNN) Regression, and Support Vector Machine (SVM) Regression in predicting HFCE, considering the dependent variables. Orange was an open-source data visualization, machine learning, and data mining toolkit. It featured a visual programming front-end for explorative rapid qualitative data analysis and interactive data visualization.

2.1.2 Statistical Treatment of Data

2.1.2.1 Seasonal Autoregressive Integrated Moving Average (SARIMA)

SARIMA stands for Seasonal-ARIMA, and it includes seasonality contribution to the forecast. The importance of seasonality is quite evident, and Auto Regression Integrated Moving Average (ARIMA) fails to encapsulate that information implicitly. The Autoregressive (AR), Integrated (I), and Moving Average (MA) parts of the model remain as that of ARIMA. The addition of Seasonality adds robustness to the SARIMA model. It is represented as:

ARIMA (p, d, q) (P, D, Q)

Non-seasonal part of the model — Seasonal part of the model

where m is the number of observations per year. We used the uppercase notation for the seasonal parts of the model, and lowercase notation for the non-seasonal parts of the model. Like ARIMA, the P, D, and Q values for seasonal parts of the model can be deduced from the ACF and PACF plots of the data. The researchers used this model to predict the next five years' quarterly data on HFCE Growth Rate, from 2022 to 2026.

Assumptions:

i. Data should be univariate

The data type that should be used consists of observations with a single characteristic or attribute.

ii. Data should be stationary

The properties of a series should not depend on the time when it is captured. In addition, it must have a constant variance, covariance, and mean.

2.1.2.2 Triple Exponential Smoothing (Holt-Winters method)

Triple exponential smoothing can model seasonality, trend, and level components for univariate time series data. Seasonal cycles are patterns in the data that occur over a standard number of observations. Triple exponential smoothing is also known as Holt-Winters Exponential Smoothing. This method adds in the gamma (γ) parameter to account for the seasonal component. For this method, you must specify the period for the seasonal cycle. This study has used the additive method. The component form for the additive method is:

$$\hat{y}_{t+h\backslash t} = \ell t + hb_t + s_{t+h-m(k+1)}$$
$$\ell t = \alpha(y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1})$$
$$bt = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$$
$$st = \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m,}$$

where k is the integer part of $(h-1)/m$, which ensures that the estimates of the seasonal indices used for forecasting come from the final year of the sample. The level equation showed a weighted average between the seasonally adjusted observation $y_t - s_{t-m}$and the non-seasonal forecast $(\ell_{t-1} + b_{t-1})$ for time t. The trend equation was identical to Holt's linear method. The seasonal equation showed a weighted average between the current seasonal index, $(y_t - \ell_{t-1} - b_{t-1})$, and the seasonal index of the same season last year (i.e., mm time periods ago).

The equation for the seasonal component is often expressed as:

$$s_t = \gamma^*(y_t - \ell_t) + (1-\gamma^*)s_{t-m}.$$

If we substitute ℓt from the smoothing equation for the level of the component form above, we get

$$s_t = \gamma^*(1 - \alpha)(y_t - \ell_{t-1} - b_{t-1}) + [1 - \gamma^*(1 - \alpha)]s_{t-m},$$

which is identical to the smoothing equation for the seasonal component we specify here, with $\gamma = \gamma^*(1-\alpha)$. The usual parameter restriction is $0 \leq \gamma^* \leq 1$, which translates to $0 \leq \gamma \leq 1 - \alpha$.

2.1.2.3 TBATS

The names were acronyms for key features of the models: Trigonometric seasonality, Box-Cox transformation, Auto Regression Integrated Moving Average (ARMA) errors, and Trend and Seasonal components. TBATS model took its roots in exponential smoothing methods and can be described by the following equations:

$$y_t^\lambda = l_{t-1} + \phi b_{t-1} + \sum_{i=1}^{T} s_{t-m_i}^{(i)} + d_t$$
$$l_t = l_{t-1} + \phi b_{t-1} + \alpha d_t$$
$$b_t = \phi b_{t-1} + \beta d_t$$
$$d_t = \sum_{i=1}^{p} \varphi_i d_{t-i} + \sum_{i=1}^{q} \theta_i e_{t-i} + e_t$$

where:

y_t^λ- time series at moment t (Box-Cox transformed)
$s_t^{(i)}$- i^{th} seasonal component
l_t- local level
b_t- trend with damping
d_t- ARMA(p,q) process for residuals
e_t- Gaussian white noise

Seasonal Part:

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)}$$
$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} cos(\omega_i) + s_{j,t-1}^{*(i)} sin(\omega_i) + \gamma_1^{(i)} d_t$$
$$s_{j,t}^{(i)} = -s_{j,t-1}^{(i)} sin(\omega_i) + s_{j,t-1}^{*(i)} cos(\omega_i) + \gamma_2^{(i)} d_t$$
$$\omega_i = 2\pi j / m_i$$

Model Parameters:

T - Amount of seasonalities
m_i - Length of the i^{th} seasonal period
k_i - Amount of harmonics for the i^{th} seasonal period
λ – Box-Cox transformation
α, β – Smoothing
ϕ - Trend damping
φ_i, θ_i – ARMA(p,q) coefficients
$\gamma_1^{(i)}, \gamma_2^{(i)}$ – Seasonal smoothing (two for each period)

Each seasonality was modeled by a trigonometric representation based on the Fourier series. One major advantage of this approach was that it required only (two) 2 seed states regardless of the length of the period. Another advantage was the ability to model seasonal effects of non-integer lengths. For example, given a series of daily observations, one can model leap years with a season of length 365.25. BATS, which stands for Box-Cox transformation ARMA residuals Trend component in the model Seasonal components, differed from TBATS only in the way it models seasonal effects. In BATS, we had a more traditional approach where each seasonality was modeled by:

$$s_t^{(i)} = s_{t-m_i}^{(i)} + \gamma_i d_t.$$

This implied that BATS can only model integer period lengths. The approach taken in BATS requires m_i seed states for season i, if this season is long the model may become intractable.

2.1.2.4 *Extreme Gradient Boosting (XGBoost)*

XGBoost was a short-term for the eXtreme Gradient Boosting algorithm developed by Chen and Guestrin (2016). It was an implementation of gradient-boosted decision trees designed for speed and performance and was a more efficient version of gradient-boosting decision trees. The main objective of the algorithm was to optimize parameters given an objective function that contains a loss function and a regularization parameter. The regularization term aimed to reduce the likelihood of overfitting by controlling the complexity of constructed trees. The complexity of each tree follows the equation:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} \omega_j^2$$

where T is the number of leaves and ω is the vector scores on leaves (Chen and Guestrin, 2016). The structure score, objective function, of the algorithm is defined as:

$$F = \sum_{j=1}^{T} (G_j \omega_j + \frac{1}{2}\left(H_j + \lambda\right)\omega_j^2) + \gamma T$$

whereω_j are independent of each other and the form $G_j \omega_j + \frac{1}{2}\left(H_j + \lambda\right)\omega_j^2$ is quadratic.

2.1.2.5 *K-nearest neighbors (kNN) regression*

A simple implementation of kNN regression was to calculate the average of the numerical target of the K nearest neighbors. Another approach used an inverse distance weighted average of the K nearest neighbors. kNN regression used the same distance functions as kNN classification.

Distance Functions

Euclidean: $\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$

Manhattan $\sum_{i=1}^{k}|x_i - y_i|$

Minkowski$\left(\sum_{i=1}^{k}(|x_i - y_i|^q\right)^{\frac{1}{q}}$

The above three distance measures were only valid for continuous variables. Thus, this study used the Euclidean Distance Function.

2.1.2.6 Support Vector Regression (SVR)

This was a regression algorithm that supported both linear and non-linear regressions. This method worked on the principle of the Support Vector Machine. SVR was a regression that was used for predicting continuous ordered variables. In simple regression, the idea was to minimize the error rate while in SVR the idea was to fit the error inside a certain threshold, which means that SVR's work was to approximate the best value within a given margin called ε- tube. Moreover, this study utilized polynomial kernels. In general, the polynomial kernel was defined as:

$$K(X_1, X_2) = (a + X_1^T X_2)^b$$

2.1.2.7 Mean Squared Error (MSE)

The mean squared error of a model concerning a test set was the mean of the squared prediction errors over all instances in the test set. The prediction error was the difference between the true value and the predicted value for an instance.

$$MSE = \frac{\sum_{i=1}^{n}(y_i - \overline{y_i})^2}{n}$$

where:

n - the total number of terms for which the error is to be calculated

y_i - the observed value of the variable

$\overline{y_i}$ - the predicted value of the variable

2.1.2.8 Root Mean Square Error (RMSE)

Root Mean Squared Error Root mean squared error (RMSE) was the square root of the mean of the square of all the errors. The use of RMSE was widespread, and it was regarded as an ideal general-purpose error metric for numerical forecasts.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2}$$

where:

O_i are the observations,
S_i are the predicted values of a variable, and
n is the number of observations available for analysis.

RMSE was a good measure of accuracy, but only to compare prediction errors of different models or model configurations for a particular variable and not between variables, as it is scale-dependent. Meanwhile, the smaller the value, the better the model's performance.

2.1.2.9 Mean Absolute Error (MAE)

Mean Absolute Error was a model evaluation metric used with regression models. The mean absolute error of a model to a test set was the mean of the absolute values of the individual prediction errors on overall instances in the test set. Each prediction error was the difference between the true value and the predicted value for the instance.

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

where:

n = the number of errors
Σ = summation symbol (which means "add them all up")
$|(x_i - x)|$ = the absolute errors

2.1.2.10 Coefficient of determination (R²)

This referred to the proportion of variation of data points explained by the regression line or model. It can be determined as a ratio of the total variation of data points explained by the regression line (Sum of squared regression) and the total variation of data points from the mean (also termed as sum of squares total or total sum of squares). The following formula represents the ratio.

$$R^2 = \frac{SSR}{SST} = \frac{\sum(\hat{y}_i - \bar{y})^2}{\sum(y_i - \bar{y})^2}$$

where:

$\hat{y}_i$ represents the prediction or a point on the regression line,

$\bar{y}$ represents the mean of all the values, and

y_i represents the actual values or the points.

2.1.2.11 Auto-Correlation Function (ACF)

Auto-correlation function (ACF) was a statistical technique used to identify how correlated the values in a time series are with each other by plotting the correlation coefficient against lag. The data values beyond the significance limits were statistically significant at approximately α = 0.05, which shows evidence of correlation. ACF was formulated as follows:

$$\hat{r}_k = \frac{\sum_{t=k+1}^{n-k}\left(x_{t-k} - \underline{x}\right)\left(x_t - \underline{x}\right)}{\sum_{t=1}^{n}\left(x_t - \underline{x}\right)^2}$$

where:

k = Lag; $k = 1,2, \dots, n$

x_t= Value of x at row t

$\underline{x}$= Mean of x

n= Number of observations in the series

2.1.2.12 Augmented Dickey-Fuller Test (ADF)

Augmented Dickey-Fuller Test (ADF) was a statistical test for analyzing the stationary of a series. The ADF test expanded the Dickey-Fuller test equation to include a high-order regressive process in the model. The null hypothesis assumed the presence of a unit root, that was α=1; the p-value obtained should be less than the significance level to reject the null hypothesis; thereby, inferring that the series was stationary. ADF was formulated as follows:

$$y_t = c + \beta t + \alpha y_{t-1} + \phi_1 \triangle Y_{t-1} + \phi_2 \triangle Y_{t-2} .. + \phi_p \triangle Y_{t-p} + e_t$$

where:

t = Time index,

α = Intercept constant called a drift,

β = Coefficient on a time trend,

γ = Coefficient presenting process root, i.e. the focus of testing,

p = Lag order of the first-differences autoregressive process,

e_t= Independent identically distributed residual term.

3. RESULTS AND DISCUSSION

This section presented the purpose of the study, research design, data source for secondary data, and statistical data analysis procedures.

3.1 Graphs of the Behavior of Specific Variables

3.1.1 Household Final Consumption Expenditure

Figure 3 shows that the graph exhibited a major downward trend from the 2nd quarter of 2020 to the 1st quarter of 2021, recording all quarters within this duration with a negative growth rate. The lowest HFCE growth rate recorded for 2000-2021 was during the 2nd quarter of 2020 with -15.32%. One of the reasons for this decline was due to the government's preventive measures, primarily when lockdowns were implemented; thus, limiting the exposure of people outside their homes. On the other hand, in the 2nd quarter of 2021 began to display a growth rate of 7.31%.

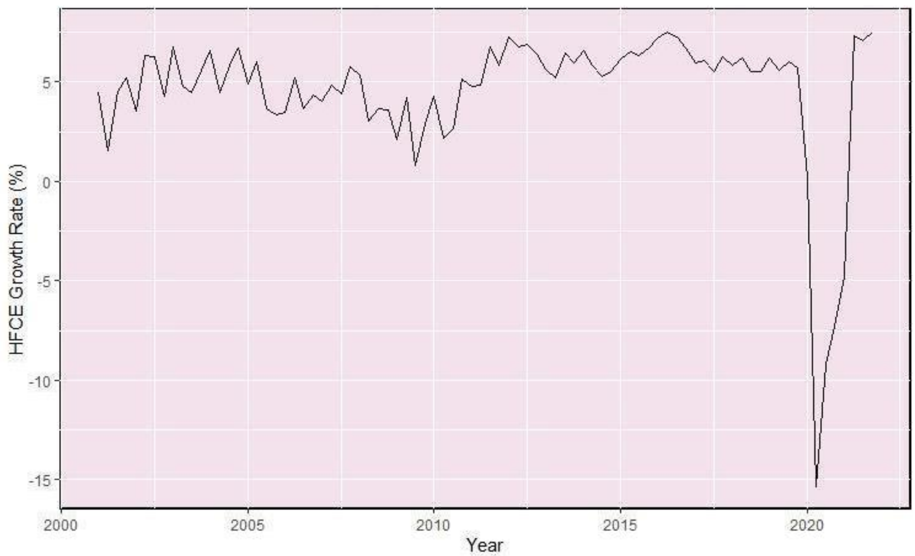

Figure 3. Philippines' household final consumption expenditure from Q1 2000 to Q4 2001.

3.1.2 Inflation rate

Based on Figure 4, the inflation rate in the country from the 2nd quarter of 2007 was at 2.4% and continuously increased until the 3rd quarter of 2008, reaching its peak at 12.20%. The lowest point of the quarterly data of inflation rate for 2000-2021 was in the third quarter of 2009 with 0.3%. On the other hand, the inflation rate during the COVID-19 pandemic caused no significant changes.

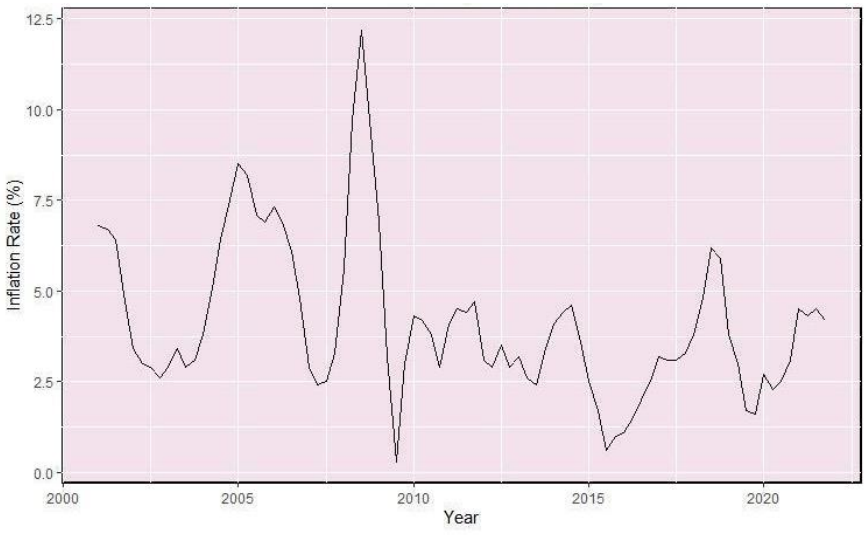

Figure 4. Philippines' inflation rate from Q1 2000 to Q4 2001.

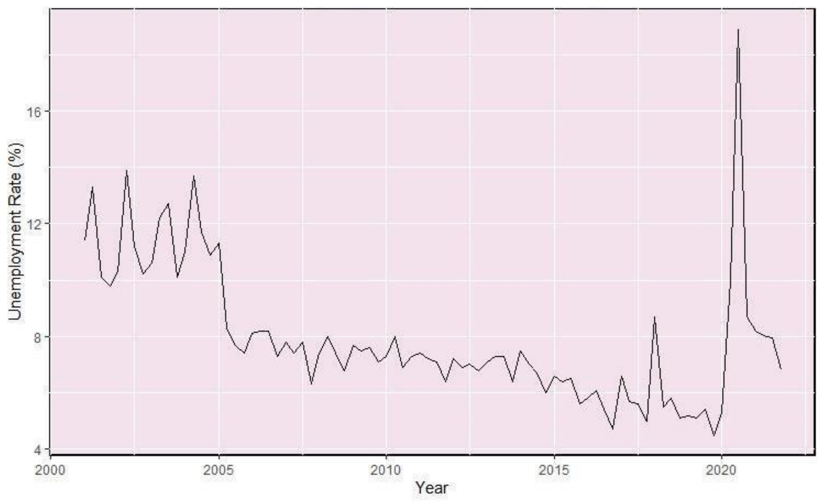

Figure 5. Philippines' unemployment rate from Q1 2000 to Q4 2001.

3.1.3 Unemployment Rate

Figure 5 shows the unemployment rate in the Philippines from the 1st quarter of 2000 to the 4th quarter of 2021. It can be inferred that in the 4th quarter of 2005, there was a sudden decline in the unemployment rate. It continued to decline until it rose to 8.7% in the first quarter of 2018. It immediately declined again for the next quarters up to the extent that its lowest record was at 4.5% during the 4th quarter of 2019, which is a good indication in terms of unemployment. However, due to the COVID-19 pandemic, the unemployment growth rate in the country began to increase rapidly starting from the 2nd quarter of 2020 with 10% and 18.9% during the 3rd quarter of 2020.

3.1.4 Import of Goods

Figure 6 shows the growth rate of import of goods in the Philippines from the 1st quarter of 2000 to the 4th quarter of 2021. The import of goods growth rate experienced a major decline that started in the 3rd quarter of 2001, from 20.67% to -0.22%. It continued to decline until it rose to 18.48% in the 4th quarter of 2002. Unfortunately, it immediately declined again for the following quarters, until it showed another major decline in the 1st quarter of 2009, which had a -10.69% rate. In the 1st quarter of 2010, it showed a major increase with a 28.36% rate, and though it experienced a downward trend, it stayed stable for the following quarters. In the 2nd quarter of 2020, the lowest import of goods was recorded at -38.48% and continued to decline until the last quarter of the year. This decline was a visible result of the COVID-19 pandemic. Fortunately, it was slowly showing a major upward trend starting from the 2nd quarter of 2021, with 48.45%.

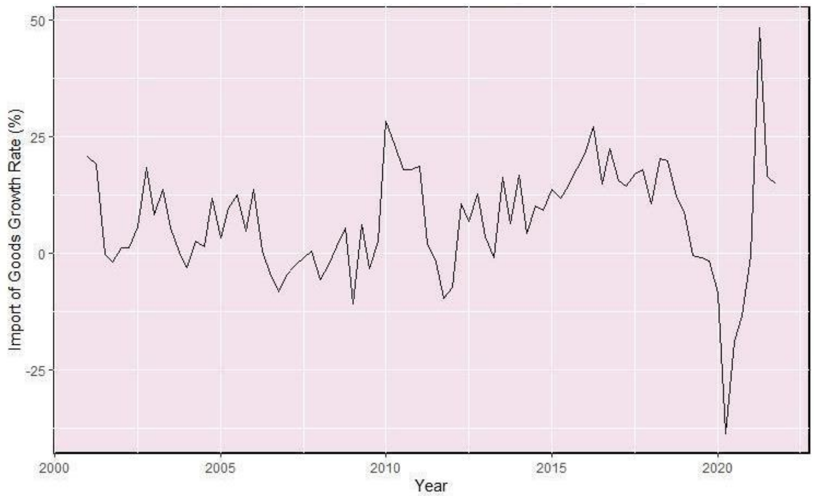

Figure 6. Philippines' import of goods growth rate from Q1 2000 to Q4 2001.

3.1.5 Import of Services

Figure 7 shows the growth rate of import of services in the Philippines from the 1st quarter of 2000 to the 4th quarter of 2021. The import of services growth rate experienced a major decline that started in the 4th quarter of 2001, from 31.16% to -8.33%. As the import of services gradually increased through the years, reaching its peak at 39.86% during the 3rd quarter of 2008, it immediately went down in the following years and the lowest ever recorded was from the 4th quarter of 2020 with a value of -43.73%. Fortunately, it was slowly showing a major upward trend starting from the 2nd quarter of 2021 at 1.03%.

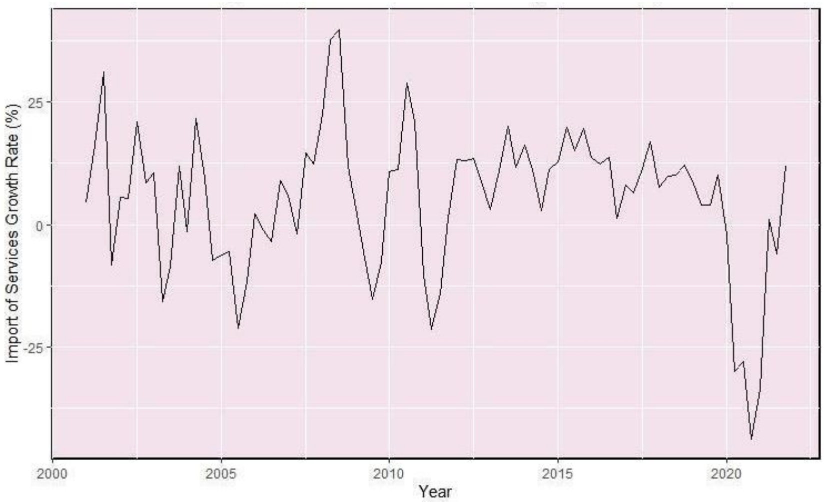

Figure 7. Philippines' import of services growth rate from Q1 2000 to Q4 2001.

3.1.6 Export of Goods

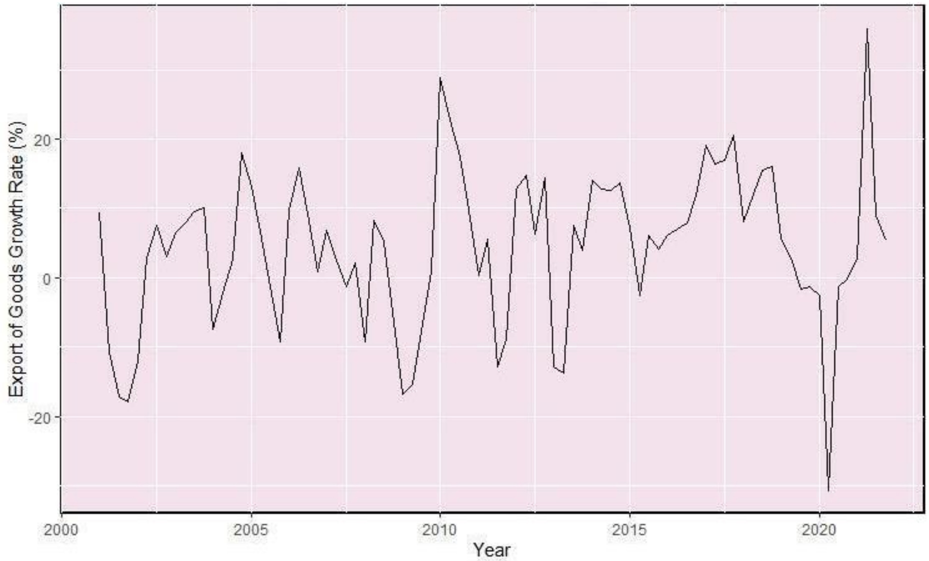

Figure 8. Philippines' export of goods growth rate from Q1 2000 to Q4 2001.

Figure 8 shows the growth rate of export of goods in the Philippines from the 1st quarter of 2000 to the 4th quarter of 2021. The export of goods' growth rate experienced a major decline that started in the 2nd quarter of 2001, from 9.32% to -10.56%. It continued to decline until it rose to 28.88% in the 1st quarter of 2010. Unfortunately, it immediately declined again for the following quarters until it showed another major decline in the 1st quarter of 2013 which had a -12.72% rate. In the 1st quarter of 2014, it showed a major increase with a 14.13% rate, and though it experienced a downward trend, it stayed stable for the following quarters. In the 2nd quarter of 2020, the lowest export of goods was recorded at -30.57% and continued to decline until the last quarter of the year. This decline was a visible result of the COVID-19 pandemic. Fortunately, it was slowly showing a major upward trend starting from the 2nd quarter of 2021, with 35.94%.

3.1.7 Export of Services

Figure 9 shows the growth rate of export of services in the Philippines from the 1st quarter of 2000 to the 4th quarter of 2021. The export of services growth rate experienced a major decline that started in the 4th quarter of 2003, from 28% to 0.47%. As the import of services gradually increased through the years reaching its peak at 57.09% during the 3rd quarter of 2005, it immediately went down in the following years and the lowest ever recorded was from the 2nd quarter of 2020 with a value of -36.01%. Fortunately, it was slowly showing a major upward trend starting from the 2nd quarter of 2021 at 20.17%.

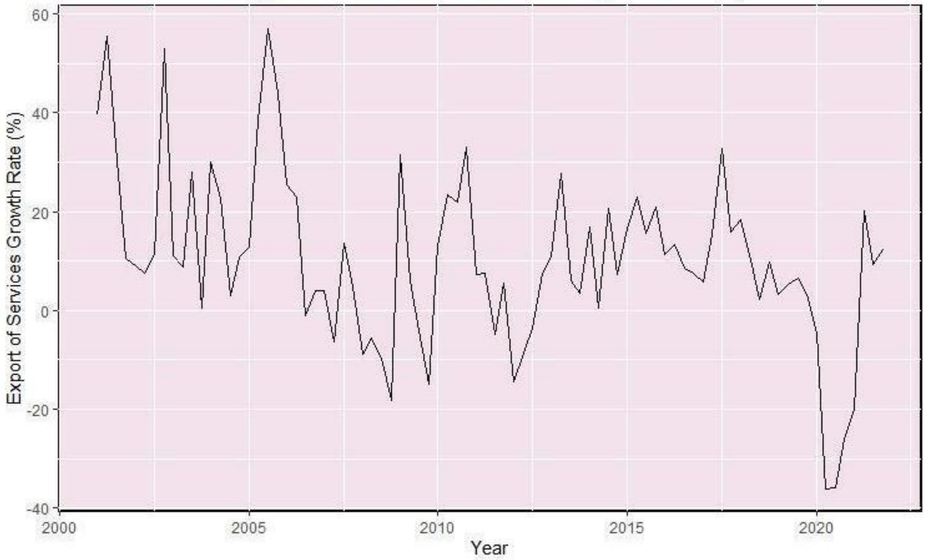

Figure 9. Philippines' export of services growth rate from Q1 2000 to Q4 2001.

3.2 Five-year Predicted Values of the Household Final Consumption Expenditure

3.2.1 SARIMA Model

Figure 10 presents the plot of the Household Final Consumption Expenditure Growth Rate prediction for 2022 to 2026 using the SARIMA model. It exhibited the best model with SARIMA (1,0,0) (0,0,1) [4], which had the lowest Akaike Information Criterion (AIC).

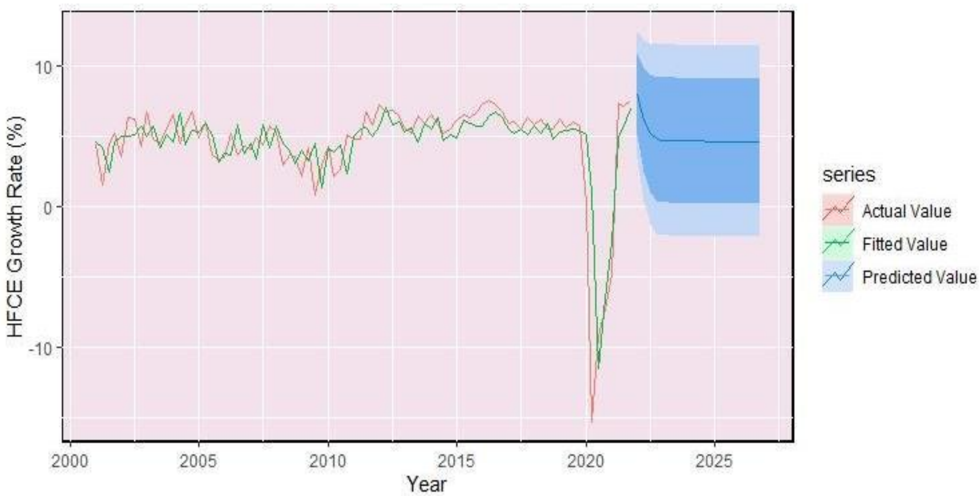

Figure 10. HFCE growth rate predicted values for 2022 – 2026 using SARIMA.

3.2.2 Triple Exponential Smoothing Model

Figure 11. HFCE growth rate predicted values for 2022 - 2026 using exponential smoothing.

Figure 11 exhibited the plot of Household Final Consumption Expenditure Growth Rate prediction for 2022 to 2026 using the Triple Exponential Smoothing model. The best model was ETS (1,0,0**)** which incorporated a smoothing factor of 0.9454, a trend smoothing factor of 0.0002, and a 0.0001 seasonal change smoothing factor.

3.2.3 TBATS model

Figure 12 shows the plot of household final consumption expenditure growth rate prediction for 2022 to 2026 using the TBATS model. The best model was calculated using TBATS () functions in the R program with **TBATS (1, {0, 0}, 0.8, -)**. Furthermore, this model constituted a damping parameter of 0.8, an alpha of 1.0222, and a beta of -0.2627.

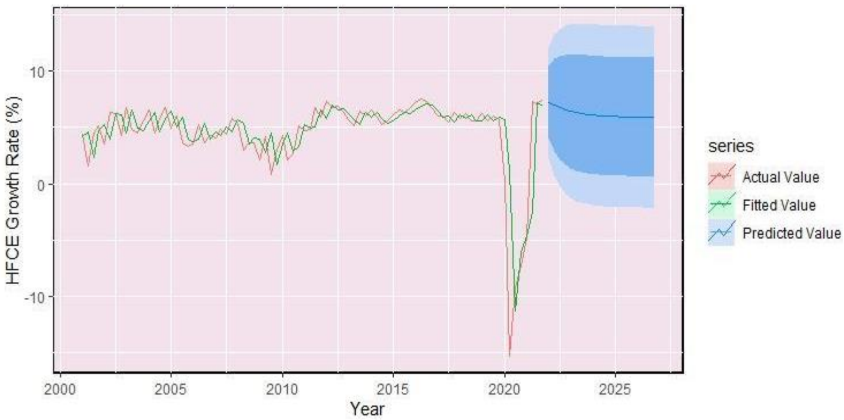

Figure 12. HFCE growth rate predicted values for 2022 - 2026 using TBATS.

3.3 Best Statistical Model for Predicting Household Final Consumption Expenditure

Table 1 presents the comparison of accuracy for the five-year forecast of Household Final Consumption Expenditure Growth Rate using SARIMA, Triple Exponential Smoothing, and TBATS. The models with the lowest combined Mean Squared Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) for train and test sets were chosen as the best models. This depicted that SARIMA (1,0,0) (0,0,1) [4] performed the best model for predicting the HFCE from 2022 to 2026 with combined train (MSE = 5.0330, RMSE = 2.2434, MAE = 1.2566) and test (MSE = 0.3101, RMSE = 0.5569, MAE = 0.2677) set, followed by TBATS (1, {0,0}, 0.8, -) and ETS (1,0,0).

Table 1. Comparison of accuracy for SARIMA, exponential smoothing, and TBATS.

ACCURACY	**MODELS**					
	SARIMA		**Exponential Smoothing**		**TBATS**	
	Train	**Test**	**Train**	**Test**	**Train**	**Test**
MSE	5.0330	0.3101	6.9866	13.0627	6.1459	0.4742
RMSE	2.2434	0.5569	2.6432	3.6142	2.4791	0.6887
MAE	1.2566	0.2677	1.4267	2.6146	1.2553	0.2484

3.4 Best machine Learning Regression Algorithm for predicting Household final consumption expenditure

Table 2 shows the obtained regression metrics results for Extreme Gradient Boosting (XGBoost), k-nearest neighbors (kNN), and Support Vector Regression (SVR). The results showed that the SVR algorithm outperformed the other two models in predicting the Philippines' Quarterly Household Final Consumption Expenditure (HFCE). The table reflected the lowest MSE (6.413), RMSE (2.532), and MAE (1.115) on SVR. Moreover, the R-squared value of SVR (0.806) was the highest among the three algorithms, implying that it best describes how well the regression model explains observed data. Thus, 80.6% of the variability observed in the target variable was explained by the regression model. It was also found that the XGBoost algorithm had the lowest performance reflected by the highest MSE, RMSE, MAE, and R^2 values. Moreover, it was also revealed that the XGBoost had almost equal performance with kNN in predicting the HFCE Growth Rate. Thus, among the three models, SVR was the best regression algorithm for predicting the country's quarterly HFCE Growth Rate.

Table 2. Comparison of accuracy of regression algorithm (XGBoost, KNN, and SVR).

ACCURACY	**REGRESSION ALGORITHM**		
	XGBoost	**kNN**	**SVR**
MSE	6.4130	5.4230	2.3970
RMSE	2.5320	2.3290	1.5480
MAE	1.5710	1.3120	1.1150
R^2	0.4810	0.5610	0.8060

4. CONCLUSIONS

In this study, the researchers have analyzed the impact of COVID-19 on the Philippines' quarterly Household Final Consumption Expenditure (HFCE). Time-series analyses were used to forecast the quarterly HFCE of the country covering the period of 2022 to 2026. The visualization of the trajectory of the pandemic was shown using line graphs.

Moreover, the researchers created a model to forecast the HFCE growth rate from 2022 to 2026 using SARIMA, Triple Exponential Smoothing, and the TBATS model. Using MSE, RMSE, and MAE, the researchers built a model selection table containing the best forecasting outcomes. The results showed that SARIMA (1,0,0) (0,0,1) [4] was the best model for predicting the HFCE growth rate for the next five years. Wherein, it implied that the Household Final Consumption Expenditure growth rate will gradually decline during the span of forecasted years.

Furthermore, regression algorithms in machine learning, specifically XGBoost, kNN, and SVR were compared in terms of error metrics (RMSE, MSE, and MAE) and the goodness of fit of regression models (R^2) to identify which among them has the highest performance in predicting HFCE. Thus, the results revealed that with the Inflation Rate, Unemployment Rate, Import of Goods and Services Growth Rate, Export of Goods and Services Growth Rate being the predictor variables and HFCE Growth Rate as the outcome variable, Support Vector Regression was the best regression algorithm to be used for prediction.

In conclusion, based on the data, a drastic decline in the HFCE growth rate was observed when COVID-19 spread throughout the country. Thus, the use of historical data, including the years when COVID-19 occurred, dramatically affected the model for forecasting the HFCE growth rate for the next five (5) years.

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