Forecasting The Top Five Philippine Import and Export Commodities Using XGBoost and Hybrid Models

Marvin T. Palabon

Graduate Student, Polytechnic University of the Philippines, Manila

Abstract:
This study forecasts the quarterly import and export performance of the Philippines at the commodity level for the period 2025–2030. Using quarterly data from 2005 to 2024, the study examines the historical behavior of the top five import and export commodities, compares the forecasting performance of different models, and generates medium-term trade projections. Extreme Gradient Boosting (XGBoost) is employed as the primary forecasting method to capture nonlinear and lagged dynamics in trade series, while traditional ARIMA and Hybrid ARIMA–XGBoost models are used as benchmark specifications for model comparison. Long-term trade trends are also assessed using Compound Annual Growth Rate (CAGR) analysis. The results show that machine learning–based models, particularly Univariate XGBoost, outperform traditional ARIMA models for most import and export series in terms of forecast accuracy. Hybrid models provide additional gains for selected commodities with more complex dynamics. The forecast indicates sustained demand for transport equipment and mineral fuels for imports, while electronics-related products—especially semiconductors and ignition wiring sets—remain dominant among export commodities.

Overall, the study demonstrates the effectiveness of combining econometric and machine learning approaches in forecasting international trade at the commodity level. The findings provide forward-looking and data-driven insights that can support trade monitoring, policy analysis, and strategic planning for the Philippine economy.

Keywords: Trade Forecasting, XGBoost, ARIMA, Imports, Exports.

I. INTRODUCTION

International trade remains a central driver of global economic growth and structural transformation. Over the past two centuries, world trade volumes have expanded significantly, outpacing overall economic output (Fouquin & Hugot, 2016). Merchandise exports, which once accounted for less than 10% of global GDP, now represent nearly one-quarter of global production. As of 2023, exports of goods and services accounted for 29.32% of global GDP (Trading Economics, 2025). This expansion reflects deeper global integration, specialization, and participation in international value chains.

Trade openness enhances productivity by enabling countries to specialize according to comparative advantage while facilitating technology diffusion and market expansion. Since 1990, rising global trade has been associated with higher average incomes and substantial poverty reduction (World Bank, 2023). However, increasing interdependence also exposes economies to external shocks, as supply chain disruptions and geopolitical tensions can transmit volatility across regions (OECD, 2025).

The Philippines, like many developing economies, relies heavily on international trade to support growth, employment, and industrial development. Trade accounts for a substantial share of national output, with imports representing approximately 37–40% of GDP and exports contributing around 27–29% in recent years (Philippine Statistics Authority [PSA], 2024). Export-oriented industries, particularly electronics and semiconductor manufacturing, play a critical role in industrial activity, while imports of petroleum, raw materials, and capital goods remain essential for domestic production and infrastructure.

Trade patterns in the Philippines have evolved alongside policy reforms and global economic cycles. Liberalization efforts in the 1990s shifted the economy toward a more outward-oriented strategy. More recently, the COVID-19 pandemic caused significant contractions in trade flows in 2020, followed by a strong rebound in 2021 (PSA, 2025). The ratification of the Regional Comprehensive Economic Partnership (RCEP) in 2023 further strengthened regional trade integration (ASEAN Briefing, 2023).

While aggregate trade indicators provide a broad assessment of external sector performance, they conceal substantial variation across commodity groups. Commodity-level analysis is crucial because each product category is influenced by distinct global demand conditions, price movements, technological changes, and policy environments. For example, semiconductors remain the country’s leading export, while transport equipment and mineral fuels constitute major import categories (PSA, 2024). A disaggregated perspective therefore provides more precise insights into sector-specific risks and opportunities.

Accurate forecasting of import and export flows at the commodity level is essential for economic planning, trade policy formulation, and strategic decision-making. Traditional econometric approaches such as the Autoregressive Integrated Moving Average (ARIMA) model are widely used in time series forecasting due to their interpretability and statistical foundations. However, trade data often exhibit nonlinear patterns, structural breaks, and complex lag relationships that may limit the performance of purely linear models.

Advances in machine learning offer alternative forecasting tools capable of capturing nonlinear dynamics. Extreme Gradient Boosting (XGBoost), in particular, has gained attention for its predictive accuracy and ability to model complex interactions. Hybrid approaches combining ARIMA and machine learning techniques have also emerged to leverage both linear and nonlinear components of time series data.

Despite the increasing application of machine learning in economic forecasting, limited research has systematically compared ARIMA, XGBoost, and hybrid approaches in forecasting Philippine trade at the commodity level. This study addresses this gap by analyzing the historical behavior of the top five Philippine import and export commodities using quarterly data from 2005 to 2024 and generating projections for 2025–2030. Specifically, the study (1) examines commodity-level trade behavior, (2) evaluates the comparative forecasting performance of ARIMA, Univariate XGBoost, and Hybrid ARIMA–XGBoost models, and (3) produces medium-term trade forecasts.

This study contributes to the literature in three ways. First, it provides the first commodity-level comparative forecasting analysis for Philippine trade using machine learning methods. Second, it integrates structural break modeling within a hybrid ARIMA–XGBoost framework. Third, it evaluates model robustness using multiple out-of-sample accuracy metrics.

By integrating econometric and machine learning methods, this research contributes to the methodological literature on trade forecasting while providing forward-looking insights relevant to policymakers, trade analysts, and economic planners.

II. METHODS

Research Design

This study adopts a quantitative time-series forecasting framework to project quarterly values of the top five Philippine import and export commodities for the period 2025–2030. The approach combines descriptive trend analysis with econometric diagnostics and machine learning–based predictive modeling. The primary objective is to evaluate and compare the forecasting performance of traditional linear models and nonlinear machine learning techniques at the commodity level.

The analysis focuses on predictive performance rather than causal identification. Trade dynamics are examined using historical quarterly data to assess growth behavior, structural changes, and forecast accuracy across competing model specifications.

Data Sources and Coverage
Quarterly import and export data were obtained from the Philippine Statistics Authority (PSA), which compiles International Merchandise Trade Statistics (IMTS) based on export and import documents submitted to the Bureau of Customs. The study covers the period 2005Q1 to 2024Q4.

The analysis focuses on the top five import and export commodities based on trade value. Structural break indicators corresponding to major economic disruptions—including the Global Financial Crisis (2008–2009) and the COVID-19 pandemic (2020–2021)—were incorporated to capture regime shifts in trade behavior. All time-series processing and model estimation were conducted using R statistical software.

Statistical Techniques
Long-term growth trends were examined using Compound Annual Growth Rate (CAGR) to identify commodities with sustained expansion over the sample period. Prior to model estimation, stationarity was assessed using the Augmented Dickey-Fuller test, with differencing applied when necessary. Structural changes in trade dynamics associated with major economic disruptions were identified using the Bai–Perron multiple breakpoint test. Linearity and functional form adequacy of benchmark specifications were evaluated using the Ramsey RESET test, providing justification for the application of nonlinear machine learning models. Residual serial correlation was assessed using the Ljung–Box test to ensure the adequacy of baseline model assumptions.

Forecasting Models
Autoregressive Integrated Moving Average (ARIMA) models were estimated as benchmark linear forecasting specifications, with model orders selected using information criteria and residual diagnostics. Extreme Gradient Boosting (XGBoost) served as the primary nonlinear forecasting method, utilizing lagged trade values and structural break indicators as input features, with hyperparameters selected through time-series cross-validation. A hybrid ARIMA–XGBoost approach was also implemented, combining linear ARIMA forecasts with nonlinear residual modeling using XGBoost to capture complex trade dynamics.

Forecast Evaluation
Forecast performance was evaluated using out-of-sample accuracy measures, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA). For each commodity series, the model with the lowest forecast error was selected to generate projections for 2025–2030.

III. RESULTS AND DISCUSSION
Historical Behavior of Import and Export Series
Quarterly import and export series from 2005 to 2024 exhibit pronounced cyclical behavior and structural shifts consistent with major global disruptions. Most import categories display upward long-run trends prior to 2020, interrupted by sharp contractions during the Global Financial Crisis (2008–2009) and the COVID-19 pandemic (2020–2021), followed by post-shock recoveries.

Among imports, transport equipment and industrial machinery show strong pre-pandemic expansion, reflecting sustained capital formation and infrastructure investment. Mineral fuels exhibit high volatility, driven by global energy price fluctuations. Semiconductor imports display cyclical but trend-driven behavior, while electronic data processing imports show relatively moderate variability.

On the export side, semiconductors remain the dominant export category, characterized by cyclical expansions and contractions aligned with global electronics demand. Ignition wiring sets demonstrate sustained upward movement over the sample period, indicating deeper integration into global automotive supply chains. In contrast, apparel and woodcraft exports show persistent structural decline, reflecting weakening competitiveness in traditional labor-intensive industries.

These patterns confirm that most series are non-stationary in levels and subject to structural breaks, supporting the application of adaptive time-series forecasting models.

Growth Dynamics

Table 1A: Compound Annual Growth Rate of Top 5 Imports and Exports in the Philippines; 2005-2024

Variable Name	Variable Description	Compound Annual Growth Rate	Ranking
Imports_1	Components/Devices (Semiconductors)	0.86%	4
Imports_2	Mineral Fuels, Lubricants and Related Materials	6.20%	3
Imports_3	Transport Equipment	12.41%	1
Imports_4	Industrial Machinery and Equipment	6.55%	2
Imports_5	Electronic Data Processing	0.10%	5
Exports_1	Components/Devices (Semiconductors)	1.14%	2
Exports_2	Electronic Data Processing	0.25%	3
Exports_3	Articles of Apparel and Clothing Accessories	-6.47%	5
Exports_4	Ignition Wiring Set and Other Wiring Sets Used in Vehicles, Aircrafts and Ships	6.47%	1
Exports_5	Woodcrafts and Furniture	-1.80%	4

Compound Annual Growth Rate (CAGR) results indicate structural divergence across commodity groups. For imports, transport equipment records the highest long-term growth, followed by industrial machinery and mineral fuels. Semiconductor and electronic data processing imports exhibit relatively modest growth, suggesting maturing demand patterns.

For exports, ignition wiring sets register the strongest expansion, reinforcing the Philippines’ position in higher-value manufacturing segments. Semiconductor exports show moderate positive growth, while apparel and woodcraft exports record negative growth rates, highlighting sustained contraction in traditional export sectors.

Overall, results indicate a structural shift toward capital-intensive and technology-based trade composition, with declining performance in labor-intensive industries.

Structural Breaks and Linearity

Table 1B: Structural Breaks in Import Series (Bai-Perron Test

Variable	Optimal Breakpoints (m)	Break Years (Quarter)	Lowest BIC
Imports_1	3	2008 Q1, 2014 Q3, 2017 Q3	3,474
Imports_2	4	2010 Q4, 2014 Q3, 2017 Q3, 2021 Q3	3,500
Imports_3	3	2012 Q3, 2016 Q1, 2021 Q4	3,433
Imports_4	3	2010 Q3, 2015 Q2, 2019 Q4	3,228
Imports_5	4	2008 Q3, 2015 Q4, 2018 Q4, 2021 Q4	3,249
Exports_1	3	2008 Q3, 2016 Q4, 2021 Q1	3,532
Exports_2	2	2010 Q2, 2013 Q2	3,340

Exports_3	4	2007 Q4, 2012 Q2, 2015 Q2, 2019 Q3	3,116
Exports_4	3	2010 Q2, 2013 Q3, 2020 Q3	3,134
Exports_5	4	2009 Q2, 2012 Q2, 2017 Q2, 2021 Q4	3,198

The Bai–Perron test identifies structural breakpoints clustered around major macroeconomic events, particularly 2008–2009 and 2020–2021. These break regimes were incorporated as dummy variables in subsequent modeling.

Linearity diagnostics using the Ramsey RESET test indicate nonlinear dynamics in selected series, notably industrial machinery imports, semiconductor exports, and woodcraft exports. The presence of nonlinear structures justifies the inclusion of machine learning–based forecasting approaches.

Model Selection and Forecast Performance

Table 2: Forecast Accuracy Comparison for Import Series Across ARIMA, XGBoost and Hybrid Models

Variable	Model	RMSE	MAE	Ljung_Box_p
Imports 1	ARIMA(0,1,1)(0,0,0)[4]	1,389,804,663	1,357,506,051	0.49669
Imports 1	Univariate XG Boost	290,046,206	217,035,556	
Imports 1	Hybrid_ARIMA&XGB	1,533,316,450	1,498,615,602	
Imports 2	ARIMA(1,1,0)(0,0,0)[4]	567,860,698	481,525,694	0.12958
Imports 2	Univariate XG Boost	331,993,232	283,802,874	
Imports 2	Hybrid_ARIMA&XGB	441,718,337	402,521,705	
Imports 3	ARIMA(0,1,1)(0,0,0)[4]	459,822,158	373,888,572	0.05427
Imports 3	Univariate XG Boost	809,107,006	690,819,118	
Imports 3	Hybrid_ARIMA&XGB	283,488,495	260,519,192	
Imports 4	ARIMA(0,1,1)(0,0,0)[4]	74,328,773	64,599,046	0.97692
Imports 4	Univariate XG Boost	53,071,051	43,709,894	
Imports 4	Hybrid_ARIMA&XGB	143,698,718	112,233,718	
Imports 5	ARIMA(1,1,1)(0,0,0)[4]	210,490,814	200,609,427	0.06207
Imports 5	Univariate XG Boost	72,009,698	56,224,909	
Imports 5	Hybrid_ARIMA&XGB	113,704,381	95,012,383	

Table 3: Forecast Accuracy Comparison for Export Series Across ARIMA, XGBoost and Hybrid Models

Variable	Model	RMSE	MAE	Ljung_Box_p
Exports 1	ARIMA(1,1,1)(1,1,1)[4]	3,452,812,176	3,233,217,102	0.08666
Exports 1	Univariate XG Boost	1,009,077,758	827,481,878	
Exports 1	Hybrid_ARIMA&XGB	4,026,967,568	3,800,223,030	
Exports 2	ARIMA(1,1,0)(0,1,1)[4]	170,804,758	132,823,446	0.41856
Exports 2	Univariate XG Boost	147,667,605	120,344,088	
Exports 2	Hybrid_ARIMA&XGB	182,620,465	160,830,191	
Exports 3	ARIMA(1,1,1)(0,1,1)[4]	32,186,507	28,174,498	0.96744
Exports 3	Univariate XG Boost	20,144,062	17,070,651	
Exports 3	Hybrid_ARIMA&XGB	35,146,667	29,339,640	
Exports 4	ARIMA(1,1,1)(1,1,0)[4]	45,358,712	35,681,232	0.07875
Exports 4	Univariate XG Boost	158,260,575	148,719,163	
Exports 4	Hybrid_ARIMA&XGB	78,126,237	62,005,904	
Exports 5	ARIMA(0,1,1)(0,1,1)[4]	17,987,227	12,806,460	0.54702
Exports 5	Univariate XG Boost	6,523,742	4,758,202	
Exports 5	Hybrid_ARIMA&XGB	16,996,919	15,758,197	

ARIMA Benchmark

Selected ARIMA specifications adequately capture linear components of the trade series, with residual diagnostics indicating absence of serial correlation. However, forecast errors vary substantially across commodities, particularly for highly volatile series such as semiconductor imports and exports.

XGBoost Performance

Univariate XGBoost consistently achieves lower out-of-sample forecast errors for the majority of import and export series. The model performs particularly well for semiconductor imports, electronic data processing imports, and most export categories, indicating superior ability to capture nonlinear and complex dynamics.

Hybrid Model Performance

The hybrid ARIMA–XGBoost approach provides additional improvements for selected commodities, particularly transport equipment imports and ignition wiring set exports, where both linear seasonal patterns and nonlinear residual structures coexist.

Overall, machine learning–based models outperform traditional ARIMA specifications in most cases, while hybrid models offer marginal gains for series exhibiting mixed linear–nonlinear dynamics.

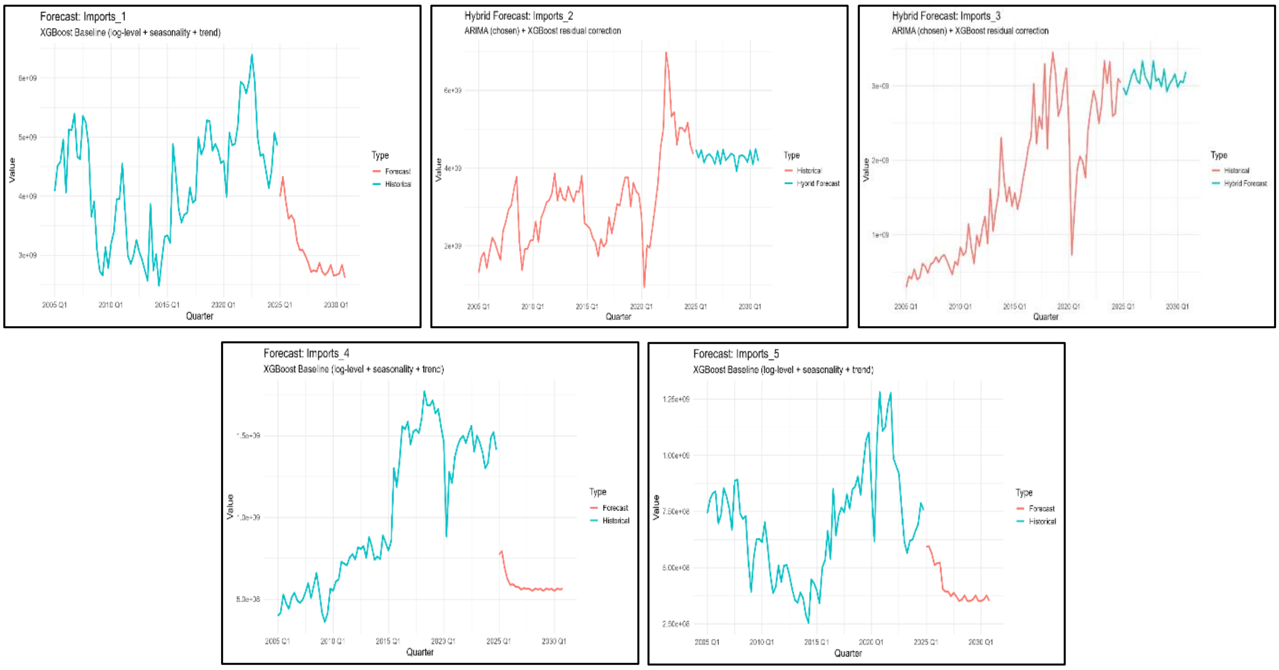
Table 4: Best Performing Forecasting Model for Each Import Series

Import Series	Best Model	Interpretation
Imports 1	Univariate XGBoost	XGBoost captures nonlinear patterns better than ARIMA and Hybrid, resulting in superior predictive accuracy.
Imports 2	Hybrid ARIMA–XGBoost	Hybrid model is selected for its robustness and economic interpretability, not just minimum error.
Imports 3	Hybrid ARIMA–XGBoost	Combining linear seasonal structure (ARIMA) with nonlinear residual learning (XGBoost) improves forecast accuracy.
Imports 4	Univariate XGBoost	The relatively smooth dynamics of the series are well captured by XGBoost’s nonlinear learning mechanism.
Imports 5	Univariate XGBoost	XGBoost outperforms both ARIMA and Hybrid by effectively modeling short-term fluctuations.

Table 5: Best Performing Forecasting Model for Each Export Series

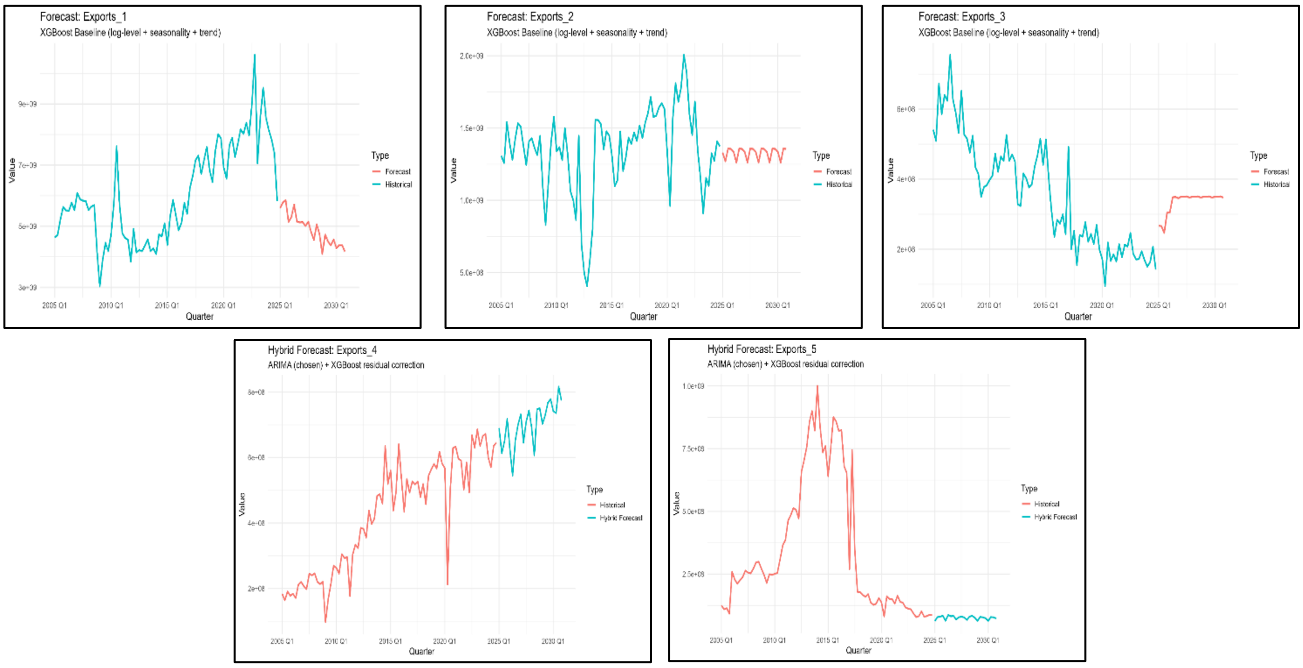
Export Series	Best Model	Interpretation
Exports 1	Univariate XGBoost	XGBoost captures nonlinear dynamics in semiconductor exports better than ARIMA and Hybrid.
Exports 2	Univariate XGBoost	The flexible tree-based structure of XGBoost models irregular export fluctuations effectively.
Exports 3	Univariate XGBoost	XGBoost learns complex short-term patterns better than linear models.
Exports 4	Hybrid ARIMA–XGBoost	Although ARIMA has slightly lower errors, the Hybrid model captures both linear seasonality and nonlinear residual patterns, making it more robust for structural changes.
Exports 5	Univariate XGBoost	XGBoost provides the most accurate forecasts for woodcrafts and furniture exports.

Forecast Projections (2025–2030)



Imports

Forecast results suggest continued strength in transport equipment imports, reflecting sustained capital demand. Mineral fuel imports are projected to stabilize at elevated levels, indicating persistent energy dependence. Industrial machinery and electronic data processing imports show moderate downward adjustments, potentially signaling slower capital deepening or shifts in technology investment patterns. Semiconductor imports exhibit cyclical moderation over the forecast horizon.



Exports

Semiconductor exports are projected to moderate from recent peaks, suggesting normalization in global electronics demand. Electronic data processing exports remain relatively stable, indicating maturity in this segment. Apparel and woodcraft exports are expected to remain structurally weak. In contrast, ignition wiring set exports continue their upward trajectory, reinforcing the Philippines' integration into automotive-related global value chains.

CONCLUSION

This study examined the forecasting performance of ARIMA, XGBoost, and hybrid ARIMA–XGBoost models in projecting the quarterly values of the top five Philippine import and export commodities for 2025–2030. The empirical findings indicate that Philippine trade dynamics are nonlinear, shock-sensitive, and structurally evolving, limiting the predictive capacity of purely linear time-series models. The consistent outperformance of XGBoost across most commodity series highlights the value of flexible machine learning approaches in capturing complex trade behavior.

The results further reveal an ongoing structural transformation in Philippine trade. Import growth remains concentrated in capital goods and energy-related commodities, underscoring the economy's dependence on external inputs to sustain domestic production and infrastructure development. On the export side, performance is increasingly driven by specialized manufacturing segments, particularly electronics and automotive components, while traditional labor-intensive exports such as apparel and woodcrafts continue to weaken.

Despite the strong predictive performance, the study is limited by the exclusion of exogenous macroeconomic variables such as exchange rates and global demand indicators. Future research may incorporate multivariate machine learning frameworks to improve forecast robustness.

Overall, this study demonstrates the practical relevance of integrating econometric and machine learning techniques in commodity-level trade forecasting. By providing forward-looking insights into trade composition and structural dynamics, the findings contribute to improved trade monitoring, strategic planning, and policy formulation in the Philippines. Future research may incorporate additional exogenous macroeconomic variables or explore multivariate machine learning frameworks to further enhance predictive performance.

REFERENCES:

1. Fouquin, M., & Hugot, J. (2016). Two centuries of bilateral trade and gravity data: 1827–2014 (CEPII Working Paper No. 2016-14). Centre d'Études Prospectives et d'Informations Internationales. https://www.cepii.fr/pdf_pub/wp/2016/wp2016-14.pdf
2. Trading Economics. (2025). World exports as percent of GDP. https://tradingeconomics.com/world/exports-of-goods-and-services-percent-of-gdp-wb-data.html
3. World Bank. (2023). World development report 2023: Migrants, refugees, and societies. World Bank. https://www.worldbank.org/en/publication/wdr2023
4. Organisation for Economic Co-operation and Development. (2025). Global value and supply chains. https://www.oecd.org/en/topics/policy-issues/global-value-and-supply-chains.html
5. Philippine Statistics Authority. (2024). International merchandise trade statistics of the Philippines. https://psa.gov.ph
6. Philippine Statistics Authority. (2025). International merchandise trade statistics of the Philippines. https://psa.gov.ph
7. ASEAN Briefing. (2023). How RCEP ratification benefits the Philippines. https://www.aseanbriefing.com/news/rcep-comes-into-force-in-the-philippines/
8. Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. Journal of Applied Econometrics, 18(1), 1–22. https://doi.org/10.1002/jae.659
9. Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 785–794). https://doi.org/10.1145/2939672.2939785