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Forecasting Indonesian Shrimp Exports for Business Strategy and Sustainable Blue Economy Policy: Evidence from Machine Learning

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Abstract: Fisheries are a strategic sector in Indonesia and are often linked to the country's blue economy agenda. Shrimp remains a major export commodity, where performance is influenced by managerial and policy factors such as product quality compliance and cold-chain readiness, which are frequently discussed in relation to rejection risks in destination markets. This study provides a forecasting-based input for business strategy and policy by developing a machine-learning model to project Indonesia's shrimp export trends and linking the results to blue economy policy analysis. XGBoost, CatBoost, and LightGBM were compared to identify the most suitable model. XGBoost produced the best results, with RMSE 1.87, MAE 0.48, and R^2 1.00. In the first quarter, export values peaked in January, and whiteleg shrimp (udang vaname) dominated exports. The findings indicate that forecasting can support more targeted export planning, including aligning quality control and cold-chain capacity with peak periods, strengthening market coordination, and improving trade cooperation. Overall, this study highlights how predictive insights can inform practical strategies and policy direction while remaining aligned with sustainable blue economy goals.

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INTRODUCTION

The fisheries sector plays a strategic role in supporting Indonesia's blue economy agenda. According to (FAO, 2024), Indonesia produced 6,843,000 tons of fishery products in 2022, making it the largest producer in Southeast Asia and the second largest globally. However, Indonesia was ranked 12th among the world's largest exporters, with an export value of USD 4,032,969,000 (ITC, 2025). This indicates an empirical gap between production capacity and actual export performance. Export trends are also uncertain, and this condition is exacerbated by climate change, supply chain disruptions, and logistics systems that remain suboptimal, including cold chain infrastructure (Azzahra et al., 2025; FAO, 2022)

Previous studies have identified multiple determinants of export performance. Villasante et al. (2024) reported export surges during holiday seasons. Indrotristanto et al. (2023) found that shipping time affects rejection rates. Msukwa & Jere (2025) and Benmehaia et al. (2024) highlighted the association between export volumes and transaction years. Product type and form also matter, as processed products tend to generate higher value added (Sandaruwan & Banerjee, 2020), and certain commodities such as shrimp, tuna, and anchovies face higher rejection rates in the US and European markets (Indrotristanto et al., 2022). Destination-country factors are also significant,

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including GDP, population, language, and geographic distance (Alamri et al., 2024; Herianingrum et al., 2024), as well as the strength of the destination's food security system (Campbell, 2024). In addition, product adaptation and destination-market dynamics influence export outcomes (Wasik & Handriana, 2023), and free trade policies can increase export value (Xia et al., 2025). Despite these findings, no study has comprehensively organised these relationships into a structured model for explaining export value patterns.

In predictive modelling, Khiem et al. (2022) showed that Gradient Boosting Trees (GBT) perform well for short-term forecasting. Lu (2022), Qian & Zhang (2025), and Silva et al. (2024) reported that XGBoost, CatBoost, and LightGBM outperform SVM and kNN in forecasting related to global trade economics. CatBoost has also demonstrated strong accuracy for rice export forecasting (Phan et al., 2024). Zhu (2025) further supports the evidence that machine learning is effective for predicting national export-import volumes. However, there has been no systematic comparison of XGBoost, CatBoost, and LightGBM in the context of Indonesia's fisheries exports.

From a strategic perspective, the use of forecasting results to design export policies remains limited. Setiawan et al. (2023) developed a long-term forecasting approach for Indonesian exports, while Rianawati et al. (2024) showed that strategic innovation is an important driver of competitiveness in the fisheries sector. At the same time, weak data systems and limited inter-agency coordination continue to hinder effective policy implementation (Wuwung et al., 2024). To date, export trend forecasting has rarely been explicitly integrated into blue economy policy design, particularly in the context of Indonesian shrimp exports to the United States.

However, the existing literature still reveals several important gaps. First, previous studies have identified various determinants of export performance, but these factors have not yet been comprehensively organised into a structured explanation of export value patterns in the context of Indonesian shrimp exports. Second, although machine learning has been widely used in forecasting and trade-related studies, limited studies have systematically compared XGBoost, CatBoost, and LightGBM for forecasting Indonesian shrimp exports. Third, from a strategic perspective, forecasting results have rarely been linked explicitly to blue economy policy formulation. This limitation is important because stakeholders need not only accurate predictions but also practical guidance for export planning, competitiveness, and sustainability. Therefore, this study addresses the following research questions: (1) Which of XGBoost, CatBoost, and LightGBM provides the most suitable model for forecasting Indonesian shrimp export values to the United States? and (2) How can the forecasting results be translated into strategic recommendations for blue economy policy and export management?

The novelty of this study lies in the systematic comparison of leading machine learning algorithms in the context of Indonesian shrimp exports and in the integration of forecasting outputs into policy formulation through a strategic management lens. The selected algorithms were chosen based on their reported strengths in predictive accuracy and their ability to handle complex data patterns (Khiem et al., 2022; Lu, 2022; Qian & Zhang, 2025; R et al., 2025; Silva et al., 2024). In addition, this study contributes by showing that export forecasting can be used not only as a predictive tool but also as a basis for evidence-based policy actions to support demand planning, export readiness, competitiveness, and sustainability within the Blue Economy framework.

LITERATURE REVIEW

Blue Economy

The blue economy is a development approach that seeks to balance the utilisation of marine resources with the conservation of coastal and marine ecosystems. In the fisheries sector, this approach is operationalised through policies that prioritise sustainability, inclusiveness, and economic efficiency, particularly in export activities that contribute substantially to national income. Indonesia has identified several priority fishery export commodities, including whiteleg shrimp (vannamei), tuna, skipjack, frigate tuna, crab, blue swimming crab, and seaweed. These commodities face strong demand in global markets and serve as key pillars for the development of sustainable capture fisheries and aquaculture (Wibowo et al., 2023). Policy priorities commonly include logistics strengthening, overfishing control, and measurable fishing zones and quotas.

Within the export framework, Wibowo et al. (2023) highlight that policy should not focus solely on increasing trade volumes, but also on transforming production and distribution systems to comply with international standards. The adoption of principles such as traceability, eco-label certification, and value-added processing is considered a core strategy for improving competitiveness in major export markets such as the United States, the European Union, and Japan. In addition, technology-driven product diversification is emphasised as an important element in advancing an inclusive and environmentally responsible fisheries industrialisation process. This approach links export growth with environmental sustainability goals.

Machine Learning

This study is grounded in CRISP-DM data mining principles (Chapman et al., 2000), which aim to extract patterns from large datasets to support decision making. In the context of the blue economy, these techniques are relevant for managing fisheries export data, which are complex and dynamic, to produce accurate and actionable trend forecasts.

This study applies three main algorithms developed from Gradient Boosting Trees (GBT), namely eXtreme Gradient Boosting (XGBoost), Categorical Boosting (CatBoost), and LightGBM, following the approach discussed by Boldini et al. (2023).

Gradient boosting models are suitable for export value forecasting because they can capture non-linear relationships, handle mixed feature types (including categorical features), and perform well with complex patterns such as seasonality (Khiem et al., 2022; Silva et al., 2024). XGBoost is widely used due to its strong accuracy and regularisation mechanisms that help reduce overfitting in complex datasets. CatBoost is designed to handle categorical features effectively and can reduce overfitting risk when categorical variables are important. LightGBM is designed for efficient training and can perform well when the dataset includes many features and complex interactions (Boldini et al., 2023).

Strategic Management

Strategic management is the process of formulating, implementing, and evaluating decisions that enable an organisation to achieve long-term objectives by managing resources and leveraging opportunities in competitive markets. This framework provides a practical structure for translating forecasting results into policy priorities and implementation plans, including market access, quality assurance, sustainability, and infrastructure readiness. The stages of environmental scanning, strategy formulation, implementation, evaluation, and control are used in this study to frame blue economy policy recommendations (Wheelen et al., 2018).

Research Propositions

Based on the literature review, this study formulates three propositions. First, gradient boosting-based machine learning models are suitable for forecasting

Indonesian shrimp export values because they can handle complex and dynamic data patterns. Second, XGBoost, CatBoost, and LightGBM are expected to produce different predictive performances, so model comparison is needed to determine the most suitable approach. Third, forecasting results are expected to provide a relevant basis for strategic recommendations in blue economy policy, especially for export competitiveness, sustainability, and infrastructure readiness.

METHODS

This study uses a descriptive quantitative approach. Data were collected using a secondary data method and obtained from the Indonesian Ministry of Marine Affairs and Fisheries (MMAF). The data cover export transactions for Indonesian fisheries commodities during the first quarter of 2024. The initial dataset consisted of 177,935 records. After the data preparation process, the final dataset used in this study contained 3,743 records. The dataset contains information on fisheries export activities and includes the variables presented in Table 1.

Table 1. Operational Definition of Variables Used

Variable	Indicator	Data Type	Description
Date	Transaction date	Datetime	The date column was converted into a numeric format to make it easier for the model to process. The value represents the number of days since the first date in the dataset.
Commodity type	Udang, Udang Vaname, Udang Hias, Udang Windu, Udang Air Tawar, Udang Pink, Udang Putih, Kerupuk Udang, Udang Kipas, Udang Beku, Udang Air Laut, Udang Merah, Udang Ronggeng, Tepung Udang, Udang Kaleng	String	Product categories that were originally text were converted into numbers using label encoding to support model processing.
Destination country	United States	String	The destination-country variable was encoded using label encoding to replace the country category with a numeric value.
Export value	Export value (USD)	Float	The export value (USD) was transformed using Box–Cox to reduce skewness and make the distribution closer to normal.

Source: KKP (2024), processed by the authors

Python was used for data preparation, modelling, and visualisation. The conceptual framework of this study follows the CRISP-DM framework, as shown in Figure 1.

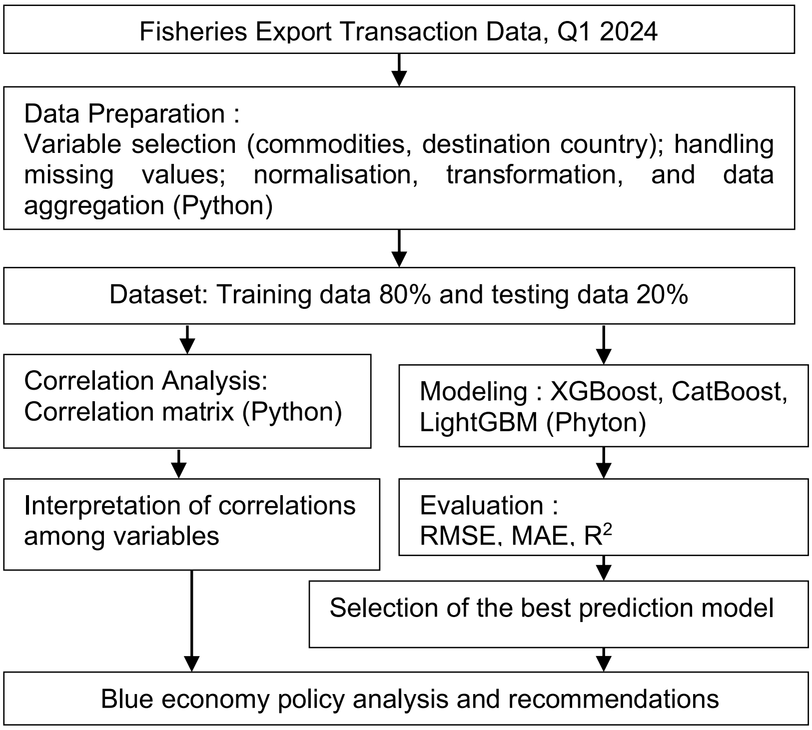

Figure 1. Conceptual framework of the study
Source: Developed by the author based on Chapman et al. (2000)

The analytical technique employed in this study is based on the CRISP-DM framework, which includes business understanding, data understanding, data preparation, modelling (XGBoost, CatBoost, and LightGBM), evaluation (RMSE, MAE, and R^2), and deployment (strategic management analysis). The forecasting results will be integrated with a strategic management analysis using the framework proposed by, which comprises environmental scanning, strategy formulation, strategy implementation, and evaluation and control.

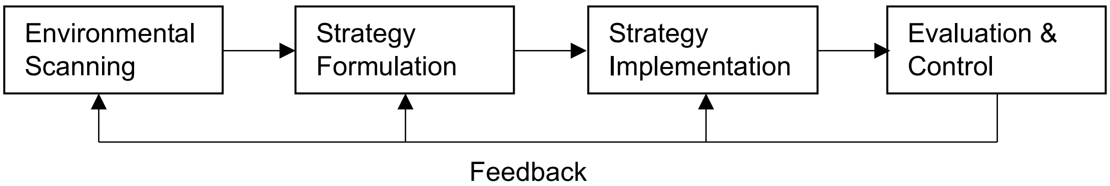

Figure 2. Strategic Management Conceptual Framework
Source: Adapted from Wheelen et al. (2018)

The research process begins with the collection of Fisheries Export Transaction Data for the first quarter of 2024. The data are then prepared through variable selection, handling of missing values, normalisation, and data transformation. The dataset is split into 80% training data and 20% testing data. Next, correlation analysis is conducted to examine relationships among variables using a correlation matrix. Predictive models are developed using XGBoost, CatBoost, LightGBM, and evaluated using RMSE, MAE, and R^2 to select the best-performing model. The selected model's predictions are then used as inputs for strategic management analysis of blue economy policies and to formulate recommendations that can support blue economy strategies in Indonesia's fisheries sector.

RESULTS AND DISCUSSION

Preprocessing data was conducted using Python. The study loaded the shrimp export dataset containing information on Date, Destination Country, Product, and Export Value (USD). First, the Destination_Country and Product columns, which contain country names and product categories, were converted into numeric values using label encoding to facilitate model processing. Next, a Box–Cox transformation was applied to the Export Value (USD) column to reduce skewness and make the distribution closer to normal, to improve model accuracy. Several additional features were then created, including Month, Month_Country, Product_Country, and Lag_1 (the previous month's export value). These engineered features were included to help the models identify seasonal patterns and interactions across variables. Finally, columns that were no longer needed, such as Destination_Country and Export_Value_USD_BoxCox, were removed to reduce redundancy and avoid duplicated information that could negatively affect model performance. These steps prepared the data for model training and improved predictive stability. Table 1 in the Methods section provides a detailed description of the dataset structure. Key variables include Day_Index (Date), Product, and Export_Value_USD (target).

There are 15 processed shrimp product types in the dataset, and the destination country is the United States. The distribution plot indicates that export values are highly skewed and show seasonal tendencies at the beginning and end of the month. This pattern supports the need for non-linear predictive models that can capture such dynamics.

XGBoost, CatBoost, and LightGBM were selected because they are robust gradient boosting models for non-linear prediction with mixed feature types. Each model was trained on 80% of the data and tested on the remaining 20%. Model performance was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2. A correlation matrix analysis was also conducted to examine correlations among variables.

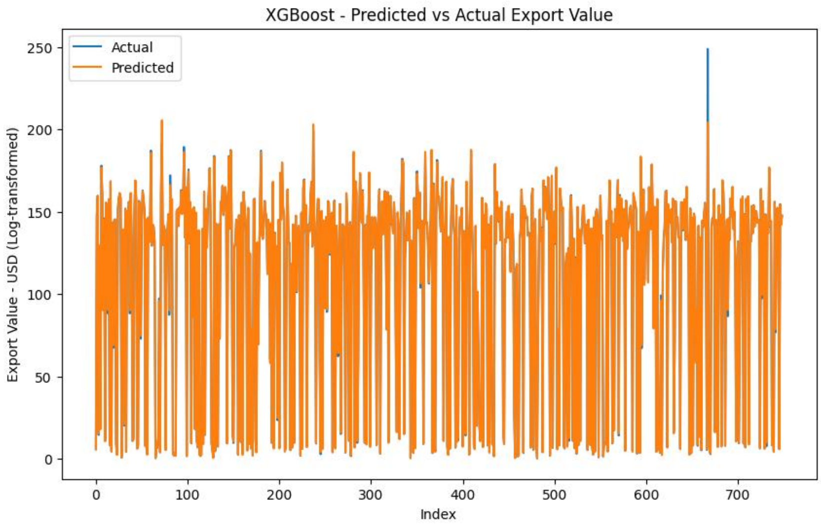

Figure 3. Predicted vs. Actual Export Values Using the XGBoost Algorithm
Source: KKP (2024), processed by the authors

Table 2. Evaluation of Export Value Prediction Models

Algorithm	RMSE	% (RMSE/Mean)	MAE	% (MAE/Mean)	R^2
XGBoost	1.87	1.76%	0.48	0.45%	1.00
CatBoost	9.02	8.51%	0.63	0.59%	0.98
LightGBM	9.09	8.57%	0.57	0.54%	0.98

Source: KKP (2024), processed by the authors

The modelling results indicate strong performance across XGBoost, LightGBM, and CatBoost in predicting export values. This is consistent with prior studies by Khiem et al. (2022); Phan et al. (2024); Silva et al. (2024), which report that these algorithms perform well for forecasting tasks. XGBoost produced an RMSE of 1.87, an MAE of 0.48, and an R^2 of 1.00, suggesting near-perfect predictive performance with very small errors. LightGBM achieved an RMSE of 9.09, an MAE of 0.57, and an R^2 of 0.98, indicating high accuracy with relatively low prediction error. CatBoost showed comparable performance, with an RMSE of 9.02, an MAE of 0.63, and an R^2 of 0.98, although slightly lower than LightGBM in this comparison. Overall, XGBoost delivered the best performance among the three models, with the highest R^2 and the smallest error values, while LightGBM and CatBoost also demonstrated strong predictive accuracy. These findings align with evidence reported by Khiem et al. (2022); Lu (2022); Qian & Zhang (2025); R et al. (2025); Silva et al. (2024), which highlights the strengths of XGBoost, CatBoost, and LightGBM in handling complex data and achieving high predictive accuracy.

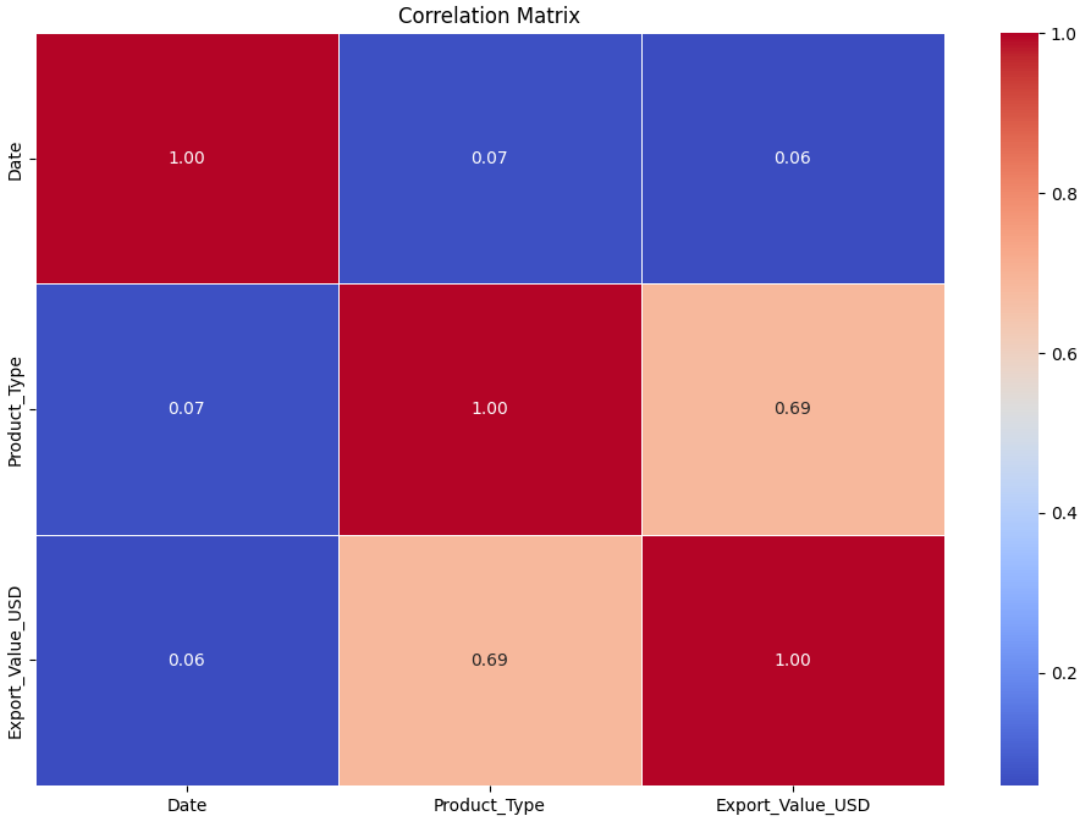

Figure 4. Correlation Matrix Across Variables
Source: KKP (2024), processed by the authors

The correlation matrix presented in Figure 4 summarises the relationships among variables in the dataset with respect to export value. The correlation between Date and Export Value (USD) is very low (r = 0.06), indicating that transaction timing has no meaningful linear association with export value. In contrast, the relationship between Product and Export Value (USD) is substantially stronger (r = 0.69), suggesting that product type plays an important role in explaining variation in export values. Overall, product type shows the strongest association with export value, supporting the model’s emphasis on product-driven variation.

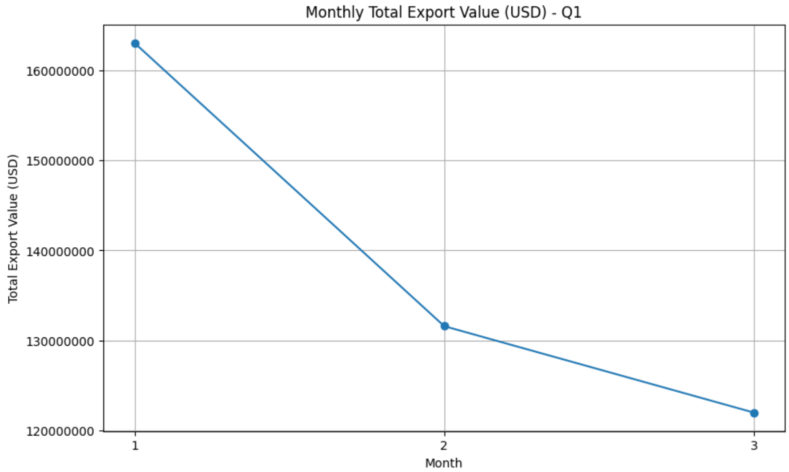

Figure 5. Seasonal Pattern of Exports in the First Quarter
Source: KKP (2024), processed by the authors

Seasonality is an important factor in forecasting export values. This is consistent with Villasante et al. (2024), who reported export surges for seafood during holiday seasons. Based on the model output, Month 1 (January) tends to exhibit higher demand than Month 2 (February) and Month 3 (March). This suggests that export planning should prioritise early-year readiness in inventory and logistics, followed by adjustment in February and March.

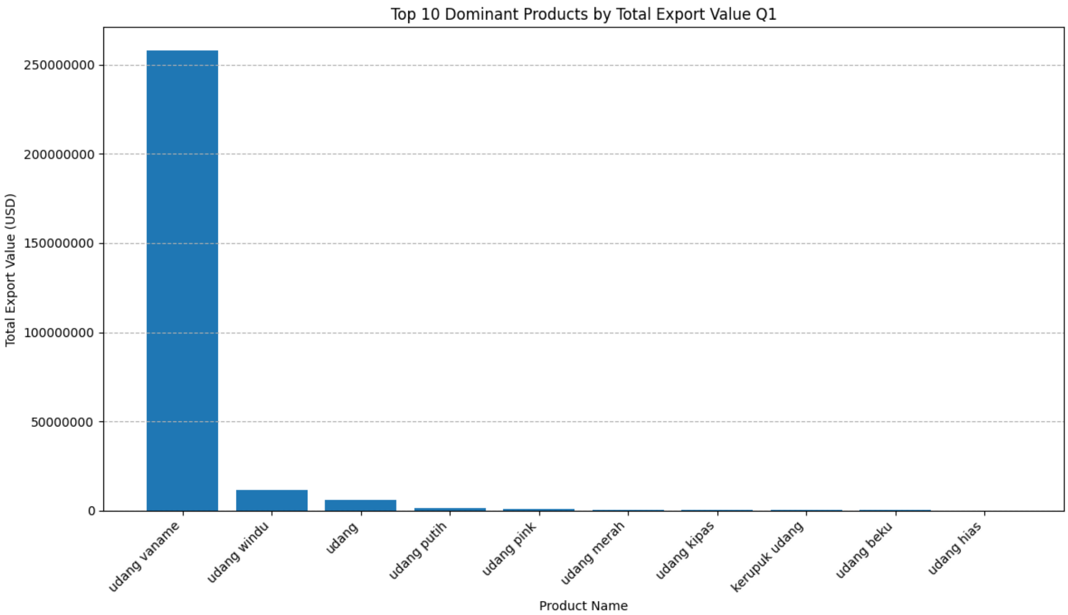

Figure 6. Total Shrimp Export Value for the Top 10 Products in the First Quarter
Source: KKP (2024), processed by the authors

Table 3. Top 10 Dominant Shrimp Export Products in the First Quarter

Rank	Product Name	Total Export Value (USD)	% of Total Exports
1	udang vaname	258,019,877.42	92.38%
2	udang windu	11,628,688.06	4.16%
3	udang	6,091,891.42	2.18%
4	udang putih	1,370,284.26	0.49%
5	udang pink	709,045.87	0.25%
6	udang merah	539,012.28	0.19%
7	udang kipas	388,581.13	0.14%

Rank	Product Name	Total Export Value (USD)	% of Total Exports
8	kerupuk udang	314,498.18	0.11%
9	udang beku	177,761.19	0.06%
10	udang hias	41,362.57	0.01%

Source: KKP (2024), processed by the authors

Figure 6, which presents the top 10 products ranked by total export value in the first quarter, shows a very high concentration in a single commodity—*udang vaname* (vannamei shrimp)—whose export value far exceeds that of the other products. This pattern indicates that first-quarter export performance is primarily driven by one dominant product, while the contributions of other products are relatively small. This finding implies a concentrated export structure, meaning that changes in demand, prices, or trade barriers that specifically affect the dominant product could have a substantial impact on total export value during the period. This interpretation aligns with prior evidence showing that product type influences export outcomes (Bennett et al., 2025; Löfstedt et al., 2025; Rey et al., 2023; Straume et al., 2024).

The dominance of Indonesia's vannamei shrimp exports to the United States in the first quarter can be explained by a combination of supply- and demand-side factors. On the supply side, Pacific white shrimp (*Litopenaeus vannamei*) is widely recognised as the most commercially valuable farmed shrimp species and has been reported to account for more than 70% of global farmed shrimp production. As a result, the export composition of major producing countries tends to be concentrated in vannamei products (Bardera et al., 2021). Forecast-informed planning can support inventory and logistics readiness for early-year demand peaks, while reducing the risk of overstocking after the peak period.

Based on the forecasting results and the analysis of factors influencing exports, a data-driven blue economy policy can be focused on several key areas:

Enhancing the Competitiveness of the Fisheries Sector

By leveraging forecast-based insights, policy can be directed toward optimising the distribution of fisheries products to destination markets with high demand, as indicated by the model's predicted patterns. For example, if the model forecasts an increase in demand for vannamei shrimp in the United States (US), policy measures can prioritize strengthening trade cooperation with the US and reducing trade barriers (e.g., tariffs or restrictive import regulations). This would enable Indonesia's fisheries industry to expand market access and meet international demand more efficiently.

In addition, strategic innovation is a key driver of competitiveness in the fisheries sector. Rianawati et al. (2024) found that product innovation strategies—such as introducing higher-quality fisheries products or more sustainable product offerings—are a dominant factor in improving competitiveness in the fisheries and marine sector. By integrating demand forecasts into policy design, the government can focus efforts on developing more innovative products, implementing more effective marketing strategies, and strengthening trade cooperation with countries projected to have high demand.

This also aligns with Indrotristanto et al. (2022), who reported that fisheries products can face rejection on specific dates, indicating the need to strengthen competitiveness through consistent quality assurance. This is closely linked to the provision of infrastructure and cold-chain facilities to maintain product quality during distribution, including under warmer weather conditions.

Sustainable Natural Resource Management

Blue economy policy that prioritises sustainability can be informed by predicted demand patterns to ensure balanced production and consumption. For instance, if the forecasts indicate a declining export trend, policy can prioritise sustainable stock management and product quality upgrading to maintain competitiveness in global markets.

This is consistent with Wuwung et al. (2024), who evaluated Indonesia's blue economy policy implementation and found that weak data systems and limited inter-agency coordination hinder policy effectiveness. Accordingly, stronger coordination is needed among ministries and agencies responsible for Maximum Sustainable Yield (MSY) policy, fishers, and industrial firms to ensure sustainability while optimising the fulfilment of market demand.

If the model predicts reduced demand during certain periods, policy can be designed to prevent overfishing or excess production that is misaligned with market needs. This is crucial for protecting natural resources and maintaining the balance of marine ecosystems. One practical approach is strengthening sustainable fisheries stock management. When export declines are expected, policies can focus on supporting natural stock recovery rather than increasing pressure on already constrained stocks.

In parallel, improving product quality can be prioritised to strengthen Indonesia's competitiveness in global markets. This includes enhancing aquaculture practices and processing standards, which can help maintain the presence of Indonesian fisheries products in international markets even when demand decreases in certain months.

Infrastructure and Facility Development

Export trend forecasts can support infrastructure planning for fisheries exports, including ports, processing facilities, and more efficient transportation systems, to ensure that products reach destination markets in good condition and with maintained quality. For example, if the model predicts demand surges in certain months, relevant stakeholders can plan upgrades to port capacity and cold-chain facilities to accommodate higher export volumes and ensure timely shipments.

This finding is also consistent with Wuwung et al. (2024), which highlights the importance of inter-agency coordination for infrastructure and facility development. The Ministry of Marine Affairs and Fisheries (KKP), for example, can provide cold-chain facilities to maintain product quality during distribution, while other ministries can support improved transport infrastructure, such as port development and more efficient logistics systems.

Table 4. Summary of the Strategic Plan for Indonesian Shrimp Exports to the United States, Q1 2024

Environmental Analysis	Strategy Formulation	Strategic Plan	Implementation Plan	Monitoring & Evaluation Plan	Supporting Literature
Internal: Export product portfolio highly concentrated in vannamei; limited diversification into higher value-added forms. **External:** US market demand and strict import controls; competition from major shrimp exporters.	**Competitive focus (SO):** Prioritise dominant products (vannamei) while increasing value added and differentiation to protect market share.	**Product upgrading and differentiation:** expand value-added shrimp products and sustainability attributes for US buyers.	(i) support processors to produce value-added products; (ii) buyer-linked product specs and packaging; (iii) promote sustainability claims supported by documentation.	KPIs: share of value-added exports; average export value per shipment; repeat buyer contracts; product mix diversification index.	(Rianawati et al., 2024; Sandaruwan & Banerjee, 2020; Wibowo et al., 2023)

Environmental Analysis	Strategy Formulation	Strategic Plan	Implementation Plan	Monitoring & Evaluation Plan	Supporting Literature
Internal: Quality management and documentation vary across exporters; cold-chain and handling gaps increase risk. **External:** product refusals/rejections risk in export markets; food safety and inspection pressure.	**Risk reduction (WT):** strengthen quality assurance and compliance to reduce refusals and protect export value.	**Export quality assurance:** strengthen traceability, SOPs, and compliance readiness across the chain.	(i) implement compliance audits for processors and logistics; (ii) standardise SOPs for handling and packaging; (iii) traceability and recordkeeping improvements.	KPIs: refusal/rejection cases; compliance audit pass rate; corrective action closure rate; quality incident frequency.	(Indrotristanto et al., 2022, 2023)
Internal: production planning is often not linked to demand signals; coordination gaps across agencies and actors. **External:** demand uncertainty; volatility in trade conditions; seasonal export patterns.	**Demand alignment (ST):** Use forecasts to reduce supply–demand mismatch and improve export readiness in peak periods.	**Forecast-informed planning:** align inventory, processing capacity, and shipment schedules with predicted demand peaks.	(i) establish monthly export planning based on forecast outputs; (ii) adjust processing shifts and inventory; (iii) coordinate shipment slots and logistics capacity for peak months.	KPIs: forecast error tracking; stock-out/overstock incidence; on-time shipment rate; capacity utilisation during peak months.	(Khiem et al., 2022; Silva et al., 2024; Villasante et al., 2024)
Internal: stock data and enforcement capacity vary; sustainability implementation requires coordination. **External:** climate variability; sustainability requirements; risk of overproduction/overfishing when demand weakens.	**Sustainability governance (ST/WT):** integrate demand forecasts with MSY-based management to support blue economy objectives.	**Sustainable resource management:** align production intensity with MSY principles and market signals.	(i) integrate forecast signals into production guidance; (ii) strengthen MSY coordination and reporting; (iii) capacity building for sustainable aquaculture practices.	KPIs: MSY compliance indicators; stock/harvest metrics; mismatch index (production vs demand proxy); sustainability compliance rate.	(Wibowo et al., 2023; Wuwung et al., 2024)
Internal: cold-chain, port capacity, and logistics integration remain uneven; quality can degrade during distribution. **External:** temperature and lead-time risks; international standards; logistics costs and delays.	**Infrastructure readiness (WO):** improve cold chain and logistics efficiency to protect quality and reduce export losses.	**Cold-chain and logistics strengthening:** increase storage/reefer capacity and monitoring to maintain quality.	(i) strengthen cold-chain capacity; (ii) standardize temperature handling; (iii) improve port logistics coordination.	KPIs: cold-chain utilisation; lead time; quality loss proxy; on-time shipment rate; logistics cost per shipment.	(Indrotristanto et al., 2022; Pusporini & Dahdah, 2020; Wuwung et al., 2024).

Source: Developed by the authors based on KKP (2024), forecasting results, and supporting literature.

The strong model evaluation results indicate that the data used in this study explain most of the variance in export values. Factors such as month, destination country, and product type have a substantial influence on export value. The export trend forecasts generated by the model can support demand projections, inventory preparedness, and the development of data-driven blue economy policies that promote the sustainability of the fisheries sector and enhance the competitiveness of export products. Overall, export value forecasting supports policy planning for sustainable production and infrastructure readiness to meet global demand more efficiently and responsibly.

CONCLUSION

This study shows that machine learning can effectively support the forecasting of Indonesian shrimp export values to the United States and provide a practical basis for export strategies aligned with the blue economy. Among the models compared, XGBoost was the most suitable for this study, indicating that data-driven forecasting can identify export patterns more reliably and support better planning. The findings also show that export activity tends to peak in January and is strongly dominated by vannamei shrimp, suggesting the need to strengthen cold-chain capacity, quality assurance, and port logistics coordination during peak periods. Therefore, forecasting is useful not only for predicting export trends but also for generating strategic recommendations to improve export readiness, competitiveness, and sustainability. However, this study is limited to shrimp exports to the United States and to the observation period used in the dataset, so future research should expand the scope to other commodities, destination markets, external variables, and alternative modelling approaches. The authors gratefully acknowledge the support of the Center for Marine and Fisheries Education, Ministry of Marine Affairs and Fisheries, for facilitating this research.

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