Journal of Applied Informatics and Computing (JAIC)
Vol.10, No.3, June 2026, pp. 2400~2414
e-ISSN: 2548-6861

An Integrated Predictive-Prescriptive Framework for Indonesian Export Allocation Using Hierarchical Commodity Classification and Gurobi Optimization

Zekko Jotty Nugroho [1], Farrikh Alzami [2]*, Amiq Fahmi [3], Agus Winarno [4], Siti Hadiati Nugraini [5], Muhammad Naufal [6], Ifan Rizqa [7]
[1234] Program Studi Sistem Informasi, Fakultas Ilmu Komputer, Universitas Dian Nuswantoro, Semarang, Indonesia
[567] Fakultas Ilmu Komputer, Universitas Dian Nuswantoro, Semarang, Indonesia
112202206860@mhs.dinus.ac.id [1], alzami@dsn.dinus.ac.id [2], amiq_fahmi@dosen.dinus.ac.id [3], agus.winarno@dsn.dinus.ac.id [4], shnugraini@dsn.dinus.ac.id [5], m.naufal@dsn.dinus.ac.id [6], risqa.ifan@dsn.dinus.ac.id [7]

Article Info

Article history:

Received 2026-04-18
Revised 2026-05-07
Accepted 2026-05-25

Keyword:

Export Allocation,
Hierarchical Classification,
Forecasting,
Ensemble Learning ,
Prescriptive Optimization.

ABSTRACT

Exports play a critical role in economic growth; however, existing studies often rely on aggregate data and lack integration between predictive analysis and prescriptive decision-making. This study aims to develop an integrated predictive–prescriptive framework for optimizing Indonesian export allocation using hierarchical commodity classification, multi-model forecasting, and linear programming optimization. Using United Nations Commodity Trade Statistics Database (2019-2024), commodities were classified into raw, semi-finished, and finished categories through a Large Language Model-based approach. Forecasting performance was evaluated using SARIMA, Holt-Winters, Random Forest, Gradient Boosting, and XGBoost based on Mean Absolute Percentage Error (MAPE). The results show that model performance varies across commodity stages, where Random Forest achieved 18.11% MAPE for volatile raw shrimp, while SARIMA obtained 8.07% MAPE for stable finished cassava leaves. The forecasting results were integrated into a Gurobi optimization model to generate export allocation strategies. The model increased export destination coverage for eucalyptus leaves from 79 to 130 countries and improved revenue for raw cassava leaves from USD 1,443,290 to USD 1,560,651 despite reduced export volume. This study contributes by explicitly integrating hierarchical commodity classification, multi-model forecasting, and prescriptive optimization into a unified decision-support framework, addressing the limitations of prior studies that primarily focus on forecasting without actionable optimization. However, the model remains sensitive to volatile trade data and does not yet incorporate external factors such as trade policies and regulatory dynamics, which may influence real-world applicability.

I. INTRODUCTION

Exports are a crucial factor in economic growth and stability, reflecting national productivity in the global market. This statement aligns with research by [1], which emphasizes that exports are a crucial element in maintaining a country's economic growth. These findings are also consistent with studies by [2] and [3] which indicate a link between exports, economic activity, and international competitiveness. However, commodity markets are vulnerable to various external disruptions, such as global pandemics and geopolitical conflicts, which can impact market and trade dynamics [4]. This situation is further fuelled by increasing global uncertainty, changes in trade policies, and protectionism, as explained by [5]. Therefore, the ability to predict export volume and value is essential as part of a country's trade planning and strategy [6]. This urgency is further reinforced by [2] and [7] who proved that an optimization-based analytical approach can support more structured and efficient decision making.

Research on export forecasting has advanced rapidly in recent years. For example, a study by [1] predicted Indonesian exports using a hybrid ARIMA-LSTM model, utilizing monthly data from the Federal Reserve Economic Data Centre for the 1998-2019 period. In this approach, time-series data were decomposed into trend, seasonal, and residual components, combining statistical and deep learning methods. The ARIMA model was employed to capture linear patterns in the trend component, while the LSTM model was used to model non-linear patterns in the seasonal and residual components ([8]; [9]). Evaluation results demonstrated that this hybrid approach provided more accurate and stable performance compared to single-model approaches, as indicated by lower error rates [2]. However, despite its effectiveness, this approach relied on national aggregate export data, which may not adequately represent the heterogeneity across commodities. Aggregate-level data tend to obscure differences in characteristics between commodity categories, such as volatility, price dynamics, and value-added structures. Consequently, variations across commodity stages such as raw materials, semi-finished products, and finished goods cannot be explicitly captured. This limitation reduces the relevance of predictive results for decision-making at a more granular, commodity-specific level. In the context of global trade, such differences are critical, as they influence value-added dynamics and trade patterns, aligning with the global value chain perspective that emphasizes the interconnectedness of production stages across countries [10].

Beyond data representation, another weakness identified in [1] study is the lack of integration of prediction results into strategic decision-making. This literature generally stops at the predictive stage. However, [6] and [8] emphasize that forecasting results should ideally contribute significantly to the actual policy planning process. This absence of a prescriptive stage highlights the gap in the utilization of data analytics. Complementing this idea, [11] demonstrated that optimization approaches can improve decision quality in large-scale systems. Referring to modern approaches, the integration of predictive and optimization models, such as within a prescriptive analytics framework, can be deployed to maximize economic objectives based on prediction results, as explained by [12].

Following the development of other predictive literature, various studies have begun to utilize more complex data and methods. One such study is by [13], which integrates sales data with external variables into SARIMAX and VAR models to predict demand in the MSME sector. This approach shares similarities with the research [14], which concluded that external variables (such as rainfall and inflation) are closely related to commodity price dynamics. Furthermore, [15] also integrated various variables into a machine learning framework to boost prediction accuracy. The evaluation results of [13] show that the SARIMAX model, supplemented with weather variables, produces superior performance, although the relationship between weather indicators and sales is not always strong.

In the context of algorithm comparison, a study by [16] attempted to predict arecanut prices in Kerala using monthly price data from 2007-2017 from 14 districts. The data underwent preprocessing, including handling missing values using interpolation and linear regression methods, and were then aggregated into monthly average prices. Initial analysis using boxplots and the autocorrelation function (ACF) revealed trends and seasonal patterns in the data. The study then compared SARIMA, Holt-Winters, and LSTM methods. Evaluation using Root Mean Square Error (RMSE) concluded that LSTM performed better in capturing nonlinear patterns. However, this research comparison was limited to time series and deep learning datasets and did not include ensemble-based approaches. However, tree-based ensemble algorithms such as gradient boosting, specifically XGBoost, designed by [17], have proven to be highly capable of efficiently handling large-scale data. The strength of this tree-based algorithm is also validated by the findings of [18] and supported by studies by [14] and [15], which documented its competitive performance on complex data relationships. Furthermore, the evaluation in [16] study focused solely on a single price variable with a single metric, without including volume or revenue indicators, and did not integrate comprehensive evaluation metrics such as MAE and MAPE, as suggested by [9] and [2].

A series of limitations in the previous literature highlight the urgency to develop a much more integrated approach. With the identification of these gaps, this study formulates its exploratory objectives into several research questions as follows: (1) How does the application of hierarchical commodity classification (raw, semi, finished) affect the accuracy of export predictions compared to the use of aggregate export data?; (2) Which model provides the best prediction results based on a comparative evaluation between statistical models and tree-based ensemble algorithms at each stage of commodity down streaming?; (3) Which algorithm is best selected to predict target volume and revenue variables at each commodity stage based on the lowest MAPE metric?; and (4) How does the integration of predictive models with prescriptive optimization using the Gurobi Optimizer produce export allocation recommendations that can maximize state foreign exchange?

This study differs from prior research not only by integrating predictive analytics with prescriptive optimization for export allocation, which has been widely explored in the supply chain literature, but more importantly by introducing a hierarchical commodity-based modelling approach that explicitly captures value chain stages (raw, semi-finished, and finished). In contrast to aggregate-based approaches, this framework enables a more granular and structured analysis of export dynamics, resulting in an integrated predictive-prescriptive decision-support framework.

In order to address the research questions, this study evaluates whether hierarchical commodity classification and multi-model forecasting can improve prediction accuracy across different commodity stages. Furthermore, it investigates how predictive outputs can be systematically integrated into a prescriptive optimization model to generate optimal export allocation strategies in Indonesia. In addition, this study employs an LLM-based commodity classification approach with a structured validation procedure to improve consistency and mitigate potential bias in the classification results. This combination has not been explicitly addressed in prior export allocation studies, particularly in the context of developing countries such as Indonesia.

The contributions of this research are summarized into four main aspects, namely: (1) Application of commodity stage classification, namely grouping data into raw, semi, and finished using the help of Large Language Model (Gemini API) to improve the weaknesses of aggregate data models in previous research; (2) Comprehensive model evaluation, namely conducting comparisons between statistical models (SARIMA, Holt-Winters) and tree-based ensemble algorithms (Random Forest, Gradient Boosting, XGBoost) to fill the gap in methodological comparison; (3) Determination of the best and most accurate predictive model based on the Mean Absolute Percentage Error (MAPE) metric at each commodity stage for both volume and revenue target variables; and (4) Prescriptive optimization, namely deploying the Gurobi Optimizer to transform prediction results into recommendations for export resource allocation to maximize the country's foreign exchange, which also addresses the limitations of previous research which generally only stops at the forecasting stage.

II. METHOD

To provide a systematic overview of the research stages carried out, this research methodology is structured in the form of a structured process flow starting from data collection to the prescriptive optimization stage, as shown in the following figure 1. This research begins with the (1) Gemini API Setup and (2) Harmonized System (HS) Code Mapping stages implemented in the GeminiComtrade_API.ipynb notebook. In the initial stage, the system installs and initializes Google Generative AI by configuring multiple Gemini API keys with a fallback mechanism. This design ensures continuity of the classification process, as the system automatically switches to an alternative key when the usage limit of a primary key is reached.

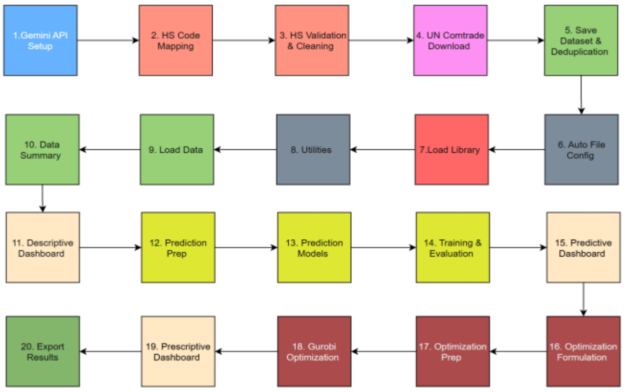


Figure 1. Research Methodology Flow for Predictive and Prescriptive Export Analysis

In the HS Code Mapping stage, the system receives commodity input and processes it using a structured prompt designed to guide the Large Language Model (LLM) in generating a hierarchical representation of the commodity value chain. Specifically, the model is instructed to identify and classify the commodity into three downstream stages: raw, semi-finished, and finished products. The output is generated in a structured JSON format containing (1) candidate HS codes, (2) commodity descriptions, and (3) justification for each classification decision. This approach allows the model not only to perform code mapping but also to capture the logical transformation pathway of the commodity within a value chain context.

The next stage is (3) HS Validation and Cleaning, which aims to ensure consistency and reliability of the LLM-generated outputs. First, all HS codes are normalized to the standard 6-digit UN Comtrade format by removing non-numeric characters and enforcing consistent formatting. Second, duplicate HS codes are eliminated to avoid redundancy. Third, a conflict resolution mechanism is applied: if a single HS code appears across multiple categories (raw, semi-finished, or finished), the system automatically identifies and replaces it with an alternative code that better reflects the hierarchical structure. In addition, HS code descriptions are cross-checked to ensure logical alignment with the commodity transformation pathway. This validation process serves as a rule-based consistency check to reduce potential inconsistencies arising from the probabilistic nature of the LLM. However, further validation through domain experts or integration with official classification standards is recommended to improve classification robustness and reduce potential bias.

After the HS codes are validated, stage (4) UN Comtrade Download is conducted to retrieve international trade data from the United Nations Commodity Trade Statistics Database (UN Comtrade). The data extraction process utilizes multi-year batching, pagination, and rotation of multiple subscription keys to overcome API limitations. The retrieved dataset includes Indonesian export and import data for the period 2019–2024, consisting of variables such as netWgt (volume), primaryValue (trade value), partnerCode, cmdCode, flowCode, and period.

Finally, stage (5) Dataset Saving and Deduplication is performed. The collected data are merged and processed through a deduplication procedure based on key identity attributes (including period, reporterCode, partnerCode, cmdCode, and flowCode) to ensure data uniqueness and integrity. The cleaned dataset is then stored in CSV format with a structured naming convention to support the subsequent analysis stages.

Despite its wide coverage and standardized reporting structure, the UN Comtrade database may still contain data quality limitations. In particular, missing values, reporting delays, and inconsistencies across reporting countries may affect data completeness and reliability. In addition, differences in national reporting standards and classification practices may introduce potential reporting bias in trade records. Although data cleaning and deduplication procedures are applied in this study to improve data consistency, these inherent limitations should be considered when interpreting the results.

In the second notebook, BI_Perdagangan_Indonesia.ipynb, the process continues with stages (6) Auto File Config, (7) Load Library, and (8) Utilities. The system automatically reads all CSV files in the folder and configures them without manual input, extracting information such as trade type, commodity category, HS code, and year range from the file name. Next, various required libraries such as pandas, numpy, plotly, statsmodels, scikit-learn, xgboost, and gurobipy are loaded to support the entire analysis pipeline. In the utilities stage, important functions are defined such as numeric data format, USD value conversion, and price per kilogram calculation obtained from the ratio between primaryValue and netWgt. In addition, a filtering process is carried out to only retrieve data with Indonesia as the reporter and eliminate the global total aggregation.

Stage (9) Load Data loads all detected datasets into an organized data structure to store raw data and filtered data from Indonesia in each commodity category. Next, in stage (10) Data Summary, descriptive statistics are calculated, including the number of rows of data (records), number of partner countries, total export volume, total trade value in USD, average price per kilogram, and time period coverage. This information is then visualized in stage (11) Descriptive Dashboard in the form of monthly and annual volume and price trend graphs, destination country distribution, and a comparison between Indonesian supply and global demand proxies. This stage provides a comprehensive understanding of the historical state of trade, while also answering questions about what has happened to the data.

Next, the predictive analysis stage is carried out through stages (12) Prediction Prep and (13) Prediction Models. Data is focused on exports for the raw, semi, and finished categories, which are then divided into training data (2019-2023) and testing (2024). The data is aggregated monthly for all partner countries so that market patterns can be mapped comprehensively. The models used consist of SARIMA and Holt-Winters as classic time series approaches, as well as Random Forest, Gradient Boosting, and XGBoost as tree-based ensemble models. Specifically for machine learning-based models, feature engineering is carried out using the variables month, year, lag_1, lag_12, rolling_mean_3, and rolling_std_3 to identify trends, seasonality, and data volatility patterns. The prediction targets set are volume (netWgt) and trade value (primaryValue).

In the (14) Training & Evaluation stage, each model is trained and evaluated using MAE, RMSE, and MAPE metrics against 2024 data. Although multiple evaluation metrics are employed, MAPE is selected as the primary criterion for model selection due to its interpretability in percentage terms, allowing comparison across commodities with different scales. However, MAPE has known limitations, particularly for volatile data or when actual values approach zero, which may lead to inflated error values. Therefore, model performance is also interpreted in conjunction with MAE and RMSE to ensure robustness and consistency of the evaluation. The results of this evaluation are used to determine the best model based on the lowest MAPE value for each target variable and commodity category. All of this data is then visualized in the (15) Predictive Dashboard stage in the form of volume and revenue forecast graphs, model performance comparisons, evaluation metric heatmaps, and feature importance. This aims to provide an overview of future predictions and the factors that influence them.

The final stage of the research is the integration of predictive analysis with prescriptive optimization through stages (16) Optimization Formulation, (17) Optimization Prep, and (18) Gurobi Optimization. To explicitly establish the integration between forecasting and optimization, the outputs from the prediction stage are directly used as key inputs in the optimization model.

At this stage, the optimization model is formulated in the form of linear programming to allocate Indonesia's export volume to each partner country each month with the aim of maximizing the total predicted revenue. In this study, linear programming is selected as the primary optimization approach due to its ability to provide a globally optimal solution under deterministic assumptions and its computational efficiency when handling structured trade data. Compared to heuristic methods, which typically generate near-optimal solutions without guaranteeing optimality, linear programming offers a more rigorous and interpretable solution framework for policy-oriented decision-making.

On the other hand, stochastic and robust optimization approaches are capable of incorporating uncertainty in key parameters such as demand fluctuations, price volatility, and trade dynamics. However, these approaches require more complex model structures and additional assumptions regarding probability distributions or uncertainty sets, which are beyond the scope of this study. Therefore, this research adopts a deterministic linear programming formulation as a baseline model, while acknowledging that future extensions may incorporate stochastic or robust optimization to enhance model realism under uncertain economic conditions.

The time index is stated as $m \in \{1, 2, \dots, 12\}$ representing the month, while p represents the partner country of export destination. From the results of the prediction stage, $\widehat{V_m^{\text{export}}}$ the forecast export volume and $\widehat{R_m^{\text{export}}}$ the forecast revenue is obtained. The predicted export volume is used as a constraint representing national supply capacity, while the predicted revenue is used to derive the price component in the objective function. Based on these two values, the monthly base price is calculated as part of the overall optimization formulation.

To provide a clearer mathematical structure of the optimization model, the formulation is organized into three main components: decision variables, objective function, and constraints, supported by intermediate formulations derived from both predictive outputs and historical trade data. The decision variable is defined as $x_{p,m}$ representing the export volume allocated to partner country (p) in month (m). The formulation begins with the transformation of forecasting outputs into economic parameters. Specifically, the predicted export volume $\widehat{V_m^{\text{export}}}$ and predicted revenue $\widehat{R_m^{\text{export}}}$ are used to compute the base price, as defined in Equation (1).

To capture market-specific dynamics, the model incorporates historical pricing behavior. The average historical price for each partner country is calculated in Equation (2), followed by the derivation of the relative monthly price adjustment factor in Equation (3). These components are combined to construct the adjusted price coefficient (price curve) in Equation (4), which serves as the economic weight in the optimization model.

Furthermore, the model incorporates demand-side constraints through the estimation of partner country import capacity using a quantile-based approach. This process includes data ordering (Equation (5)), quantile calculation (Equation (6)), position estimation (Equation (7)), and interpolation (Equation (8)), ensuring that the capacity constraints reflect realistic market demand conditions.

The objective function is formulated in Equation (9), which maximizes total export revenue based on the allocation decision variable and the constructed price coefficients. The model is subject to three main constraints: (1) national export capacity constraints derived from predicted export volume (Equation (10)), (2) partner country import capacity constraints based on historical demand estimation (Equation (11)), and (3) non-negativity constraints ensuring feasible allocation values (Equation (12)). The detailed mathematical formulation of these components is presented in the following equations.

$$\text{pred\_price}_m = \frac{\widehat{R_m^{\text{export}}}}{\widehat{V_m^{\text{export}}}} \tag{1}$$

For each partner country p, the average historical price is calculated using the following formula:

$$\text{avg\_price}_p = \frac{\sum_t \text{primaryValue}_{p,t}}{\sum_t \text{netWgt}_{p,t}} \tag{2}$$

In addition, the historical price per kilogram per month ($\text{price\_per\_kg}_{p,m}^{\text{hist}}$) is also calculated . Based on these two values, an adjustment factor is formed with the equation:

$$\alpha_{p,m} = \frac{\text{price\_per\_kg}_{p,m}^{\text{hist}}}{\text{avg\_price}_p} \tag{3}$$

This adjustment factor represents the relative price pattern of a partner country in a given month compared to its historical average. Furthermore, the objective coefficient used in the optimization, namely the price curve, is defined as:

$$\text{price\_curve}_{p,m} = \max\left(0, \text{pred\_price}_m \times \alpha_{p,m}\right) \tag{4}$$

A zero-bounded maximum function is applied to the equation above to ensure that prices are not negative. This means that the price curve represents not actual transaction prices, but rather adjusted economic weights based on predictions and historical patterns of partner countries, thus providing a basis for determining optimal allocations.

In addition, the import capacity of each partner country is determined based on historical data $h_{p,m,t}$, namely the import volume of the partner country $p$in the month $m$of observation t, with a total of observations of T. The historical data is first sorted from the smallest to the largest value as follows:

$$h_{(1)} \le h_{(2)} \le \cdots \le h_{(T)} \tag{5}$$

Based on this ordering, import capacity is calculated using the 0.80 quantile (p80) with the following formulation:

$$C_{p,m}^{\text{import}} = Q_{0.80}\left(h_{p,m,1}, h_{p,m,2}, \dots, h_{p,m,T}\right) \tag{6}$$

The quantile position is calculated using the equation:

$$pos = 1 + 0{,}80(T - 1) \tag{7}$$

This equation defines the theoretical position P_{80}in the sorted data. If the position value is not an integer, the quantile value is calculated using linear interpolation between the two nearest observations as follows:

$$Q_{0.80} = x_{(k)} + d\left(x_{(k+1)} - x_{(k)}\right) \quad (8)$$

In this equation, $x_{(k)}$ is the value in the th order k, $x_{(k+1)}$ is the value in the next order, and $d$is the decimal part of the position value.

The decision variable in this model is $x_{p,m}$, namely the export volume (kg) allocated to the partner country p in month m. The objective function of this model is to maximize the total revenue resulting from the allocation, which is formulated as follows:

$$\max \sum_{m} \sum_{p} x_{p,m} \cdot \text{price\_curve}_{p,m} \quad (9)$$

This function indicates that the model will search for a combination of export volume allocations to all partner countries each month in order to generate maximum revenue value based on the calculated price curve. To ensure the resulting solution remains realistic, the model is constrained by several constraints. The first constraint is the national export capacity limit:

$$\sum_{p} x_{p,m} \leq \widehat{V_m^{\text{export}}} \quad \forall m \quad (10)$$

This equation means that the total export allocation to all countries in month m must not exceed the predicted export volume for that month. Meanwhile, the symbol $\forall m$ confirms that this limit applies across the board for every month within the analysis period. The second constraint is the import capacity limit of partner countries:

$$x_{p,m} \leq C_{p,m}^{\text{impor}} \quad \forall p, m \quad (11)$$

This constraint ensures that the export allocation volume of each partner country in a given month cannot exceed its historical import capacity. The symbol $\forall p, m$indicates that this constraint applies to all combinations of partner countries and months. Furthermore, the final constraint is the non-negativity constraint:

$$x_{p,m} \geq 0 \quad \forall p, m \quad (12)$$

This constraint ensures that the entire volume of export allocations is positive or zero for each country and month. The solution to this model yields an optimal solution in the form of a distribution of export allocations per country and per month that maximizes revenue, while still considering the limitations of supply capacity and market demand. Interpretatively, a larger forecast export volume will expand the allocation space, while partner countries with higher price curve values will tend to receive larger allocations as long as they do not violate the p_{80}. based import capacity limit.

III. RESULT AND DISCUSSION

The initial stage of this research classifies commodities into three downstream stages: raw, semi-finished, and finished, using a Large Language Model-based approach. The HS code classification results for four main commodities are shown in Table 1.

TABLE I
HS CODE CLASSIFICATION RESULTS BASED ON COMMODITY HIERARCHY

Commodity	Stage	HS Code	Description
Shrimp	Raw	030635	Fresh/Chilled Shrimp (in shell)
Shrimp	Semi-Finished	030635	Frozen Peeled and/or Headless Shrimp
Shrimp	Finished	030617	Breaded Shrimp (Prepared for cooking)
Coconut Shell Charcoal	Raw	140490	Raw Coconut Shells
Coconut Shell Charcoal	Semi-Finished	440290	Coconut Shell Charcoal
Coconut Shell Charcoal	Finished	380210	Coconut Shell Activated Carbon
Cassava Leaves	Raw	070999	Fresh cassava leaves (Manihot esculenta Crantz)
Cassava Leaves	Semi-Finished	071290	Dried or frozen cassava leaves (whole, cut, or broken)
Cassava Leaves	Finished	210690	Cassava leaf powder (for food additive, supplement, or functional food)
Eucalyptus Leaves	Raw	121190	Fresh or dried eucalyptus leaves (Eucalyptus spp.)
Eucalyptus Leaves	Semi-Finished	330129	Crude eucalyptus essential oil, unrefined
Eucalyptus Leaves	Finished	300490	Eucalyptus-based medicaments or aromatherapy preparations for retail sale

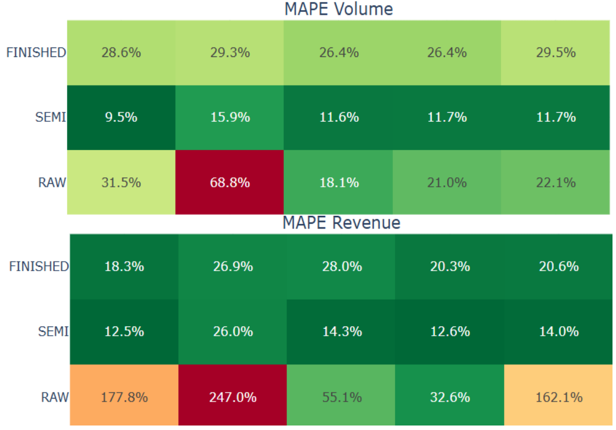
Based on this table, each commodity was successfully mapped into a logical value chain structure. For example, coconut shell charcoal starts from raw materials (HS code 140490), is processed into charcoal (440290), and finally becomes an activated carbon product (380210). This mapping demonstrates Gemini's ability to structure aggregate data into downstream stages for more precise value-added analysis. However, this approach has limitations because it absolutely uses the UN Comtrade standard 6-digit HS code benchmark, which potentially lacks specificity in detailing commodity variants.

Next, modelling performance was evaluated to compare statistical models and Tree-Based Ensembles. Modelling evaluation for shrimp is shown in Figure 2. For this commodity, the Random Forest model demonstrated impressive performance in predicting volume at the raw stage with a MAPE of 18.1%. This achievement significantly outperformed other models, including SARIMA (31.5%) and Holt-Winters, which experienced a spike in errors of up to 66.8%.

This superiority was reinforced by the low MAE (10,214) and RMSE (14,121) values, which confirmed the stability of the model's prediction accuracy against the highly volatile characteristics of raw material data.

Moving to the semi-finished stage, the SARIMA statistical model managed to record the best performance with a MAPE of only 9.5%. This figure is superior when compared to Random Forest (11.6%) and Gradient Boosting (11.7%). This is also reflected in the relatively lower error magnitude, with an MAE value of 981,673 and an RMSE of 1,237,558.

This fact confirms that statistical models are indeed more capable of capturing stable patterns in semi-finished commodities. Meanwhile, at the finished stage, all models showed quite competitive performance with a MAPE range between 26.4% and 29.3%. At this phase, Random Forest and Gradient Boosting achieved the lowest MAPE at 26.4%.

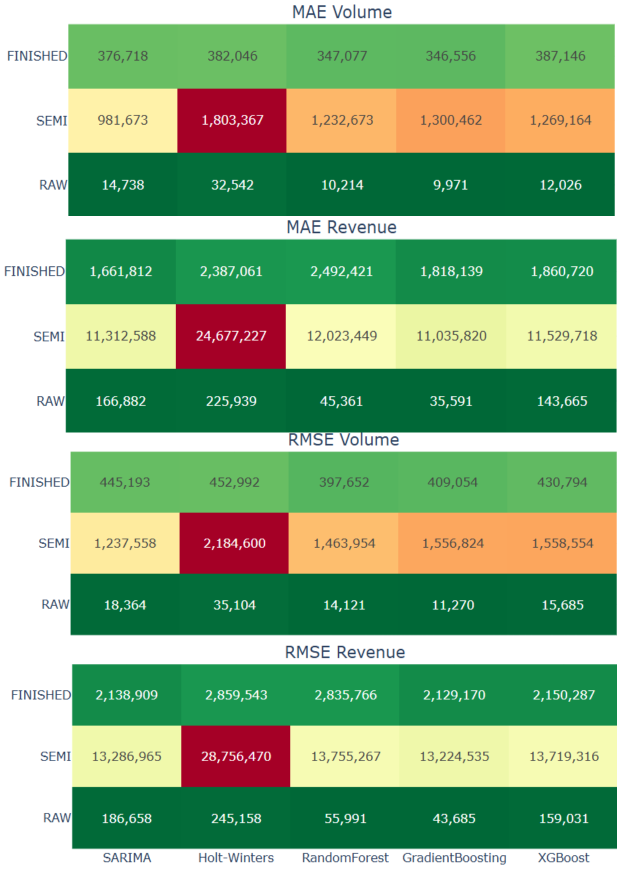


MAPE Volume

FINISHED	28.6%	29.3%	26.4%	26.4%	29.5%
SEMI	9.5%	15.9%	11.6%	11.7%	11.7%
RAW	31.5%	68.8%	18.1%	21.0%	22.1%

MAPE Revenue

FINISHED	18.3%	26.9%	28.0%	20.3%	20.6%
SEMI	12.5%	26.0%	14.3%	12.6%	14.0%
RAW	177.8%	247.0%	55.1%	32.6%	162.1%



MAE Volume

	SARIMA	Holt-Winters	RandomForest	GradientBoosting	XGBoost
FINISHED	376,718	382,046	347,077	346,556	387,146
SEMI	981,673	1,803,367	1,232,673	1,300,462	1,269,164
RAW	14,738	32,542	10,214	9,971	12,026

MAE Revenue

	SARIMA	Holt-Winters	RandomForest	GradientBoosting	XGBoost
FINISHED	1,661,812	2,387,061	2,492,421	1,818,139	1,860,720
SEMI	11,312,588	24,677,227	12,023,449	11,035,820	11,529,718
RAW	166,882	225,939	45,361	35,591	143,665

RMSE Volume

	SARIMA	Holt-Winters	RandomForest	GradientBoosting	XGBoost
FINISHED	445,193	452,992	397,652	409,054	430,794
SEMI	1,237,558	2,184,600	1,463,954	1,556,824	1,558,554
RAW	18,364	35,104	14,121	11,270	15,685

RMSE Revenue

	SARIMA	Holt-Winters	RandomForest	GradientBoosting	XGBoost
FINISHED	2,138,909	2,859,543	2,835,766	2,129,170	2,150,287
SEMI	13,286,965	28,756,470	13,755,267	13,224,535	13,719,316
RAW	186,658	245,158	55,991	43,685	159,031

Figure 2 Commodity Model Evaluation 1: Shrimp

The consistency of the ensemble model's performance is also supported by comparable MAE values (347,077 and 346,556) and RMSE (397,652 and 409,054), indicating a more regular and predictable data pattern. Viewed from a revenue perspective, a similar pattern was again found.

Random Forest recorded a lower error at the raw stage with a MAPE of 32.6%, far surpassing the performance of Holt-Winters which recorded an extreme error with a MAPE of 247.0% and an RMSE of 28,756,470.

For the semi-finished stage, Gradient Boosting and SARIMA showed tight competition with MAPE values of 12.6% and 12.5%, respectively. Finally, in the finished stage, SARIMA successfully locked in the best performance with the lowest MAPE of 18.3%, supported by a relatively low RMSE value (2,138,909), which proves its robustness in modelling stable income patterns. Overall, the results of this evaluation confirm that model performance is highly dependent on data characteristics.

Tree-based ensemble algorithms such as Random Forest proved superior in handling fluctuating raw data, while statistical models such as SARIMA were much more effective for stable and structured data, especially in the semi-finished and finished stages.

The evaluation for coconut shell charcoal is detailed in Figure 3. Modelling performance for this commodity appears significantly more stable than for other commodities, particularly in the raw stage, where error distributions are relatively consistent across models. For raw volume prediction, Random Forest achieved the best performance with a MAPE of 19.1%, slightly outperforming Gradient Boosting (19.8%) and XGBoost (20.9%). This result is supported by lower MAE (70,216,766) and RMSE (77,617,073) values compared to other models, indicating more reliable predictions under conditions of moderate data variability.

In the semi-finished stage, model performance became more variable. Holt-Winters achieved the lowest MAPE for volume prediction at 21.3%, compared to Random Forest (31.5%) and Gradient Boosting (34.8%). This superiority is also reflected in the low MAE (4,574.252) and RMSE (6,061.740) values, implying that the statistical approach is more effective in capturing structured patterns in semi-finished commodities.

For the finished stage, Holt-Winters again dominated with superior performance with the lowest MAPE of 19.3%, followed by XGBoost (23.5%) and Random Forest (24.5%). This consistency is further supported by the MAE (342.959) and RMSE (399.838) values, indicating stable and predictable behavior of finished commodity data.

From a revenue perspective, XGBoost delivered outstanding performance at the raw stage with the lowest MAPE of 12.4%, significantly outperforming SARIMA (35.0%) and Holt-Winters (29.4%). This achievement is reinforced by the significantly lower MAE (5,459,495) and RMSE (6,306,583) values, highlighting the effectiveness of the ensemble method in modeling complex revenue patterns.

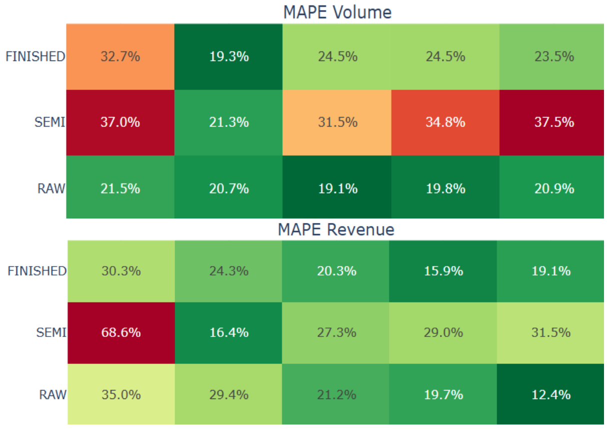


Figure 3. Commodity Model Evaluation 2: Coconut shell charcoal

In the semi-finished stage, Holt-Winters achieved the best performance with a MAPE of 16.4%, supported by the lowest MAE (1,723,672) and RMSE (2,323,498), indicating strong performance on moderate and stable data. Meanwhile, in the finished stage, Gradient Boosting recorded the lowest MAPE of 15.9%, with a relatively low RMSE (429,847), indicating its robustness in capturing smoother and more stable revenue patterns.

Overall, these results confirm that model performance is highly dependent on the characteristics of each commodity stage. Ensemble models such as Random Forest and XGBoost tend to be superior in handling variability in raw data, while statistical models such as Holt-Winters are more effective for structured and stable patterns in the semi-finished and finished stages.

Figure 4 shows the model evaluation results for cassava leaves, which reveal a sharp contrast in performance across commodity levels. The semi-finished stage proved particularly difficult to predict, with MAPE values exceeding 100% for several models, such as Holt-Winters (132.3%), Random Forest (129.6%), and Gradient Boosting (128.8%). Even the lowest MAPE at this stage, achieved by SARIMA, remained high at 108.9%, indicating substantial prediction uncertainty. This instability is further reflected in the relatively high RMSE values, such as 337.983 (Gradient

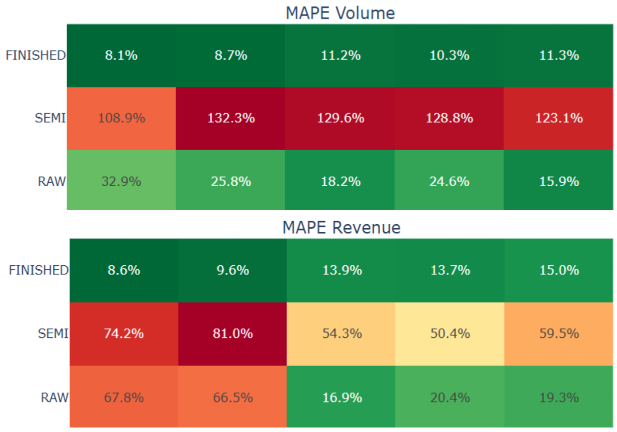
Boosting) and 325.944 (Random Forest), suggesting that the semi-finished cassava leaf data exhibits an irregular and highly unpredictable pattern.

In contrast, the finished stage exhibits a much more stable and predictable pattern. SARIMA performed best with a MAPE of 8.1% for volume and 8.6% for revenue, outperforming other models such as Holt-Winters (8.7%) and Random Forest (11.2%). This superior performance was also supported by a relatively lower RMSE (3,135,208) compared to other models, confirming that the statistical approach is well-suited for stable and structured data at the final stage of the value chain.

For the raw stage, ensemble models demonstrated stronger performance than statistical methods. XGBoost achieved the lowest MAPE for volume at 15.9%, followed by Random Forest (18.2%), which significantly outperformed SARIMA (32.9%). These results were supported by the lower MAE (23,857) and RMSE (35,922), indicating that the ensemble model was more effective in capturing variability in the raw commodity data.

From a revenue perspective, a similar pattern emerged. The semi-finished stage again exhibited high prediction errors, with MAPE values ranging from 50.4% to 81.0%, confirming its instability. In the raw stage, Random Forest achieved the lowest MAPE of 16.9%, supported by low MAE (19.818) and RMSE (25.184), indicating strong performance in modelling volatile revenue patterns. Meanwhile, in the finished stage, SARIMA remained the most accurate model with an MAPE of 8.6% (rounded from 8.57%), reinforcing its robustness under stable conditions.

Overall, these results highlight that cassava leaves exhibit highly heterogeneous behavior across stages. The semi-finished stage is characterized by extreme volatility and irregularity, while the finished stage is relatively stable. Consequently, statistical models like SARIMA are better suited for stable data, while ensemble models excel at handling complexity in the early stages. Models such as Random Forest and XGBoost perform better in handling variability in raw data.



MAPE Volume

FINISHED	8.1%	8.7%	11.2%	10.3%	11.3%
SEMI	108.9%	132.3%	129.6%	128.8%	123.1%
RAW	32.9%	25.8%	18.2%	24.6%	15.9%

MAPE Revenue

FINISHED	8.6%	9.6%	13.9%	13.7%	15.0%
SEMI	74.2%	81.0%	54.3%	50.4%	59.5%
RAW	67.8%	66.5%	16.9%	20.4%	19.3%

MAE Volume

	SARIMA	Holt-Winters	RandomForest	GradientBoosting	XGBoost
FINISHED	2,300,983	2,541,373	3,446,350	3,094,615	3,527,338
SEMI	215,443	217,084	236,743	246,730	234,245
RAW	40,788	29,282	27,147	36,136	23,857

MAE Revenue

	SARIMA	Holt-Winters	RandomForest	GradientBoosting	XGBoost
FINISHED	4,961,570	5,695,778	8,608,666	8,483,873	9,399,672
SEMI	788,647	765,024	714,734	691,251	875,114
RAW	83,091	79,243	19,818	26,942	22,411

RMSE Volume

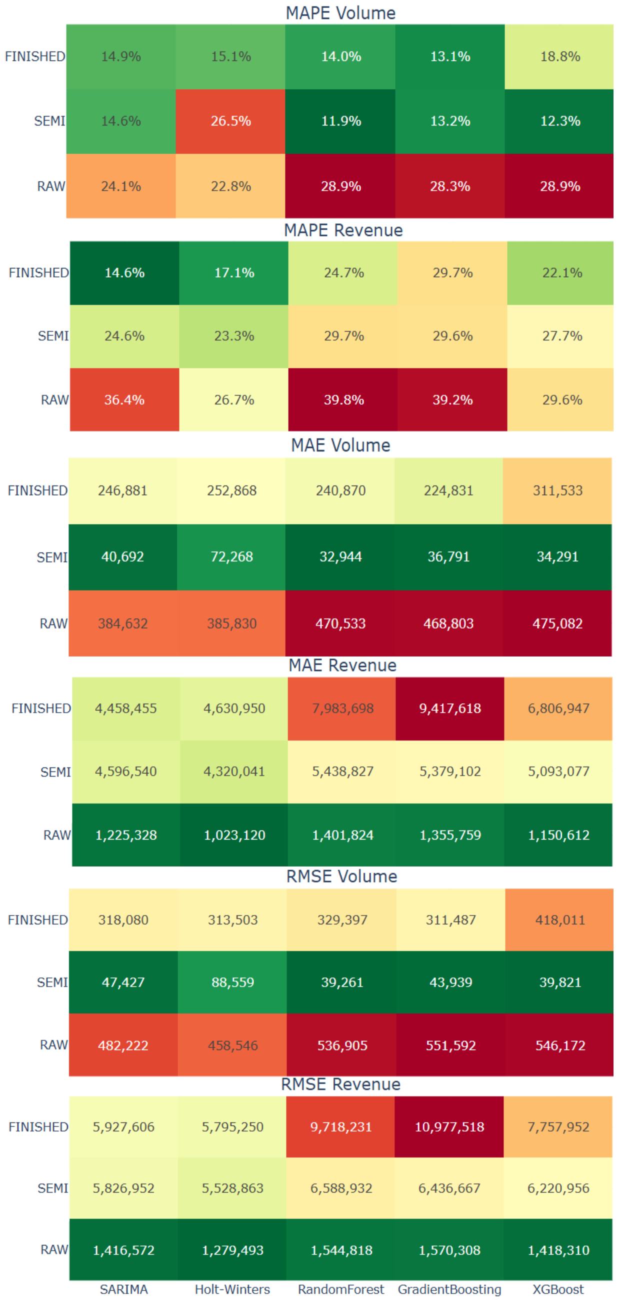
	SARIMA	Holt-Winters	RandomForest	GradientBoosting	XGBoost
FINISHED	3,135,208	3,492,449	4,305,867	4,086,218	4,313,141
SEMI	303,533	302,414	325,944	337,983	321,208
RAW	45,254	34,339	38,930	47,214	35,922

RMSE Revenue

	SARIMA	Holt-Winters	RandomForest	GradientBoosting	XGBoost
FINISHED	6,482,751	7,377,982	9,738,827	9,756,032	10,873,485
SEMI	1,149,418	1,110,405	1,210,690	1,183,222	1,351,526
RAW	96,826	88,695	25,184	35,023	28,404

Figure 4. Commodity Model Evaluation 3: Cassava leaves

The model evaluation results are then presented for eucalyptus leaves in Figure 5. For this commodity, model performance shows moderate variability across stages, with clearer differentiation between statistical and ensemble approaches. At the semi-finished stage, Random Forest achieved the best volume prediction performance with a MAPE of 11.9%, outperforming Gradient Boosting (13.2%) and XGBoost (12.3%). This result is supported by the lowest MAE (32,944) and RMSE (39,261), indicating that ensemble models are effective in capturing structured yet moderately variable patterns in semi-processed eucalyptus data.



MAPE Volume

	SARIMA	Holt-Winters	RandomForest	GradientBoosting	XGBoost
FINISHED	14.9%	15.1%	14.0%	13.1%	18.8%
SEMI	14.6%	26.5%	11.9%	13.2%	12.3%
RAW	24.1%	22.8%	28.9%	28.3%	28.9%

MAPE Revenue

	SARIMA	Holt-Winters	RandomForest	GradientBoosting	XGBoost
FINISHED	14.6%	17.1%	24.7%	29.7%	22.1%
SEMI	24.6%	23.3%	29.7%	29.6%	27.7%
RAW	36.4%	26.7%	39.8%	39.2%	29.6%

MAE Volume

	SARIMA	Holt-Winters	RandomForest	GradientBoosting	XGBoost
FINISHED	246,881	252,868	240,870	224,831	311,533
SEMI	40,692	72,268	32,944	36,791	34,291
RAW	384,632	385,830	470,533	468,803	475,082

MAE Revenue

	SARIMA	Holt-Winters	RandomForest	GradientBoosting	XGBoost
FINISHED	4,458,455	4,630,950	7,983,698	9,417,618	6,806,947
SEMI	4,596,540	4,320,041	5,438,827	5,379,102	5,093,077
RAW	1,225,328	1,023,120	1,401,824	1,355,759	1,150,612

RMSE Volume

	SARIMA	Holt-Winters	RandomForest	GradientBoosting	XGBoost
FINISHED	318,080	313,503	329,397	311,487	418,011
SEMI	47,427	88,559	39,261	43,939	39,821
RAW	482,222	458,546	536,905	551,592	546,172

RMSE Revenue

	SARIMA	Holt-Winters	RandomForest	GradientBoosting	XGBoost
FINISHED	5,927,606	5,795,250	9,718,231	10,977,518	7,757,952
SEMI	5,826,952	5,528,863	6,588,932	6,436,667	6,220,956
RAW	1,416,572	1,279,493	1,544,818	1,570,308	1,418,310

Figure 5. Commodity Model Evaluation 4: Eucalyptus leaves

In contrast, the finished stage demonstrates relatively stable behavior, with Gradient Boosting achieving the lowest MAPE of 13.1%, followed closely by Random Forest (14.0%) and SARIMA (14.9%). This stability is reflected in relatively consistent MAE values (e.g., 224,831 for Gradient Boosting) and RMSE values (311,487), indicating predictable patterns in finished commodity data. At the raw stage, however, prediction errors increase significantly. Random Forest and Gradient Boosting produce higher MAPE values of 28.9% and 28.3%, respectively, while SARIMA performs slightly better at 24.1%. This higher error level is also evident in large MAE values (e.g., 470,533 for Random Forest) and RMSE values (536,905), indicating that raw eucalyptus data is more volatile and difficult to model accurately.

From the revenue perspective, a similar pattern is observed. The raw stage shows the highest prediction error, where Random Forest (39.8%) and Gradient Boosting (39.2%) produce substantially higher MAPE values compared to XGBoost (29.6%). This is further supported by high RMSE values such as 1,544,818 (Random Forest) and 1,570,308 (Gradient Boosting), confirming strong price fluctuations in raw eucalyptus markets.

At the semi-finished stage, model performance becomes more consistent, with Holt-Winters achieving the lowest MAPE of 23.3%, supported by relatively low RMSE (5,528,863). Meanwhile, in the finished stage, SARIMA achieved the best performance with a MAPE of 14.6%, followed by Holt-Winters (17.1%), indicating that statistical models remain effective for more stable revenue patterns.

Overall, the results suggest that eucalyptus leaves exhibit moderate stability in semi-finished and finished stages, while the raw stage remains highly volatile, particularly in terms of revenue. Ensemble models such as Random Forest perform well in structured semi-stage data, while statistical models such as SARIMA provide more consistent performance in stable finished-stage conditions.

The forecasting performance across commodities and their respective stages (raw, semi-finished, and finished) does not follow a uniform pattern. As shown in Figures 2–5, the results indicate significant variation depending on the characteristics of each commodity.For certain commodities, lower forecasting errors are observed at the raw stage, which may be associated with relatively stable production patterns and more consistent export behavior. However, this pattern is not consistent across all commodities. In some cases, semi-finished or finished stages exhibit comparable or even better performance, indicating that the relationship between processing stage and forecasting accuracy is not linear.This variation suggests that forecasting performance is strongly influenced by commodity-specific factors, including market volatility, demand fluctuations, and the complexity of value chain transformations. Commodities that are more exposed to international market dynamics or price sensitivity tend to exhibit higher forecasting errors, particularly in later stages of processing.Therefore, the observed differences in model performance cannot be generalized into a single trend across all commodities, but rather reflect the heterogeneous nature of trade data and commodity-specific dynamics.

Based on the overall evaluation metrics, the model with the lowest error rate was definitively selected for each commodity. A summary of the best model results for shrimp is shown in Table II.

TABLE II
BEST MODEL OF COMMODITY 1: SHRIMP

Category	Prediction Target	Best Model	MAPE (%)
RAW	Volume	Random Forest	18.11%
RAW	Revenue	Gradient Boosting	31.56%
SEMI FINISHED	Volume	SARIMA	9.54%
SEMI FINISHED	Revenue	SARIMA	12.48%
FINISHED	Volume	Random Forest	26.40%
FINISHED	Revenue	SARIMA	18.28%

In Table II, Random Forest dominates volume forecasting in the raw and finished stages, while SARIMA leads in absolute accuracy in the semi-finished stage, for both volume and revenue variables. For coconut shell charcoal, the best model is shown in Table III.

TABLE III
BEST MODEL OF COMMODITY 2: COCONUT SHELL CHARCOAL

Category	Prediction Target	Best Model	MAPE (%)
RAW	Volume	Random Forest	19.09%
RAW	Revenue	XGBoost	12.42%
SEMI FINISHED	Volume	Holt-Winters	21.27%
SEMI FINISHED	Revenue	Holt-Winters	16.39%
FINISHED	Volume	Holt-Winters	19.30%
FINISHED	Revenue	Gradient Boosting	15.86%

This Table demonstrates Holt-Winters' dominance in the semi-process stage, as well as its superiority in predicting finished volume (19.30%). Meanwhile, Random Forest and XGBoost alternately emerged as the most capable algorithms in the raw stage for volume and revenue. For cassava leaves, the best model selection is shown in Table IV.

TABLE IV
BEST MODEL OF COMMODITY 3: CASSAVA LEAVES

Category	Prediction Target	Best Model	MAPE (%)
RAW	Volume	XGBoost	15.85%
RAW	Revenue	Random Forest	16.91%
SEMI FINISHED	Volume	SARIMA	108.86%
SEMI FINISHED	Revenue	Gradient Boosting	50.36%
FINISHED	Volume	SARIMA	8.07%
FINISHED	Revenue	SARIMA	8.57%

XGBoost and Random Forest performed superiorly in the raw stage. Referring to this table, SARIMA reaffirmed its position as the best algorithm in the finished stage for all variables, achieving a very stable single-digit error rate. A summary of the final best-fit model determination, for eucalyptus leaves, is presented in Table V.

TABLE V
BEST MODEL OF COMMODITY 4: EUCALYPTUS LEAVES

Category	Prediction Target	Best Model	MAPE (%)
RAW	Volume	Holt-Winters	22.84%
RAW	Revenue	Holt-Winters	26.73%
SEMI FINISHED	Volume	Random Forest	11.86%
SEMI FINISHED	Revenue	Holt-Winters	23.26%
FINISHED	Volume	Gradient Boosting	13.12%
FINISHED	Revenue	SARIMA	14.58%

Holt-Winters demonstrated its leadership in the raw stage, while Random Forest performed better in the semi-volume stage. At the end of the value chain (finished), Gradient Boosting and SARIMA were selected as the most robust predictors for volume and revenue, respectively. To go beyond mere forecasting, the prediction results were then integrated into the prescriptive stage using Gurobi optimization.

TABLE VI
COMPARISON OF DESTINATION COUNTRY ALLOCATIONS 2024

Commodity	Stage	Actual Number of Countries	Number of Optimization Countries	Differ ence
Shrimp	Raw	9	27	+18
Shrimp	Semi	46	52	+6
Shrimp	Finis hed	25	36	+11
Coconut shell charcoal	Raw	32	46	+14
Coconut shell charcoal	Semi	79	115	+36
Coconut shell charcoal	Finis hed	30	58	+28
Cassava leaves	Raw	15	27	+12
Cassava leaves	Semi	23	36	+13

Cassava leaves	Finished	126	144	+18
Eucalyptus leaves	Raw	46	70	+24
Eucalyptus leaves	Semi	49	70	+21
Eucalyptus leaves	Finished	79	130	+51

Table VI presents a comparison of the allocation of export destination countries. This table shows a surge in destination country expansion across all commodities (for example, finished eucalyptus expanded from 79 to 130 countries), directly demonstrating that the Gurobi optimization algorithm successfully expanded and more equitable export distribution compared to actual conditions. The detailed comparison of actual values, predicted results, and optimization achievements for the grand total of commodity 1 (Shrimp) is visualized in Table VII.

TABLE VII
GRAND TOTAL COMMODITY 1: SHRIMP 2024

Category	Volume (Actual)	Volume (Forecast)	Volume (Optimization)
Grand Total Volume (KG) 2024			
RAW	579.681	475.895	475.895
SEMI FINISHED	134.991.065	137.461.725	137.461.725
FINISHED	17.599.229	20.785.260	20.785.260
Grand Total Revenue ($) 2024			
RAW	1.208.003	1.015.111	1.157.916
SEMI FINISHED	1.080.182.157	1.014.102.544	1.021.999.747
FINISHED	117.013.429	123.700.969	126.532.511
Grand Total Average Price ($/KG) 2024			
RAW	2,0839	2,1331	2,4331
SEMI FINISHED	8,0019	7,3773	7,4348
FINISHED	6,6639	5,9514	6,0876

Using actual data as a benchmark, the actual raw export volume was recorded at 579.681. The prediction model predicted a volume contraction to 475.895, a figure maintained by the optimization model. An interesting finding was recorded in the revenue variable. The actual revenue recorded was USD 1.208.003, which was projected to plummet to USD 1.015.111 at the prediction stage. This is where the optimization algorithm demonstrated its effectiveness; although unable to surpass its actual historical performance, the optimization model successfully mitigated the loss by recovering revenue to USD 1.157.916. This financial recovery occurred because the model intelligently distributed the reduced quantity across partner countries, reallocating export volumes from lower-value destinations to higher-price markets, resulting in an increase in the average export price, raising the actual price from USD 2,08/kg to USD 2,43/kg at the optimization stage. For coconut shell charcoal, the grand total comparison results are illustrated in Table VIII.

TABLE VIII
GRAND TOTAL COMMODITY 2: COCONUT SHELL CHARCOAL 2024

Category	Volume (Actual)	Volume (Forecast)	Volume (Optimization)
Grand Total Volume (KG) 2024			
RAW	4.827.179.562	5.255.681.945	4.998.970.716
SEMI FINISHED	295.836.785	298.437.191	298.437.191
FINISHED	22.454.165	25.631.593	25.631.593
Grand Total Revenue ($) 2024			
RAW	552.738.302	567.496.576	539.962.970
SEMI FINISHED	142.153.905	137.876.574	145.253.642
FINISHED	29.077.683	32.871.409	34.594.788
Grand Total Average Price ($/KG) 2024			
RAW	0,1145	0.1080	0.1080
SEMI FINISHED	0.4805	0,4620	0,4867
FINISHED	1,2950	1,2825	1,3497

At the finished stage, the actual condition recorded a volume of 22,454,165 with revenue of 29,077,683 USD and an average price of 1,2950 USD/kg. The prediction model projected an increase in volume to 25.631.593 USD with a price that actually weakened to 1,2825 USD/kg. This is where the optimization algorithm maintained the predicted volume, Gurobi successfully corrected the price back up to 1,3497 USD/kg. As a result, the optimization model successfully maximized revenue to reach 34.594.788 USD, far exceeding both the actual conditions and the forecast figures. The post-optimization dynamics of cassava leaves are detailed in Table IX.

TABLE IX
GRAND TOTAL COMMODITY 3: CASSAVA LEAVES 2024

Category	Volume (Actual)	Volume (Forecast)	Volume (Optimization)
Grand Total Volume (KG) 2024			
RAW	1.556.981	1.438.321	1.422.581
SEMI FINISHED	4.322.628	2.917.215	2.842.563
FINISHED	384.248.000	395.310.496	372.522.798
Grand Total Revenue ($) 2024			
RAW	1.443.290	1.416.485	1.560.651
SEMI FINISHED	14.547.590	7.284.376	7.151.539

FINISHED	749.684.588	739.736.174	697.577.368
Grand Total Average Price ($/KG) 2024			
RAW	0,9270	0,9848	1,0971
SEMI FINISHED	3,3655	2,4970	2,5159
FINISHED	1,9510	1,8713	1,8726

Comparing it to actual data as a baseline, the recommended raw export volume dropped from 1,556,981 (actual) to 1,422,581 (optimized). Even though the quantity was trimmed from real conditions, the optimization model brilliantly managed to boost revenue from 1,443,290 USD (actual) to 1,560,651 USD. This surge in revenue was driven purely by the model's astuteness in prescriptively exploiting the average price increase through the reallocation of export volumes toward higher-value partner countries, from an initial 0.9270 USD/kg (actual) to 1.0971 USD/kg (optimized).

This analytical fact confirms that Gurobi does not simply boost volume quantities blindly, but rather works by mapping allocations across partner countries based on the price curve, enabling the model to reallocate export volumes from lower-value destinations to higher-price markets.

Finally, the grand total optimization for eucalyptus leaves is presented in Table X.

TABLE X
GRAND TOTAL COMMODITY 4: EUCALYPTUS LEAVES 2024

Category	Volume (Actual)	Volume (Forecast)	Volume (Optimization)
Grand Total Volume (KG) 2024			
RAW	20.574.246	20.984.259	20.348.774
SEMI FINISHED	3.514.719	3.667.796	3.667.796
FINISHED	19.715.579	18.332.717	18.285.395
Grand Total Revenue ($) 2024			
RAW	50.980.613	52.002.358	51.600.103
SEMI FINISHED	197.555.776	153.685.309	170.281.873
FINISHED	350.039.530	325.742.976	350.628.488
Grand Total Average Price ($/KG) 2024			
RAW	2,4779	2,4782	2,5358
SEMI FINISHED	56,2081	41,9013	46,4262
FINISHED	17,7545	17,7684	19,1753

At the finished stage, the actual export volume was recorded at 19.715.579. The prediction model predicted a volume contraction to 18.332.717, and the optimization model recommended a similar figure of 18.285.395. Remarkably, despite the volume being reduced compared to the actual achievement, the optimization model proved effective in maintaining revenue growth above its actual baseline, climbing from 350.039.530 USD (actual) to 350.628.488 USD (optimized). The success of turning the weakening quantity into financial gain was further demonstrated by the algorithm's ability to allocate exports to increase the average price from 17,7545 USD/kg (actual) to 19,1753 USD/kg (optimized), through the redistribution of export allocations across partner countries toward higher-price markets.

Overall, the integration of this predictive and prescriptive framework ensures that research findings go beyond mere estimates. This integrated system proves highly effective as a strategic decision-making tool. While this approach yields practical recommendations that maximize foreign exchange, it's important to emphasize that the optimizer operates purely based on mathematical objective functions and constraints. Therefore, the final results cannot completely replace human intervention and require critical review by a validator or policymaker before the export allocation recommendations are actually implemented.

IV. CONCLUSION

This research has produced an analytical framework in the context of Indonesian export trade utilizing a hierarchical commodity classification. Based on all implemented stages, several key conclusions were formulated. The application of a hierarchical classification of commodities into raw, semi-finished, and finished indicates an improvement in the quality of data representation compared to an aggregate approach. Through this grouping, the differences in characteristics at each commodity stage, such as volume, price, and market distribution, can be analyzed more specifically, resulting in a deeper understanding of the value-added structure within the export chain.

Moving on to the forecasting stage, the evaluation results demonstrate that no single predictive model is universally superior for all commodity categories. Statistical models such as SARIMA tend to perform well on stable data, while tree-based ensemble algorithms such as Random Forest, Gradient Boosting, and XGBoost are more effective at capturing non-linear patterns in data with high volatility. This finding emphasizes that the selection of the best model should be tailored to the specific characteristics of the data at each stage.

In the selection process, using the MAPE metric as the basis for determining the best model for each combination of target variables (volume and revenue) indicates more optimal results compared to a single-model approach. Through this selection method, the model used for the prediction stage becomes more adaptive to the dynamics of existing data conditions. As a final step, the integration of predictive analytics with prescriptive optimization using Gurobi demonstrates the potential to transform prediction outputs into export allocation recommendations. This optimization model is able to calculate export and import capacity constraints and price variations between partner countries, generating a distribution strategy that has the potential to maximize state revenue.

Overall, this study concludes that the combination of commodity hierarchy classification, adaptive predictive model selection, and prescriptive optimization provides a more comprehensive framework to support strategic decision-making in the export sector. Despite its contributions, this framework is not without several limitations that also open up opportunities for further research.

In addition, this study has not yet incorporated a formal sensitivity analysis of the optimization model. Variations in key trade parameters, such as export prices, partner country demand, and supply capacity constraints, may influence the resulting allocation decisions. Changes in these parameters could potentially alter the distribution of export volumes across partner countries and affect the stability of the optimization outcomes. Therefore, future research is recommended to include sensitivity analysis to evaluate the robustness of the model under different economic scenarios.

In terms of data coverage, this study relies on historical data over a relatively limited timeframe (2019-2024). This condition means the model is not fully able to capture long-term dynamics or external shocks such as global crises or changes in trade policy. As a result, the generalizability of the proposed model to different time periods or changing global economic conditions may be limited, as the relationships captured by the model are dependent on the underlying data patterns within the observed timeframe.

Therefore, the findings of this study should be interpreted as exploratory rather than definitive. Further research is strongly recommended to expand the data coverage, both temporally and spatially, to improve the model's generalizability. Therefore, the findings of this study should be interpreted as exploratory rather than definitive. Further research is strongly recommended to expand the data coverage, both temporally and spatially, to improve the model's generalizability.

Furthermore, in terms of initial processing, the current commodity hierarchy classification process still relies on the Large Language Model (Gemini API) algorithm. Due to its probabilistic nature, this approach may introduce potential bias or inconsistencies in HS code mapping, particularly for commodities with overlapping definitions or ambiguous processing stages. Therefore, validation by domain experts or integration with official classification standards is required to ensure reliability. In addition, the use of 6-digit HS codes may limit classification granularity, which can affect the precision of downstream analysis. In the future, this method could be combined with official databases or trade ontology-based validation systems to ensure greater classification accuracy.

Regarding forecasting methodology, the predictive models developed are still limited to classical statistical and tree-based ensemble approaches. Future developments could explore more sophisticated architectures, such as Transformer-based time series or hybrid deep learning, which are considered more capable of recognizing highly complex temporal patterns. Meanwhile, in the prescriptive optimization stage, the current formulation is still based on linear programming, relying on certain basic assumptions, such as relative price stability and historical track record-based import capacity determination. Therefore, the resulting optimization recommendations require validation by policymakers or domain experts to ensure feasibility within real-world trade regulations and market conditions, particularly in the context of the expanded number of export destination countries, which may face practical constraints related to logistics capacity, trade agreements, and regulatory compliance. Future studies could design more realistic optimization models that take into account uncertainty factors (stochastic optimization) and dynamic scenarios (robust optimization).

Finally, this framework does not yet integrate external macroeconomic variables, such as geopolitical conditions, tariff policies, logistics costs, and currency exchange rate fluctuations, which can significantly influence export decisions and limit the practical applicability of the model in capturing real-world trade complexities. The inclusion of these variables in future research is expected to improve the accuracy of predictions while increasing the relevance of the resulting policy recommendations.

From a practical perspective, the findings of this study can support policymakers and export stakeholders in making more informed decisions. For government institutions, the proposed framework can be utilized not only to design export strategies and identify potential market expansion opportunities, but also to prioritize high-value destination countries and evaluate trade-offs between export volume and revenue under different allocation scenarios. For exporters, the results provide actionable insights into selecting target markets with higher economic value, adjusting export volumes based on price differentials, and reallocating shipments toward more profitable destinations. By integrating predictive and prescriptive analytics, this framework offers a structured approach to improve both planning accuracy and strategic responsiveness in international trade.

ACKNOWLEDGEMENT

The authors extend their profound appreciation to the United Nations Commodity Trade Statistics Database (UN Comtrade) for providing access to the international export trade dataset, which served as a fundamental resource for this research. The authors also acknowledge the utilization of the Gemini API (Large Language Model), which significantly assisted in the hierarchical classification process of the commodity data. Furthermore, the first author convey deepest gratitude to co-authors, whose insightful suggestions, continuous guidance, and constructive feedback greatly contributed to refining and improving the quality of this study.

REFERENCES

[1] E. Dave, A. Leonardo, M. Jeanice, and N. Hanafiah, "Forecasting Indonesia Exports using a Hybrid Model ARIMA-LSTM," *Procedia Computer Science*, vol. 179, pp. 480–487, 2021, doi: 10.1016/j.procs.2021.01.031.

[2] W. Wang, S. Shen, and Y. Yuan, "Forecasting Short-Term Export Volumes with Hybrid Models Integrating SARIMA with Attention-Based LSTM," *ISTAER*, vol. 4, no. 1, pp. 1–22, Jan. 2026, doi: 10.71451/ISTAER2601.

[3] Abdiyanto *et al.*, "The Effect of Exports and Imports on Agribusiness Activities on the Development of Indonesia's Economic Growth," *Res. World Agric. Econ.*, pp. 547–557, Oct. 2025, doi: 10.36956/rwae.v6i4.2034.

[4] P. K. Sarangi, E. Singh, A. Kaushal, B. Sharma, M. Dutta, and V. P. Dubey, "Analysing the Fluctuations in Commodity Prices and Forecasting the Future Directions Using Machine Learning Techniques," *Procedia Computer Science*, vol. 259, pp. 1827–1836, 2025, doi: 10.1016/j.procs.2025.04.138.

[5] M. Muhyiddin, "Indonesia Economic and Development Outlook 2026: Why Five Percent Growth Is No Longer Enough for a Rising Economy," *JPP*, vol. 9, no. 3, pp. 292–297, Dec. 2025, doi: 10.36574/jpp.v9i3.791.

[6] A. Demir, Ö. Özmen, and A. Rashid, "An Estimation of Turkey's Export Loss to Iraq," *Procedia - Social and Behavioral Sciences*, vol. 150, pp. 1240–1247, Sep. 2014, doi: 10.1016/j.sbspro.2014.09.140.

[7] A. G. Rosa, P. H. F. Azevedo, V. R. R. Celestino, and S. A. D. Reis, "An analytical approach to optimizing sustainable farm operations through linear reformulation," *Decision Analytics Journal*, vol. 17, p. 100632, Dec. 2025, doi: 10.1016/j.dajour.2025.100632.

[8] B. T. Halima Fatima, "Hybrid ARIMA And LSTM Deep Learning Models Empowering and Enhancing Forecast Accuracy in Sales," Sep. 2025, doi: 10.5281/ZENODO.17077720.

[9] A. Mahmud *et al.*, "Hybrid ARIMA-LSTM for COVID-19 forecasting: a comparative AI modeling study," *PeerJ Computer Science*, vol. 11, p. e3195, Sep. 2025, doi: 10.7717/peerj-cs.3195.

[10] R. C. Johnson, "Measuring Global Value Chains," *Annu. Rev. Econ.*, vol. 10, no. 1, pp. 207–236, Aug. 2018, doi: 10.1146/annurev-economics-080217-053600.

[11] S. J. Subramanya, D. K. Dennis, V. Smith, and G. R. Ganger, "COpter: Efficient Large-Scale Resource-Allocation via Continual Optimization," in *Proceedings of the ACM SIGOPS 31st Symposium on Operating Systems Principles*, Lotte Hotel World Seoul Republic of Korea: ACM, Oct. 2025, pp. 322–340. doi: 10.1145/3731569.3764846.

[12] S. Ikeda, N. Nishimura, N. Sukegawa, and Y. Takano, "Prescriptive price optimization using optimal regression trees," *Operations Research Perspectives*, vol. 11, p. 100290, Dec. 2023, doi: 10.1016/j.orp.2023.100290.

[13] F. Alzami *et al.*, "Demand Prediction for Food and Beverage SMEs Using SARIMAX and Weather Data," *ISI*, vol. 29, no. 1, pp. 293–300, Feb. 2024, doi: 10.18280/isi.290129.

[14] D. R. Lestari, E. A. S. Bangun, F. L. Gaol, and T. Matsuo, "Machine Learning-Based Forecasting of Agricultural Commodity Prices Using Ensemble Models," *J. Hum. Earth Future*, vol. 6, no. 4, pp. 887–899, Dec. 2025, doi: 10.28991/HEF-2025-06-04-09.

[15] S. N. B, B. V. S. Reddy, V. S. S. Sujan, C. C. Sastry, J. Krishnaiah, and S. Jitpichitchai, "A machine learning framework for long-term forecasting of spare part demand in end-of-life product scenarios," *Sci Rep*, vol. 16, no. 1, p. 1394, Dec. 2025, doi: 10.1038/s41598-025-31171-2.

[16] K. M. Sabu and T. K. M. Kumar, "Predictive analytics in Agriculture: Forecasting prices of Arecanuts in Kerala," *Procedia Computer Science*, vol. 171, pp. 699–708, 2020, doi: 10.1016/j.procs.2020.04.076.

[17] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, San Francisco California USA: ACM, Aug. 2016, pp. 785–794. doi: 10.1145/2939672.2939785.

[18] S. Uddin and H. Lu, "Confirming the statistically significant superiority of tree-based machine learning algorithms over their counterparts for tabular data," *PLoS ONE*, vol. 19, no. 4, p. e0301541, Apr. 2024, doi: 10.1371/journal.pone.0301541.