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IMPORT PRICE ANOMALY DETECTION AUTOMATIC DATA PROCESSING MACHINES: A PUBLIC DATA-BASED MACHINE LEARNING STRATEGY

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Abstract
The practice of international trade price manipulation has come under scrutiny in Indonesia. However, the confidentiality of internal customs data hinders external researchers from detecting import price manipulation. This research offers novelty by developing a machine learning model prototype that exclusively utilizes public data from the Indonesian Central Bureau of Statistics. This research method applies a quantitative case study on the import of automatic data processing machines (HS Code 8471) from 2022 to 2025 by constructing a "Unit Value" (price/kg) proxy as a macro-risk indicator. The training data was labeled using Isolation Forest (contamination=5%) to train several classification models. The 20-fold stratified CV evaluation results showed Gradient Boosting as the best-performing model (F1-Score 0.904), with Country and HS Code as the strongest predictors. This model identified 51 anomalies (4.76%) in the 2025 data. A key finding was the detection asymmetry: a dominance of 26 cases of over-invoicing and only 2 cases of under-invoicing. This research contribution not only proved the feasibility of using public BPS data as an early warning system capable of detecting structural anomalies, but also confirmed the capability of machine learning in reducing information asymmetry and closing the "opportunity" gap within the Fraud Triangle Theory.
Keywords: Anomaly Detection; Fraud Triangle; Gradient Boosting; Isolation Forest; Machine Learning; Public Data

Abstrak
Praktik manipulasi harga perdagangan internasional menjadi sorotan di Indonesia. Akan tetapi, kerahasiaan data internal kepabeanan menjadi penghalang bagi peneliti eksternal untuk mendeteksi manipulasi harga impor. Penelitian ini menawarkan kebaruan dengan membangun prototipe model machine learning yang hanya memanfaatkan data publik Badan Pusat Statistik. Metode penelitian ini menerapkan studi kasus kuantitatif pada impor mesin pengolah data otomatis (Kode HS 8471) pada 2022-2025 dengan mengkonstruksi proksi "Nilai Unit" (harga/kg) sebagai indikator risiko makro. Data latih dilabeli menggunakan Isolation Forest (contamination=5%) untuk melatih beberapa model klasifikasi. Hasil evaluasi 20-fold stratified CV menunjukkan Gradient Boosting sebagai model terbaik (F1-Score 0.904), dengan Negara dan Kode HS sebagai prediktor terkuat. Model ini mengidentifikasi 51 anomali (4,76%) pada data 2025. Temuan kunci adalah asimetri deteksi: dominasi 26 kasus over-invoicing dan hanya 2 kasus under-invoicing. Kontribusi penelitian ini tidak hanya membuktikan kelayakan data publik BPS sebagai sistem peringatan dini terhadap anomali struktural, tetapi juga mengonfirmasi kapabilitas machine learning dalam mereduksi asimetri informasi dan menutup celah peluang dalam Fraud Triangle Theory.
Kata Kunci: Data Publik; Deteksi Anomali; Fraud Triangle; Gradient Boosting; Isolation Forest; Machine Learning

INTRODUCTION

Illegal practices in international trade, particularly price manipulation, have once again become a prominent issue in Indonesia. Price manipulation primarily takes two forms: under-invoicing and over-invoicing (Rusydi et al., 2023). Under-invoicing (reporting lower prices) generally aims to evade state revenues such as import duties and import-related taxes, whereas over-invoicing (reporting higher prices) is indicated as a method for capital flight or money laundering. Both practices equally undermine economic integrity, distort statistical data, and create unfair business competition (Brandt, 2023). The urgency of addressing this issue was emphasized by the Minister of Finance of the Republic of Indonesia, Purbaya Yudhi Sadewa, who stated that President Prabowo Subianto specifically highlighted these fraudulent practices (Nugraheny & Arief, 2025). As a follow-up, the Ministry of Finance plans to utilize artificial

intelligence to narrow the scope for manipulation in customs. This statement underscores the national urgency to adopt solutions using advanced technology.

The context of this problem is further clarified by the self-assessment system in Indonesia, where limited resources and inspection time make it difficult to conduct in-depth audits of all transactions (Sa'adah & Hartanto, 2023). This condition creates a pressing need for risk-based assistive tools. Supervisory approaches that rely solely on manual descriptive statistical analysis (such as comparing average prices) are no longer adequate to dissect complex variable interactions. In line with this need, machine learning offers a potential solution with its capability to simultaneously identify non-linear anomalous patterns (Sánchez-Aguayo et al., 2021). Several previous studies have proven its feasibility in detecting trade anomalies in Indonesia, ranging from unsupervised methods to identify patterns and risk profiles (Prastuti et al., 2023), to supervised methods for fraud classification (Novith et al., 2023; Sa'adah & Hartanto, 2023). The variety of models used in these studies indicates that there is no single consensus on which algorithm is the most superior for the context of trade anomalies in Indonesia.

Another fundamental challenge is the reliance of previous studies on confidential internal customs data, which poses a barrier for researchers outside the Directorate General of Customs and Excise. The primary novelty of this research lies in its approach, which focuses on building a detection model by utilizing public data from Statistics Indonesia (BPS) that has limited features (only import value and net weight). From these two quantitative features, a price proxy known as "Unit Value" can be derived. Therefore, this research tests the hypothesis of whether this single price proxy, when combined with categorical features (HS Code and Country), is capable of training an effective model to identify transactions that statistically deviate from the norm. It should be emphasized that the use of the "Unit Value" proxy (price per kilogram) in this study does not aim to replace the Transaction Value principle mandated in Article VII of the General Agreement on Tariffs and Trade (GATT), which is adopted by the Customs Law. Given that public data does not contain detailed actual transaction values, this quantitative proxy functions purely as a macro-risk indicator (early warning system).

Furthermore, to test the effectiveness of this indicator, the research focuses its analysis on automatic data processing machines under HS Code 8471. Although conventional commodities such as textiles or footwear from China under the Free Trade Agreement (FTA) scheme are often the main focus of under-invoicing practices, the selection of HS 8471 was deliberately made as a stress test for the machine learning algorithms. The selection of HS Code 8471 is based on two justifications: first, its parent category (HS Code 84) represents the non-oil and gas category with the largest import value in August 2025 (Badan Pusat Statistik, 2025b). Second, this commodity is heterogeneous with a very wide price range, making its complex variations an ideal case study for machine learning (Hardianto et al., 2024). If the model proves effective in mapping anomalies in a commodity as complex as HS 8471 using limited BPS data, then the same framework is projected to perform significantly better when applied to commodities with conventional risk profiles. Subsequently, the analysis focuses on the nine countries with the largest import values in 2024 (Australia, China, Japan, South Korea, Malaysia, Singapore, Thailand, the United States, and Vietnam) (Badan Pusat Statistik, 2024). The data period begins in 2022 as it aligns with the post-COVID-19 crisis recovery (Adeline et al., 2024) and the update of the HS Code classification system.

Specifically, this research applies a methodological strategy consisting of three main stages: (1) determining the best machine learning model through systematic performance evaluation on the training data (2022-2024); (2) identifying the primary driving factors used by the model to make decisions; and (3) applying the best model to detect anomalies in the 2025 data and conducting multi-stage validation. This validation includes (a) a quantitative case

study analysis against the "Fair Price" to identify indications of price manipulation (under-invoicing and over-invoicing), and (b) a qualitative validation against external data to confirm structural anomalies as valid signals of new trade trends. This research is expected to provide a risk-based model prototype derived from public data as a consideration for relevant authorities.

LITERATURE REVIEW

Fraud Triangle Theory

One of the theoretical foundations in the analysis of price manipulation in this study is the Fraud Triangle Theory, which states that fraud occurs due to the interaction of three main elements: pressure, opportunity, and rationalization (Rasheed et al., 2023). In the context of international trade, the pressure element often manifests as financial pressure, where importers are motivated to engage in under-invoicing to evade taxes, or over-invoicing for capital flight (Abdullahi & Mansor, 2015). The second element, opportunity, is created by the weakness or ineffectiveness of the supervisory control system (Abdullahi & Mansor, 2015). In the Indonesian customs sector, the implementation of the self-assessment system, coupled with limited audit time and resources, creates information asymmetry and significant opportunities for importers to manipulate price declarations. Meanwhile, the rationalization element occurs when perpetrators justify such illegal actions as normal business practices or for the benefit of the company (Abdullahi & Mansor, 2015). According to (Sánchez-Aguayo et al., 2021), the application of machine learning has proven effective in intervening with the opportunity element. Given that the human behavior underlying the Fraud Triangle Theory is difficult to measure directly, machine learning algorithms assist authorities in discovering hidden price anomaly patterns, thereby narrowing the opportunity for successful manipulation before the fraud is realized.

Trade Price Manipulation

The theoretical framework of price manipulation is rooted in Illicit Financial Flows (IFF), which is the illegal movement of capital across borders(Rusydi et al., 2023). Its largest component is trade misinvoicing, or the manipulation of transaction values. This practice has two forms: under-invoicing (reporting low prices) and over-invoicing (reporting high prices). The motive for under-invoicing is to avoid import duties and taxes. Conversely, the motives for over-invoicing are more complex, such as capital flight or money laundering, and often occur with goods subjected to a 0% tariff. This issue is related to transfer pricing, which creates a challenge between tax authorities, who desire low prices (lower prices result in lower company costs, thereby increasing income tax), and customs authorities, who desire high prices (higher prices result in higher import duties). There is also a debate on whether IFF only encompasses illegal activities or also includes legal yet immoral practices, such as aggressive tax avoidance (Brandt, 2023).

Anomaly Detection

This theoretical foundation originates from the concept of anomalies. An anomaly is a value or outcome that deviates from expected or normal conditions (Zulfikar et al., 2023). The characteristics of anomalous data, which differ from normal data, are what enable their detection. To identify these anomalies, research can apply the Isolation Forest method, which is an unsupervised machine learning anomaly detection algorithm (Xu et al., 2023). This decision tree-based nonparametric method operates through two phases: training and evaluation. In the training phase, a number of isolation trees are built using a data sample. Subsequently, in the evaluation phase, each data instance passes through these trees to calculate its anomaly score, indicating the extent of the data's deviation (Zulfikar et al., 2023).

Machine Learning

Machine learning (ML) is an essential data analysis technique for processing big data (Zulfikar et al., 2023). As a branch of artificial intelligence, ML is the study of algorithms that allow computers to learn from experience and make data-driven decisions without being explicitly programmed. Machine learning is divided into supervised learning and unsupervised learning (Zulfikar et al., 2023). Supervised learning utilizes labeled data for classification (separating data into categories) or regression (understanding the relationships between variables). In contrast, unsupervised learning is implemented on unlabeled data so that the machine can independently discover hidden patterns, for example, through clustering (grouping similarities) or association (finding relationships). Both approaches can be used for anomaly detection. The unsupervised approach is often used for initial labeling due to the absence of "fair" or "anomalous" labels in raw data.

Previous Research

The application of machine learning for customs anomaly detection in Indonesia has evolved. Canrakerta et al. (2020) applied supervised learning (Gradient Boosted Trees) to internal data, proving the importance of the SMOTE technique in handling imbalanced data. Sa'adah & Hartanto (2023) specifically focused on under-invoicing detection using labeled internal data, where Xtreme Gradient Boost (XGBoost) demonstrated the best performance. Novith et al. (2023) continued this supervised approach with internal data, proposing an ensemble model (XBNet) to address the imbalanced dataset. A different approach was taken by Prastuti et al. (2023) who utilized unsupervised methods (K-Means Clustering and Isolation Forest) on the Directorate General of Taxes' internal data. Their research focused on identifying patterns and risk profiles of inter-affiliate transactions, such as transactions with low-tax jurisdictions.

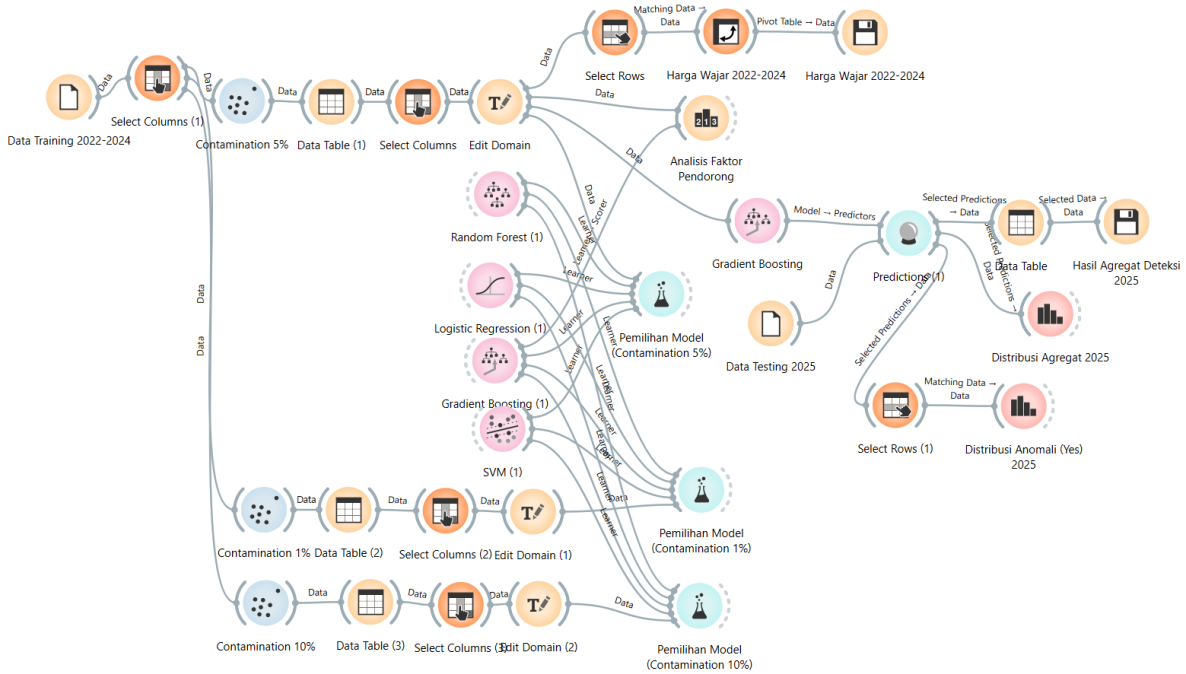
A review of previous studies (Canrakerta et al., 2020; Novith et al., 2023; Prastuti et al., 2023; Sa'adah & Hartanto, 2023) demonstrates the success of applying machine learning for fraud detection. However, these studies have a fundamental reliance on confidential internal customs or tax data. This reliance creates a significant research gap for external researchers, academics, and the public who do not have access to such data, thereby hindering independent oversight. Therefore, this research tests the hypothesis that the "Unit Value" price proxy (price/kg), constructed solely from limited BPS public data, can be used to train an effective and valid machine learning model in identifying import price anomalies.

RESEARCH METHOD

This research method is designed as a systematic quantitative workflow to apply and evaluate machine learning models. The primary focus is to test the feasibility of BPS public data for detecting price anomalies. The entire workflow, from data pre-processing to modeling and evaluation, is implemented using the open-source software Orange Data Mining.

The research flow is divided into four main stages, elaborated as follows: (1) data acquisition and scope, (2) data pre-processing and feature construction, (3) modeling and comparative evaluation, and (4) case study application and validation. To provide a comprehensive overview and visualization of the framework of these four stages, the modeling architecture built within the Orange Data Mining software is represented in Figure 1 below.

Figure 1. Machine Learning Modeling Framework in Orange Data Mining



Source: Author's Processed Data (2025)

Based on Figure 1, the modeling architecture is divided into three main operational clusters:

a. Left Cluster (Unsupervised Labeling & Sensitivity Analysis): The flow begins by inputting the training data (2022-2024). This data is then channeled to the Outliers (Isolation Forest) widget with a primary contamination parameter of 5% to generate "Anomaly Yes/No" labels. In parallel, the lower flow displays the labeling process for sensitivity analysis with parameters of 1% and 10%.
b. Middle Cluster (Supervised Evaluation & Predictor Determination): The labeled data is tested using four machine learning algorithms (Random Forest, Logistic Regression, Gradient Boosting, and SVM) to evaluate their performance. In this cluster, there is also a data flow branch directed to the Rank widget ("Driving Factor Analysis") to extract which features (such as Country or HS Code) most influence the model. Additionally, there is a branch to calculate the "Fair Price" as a baseline for validation.
c. Right Cluster (Application & Prediction): The best-performing model (Gradient Boosting) is applied to new, unlabeled data ("Data Testing 2025") through the Predictions widget. The results are then extracted into an aggregate detection and their distribution is visualized to separate normal transactions from anomalous ones.

Data Acquisition and Scope

This study utilizes secondary public data obtained from the official statistical publications of Statistics Indonesia (BPS). The data utilized comprises monthly aggregate data per 8-digit HS Code per Country of Origin, covering the period from January 2022 to August 2025 (the latest data available at the time of the study). This period is divided into two datasets: the training data spanning 2022-2024, and the testing data covering the period from January 2025 to August 2025. The selection of 2022 as the starting point is based on two methodological justifications: (1) it reflects trade conditions that have recovered post-COVID-19 crisis (Adeline

et al., 2024), and (2) it aligns with the latest update of the HS Code classification system implemented by BPS Indonesia (Badan Pusat Statistik, 2025a).

The scope of this case study is specifically limited to automatic data processing machine commodities under HS Code 8471, focusing on the nine countries of origin with the largest import values in 2024, namely Australia, China, Japan, South Korea, Malaysia, Singapore, Thailand, the United States, and Vietnam. The raw features extracted from BPS Indonesia for each monthly transaction are Year, Month, Country of Origin, HS Code, Import Value (USD), and Net Weight (Kg).

Data Pre-processing and Feature Construction

- **Feature Engineering**

BPS public data does not contain a price per unit. Therefore, a "Unit Value" price proxy (price per kilogram) feature was created. This feature is the core of the anomaly detection and serving as the primary quantitative variable to be analyzed. It is calculated using the formula:

$$\text{Nilai Unit} = \frac{\text{Nilai Impor (USD)}}{\text{Berat Bersih (Kg)}}$$

- **Target Variable Construction (Labeling)**

The BPS data does not possess "Anomaly Yes" or "Anomaly No" labels, rendering it an unsupervised problem. To transform it into a supervised problem, the training data (2022-2024) must first be labeled. This labeling process is based on a primary methodological assumption: it is assumed that extreme under-invoicing or over-invoicing transactions will manifest as statistical outliers in the "Unit Value" feature when compared to other fair transactions (Zulfikar et al., 2023). Based on this assumption, the labeling of the training data (2022-2024) was conducted using the unsupervised anomaly detection algorithm, Isolation Forest (Xu et al., 2023), implemented via the Outliers widget in Orange.

This method was selected due to two main advantages: (1) Isolation Forest does not rely on data distribution assumptions (the data does not have to be normally distributed), making it suitable for import price data which is frequently skewed; and (2) this method is known to be efficient and effective in isolating anomalies (Xu et al., 2023). This algorithm operates by randomly building a set of isolation trees, and anomalies are data points that require fewer partitions to be isolated (Xu et al., 2023).

The key parameter of this method, namely "contamination" (contamination rate), was set at 5% (0.05). The 5% designation is a common methodological assumption used in anomaly detection studies when the a priori proportion of anomalies is unknown, serving to balance sensitivity (capturing anomalies) and specificity (avoiding false positives) (Farizi et al., 2021).

The training data (2022-2024) was subsequently assigned a new binary label based on the Isolation Forest detection results: "Anomaly Yes" (if detected as an outlier) and "Anomaly No" (if deemed normal). Furthermore, the Select Columns widget was used to configure the variable roles: the "Anomaly" (Yes/No) column was set as the target variable, while features such as HS Code, Country, and Unit Value were designated as features. Temporal features (Month and Year) were excluded as model predictors to avoid overfitting on seasonal patterns or annual trends, but they will be analyzed separately in the driving factor analysis stage.

Modeling and Comparative Evaluation

This stage focuses on Research Objectives 1 and 2, which are determining the best model and identifying the primary driving factors using the training data (2022-2024).

- **Model Selection and Evaluation (Objective 1)**

Four machine learning models representing various algorithm families were selected for comparative evaluation. The selection of these four models is based on their proven effectiveness in relevant previous studies concerning anomaly detection.

a. Random Forest (RF) dan Gradient Boosting (GB): Both of these models were utilized by (Imam Mulyana & Muhamad Bahrul Ulum, 2025; Sa'adah & Hartanto, 2023) to detect data manipulation. RF is a machine learning algorithm that creates multiple decision trees using a subset of training data and randomly selected variables, while GB is known as one of the best-performing supervised machine learning algorithms that also minimizes model prediction volatility (Sa'adah & Hartanto, 2023).
b. Logistic Regression (LR): LR is recognized as a multivariable method for modeling the relationship between several independent variables and a categorical dependent variable (Boateng & Abaye, 2019). (Dangsawang & Nuchitprasitchai, 2024) specifically highlighted the use of LR to detect anomalies in customs data.
c. Support Vector Machine (SVM): (Seck, 2024) also incorporated SVM in his analysis on customs declaration fraud detection. SVM is known to be effective on imbalanced data.

These four models were tested on the training data (2022-2024) using the Test & Score widget. The evaluation method employed was 20-fold Stratified Cross-Validation to ensure a robust and fair evaluation on the imbalanced data (Abioye et al., 2025). The best model was selected based on the highest F1-Score because this metric indicates the optimal balance between Precision (the model's ability not to mislabel anomalies) and Recall (the model's ability to find all anomalies), which is highly crucial for imbalanced data such as fraud detection. However, to ensure the robustness of the model selection against the methodological assumptions at the labeling stage, a sensitivity analysis was also conducted. This analysis re-evaluated the performance of the four models on the training data labeled with different contamination parameters, namely 1% and 10%.

- **Driving Factor Analysis (Objective 2)**

To understand the driving factors of anomalies, the Rank widget was utilized on the training data. This analysis evaluates the statistical correlation between the features used by the model (HS Code, Country, and Unit Value) and the target variable (Anomaly Yes/No column). As an additional analysis, the correlation of temporal features (Month and Year) that were not included in the model was also evaluated to observe if there were seasonal patterns or annual trends. This analysis employs various metrics, namely Gain Ratio, Gini, and ReliefF.

Case Study Application and Validation

This final stage focuses on Research Objective 3, which is applying the best model to new data (2025) and validating the results.

a. Model Application: The best model was applied to the 2025 data (which lacked labels) using the Predictions widget. The output is a list of 2025 transactions that have now been assigned prediction labels ("Anomaly Yes" or "Anomaly No"). In addition to providing prediction labels ("Anomaly Yes" / "Anomaly No"), the model also generates a probability score (confidence level) for each prediction, indicating how confident the model is in its decision.
b. Aggregate Analysis: These prediction results were aggregated using the Distributions widget to view the total number and percentage of cases detected in 2025.
c. Case Study Validation: To validate whether the "Anomaly Yes" detections were logical, a comparative analysis was conducted.
    1) First, a "Fair Price" benchmark was created. This price was calculated by taking the Median of the Unit Value from the 2022-2024 data labeled "Anomaly No" and grouped by HS Code and Country using the Pivot Table widget. The use of Median was chosen over Mean because the Median is more robust against outlier values that might still exist within the "Anomaly No" data (Hanifah et al., 2025). This provides a more stable "Fair Price" benchmark for price data that tends to be non-normally distributed (skewed).

2) Second, the Unit Values from the 2025 data detected as "Anomaly Yes" were manually compared with the relevant "Fair Price". A significant difference between the two variables was utilized as evidence for the case study validation.

d. External Validation of Structural Anomalies: For cases where a "Fair Price" was not found (indicating a structural anomaly), a secondary qualitative validation method was applied. This method involved searching business news databases and industry reports to find real-world economic events (e.g., new trade agreements, regional production surges, or the opening of new factories) during the 2024-2025 period that could explain the emergence of these new trade patterns.

RESULT AND DISCUSSION

This section presents the results of the data analysis conducted in accordance with the methodological strategy outlined in the previous section. The discussion is divided into six parts: (1) comparative analysis and model selection; (2) driving factor analysis; (3) aggregate detection results on the 2025 data; (4) case study analysis; (5) discussion of the implications of the findings; and (6) research limitations.

Comparative Analysis and Model Selection

The first stage in the analysis was evaluating and selecting the best machine learning model for detecting price anomalies. Four models (Random Forest, Logistic Regression, Gradient Boosting, and SVM) were evaluated for their performance using the training data (n=4,712, covering the 2022-2024 period).

The evaluation method employed was 20-fold Stratified Cross-Validation. The evaluation focused on the model's ability to detect the "Anomaly Yes" class. The evaluation results using the primary assumption of 5% contamination are presented in Table 1.

Table 1. Model Performance Comparison Results (20-fold Stratified CV)

Model	AUC	CA	F1	Prec	Recall
Random Forest	0.998	0.988	0.868	0.974	0.783
Logistic Regression	0.987	0.985	0.834	0.941	0.749
Gradient Boosting	0.995	0.991	**0.904**	0.953	0.860
SVM	0.976	0.989	0.881	0.974	0.804

Source: Author's Processed Data (2025)

Based on Table 1, Gradient Boosting demonstrated the most superior overall performance. This model not only achieved the highest Accuracy (CA) at 0.991 but also the highest Recall (0.860), meaning it is the most effective in capturing anomalous cases. Although Random Forest and SVM had the highest Precision (0.974), Gradient Boosting significantly excelled in the balance metric.

In line with the objective of obtaining the most balanced model, the F1-Score metric served as the primary reference. Based on Table 1, Gradient Boosting was selected as the best model because it achieved the highest F1-Score (0.904). This value reflects the optimal balance between a high Precision (0.953) and high Recall (0.860), making it the optimal choice for subsequent analysis. This result is supported by (Sa'adah & Hartanto, 2023) who stated that Gradient Boosting is known as one of the best-performing supervised machine learning algorithms.

Table 2. Sensitivity Analysis Results of Contamination Parameters (F1-Score)

Model	F1-Score with Contamination		
	1%	5%	10%
Random Forest	0.693	0.868	**0.890**
Logistic Regression	0.535	0.834	0.732
Gradient Boosting	**0.839**	**0.904**	**0.880**
SVM	0.419	0.881	0.695

Source: Author's Processed Data (2025)

The results in Table 2 reveal a crucial finding. Under the 1% and 5% contamination scenarios, Gradient Boosting consistently exhibited the highest F1-Score. However, in the 10% contamination scenario (which makes the training data more balanced), Random Forest (F1-Score 0.890) showed a slightly superior performance compared to Gradient Boosting (F1-Score 0.880).

This finding indicates that the model selection can be sensitive to the initial assumption of the anomaly proportion. However, considering that (1) 5% contamination is a common methodological assumption used in anomaly detection studies, (2) Gradient Boosting proved superior in the 1% and 5% scenarios, and (3) the performance difference in the 10% scenario was very marginal (0.01), Gradient Boosting was retained as the best and most representative model for the in-depth analysis in the subsequent sections, utilizing 5% contamination for the primary analysis.

Driving Factor Analysis

This stage aims to validate which features contribute the most to the model's decisions (Objective 2). This analysis utilizes the Rank widget to evaluate the statistical significance of each feature against the target variable ("Anomaly Yes/No").

Table 3. Driving Factor Rankings

Rank	Feature	Gain Ratio	Gini	ReliefF
1	Country	0.021	0.012	0.538
2	HS Code	0.013	0.008	0.352
3	Unit Value	0.011	0.003	0.025
4	Month	0.000	0.000	0.040
5	Year	0.000	0.000	-0.006

Source: Author's Processed Data (2025)

Table 3 demonstrate consistent findings and provide two important methodological results:

a. Validation of Temporal Feature Exclusion: The Month and Year features, which were intentionally excluded from the model, accurately yielded Gain Ratio and Gini scores of zero (0.000). This is a technical confirmation that the model did not utilize these features to make predictions, thereby successfully avoiding overfitting on seasonal patterns or annual trends.
b. Hierarchy of Driving Factors: The three features used by the model exhibit a clear and consistent hierarchy (order) of importance across various evaluation methods (Gain Ratio, Gini, and ReliefF). Country consistently emerged as the most significant predictor (Rank 1). This was followed by HS Code (Rank 2) and Unit Value (Rank 3).

These findings validate that the Gradient Boosting model has learned that to predict anomalies, the country of origin of the goods is the most important factor, followed by the specific type of goods and their price.

Aggregate Detection Results on 2025 Data

After the Gradient Boosting model was validated and selected as the best model, it was subsequently applied to the testing data, namely the import data of automatic data processing

machines throughout 2025 (n=1,071 transactions). The aggregate detection results are presented in Table 4.

Table 4. Aggregate Results of Model Predictions on 2025 Data

Prediction Category	Number of Transactions	Percentage (%)
Anomaly *(Yes)*	51	4.76
Anomaly *(No)*	1,020	95.2
Total	1,071	100

Source: Author's Processed Data (2025)

Out of a total of 1,071 import transactions in 2025, the Gradient Boosting model successfully identified 51 transactions (accounting for 4.76% of total imports) as cases with a high potential for import price anomalies. The anomalous results are derived from data instances whose anomaly scores have been calculated, indicating the extent to which the data deviates (Zulfikar et al., 2023). This finding provides an initial quantitative overview of the scale of the problem in the 2025 data.

Case Study Analysis (Model Validation)

After the model identified 51 "Anomaly Yes" transactions in the 2025 data, the next step was to analyze the characteristics of these 51 cases to validate the model's findings (Objective 3). The analysis was divided into two stages: aggregate characterization and comparative validation.

- **Aggregate Characterization of Detected Anomalies**

First, the 51 anomalous transactions were grouped based on the two strongest predictor features (according to Table 3), namely Country and HS Code, to observe detection patterns.

Table 5. Distribution of Detected Anomalies (n=51) by Country of Origin

Country of Origin	Number of Transactions	Percentage (%)
Australia	19	37,25
Thailand	14	27,45
Singapore	9	17,65
United States	3	5,88
Japan	2	3,92
South Korea	2	3,92
Malaysia	2	3,92
Total	**51**	**100**

Source: Author's Processed Data (2025)

The analysis results in Table 5 indicate that anomaly detections were heavily concentrated on imports from Australia. A total of 19 out of the 51 cases (37.25%) originated from this country. Thailand (27.45%) and Singapore (17.65%) were the second and third most frequently detected countries of origin.

Table 6. Distribution of Detected Anomalies (n=51) by HS Code

HS Code	Number of Transactions	Percentage (%)
84713020	13	25,49%
84717040	11	21,57%
84714990	9	17,65%
84718070	4	7,84%
Other 8471	14	27,45%
Total	**51**	**100%**

Source: Author's Processed Data (2025)

Viewed from the type of goods (Table 6), anomalies were most frequently detected in HS Code 84713020 (laptops, including notebooks and subnotebooks), which accounted for 13 cases (25.49%) of the total anomalies. This was followed by HS Code 84717040 (optical disk

drives, including CD-ROM drives, DVD drives, and CD-R drives) with 11 cases (21.57%) and HS Code 84714990 (other personal computers in the form of systems other than portable computers) with 9 cases (17.65%). This characterization provides a sharp investigative focus: the model specifically highlights laptop imports (HS Code 84713020) and Australia as the areas with the highest potential for price anomalies in the 2025 data.

- **Comparative Validation with the Fair Price**

The final stage was to validate the 51 "Anomaly Yes" transactions. The validation was conducted by comparing the Unit Value (price per kg) of these 51 anomalous transactions against the "Fair Price" benchmark (Median Unit Value 2022-2024) for the same HS Code and Country. The results of this comparative comparison yielded significant findings:

a. 2 cases (3.9%) showed a Unit Value significantly lower than their fair benchmark (an indication of under-invoicing).
b. 26 cases (51.0%) showed a Unit Value significantly higher than their fair benchmark (an indication of over-invoicing).
c. 23 cases (45.1%) could not be validated using the "Fair Price" method because no historical benchmark was found. These cases were classified as "Structural Anomalies" and will be analyzed further using external validation in the discussion of the findings' implications.

These findings indicate that the trained model is not only capable of detecting under-invoicing but also dominantly detects over-invoicing. To provide a more structured comparative overview, Table 7 presents the details of three representative case studies successfully identified by the model.

Table 7. Comparative Analysis of Price Anomaly Detection Case Studies in 2025

Case Study	Commodity & HS Code	Country of Origin	Confidence Level	Reported Price ($/Kg)	Fair Price Benchmark ($/Kg)	Price Difference	Indication
1	Laptop (84713020)	Thailand	61.02%	$20.80	$100.85	- 79.38%	Under-invoicing
2	Other Personal Computers (84714990)	Australia	91.64%	$82,272.70	$221.20	+ 37,093%	Over-invoicing
3	Optical Disk Drive (84717040)	United States	50.41%	$1,904.47	$143.25	+ 1,229.47%	Over-invoicing

Source: Author's Processed Data (2025)

Based on Table 7, the comparative case study analysis demonstrates a consistent pattern: transactions marked as "Anomaly Yes" by the Gradient Boosting model objectively exhibited Unit Values that were statistically very far apart (either much lower or much higher) compared to their historical normal price benchmarks (the 2022-2024 median values). Findings such as an extreme price difference of over 37,000% in the case of imports from Australia provide strong evidence that the model developed from BPS public data (Import Value and Net Weight) is not merely guessing, but is highly effective and valid. This model has proven capable of isolating transactions with a high risk of price anomalies, which logically indicates the presence of price manipulation practices, either in the form of reporting lower values (under-invoicing) or reporting higher values (over-invoicing).

Discussion of the Implications of the Findings

- **First Implication: Anomaly Detection Asymmetry (Over-invoicing vs. Under-invoicing)**

The most significant finding of this research is the clear asymmetry in anomaly detection. Although the introduction identified under-invoicing and over-invoicing as two equally destructive forms of price manipulation, the model validation results demonstrate highly skewed findings. The model detected 26 cases (51.0%) indicating over-invoicing, yet only 2 cases (3.9%) indicating under-invoicing. The implications of this finding are:

a. Model Objectivity Validation: This proves that the trained model (based on Isolation Forest and Gradient Boosting) is an objective statistical anomaly detector. The model is not biased towards the human assumption that tends to look for under-invoicing; instead, it factually demonstrates that in the 2025 data for HS 8471, upward price deviations are the more frequently occurring anomalies.
b. Sharpening of Risk Focus (Commodity-Specific): This finding indicates that for the specific commodity of HS 8471 in the 2025 data, the risk of over-invoicing (potentially related to capital flight) is statistically identified as far more dominant than the risk of under-invoicing (associated with state revenue loss). This dominance becomes highly logical when associated with tariff regulations, where HS 8471 commodities generally have an Import Duty tariff of 0% (BPS, 2025). The absence of tax disincentives means importers bear no additional burden when reporting high prices, making the over-invoicing scheme a minimal-risk loophole for capital flight or transfer pricing (Laksmana, 2013).
c. Contextualization of the Australian Case (Compliance vs. Structural Shift): The concentration of extreme upward price anomalies from developed countries, specifically Australia (19 cases), requires careful interpretation. A very high price per kilogram (as in Case Study 2) does not always signify fraud, but rather indicates data asymmetry due to BPS aggregation. This highly likely reflects a shift in the Business-to-Business (B2B) import structure from standard commercial devices to Enterprise-grade devices or high-level computing units (AI accelerators/data center servers). Given that the BPS 8-digit HS code does not distinguish standard devices from premium servers, this leap in specifications is captured by the algorithm as an anomaly. This proves the model does not merely track compliance anomalies but is also sensitive to economic structural shifts.

- **Second Implication: Model Validation as an Early Warning System (Structural Anomalies)**

The second crucial finding of this research is the detection of 23 cases (45.1%) of anomalies that could not be validated using the “Fair Price” comparative method. This occurred because no normal historical price benchmarks were found for those specific HS Code and Country combinations in the 2022-2024 training data. In the initial analysis, this finding was interpreted as evidence of the model's dual function: (1) as a price checker for existing trade routes (28 cases), and (2) as an early warning system for structural anomalies (the emergence of new trade patterns or routes lacking a baseline). The strength of this early warning function can now be empirically validated through external data tracing. The model's findings were found to strongly correlate with specific real-world economic events and trade trends occurring during the 2024-2025 period.

a. Thailand Case Study (HS 8471.70): The model detected 9 structural anomaly cases from Thailand, dominated by storage units such as Optical Disk Drives (8 cases, HS 84717040) and Tape Drives (1 case, HS 84717030). This detection aligns with industry reports noting a 104% surge in computer component exports from Thailand between May 2024 and May 2025 (DHL, 2025). Thailand's surge in exports of computers and electronic parts stems from a combination of factors, ranging from honed domestic capabilities to shifting global economic currents. The report specifically highlights Thailand's strength in the manufacturing ecosystem (storage units), which explains the sudden emergence of

exports in related product categories (HS 8471.70) to Indonesia that were not recorded in the 2022-2024 data.

b. Australia Case Study (HS 8471.30 & 8471.50/80): The model detected 14 structural anomaly cases from Australia, dominated by laptops (8 cases, HS 84713020) and processing/control unit components (4 cases, HS 84715010 & 84718090). This finding can be explained by two concurrent driving factors:
   - Policy Pillar: The implementation of the Indonesia-Australia Comprehensive Economic Partnership Agreement (IA-CEPA), which aims to liberalize trade in goods and create a new framework for trade in information media and telecommunications services, as well as digital trade (Australian Government, n.d.).
   - Market Pillar: The investment boom in Australia's data center market in 2024-2025, experiencing very rapid growth (Lobb, 2025), which coincided with Indonesia's investment interests that specifically targeted data centers as well (Ngui, 2025).

   The combination of trade liberalization (IA-CEPA) and new market demand (data centers) created the ideal conditions for the emergence of new Business-to-Business (B2B) trade routes for laptops and specialized server components from Australia that previously did not exist.

This external validation proves that the 23 "Structural Anomalies" flagged by the model are not statistical noise. On the contrary, they are valid signals of shifting trends and the opening of new trade routes. This empirically confirms that the proposed framework functions not only as a price checker but also as an effective early warning system.

- **Third Implication: Validation of the Main Hypothesis (Public Data)**

Despite all its limitations, this research practically proves its main hypothesis: the highly limited BPS public data (only Import Value and Net Weight) is sufficient to build an effective and valid anomaly detection model prototype. This model successfully identified anomalies, validated its predictors (Table 3), and uncovered new insights (the dominance of over-invoicing). This opens up opportunities for researchers outside official institutions to conduct data-driven oversight.

- **Fourth Implication: Systematic Intervention on the Opportunity Element in the Fraud Triangle**

From a theoretical perspective, the results of this study provide a new dimension to the application of the Fraud Triangle Theory in the customs sector. As is known, price manipulation is not only driven by financial pressure but is also highly dependent on the existence of opportunity arising from the weaknesses of manual supervision and information asymmetry (Abdullahi & Mansor, 2015; Rasheed et al., 2023). The success of the Gradient Boosting model in processing large-scale aggregate data and automatically identifying 51 anomalies aligns with Sánchez-Aguayo et al. (2021), who stated that machine learning can transform from a mere statistical analysis tool into a behavioral control instrument. With the early detection of extreme price anomalies, even in structural anomalies that lack historical price benchmarks, this algorithm effectively reduces information asymmetry between importers and authorities. Conceptually, the integration of this public data-based detection model serves to close this opportunity loophole, thereby breaking one of the main chains that are a prerequisite for fraud to occur.

Research Limitations

Although this research provides valid findings, there are several inherent limitations that can serve as a reference for future research.

1. Limitations of External Validation: Although the external validation in the discussion of the findings' implications successfully linked structural anomalies with macro trends (such as IA-CEPA and the surge in Thailand's exports), this validation is qualitative in

nature. This research cannot quantitatively prove a direct causal link between these trade agreements and each individual transaction.

2. Limitations of BPS Data Aggregation: This research uses BPS public data, which is often aggregate data. It is possible that this aggregate data has masked extreme transaction-level anomalies. An extreme under-invoicing transaction might be disguised by fair transactions within the same month, making the monthly average appear normal.
3. Limitations of Labeling Assumptions (Ground Truth): All supervised models are built upon the labels generated by the Isolation Forest. Setting the contamination=5% parameter in the Isolation Forest is a methodological assumption (an educated guess), not the ground truth. This limitation has been empirically confirmed through the sensitivity analysis presented in the comparative analysis and model selection. The analysis showed that the choice of the best model (between Gradient Boosting and Random Forest) is sensitive to this parameter. This clearly proves that model performance (Table 1) and the number of detections (Table 4) could change if the ground truth proportion of anomalies in the field differs from the 5% assumption used in this study.
4. Limitations of Generalization and Extreme Heterogeneity: This case study is highly specific to automatic data processing machine commodities (HS Code 8471). Even within the 8-digit HS level, this commodity has an excessively broad spectrum—ranging from simple components like mice and mainstream laptop devices to high-specification server racks. Furthermore, a model based solely on aggregate data cannot capture innovation variables and premium brands (e.g., the price per kilogram difference between an Apple product and a generic product). This has the potential to distort the "Fair Price" calculation.
5. Limitations of the Technology Depreciation Cycle: The combined research timeframe covers four years (2022-2025). This grouping does not specifically account for the rapidly moving depreciation rate of global technology goods. Computer hardware prices are susceptible to drastic year-over-year declines, so the use of multi-year historical price benchmarks may introduce a comparative bias against the latest transaction data.

CONCLUSION

Conclusion

This research successfully proved its main hypothesis, namely that public data from Statistics Indonesia (BPS), despite being highly limited (only import value and net weight), can be effectively utilized to build a machine learning model prototype for import price anomaly detection. Through comparative evaluation, the Gradient Boosting model was identified as the most superior (F1-Score 0.904) in learning the anomaly patterns labeled by the unsupervised Isolation Forest algorithm. The driving factor analysis also quantitatively confirmed that Country and HS Code are the two most important predictors. The application of the model to the 2025 data identified 51 transactions (4.76%) as anomalies. The key finding of this research is a clear asymmetry in detection: the majority of validated anomalies (26 cases) indicate over-invoicing, while only 2 cases indicate under-invoicing.

The novelty contribution of this research lies in two aspects: (1) The validation of the "Unit Value" (price per Kg) proxy methodology from BPS public data as a viable alternative to confidential internal customs data. (2) The proof that machine learning (Gradient Boosting) possesses superiority over manual statistical analysis. This model is capable of simultaneously analyzing multidimensional interactions among features, proving that the algorithmic approach functions not only as a price checker but also as an early warning system in detecting structural anomalies (23 cases), which effectively closes the "opportunity" loophole in the Fraud Triangle.

Policy Recommendations

Based on the research findings, there are several practical and strategic recommendations, particularly for the Directorate General of Customs and Excise (DJBC), to follow up on this model prototype:

1. Pre-Clearance System Integration: It is recommended that DJBC integrates this Gradient Boosting algorithm into the customs and excise information system as an automated anomaly filter engine (automated risk-engine) at the pre-clearance stage. This model can sort through thousands of Import Declarations in a matter of seconds to determine which ones require physical inspection or an in-depth customs valuation audit.
2. Refinement with Internal Data (Goods Description): To overcome distortions caused by brand heterogeneity (e.g., Apple vs. generic brands) and technology depreciation, this model should be periodically retrained using DJBC's internal data. Internal data that includes specific goods description features will significantly reduce the number of false positives that arise in high-tech commodities.
3. Scaling Up to Vulnerable Commodities: The machine learning framework, whose complexity has been tested on HS 8471, must be immediately replicated for commodities vulnerable to under-invoicing. The primary focus could be directed at imports of textiles, garments, and footwear, particularly those originating from major trading partner countries like China that utilize preferential tariff schemes.
4. Continuous Ground Truth Updating: Actual audit results must be fed back into the system as the true "Anomaly Yes/No" labels (ground truth). This will replace the initial 5% contamination parameter assumption in the Isolation Forest, enabling the model to continuously learn and adapt to the latest, constantly evolving fraud modus operandi.

DECLARATION OF AI-ASSISTED TECHNOLOGIES USE

During the preparation of this work, the author used Gemini (Google) in order to translate the manuscript, check grammar, enhance English language clarity, and improve overall academic readability. After using this tool, the author thoroughly reviewed, verified, and edited the content as needed, and takes full responsibility for the content of the published article.

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