Journal Management, Informatics, Software Engineering and Communication Technology
Vol. 5 No. 1, December (2026) pp. 116-126
Published by: Marq & Cha Institute
Journal Management, Informatics, Software Engineering and Communication Technology
Journal homepage: www.ejournal.marqchainstitute.or.id/index.php/jmirte

Fast- and Slow-Moving Product Classification Using XGBoost

Felisia Aquerah[1], Mahardika Abdi Prawira Tanjung[2]
[1,2] Program Studi Sistem Informasi, Fakultas Ilmu Komputer dan Teknologi Informasi, Universitas Muhammadiyah Sumatera Utara, Medan, Indonesia

Article Info

Article history

Received : Sep 14, 2026
Revised : Sep 29, 2026
Accepted : Oct 11, 2026

Keywords:

Fast-Moving Items;
Slow-Moving Items;
Sales Transaction Data;
Extreme Gradient Boosting;
Classification.

Abstract

Inventory management is essential to ensure proper product availability and movement within a company. PT Rodes Chemindo classified fast-moving and slow-moving items manually using Microsoft Excel, a method that underutilized available transaction data, was time-consuming, and was prone to error. This study applied the Extreme Gradient Boosting method to classify items based on total sales quantity and transaction frequency, using 17,973 sales transactions recorded from January to December 2025 covering 413 distinct items. The data were preprocessed, aggregated, and split into 330 training and 83 testing sets with an 80:20 ratio. The Turnover Ratio determined the fast-moving and slow-moving categories. The resulting model achieved accuracy, precision, recall, and F1-score values of 1.00 for all 83 test data points. The model was then integrated into a web-based system supporting data upload, processing, classification, and visualization to support inventory management decisions at PT Rodes Chemindo.

Corresponding Author:

Felisia Aquerah,
Program Studi Sistem Informasi,
Universitas Muhammadiyah Sumatera Utara,
Jl. Kapten Mukhtar Basri No. 3, Medan, 20238, Indonesia.
Email : fellisaq1@gmail.com

This is an open access article under the CC BY-NC license.

1. Introduction

Inventory is one of the most critical factors in business operations, as it is closely related to product availability, cost efficiency, and the smoothness of the distribution process. Effective inventory management involves the processes of planning, monitoring, and controlling stock levels so that production and distribution activities can run efficiently without wasting resources (Suriyani et al., 2020). In companies that distribute chemical products, such as PT Rodes Chemindo, inventory management becomes more complex because each product has a different stock movement rate, ranging from fast-moving to slow-moving items. The classification of products based on stock movement rate is commonly known as the Fast, Slow, and Non-Moving (FSN) method, which classifies products based on turnover frequency using the Turnover Ratio (TOR) indicator; a high TOR value indicates that a product is fast-moving, whereas a low TOR value indicates that the product is slow-moving (Rodjimin et al., 2023). The application of the FSN method has been shown to help companies optimize the procurement process in order to minimize storage costs (Habibi & Ulkhaq, 2025).

At present, PT Rodes Chemindo still classifies fast-moving and slow-moving products manually using rule-based formulas in Microsoft Excel. With a total of 17,973 sales transactions recorded from January to December 2025 across 413 distinct products, this manual approach has become increasingly inefficient, time-consuming in terms of computation, and prone to human error as the volume of

transaction data continues to grow over time. This condition highlights the need for a machine-learning-based approach capable of performing product classification automatically, quickly, and accurately.

Extreme Gradient Boosting (XGBoost) is a supervised learning algorithm based on ensemble decision tree boosting that offers superior accuracy, speed, and computational efficiency, particularly for large-scale data classification (Massaro et al., 2021). Its structured and optimized tree-boosting mechanism has been proven to improve classification accuracy compared with conventional methods (Kurniawansyah et al., 2025). The effectiveness of XGBoost is further supported by several prior studies: Wang (2023) demonstrated that XGBoost could reduce the Mean Absolute Error by up to 29% in retail sales forecasting compared with conventional methods; Astrani and Rahayuda (2025) reported that the Gradient Boosting Decision Tree algorithm improved retail sales prediction accuracy by up to 92% compared with K-Nearest Neighbors (KNN); and Arai et al. (2023) proved that boosting algorithms such as XGBoost and LightGBM performed better than traditional methods in analyzing customer behavior and large-scale sales data.

Although previous studies have demonstrated the advantages of XGBoost in the context of classification and sales prediction, existing research — such as the study by Arai et al. (2023) on customer churn estimation, Arifin et al. (2023), which limited its FSN analysis to a descriptive approach based on TOR, and Astrani and Rahayuda (2025), which focused solely on retail sales prediction — generally stops at the classification analysis stage without integrating the results into a system that can be directly used by business practitioners. This gap represents both the research gap and the novelty of the present study: in addition to applying the XGBoost algorithm to classify fast-moving and slow-moving products based on aggregate features of total quantity sold (total_qty) and transaction frequency, this study also develops a web-based classification system that integrates data input, preprocessing, classification, and result visualization within a single platform using Flask and MySQL — thereby enabling managers at PT Rodes Chemindo to operate the machine learning model without needing to understand the underlying program code.

The urgency of this research is further reinforced by the continuously increasing transaction volume and sales complexity at PT Rodes Chemindo over time, which renders manual, spreadsheet-based methods increasingly inadequate as a tool for operational decision-making. Therefore, this study aims to analyze PT Rodes Chemindo's sales transaction data to more accurately identify fast-moving and slow-moving product categories using the XGBoost algorithm, while also developing a web-based system capable of automating this classification process to support more effective and efficient inventory management decision-making.

2. Research Methodolgy

2.1. Research Paradigm and Approach

This study employs a quantitative approach with a case study research type, conducted at PT Rodes Chemindo, a chemical product distribution company located in Medan, North Sumatra. The quantitative approach was selected because this study processes numerical data in the form of transactional data, which is analyzed using statistical methods and machine learning algorithms in a systematic, objective, and comprehensive manner (Sugiyono, 2022). The case study type was chosen because the research focuses on a single object, namely the fast-moving and slow-moving product classification process at PT Rodes Chemindo, allowing the analysis to be conducted consistently with the company's real business conditions.

2.2. Unit of Analysis

The unit of analysis in this study is the sales transaction history data of PT Rodes Chemindo. The main dataset used to build the classification model covers the period from January to December 2025, comprising a total of 17,973 transaction records, which produced 413 unique products as classification objects. Two main aggregate features were used as research variables, namely the total quantity sold (total_qty) and transaction frequency, which were subsequently used to determine the

fast-moving and slow-moving category labels based on the Turnover Ratio (TOR). A summary of the unit of analysis is presented in Table 1.

Table 1. Summary of the Research Dataset

No	Dataset Parameter	Actual Value / Size	Unit of Analysis	Purpose
1	Total Data Volume	17,973	Rows/Records	Raw transaction data
2	Total Attributes	16	Columns	Dataset structure
3	Unique Products	413	Products	Classification objects
4	Main Features	5	Variables	Total_qty and transaction frequency

2.3. Data Collection Technique

Data collection was carried out through three methods:

1. Documentation study — the collection and review of primary data on sales transaction history, including transaction date, product code and name, and total units sold.
2. Semi-structured interviews — conducted with personnel directly involved in the company's operations (Logistics Supervisor, Warehouse Administration Staff, Sales Division, and Warehouse Head) to explore the factors affecting product performance, the challenges of manual inventory management, and the product classification strategies currently applied.
3. Field observation — conducted at the warehouse area and distribution process to directly observe the mechanism of recording incoming and outgoing goods.

The combination of these three techniques was used to obtain valid, accurate, and relevant data to support the analysis process and the development of the classification model.

2.4. Data Analysis Procedure

Data analysis in this study was carried out through seven interconnected stages:

1. Problem analysis — identifying the weaknesses of the manual, Excel-based classification process, which is prone to human error and has not fully utilized large-scale transaction data.
2. Determination of the analysis method — selecting the Extreme Gradient Boosting (XGBoost) algorithm for its ability to handle large-scale data with high accuracy through its boosting mechanism.
3. Data preprocessing — including data cleaning (removal of duplicates and missing values) and data transformation into aggregate features (total_qty and transaction frequency), followed by category labeling based on the TOR.
4. Dataset splitting — the data were divided into 80% training data (330 products) and 20% testing data (83 products) using random_state = 42 to ensure the reproducibility of the results.
5. Classification model development — the XGBoost model was trained using the main parameters learning_rate = 0.1, max_depth = 5, and n_estimators = 100, along with additional parameters such as subsample, gamma, min_child_weight, and L1/L2 regularization (reg_alpha and reg_lambda) to prevent overfitting.
6. Model evaluation — model performance was measured using the Confusion Matrix, Accuracy, Precision, Recall, and F1-Score on 83 test data points.

7. Presentation of results — the classification results were integrated into a web-based system to support inventory management decision-making at PT Rodes Chemindo.

The overall flow of this process is visualized in the form of a system flowchart, as shown in Figure 1.

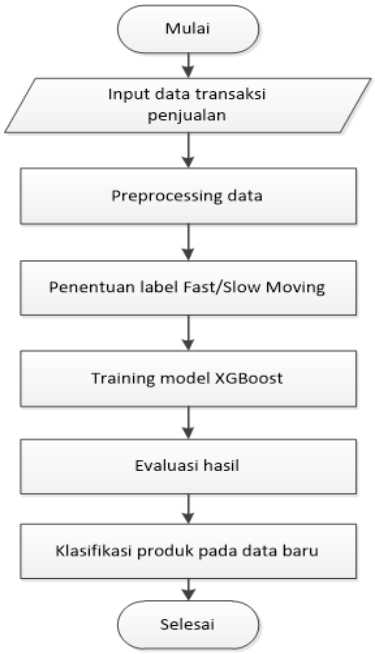


Figure 1. Flowchart of the Fast-Moving and Slow-Moving Classification System

2.5. System Development

In addition to building the classification model, this study also developed a web-based system using the Python programming language with the Flask framework, data analysis libraries (Pandas, NumPy, Scikit-Learn), front-end technologies (HTML5, CSS/Bootstrap, JavaScript), and MySQL as the database management system. The system design includes the data structure (Entity Relationship Diagram), Use Case Diagram, Activity Diagram, Sequence Diagram, and Class Diagram, which collectively illustrate the flow of user interaction with the system — from transaction data upload and automatic classification to the presentation of results in the form of tables and graphical visualizations.

3. Results And Discussions

System Implementation Overview

The classification model developed in Section 2 was implemented as a prototype web-based information system built with the Python Flask framework, the Pandas and NumPy libraries for data handling, the XGBoost library for the classification engine, and MySQL as the relational database management system. The front end was built using HTML5, CSS/Bootstrap, and JavaScript. The system applies role-based, multi-user authentication: an Administrator account can upload a transaction dataset (in .CSV format) or add transactions manually through an input form, trigger the preprocessing and classification pipeline, and manage the reference product master data, while a standard User account has read-only access to the classification dashboard and reports.

Once a dataset is supplied and an analysis date range is selected, the system performs data cleaning (duplicate removal and null-value handling using drop_duplicates and dropna), converts the transaction date field with pd.to_datetime, and aggregates the cleaned records by product code to

generate the two predictor features used for classification, namely total quantity sold (total_qty) and transaction frequency. The trained XGBoost model then assigns each product a binary class label together with a prediction-confidence score obtained from predict_proba, before the results are written back to the MySQL database and rendered on the dashboard as summary statistic cards, a bar chart comparing Fast-Moving and Slow-Moving product counts, a pie chart of the classification distribution, a detailed results table, and a monthly sales pivot matrix. Classification outputs can subsequently be exported to Excel (.xlsx) or PDF for reporting purposes. The relationship between the three core data entities used by the system, Produk (Product), Transaksi (Transaction), and Hasil_Klasifikasi (Classification Result), is illustrated by the Entity Relationship Diagram in Figure 2.

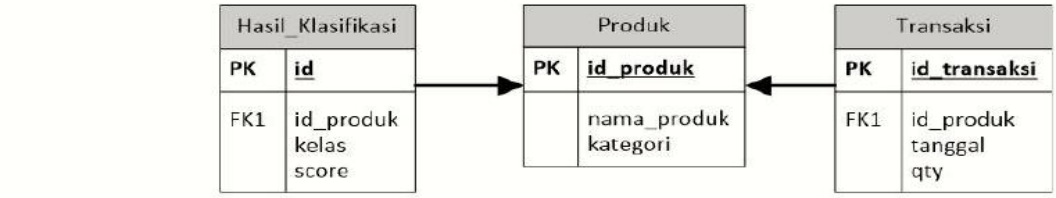


Figure 2. Entity Relationship Diagram (ERD) of the Classification System

Feature Engineering, Labeling, and Dataset Partitioning

Aggregating the 17,973 cleaned transaction records by product code yielded 413 unique products, each represented by the two aggregate features described above. A rule-based labeling scheme derived from the Turnover Ratio (TOR) concept was then applied: a product whose annual total_qty was greater than or equal to 1,000 units was labeled 1 (Fast-Moving), while a product below this threshold was labeled 0 (Slow-Moving). The resulting labeled dataset was partitioned using scikit-learn's train_test_split function with an 80:20 ratio and a fixed random_state of 42 to ensure reproducibility, producing 330 products for model training and 83 products reserved exclusively for testing. Table 2 summarizes the final hyperparameter configuration of the XGBClassifier together with the labeling threshold and the resulting data partition.

Table 2. XGBoost Hyperparameter Configuration and Dataset Partitioning

Parameter	Configuration / Value
learning_rate	0.1
max_depth	5
n_estimators	100
eval_metric	logloss
Regularization	subsample, gamma, min_child_weight, reg_alpha, reg_lambda
Classification threshold (total_qty)	≥ 1,000 units → Fast-Moving (1); < 1,000 units → Slow-Moving (0)
Training data	330 products (80%)
Testing data	83 products (20%)
random_state	42

Functional (Blackbox) Testing

Prior to performance evaluation, the web application was tested using the blackbox testing method to verify that every major functional component, covering authentication, data input, the classification trigger, and reporting, produced the output expected by its design without inspecting the underlying source code. Fifteen test scenarios were executed in total; Table 3 presents a representative summary of these scenarios and their outcomes.

Table 3. Summary of Functional (Blackbox) Testing Results

No	Feature Tested	Test Scenario	Expected Result	Status
1	Admin login	Valid credentials submitted	Session created; redirected to admin dashboard	Valid
2	Login (failure case)	Invalid credentials submitted	Error message displayed; access denied	Valid
3	CSV dataset upload	Upload a 2024–2026 transaction file	File structure verified and loaded into memory	Valid
4	Manual transaction entry	Fill in product ID, date, quantity, etc.	Data saved to the MySQL database	Valid
5	Run classification	Administrator triggers the classification function	XGBoost model executes and returns class labels	Valid
6	Fast-/Slow-Moving label display	Sample high- and low-volume products classified	Correct colored class badge shown in the results table	Valid
7	Confidence score display	Compute predict_proba for a sample product	Probability score rendered as a progress indicator	Valid
8	Monthly sales matrix	Build a year-over-year pivot table	Structured monthly pivot table displayed	Valid
9	Excel / PDF export	Export the classification table	Downloadable .xlsx / .pdf report generated without data loss	Valid
10	Unauthorized access control	Access the dashboard URL directly without a session token	User blocked and redirected to the login form	Valid

All fifteen scenarios, including the ten summarized in Table 3, returned the status "Valid," indicating that the login mechanism, data-input pathways, classification trigger, visualization components, export functions, and access-control safeguards of the system operate as intended and free of fatal errors.

Model Evaluation

Quantitative evaluation of the XGBoost classifier was carried out on the 83 isolated testing products using the Confusion Matrix together with the Accuracy, Precision, Recall, and F1-Score metrics computed with a weighted average and zero_division = 0 to accommodate the class imbalance between the two categories. The resulting confusion matrix is presented in Table 4.

Table 4. Confusion Matrix of the XGBoost Classification Model on Test Data

	Predicted Fast-Moving (1)	Predicted Slow-Moving (0)

Actual Fast-Moving (1)	6 (True Positive)	0 (False Negative)
Actual Slow-Moving (0)	0 (False Positive)	77 (True Negative)

Based on Table 4, TP = 6, TN = 77, FP = 0, and FN = 0, so that Accuracy = (TP+TN)/(TP+TN+FP+FN) = 83/83 = 1.00, Precision = TP/(TP+FP) = 6/6 = 1.00, Recall = TP/(TP+FN) = 6/6 = 1.00, and F1-Score = 2×(Precision×Recall)/(Precision+Recall) = 1.00. These final results are summarized in Table 5 and illustrated in Figure 3.

Table 5. Final Evaluation Results of the XGBoost Classification Model

No	Evaluation Metric	Result (%)
1	Accuracy	100.00 (1.00)
2	Precision	100.00 (1.00)
3	Recall	100.00 (1.00)
4	F1-Score	100.00 (1.00)

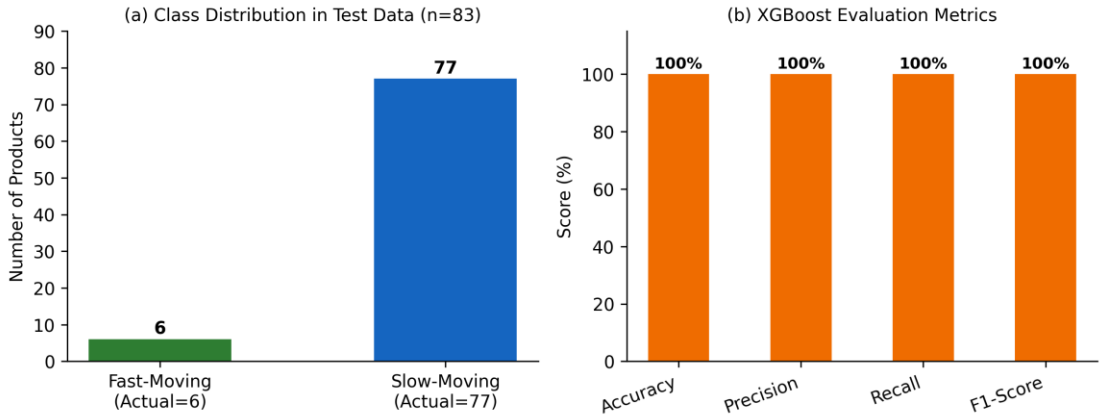


Figure 3. (a) Class Distribution and (b) Evaluation Metrics of the XGBoost Model on Test Data (source: author's analysis)

The perfect scores obtained on all four metrics indicate that the sequential decision trees built by the XGBoost classifier were able to fully separate the two classes without any misclassification on the isolated test set. This outcome should, however, be interpreted with an important caveat: because the Fast-Moving and Slow-Moving labels were themselves generated from a deterministic total_qty threshold of 1,000 units, the two classes are linearly and cleanly separable by construction, with no overlapping or borderline cases in the 2025 dataset. The model is therefore best understood as having successfully learned and reproduced this decision boundary rather than having resolved genuine ambiguity between classes. It is also worth noting that the test set is considerably imbalanced (6 Fast-Moving versus 77 Slow-Moving products), which is characteristic of inventory data in which only a small proportion of items are true fast movers; the weighted-average evaluation setting was chosen specifically to keep the reported metrics representative under this imbalance. Consequently, while the 100% scores confirm that the modeling pipeline, feature engineering, and implementation are functioning correctly, achieving equally perfect performance on future data with noisier or borderline sales patterns cannot be guaranteed and should be verified through periodic re-evaluation as new transaction data accumulates. In addition to the aggregate metrics, the system reports a per-product Confidence Score derived from predict_proba, which gives PT Rodes Chemindo management a transparent, product-level indication of how strongly the model supports each individual classification

decision, complementing the overall Confusion Matrix-based validation.

Sales Pattern Analysis and Strategic Implications

To relate the classification results to actual business conditions, the monthly 2025 sales volumes of ten sample products were examined. Table 6 lists the total annual quantity sold for each sample product together with the resulting classification under the 1,000-unit threshold.

Table 6. Annual Sales Volume and Classification of Sample Products 2025

Product	Total Annual Quantity (Units, 2025)	Classification
INTRA WHITE 12C75	509,584	Fast-Moving
MAT 300 JUSHI 1040 @30KG	241,798	Fast-Moving
AQUAPROOF PUTIH @4KG	127,622	Fast-Moving
TRANSPARENT 1/4" 100M	2,957	Fast-Moving
BASILIUM @500ML	1,115	Fast-Moving
POLYTANK CAHAYA @200L	901	Slow-Moving
SEPATU LYONS	111	Slow-Moving
SILICONE EMULSION 320 HV	20	Slow-Moving
SELANG HITPRO 1/2" @20M	39	Slow-Moving
YELLOW METERAN 5MM	7	Slow-Moving

Table 6 shows that turnover volume varies substantially across the product portfolio, from a high-demand chemical product such as INTRA WHITE 12C75 (509,584 units) down to near-dormant items such as YELLOW METERAN 5MM (7 units). Notably, BASILIUM @500ML (1,115 units) illustrates a borderline case that remains just above the 1,000-unit cut-off, underscoring the sensitivity of a single fixed threshold and suggesting that a more adaptive or percentile-based threshold could be explored in future iterations of the model. Based on this pattern, three strategic implications for PT Rodes Chemindo's inventory management can be drawn. First, procurement optimization: chemical products classified as Fast-Moving should be prioritized in the replenishment cycle to minimize the risk of stockouts. Second, storage efficiency: Slow-Moving products can be considered for bundling promotions, discounted clearance, or reduced reorder quantities to minimize warehouse space and holding costs. Third, data-driven managerial decision support: the cluster visualization on the dashboard enables operational managers to make logistics decisions based on clear, concise, and objective data rather than subjective manual judgment.

System Validation, Advantages, and Limitations

A cross-validation check between the dynamic dashboard table and the exported Excel/PDF files was performed across all 413 unique product records, comparing attributes such as product code, product name, total_qty, transaction frequency, the binary classification label, and the confidence score. No discrepancies in character formatting, row alignment, or numerical values were found, confirming 100% consistency between the on-screen results and the exported reports with zero data loss during the Excel- and PDF-generation process.

Based on the functional testing and performance evaluation described above, the system offers several key advantages: (1) fully automated, machine-learning-based classification that removes the subjectivity of manual, rule-based spreadsheet classification; (2) transparent, per-product confidence scores that support accountable decision-making; (3) an automatic schema-synchronization mechanism that registers previously unseen product codes during CSV upload, preventing foreign-key

failures in the database; and (4) a portable, self-contained source-code structure that facilitates future deployment and maintenance. Nevertheless, several limitations were identified that outline directions for future development: (1) the prototype currently runs on a local development server and is not yet accessible from outside the company's local network; (2) the CSV upload module is rigidly bound to a fixed 16-column input schema, limiting flexibility for differently structured source data; (3) the classification model relies on only two aggregate predictor features (total_qty and transaction frequency) without incorporating seasonal or trend-based variables; and (4) processing time increases proportionally as transaction volume grows, since data cleaning, aggregation, and prediction are executed sequentially in local computer memory.

4. Conclusion

This study applied the Extreme Gradient Boosting (XGBoost) algorithm to classify 413 products of PT Rodes Chemindo into Fast-Moving and Slow-Moving categories based on 17,973 sales transactions recorded from January to December 2025, and integrated the resulting model into a prototype web-based information system. Four main conclusions can be drawn. First, the XGBClassifier configured with a learning rate of 0.1 and a maximum depth of 5 achieved Accuracy, Precision, Recall, and F1-Score of 100.00% on the 83 isolated test products, a result made possible by the highly consistent and linearly separable total_qty and transaction-frequency features in the 2025 dataset, and it further provides per-product Confidence Scores that make the classification results auditable rather than a black box. Second, a session-token-based, role-based multi-user login mechanism was successfully implemented, restricting dataset upload and model-training privileges to Administrator accounts while preserving read-only reporting access for standard Users, thereby safeguarding the integrity of the underlying MySQL database. Third, the interactive dashboard, the .CSV upload pathway, and the Excel/PDF export pipeline were all verified to function correctly with zero data loss, as confirmed by blackbox testing and cross-validation of the exported reports. Fourth, and most importantly from a managerial standpoint, the system equips PT Rodes Chemindo with an objective, data-driven basis for setting procurement priorities, helping the company reduce the risk of dead stock while minimizing the likelihood of stockouts for high-turnover chemical products. For future research and development, three recommendations are proposed. First, the classification capability could be extended with a time-series forecasting component, such as LSTM or ARIMA, so that the system not only classifies the current turnover status of a product but also predicts future stock requirements. Second, the system's data-input mechanism could be upgraded from manual .CSV uploads to a real-time Application Programming Interface (API) integration with the company's internal Enterprise Resource Planning (ERP) system, eliminating the need for administrators to manually re-upload transaction files. Third, given the caveat discussed in Section 3.4 regarding the deterministic, threshold-based labeling scheme, subsequent studies should broaden the predictor feature space, for example by incorporating product category, profit margin, or seasonal demand trend variables, and should validate the model across multiple years of transaction data to further strengthen its robustness and generalizability beyond the single-year dataset used in this study.

Acknowledgements

The authors would like to thank PT Rodes Chemindo, Medan, for granting access to its 2024–2026 sales transaction data and for the support of its Logistics, Warehouse, and Sales

divisions during the data collection process, and Universitas Muhammadiyah Sumatera Utara for its academic guidance throughout this research.

References

Arai, K., Fujikawa, I., Nakagawa, Y., Momozaki, R., & Ogawa, S. (2023). Churn customer estimation method based on LightGBM for improving sales. International Journal of Advanced Computer Science and Applications (IJACSA), 14(2), 119–125. https://doi.org/10.14569/IJACSA.2023.0140215

Arifin, C. A. Z., Nugraha, A. E., & Winarno. (2023). Klasifikasi persediaan pada gudang bahan kemasan XYZ dengan metode FSN analysis (fast, slow, non-moving) berdasarkan turn over ratio (TOR). Go-Integratif: Jurnal Teknik Sistem dan Industri, 4(2), 76–87. https://doi.org/10.35261/gijtsi.v4i02.8906

Arunika, K. R., & Dewi, L. J. E. (2025). Perbandingan model SARIMA, exponential smoothing, dan XGBoost untuk prediksi penjualan super store. JITET (Jurnal Informatika dan Teknik Elektro Terapan), 13(3S1), 2021–2032. https://doi.org/10.23960/jitet.v13i3S1.8173

Astrani, I. G. A. R., & Rahayuda, I. G. S. (2025). Analisis perbandingan XGBoost dan LightGBM dalam prediksi penjualan ritel Walmart store sales. Jurnal Nasional Teknologi Informasi dan Aplikasinya (JNATIA), 3(4), 717–728. https://doi.org/10.24843/JNATIA.2025.v03.i04.p01

Dachi, J. M. A. S., & Sitompul, P. (2023). Analisis perbandingan algoritma XGBoost dan algoritma random forest ensemble learning pada klasifikasi keputusan kredit. Jurnal Riset Rumpun Matematika dan Ilmu Pengetahuan Alam (JURRIMIPA), 2(2), 87–103. https://doi.org/10.55606/jurrimipa.v2i2.1336

Habibi, N. H., & Ulkhaq, M. M. (2025). Strategi pengendalian persediaan dengan pendekatan klasifikasi ABC-FSN dan metode Min-Max pada material Spiral Wound Gaskets di PT XYZ. Jurnal Teknik Industri, 20(1), 1–10.

Kurniawansyah, K., Marthiawati, N., Rohayani, H., & Nugraha, H. (2025). Pelatihan pengelolaan database menggunakan XAMPP untuk meningkatkan keterampilan mahasiswa di Universitas Muhammadiyah Jambi. Masyarakat Berkarya: Jurnal Pengabdian dan Perubahan Sosial, 2(2), 151–161.

Latif, A., & Wildah, S. K. (2025). Analisis kinerja algoritma ensemble dalam prediksi perilaku pembelian pelanggan. JATI (Jurnal Mahasiswa Teknik Informatika), 9(1), 557–563. https://doi.org/10.36040/jati.v9i1.12413

Massaro, A., Panarese, A., Giannone, D., & Galiano, A. (2021). Augmented data and XGBoost improvement for sales forecasting in the large-scale retail sector. Applied Sciences, 11(17), 1–22. https://doi.org/10.3390/app11177793

Muludin, L., Aisyah, N., Suwanita, T., Zahra, R. A., & Stinka, E. (2025). Integrasi dan optimalisasi alur kerja pengembangan website lokal menggunakan aplikasi XAMPP tools berbasis electron. OKTAL: Jurnal Ilmu Komputer dan Science, 4(5), 115–124.

Munyaka, J.-C. B., & Yadavalli, S. V. (2022). Inventory management concepts and implementations: A systematic review. The South African Journal of Industrial Engineering, 33(2), 15–36. https://doi.org/10.7166/33-2-2527

Opitasari, Natsir, F., & Marsiani, E. S. (2024). Klasifikasi diagnosis untuk penyakit kanker serviks menggunakan algoritma extreme gradient boosting (XGBoost). Jurnal Ilmiah FIFO, 16(1), 55–63. https://doi.org/10.22441/fifo.2024.v16i1.006

Rahman, M. F., & Nursyamsiah, S. (2023). Pengaruh praktik manajemen persediaan terhadap kinerja perusahaan yang dimediasi oleh pengetahuan manajemen persediaan: Studi empiris pada toko ritel di D.I. Yogyakarta. Selekta Manajemen: Jurnal Mahasiswa Bisnis & Manajemen, 2(5), 194–206.

Rodjimin, Y. B., Isnainny, & Situmorang, E. (2023). Analisis kelompok persediaan barang menggunakan FSN (fast, slow, non-moving) berdasarkan analisis turn over ratio pada gudang pabrik PT

Sasana Yudha Bhakti. Jurnal Citra Widya Edukasi, 15(1), 35–44.
Singh, D. J. (2022). Concepts of inventory and related technical terminologies: A literature review. International Journal for Research Trends and Innovation (IJRTI), 7(8), 1784–1796.
Sugiyono. (2022). Metode penelitian kuantitatif, kualitatif, dan R&D. Alfabeta.
Suriyani, N., Siregar, L. H., & Zahari. (2020). Analisis perencanaan dan pengawasan persediaan barang dagang pada CV. Sumber Indoraya. Jurnal Bisnis Net, 3(1), 62–69.
Wang, G. (2023). Sales forecast of retail commodity on the basis of LightGBM and XGBoost. In Proceedings of the 2022 International Conference on Frontiers of Finance and Information Technology (FFIT 2022) (pp. 1–9). https://doi.org/10.4108/eai.28-10-2022.2328402
Yahya, R., Wisnugroho, A. D. H., & Asrory, F. F. (2023). Perencanaan re-layout penempatan barang ownstok dengan menggunakan metode class based storage (CBS) di warehouse PT Pamapersada Nusantara Site BRCB (Binungan Blok 8). G-Tech: Jurnal Teknologi Terapan, 7(3), 816–826. https://doi.org/10.33379/gtech.v7i3.2477
Zahra, A., Aulia, S. I., Destiyani, S., Susilo, & Togatorop, Y. F. (2025). Inventory management as the key to improving the company's operational performance. Jurnal Ilmiah Ekonomi dan Manajemen, 3(3), 418–428.