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Evaluating Classification Models for Predicting Product Success in Indonesian E-Commerce

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Abstract

The intense competition within the Indonesian e-commerce landscape presents a significant challenge for sellers in forecasting product performance. This study offers a unique contribution by systematically comparing seven machine learning classification algorithms to predict product success across Indonesia's three largest platforms: Shopee, Tokopedia, and Lazada. The primary objective is to identify the most effective algorithm for predicting whether a product's sales will surpass the market median. The methodology involved aggregating and preprocessing a dataset of 3,673 product listings. Product success was defined as a binary variable based on sales volume exceeding the dataset's median. Seven models, including Logistic Regression, KNN, SVM, and tree-based ensembles like Random Forest, XGBoost, and LightGBM, were trained and optimized using a 5-fold cross-validated GridSearchCV. Evaluation was based on accuracy, ROC AUC, and F1-score. The results demonstrate a clear performance hierarchy, with tree-based ensemble models achieving superior results. Random Forest emerged as the premier model, attaining an accuracy of 83.2% and an AUC of 0.907. A subsequent feature importance analysis revealed that shop_followers and price were the most significant predictors of success. This finding has crucial practical implications, particularly for Micro, Small, and Medium Enterprises (MSMEs), by providing a data-driven framework for decision-making. The model enables them to focus resources on actionable strategies—building seller reputation and optimizing pricing—to enhance their competitiveness effectively.

Keywords : *Classification, Comparative Analysis, E-commerce, Machine Learning, Product Success Prediction, Random Forest*

1. INTRODUCTION

The proliferation of the digital economy has become a primary catalyst for economic transformation in Indonesia, with e-commerce emerging as its most significant pillar [1], [2]. This sector is experiencing exponential growth driven by increased internet penetration, widespread smartphone adoption, and a large, digitally literate population with growing purchasing power [3]. The SEA 2024 economy report indicates that Indonesia's digital economy Gross Merchandise Value (GMV) is expected to reach USD 90 billion in 2024, with e-commerce being the most significant contributor, accounting for a GMV of USD 65 billion. This growth is supported by an internet penetration rate of 74.6% at the beginning of the year, with 212 million active users. The COVID-19 pandemic further accelerated this digital shift, compelling consumers and businesses to migrate from offline to online channels, a trend that has solidified the dominance of major platforms [4]. In this highly dynamic landscape, platforms such as Shopee, Tokopedia, and Lazada have become the primary arenas for commerce, consistently attracting hundreds of millions of monthly visitors and competing fiercely for market share through aggressive marketing strategies and technological innovation [5], [6], [7].

This intense competition creates immense pressure for millions of sellers, particularly Micro, Small, and Medium Enterprises (MSMEs), which form the backbone of the Indonesian economy [8],

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[9]. For these businesses, the ability to make data-driven decisions is no longer a competitive advantage but a fundamental necessity for survival [10], [11]. One of the most critical and persistent challenges they face is the uncertainty in demand forecasting, which directly impacts inventory management. Inaccurate product sales predictions can lead to severe financial consequences; overestimation results in overstocking, which ties up capital and increases storage costs, while underestimation leads to stockouts, resulting in lost sales opportunities and decreased customer satisfaction [12], [13], [14], [15]. This challenge is exacerbated by limited resources, low digital literacy, and access to financing, which are common constraints for MSMEs in Indonesia [16]. Therefore, accurately predicting which products will succeed is crucial for optimizing operational efficiency and profitability. The Indonesian market context is also shaped by unique consumer behaviors. Studies show that consumers exhibit high price sensitivity, actively seeking promotions and discounts. However, a more fundamental factor is the crucial role of trust and social proof. A lack of trust has been identified as a significant barrier for many consumers to shop online , and in a culture where purchasing decisions are heavily influenced by recommendations and reputation, trust in the seller becomes a determining factor [17], [18].

In response to this challenge, the application of machine learning for predictive analytics in e-commerce has become an active area of research. [19] Focused on predicting product demand on Shopee by combining K-Means and KNN algorithms, reporting that this hybrid method could achieve sales prediction accuracy of up to 96%. This study contributes to optimizing demand forecasting on the Shopee platform through clustering and classification techniques. Meanwhile, other researchers [20] conducted a sentiment analysis of Shopee product reviews using Naïve Bayes and SVM algorithms. They found that SVM performed better (average accuracy of ~86.14%) than Naïve Bayes for classifying the sentiment of product reviews, highlighting the importance of understanding user perceptions through consumer feedback. In a different domain, Febima [21] Applied SVM, Random Forest, and XGBoost algorithms to predict customer churn and on-time delivery in a general e-commerce context. They reported SVM as the best algorithm with a prediction accuracy of 83.45% for churn and 68.42% for on-time delivery. The contribution of this study lies in applying classification models to analyze e-commerce customer behavior (retention and delivery), although it did not focus on a specific platform. Nevertheless, a significant knowledge gap remains. Few systematic comparative studies evaluate the performance of a broad spectrum of modern classification algorithms specifically for predicting product sales success across Indonesia's three most extensive and most competitive e-commerce platforms—Shopee, Tokopedia, and Lazada—simultaneously. Previous comparative analyses have often been limited to a few algorithms or have not addressed the Indonesian market's unique and heterogeneous data environment. This gives rise to the "Platform Effect" hypothesis: the unique characteristics of user behavior and data patterns on each platform may mean that no single algorithm is universally optimal. This effect is critical because each platform cultivates a distinct ecosystem: Shopee is known for its aggressive promotions and focus on a price-sensitive audience, Tokopedia emphasizes the empowerment of local MSMEs through hyperlocal initiatives, and Lazada leverages its robust logistics network and official brand stores. These strategic differences create unique data patterns that directly influence predictive model [22], [23], [24]. For example, the factors driving success on one platform may have a different weight or importance on another, meaning a generalized model may not achieve optimal accuracy for any single platform.

This research aims to fill this gap by conducting a comprehensive comparative analysis of seven machine learning classification algorithms: Logistic Regression, K-Nearest Neighbors (KNN), Decision Tree, Random Forest, Support Vector Machine (SVM), XGBoost, and LightGBM. The main contribution of this study is a novel problem formulation that transforms the sales prediction task from a regression problem into a more business-relevant binary classification task. We define "product success" based on whether a product's sales volume exceeds the median sales of the entire dataset,

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providing a clear and actionable metric for sellers. Using a carefully collected and preprocessed combined dataset from Shopee, Tokopedia, and Lazada, this study systematically evaluates the predictive power of each algorithm. The primary objective is to identify the most accurate and reliable model for predicting product success in the Indonesian e-commerce landscape and to investigate evidence of the "Platform Effect".

2. METHOD

This study aims to identify the best predictive model for product sales success in e-commerce. To achieve this, a comparative analysis of seven machine learning algorithms was conducted, covering linear models, distance-based models, and ensembles. The research methodology process is illustrated in Figure 1.

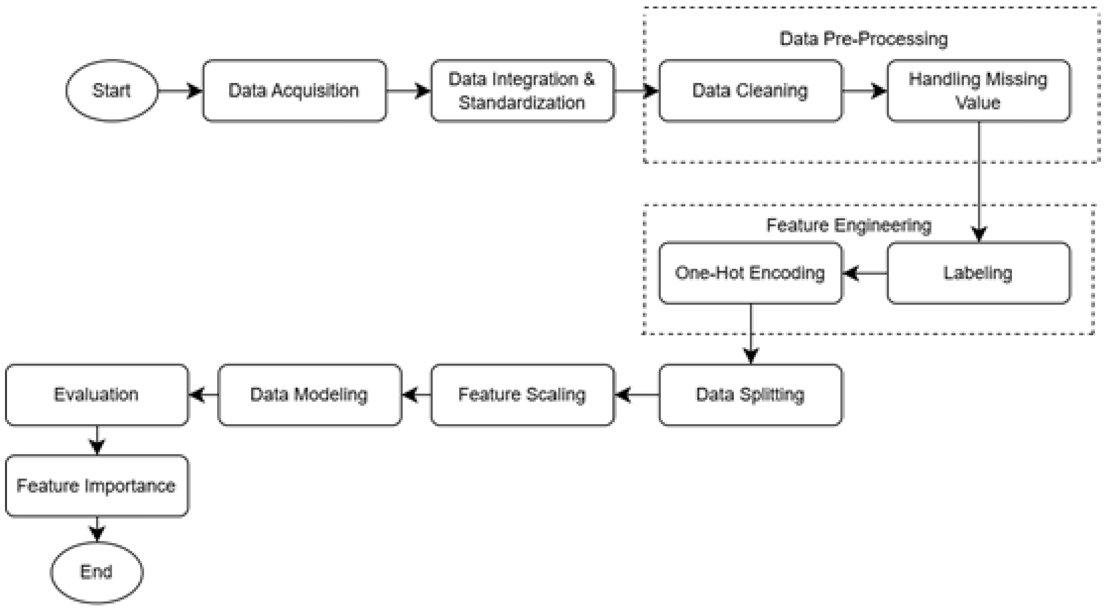

Figure 1. Research flow

2.1. Data Acquisition and Integration

Data collection in this study was performed using a scraping technique. This technique was applied to the Shopee, Tokopedia, and Lazada marketplaces to extract dynamic market data from web pages. The obtained data was combined into a single dataset and exported in CSV format.

2.2. Data Pre-Processing and Feature Engineering

This stage is crucial in converting the structured dataset into an optimal configuration conducive to modeling. The procedure includes data cleaning, handling missing values, and feature engineering. The raw data extracted from the platforms contained inconsistencies in formatting, such as textual representations for numerical values. Table 1 presents a sample of the raw data before any cleaning procedures were applied to illustrate these initial challenges.

First, data cleaning was performed to ensure uniformity of numerical formats, where attributes such as price, quantity sold, and followers were standardized from their textual representations using a series of custom-designed cleaning functions. Second, missing values were managed through an imputation methodology. For the sold column was filled with 0, a decision informed by empirical validation; a manual cross-referencing of the source web pages confirmed that missing entries corresponded directly to product listings with no sales activity, thus representing a factual state rather than an assumption, while the rating column was populated with the median value to reduce data

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distortion. This choice, being robust against outliers, provides a more accurate representation of the central tendency for such distributions, thus preserving data integrity [25].

Table 1. Data Before Cleaning

Product Name	Price	Rating	Sold	Followers
BATA COMFIT - FANNY "Anti Bacterial" Sepatu We...	Rp\n259.999	4.9	1,5RB terjual	1,1JT
NORTH STAR - SKATER BASIC "Anti Bacterial" Sep...	Rp\n159.900	4.9	10RB+ terjual	1,1JT
NORTH STAR - ESSIE "Anti Bacterial" Sepatu Sne...	Rp\n244.999	4.9	996 terjual	1,1JT
BATA COMFIT - AMANDA SLINGBACK "Comfit Cushion...	Rp\n219.999	4.9	1,3RB terjual	1,1JT
POWER - EILEEN "Cushion Mat" Sepatu Sneakers O.	Rp\n239.999	4.9	1,5RB terjual	1,1JT

After completing data cleaning, the next stage was feature engineering. A binary target variable indicating success was created through a labeling methodology, where products were categorized as 'successful' (1) or 'unsuccessful' (0) based on the sales median. Using the median as the standard for product success is a more accurate and fair choice for e-commerce sales data. This is because sales data is often skewed, with only a handful of "viral" products selling in exceptionally high volumes, while most other products sell in reasonable quantities. If the mean were used, the sales figures of viral products would significantly inflate the average, creating an unrealistically high standard for "success." Conversely, these extreme numbers do not affect the median, which is the exact middle value after all data is sorted. Therefore, the median provides a more honest representation of typical product performance and ensures that a product is judged as successful based on a fair comparison to the actual market conditions, rather than a standard biased by a few superstar products.

Finally, the categorical platform attribute was transformed using one-hot encoding to generate a numerical representation. The features used for modeling are detailed in Table 2.

Table 2. Features for modeling

Feature Name	Description	Data Type
price	Product price after cleaning	Numeric
rating	Rating product (scale 1-5)	Numeric
shop_followers	Number of shop followers	Numeric
platform_shopee	Variable binary, 1 jika Shopee, 0 jika bukan	Binary
platform_tokopedia	Variable binary, 1 jika Tokopedia, 0 jika bukan	Binary
success	Varibel target, 1 jika sukses, 0 jika tidak	Binary

2.3. Classification Algorithm

This study systematically compares seven classification algorithms, an approach predicated on the diverse and sometimes conflicting findings in the literature regarding predictive models for business and e-commerce data. A review of the literature reveals no single consensus on a superior algorithm; some studies report the superiority of Support Vector Machine (SVM) or K-Nearest Neighbors (KNN)

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in specific business contexts, while a more recent and growing consensus consistently points to tree-based ensembles (such as Random Forest, XGBoost, and LightGBM) as the state-of-the-art models for heterogeneous tabular data, such as that found in e-commerce [19], [20], [21], [26], [27] .

This contradiction is theoretically explained by the "No Free Lunch Theorem," which posits that no single algorithm is universally optimal across all problems, thus making empirical comparison within a specific domain a necessity [28]. Therefore, to address this uncertainty, our research adopts a comprehensive experimental design. We not only evaluate the recognized high-performance ensemble models but also directly compare them against classic non-linear models and interpretable baseline models like Logistic Regression and Decision Tree. This broad comparative approach is necessary to empirically validate and identify the most effective and reliable algorithm specifically for the task of predicting product success within this landscape [29].

2.3.1. Logistic Regression

Selected as the baseline model due to its computational efficiency and the clear interpretability of its coefficients. This model estimates the probability of the target class using a logistic function, assuming a linear relationship between the features and the log-odds [30].

2.3.2. K-Nearest Neighbors (KNN)

A non-parametric, instance-based algorithm that classifies a new data point based on the majority class of its 'k' nearest neighbors in the feature space. KNN was chosen for its simplicity and ability to capture complex local decision boundaries without making assumptions about the data distribution [31].

2.3.3. Decision Tree

Selected for its high interpretability, as the model resembles a human decision-making flowchart. It recursively partitions the feature space to create a set of decision rules. However, a single decision tree is prone to overfitting if its depth is not constrained [32].

2.3.4. Support Vector Machine (SVM)

Aims to find the optimal hyperplane that maximizes the margin between data classes. Using the kernel trick (e.g., Radial Basis Function or RBF), SVM can effectively model non-linear decision boundaries, making it a powerful choice for non-linearly separable data [19] .

2.3.5. Random Forest

An ensemble method that addresses the weaknesses of Decision Trees through bagging (Bootstrap Aggregating) to reduce variance. By constructing numerous decision trees on different data samples and combining their results, Random Forest often achieves high accuracy and robustness against overfitting [33].

2.3.6. XGBoost

A highly optimized and efficient implementation of gradient boosting. XGBoost builds trees sequentially, where each new tree is trained to correct the errors of the previous ones. Features such as built-in regularization, handling of missing values, and parallel processing make it a popular and high-performing choice for tabular data [34], [30].

2.3.7. LightGBM

Another variant of gradient boosting is designed for speed and efficiency, especially on large datasets. LightGBM uses a histogram-based technique to speed up the split-finding process and a leaf-wise growth strategy to achieve faster convergence, often with accuracy comparable to XGBoost.

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For model validation, the dataset was divided into 80% training data and 20% testing data using a stratified split, a standard practice to maintain class distribution and ensure an unbiased evaluation [35].

2.4. Evaluation

Each model was optimized using GridSearchCV with 5-fold cross-validation to ensure a fair comparison. Cross-validation is a standard method for reliable model performance estimation, while GridSearchCV is used for systematic hyperparameter tuning [36]. The performance of the optimized models was then evaluated on the test data using a set of standard metrics for classification tasks. This evaluation centers on the confusion matrix. The Confusion Matrix represents a critical instrument for assessing the efficacy of classification models, facilitating an examination of the model's accuracy in predicting different classes. This methodology details the allocation of correct and incorrect predictions across related categories, thus offering a more comprehensive understanding of the nature of classification errors made by the model [37], [38].

The Confusion Matrix includes four different combinations that describe classification outcomes: True Positive (TP) for correctly predicted positive data, False Positive (FP) for incorrectly predicted positive data, True Negative (TN) for correctly predicted negative data, and False Negative (FN) for incorrectly predicted negative data [39]. The performance of the classification model is evaluated based on values derived from the confusion matrix, which include Accuracy, Precision, Recall, and F1-score. The following are the formulas used to calculate these four metrics.

$$Accuracy = \frac{TP + TN}{TP+FP+TN+FN} \quad (1)$$

Accuracy is the most fundamental and commonly used evaluation metric in classification models. This metric measures the proportion of total correct predictions by comparing the number of accurate classifications (for both positive and negative classes) against the total number of tested data.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Precision is a metric that measures the accuracy of optimistic predictions made by a model. Specifically, this metric calculates the ratio of accurate optimistic predictions to the number of positive predictions made. A high precision value indicates the model has a low error rate in predicting the positive class (a low false positive rate).

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

Recall, or sensitivity, is a metric that measures a model's ability to identify all positive class samples within the data. This metric indicates how many of the total positive class samples were correctly identified by the model. The primary focus of Recall is on the model's sensitivity to minimize the number of false negatives (positive cases that were missed), making it highly relevant for cases involving the identification of minority classes.

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision \times Recall} \quad (4)$$

The F1-score is an evaluation metric that combines Precision and recall into a single value. This metric is handy when prioritizing a balanced performance between Precision and Recall. A high F1-score indicates the model has an optimal balance between Precision and Recall. Due to this capability, the F1-score is often used as the primary metric in classification problems with imbalanced data.

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3. RESULT

This section presents the empirical findings of the study, obtained from the execution of the models on 735 separate test data samples. The analysis focuses on the quantitative evaluation of model performance, the decomposition of predictive results from the best-performing model, identifying key determinants of product success, and a cross-platform performance analysis to test the Platform Effect.

3.1. Data Acquisition and Integration

The data acquisition and integration process resulted in a unified dataset consisting of 3,673 unique product entries from the three e-commerce platforms. Table 2 presents a detailed breakdown of this dataset's composition, showing the number of products successfully collected from Shopee, Tokopedia, and Lazada. This combined dataset formed the basis for all subsequent analysis.

Table 2. Initial Dataset

Platform	Number of Products
Shopee	980
Tokopedia	1807
Lazada	886
Total	3673

3.2. Data Pre-Processing and Feature Engineering

Table 3 presents a sample of the cleaned data, ready for the next feature engineering steps. A key step in this process was the creation of the binary target variable, success, which was engineered using a sales median of 1,000 units as the threshold. This resulted in a nearly balanced class distribution, with 51.5% of products classified as 'unsuccessful' (0) and 48.5% as 'successful' (1). This balanced distribution provides a robust foundation for binary classification, mitigating potential biases that can arise from severe class imbalance. The final dataset, including the engineered 'success' target variable, is illustrated in Table 4.

Table 3. Data After Cleaning

Product Name	Price	Rating	Sold	Followers
BATA COMFIT - FANNY "Anti Bacterial" Sepatu We...	259999	4.9	1500	1100000
NORTH STAR - SKATER BASIC "Anti Bacterial" Sep...	159900	4.9	10000	1100000
NORTH STAR - ESSIE "Anti Bacterial" Sepatu Sne...	244999	4.9	996	1100000
BATA COMFIT - AMANDA SLINGBACK "Comfit Cushion...	219999	4.9	1300	1100000
POWER - EILEEN "Cushion Mat" Sepatu Sneakers O.	239999	4.9	1500	1100000

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Table 4. Labeling

Product Name	Price	Rating	Sold	Followers	Success
BATA COMFIT - FANNY "Anti Bacterial" Sepatu We...	259999	4.9	1500	1100000	1
NORTH STAR - SKATER BASIC "Anti Bacterial" Sep...	159900	4.9	10000	1100000	1
NORTH STAR - ESSIE "Anti Bacterial" Sepatu Sne...	244999	4.9	996	1100000	0
BATA COMFIT - AMANDA SLINGBACK "Comfit Cushion...	219999	4.9	1300	1100000	1
POWER - EILEEN "Cushion Mat" Sepatu Sneakers O.	239999	4.9	1500	1100000	1

3.3. Classification Algorithm

A systematic assessment of the seven optimized classification algorithms revealed a clear and significant performance hierarchy, measured using a set of industry-standard metrics. The performance of each model on the 735 test data samples is presented in Table 5. The result show tree-based ensemble models (Random Forest, XGBoost, LightGBM) consistently occupied the top tier with accuracies above 82%. The second tier was occupied by distance-based and single-tree models (KNN, Decision Tree), while linear models (SVM, Logistic Regression) showed the lowest performance with accuracies below 70%.

Table 5. Classification Model Performance

Model Classifier	Accuracy	AUC	Precision (success)	Recall (success)	F1-Score (success)
Random Forest	0.832653	0.907259	0.817935	0.843137	0.830345
XGBoost	0.831293	0.902483	0.817439	0.840336	0.828729
LightGBM	0.829932	0.902687	0.816940	0.837535	0.827109
KNN	0.827211	0.889845	0.812500	0.837535	0.824828
Decision Tree	0.805442	0.860578	0.778646	0.837535	0.807018
SVM	0.680272	0.811280	0.850575	0.414566	0.557439
Logistic Regression	0.677551	0.764195	0.844828	0.411765	0.553672

The substantial performance disparities observed across the seven evaluated algorithms can be attributed to fundamental differences in their underlying assumptions and computational mechanisms. Ensemble methods (Random Forest, XGBoost, LightGBM) achieved superior performance primarily due to their inherent capability to model complex feature interactions and non-linear relationships present in e-commerce data. Random Forest's bootstrap aggregating approach creates diverse decision trees, each capturing different aspects of the feature space, which collectively provide robust predictions against the noise and outliers commonly encountered in web-scraped data. The ensemble's ability to model interactions between features such as price and shop_followers—where premium pricing becomes acceptable only when supported by high seller reputation—demonstrates its suitability for capturing the nuanced relationships in e-commerce success prediction [40].

Conversely, linear models (Logistic Regression and SVM) exhibited significantly lower performance due to their fundamental assumption of linear separability between classes. E-commerce

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data rarely exhibits simple linear relationships; for instance, the relationship between price and sales success follows a non-monotonic pattern where both extremely low and high prices can negatively impact success through different mechanisms—quality perception and affordability, respectively. The K-Nearest Neighbors algorithm, while capable of capturing local patterns, struggled with the high-dimensional feature space and the varying importance of different features, resulting in suboptimal decision boundaries. These algorithmic characteristics explain the clear performance hierarchy observed, with tree-based ensembles consistently outperforming traditional approaches across all evaluation metrics [41].

The superior performance of these ensemble models aligns with recent research indicating that ensemble learning methods are effective for sales prediction in e-commerce. This advantage stems from their inherent ability to model complex non-linear relationships between features (e.g., price, rating, followers) and sales success and their robustness against overfitting [42]. Conversely, linear models like Logistic Regression and SVM demonstrated significantly lower performance. These models assume a linear relationship between variables. This assumption does not hold for dynamic e-commerce data, rendering a linear decision boundary insufficient to separate successful and unsuccessful products in this feature space.

The assessment of each classifier, as depicted in Table 3, was conducted using a uniform set of training parameters after a systematic hyperparameter optimization process using GridSearchCV with 5-fold cross-validation [27].

3.4. Evaluation

A deeper analysis was conducted on the premier-performing model, Random Forest, to understand its predictive behavior and test the "Platform Effect" hypothesis.

3.4.1. Performance Analysis

A diagnostic analysis was conducted using a confusion matrix to measure the performance of the Random Forest model. This matrix provides a detailed decomposition of the model's performance on the 735 test data samples, outlining the types of errors made and their business implications.

Based on the confusion matrix in Figure 2, the model's performance in classifying products into 'successful' (positive) and 'unsuccessful' (negative) categories can be evaluated in detail. The model correctly identified 311 products as 'unsuccessful' (True Negatives) and 301 as 'successful' (True Positives). However, two types of errors occurred. First, 67 unsuccessful products were incorrectly predicted as successful (False Positives). Second, 56 successful products were incorrectly predicted as unsuccessful (False Negatives). The slightly higher number of False Positives (67) compared to False Negatives (56) indicates a minor tendency for the model to be more optimistic in predicting success [34].

In the e-commerce business, these two types of errors have asymmetric costs. A False Positive (FP) represents an efficiency loss. When the model predicts a product will be successful when it is not, sellers may ineffectively allocate marketing budgets, order excess inventory leading to high storage costs (overstocking), and tie up capital in unsold products. Conversely, a False Negative (FN) represents an opportunity loss. When the model fails to identify a potentially successful product, sellers lose potential revenue, face the risk of stockouts that disappoint customers, and may lose market share to competitors who stock the product.

The slightly higher number of False Positives (67) compared to False Negatives (56) indicates a minor tendency for the model to be more optimistic in predicting success [34]. This balance is reflected in the high F1-Score (0.8303), which shows a good harmony between Precision (the ability to not mislabel a failed product as successful) and Recall (the ability to identify all truly successful products).

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This balance makes the model highly reliable for business applications that demand a balance between not missing sales opportunities (minimizing FN) and not wasting resources (minimizing FP).

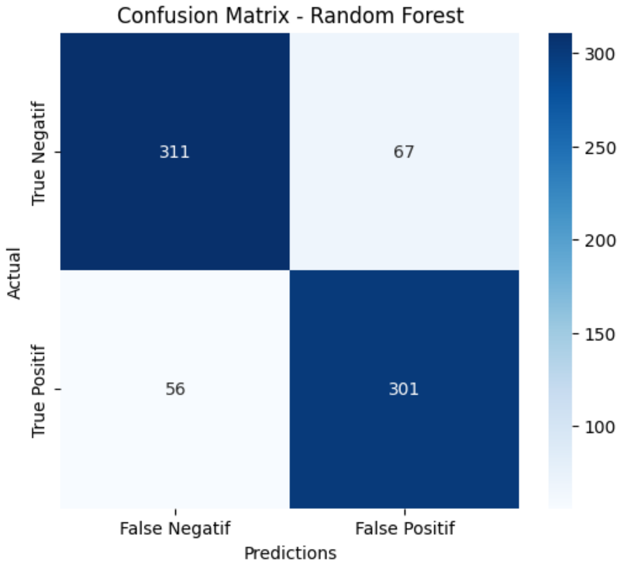

Figure 2. Confusion Matrix

3.4.2. Feature Importance

The analysis of feature importance aims to enhance model interpretability (explainable AI), providing sellers with insights to improve their strategiesc[43]. The importance of each feature was calculated based on the Gini Impurity metric, which measures the feature's contribution to increasing node purity during model construction [33].

Table 6. Feature Importance

Feature	Score
shop_followers	0.393457
price	0.363480
platform_shopee	0.119696
rating	0.075786
platform_tokopedia	0.047582

The data in Table 6 shows that shop_followers is the most dominant predictor (39.3%). This confirms that seller reputation, represented by the follower base, is a strong proxy for consumer trust in the digital market. This finding is consistent with recent studies that identify seller reputation as a key factor influencing purchase intention and customer trust in the Indonesian digital market [47]. This is highly relevant given the characteristics of Indonesian consumers, who tend to be collective, risk-averse, and heavily reliant on social proof before making a purchase [48]. Studies show that trust is a key factor influencing purchase intention in Indonesian e-commerce, and reputation is the primary mechanism for building that trust. A high number of followers serves as a strong reputational signal, and a form of social proof assures potential buyers that many others trust the seller. The hierarchy of feature importance is visualized in Figure 3.

The second predictor, price sensitivity, is represented by the price feature, ranked second with a score of 0.363. This provides strong quantitative evidence of the Indonesian market's high price sensitivity, where consumers actively seek the best value, discounts, and promotions. Other predictors

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include rating and platform. The platform variable, particularly platform_shopee (score 0.120), shows greater predictive power than platform_tokopedia (score 0.048). The rating feature (score 0.076) also contributes, although its influence is significantly lower than reputation and price. This hierarchy implies that other factors have secondary predictive power in this model after accounting for seller reputation and price.

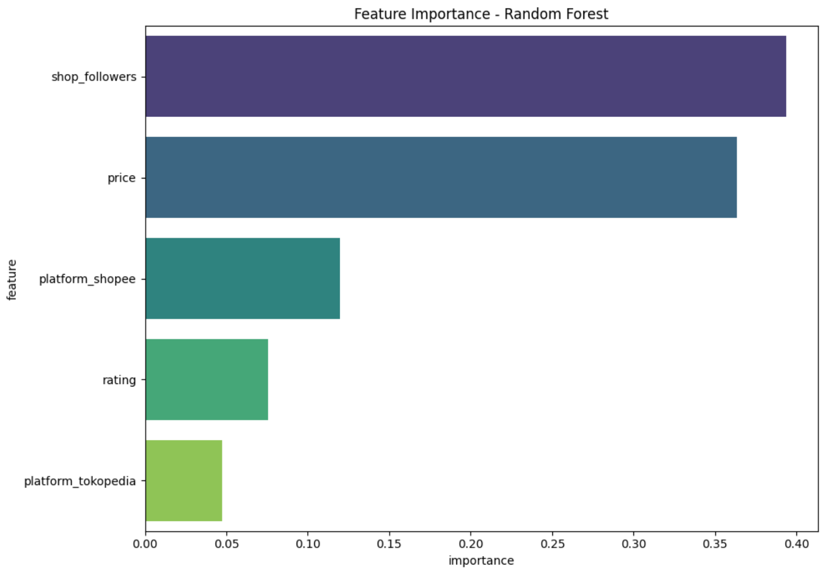

Figure 3. Feature Importance

These findings have direct practical implications for business strategies, particularly for MSMEs seeking to improve performance in competitive online marketplaces. First, the strong influence of shop_followers aligns with evidence that seller or marketplace reputation significantly enhances consumer trust and loyalty in Indonesian e-commerce. Second, the high predictive value of price reflects documented price sensitivity among Indonesian consumers, especially in student and fast-fashion segments [44]. Therefore, sellers can optimize success rates by employing data-driven pricing strategies — such as promotions, bundling, and dynamic pricing — strategies widely recognized for influencing consumer decisions in Indonesia [45].

3.4.3. Platform Performance

To test the Platform Effect hypothesis, the performance of the Random Forest model was evaluated separately on the test data subset for each platform. The results, presented in Table 7, reveal an interesting performance pattern.

Table 7. Accuracy by Platform

Platform	Accuracy
Shopee	0.8492
Tokopedia	0.8447
Lazada	0.7937

The model achieved very high and nearly identical accuracy on the two largest platforms in Indonesia, Shopee (84.92%) and Tokopedia (84.47%). This strong and consistent performance indicates that the model generalizes well between these two dominant platforms, which command most of the

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Indonesian e-commerce market share [46]. It also implies that the identified success factors, primarily shop_followers and price, have a similar and strong influence in both market ecosystems.

Conversely, the model's accuracy experienced a noticeable decline on the Lazada platform, reaching only 79.37%. This decrease is very likely due to the data imbalance in the combined dataset, where Lazada had the fewest samples (886 rows) compared to Tokopedia (1807 rows) and Shopee (980 rows). This inadequate data representation could lead to suboptimal generalization, where the model fails to capture particular patterns in the smaller data subset. This result indicates that while fundamental business principles are general, the unique characteristics of smaller-scale platforms may require a more substantial volume of data to be modeled with comparable accuracy.

4. DISCUSSIONS

This research extends beyond a mere business case analysis to offer significant contributions and address pressing challenges within the fields of informatics and computer science. Its importance is fourfold: First, it provides a definitive empirical benchmark for the state-of-the-art in predictive modeling on heterogeneous tabular data, a ubiquitous data format where tree-based ensembles continue to challenge more complex deep learning paradigms [26]. Second, it serves as a practical, real-world case study in applied Explainable AI (XAI), demonstrating how feature importance techniques can deconstruct "black-box" models to produce transparent and actionable strategic insights—a critical hurdle for industry adoption. Third, the "Platform Effect" identified in the results offers a compelling, non-simulated example of the non-Independent and Identically Distributed (non-IID) data problem, a fundamental and urgent challenge in distributed systems and federated learning. Finally, by creating an interpretable, high-performance model, this work addresses the socio-economic imperative to democratize predictive analytics, providing a tangible tool to bridge the digital divide for millions of Micro, Small, and Medium Enterprises (MSMEs) in a major emerging economy.

The comparative analysis of the seven empirically evaluated classification algorithms reveals a definitive performance hierarchy, where ensemble-based models (Random Forest, XGBoost, LightGBM) consistently demonstrate significant predictive superiority over linear models (Logistic Regression, SVM) and distance-based models (KNN). This performance gap, with ensemble model accuracies exceeding 82% while linear models remain below 70%, is not a statistical artifact but a reflection of the inherent inability of linear models to capture the complex non-linear relationships that characterize e-commerce data.

The substantial performance disparity among these algorithms can be explained by their fundamental architectural differences and how each interacts with the complex nature of e-commerce data. Linear models (Logistic Regression and SVM) performed the poorest due to their core assumption of linear separability, which is fundamentally violated by this dataset. E-commerce data is characterized by strong non-linear relationships, such as the non-monotonic link between price and success and complec feature interactions. This mismatch results in high bias, causing the models to significantly underfit the data. In contrast, the superiority of ensemble models lies in their effective management of this trade-off. Random Forest targets variance reduction: it builds numerous deep decision trees (low-bias, high-variance models) and drastically reduces the overall ensemble's variance by averaging their predictions after training them on different bootstrap samples and random feature subsets. Meanwhile, XGBoost and LightGBM employ a boosting approach focused on bias reduction: they build shallow trees (high-bias, low-variance models) sequentially, where each new tree is trained to correct the errors of the preceding ensemble, thereby aggressively reducing bias while controlling variance through built-in regularization [47].

This finding also underscores the validity of the "No Free Lunch Theorem" in applied machine learning. For instance, the relatively low performance of SVM in this study contrasts with Febima's

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report, where SVM excelled in a churn prediction task [21]. This contrast is further highlighted by other studies in the Indonesian e-commerce context where SVM was found to be the superior model for sentiment analysis of product reviews, achieving accuracies as high as 95.875%, likely because high-dimensional text data often becomes linearly separable [48]. This difference empirically demonstrates that an algorithm's optimality is highly problem-specific and dependent on the underlying data structure. Thus, the superiority of ensemble models in this research is not a universal claim, but a conclusion based on strong empirical evidence for the specific task of predicting product success in the Indonesian e-commerce landscape.

The most significant contribution of this research is the empirical validation that seller reputation, operationalized as shop_followers, is the most dominant predictor (importance score: 39.3%) of a product's commercial success. This finding goes beyond mere correlation; it provides a measurable quantitative proxy for the concept of consumer trust—a theoretically crucial but often difficult-to-measure construct, especially in the context of the Indonesian digital market. In a high-context culture like Indonesia, where purchasing decisions are heavily influenced by recommendations and social proof, many followers serve as a strong signal of trust. This aligns with research by Zahara, who identified seller reputation as a critical antecedent of trust and purchase intention. This is further supported by literature on social proof in Indonesia, which explicitly identifies the "number of followers" as a key dimension that creates a perception of good reputation and fosters consumer trust.

Besides reputation, price emerges as the second most important predictor (score: 36.3%), quantitatively confirming the hypothesis that the Indonesian market is highly price-sensitive. This finding is consistent with numerous studies indicating that promotions and competitive pricing are primary drivers of purchasing decisions on Indonesian platforms like Lazada and Shopee. Consumers actively seek value, discounts, and promotions, making a competitive pricing strategy the second fundamental pillar for sellers.

Furthermore, the cross-platform performance analysis indicates a "Platform Effect." The high and comparable accuracy of the model on Shopee (84.9%) and Tokopedia (84.5%), followed by a performance drop on Lazada (79.4%), can be attributed to two main factors. First, the data imbalance reflects the fundamental market structure. Second, and more strategically, each platform has a different focus—Shopee targets the price-sensitive mass market with aggressive promotions, Tokopedia focuses on empowering local MSMEs, and Lazada increasingly differentiates itself through the premium, brand-oriented LazMall. This divergence creates unique data ecosystems, making this study a valuable case of the non-IID data challenge. It implies that a "one-model-fits-all" approach is suboptimal and highlights the need for more advanced techniques like domain adaptation or platform-specific models in applied machine learning.

5. CONCLUSION

In this study, the researchers successfully developed and validated a series of classification models to predict product success in the highly competitive Indonesian e-commerce landscape. Using a dataset comprising 3,673 product listings from Shopee, Tokopedia, and Lazada, this research systematically compared seven machine learning algorithms to identify the most effective model. The evaluation results show that ensemble models, particularly Random Forest, exhibited the most superior predictive performance, achieving an accuracy of 83.3%. Further feature importance analysis revealed that shop_followers and price are the two most dominant predictors, quantitatively confirming the importance of seller reputation and price sensitivity in the Indonesian market.

The main contribution of this research lies in the empirical validation that seller reputation, quantified by the number of followers, serves as the strongest proxy for consumer trust and commercial success potential. This finding offers a data-driven strategic framework for sellers, emphasizing the importance of building a measurable reputation and implementing competitive pricing strategies to enhance success opportunities. Additionally, this study provides evidence of a "Platform Effect," where model performance varies across platforms, highlighting the challenges posed by data heterogeneity in e-commerce modeling.

The specific contribution of this research is particularly impactful for Micro, Small, and Medium Enterprises (MSMEs), which often operate with limited resources and digital literacy. By empirically validating that seller reputation (shop_followers) and price are the most dominant predictors, this study provides a simple yet powerful strategic framework. Instead of complex and costly marketing campaigns, MSMEs can focus their efforts on two actionable pillars, first building a measurable reputation through excellent customer service to enhance trust and social proof, which is their most powerful predictive asset , and second implementing competitive and agile pricing strategies using platform promotional tools. This method directly empowers MSMEs to compete more effectively by translating data-driven insights into low-cost, high-impact actions.

Nevertheless, this study has several limitations, including using cross-sectional data, which restricts the drawing of causal conclusions, and the potential for omitted variable bias. Although shop_followers proved to be a strong quantitative proxy for consumer trust in this model, it must be acknowledged that this metric can be manipulated through the purchase of fake followers. Future research should explore more robust and difficult-to-manipulate reputation metrics, such as sentiment analysis of reviews or seller response speed, to build a more resilient model .For future research, several promising directions are recommended to build more robust models. First, future work should leverage larger and richer datasets, including longitudinal data to track product performance over time, enabling dynamic trend analysis and a shift toward causal inference. Second, integrating external variables—such as macroeconomic indicators (e.g., inflation) and commercial event markers (e.g., Harbolnas)—would create more context-aware models that can adapt to broader market dynamics. Finally, incorporating unstructured data would greatly enhance predictive accuracy by applying sentiment analysis on product reviews to capture a more nuanced measure of quality and using computer vision techniques to analyze visual attributes from product images.

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