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Predictive Modeling of Delivery Delays in Transportation Using Machine Learning: A Comparative Study of Service Types

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Abstract: Traditional predictive models such as linear regression often struggle to capture the nonlinear interactions among operational factors that cause delivery delays in multi-category courier services. This study addresses that gap by developing and comparing machine learning (ML) algorithms to predict delivery delays across different service types at PT Pos Indonesia. The primary objective is to identify the most accurate predictive model and the dominant variables influencing delays across high-speed (Same Day, Next Day) and economical delivery services. A quantitative experimental design was employed using operational data from PT Pos Indonesia, consisting of 10,999 records and 12 variables. Three ML algorithms Logistic Regression, Random Forest, and XGBoost were trained and evaluated using standardized preprocessing, feature encoding, and stratified data splitting. Results show that Random Forest and XGBoost outperform Logistic Regression, each achieving approximately 65% accuracy with an AUC of 0.73, indicating moderate yet consistent predictive capabilities. Feature importance analysis reveals that *Discount_offered*, *Weight_in_gms*, and *Prior_purchases* are the most influential predictors of delivery timeliness.This study provides theoretical and practical contributions by introducing the first comparative ML framework for delay prediction in a national logistics context. The findings offer actionable insights for optimizing scheduling, load balancing, and promotional strategies, while advancing the integration of AI-based predictive analytics within postal logistics operations.

Keywords: Machine learning, Delivery delay prediction, Logistics performance, Random Forest, XGBoost

INTRODUCTION

The rapid growth of e-commerce and the rising expectations of consumers have triggered a global phenomenon characterized by an increasing demand for time-sensitive deliveries. Amid these challenges, logistics companies are required to ensure on-time delivery as a means to attract and retain customers. Delivery delays not only undermine customer satisfaction but also negatively affect operational efficiency and corporate reputation (Zhang, 2024). In an increasingly competitive market, such delays can escalate operational costs and erode long-term customer relationships, ultimately threatening business sustainability.

To address these challenges, previous studies have shown that disruptions in delivery services often lead to a decline in consumer trust (Pan et al., 2021). In response, logistics providers are increasingly striving to streamline their delivery processes while enhancing service reliability. One of the most promising solutions involves the use of predictive modeling techniques based on machine learning. By applying these methods, companies can more accurately predict potential delivery delays and take preventive actions in advance. This approach continuously evolving with advancements in artificial intelligence offers substantial potential to manage the complexities of delivery scheduling, particularly in multi-service logistics operations.

In Indonesia, PT Pos Indonesia faces significant operational challenges as a multi-category logistics service provider offering a wide range of services, including Pos Same Day, Pos Next Day, Pos Regular, Pos Kargo, and Pos Ekonomi. The company operates within an intensely competitive industry, where numerous courier providers compete to capture segments of a rapidly expanding logistics market driven by accelerating digitalization (Kusrini et al., 2020). Within this context, PT Pos Indonesia must consistently enhance the reliability and speed of its services to meet growing customer expectations. Recent empirical data indicate that the company faces a high risk of delivery delays, influenced by dynamic factors such as adverse weather conditions, heavy traffic congestion, and inefficient route management (Yaseen et al., 2020).

This situation underscores the importance of innovation in corporate operational strategies, particularly through the utilization of data analytics to enhance the accuracy and reliability of delivery scheduling. Innovative approaches in logistics especially those leveraging advanced analytics are vital for adapting to unpredictable internal and external conditions that affect delivery performance (Syafrianita et al., 2025; Jefroy et al., 2022). Considering the multiple factors that significantly influence delivery efficiency, the adoption of technology-driven solutions capable of forecasting potential delays has become increasingly urgent (Liu, 2024). The integration of such technologies is expected not only to improve operational efficiency but also to strengthen PT Pos Indonesia's competitiveness within an increasingly complex and dynamic logistics market (Chen et al., 2024).

In the field of predictive modeling for logistics, many prior studies fail to differentiate between various categories of delivery services, resulting in overly generalized insights that overlook distinct risk patterns between service types such as same-day versus economy deliveries (Sun & Shi, 2021). Furthermore, the lack of integration between real-time operational variables (e.g., weather conditions and traffic congestion) and historical data in multi-category postal services often limits the effectiveness of predictive models. This analytical gap highlights the necessity for a more contextually adaptive approach that can capture the heterogeneity of logistics environments.

Building on these limitations, this research proposes a comparative analysis of machine learning models using a multi-domain approach that integrates operational, environmental, and historical datasets to improve logistics performance (Liu et al., 2024; Draksler et al., 2023). The study addresses the need for predictive algorithms tailored to service differences in terms of speed, capacity, and pricing (Kusrini et al., 2020), while exploring the potential of machine learning in forecasting delivery delays to enhance reliability and customer satisfaction (Zhu, 2024). By leveraging operational metrics such as departure time and delay history, the proposed model provides actionable insights that can improve the delivery mechanisms of PT Pos Indonesia and similar logistics organizations.

This study seeks to bridge the predictive gap in delivery delay estimation by conducting a comparative evaluation of machine learning algorithms across multiple service types through a multi-domain integration framework. This approach combines operational, environmental, and historical dimensions to strengthen both predictability and logistics performance (Liu et al., 2024; Draksler et al., 2023). The study's urgency lies in the need for customized predictive algorithms aligned with variations in delivery speed, capacity, and pricing (Kusrini et al., 2020), as well as the broader potential of machine learning to optimize adaptive logistics frameworks. The application of ML has demonstrated substantial capability in predicting delays, thereby enhancing service reliability and customer satisfaction (Purnomo et al., 2024; Zhu, 2024). Moreover, the use of operational data such as departure schedules and delay records enables the generation of actionable intelligence to strengthen delivery systems at PT Pos Indonesia and comparable logistics enterprises.

Accordingly, the core issue addressed in this research lies in the limitations of traditional predictive models such as linear regression in handling the complexity and non-linearity of factors contributing to delivery delays in multi-category courier services. Conventional approaches often fail to capture the intricate interactions among operational variables such as departure time, traffic conditions, and weather variability. Moreover, no existing predictive framework differentiates the varying levels of time sensitivity across service types; for instance, Same Day delivery is far more vulnerable to adverse weather conditions than Regular services. Therefore, this study seeks to answer two key research questions: Which machine learning (ML) models demonstrate the highest accuracy in predicting delays across different service categories? And which dominant factors most influence delays in high-speed services such as Same Day and Next Day compared to more economical options?

The primary objective of this research is to develop and compare classification and regression-based machine learning models capable of predicting the likelihood of delivery delays across multiple service types offered by PT Pos Indonesia. A secondary goal is to identify the most influential predictive features such as weather conditions, transit duration, and other operational variables within each service category. This dual focus enables a more nuanced understanding of how heterogeneous operational environments influence model performance and delay prediction accuracy.

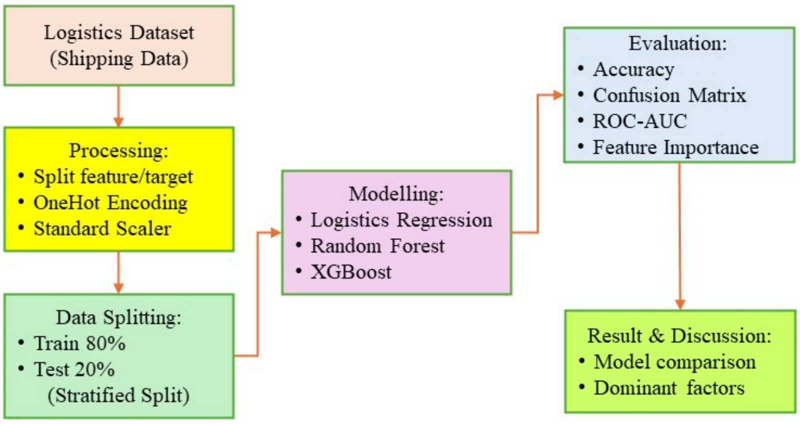
This study offers a novel contribution to the field of logistics delay prediction by introducing the first comparative approach that explicitly evaluates the performance of different machine learning models across multi-category logistics services with distinct characteristics. The use of real-world operational data from PT Pos Indonesia a national logistics enterprise whose data have not previously been analyzed in academic research provides a fresh empirical perspective on the application of ML techniques for delivery delay prediction.

The scientific contributions of this study are fourfold: (1) expanding the body of supply chain analytics literature by developing a predictive framework that incorporates service-type differentiation, (2) providing insights into the optimal deployment of ML models for distinct logistics service types, (3) identifying the dominant variables affecting delivery delays, (4) offering data-driven recommendations for service-specific risk management policies, and (5) advancing operational sustainability and logistical efficiency in alignment with the Sustainable Development Goals (SDGs) particularly by supporting waste and emission reduction through improved delivery timeliness and efficiency. Collectively, these contributions provide a solid foundation for the development of more adaptive and efficient logistics strategies in the future.

METHOD

Research Design

This study employs a quantitative experimental approach with a comparative modelling design to evaluate and compare the effectiveness of three machine learning algorithms Logistic Regression, Random Forest, and XGBoost in predicting delivery delays in the courier services of PT Pos Indonesia. Figure 1 illustrates the sequential stages of the research process, beginning with data collection and cleaning, followed by model training and evaluation. Each step is systematically structured to develop a reliable predictive model capable of identifying the most influential operational factors that affect on-time delivery performance.



Source: Authors' analysis (2025)

Figure 1. The proposed research methodology

Data Sources and Types

This study utilizes secondary data obtained from the operational systems of PT Pos Indonesia, encompassing shipment transaction records across multiple service categories, including Same Day, Next Day, Regular, Cargo, and Economy. The dataset is historical in nature and reflects the operational dynamics of parcel delivery, consisting of 10,999 observations with 12 variables, both categorical and numerical. The attributes include shipment identifiers, service types, departure and arrival times, estimated transit duration, package weight, weather conditions, distance, and route information. Collectively, these variables form the foundation for developing a comprehensive predictive model of delivery delays.

Data Preprocessing

A systematic data pre-processing phase was conducted to ensure data quality and consistency prior to model development. The target variable was defined as the delivery delay status, while the feature variables consisted of operational, geographical, and temporal factors relevant to PT Pos Indonesia's delivery activities. Categorical features such as service type, region, and weather conditions were transformed into numerical representations using One-Hot Encoding. Meanwhile, numerical features were standardized through the Standard Scaler method to ensure balanced scaling and proportional contribution of each variable to the predictive model's performance.

Data Splitting

To ensure robust model generalization on unseen data, the dataset was divided into two subsets: 80% for training and 20% for testing. A Stratified Split technique was applied to maintain proportional class distribution between on-time and delayed deliveries in both subsets. This approach ensures that the evaluation metrics accurately reflect the model's real-world performance under actual operational conditions.

Modeling

The modeling phase involved constructing and comparing three machine learning algorithms: Logistic Regression, Random Forest, and XGBoost. Logistic Regression served as the baseline model due to its simplicity and linear interpretability, providing a reference for evaluating model improvements. Random Forest was employed to capture nonlinear patterns and complex feature interactions across operational variables, while XGBoost was utilized for its superior gradient optimization and computational efficiency. All three models were trained using the training dataset and evaluated on the testing dataset to assess their accuracy, stability, and generalization capability in predicting delivery delays within PT Pos Indonesia's logistics operations.

Model Evaluation

Model evaluation was conducted to measure the predictive effectiveness of each algorithm in identifying delivery delays across PT Pos Indonesia's service categories. The performance of each model was assessed using several key metrics, including accuracy, to determine the proportion of correct predictions; the confusion matrix, to visualize class distribution and classification errors; and ROC-AUC, to evaluate the model's ability to distinguish between on-time and delayed deliveries. Additionally, feature importance analysis and SHAP (Shapley Additive explanations) values were employed to identify the most influential variables contributing to delivery delays, thereby offering deeper insights for data-driven operational decision-making.

Results and Discussion

The results and discussion focus on comparing the performance of the three machine learning algorithms to determine the most effective model for predicting delays across PT Pos Indonesia's various service types. The evaluation results revealed notable differences in accuracy and stability among the models, particularly between fast-delivery services such as Same Day and more economical services. Through feature importance and SHAP-based interpretation, the study identified the dominant factors influencing delivery delays and provided strategic recommendations for PT Pos Indonesia. These include optimizing delivery routes, enhancing resource allocation, and improving service reliability through predictive operational planning.

Tools and Computational Environment

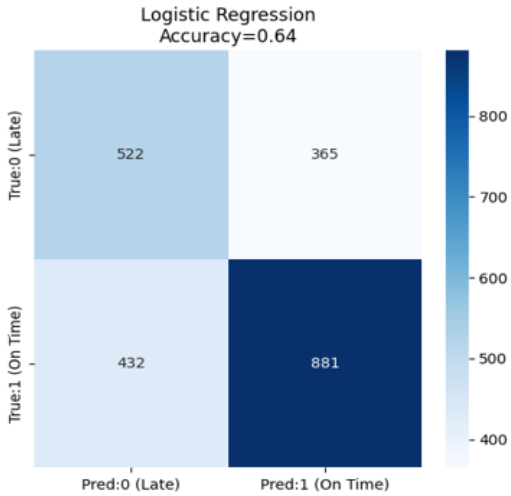
This study was implemented using Python 3.12, a widely adopted programming language for machine learning and data analytics. The analysis and modelling processes were conducted in Jupyter Notebook, supported by several key libraries: pandas for data manipulation, scikit-learn for model development and evaluation, boost for gradient boosting, matplotlib for result visualization, and shap for model interpretability. All computational tasks were executed on a laptop equipped with an Intel Core i7 processor and 16 GB of RAM, which provided sufficient capability to efficiently process a medium-sized dataset.

RESULTS AND DISCUSSION

Result

In the initial stage, the dataset was divided into features and the target variable, where Reached.on.Time_Y.N served as the target for predicting delivery punctuality. The preprocessing phase involved applying One-Hot Encoding to categorical features such as *Warehouse_block* and *Mode_of_Shipment*, while numerical features like *Cost_of_the_Product* and *Weight_in_gms* were standardized using the Standard Scaler technique. Subsequently, the dataset was split into training and testing subsets using an 80:20 ratio to ensure an objective and unbiased model evaluation process.

As illustrated in Figure 1, the Logistic Regression model achieved an accuracy of 64%, indicating its moderate ability to correctly classify most shipments as either on-time or delayed. According to the confusion matrix, the model accurately predicted 881 shipments as on-time and 522 shipments as delayed. However, it also produced a substantial number of misclassifications, including 365 false positives and 432 false negatives. These results suggest that linear models such as Logistic Regression are insufficient to capture the nonlinear relationships among operational factors influencing courier performance at PT Pos Indonesia. Consequently, more advanced and nonlinear models are required to achieve higher predictive accuracy and reliability in delay prediction.

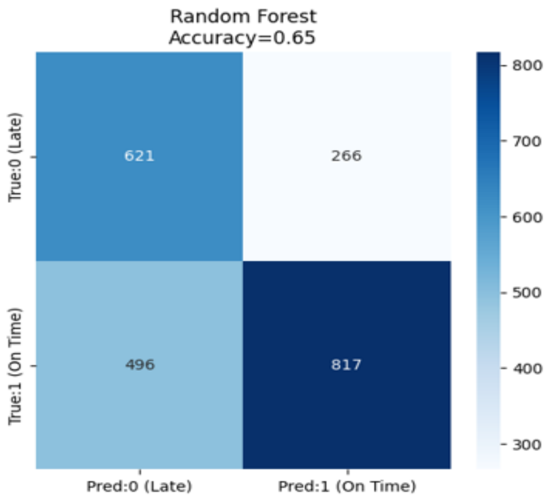


Source: Authors' analysis (2025)

Figure 2. Logistic Regression model test results

The Random Forest model demonstrated improved performance compared to Logistic Regression, achieving an accuracy of 65% (Figure 3). According to the confusion matrix, the model correctly classified 621 delayed deliveries and 817 on-time deliveries. However, it also produced 266 false positives for delayed shipments and 496 false negatives for on-time deliveries. These findings suggest that the Random Forest model's ability to capture non-linear relationships among variables such as the interaction between service type, distance, and weather enhances its predictive capability for PT Pos Indonesia. This improvement is particularly significant in identifying delivery patterns with complex operational delay risks.

Figure 4 presents the results of the XGBoost model test, which achieved an accuracy rate of 65%, indicating a fairly strong capability in predicting on-time deliveries at PT Pos Indonesia. The confusion matrix reveals that 845 deliveries were correctly classified as on time, while 593 delayed deliveries were also accurately identified. However, there were still 294 delayed shipments misclassified as on time and 468 cases of the reverse.



Source: Authors' analysis (2025)

Figure 3. Random Forest model test results

This imbalance highlights the need for further refinement of features related to delay factors, such as route conditions, load volume, and weather variability. By improving the accuracy of on-time delivery predictions, PT Pos Indonesia can optimize scheduling, resource allocation, and service strategies, making them more adaptive to the operational dynamics of daily courier activities.

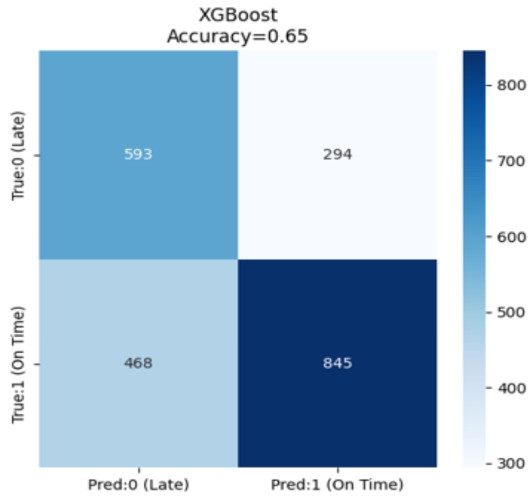


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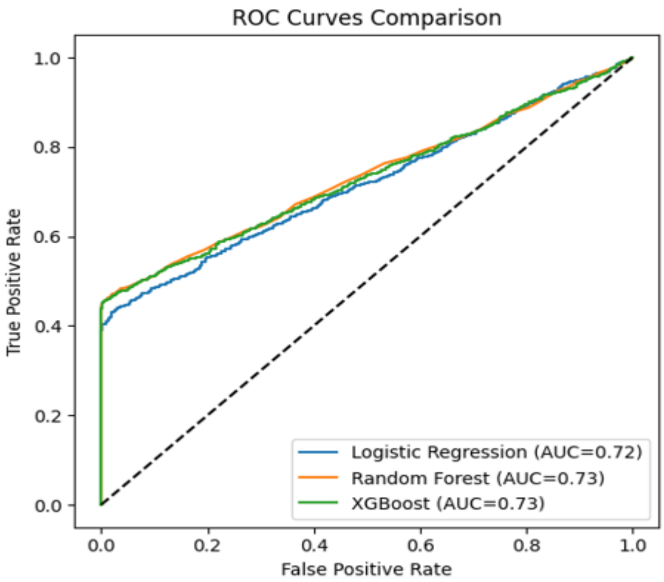
Figure 4. XGBoost model test results

The ROC Curve Comparison illustrated in Figure 5 presents the performance comparison among three classification models—Logistic Regression, Random Forest, and XGBoost—in predicting delivery timeliness. The Area Under the Curve (AUC) serves as the primary indicator of each model's ability to distinguish between on-time and delayed deliveries. The results demonstrate that both Random Forest and XGBoost achieved the highest performance with an AUC of 0.73, slightly outperforming Logistic Regression, which attained an AUC of 0.72. This marginal difference suggests that ensemble learning models are better equipped to capture the complex, non-linear relationships among features compared to simpler linear models. Overall, all three models performed above the diagonal baseline line, indicating predictive capabilities superior to random guessing. Nevertheless, for operational applications such as courier scheduling and delay prediction, XGBoost emerges as the most suitable model due to its consistent balance between true positive and false positive rates, as well as its efficiency in processing large-scale data with interacting features.



Source: Authors' analysis (2025)

Figure 5. ROC Curve Comparison Chart

Figure 6 presents the Model Accuracy Comparison, illustrating that the three algorithms—Logistic Regression, Random Forest, and XGBoost—demonstrated relatively balanced accuracy levels, ranging from 0.64 to 0.65. This indicates that all three models successfully predicted delivery timeliness with an accuracy of approximately two-thirds of the test data. For a courier service such as PT Pos Indonesia, this performance is considered promising, given the inherently complex and heterogeneous nature of delivery data. Among the models, Random Forest showed a slight advantage, highlighting its strong capability in managing nonlinear relationships and interacting features. Nevertheless, XGBoost remains an efficient alternative due to its shorter computation time and stable predictive performance, positioning it as a strong candidate for operational implementation in delivery delay prediction systems.

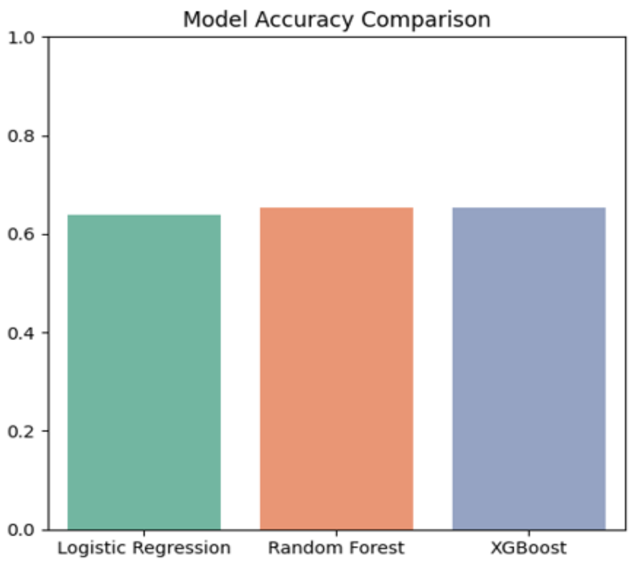


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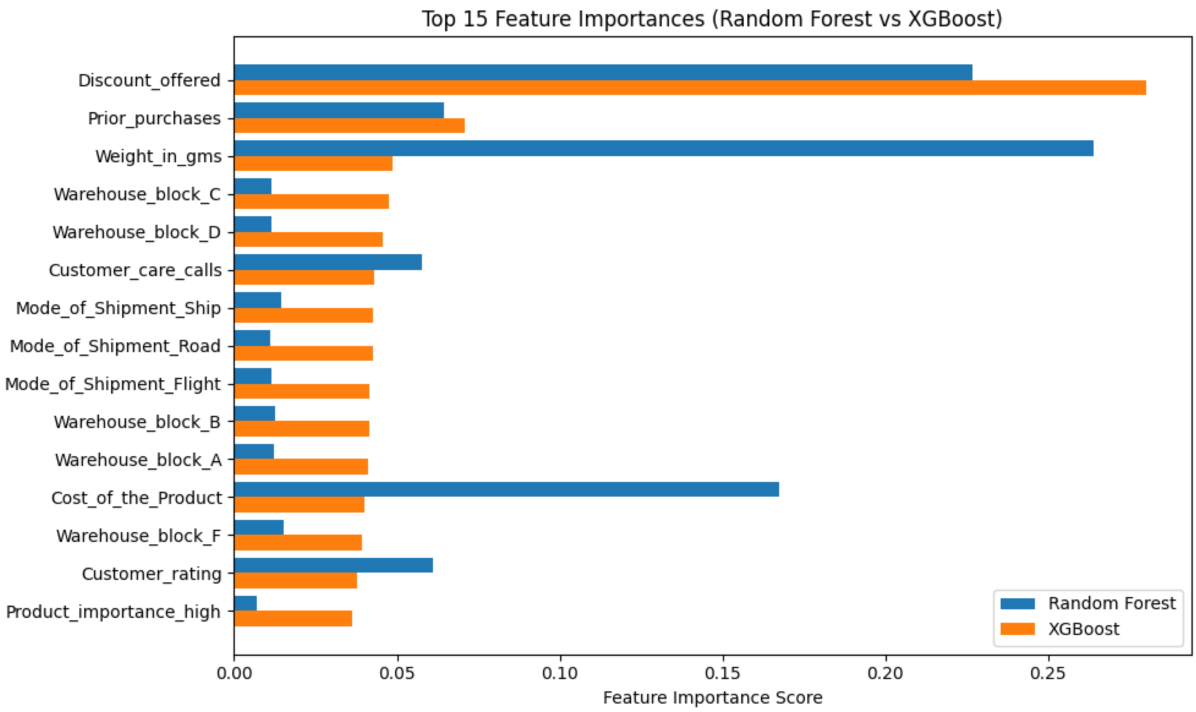
Figure 6. Model Accuracy Comparison result

The Top 15 Feature Importances (Random Forest vs. XGBoost) presented in Figure 7 reveal that the variables *Discount_offered*, *Weight_in_gms*, and *Prior_purchases* are the most influential factors affecting delivery timeliness in PT Pos Indonesia's courier service. The

XGBoost model identified *Discount_offered* as the dominant variable, indicating that higher discount levels tend to increase the likelihood of delivery delays due to surging customer demand. Meanwhile, *Weight_in_gms*, which ranks among the most important features in the Random Forest model, underscores the critical role of package weight in determining logistics processing speed. Additionally, *Cost_of_the_Product* and *Customer_care_calls* were found to have significant impacts, suggesting a linkage between product value, customer interaction intensity, and delivery performance. These findings provide practical insights for PT Pos Indonesia to optimize its operational load management and promotional strategies to maintain efficient and timely delivery performance.



Source: Authors' analysis (2025)

Figure 7. Top 15 Feature Importances (Random Forest vs XGBoost)

Discussion

Our research shows that the performance differences between Logistic Regression, Random Forest, and XGBoost are relatively small, consistent with findings by Wan et al. (2025), who observed comparable gaps among these models in predictive performance. Logistic Regression, as the baseline model, provides 64% accuracy with an ROC-AUC of 0.72. This model tends to struggle to capture non-linear relationships between variables, often misclassifying shipments that are actually "On Time" as "Late." Nevertheless, this performance is still important as a baseline because it demonstrates how linear models perform on complex logistics data (Wan et al., 2025).

Recent studies align with our findings that Random Forest (RF) and XGBoost (XGB) show only modest improvements over simpler models in terms of predictive performance. Both models achieved around 65% accuracy with ROC-AUC values near 0.73, reflecting slightly better class discrimination compared to Logistic Regression. This small improvement mirrors results from comparative analyses in domains such as rental prediction (Wan et al., 2025), ocean wave forecasting (Lasmana et al., 2025; Erutjahjo & Supriyanto, 2025), and healthcare modeling (Haider et al., 2025).

These studies consistently show that while both RF and XGB outperform linear baselines by learning non-linear relationships, their relative performances are often comparable because both are tree-based ensemble methods. XGBoost's gradient boosting approach tends to correct residual errors more efficiently, but the margin of improvement is typically small, confirming that even advanced models can struggle to extract deeper signal patterns from complex datasets. Further analysis using feature-importance techniques revealed that Discount_offered, Prior_purchases, and Weight_in_gms were the most influential predictors of on-time delivery.

This outcome is consistent with recent findings in logistics analytics, where product- and order-level features such as item weight, discount magnitude, and purchasing frequency have been shown to significantly affect delivery performance and operational reliability (Rokoss et al., 2024). Heavier items generally require more handling and transport time, while higher discounts may lead to sudden demand spikes that strain distribution capacity. Moreover, frequent prior purchases can influence fulfillment prioritization and supply chain workload (Khedr et al., 2024). Other variables, including Cost_of_the_Product, Customer_care_calls, and Warehouse_block, also contribute to delivery accuracy, though their effects are comparatively minor. Collectively, these insights underscore the importance of focusing on critical, data-driven determinants to enhance logistics performance and ensure consistent on-time delivery.

Although the accuracy and AUC remain relatively stable, a performance level of about 64–65% is still only moderate, suggesting that the model has not fully captured the complexity inherent in the data. Several factors might contribute to this limitation: the dataset may lack critical features, there may be unobserved latent variables (such as true distribution distances or real-time traffic conditions), and the current feature set may not be rich enough to represent deeper patterns. To enhance the model, further work is necessary: tuning hyperparameters of XGBoost and Random Forest more thoroughly, applying data balancing techniques when the target classes are imbalanced, and exploring stacking or other ensemble approaches to combine complementary strengths across algorithms. Ensemble stacking in particular has been shown to improve predictive performance beyond individual models, when properly designed and tuned (Kablan et al., 2023; Ravindiran et al., 2025).

Although the developed models have provided an initial understanding of on-time delivery prediction, several limitations remain that open opportunities for further research. First, the achieved accuracy level of around 64–65% indicates the need for more advanced approaches to enhance model performance. Improvement efforts can be made through deeper hyperparameter tuning, particularly for tree-based algorithms such as Random Forest and XGBoost, so that the model can capture data patterns more effectively.

Second, richer feature engineering exploration is required. New variables such as the distance between warehouse and destination, estimated travel time based on transportation mode, and external factors like weather conditions or traffic congestion could potentially improve the model's predictive power. Interaction features, such as the combination of Weight_in_gms and Mode_of_Shipment, may also yield additional insights. Third, future studies could implement data-balancing techniques such as SMOTE to address potential class imbalance between "On Time" and "Late" deliveries, which is crucial since imbalance can weaken the model's ability to identify minority cases.

Furthermore, more sophisticated ensemble approaches such as stacking or blending could be explored to integrate the strengths of both linear and non-linear models. Experiments with alternative algorithms such as LightGBM or CatBoost would also be relevant for comparison with Random Forest and XGBoost results. Finally, to improve the robustness of findings, model evaluation should be expanded using cross-validation to ensure more stable and unbiased performance across datasets. Developing a predictive dashboard as an operational tool could also be a practical direction to support real-time monitoring and decision-making for logistics companies.

CONCLUSION

This study successfully achieved its objectives by developing predictive models for delivery delays using several machine learning algorithms and identifying the most influential logistics factors. The analysis revealed that the ensemble learning approach (Voting Classifier) delivered the highest performance after applying data balancing techniques such as SMOTE and ClassWeight. Among all predictors, Discount_offered, Prior_purchases, and Weight_in_gms were found to be the most significant determinants of delivery timeliness. Accordingly, the developed model effectively captured the complex interrelationships among variables and produced stable, reliable predictions suitable for operational applications at PT Pos Indonesia.

Despite its promising outcomes, this study has several limitations, particularly the use of data from a single operational region and the exclusion of external variables such as weather conditions and traffic congestion. Future research should expand the dataset across multiple regions and incorporate real-time tracking variables to improve model generalization. Practically, the proposed model could evolve into an interactive predictive analytics dashboard that supports operational decision-making and delivery planning. At a broader level, the findings highlight the growing importance of artificial intelligence in enhancing supply chain efficiency and strengthening logistics resilience in the face of dynamic service demands.

Theoretically, this research contributes to the logistics analytics literature by demonstrating the effectiveness of ensemble learning techniques for delay prediction in courier operations. From a practical standpoint, the findings can guide logistics providers in optimizing shipment management, minimizing delay risks, and improving customer satisfaction. Moreover, the results offer valuable insights for policymakers seeking to promote digital transformation and the adoption of predictive systems across national logistics networks advancing efficiency, transparency, and service quality within the public logistics sector.

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