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Preliminary Analysis of B2B Courier Charge Accuracy Using ML

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ABSTRACT

Accurate estimation and validation of courier charges are essential because they underpin B2B logistics operations, enabling cost control, maintaining billing transparency, and building trust between logistics providers and their business clients. The pricing of courier services in extensive supply chain systems is affected by several changing factors, including shipment weight, transportation distance, service type, scheduled delivery time, and specific pricing rules established by different carriers. The differences between estimated amounts and actual billed amounts create situations that lead to revenue loss and operational inefficiency. The research paper establishes an initial examination of B2B courier charge accuracy by employing machine learning methods to create models that assess the existing variations. By analysing past shipment data, the study identifies key factors driving charge deviations and develops a predictive regression model to determine final courier charges—a Forest at Random. To improve prediction accuracy, a regressor is used to find nonlinear relationships between shipment characteristics. To identify discrepancies, the study compares predicted charges with actual billing records and evaluates model performance using standard regression metrics. The research findings are further examined through statistical summaries and graphical representations that provide useful information for decision-making. The study shows that automated systems for charge validation and cost optimisation can be developed using machine learning techniques. This study lays the groundwork for developing scalable, data-driven systems that will reduce billing disparities in B2B logistics operations and increase pricing transparency. Index Terms: Random Forest Regressor, Machine Learning, B2B Logistics, Courier Charge Prediction, and Cost Optimisation

***Keywords**:* B2B Logistics, Courier Charge Prediction, Machine Learning, Random Forest Regressor, Cost Optimisation

1. Introduction

To improve operational efficiency and lower costs, modern supply chain and logistics systems are increasingly relying on data-driven strategies. To move goods through B2B logistics networks, courier services serve as crucial links in the transportation chain. Three crucial goals are served by the entire process of estimating and verifying courier fees: cost control, delivery billing accessibility, and fostering trust between service providers and commercial clients [1] [4]. Pricing systems become more flexible as logistics networks grow because different operational factors now influence pricing decisions. Statistical regression models and predetermined pricing rules have been the mainstays of traditional logistics cost estimation techniques [1] [2]. Because they address multicollinearity issues arising from multiple features and dynamic pricing conditions, structured cost analysis methods encounter challenges. Research findings indicate that the accuracy of logistics cost forecasting improves when advanced regression techniques are combined with support vector regression models [3]. The methods face difficulties because they must deal with intricate, non-linear relationships among combinations of shipment attributes. Machine learning techniques, including ensemble-based models such as Random Forest, yield better predictive performance across different regression tasks [6] [8]. The Random Forest model successfully identifies complex non-linear connections

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while using ensemble averaging to decrease the risk of overfitting. These features enable the model to simulate how courier charges vary based on four factors: shipment weight, distance, service type, and carrier-specific policies. The present work develops an initial study of B2B courier charge accuracy through machine learning analysis. The proposed model uses historical shipment data to forecast expected courier charges, which it compares against actual billed amounts to identify discrepancies. The study applies Random Forest regression within its structured data processing pipeline to enhance B2B logistics operations by improving pricing transparency, optimising costs, and enabling data-driven decision-making.

2. Research Methodology

A. Data Preparation

Data analysis libraries were used to import the historical courier dataset into the Python environment. Managing missing values, confirming data consistency, and eliminating duplicate entries were all part of the initial preprocessing. To make them suitable for regression modelling, categorical variables such as service type and carrier were encoded as numerical values.

B. Feature Selection

Weight, distance, service type, and carrier details were among the pertinent shipment characteristics chosen as input features for model training. To ensure the selected features had significant associations with the target variable, a correlation analysis was conducted.

C. Model Development

The scikit-learn library was used to implement multiple regression models. Decision Tree Regressor, Random Forest Regressor, Support Vector Regression, and Linear Regression were all trained and assessed. To enhance performance, the Random Forest model's hyperparameters were experimentally adjusted. As per Figure 1

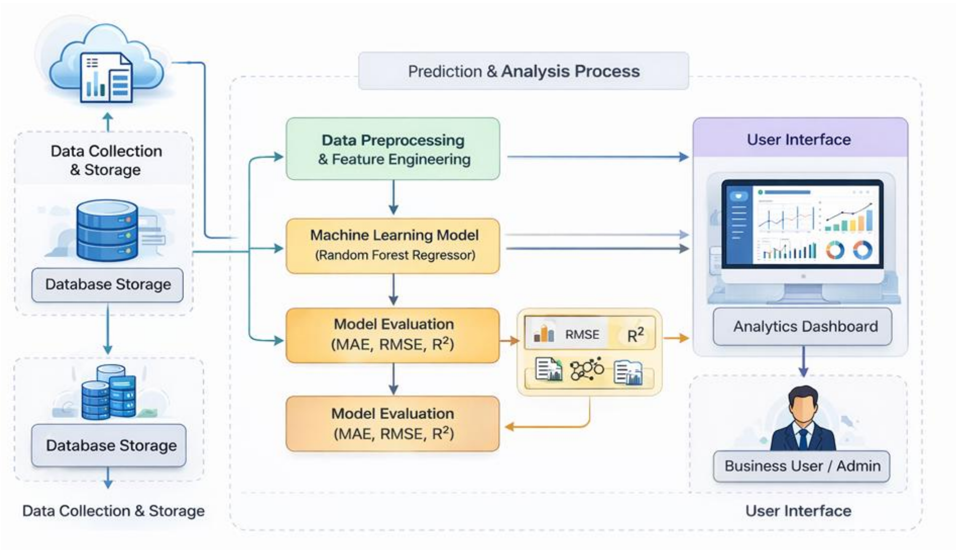

Figure 1: System Architecture of the Proposed B2B Courier Charge Prediction System

D. Model Evaluation

Performance metrics such as MAE, RMSE, and R2 were used to evaluate the trained models. To evaluate the model's accuracy, predictions were made on the test dataset and compared with the actual courier charges.

E. Visualisation and Dashboard Development

Plotting libraries were used to create graphical representations for analysing residual errors and predicting trends. To make it easier to understand courier charge variations, a straightforward analytical dashboard was created to display key metrics and comparative results.

3. Theory and Calculation

Logistics cost prediction has evolved significantly from simple statistical models to advanced machine learning techniques. Early approaches relied on linear regression and principal component regression to capture cost relationships, but these struggled with non-linear pricing patterns and dynamic market conditions. As logistics systems grew more complex, Support Vector Regression and neural networks were introduced to handle multi-factor pricing environments. However, ensemble learning methods — particularly Random Forest — emerged as more robust solutions due to their ability to capture complex feature interactions while reducing overfitting.

3.1. Dataset details:

Historical B2B courier shipment data with characteristics like shipment weight, delivery distance, service type, and carrier information were used for the experimental evaluation. An 80:20 split was used to split the dataset into training and test subsets. Several regression algorithms, such as Random Forest Regressor, Decision Tree Regressor, Support Vector Regression (SVR), and Linear Regression, were used and compared. Standard regression metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R2 score, were used to assess the model's performance.

MAE (Mean Absolute Error): $$\frac{1}{n}\sum_{i=1}^{n}|yi - \widehat{yi}|$$ **(1)**

RMSE (Root Mean Squared Error): $$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$ **(2)**

R² (Coefficient of Determination): $$1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$ **(3)**

Where:

- n= total number of samples
- y_i= actual courier charge
- $\hat{y}_i$= predicted courier charge
- $\bar{y}$= mean of actual courier charges

4. Results and Discussion

The Random Forest model proposed in this paper shows better predictive performance than the methods reported in previous logistics cost studies. Yang Jing et al. [3] showed that

Support Vector Regression outperformed linear models; however, it still had a higher error rate than the ensemble-based approach used in this study. Meanwhile, Liu Fuqiang et al. [6] have shown that Random Forest is superior to traditional regression for engineering prediction, consistent with the results of this paper. Ensemble learning frameworks in logistics pricing [13] further confirm that machine learning techniques are significantly better in prediction accuracy than static rule-based pricing models. The results of this study are consistent with these findings, but specifically address the gap in B2B courier charge validation, which has not been sufficiently explored in the existing literature as per Table: 1 and Figure 2.

Model	MAE	RMSE	R^2
Linear Regression	24.36	31.12	0.78
Support Vector Regression	19.85	25.47	0.84
Decision Tree Regressor	16.92	21.34	0.88
Random Forest Regressor	**12.47**	**17.56**	**0.92**

Table 1**:** Performance comparison of regression models

Model Output Visualisation:

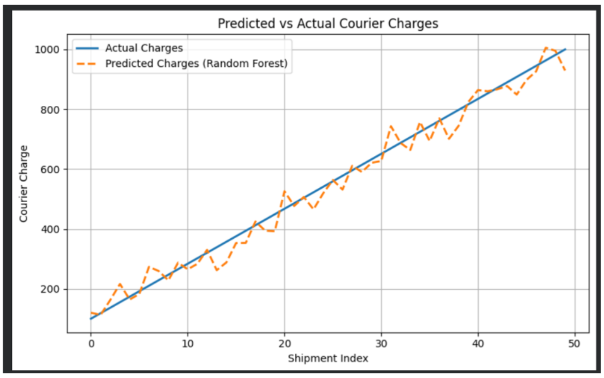

Figure 2: Comparison Between Predicted and Actual Courier Charges

5. Conclusions

The study conducted an initial evaluation of B2B courier charge accuracy using machine learning techniques. The proposed method enabled the prediction of courier charges and the detection of billing discrepancies by analysing historical shipment data, combined with key factors such as weight, distance, service type, and carrier. The Random Forest Regressor and other regression-based models enabled the effective modelling of complex B2B logistics pricing patterns. Machine learning technology enables organisations to achieve greater pricing transparency while optimising costs and making data-driven decisions. The research establishes a foundation for developing advanced courier cost prediction systems that reduce billing discrepancies in B2B logistics operations.

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Conflict of Interest

The authors declare no conflict of interest.

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